A FRAMEWORK FOR AN EARLY WARNING SYSTEM FOR THE MANAGEMENT OF THE SPREAD OF LOCUST INVASION BASED ON ARTIFICIAL INTELLIGENCE TECHNOLOGIES.

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DECLARATION

I, Brian Halubanza do hereby declare that this dissertation is my own original work and has not been submitted to any other college, institution or university other than the University of Zambia.

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APPROVAL

This dissertation, by Brian Halubanza has been approved as partial fulfilment of the requirements for the award of Doctor of Philosophy (PhD) in Computer Science by the University of Zambia.

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DEDICATION

To my family, for their support throughout this process.

ABSTRACT

As the global population continues to grow, ensuring food security remains a paramount challenge, especially in light of threats like devastating locust invasions. The agricultural sector in Zambia, particularly in the Sikaunzwe area of Kazungula district, Southern Province, faces unique challenges including inaccurate locust species identification, a lack of field staff, and the inaccessibility of infested areas. Despite advancements in AI and sensor applications for pest management, existing approaches often fail to robustly adapt to varied agronomic conditions or to integrate real-time environmental data effectively. Furthermore, these methods generally lack sufficient engagement of local communities, crucial for the sustained success of locust management strategies. This research addresses these problems by introducing a comprehensive framework that enhances early warning and management of locust invasions. The methodologies employed include Focus Group Discussions (FGDs), semi-structured questionnaires, and field experiments using a Deep Learning model embedded in Internet of Things (IoT) devices and Cloud Computing. The research is guided by the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Design Science Research Methodology, facilitating systematic development and evaluation of an AI-based early warning system. The development of mobile applications and SMS services has significantly enhanced the reach and effectiveness of locust management strategies. The research culminated in the creation and implementation of an advanced Convolutional Neural Network (CNN) model, specifically the MobileNet version 2 quantized model, tailored for automatic identification of locust species. This model achieved an average precision rate of 91% for Locusta migratoria and 85% for Nomadacris septemfasciata using a custom dataset of 1700 images from the study area. Beyond AI-driven identification, the research integrated low-cost IoT devices capable of capturing real-time locust images and uploading them to an online database only if they met an 80% accuracy threshold, while also collecting vital environmental data like temperature and humidity. This integration of AI, IoT, and real-time data collection represents a transformative approach to integrated locust pest management, setting a scalable model for future adoption in similar agricultural contexts. The framework not only addresses immediate locust management challenges but also enhances the broader path of technological progress in agriculture.

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LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
AML	-	African Migratory Locust
CNN	-	Convolution Neural Network
DHT22	-	Digital Humidity and Temperature Sensor
GIS	-	Geographic Information System
GPRS	-	General Packet Radio Service
GPS	-	Global Positioning System
HDMI	-	High-Definition Multimedia Interface
IoT	-	Internet of Things
OpenCV	-	Open Source Computer Vision Library
OS	-	Open Source
SD card	-	Secure Digital card
SIM	-	Subscriber Identity Module
USB	-	Universal Serial Bus
UTAUT	-	The Unified Theory of Acceptance and Use of Technology
WSN	-	Wireless Sensor Network

CHAPTER 1: INTRODUCTION

1.0 Background

Locusts, under the family Acrididae, are short-horned grasshoppers that have been the bane of agriculture and a symbol of ecological disruption for millennia [1], [2]. These creatures are not just simple insects; they possess an ability for significant phenotypic plasticity, allowing them to shift between two primary behavioural phases: solitary and gregarious [3],[4], [5]. Their solitary state transforms dramatically under specific climatic conditions. Propelled by favourable environmental conditions, locusts band together, forming colossal swarms that traverse vast distances, leaving desolation in their wake. This dramatic change, distinguished by marked morphological, physiological, and behavioural shifts, is what sets locusts apart from their more placid grasshopper counterparts. It's this ability to swarm, magnifying their potential for ecological and agricultural havoc, that has made them a subject of intense study and concern.

The complexity of locusts extends to their taxonomy. Numerous species like the African migratory locust (*Locusta migratoria migratorioides*), Brown locust (*Locustana pardalina*), Red locust (*Nomadacris septemfasciata*), and Desert locust (*Schistocerca gragaria*) exist, each with its own set of ecological patterns and behavioural tendencies.

Locusts, a subgroup of grasshoppers, are infamous for their swarm-forming behavior that leads to extensive destruction of vegetation and crops [6], [7]. These pests have profound socioeconomic impacts, particularly in agricultural regions critical for food security and economic stability [8],[9], [10], [11]. The devastation caused by locust swarms can drastically reduce crop yields and even result in complete crop failures. For instance, a single square kilometer swarm of desert locusts can consume an amount of food in one day that would suffice for 35,000 people [8],[9], [10], leading to severe implications for food availability, especially in areas already susceptible to food shortages [10].

Research highlights significant historical locust infestations, such as the 2003 outbreak in Ethiopia, which led to a 70% drop in cereal production, causing widespread food scarcity and elevated malnutrition rates [12]. In Mauritania during 2004, locusts reduced cereal production by 30%, triggering food shortages and inflation [13]. These invasions severely affect the livelihoods of those reliant on agriculture. For example, in Yemen (2003), locusts caused considerable financial losses to farmers due to crop failures, resulting in decreased incomes [14]. A similar situation occurred in Mali in 2004, where locusts diminished farmers' earnings and heightened poverty and food insecurity [15].

Locust plagues also adversely affect national economies, particularly those dependent on agricultural exports. A notable case was the 2013 locust outbreak in Madagascar, which sharply decreased rice production and had a significant economic impact [16]. Additionally, a 2004 outbreak in West Africa led to reduced cereal production, lower exports, and losses in foreign exchange [17]. Beyond economic impacts, locusts pose health risks; individuals in Sudan exposed to locusts reported respiratory issues, skin allergies, and eye irritations [18], and similar health effects were observed in Ethiopia [19].

1.2 Importance of locust knowledge

Understanding locust dynamics is crucial for the effective prevention and mitigation of their impact on agriculture and livelihoods. Recognizing the types of locusts prevalent in an area, identifying their indicators, and managing their presence are essential for the development of early warning systems, readiness, and proactive measures. Reference [20] underscores the role of satellite technology in providing early warnings for locust invasions in West Africa, highlighting the necessity of grasping locust behaviors for apt responses. Similarly, research noted in [21] explores the perceptions and management techniques of desert locusts among rural communities in Pakistan, underlining the value of local insights and approaches in crafting effective management strategies. Additionally, [22] investigates existing management tactics and the needs for improving locust and grasshopper control in West Africa, pointing out the critical need for enhancing capacities and disseminating knowledge.

A report by the Food and Agriculture Organization (FAO) describes how locust outbreaks severely affect crops and livelihoods, especially in developing regions where agriculture plays a pivotal economic role. The report advocates for robust early warning systems, continuous monitoring, and effective control actions to equip farmers against locust threats [23]. Research published in Agriculture, Ecosystems & Environment by scholars from Ethiopia and Kenya illustrates that locust invasions can lead to substantial agricultural losses, potentially triggering food scarcity and famine in impacted locales. The study emphasizes the significance of local monitoring and early warning frameworks in assisting farmers to prepare and tackle locust invasions [24]. Furthermore, a study by the International Centre for Insect Physiology and Ecology (ICIPE) underscores the importance of indigenous knowledge in locust management. It notes that local farmers have developed various indigenous strategies, such as utilizing natural plant repellents or smoke to disperse swarms, which could enhance the effectiveness and sustainability of management programs [25].

This research aims to investigate how digital tools can augment early warning systems and response strategies in the Sikaunzwe agricultural camp in Kazungula district, located in Zambia's Southern Province. By focusing on these objectives, the study seeks to forge potent strategies and interventions for locust management in the Sikaunzwe camp, ultimately bolstering the community's resilience against the detrimental impacts of locust plagues on their agricultural livelihoods.

1.2.1 The African Migratory Locust (Locusta migratoria migratorioides)

The African Migratory Locust, scientifically referred to as Locusta migratoria migratorioides, is a species that has earned its reputation as one of the most consequential locust species in sub-Saharan Africa. Belonging to the Acrididae family, this locust species has displayed characteristics that have fascinated entomologists, ecologists, and farmers for centuries. It is a creature that has, on one hand, bewildered humans with its immense migratory swarms, and on the other, has been the cause of agricultural nightmares due to its potential for large-scale devastation. As mentioned in the study by [23], the African Migratory Locust has primary breeding grounds along the lush, verdant floodplains of the Niger River in West Africa [26]. This geographical location is no coincidence. The conditions here provide the perfect ambiance for the locusts to breed, with an abundant food supply and the ideal moisture levels for their lifecycle.

The lifecycle of this locust species is intriguing, complex, and is characterized by distinct stages of growth and behavior.

Egg Stage: The lifecycle begins when the female locusts lay their eggs in moist soil terrains. They seek terrains such as rain-soaked areas, recently flooded zones, and pastures that have been regularly tread upon by cattle. These areas provide the right moisture level, making it conducive for the eggs to develop without desiccation. Moreover, these conditions offer a level of protection from predators. The egg-laying habits vary between the two behavioural phases of the locusts, solitary and gregarious. Solitary females, which are usually not in swarm mode, deposit larger egg pods, ensuring that their genetic material is well represented in the subsequent generation. Gregarious females, typically found in the more active and often destructive swarming phase, lay eggs more frequently, albeit in smaller quantities. Every single egg is enveloped in a protective foam. This foam acts like an incubator, offering the egg warmth, moisture, and protection.

Nymph Stage: After a relatively short incubation period, the egg gives rise to the nymph. These nymphs are initially wingless and resemble miniature adult locusts. This stage is characterized by voracious feeding. Their primary goal is to eat, grow, and moult. Nymphs will consume a vast array of vegetation, often causing significant damage to crops and pastures. Nymphs undergo multiple moulting stages. Each moult allows them to grow, and with each successive moult, they shed their exoskeleton, giving way to a larger one fitting their new size. This process is known as 'ecdysis.' There are usually five moults before they transition into the final adult stage. Each of these intermediate stages between moults is referred to as an 'instar.' With every instar, the nymphs come closer to their adult form, with noticeable changes in size, coloration, and the development of wing pads.

Adult Stage: After the final moult, the locust emerges as a winged adult. At this stage, they have the capability to reproduce and continue the cycle. Adults can be either in the solitary or gregarious phase, and their behavior and even morphology can differ based on this phase.

The solitary adults tend to be more inconspicuous, usually avoiding large gatherings and refraining from long-distance migrations. Gregarious adults, however, band together to form swarms. These swarms can be immense, covering large areas and comprising millions, if not billions, of individual locusts.

Understanding the growth stages of the African Migratory Locust is crucial for various reasons. For farmers and agriculturists, knowledge of these stages can help devise strategies to combat and manage locust infestations. The vulnerability of locusts differs at each stage. For instance, while the eggs and early nymph stages can be targeted with specific biopesticides, adult locusts may require different strategies, such as the use of barriers or deterrents. Additionally, for scientists and researchers, studying the intricate lifecycle stages can offer insights into insect behavior, metamorphosis, and even broader ecological patterns and interactions. Figure 1 shows an image of an AML Solitary Locust while figure 2 depicts the image of a gregarious AML locust.

Figure 1:Solitary AML

Figure 2:Gregarious AML

1.2.2 Red Locust (Nomadacris septemfasciata)

The Red Locust, scientifically identified as Nomadacris septemfasciata, resides primarily within the African savannah ecosystems. While it shares certain ecological and behavioural parallels with the African Migratory Locust, the Red Locust has its own unique set of attributes that define its interaction with its environment. The African Savannah's ecosystems are periodically disrupted by the presence of the Red Locust. With a life cycle echoing complexities akin to the African Migratory Locust, it too undergoes distinct stages, morphing from eggs to nymphs, and eventually mature adults equipped for flight and reproduction [27].

The journey of a Red Locust, like many other orthopterans, is partitioned into well-defined growth stages as follows:

Egg Stage: Female Red Locusts, equipped with a specialized ovipositor, pierce the soil's upper layers to deposit their eggs. These eggs, encased in a foamy protective substance, are typically laid in pods, ensuring a modicum of safety against predators and environmental factors. The protective foam plays an essential role, serving as an adhesive substance that binds soil particles, creating an armour of sorts for these developing embryos.

Nymph Stage: Following an incubation period, these eggs give rise to nymphs. Resembling miniature adults, these nymphs, however, lack functional wings. This stage is particularly fascinating, as the nymphs undergo a series of moulting processes. With each moult, they shed their exoskeleton, paving the way for growth. As they progress through these sub-stages, they inch closer to their adult form. It's during these stages that one can witness the marvel of insect development, observing the gradual formation of wing buds that eventually metamorphose into functional wings in adults.

Adult Stage: Upon completing their nymph moults, the Red Locusts emerge as fully-formed adults, boasting well-developed wings, reproductive organs, and the instinctual drive to propagate their species. These mature locusts, when conditions are ripe, embark on their swarming phase, gathering in vast numbers and covering vast distances in search of food but the real intrigue lies in their behavioural transitions.

Red Locusts exhibit remarkable adaptability in response to environmental stimuli such as population density, temperature fluctuations, and humidity variations. These triggers can prompt them to transition from a solitary lifestyle to forming vast swarms, a phenomenon studied extensively by researchers like Sword in 2005. The ideal conditions for such transformations often arise after periods of significant rainfall. This enhanced moisture promotes vegetation growth, which in turn provides ample food sources for these insects, leading to rapid population increases. As the Red Locusts experience these conditions, they undergo significant physiological and behavioural modifications. They become increasingly active and might exhibit changes in their coloration. What starts as mere aggregations of these creatures soon evolves into larger groups, which, under optimal conditions, can culminate into swarms of staggering dimensions, sometimes likened to biblical descriptions. Such vast swarms, while undoubtedly a marvel from a biological perspective, pose severe threats to agriculture. They can decimate crops, leading to heightened concerns regarding food security.

Addressing the challenges presented by these locust swarms necessitates a diverse range of solutions. These range from conventional chemical pesticides to innovative, biologically derived control agents. However, each method carries its own challenges. For instance, while chemical solutions might offer immediate relief, they can also raise sustainability issues and potentially harm non-target organisms. Mvumi and colleagues in 2018 discussed the potential repercussions of such solutions, highlighting the need for a delicate balance between immediate pest control and long-term environmental sustainability. Figure 3 shows the solitary Red Locust.

Figure 3:Red Locust (Solitary)

1.2.3 The Complexity of Locust Management

Handling locust outbreaks is no small feat. Swarming is a culmination of multifaceted factors such as ecological, genetic and environmental. Comprehensive strategies for locust control mandate an intricate understanding of these underlying determinants. In a world where climate patterns are being increasingly influenced by human activities, constant surveillance of locust populations becomes crucial. This surveillance aims not just to monitor but to predict, preparing for potential outbreaks and safeguarding agricultural outputs essential for human sustenance. Historically, locust infestations have wreaked havoc on global agriculture. The statistics are staggering; pests like locusts are responsible for a significant dent, about 30% to 40%, in global food production [4]. This menace isn't just relegated to numbers. Real-world implications of locust invasions resonate in the annals of history, from the desert locust outbreak that crippled Africa in 2003-2005, resulting in monumental crop damages.

1.3 Application of Artificial Intelligence (AI) in Locust management

Artificial Intelligence (AI) has garnered significant prominence across various domains, owing to the escalating global prevalence of locust infestations, which present considerable challenges to the agriculture sector. Notably, AI methodologies have found fruitful application in the fields of precision agriculture and pest behavior analysis, offering valuable insights and potential solutions. The incorporation of AI techniques in locust management has emerged as a viable strategy to confront the identification complexities associated with locust infestations. The utilization of AI tools in locust management holds the potential to optimize agricultural practices, streamline monitoring procedures, and ultimately enhance the overall efficacy and quality of pest control measures. There is hence a growing demand for more efficient and effective solutions to address locust invasions while minimizing associated costs. The integration of Internet of Things (IoT) technology, with its embedded sensors and cloud computing, along with deep learning methodologies, has demonstrated promise in augmenting locust management efforts through continuous and precise monitoring capabilities.

1.4 Statement of the Problem

Distinguishing between various locust species is a pivotal requirement for tailoring effective management strategies. However, the task is complicated by the morphological similarities that exist among different species, making accurate identification a demanding task. The scarcity of expert field staff specialized in locust behavior and activity is a significant obstacle to efficient locust management. In remote areas, accessing locust-infested fields is challenging, resulting in inadequate acquisition of crucial locust activity data. This lack of real-time, on-ground information hampers the ability to monitor and predict locust invasions effectively.

1.5 Aim of the Study

To develop a framework for an early warning system for the management of the spread of Locust invasion, based on Artificial Intelligence.

1.5.1 Research Objectives

The specific objectives of this research are as follows:

i. To identify challenges faced by farmers and government in controlling AML and RL invasion using existing early warning models.
ii. To explore how Artificial Intelligence and other emerging technologies such as IoT and cloud computing can be used to detect AML and RL invasion.
iii. To design an early warning system framework for AML and RL invasion based on Artificial Intelligence.
iv. To validate an early warning system framework for AML and RL Invasion.

1.5.2 Research Questions

i. What challenges are faced by farmers and government in controlling AML and RL invasion using existing early warning models?
ii. How can Artificial Intelligence and other emerging technologies such as IoT, Geospatial and cloud computing be used to detect AML and RL invasion?
iii. How can an early warning system framework for AML and RL invasion be designed based on Artificial Intelligence?
iv. How can an early warning system framework for AML and RL invasion be validated?

1.6 Significance of the Study

The proposed study assumes a pivotal role in addressing a pressing concern within the context of locust invasion management, while also aligning seamlessly with the broader aspirations articulated by the Sustainable Development Goals (SDGs). Through its multifaceted contributions, this research endeavour holds direct relevance to several key SDGs, highlighting its transformative potential. With respect to Goal 2: Zero Hunger, the innovative framework proposed by this study holds the promise to significantly mitigate the adverse impact of locust invasions on agricultural productivity. By augmenting locust monitoring and management practices, the study inherently reinforces the overarching objective of eradicating hunger, thereby bolstering food security and resilience in the face of evolving agricultural challenges.

The study's emphasis on safeguarding livelihoods, particularly among vulnerable segments such as women and children who are reliant on agricultural activities, resonates harmoniously with Goal 1: No Poverty. Effective locust management, as facilitated by this study, translates into the preservation of income-generating avenues and the improvement of economic prospects for these marginalized demographics.

The study's embrace of cutting-edge technologies, exemplified by the incorporation of IoT connectivity and cloud computing, is in direct alignment with the spirit of Goal 9: Industry, Innovation, and Infrastructure. The study not only enhances locust management practices but also contributes to the broader trajectory of technological progress, fostering innovation and advancing infrastructure.

In addressing Goal 13: Climate Action, the study's potential to mitigate locust invasions resonates with the objectives of climate resilience. By mitigating agricultural losses attributable to locust infestations, the study indirectly contributes to sustainable land use practices and the cultivation of climate-resilient ecosystems.

The study's dedicated focus on effective locust management also encapsulates the spirit of Goal 15: Life on Land. By curbing the environmental disruptions linked to locust invasions, the study aligns harmoniously with the goal of safeguarding terrestrial ecosystems, contributing to the conservation of biodiversity and the overall health of the land.

The study's interdisciplinary approach, wherein technological innovation converges with ecological management, epitomizes Goal 17: Partnerships for the Goals. By fostering collaborative synergies among diverse stakeholders, the study exemplifies the ethos of collective action for sustainable development, thereby catalysing the pursuit of transformative change on multiple fronts.

1.7 Scope of the study

The proposed study intends to conceptualize and architect an advanced early warning system tailored for efficient locust invasion management. Central to this framework is the prowess of Artificial Intelligence (AI), further augmented by synergies with emerging technological domains, namely Geospatial technology, Internet of Things (IoT), and Cloud Computing.

Kazungula district, Sikaunzwe plains in particular, located in the Southern Provinces of Zambia, is the selected validation ground for this system. This district bears significant relevance due to its pronounced susceptibility to locust invasions, as evinced by the extensive infestation episodes witnessed in December 2020 and the initial months of 2021.

A foundational step in this research involves a comprehensive baseline study. This study endeavours to garner a deep-seated understanding of the hurdles and impediments encountered by the dual stakeholders, the farming community and the governmental authorities. Their experiences and challenges, vis-à-vis the existing early warning methodologies for locust management, will be the focal point. To achieve a holistic insight, the study involved the participation of 3 agricultural extension officers with ground-level knowledge and expertise. Additionally, perspectives from a sizable group of 250 farmers was solicited, ensuring a broad-based understanding of the issues at hand.

1.8 Organization of the Dissertation

The dissertation is divided into six chapters as follows.

Chapter One: Introduction

This chapter introduces the dissertation, elaborating on the historical and relevance of managing AML and RL invasions. Beginning with the background of the study, it delves into the specific issues prompting the research. The chapter then elucidates the statement of the problem, the aim, and the pinpointed objectives. This chapter also indicates the research questions intended to guide the inquiry, followed by the study’s scope and its inherent significance.

Chapter Two: Literature Review

A rigorous exploration of existing literature forms the core of this chapter. Scholars' previous works on AML and RL invasions, as well as the potential integration of Artificial Intelligence and other emerging technologies for invasion detection and management, are critically examined. This chapter endeavours to unveil the pre-existing findings and identify discernible gaps in knowledge, thereby underscoring the dissertation's relevance.

Chapter Three: Theoretical and Conceptual Model/Frameworks

This Chapter presents an in-depth exploration of two foundational frameworks: The Unified Theory of Acceptance and Use of Technology (UTAUT) and the Design Science Research Methodology (DSRM). This chapter aims to offer a comprehensive understanding of both the UTAUT and DSRM models. The UTAUT model, a significant theoretical framework in technology acceptance, will be examined in detail. This includes its origins, key components, and how it has evolved over time to remain relevant in contemporary technology studies. The discussion will focus on how UTAUT effectively predicts user acceptance and use of technology, highlighting its various constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions. Similarly, the chapter will delve into the Design Science Research Methodology, an important approach in the field of information systems and technology. The focus will be on its principles, process models, and the guidelines it provides for conducting research. DSRM's role in bridging the gap between theory and practice in technology research will be underscored, demonstrating its utility in developing and evaluating IT artifacts.

Chapter Four: Research Methodology

The fourth chapter is dedicated to articulating the methodological underpinnings of the study. Beginning with a discussion on the research design, the chapter delves into the study population and the rationale behind its selection. Detailed discussions on the methods, techniques, and tools for data collection ensue. The chapter also expounds on the proposed analytical methods. Ethical considerations, which are paramount for maintaining the research's integrity, are also addressed in this segment.

Chapter Five: Results

Primarily, this chapter is tasked with presenting the analysed data gathered during the research phase. Interpreting the data, this chapter seeks to elucidate the insights, drawing potential correlations and causations where applicable. The discussions in this chapter are aimed at offering conclusive evidence regarding the research results, particularly the challenges faced by stakeholders in AML and RL invasions and the potential role of Artificial Intelligence in alleviating them.

Chapter Six: Discussion and Conclusions

In this chapter, the research narrative comes full circle, returning to the questions introduced at the beginning of the research. Drawing from the empirical findings, this chapter provides succinct, yet comprehensive answers to the research questions, encapsulating the core essence of the entire investigation. The focus here is twofold. Firstly, the chapter distils the salient conclusions surrounding the key objectives of the study. These span from understanding the challenges faced in managing AML and RL invasions, to the transformative role AI can play in early detection and mitigation, to the intricacies of designing an effective early warning system, and ultimately, its rigorous validation in real-world scenarios. Secondly, the chapter navigates towards the actionable frontier of the research. Using insights from the study, it presents a set of pragmatic recommendations. These recommendations are tailored to empower both the farming community and governmental bodies, equipping them with strategies and tools to bolster their defence mechanisms against the threats of AML and RL invasions. This chapter hence acts as an interpretative lens, decoding the raw findings and drawing connections to the broader implications of the study.

Objective I - Challenges in AML and RL Invasion Control: This section provides a thorough examination of the challenges unearthed during the research. Through a comparative lens, these challenges are compared against the backdrop of existing literature.

Objective II - AI’s Potential Role in Invasion Detection: A deep dive into the technological dimension of the study, this subsection dissects the capabilities of AI in detecting AML and RL invasions. The discourse weighs AI against traditional methods, emphasizing its potential advantages and breakthroughs.

Objective III - Designing an Early Warning System: Here, the focus narrows down to the design intricacies of the proposed early warning system. It critically evaluates the harmonious integration of AI with other emergent technologies such as IoT and Cloud Computing, discussing the system's feasibility, scalability, and adaptability in real-world contexts.

Objective IV - Validating the Warning System’s Efficacy: A critical examination of the validation process forms the root of this segment. Questions surrounding the system's reliability, accuracy, and responsiveness are addressed. Furthermore, any potential pitfalls or shortcomings are also brought to the forefront, painting a comprehensive picture of the system's overall efficacy. The chapter draws to a close by weaving together the threads of each objective-based discussion. It emphasizes the overarching conclusions, key takeaways, and the broader implications these findings might have on the domain of AML and RL invasion management in the foreseeable future.

1.9 Chapter Summary

The initial chapter of the dissertation, Chapter One, plays an instrumental role in setting the stage for the subsequent discourse on African Migratory Locust (AML) and Red Locust (RL) invasions. These invasions, while not new to the African landscape, have been a matter of significant concern due to their detrimental impacts on agriculture, ecology, and local economies. By charting their historical significance, the chapter paints a vivid picture of their longstanding relationship with the continent, showcasing periodic invasions that have occurred over the centuries. This chapter meticulously documents past occurrences, patterns, and frequencies of these invasions. As the chapter unravels, it becomes evident that the challenges posed by AML and RL are multifaceted. They aren’t merely restricted to the devastation of crops but extend to disrupting ecosystems, posing threats to native flora and fauna, and inflicting severe economic hardships on affected regions. The impetus for this research emerges from the evolving challenges posed by these locust invasions. With changing climate patterns, increasing human interventions in natural habitats, and other external factors, there’s a pressing need to understand these invasions better and, more importantly, devise mechanisms to manage and mitigate their adverse effects. This urgency is echoed in the chapter's clear enunciation of the problem statement. By outlining the problem, Chapter One sets forth a clear path that the research intends to tread upon, offering a roadmap for the upcoming chapters. Beyond just defining the overarching aim, the chapter further delineates this into specific objectives. These objectives serve as pillars for the entire research endeavour. They encompass understanding the current challenges in managing these invasions, the role technology and artificial intelligence in particular can play, and the development and validation of early warning systems. These objectives are essential in that they break down a broad and complex topic into manageable segments, making the research process more structured and goal-oriented. To steer the investigation in a direction that yields meaningful outcomes, the chapter also introduces research questions. These questions are carefully crafted, ensuring they encompass the breadth and depth of the issue at hand. They act as guiding lights, ensuring the research remains anchored to its core objectives and doesn't deviate into tangential areas. Chapter One doesn’t just delineate what the research will cover but also defines its boundaries by establishing the scope of the study. Such a clear demarcation ensures that the study remains targeted and doesn't become overwhelmingly expansive. This focus is crucial to ensure depth in exploration and to maintain the research’s relevance and feasibility.

In concluding this chapter, there's an emphasis on the significance of the study. The implications of this research aren't restricted to the confines of academia. The findings, insights, and recommendations that emerge hold the potential to bring about tangible changes in the real world. Whether it's in the policies formulated by governments, the strategies adopted by agricultural communities, or the technological solutions devised by innovators, the influence of this study is far-reaching. The chapter concludes by reiterating its pivotal role, to bridge the gap between the known and the unknown in the realm of AML and RL invasions, and to pave the way for a future where these challenges are better understood, managed, and mitigated.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

The academic realm of locust invasion studies, particularly focusing on the African Migratory Locust (AML) and Red Locust (RL), is as expansive as it is diverse. Over the decades, countless scholars have delved into this subject, each contributing a unique perspective and further enriching the collective understanding of these invasions. As we embark on this chapter, the mission is to navigate this vast expanse, distilling the essential elements of previous research and identifying the emerging trends and gaps that set the stage for our study. The locust, in its various species and manifestations, has historically been a subject of intense scrutiny. These creatures, remarkable in their biology, have the potential to wreak havoc on agriculture, drastically impacting economies and food security. The imperative to understand and manage these invasions has thus been felt across a multitude of disciplines, from biology and ecology to technology and socio-economics. Recognizing this multi-disciplinary nature, the research review is comprehensive, seeking to weave together threads from diverse academic traditions.

In the initial segment of this dissertation explore the foundational literature surrounding locust invasions. We address the underlying factors that catalyse these invasions and analyze how the dynamics of these invasions have transformed over the years. This examination also encompasses methodologies that span both time-honoured practices and contemporary innovations, which have been harnessed to forecast, identify, and mitigate these invasions. Our objective is to craft a comprehensive chronology that charts the progression of research on AML and RL invasions, from their early stages to contemporary findings. This endeavour is not merely an archival retelling, but rather a rigorous critique that elucidates the employed research techniques, the data accrued, and the resultant scholarly interpretation.

In the evolving landscape of locust management strategies, the role of emerging technologies, especially Artificial Intelligence (AI), stands as a beacon of innovation. The global trajectory towards AI adoption across various sectors underscores its potential significance in the realm of locust invasion management. In the subsequent segment of this chapter, the intricate nexus between AI, other emerging technologies and locust research is discussed. The deployments of various AI models in locust studies, highlighting their successes, pinpointing challenges faced, and delineating key takeaways are discussed. Our intent is to underscore the transformative potential AI brings to the domain of locust management.

2.1 Background to the Study

Locust invasions have long posed significant threats to agriculture, with their impact being felt across various regions and throughout history. This section aims to delve deeper into the core of locust invasion studies, understanding the factors triggering these invasions, their evolving patterns over time, and the methods employed to manage them.

According to [28], the impact of locusts on agriculture has spanned decades, if not centuries. Ancient civilizations have recorded the devastating effects of locust plagues on their crops, which hints at the historical gravity of the problem. Throughout this time, humans have persistently sought ways to counteract these pests, employing various preventive and combative measures. The factors triggering locust invasions can be complex and multifaceted. Environmental conditions such as prolonged drought followed by rapid vegetation growth are known to stimulate their rapid reproduction. These factors, combined with locusts' inherent gregarious behavior, can lead to the formation of large and mobile swarms. Over time, patterns of invasions have evolved, potentially due to changing climatic conditions and land-use practices. These shifts necessitate constant research and monitoring to understand current and future locust threats. Historically, locust management has been reactive, often resorting to crude methods like digging trenches or using smoke. However, over the years, advancements in technology have enabled more proactive and sophisticated measures. Aerial and ground spraying with insecticides, both chemical and bio-based, have become standard practices in many affected regions.

Modern management approaches also leverage satellite imagery and advanced predictive models to forecast invasions. [29] highlight that despite advancements in technology and understanding, challenges persist. One significant challenge is the preparedness of nations. Prolonged periods without invasions can lead to complacency among governments and communities. This relaxed attitude manifests as diminished stock of essential equipment, a decrease in skilled manpower, and outdated training procedures. Terrains that are difficult to navigate, coupled with security instability in certain regions, further complicate effective response efforts. Additionally, when invasions span multiple countries, a lack of coordinated control efforts can hamper management initiatives.

A key challenge cited by [29] revolves around the availability and application of insecticides. Not only are there concerns about the environmental and health impacts of these chemicals, but cost implications can also limit their widespread use. However, given the economic devastation locusts can bring, many nations, such as Pakistan, have taken concerted efforts, collaborating with neighbouring countries and international organizations to undertake both land and aerial spraying campaigns.

[23] reinforces the idea that locust invasions are not just a regional problem but a global one. The interconnected nature of today's world means that a locust invasion in one country can have ripple effects, impacting food security, trade, and economies far beyond its borders.

2.1.1 Locust Prevalence

Locust infestations are a critical issue for agriculture across various African regions, significantly affecting both food security and the livelihoods of the population. The widespread presence of locusts on the continent has been extensively reported in numerous studies.

Research conducted by [20] utilized satellite imagery to track locust distributions across West Africa, identifying frequent outbreaks in countries such as Mauritania, Mali, Niger, and Senegal. Similarly, [22] reported recurring incidents of locust and grasshopper infestations in West Africa, which have profound effects on agricultural productivity and food availability. Focused research within individual countries includes a study by [30], which observed significant activity of desert locusts in Burkina Faso's Sahel region, posing a considerable challenge to local agriculture. In Tanzania, [31] noted consistent locust outbreaks that routinely resulted in extensive crop damage.

Furthermore, numerous studies have explored various management and mitigation strategies for these pests. For instance, [32] investigated the application of biopesticides in Mauritania to combat desert locusts, discovering their effectiveness and environmental benefits. Research by [33] evaluated the repercussions of the 2019-2020 locust plague in Zambia, which impacted over 66,000 hectares, damaging crops and pastures extensively. The study emphasized the outbreak's potential to spread regionally, underscoring the necessity for cooperative locust management strategies across borders. Additionally, [34] examined locust occurrences in Zambia’s Luangwa Valley, identifying the red locust as the predominant species, followed by migratory and brown locusts. This research advocated for the implementation of proactive surveillance and early warning systems to manage outbreaks effectively. Another study by [35] compared different locust management tactics in Zambia, concluding that while pesticides were effective in reducing locust numbers, they posed potential environmental and health hazards. Conversely, biological control methods, including the use of natural predators and traditional farming practices, though less immediately effective, offered a safer and more sustainable alternative.

2.1.2 Knowledge of locusts

Locust infestations pose a significant risk to agriculture throughout Africa, making it essential for farmers to have a comprehensive understanding of locust behavior for effective management and control. Literature reviews reveal significant gaps in knowledge among African farmers regarding these pests, potentially hindering effective control measures.

Research by [36] examining Ethiopian farmers' understanding and management strategies for desert locusts showed that while most were familiar with locusts and could recognize them, their knowledge on how to manage these pests was generally lacking. Similarly, a study by [37] assessing the level of awareness among Sudanese smallholder farmers indicated that their knowledge about identifying, understanding the behavior of, and controlling desert locusts was insufficient. Another investigation by [38] into Kenyan farmers' knowledge, attitudes, and practices related to desert locust control noted some awareness of locusts, but a limited grasp of their biology and ecology. This study also highlighted a heavy dependence on governmental aid for locust control, with a lack of personal resources and knowledge for independent management.

Conversely, research by [39] found that Kenyan farmers had a robust understanding of locust behavior and the critical nature of early detection and intervention. However, this study also noted challenges in accessing timely and precise information about locust outbreaks and control strategies. Further, an Ethiopian study [40] discovered that while farmers were well-informed about locust behaviors, their management and control tactics were deficient. In Niger, a study by [41] indicated partial knowledge of locusts among farmers, with specific deficiencies in management and control techniques.

Although specific studies on locust knowledge in Zambia are sparse, broader regional research includes a survey by [42] in the Kazungula district, which identified mobile phones as vital tools enhancing farmer knowledge and readiness for locust control. This survey showed that mobile devices were crucial for farmers to access updates on locust outbreaks, pest management methods, and weather forecasts. Additionally, mobile phones facilitated communication with agricultural advisors and peer farmers, promoting an exchange of knowledge and experiences.

To sum up, there remains a critical need for more focused research on locust knowledge within Zambia to pinpoint educational gaps and formulate effective control strategies.

2.1.3 Use of phones by farmers

Numerous investigations have underscored the significance of mobile phones for farmers in reporting locust activities, significantly enhancing early detection and accelerating response efforts against locust invasions. In Kenya, research [43] demonstrated that mobile technology facilitated real-time updates on locust sightings, effectively reducing the time to respond to invasions, which crucially mitigated adverse effects on agriculture and livelihoods. Likewise, a Tanzanian study [44] utilized mobile phone technology to strengthen locust surveillance and management, finding that mobile reports of locust sightings boosted the efficacy of control initiatives.

In Ethiopia, an analysis [45] revealed that mobile reporting mechanisms provided timely warnings and improved responses to locust outbreaks, advocating for mobile technology to bolster locust surveillance and management within the region. A similar study in Morocco [46] concluded that mobile technology significantly improved the efficiency of locust monitoring systems through real-time updates, recommending mobile phones as valuable tools for locust surveillance enhancement.

Furthermore, research conducted in Zambia by [47] evaluated the use of mobile phones in monitoring and reporting desert locusts, noting their effectiveness in delivering real-time information on locust outbreaks, which allowed farmers and relevant stakeholders to react promptly and appropriately. The study suggested not only the continued use of mobile phones in locust monitoring but also emphasized the importance of training and capacity building to ensure the accuracy and reliability of the data collected. Another study [48] investigated mobile phones' role in providing early warnings and facilitating rapid response to desert locusts in Zambia, highlighting how mobile devices enabled farmers to report locust sightings swiftly and accurately.

2.2 Role of technology in locust management

The role of technology in augmenting and enhancing locust management strategies cannot be overlooked. Here, the surge of interest in Artificial Intelligence (AI) becomes particularly salient. As the world increasingly turns to AI for solutions across sectors, its potential application in locust invasion management becomes a tantalizing prospect. Other technologies include the Internet of Things (IoT) and Cloud Computing. The second segment of this section, therefore, is dedicated to examining the burgeoning relationship between AI, IoT, Cloud Computing and locust studies.

2.2.1 Artificial Intelligence

Artificial Intelligence (AI) can be described as a multifaceted field of computer science dedicated to creating systems capable of performing tasks that typically require human intelligence. These tasks encompass a broad range, including learning, decision-making, problem-solving, perception, and language understanding [49]. AI systems are underpinned by algorithms, harnessing vast amounts of data and significant computational power. These systems find applications across a diverse spectrum, from natural language processing [50] to autonomous vehicles [51].

AI can be categorized into two types: narrow or weak AI, which is designed for specific tasks, and general or strong AI, which has broader capabilities akin to human intelligence [49]. The development of AI involves various subfields, including machine learning (ML), where algorithms improve through exposure to data, and deep learning (DL), a subset of ML based on artificial neural networks [52].

The ethical implications and societal impacts of AI are also an area of significant research, involving considerations about privacy, job displacement, and decision-making in critical sectors like healthcare and criminal justice [53].

2.2.1.1 Machine learning (ML)

Central to AI is the concept of machine learning (ML), a subset of AI that focuses on the development of algorithms that can learn from and make predictions or decisions based on data [52]. ML circumvents the need for explicit programming for each new problem; instead, it enables a system to adapt to new scenarios based on historical data. Machine learning algorithms are broadly categorized into supervised learning, unsupervised learning, and reinforcement learning, each differing in the nature of the 'learning' process [54]. Machine learning, particularly, has driven many recent advancements in AI. By using algorithms to parse data, learn from that data, and then make determinations or predictions, ML can be applied to an array of modern challenges[55].

The integration of AI, and particularly its machine learning and deep learning paradigms, into various domains, marks a significant shift in how data-driven decisions are made and offers a novel approach to solving complex, real-world problems.

2.2.1.2 Deep Learning

Deep learning a subset of machine learning, has gained significant attention for its ability to process large sets of unstructured data and learn complex patterns. This is achieved through artificial neural networks (ANNs), which are inspired by the biological neural networks in human brains [56]. Deep learning has been pivotal in advancements such as speech recognition, image classification, and even in complex games like. Deep learning, utilizing layered neural networks, excels in tasks like image and speech recognition, playing a crucial role in the evolution of AI technologies [56].

Deep learning involves the use of computational models with several layers for processing, enabling these models to learn data representations at varying levels of detail and abstraction. This approach has significantly enhanced the performance of various technologies in areas like speech and visual object recognition, object detection, and even in fields like pharmaceutical development and genomic studies. Backpropagation algorithm and deep learning techniques adjust the internal parameters of a model. These adjustments help the model refine how it interprets data at each layer based on the information processed in the preceding layer. In particular, deep convolutional networks have led to major advancements in the analysis of images, videos, and audio, while recurrent networks have proven to be particularly effective in understanding sequential data, such as text and spoken language [56].

2.3 Introduction Artificial Neural Networks

The human brain is an exemplar of an advanced computational network, capable of intricate perceptual acts such as face and speech recognition, as well as precise control over movement and bodily functions. The essence of the brain's computational prowess lies in its utilization of massive parallelism, a structure that performs computations simultaneously across a network of over 10 billion interconnected neurons.

2.3.1 Biological Neural Network

Each neuron engages in biochemical reactions to receive, process, and transmit information.

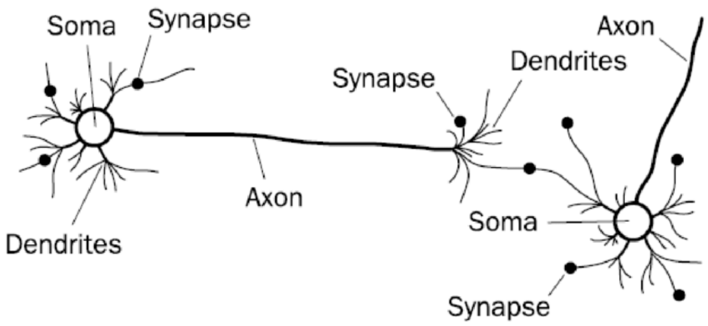


Figure 4: Biological Neural Network [57]

Also known as the cell body, the soma is the central part of a neuron. It contains the nucleus, which houses the cell's genetic material. The soma is responsible for maintaining the life of the neuron and also plays a role in analysing the data received from the dendrites to determine whether the information should be passed along.

Dendrites are the neuron's information receivers. These are tree-like extensions from the soma They collect electrical signals from the synapses of other neurons and transport them to the soma. They function like the sensory apparatus of the neuron, picking up messages from neighbouring cells.

The axon is a long, slender projection that conducts electrical impulses away from the neuron's cell body. It is a fibre that transmits information to different neurons, muscles, and glands. At the end of the axon, the signal is converted into chemical signals to cross the synapse.

A synapse is the gap between the terminal button of one neuron and the dendrite of another neuron. It is through these synapses that neurons communicate with each other. The transmission of signals across the synapse from one neuron to another involves the release of neurotransmitters, which are chemical messengers.

The complex interplay of these components enables the neuron to function as a basic signalling unit within the nervous system. In biological neural networks, this intricate system of neurons and synapses underpins the body's ability to process and respond to vast arrays of stimuli. Similarly, in artificial neural networks, the concept of neurons and synapses is abstracted to create systems capable of complex tasks such as pattern recognition, decision-making, and predictive modelling. The artificial neuron or node in a network is modelled to mimic the input-output relationship of biological neurons, albeit in a simplified, mathematical form. These artificial networks learn and adapt by adjusting the weights of connections, analogous to the strength of synapses, based on the algorithms employed during the learning process.

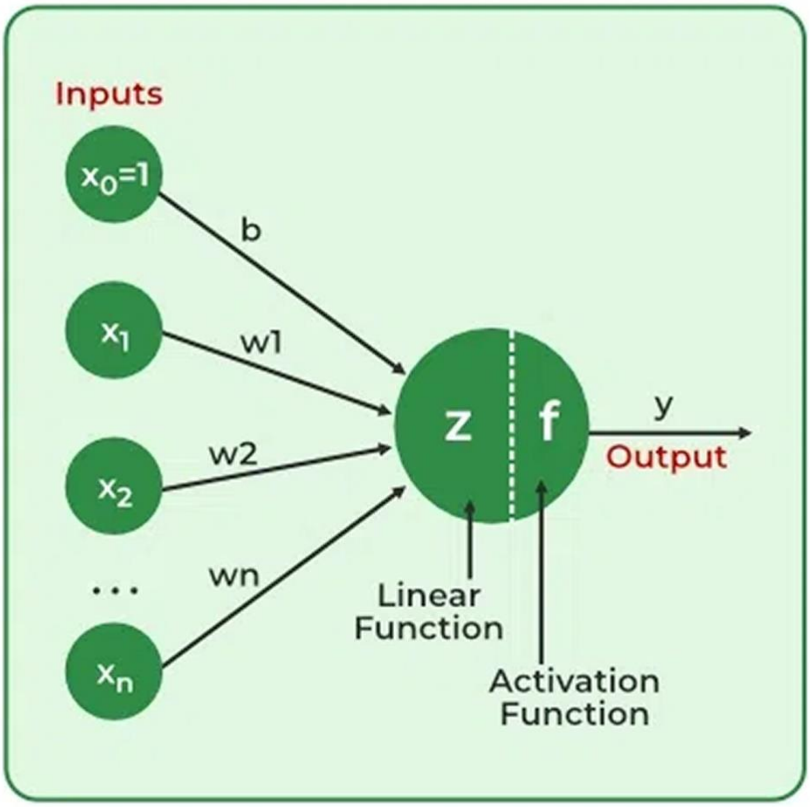


Figure 5:Neural Network [58]

Figure 5 depicts an artificial neuron, a fundamental computational unit of an artificial neural network (ANN). This simplified model illustrates how inputs, analogous to biological dendrites, receive signals to be processed by the neuron. Each input, labelled $x_1,x_2,\ldots,x_n$, represents distinct information features, while x_0 typically serves as a bias unit, set to 1, to facilitate the neuron's threshold adjustment. The input signals are each weighted by corresponding factors, $w_1,w_2,\ldots,w_n$, signifying the synaptic efficacy in biological terms. These weights determine the significance of each input and are dynamically refined during the network's learning phase to optimize the neuron's output [59].

The process within the neuron begins with a linear combination of the weighted inputs, encapsulated by the variable *z*. This operation aggregates the input signals, each multiplied by its weight, and includes the bias. The mathematical representation of this linear function is $z = b + \sum_{i=1}^{n}(\boldsymbol{w}_i \boldsymbol{x}_i)$ where *b* is the bias weight.
Following the linear summation, the resulting value *z* is passed through an activation function, denoted by *f*, which introduces non-linearity to the neuron's processing capability. This non-linear transformation is crucial as it allows the ANN to handle complex patterns and data distributions that are not linearly separable.

The output of the activation function, labelled *y*, is the final output of the artificial neuron. This output may either be used as an input to subsequent layers in a multi-layer network or represent a component of the network's final output. The ensemble of such neurons, arranged in layers and interconnected, forms the architecture of an ANN. Through a process known as training, the network adjusts the weights of each neuron using a learning algorithm, which iteratively improves the network's performance by minimizing the error between the predicted outputs and the actual data. This training empowers ANNs to perform a variety of complex tasks, from image and speech recognition to predictive modelling, emulating the cognitive functions of the human brain in a computational setting.

2.3.2 Activation Functions

Activation functions are the linchpins of artificial neural networks, serving as the gatekeepers of data flow within the network. They are the mathematical constructs that decide how much information should be passed forward through the network, thus they play a vital role in the network's ability to learn from complex and unpredictable data, such as noisy or unlabelled inputs.

The step function is one of the most elementary types of activation functions. It's a binary function that triggers a neuron to activate only if the input exceeds a certain threshold, emitting a binary output as a result. This function, while computationally not intensive, is quite limited in its application due to its binary nature, which is not conducive to tasks that require probability estimation or classifications that are not dichotomous.

To address this limitation, the sigmoid function was introduced. It delivers an output that ranges between 0 and 1, making it suitable for predicting probabilities, and has been a classic choice for binary classification problems. Despite its advantages, the sigmoid function is prone to the vanishing gradient problem, where the gradients used in the backpropagation algorithm become progressively smaller, severely hindering the network's ability to learn, particularly in deep networks.

An alternative to the sigmoid function is the hyperbolic tangent, or tanh function, which outputs values between -1 and 1. This zero-centered nature of the tanh function generally makes learning easier for subsequent layers since data is normalized around zero. However, it still shares the sigmoid's susceptibility to the vanishing gradient problem.

The Rectified Linear Unit, or ReLU function, has emerged as a solution to some of the challenges posed by the sigmoid and tanh functions. It allows the input to pass through without change if it's positive, but blocks it if it's negative, outputting zero instead. The simplicity of ReLU, along with its ability to maintain larger gradients, has made it a popular choice, speeding up the training process and enhancing network performance without the complications of vanishing gradients.

However, ReLU is not without its own issues, such as the "dying ReLU" problem, where some neurons can stop participating in the data processing altogether, constantly outputting zero. This led to the development of variants such as Leaky ReLU and Parametric ReLU (PReLU), which allow a small gradient when the unit is inactive, thereby keeping the neuron alive.

The Exponential Linear Unit (ELU) further extends the concept of ReLU by providing a small negative output for negative input values. This adjustment helps push the mean activation closer to zero, akin to the tanh function, which can lead to improved learning dynamics.

In the context of classification problems, the Softmax function is often utilized in the output layer of the network. It converts the raw output of the network into a probabilistic distribution over predicted output classes, which is instrumental for multi-class classification problems.

2.4 Deep learning Models

In the landscape of artificial intelligence (AI), deep learning models have emerged as a transformative force, particularly due to their prowess in handling complex, high-dimensional data. Central to these models are artificial neural networks, which draw inspiration from biological neural networks. These networks consist of layered nodes or neurons, with each layer capable of transforming input data into more abstract representations, thereby enabling intricate pattern recognition [52].

Among the various architectures within deep learning, Convolutional Neural Networks (CNNs) have revolutionized image and video recognition. CNNs are adept at learning spatial hierarchies of features from input images, making them particularly effective in visual recognition tasks [56]. Recurrent Neural Networks (RNNs) on the other hand have significantly impacted the processing of sequential data. Their unique architecture, which utilizes internal memory to process sequences of inputs, makes them suitable for applications in language modelling, speech recognition, and time series analysis [60].

The advent of transformers has further advanced the field, especially in natural language processing. Unlike RNNs, transformers are more efficient in handling long-range dependencies within data, thus offering improvements in tasks like language translation and content generation. Additionally, the concept of transfer learning has been pivotal in deep learning. By repurposing models developed for one task as a starting point for another, transfer learning offers a potent strategy, especially in scenarios with limited labelled data [61].

These advancements in deep learning models underscore a significant shift in the capabilities of AI systems, opening new frontiers in both academic research and practical applications.

2.4.1 Deep Learning Architectures

2.4.1.1 MobileNet

In the field of computer vision, particularly in contexts where computational efficiency is paramount, MobileNet stands out as a significant advancement. Developed by researchers at Google, MobileNet is engineered specifically for mobile and embedded vision applications, addressing the critical need for models that are both computationally economical and high-performing [62]. At the core of MobileNet's architecture are depthwise separable convolutions, which fundamentally differ from traditional convolutions in deep neural networks. This design choice significantly reduces the computational burden and the model size, making it highly suitable for devices with limited processing capabilities.

MobileNet's architecture is particularly notable for its ability to balance the trade-off between latency and accuracy. Through adjustable hyperparameters, it allows for fine-tuning the width of the network and the resolution of input images, catering to varying requirements of different applications [63]. Despite its compact and efficient structure, MobileNet does not markedly compromise performance and has been successfully employed in diverse computer vision tasks, including image classification, object detection, and facial recognition. Its compatibility with major deep learning frameworks further enhances its utility, making it a versatile tool in the AI developer's toolkit.

The development and widespread adoption of MobileNet underscore a critical trend in AI research, the movement towards models that are not only powerful but also adaptable to the constraints of real-world applications. This trend is particularly relevant in the burgeoning field of mobile and embedded systems, where efficient processing is not just a benefit but a necessity.

2.4.1.2 MobileNetV2

In the evolving landscape of deep learning architectures, MobileNetV2 stands out as a significant development, particularly in the realm of efficient neural networks. Developed by researchers at Google, MobileNetV2 is a successor to the original MobileNet and is designed specifically for mobile and embedded vision applications [63]. Its core significance lies in its ability to provide high computational efficiency while maintaining a high degree of accuracy, a balance that is crucial for deployment in devices with limited processing power and battery life.

MobileNetV2 introduces several key innovations that enhance its efficiency. The architecture utilizes an inverted residual structure where shortcut connections are placed between the thin bottleneck layers [64]. This design choice significantly reduces the model size and computational cost without sacrificing performance. Additionally, MobileNetV2 incorporates lightweight depthwise separable convolutions, further optimizing its efficiency and making it an ideal choice for real-time applications in constrained environments.

The introduction of MobileNetV2 has had a substantial impact on the field of deep learning, particularly in areas where computational resources are at a premium. Its efficiency makes it suitable for a wide range of applications, from facial recognition and augmented reality on smartphones to more complex tasks like object detection and image segmentation in embedded systems [65]. Mobile Figure 6 shows MobileNet Version 2 building block.

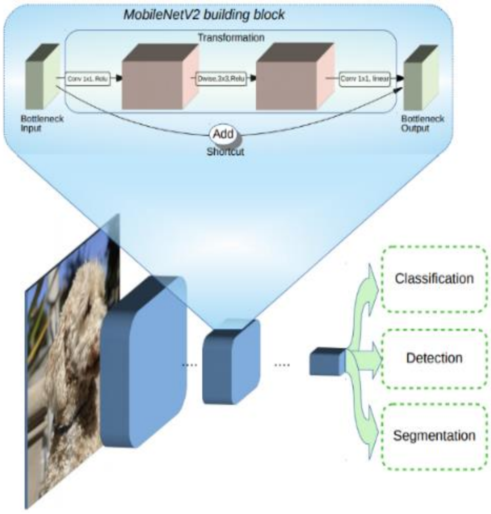


Figure 6:MobileNet Version 2 building block [66]

Bottleneck input

This is the input to a bottleneck layer, which typically reduces the dimensionality (number of channels) of the input feature map to make the network more computationally efficient.

Transformation

Inside the building block, there's a transformation process that usually involves convolutional layers. In MobileNetV2, this refer to a depthwise separable convolution, which separates the convolution operation into a depthwise spatial convolution and a pointwise convolution to reduce computation.

t-Conv

This is the depthwise convolution layer, which applies a single filter per input channel (input depth). The "t" refers to an expansion factor that MobileNetV2 uses to initially expand the number of channels before the depthwise convolution.

n-Conv

This refers to the pointwise convolution layer (1x1 convolution) that combines the outputs of the depthwise convolution from the previous step. It's used to change the number of channels and mix the information from the different channels.

Bottleneck Output

The output of the bottleneck layer that has undergone transformation. The output is a feature map that is more refined and has gone through dimensionality reduction or expansion based on the architecture's requirements.

Add Shortcut

This represents a residual connection, where the input is added to the output of the convolutional layers (after matching dimensions). It's a technique used to help gradients flow through a network and to allow the training of deeper networks by preventing the vanishing gradient problem.

Applications

Classification

This is a process where the neural network assigns the input data to one or more categories. MobileNetV2 is efficient for this task due to its lightweight architecture.

Detection

This refers to object detection, where the network not only classifies objects within an image but also detects their location, usually represented by bounding boxes.

Segmentation

In image segmentation, the network classifies each pixel of the image, resulting in a pixel-wise map of different segments or regions. This is useful for tasks where you need to understand the image at a more granular level than object detection provides.

2.4.1.3 MobileNet V2 Quantised

Most machine learning models are too big to be deployed in an edge device such as mobile phones and microcontrollers as well as other small devices [1],[67]. Using the cloud to store data and the model has not yielded much help as doing so still poses a challenge of accessibility [68]. Edge devices have a problem accessing the cloud services for object detection due to inconsistencies in internet band-width [69]. Data security has also been reported as a challenge when using the cloud services since data does not reside on the mobile phone or any other edge device [1],[2]. For applications whose operations are critical, zero-latency is normally demanded for and using a cloud storage for object detection through an API does not guarantee zero latency [70],[71]. There are various model optimization techniques that could enable machine learning models to run on resource constrained devices and among such tools is model quantization. Quantization is a technique that is used to deploy machine learning models in devices that are resource constrained [4]. The model sizes are reduced by limiting the precision formats supported by TensorFlow Lite tools. Most machine learning models use float32 and quantization enables the use of slightly lighter formats such as float16 and int8 [72]. The rate at which a model detects objects is directly related or corelated to the type of format that is used in the model.

2.4.1.4 ResNet (Residual Networks)

The introduction of Residual Networks (ResNet) marked a significant advancement in the field of deep learning, addressing some of the key challenges in training very deep neural networks. Developed by Kaiming He and colleagues, ResNet's architecture was groundbreaking for its use of "residual" or "skip connections," a simple yet effective solution to the vanishing gradient problem that often hampered the training of deep networks.

ResNet's core innovation lies in its residual blocks, which allow layers to learn residual functions with reference to the layer inputs, instead of learning unreferenced functions. This approach addresses the degradation problem, the issue where the network accuracy saturates and then degrades rapidly with the increase in depth. Each ResNet block contains a shortcut connection that bypasses one or more layers. During backpropagation, this shortcut connection enables the gradient to be directly propagated back through the network, effectively addressing the vanishing gradient problem [73].

The skip connections in ResNet do more than just solve the vanishing gradient problem; they also facilitate the training of much deeper networks than were previously possible. This capability is crucial because deeper networks, with their increased number of layers, can learn more complex patterns and representations, making them more effective for a wide range of tasks [74].

The deeper architecture of ResNet has translated into notable improvements in accuracy and performance in various tasks, especially in image classification and object detection. The

ResNet model achieved a 3.57% error rate on the ImageNet test set, a record-breaking performance at the time of its introduction [75]. This level of accuracy demonstrated the potential of deeper networks when the challenges of training them are adequately addressed.

Following the success of the original ResNet model, several variants have been developed, including ResNet-50, ResNet-101, and ResNet-152, which differ mainly in the number of layers. Each variant offers a trade-off between computational complexity and performance, with deeper models generally achieving better accuracy at the cost of increased computational resources.

In practical applications, ResNet has been widely adopted for tasks such as object detection, semantic segmentation, and image classification. Its ability to efficiently process high-resolution images makes it particularly useful in fields like medical imaging, where it has been used for tasks such as tumor detection and classification. In autonomous vehicles, ResNet aids in the critical tasks of object detection and scene understanding.

ResNet has also significantly contributed to the field of transfer learning. Pre-trained ResNet models are commonly used as feature extractors in various tasks, enabling the application of deep learning to problems where large amounts of training data are not available.

While ResNet's architecture offers many advantages, it is not without limitations. Deeper models require more computational resources and are more prone to overfitting, especially when trained on smaller datasets. Additionally, the increased complexity of the network can lead to longer training times.

Ongoing research in network architecture design is building upon the foundations laid by ResNet. Innovations in optimization algorithms, network pruning, and novel architectures continue to push the boundaries of what is possible with deep neural networks. The exploration of techniques like neural architecture search (NAS) promises to automate the design of efficient and effective network architectures, potentially leading to models that surpass the performance of ResNet.

2.4.1.5 VGG (Visual Geometry Group)

The Visual Geometry Group (VGG) at the University of Oxford introduced the VGG architecture, a defining moment in the evolution of convolutional neural networks (CNNs). Developed by [76], the VGG architecture is distinguished by its depth and simplicity, marking a significant departure from the shallower architectures that preceded it.

The primary innovation of the VGG architecture lies in its depth. VGG models, particularly VGG16 and VGG19, consist of 16 and 19 layers respectively [77]. These models utilize an architecture with uniform convolutional layers, each followed by a max-pooling layer. The convolutional layers typically use small (3x3) filters, which, despite their size, enable the network to capture complex patterns thanks to the depth of the network [76]. This structure was a radical shift at the time of its development, demonstrating the effectiveness of depth in neural networks. By stacking multiple convolutional layers, VGG networks can learn a hierarchy of features, from simple edges in the early layers to complex structures in the deeper layers. This hierarchical feature learning is fundamental to the success of CNNs in various computer vision tasks. The introduction of VGG had a considerable impact on the field of computer vision. The network achieved state-of-the-art performance in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2014. Its ability to accurately classify images into a thousand different categories solidified the importance of depth in CNNs.

One of the most notable contributions of VGG is its role in the development of transfer learning. Pre-trained VGG models, trained on large datasets like ImageNet, have been used as starting points for training models on other vision tasks. This approach has allowed for the application of deep learning in scenarios where data is too scarce to train a large network from scratch. In transfer learning, the lower layers of a pre-trained VGG model are often used as feature extractors. These layers capture general features that are useful across a variety of tasks. The higher layers can then be fine-tuned or replaced to suit the specific task at hand, whether it be object detection, segmentation, or even medical image analysis.

Beyond image classification, VGG has been applied to a range of other tasks. In object detection, systems like Faster R-CNN have used VGG as a backbone for feature extraction. In semantic segmentation, VGG's architecture has been integral in models like FCN (Fully Convolutional Networks) for pixel-wise classification. Despite its successes, VGG does have limitations. The model is computationally intensive and memory-demanding due to its depth and the number of parameters. This can make it challenging to deploy on devices with limited computational resources. Additionally, training VGG networks from scratch requires substantial computational power and large labeled datasets. The development of VGG has spurred further research into deep CNN architectures. Subsequent models, like ResNet, have built upon the idea of depth but introduced innovations like skip connections to alleviate some of the challenges posed by training very deep networks.

VGG's legacy in the field of deep learning and computer vision is substantial. Its demonstration of the effectiveness of depth in neural networks has been a guiding principle for many subsequent developments in the field. While newer architectures may surpass it in efficiency and performance, VGG’s fundamental design principles continue to influence the development of state-of-the-art deep learning models in computer vision.

2.5 Deep learning frameworks

Deep learning frameworks have become essential tools in the field of artificial intelligence, providing researchers and developers with the ability to design, train, and deploy complex neural networks. These frameworks offer pre-built functions, algorithms, and a development environment that facilitate the rapid construction and iteration of deep learning models. The most notable frameworks include TensorFlow, Keras, PyTorch, and Caffe, each with unique features catering to different aspects of deep learning research and application.

2.5.1. TensorFlow and Keras

TensorFlow, an open-source software library created by the Google Brain team, stands out for its comprehensive approach to numerical computation using data flow graphs. In these graphs, nodes signify mathematical operations, and edges represent the multidimensional data arrays, or tensors, facilitating efficient deep learning and machine learning operations [78]. Its architecture is remarkably flexible, enabling deployment across various platforms – from individual desktops to server clusters, and across CPUs, GPUs, and mobile devices. This versatility contributes to TensorFlow’s widespread adoption in both academic research and industrial applications.

The framework's capacity to support a diverse array of deep learning models and algorithms is among its primary strengths. It empowers researchers and developers to explore innovative architectures and techniques. TensorFlow encompasses a broad toolkit, including TensorFlow Lite, optimized for mobile and embedded devices, and TensorFlow Extended (TFX) for robust, end-to-end machine learning pipelines in production settings. Additionally, it provides TensorBoard, a visualization tool designed to enhance the understanding and debugging of machine learning models.

Moreover, TensorFlow's synergy with Keras, a high-level neural networks API, enhances its appeal. Keras, integrated into TensorFlow, streamlines complex processes, making the design and testing of models more approachable, particularly for those new to the field [79]. This integration underscores TensorFlow's commitment to accessibility without compromising on its core attributes of robustness and scalability, making it a preferred choice for extensive, scalable deep learning applications.

2.5.2 PyTorch

Developed by Facebook's AI Research lab, PyTorch has gained popularity for its dynamic computational graph and efficient memory usage, making it particularly suited for projects that require flexibility and speed. Its intuitive design and ease of use make it a preferred choice for researchers and developers in prototyping and experimenting with neural network architectures [80].

2.5.3 Caffe

Created by the Berkeley Vision and Learning Center, Caffe is known for its speed and modularity. It is widely used in academic research projects, particularly those involving image classification and convolutional neural networks. While not as flexible as TensorFlow or PyTorch, Caffe excels in applications where speed is a critical factor [81].

Keras, initially an independent project created by François Chollet, is a high-level neural networks API that runs on top of TensorFlow, Theano, and Microsoft Cognitive Toolkit (CNTK). In 2017, Keras was integrated into TensorFlow as tf.keras, making it an official high-level API of TensorFlow, focused on being user-friendly, modular, and extensible [79]. Keras has gained popularity for its ease of use and its ability to facilitate fast experimentation with deep neural networks. It provides simple and consistent high-level APIs, making it possible for users with varying levels of machine learning expertise to build and deploy complex machine learning models.

Keras abstracts many of the lower-level operations required in building models, allowing developers to quickly prototype and test neural networks. It supports most common neural network building blocks such as layers, objectives, activation functions, optimizers, and tools to work with image and text data. This simplification, however, does not come at the cost of reduced flexibility, as Keras models can be seamlessly integrated with low-level TensorFlow functionalities for more customized and complex operations.

TensorFlow and Keras together offer a powerful combination for developing sophisticated machine learning models, providing both the flexibility of TensorFlow's comprehensive tools and resources, and the user-friendliness and ease of model building that Keras is known for.

Each of these frameworks has its strengths and is chosen based on specific project requirements. TensorFlow and Keras are often selected for large-scale, production-ready applications and ease of use, respectively. PyTorch is favoured for its dynamic nature and rapid prototyping capabilities, making it ideal for research and development. Caffe, being highly efficient in forward pass computations, is often used in mobile applications and embedded systems.

2.6 Artificial Intelligence and Locust Management

In the realm of intelligent agriculture and pest management, innovative approaches utilizing AI and machine learning have shown promising results, particularly in the identification and management of locusts and other agricultural pests.

[82] proposed a vision-based system for counting and recognizing flying insects, a crucial development in intelligent agriculture. The challenge of capturing images of insects in motion was addressed by using a sticky trap to capture six insect species. For insect detection and coarse counting, the study employed a Convolutional Neural Networks (CNN) object detection model, specifically the You Only Look Once (YOLO) architecture. For finer classification and counting, a Support Vector Machine (SVM) was utilized. The results from this system were impressive, achieving an accuracy of 92.5% for counting and 90.18% for classification [82].

In another significant contribution, [83] explored the use of Convolutional Neural Networks to automatically identify locust swarms. They equipped drones with high-resolution cameras and pesticide tanks, targeting only the identified locust swarms for chemical treatment. This approach demonstrates effective and efficient use of chemical agents in locust control. [84] developed a model employing CNN for real-time grasshopper detection using mobile devices, even in the absence of an internet connection. Utilizing the Residual Network (ResNet) architecture, this system allows for the uploading of images to cloud storage for further analysis. This development is particularly notable for its application in remote areas where internet connectivity is limited. Furthermore, [85] implemented a CNN model for the identification of various crop insects. Their approach involved multifaceted feature extraction and the use of a Regional Proposal network for generating small windows, thereby enhancing model prediction accuracy and speeding up computations. This study illustrated a significant improvement in model performance compared to traditional classification algorithms.

[86] also contributed to this field by proposing the use of Fast and Faster CNN models for detecting desert locusts. Their study, which employed the VGG16 architecture, achieved an average accuracy of 83%, outperforming other architectures like AlexNet, ResNet, and VGG19. [87] predicted locust distribution using Recurrent Neural Networks (RNN) and achieved a precision of 60% and a recall of 81%, utilizing the FAO dataset. This approach underscores the potential of RNNs in predicting locust movement patterns, which is crucial for proactive management. [88] developed a semi-automatic machine learning model to detect two types of locust species and their associated instars. They employed the Grab Cut segmentation method for extracting body parts of locusts, achieving an accuracy of 96.1% with the polynomial kernel function.

2.7 Internet of Things

The Internet of Things (IoT), as described by [89], represents a paradigm shift in the realm of digital connectivity, extending beyond the traditional internet framework that primarily connects computers and similar devices. IoT encompasses a vast network of physical entities such as home appliances, vehicles, and various other items. These are embedded with electronics, software, sensors, actuators, and networking capabilities, enabling them to communicate and exchange data. The core distinction lies in the ability of IoT to integrate a wide array of physical objects into the digital ecosystem, facilitating a level of interaction and data exchange previously unattainable.

The implications of IoT extend across multiple industries, profoundly impacting sectors like manufacturing, healthcare, transportation, and retail, as noted by [90]. Furthermore, as [91] points out, IoT's integration into our daily lives is increasingly becoming a reality, with a growing number of everyday devices connecting to the internet. This expansion heralds a future where IoT's presence is ubiquitous, influencing various aspects of our day-to-day experiences.

Several key benefits of IoT have been identified. Increased efficiency and productivity are among the most significant, with IoT devices automating tasks and gathering data, thereby freeing human resources for more strategic endeavours [89]. In terms of decision-making, the real-time data provided by IoT devices enhances the quality and timeliness of decisions [90]. For customer experience, IoT offers personalized services and support, leading to more tailored and satisfying customer interactions [91]. Additionally, IoT is opening new business frontiers, creating opportunities for companies to innovate and market novel IoT products and services [89].

2.7.1 IoT Challenges

The proliferation of IoT also presents challenges. Security is a primary concern, as IoT devices can become targets for cyberattacks, posing risks to sensitive data [89]. Privacy issues arise from the extensive data IoT devices collect and store, leading to concerns over how this data is used and protected [90]. Moreover, the IoT ecosystem's complexity, encompassing diverse technologies and standards, presents significant challenges in managing and securing IoT networks [91]. Despite these challenges, the potential of IoT to revolutionize both professional and personal spheres is undeniable. As IoT technology continues to evolve, we can anticipate a future rich with innovative applications that transform how we interact with the world around us.

2.7.2 IoT Technologies

The Internet of Things (IoT), characterized by its network of interconnected physical devices, vehicles, home appliances, and other everyday items equipped with electronics, software, sensors, actuators, and connectivity, represents a significant leap in digital innovation. This network facilitates the connection, collection, and exchange of data across a wide range of objects, making everyday interactions smarter and more efficient.

A crucial component of IoT technologies is sensors, which gather data about the physical world, such as temperature, humidity, and pressure [92]. Actuators complement sensors by controlling physical mechanisms, enabling actions like turning lights on or off and managing door operations. Microcontrollers, essentially compact computers, play a pivotal role in directing the functionality of IoT devices, while embedded systems are specialized computer systems designed for specific tasks [92]. Wireless communication technologies, including Wi-Fi, Bluetooth, and cellular networks, are the backbone of IoT connectivity, linking devices to the internet and each other.

In the dynamic landscape of smart home technology, research has been pivotal in enhancing systems for monitoring and controlling home appliances. [93] exploration of Zigbee wireless sensor networks and [94] investigation into Arduino Uno microcontrollers have both highlighted the potential for increased energy efficiency and the facilitation of real-time automation in home environments [93.

The wearable devices sector, especially in health monitoring systems, has also experienced substantial advancements. [95] emphasized the utility of embedded sensors, like accelerometers and heart rate monitors, in gathering critical health and fitness data. Further, [96] explored the use of smartwatch-based fall detection systems, employing machine learning algorithms for precise event detection.

In the automotive industry, the concept of connected cars and vehicle-to-vehicle (V2V) communication is transforming vehicular safety and efficiency. [97] and [98] have delved into the applications of V2V communication, particularly for collision prevention and enhanced cooperative driving

Smart city initiatives have similarly attracted considerable research interest. [99] and [89] have both underscored the critical role of IoT technologies in improving various aspects of urban life, including smart grids, intelligent transportation systems, and smart buildings, thereby fostering more efficient, sustainable, and livable cities

In the realm of industrial applications, IoT technologies are reshaping conventional processes. [100] and [101] have investigated the implementation of IoT in sectors such as manufacturing, logistics, and supply chain management, highlighting the transformative impact of Industrial IoT on operational efficiency.

As IoT technologies continue to evolve, their applications are becoming increasingly diverse and impactful. Ongoing research is not only broadening the scope of IoT's capabilities but also continually redefining the ways in which these innovative technologies can be applied for more effective and significant solutions across various sectors.

2.8 AI embedded IoT for Locust Management

Artificial intelligence (AI) can be embedded into Internet of Things (IoT) systems for more advanced and efficient monitoring of locust populations. [102] describes an intelligent monitoring system for locust detection based on IoT and deep learning. The system consists of a network of IoT devices with sensors for collecting environmental data such as temperature, humidity, and sound, which are then processed by a deep learning algorithm for locust detection and classification. The authors report experimental results demonstrating the effectiveness of the system in detecting locusts in real-world environments. The authors evaluated their system in a field experiment and report an accuracy of over 90% in detecting locusts. The proposed system has the potential to provide early warning of locust outbreaks and help farmers take timely preventive measures to minimize crop damage. The system could also facilitate the monitoring and tracking of locust populations, which could aid in the development of effective control strategies.

[103] designed a system for detecting locusts based on IoT and machine learning technologies. The system utilizes an IoT device equipped with sensors to collect environmental data such as temperature, humidity, and wind speed, which are then processed by a machine learning algorithm to predict the presence of locusts. The authors report experimental results demonstrating the effectiveness of the system in detecting locusts under various environmental conditions and reported an accuracy of over 95% in detecting locusts. The proposed system has the potential to provide early warning of locust outbreaks and help farmers take timely preventive measures to minimize crop damage.

[104] presents a system for real-time monitoring of locusts using AI and IoT technologies. A notable development in this area is the design and implementation of a cloud platform-based

remote sensing monitoring system specifically for desert locusts in these regions. This system represents a leap forward in automating and enhancing the intelligence of locust monitoring processes. Its application in real-world scenarios has begun to yield promising results, highlighting its potential in effectively managing locust outbreaks.

[69] details a real-time object detection system using deep learning algorithms on a Raspberry Pi. The study utilizes a pre-trained YOLO (You Only Look Once) model, renowned for its swift and precise object detection capabilities. This model, initially trained on the COCO dataset comprising 80 diverse object categories, is adapted to function on the Raspberry Pi by code optimization for ARM architecture and input image resolution reduction. The system's effectiveness is tested across various objects such as humans, vehicles, and animals, achieving real-time detection at a rate of 5-6 frames per second on a Raspberry Pi 3 Model B. The detection accuracy parallels that of YOLO running on conventional desktop setups. The authors suggest potential applications ranging from surveillance to robotics and intelligent home systems, underscoring the feasibility of employing AI and Raspberry Pi in resource-limited settings for tasks like early locust detection and control.

In another study, [105] explores the creation and testing of a smart pest control system utilizing the Raspberry Pi for managing locust swarms, a significant threat to agriculture and food security. The research critiques traditional pest control methods such as chemical pesticides, biological control, and integrated pest management, pointing out their environmental risks, impact on non-target species, and the potential development of pest resistance. The paper then introduces a sophisticated pest control system built on the Raspberry Pi platform, which is comprised of a monitoring module, a wireless communication module, and a pest control module. The system’s design, both hardware and software, is elaborately described, and findings from multiple experiments demonstrate the system's capabilities in efficiently detecting and managing locust swarms.

2.9 Chapter Summary

This chapter provides a comprehensive overview of the intersection of technology, particularly artificial intelligence (AI) and the Internet of Things (IoT), with locust management. It begins by setting the historical context and current state of locust prevalence, alongside an exploration of general knowledge surrounding locust behavior, life cycles, and the use of mobile phones by farmers. This background is crucial for understanding the environment in which technological solutions for locust management are to be implemented. A key focus of the chapter is on the role of technology in locust management, with an in-depth look at AI's contribution to agricultural challenges. The subsection on machine learning (ML) delves into its applications in agriculture, particularly for locust prediction and control, while the discussion on deep learning highlights its significance in processing complex agricultural data. The chapter further explores various deep learning models and their functionalities in agriculture and pest control. Specific deep learning architectures such as MobileNet, MobileNetV2, its quantized version, ResNet, and VGG are examined for their later relevance in agricultural contexts, noting their efficiency and suitability for different applications.

The chapter also introduces key frameworks supporting these deep learning models, including TensorFlow and Keras, PyTorch, and Caffe. The integration of TensorFlow with Keras is discussed for facilitating deep learning development, and PyTorch is highlighted for its dynamic computational graph and utility in research and development. Caffe's efficiency in forward pass computations and its applications in real-time systems are also examined. Further, the chapter focuses on the specific application of AI in various aspects of locust management, including prediction, identification, and control strategies. It then shifts focus to IoT, exploring its role in agriculture and locust management. The challenges associated with IoT, such as security, privacy, and complexity, are critically examined, alongside an exploration of IoT technologies like sensors, actuators, microcontrollers, and embedded systems.

The chapter concludes by discussing the integration of AI with IoT in the context of locust management. This synergy is outlined as a potential pathway to innovative solutions for monitoring and controlling locust invasions, highlighting how combined AI and IoT technologies can revolutionize locust management strategies.

Chapter 1 hence provides a detailed and holistic view of the current state of research at the nexus of AI, IoT, and locust management. It establishes a foundation for understanding how these technologies can be leveraged together to develop more effective, efficient, and innovative solutions in the battle against locust invasions.

CHAPTER 3: THEORETICAL AND CONCEPTUAL MODEL/FRAMEWORKS

3.0 Introduction

Chapter 3 delves into the theoretical and conceptual frameworks that form the backbone of this research, focusing on the Unified Theory of Acceptance and Use of Technology (UTAUT) model as well as the Design Science Research Methodology (DSRM). This chapter provides a comprehensive overview of UTAUT and DSRM. We explore how UTAUT and DSRM not only underpins theoretical advancements but also propels practical applications in these domains.

3.1 Unified Theory of Acceptance and Use of Technology (UTAUT) Model

The Unified Theory of Acceptance and Use of Technology (UTAUT) model, established by [106], is a comprehensive framework designed to understand and predict user acceptance and utilization of technology. This model amalgamates elements from eight different theories and models previously utilized to explain technology acceptance and usage behaviors, including the Theory of Reasoned Action, the Technology Acceptance Model, and the Motivational Model [106].

UTAUT identifies four key constructs namely Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions as primary determinants of technology use [106]. Recent studies have continued to validate and expand upon these constructs.

Performance Expectancy is a key determinant in technology acceptance, strongly influencing whether individuals believe that using a particular technology will improve their job performance, as outlined by [107]. Alongside this, Effort Expectancy plays a crucial role. It encompasses the perceived ease of use of the technology. [108] research emphasizes that technologies deemed user-friendly are more likely to be adopted. Another critical factor is Social Influence. This concept, highlighted by Chávez Hurting in 2023, underscores the impact of social factors on technology use, where the opinions of peers or superiors can significantly influence an individual's choices. Facilitating Conditions, as detailed by [109], refer to the extent to which users believe they have adequate organizational and technical support to use the technology effectively.

The UTAUT model's robustness and applicability across various technology types and user demographics make it an invaluable tool for researchers and practitioners. Its efficacy in guiding the design of interventions to enhance technology adoption has been demonstrated in multiple sectors including healthcare, education, and business [110], [111]. Figure 7 shows the modified UTAUT Model.

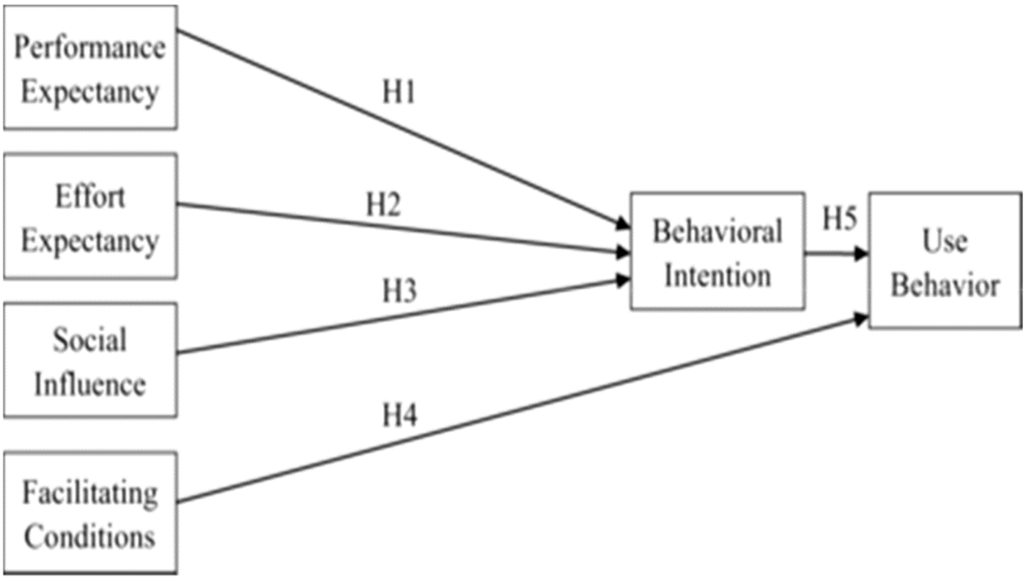


Figure 7:Modified UTAUT Model [112]

In applying the UTAUT model to locust management technology, it provides a structured lens to understand the factors influencing the acceptance and usage of mobile alerts and other technological strategies in agricultural settings [113]. This application offers critical insights into behavioural intentions and actual usage patterns, contributing significantly to the development of efficient and user-friendly solutions in locust management [114].

3.2 Design Science Research Methodology (DSRM)

Design Science Research Methodology (DSRM) is a cornerstone methodology in the realm of research, particularly for developing and evaluating innovative solutions tailored to real-world problems [115]. The initial stage in DSRM involves the identification of a problem and a clear elucidation of the motivation behind addressing this issue [116], thereby setting the stage for a targeted research inquiry. This is followed by defining specific, achievable objectives for the solution, ensuring these goals are intricately linked with the initially identified problem and the rationale for its resolution [117]. The crux of DSRM lies in the meticulous design and development phase, where creativity and technical prowess converge to create a practical and impactful solution [118]. This phase is a testament to the ingenuity and application of theoretical knowledge in a real-world context. Subsequent to the development phase, the methodology emphasizes the importance of demonstration and evaluation [119]. In this stage, the solution is rigorously tested and evaluated in situ, providing a comprehensive assessment of its functionality, effectiveness, and any limitations, guided by predefined criteria and metrics. The concluding phase of DSRM underscores the significance of communication and knowledge transfer [120]. This final step ensures that the research outcomes, insights, and the developed solution are effectively communicated to stakeholders, thereby fostering an environment conducive to the solution's adoption and practical application. Through its structured, step-by-step approach, DSRM empowers researchers to not only address complex challenges with innovative solutions but also contribute substantively to the advancement of their respective fields [121], marking a significant impact in both theoretical and practical domains.

The application of Design Science Research Methodology (DSRM) in the realms of Artificial Intelligence (AI) and the Internet of Things (IoT) has garnered significant attention in recent years. DSRM, with its focus on the creation and evaluation of artifacts designed to solve specific problems, aligns seamlessly with the goals of AI and IoT, which often revolve around the development of innovative solutions to complex, real-world challenges.

In the field of Artificial Intelligence, the relevance of DSRM is particularly pronounced. [117] article in MIS Quarterly, "Positioning and presenting design science research for maximum impact," offers a comprehensive examination of DSRM's application in AI. They argue that the methodology's strengths lie in its ability to guide researchers in structuring their work to achieve maximum impact, particularly in a field as dynamic and rapidly evolving as AI [117]. The application of DSRM in AI extends to specialized domains, such as healthcare and agriculture.

3.2.1 DSRM’s Impact on IoT Development

In the sphere of the Internet of Things (IoT), DSRM's relevance is equally significant [122]. The IoT ecosystem, characterized by its vast network of interconnected devices and sensors, presents unique challenges that require innovative solutions. DSRM offers a structured approach to tackle these challenges, guiding researchers and practitioners in developing and assessing IoT solutions that are not only technologically advanced but also practical and user-friendly. This aspect is crucial in IoT, where the integration of technology into everyday objects and environments must be seamless and intuitive.

The application of DSRM in IoT can be seen in various case studies and practical applications. For instance, the development of smart home systems, which utilize IoT to enhance home automation and energy efficiency, often leverages DSRM to ensure that the solutions are not only technologically sound but also align with users' needs and preferences. Similarly, in industrial settings, IoT applications developed using DSRM principles can lead to more efficient manufacturing processes, predictive maintenance, and enhanced safety protocols.

3.2.2 Incorporation of DSRM in the Research

In this research, DSRM has been integral in systematically developing and evaluating the AI-based early warning system. The methodology's initial stages, involving problem identification and motivation, were crucial in understanding the multifaceted nature of locust invasions and the potential role of AI and IoT in mitigating these challenges. This understanding laid the groundwork for defining clear objectives for the solution, ensuring that the goals were not only aligned with managing locust invasions but also adaptable to the dynamic nature of ecological and environmental factors.

The research used Design Science Research (DSR) Methodology. DSR is a methodology for creating and evaluating innovative artifacts or solutions to address practical problems or challenges in various domains. [123] describe the DSR methodology as a process that involves the following stages:

1. *Problem identification and motivation:* This stage involves identifying a practical problem or challenge in a specific domain that requires a solution or improvement. The motivation for solving the problem is also identified.

2. *Define objectives for a solution:* In this stage, the researcher defines the objectives or goals for the solution to be developed. These objectives should be aligned with the problem and the motivation for solving it.

3. *Design and development:* This stage involves designing and developing the solution or artifact to address the problem. The solution should be innovative, practical, and effective in addressing the identified problem.

4. *Demonstration and evaluation:* In this stage, the solution is demonstrated and evaluated in a real-world setting to determine its effectiveness in addressing the problem. The evaluation should be based on predefined criteria and metrics.

5. *Communication and knowledge transfer:* This stage involves communicating the results of the DSR process to stakeholders and transferring knowledge about the solution to ensure its adoption and use.

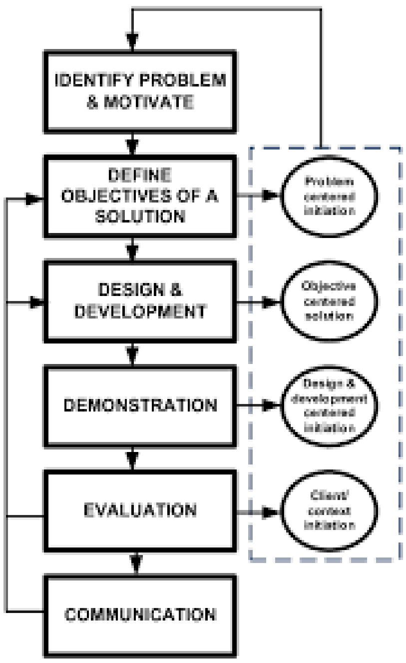


Figure 8:Design Science Research Methodology [124]

The DSR methodology is iterative and involves continuous feedback and improvement throughout the process. It is an action-oriented approach that emphasizes the creation of practical solutions to real-world problems.

3.3 Proposed Conceptual Framework

The research is proposing an early warning system for the management of the spread of Locust invasion based on AI and other emerging technologies such as IoT and cloud computing technologies. A trap, will enable effective image capturing of targeted insects. Each trap will be energy independent using a battery that will be charged by solar energy. The Raspberry Pi 4B microcomputer, connected with a Pi camera and sensors, will form part of the perception layer of the proposed IoT node. The camera will automatically take images of the captured pests daily. To enhance collection of local weather, temperature and humidity sensors shall be utilised. The local weather data will be of help in identifying the favourable conditions that influence the proliferation of Africa Migratory Locust (AML) and Red Locust (RL).

To enable the smooth gathering of data, the integration of a MiFi device to provide internet connectivity to a Raspberry Pi 4 Model 4B is highlighted as a pivotal component of the research design. This approach enables the Raspberry Pi, which serves as a compact yet powerful computing platform, to access the internet in locations where traditional wired connectivity is unavailable or impractical. The MiFi device, essentially a portable Wi-Fi hotspot, leverages cellular networks to offer wireless internet access, thereby ensuring that the Raspberry Pi remains online and functional regardless of its geographical placement [125]. This connectivity is particularly crucial for the Raspberry Pi's role in data collection, processing, and transmission in remote or mobile environments, such as in field-based research or mobile IoT applications.

A Global Positioning System (GPS), serially connected to the Raspberry Pi, will provide an automatic positioning awareness and geospatial. The captured information will be seamlessly sent to the cloud service for easy data storage and visualization. This approach is supported by [5] who developed an IoT solution to monitor agricultural activities. This will ultimately reduce the number of field visits to the area for possible locust monitoring. The model Block diagram for an early warning for the management of locust invasion was connected as shown in figure 9.

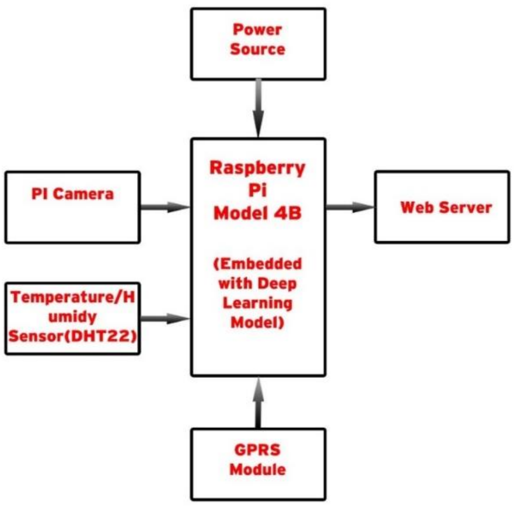


Figure 9:Model Block Diagram for an Early Warning System

3.4 Chapter Summary

Chapter 3 of the dissertation serves as a foundational exploration of the theoretical and conceptual models that underpin the research. It begins with an introduction that sets the stage for a detailed examination of the key theories and methodologies shaping the study. Central to this chapter is the Unified Theory of Acceptance and Use of Technology (UTAUT) Model, a comprehensive framework that integrates various theories to understand the factors influencing technology adoption. The UTAUT model, with its constructs of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, is critically analyzed for its relevance in predicting user behavior in the adoption of new technologies, particularly in the use of Phones in Locust management.

The chapter then transitions to a thorough discussion of the Design Science Research Methodology (DSRM), emphasizing its role in the creation and evaluation of artifacts designed to address specific problems. A significant portion of this section is devoted to elucidating DSRM's impact on the development of AI and Internet of Things (IoT) technologies, illustrating how it guides the systematic development of innovative and practical IoT solutions. This is followed by an explanation of how DSRM principles have been incorporated into the current research, detailing the steps taken to align the study with these principles, from problem identification to artefact evaluation.

The culmination of the chapter is the introduction of a proposed framework for an early warning system for the management of locust invasion. It positions itself as a key contribution to the research, offering a novel and robust approach to addressing the research problem.

CHAPTER 4: RESEARCH METHODOLOGY

4.0 Introduction

The methodology for this research is grounded in Design Science Research Methodology, which guides the systematic development and evaluation of technological solutions to complex problems. This study specifically addresses the challenge of managing locust invasions. Within this framework, the Unified Theory of Acceptance and Use of Technology (UTAUT) was also applied to assess the adoption and effectiveness of the proposed technological solutions. To implement this methodology, various methods were employed including Focus Group Discussions (FGDs), semi-structured questionnaires, and field experiments. These methods facilitated the practical application of a Deep Learning model embedded within Internet of Things (IoT) devices and integrated with Cloud Computing technologies.

4.1 Challenges faced in the management of locust invasion using existing early warning strategies

The method employed in this objective involved conducting a Focus Group Discussion (FGD) in December 2021, with the aim of exploring the challenges faced in the management of locust invasion using existing early warning strategies. The FGD was carried out in a serene outdoor setting on a round table in Kazungula District.

As described by [126], the focus group method is a research technique that involves collecting data through group interaction on a specific topic chosen by the researcher. In this case, the topic under scrutiny was the challenges related to locust invasion management.

The participants in the FGD comprised three locust experts who possessed extensive experience in locust management, averaging around 16 years, hailing from the Ministry of Agriculture and Livestock. Additionally, the FGD included an Entomology Professor, a Computer Science Doctor, and a moderator from the University of Zambia.

Before the FGD, the participants had undertaken a field visit to the Sikaunzwe plains, which served as the breeding grounds for locusts. The FGD was the initial phase of a broader research study titled "A framework for an early warning system for the management of the spread of locust invasion in Zambia; based on Artificial Intelligence Technologies."

The primary objective of this initial stage was to engage the participants in a discussion about the challenges encountered while managing locust invasion using existing early warning strategies. To address this objective, the participants were presented with a series of questions during the FGD, specifically tailored to elicit their insights and experiences regarding the management of locust invasions in the study area.

Prior to the discussion, the participants were provided with a detailed briefing by the moderator about the research study's objectives. They were explicitly informed that the outcomes of the FGD would serve as a guide for the subsequent phases of the research.

The FGD served as a valuable platform for the experts to share their knowledge, perspectives, and experiences, shedding light on the existing challenges faced in effectively managing locust invasions. The insights garnered from the FGD played a crucial role in formulating a comprehensive framework for an early warning system, incorporating Artificial Intelligence technologies, to better address and mitigate the spread of locust invasions in Zambia.

4.1.1 Locust Infestations and Mobile Phones

In the subsequent phase of the research, its scope was expanded to include a cohort of agricultural producers based in the Sikaunzwe area, which is situated within the confines of the Kazungula district. The primary objective of this expanded study was to meticulously assess the extent to which mobile phones are being integrated into the practices of locust management by local farmers. The study aimed to understand the depth of locust knowledge, experience and digital tools utilization in mitigating and managing the impact of locust infestations, which are a recurrent threat to agricultural sustainability and food security in the area.

4.1.1.1 Study design

The study utilized a quantitative approach in collecting data, which facilitated the acquisition of comprehensive and organized data that accurately reflected the opinions and perspectives of farmers regarding the variables under investigation.

4.1.1.2 Study Area

The research was carried out in the Sikaunzwe Agricultural Camp situated in the Kazungula District of the Southern Province in Zambia. Kazungula is well-known for its agricultural practices, while Sikaunzwe is a small community within the district. This location was selected due to its susceptibility to locust infestations, including the breeding of Red Locust and the recent occurrence of African Migratory Locust invasions, as highlighted by [4]. Figure 10 shows the map of Sikaunzwe.

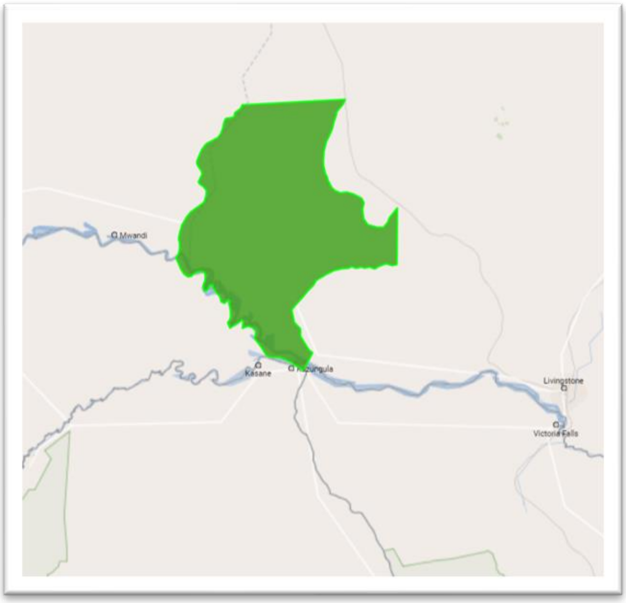


Figure 10: Sikaunzwe Area

4.1.1.3 Study population

The research was conducted among the farming community of Sikaunzwe Agricultural Camp, situated within the Kazungula District of Zambia's Southern Province. The study targeted farmers who have previously dealt with locust invasions, a factor that was instrumental in participant selection. Covering an area of 1,902 square kilometres, Sikaunzwe boasts a population density of 3.965 people per square kilometre as per the data from 2010. Sikaunzwe reveals a gender distribution that is nearly even, with males slightly exceeding females, representing 50.5% and 49.5% of the population, respectively. The age composition is predominantly youthful, with the largest demographic comprising those aged between 0-14 years, followed by the working-age populace of 15-64 years. The elderly, aged 65 and above, make up a smaller fraction of the population. The youthful dominance within the population indicates potential needs for enhanced educational, employment, and healthcare provisions in the region [179].

4.1.1.4 Data collection methods and ethics

The research study employed questionnaires as the data collection tool, which were administered to 260 respondents, resulting in a response rate of 96%. The sampling technique used in this study was purposive sampling, which involves selecting participants based on specific characteristics or attributes that are relevant to the research objectives. In this case, the researcher targeted farmers who reside in the Sikaunzwe Agricultural Camp of the Kazungula District in Zambia and have had experience with locusts.

The study followed strict ethical guidelines to ensure the well-being and privacy of the participants. Prior to their involvement, participants were fully informed about the study's purpose, potential risks and benefits, and their right to withdraw at any time. They were also assured that their responses would be kept confidential and anonymous, and all identifying information would be removed from the data. To prevent any harm, the questionnaire questions were carefully designed to avoid causing any distress or discomfort to the participants. The collected data was securely stored and handled in accordance with data protection legislation, and used solely for research purposes.

4.1.1.5 Data analysis procedure

To assess the prevalence rates and level of knowledge regarding locusts in Kazungula, the study employed descriptive statistics. Furthermore, to determine the correlation between locust knowledge and the use of mobile phones in Kazungula, the study utilized the Chi-square test. STATA 15 software was used to perform the data analysis.

4.2 Artificial Intelligence, IoT and cloud computing to detect AML invasion.

The research proposed an automatic identification of both African Migratory Locust (*Locusta migratoria*) and Red Locust (*Nomadacris septemfasciata*) using Convolution Neural Network (CNN) Single-Stage object detection (SSD) MobileNet version 2 quantised model. A custom dataset was used to train, test and validate the model using images collected from the study area.

4.2.1 Dataset design

In this research, the methodology involved a comprehensive and systematic approach to collecting and curating a diverse dataset of locust images for the purpose of training, testing, and validating the proposed AI-based detection system.

A field visit to the Sikaunzwe Agricultural Camp plains in Kazungula District, Zambia focused on capturing high-quality images of locusts over a three-day period. However, due to the inherent mobility of some locusts, which made direct capture challenging, assistance was sought from cattle headers to capture live locusts. These live specimens were then carefully placed in transparent bottles for controlled photography.

The Nikon D5300 Camera, known for its superior image quality and resolution, was selected as the primary imaging tool for capturing the locust images. The camera offers a resolution of 24.2 megapixels. The maximum image size at full resolution is typically around 6000 x 4000 pixels. This is because the sensor has a 3:2 aspect ratio, which is common in DSLR cameras. This resolution is provided by its DX-format CMOS sensor, which is capable of delivering high-quality images with fine details. The camera's resolution is sufficient for large prints and detailed cropping, making it a versatile choice for various photography needs.

To ensure a comprehensive and diverse collection of images, the captured locusts were subjected to additional image shoots. Various conditions were intentionally manipulated during these shoots, including different light intensities, foreign background details, and varying angles of image capturing. This deliberate variation aimed to capture the locusts under a range of environmental scenarios, thereby creating a dataset that is robust and representative of real-world conditions. Figure 11 shows the live capturing of images in the study area for further image pre-processing.

Figure 11:Image Capturing

The research team maintained a maximum distance of 50 centimetres between the camera and the insects during image capture to maintain consistent image quality and minimize potential distortion.

To increase the number of images in the custom dataset further, the images were augmented using a python scrip.
Given the importance of accurate classification, the locust images obtained were meticulously vetted and categorized by an expert in entomology. This classification process ensured that only relevant and authentic locust images were included in the custom dataset.

The resulting custom dataset represents a diverse and extensive collection of locust images, encompassing different species, environmental conditions, and geographic locations within the study area. This dataset serves as a critical resource for training and evaluating the performance of the Convolution Neural Network (CNN) Single-Stage object detection (SSD) MobileNet version 2 quantised model, enabling it to achieve accurate and robust automatic identification of both African Migratory Locust and Red Locust.

4.2.2 Data Pre-processing

In the data pre-processing phase, attention was given to annotating the images to facilitate accurate and reliable training of the AI-based detection system. To achieve this, the open-source software "Labelimg" was employed for physical annotation of all images in the dataset. The images were classified into two distinct classes, namely African Migratory Locust (AML) and Red Locust. Each image was then meticulously annotated using a rectangular bounding box format adhering to the PASCAL VOC (Visual Object Classes) standard.

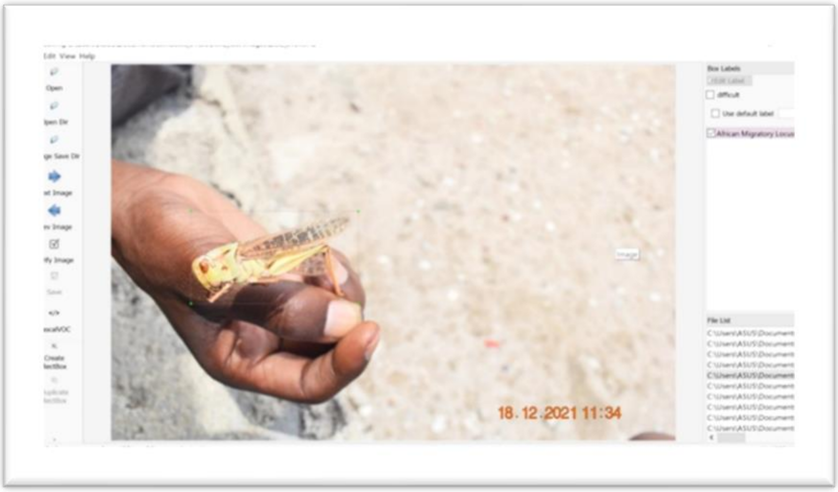


Figure 12:Image Annotation-Labelimg

The bounding boxes were subjected to thorough scrutiny to ensure their accuracy and integrity. Special care was taken to verify that the bounding boxes were devoid of any foreign objects or artifacts that could potentially interfere with the training process. Any images found to have inaccurately aligned bounding boxes were rectified, and images that were deemed unclear or captured from a considerable distance were filtered out from the dataset. This process of image selection and bounding box alignment was crucial in maintaining the high quality of the dataset, which is imperative for the success of the AI-based detection system.

The entire data annotation and verification process, performed by the researcher, spanned a period of seven days, during which a total of 1700 images were diligently curated to form the dataset. Among these images, 1410 were earmarked for training purposes, while the remaining 290 were reserved for testing and validation. The distribution of the images in the dataset resulted in 1135 images representing the African Migratory Locust class and 565 images representing the Red Locust class. This balance and diversity in the dataset were crucial for the AI model to generalize effectively and accurately detect both locust species in real-world scenarios.

Given the context of the study and the intended use of the AI-based detection system by farmers and agricultural camp officers in the study area, a custom dataset comprising images captured within the same area was considered optimal. This approach ensured that the dataset was well-suited to the specific locust species prevalent in the study area, making the detection system more relevant and effective.

During the annotation process, Labelimg generated an XML file for each image containing the annotated bounding box information. Subsequently, a Python script was utilized to convert these XML files into CSV (Comma-Separated Values) format, which streamlined the data handling and processing.

4.2.3 Model Training

The training of the Single Shot Detector (SSD) MobileNet V2 quantized model was undertaken, a decision motivated by the model's noted efficiency and effectiveness in object detection tasks. To facilitate this, Google Colab was employed as the primary platform, chosen for its substantial processing capabilities, particularly the access to Graphics Processing Units (GPUs) and significant storage capacity.

The training process was defined by a meticulous approach to hyperparameter optimization. A learning rate of 0.001 was selected, a decision grounded in its proven effectiveness in balancing adaptability with convergence towards the set objectives, fitting within the typical range for deep learning models. This learning rate played a pivotal role in guiding the optimization process of the model.

Further, the training approach involved careful consideration of several other key hyperparameters. The number of layers and neurons in the SSD MobileNet V2 is predefined, with the architecture typically encompassing 20-30 layers, designed specifically for object detection. These layers vary in neuron count, reflecting their distinct roles within the model. Activation functions were also a focal point, with ReLU6 being chosen for its compatibility with the low-precision requirements of the quantized model.

Batch size was another critical factor, with a range between 32 to 64 being optimal for balancing the computational efficiency and the learning dynamics of the model, especially considering the memory limitations on the Colab platform. Data augmentation techniques such as random cropping, horizontal flipping, and colour jittering played a significant role in enhancing the model's ability to generalize, thereby expanding the diversity of the training data and improving the model's robustness.

The quantization process, vital for reducing the model's size and improving computational speed, was conducted with precision to ensure minimal loss in accuracy. This was followed by a fine-tuning phase to regain any loss in accuracy due to reduced precision. The model's optimization was aided by the use of adaptive optimizer, Adam, and regularization techniques were applied, albeit conservatively, to prevent overfitting. These included methods such as L2 regularization and dropout, tailored to maintain the model's performance.

Weight initialization and the learning rate schedule were also integral to the training process. Standard methods were employed for weight initialization to ensure stability in weight distribution, particularly critical during the training and quantization stages. A dynamic learning rate schedule was adopted to adjust the learning rate appropriately during different training phases, enhancing the model's efficiency in convergence.

In the process of enhancing the model's performance for the task of locust species detection, a critical step was the implementation of data augmentation techniques. Data augmentation is a strategy that artificially expands the training dataset by generating modified versions of existing images. Utilizing TensorFlow's comprehensive library, this process involved transformations like rotation, scaling, and horizontal flipping of images. Such modifications enable the model to be exposed to a wider variety of scenarios, closely simulating real-world conditions. This not only increases the diversity and volume of training samples but also significantly contributes to the model's ability to generalize better to new, unseen data, ultimately leading to improved robustness and accuracy.

For the training of the model, specifically targeting the African Migratory Locust and Red Locust detection, 80% of the custom-assembled dataset was employed. This segment of the dataset acted as the training set, providing the model with a rich array of examples to learn the intricate patterns and features unique to these locust species. The training process was meticulously monitored to ensure that the model learned to recognize various aspects of the locusts under different conditions, a task made more effective by the aforementioned data augmentation techniques.

The remaining 20% of the dataset was allocated for testing purposes. This separation is crucial in machine learning to ensure that the model is evaluated on data that it has never seen before, thereby providing a genuine measure of its performance. This test set acts as a proxy for real-world scenarios, gauging the model's ability to accurately detect and classify the locust species in diverse and potentially challenging environments.

Upon the conclusion of the training phase, a frozen inference graph was generated in the form of a .pb (Protocol Buffer) file. This file is a serialized representation of the model, encapsulating the complete architecture and the learned weights. The creation of a frozen inference graph is a standard practice in deploying deep learning models, as it enables efficient and rapid inference. The utility of this graph lies in its portability and ease of integration into various application environments, making it a cornerstone for the model's deployment in real-time scenarios.

In these real-world applications, the model's ability to quickly and accurately detect and classify locust species is critical. The performance of the model in these tasks has far-reaching implications, especially in areas affected by locust invasions, where timely and accurate detection can significantly aid in control and mitigation efforts. Therefore, the effectiveness of the training process, augmented by strategic data manipulation and rigorous evaluation, is directly linked to the model’s potential impact in practical applications.

4.3 IoT Deep learning embedded model

Single Board Computers (SBCs), particularly Raspberry Pi (RPi) units, have gained widespread popularity because of their affordability, energy efficiency, and versatility across various applications. The IoT Deep Learning embedded model features a Raspberry Pi 4 Model

B, a powerful microcomputer equipped with a 64-bit Broadcom BCM2711 quad-core Cortex-A72 SoC @ 1.8 GHz. It offers 8 GB of RAM and is designed with a range of connectivity options, including a Gigabit Ethernet interface, dual-band 2.4 GHz and 5 GHz IEEE 802.11b/g/n/ac WiFi, and two USB 3.0 ports along with two USB 2.0 ports. The device also supports dual 4K display with its two micro-HDMI connectors and includes a slot for a fast microSD card for storage expansion. These features make the Raspberry Pi 4 Model B a versatile and efficient choice for advanced IoT applications [127].

The Raspberry Pi Foundation has developed a widely-used software known as Raspberry Pi OS, with the 32-bit version installed on the device. This operating system is built upon Debian Bullseye, with its latest release rolled out in October 2021.

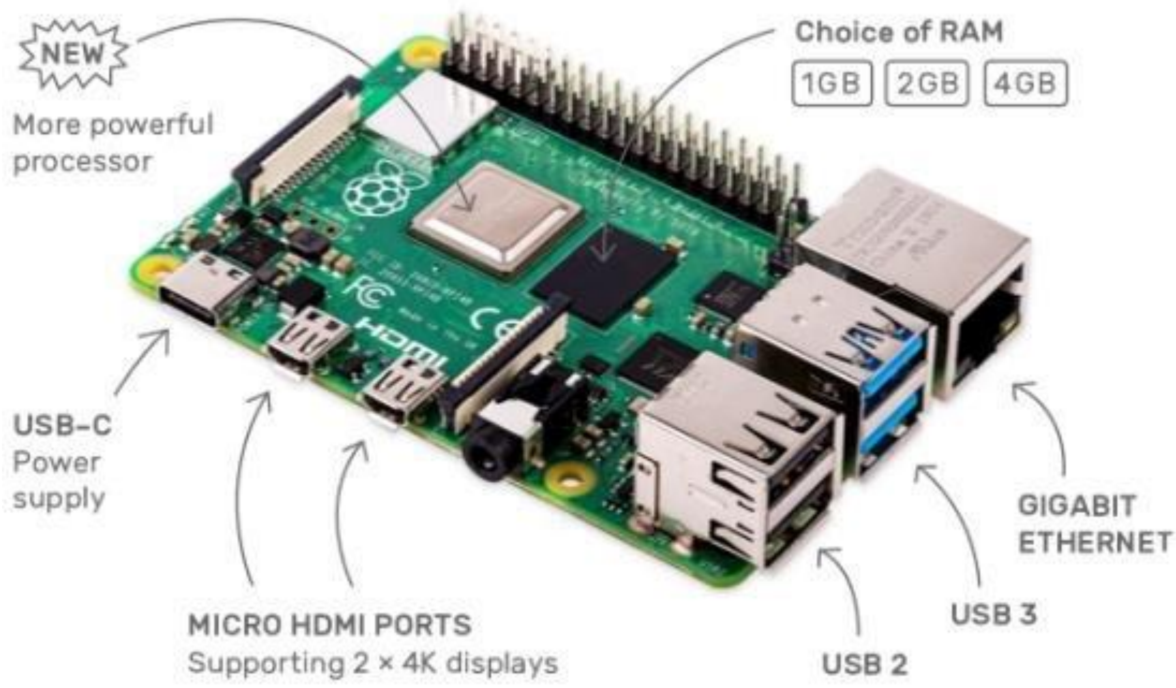


Figure 13: Raspberry Pi 4B [128]

Cconnected to the Raspberry PI 4B, is a Pi Camera whose task is to capture images in real time. The Pi Camera is an accessory tailored for the Raspberry Pi single-board computer, epitomizing a sleek, cost-effective, and multifaceted tool for incorporating photographic and video functionalities into various projects. This compact and lightweight module is perfectly suited for embedded projects where conserving space is crucial. It connects seamlessly with the Raspberry Pi via a dedicated CSI (Camera Serial Interface) port, facilitating swift data transfer to the processor. In terms of specifications, the Pi Camera has the capability to capture 5-megapixel still images and record video at multiple resolutions, up to full HD. It is equipped with fixed-focus lenses, which are pre-calibrated for general use, eliminating the need for manual focus adjustments. Additionally, the camera module has been upgraded with sensors that enhance its performance in environments with low lighting, ensuring clearer image capture under less-than-ideal light conditions. Figure 14 shows a Pi Camera.

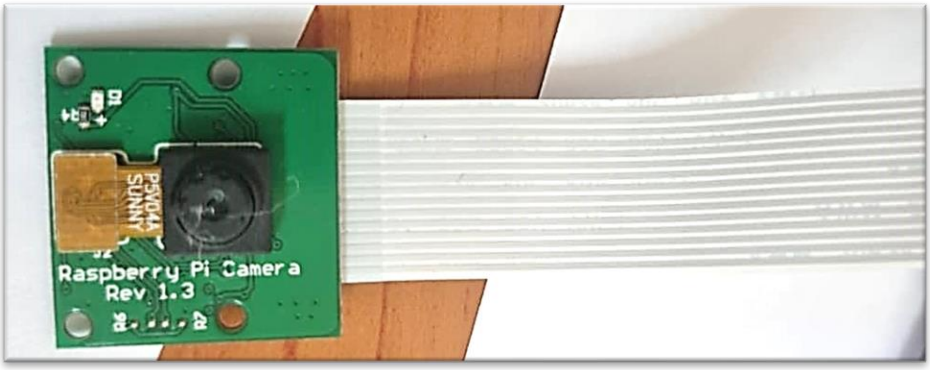


Figure 14:Pi Camera

DHT22 sensor collects both temperature and humid. Data collected through this sensor will continue to be of value in predicting the favourable conditions that favours the movement of locusts [129]. The Daily Temperature and Humidity levels at the time of capture of locust images were made possible through the use of DHT22 sensor.

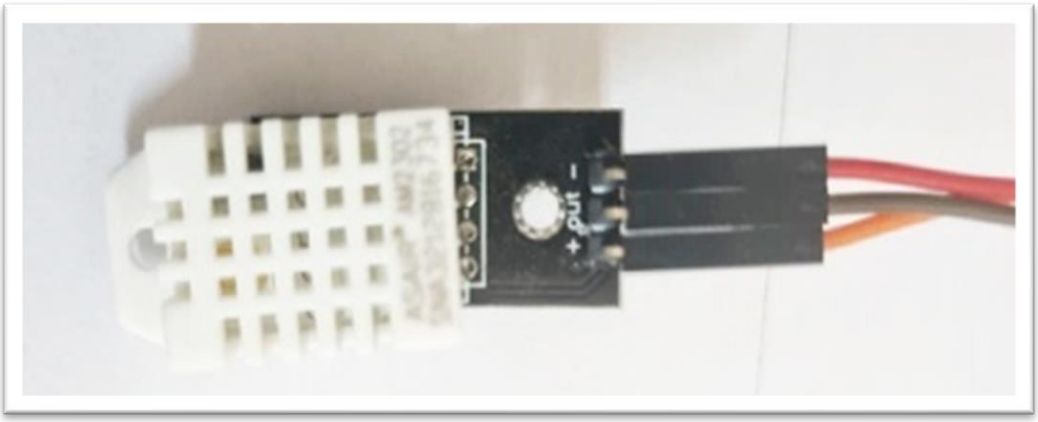


Figure 15:DHT22 Sensor

Fitted with a Simcard, the General Packet Radio Service (GPRS) enables access to the internet for easy data collection through the web browser. It also facilitates the remote access to the remote model. The GPRS/GPS provide a platform for data accessibility through the internet by use of Airtel mobile network Sim card.

Figure 16:GPRS Module

The integration of a MiFi device to provide extra internet connectivity to a Raspberry Pi 4 Model B is highlighted as a pivotal component of the research design. This approach enables the Raspberry Pi, which serves as a compact yet powerful computing platform, to access the internet in locations where traditional wired connectivity is unavailable or impractical. The MiFi device, essentially a portable Wi-Fi hotspot, also leverages cellular networks to offer wireless internet access, thereby ensuring that the Raspberry Pi remains online and functional regardless of its geographical placement [125]. This connectivity is particularly crucial for the Raspberry Pi’s role in data collection, processing, and transmission in remote or mobile environments, such as in field-based research or mobile IoT applications.

The IoT components were powered using a 30 Watts solar panel and 12 Volts battery. In the context of operating a Raspberry Pi and sensors on battery power, it was crucial to calculate the battery operated hours, especially considering the variable sunshine duration which influences solar charging capabilities in the study area. Kazungula, Zambia, located at approximately -17.7878° South latitude and 25.276° East longitude, experiences varying amounts of daily sunlight. The region gets at least 5 hours of sunshine per day, with an average duration of 7 hours and 35 minutes, and can receive up to 9 hours and 42 minutes of sunlight in a day [130]. The battery operated hours was determined using the equation: $Tb=Td-Ts$, where Tb represents the battery operated hours (in hours), Td is the total hours in a day (24 hours), and Ts is the sunshine hours per day. For this calculation, we used the minimum sunshine hours (5 hours) to ensure the Raspberry Pi and sensors had sufficient battery power during the least favourable conditions. This calculation helped in planning the energy requirements for a Raspberry Pi in Kazungula.

A solar charge controller electronic device, also known as a solar regulator regulated the voltage and current from a solar panel to a battery. It prevents overcharging and ensures that the battery is charged efficiently. To ensure that the Raspberry Pi was receiving a stable and clean power supply, a Buck DC to DC converter was added to the setup. A Buck DC to DC converter is a type of voltage regulator that steps down the voltage from the solar charge controller to a stable and regulated 5 volts required by the Raspberry Pi [131], [132]. The converter also filters out any noise or fluctuations in the input voltage, ensuring that the output voltage is stable and within the required range.

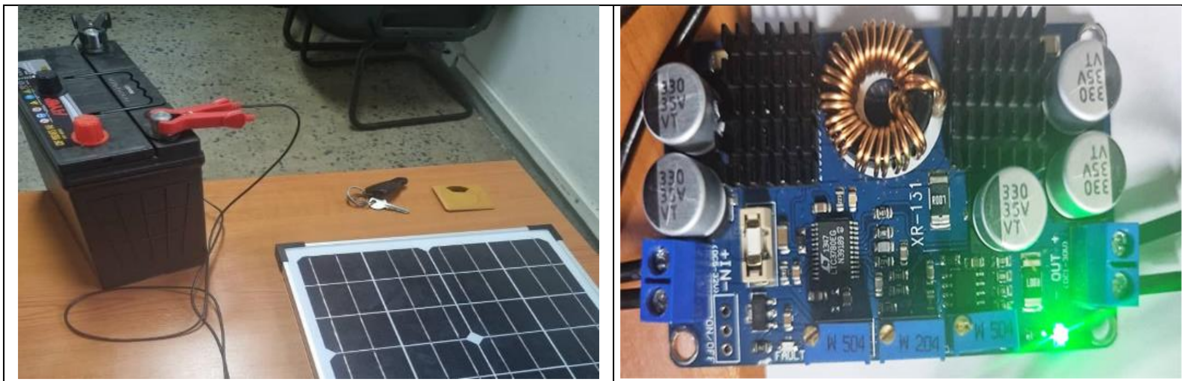


Figure 17:Solar Power and Buck DC to DC Converter

The low cost IoT- AI embedded design was first tested using the video that was captured in the study area during the African Migratory Locust outbreak in December 2020. It was further demonstrated in real time using both the AML and Red Locust insects captured in the study area. Only images that fit the criteria of 80% identification threshold were uploaded to the remote database for easy access through the browser.

This study employed the use of low-cost Internet of things (IoT) and Deep Learning technologies to monitor locust invasion at an early stage. The deep learning model and dataset aspects of the study were adopted from a recent research which looked at the "detection of *Locusta migratoria* and *Nomadacris septemfasciata*" in the study area [4]. The low cost IoT employed a Pi Camera serially connected to a deep learning embedded Raspberry Pi 4 model B to automatically capture locust images, the temperature and humidity sensors captured the environmental variables [3] that favours the proliferation of locust presence while the GPRS module, assisted by the MiFi, provided the internet access.

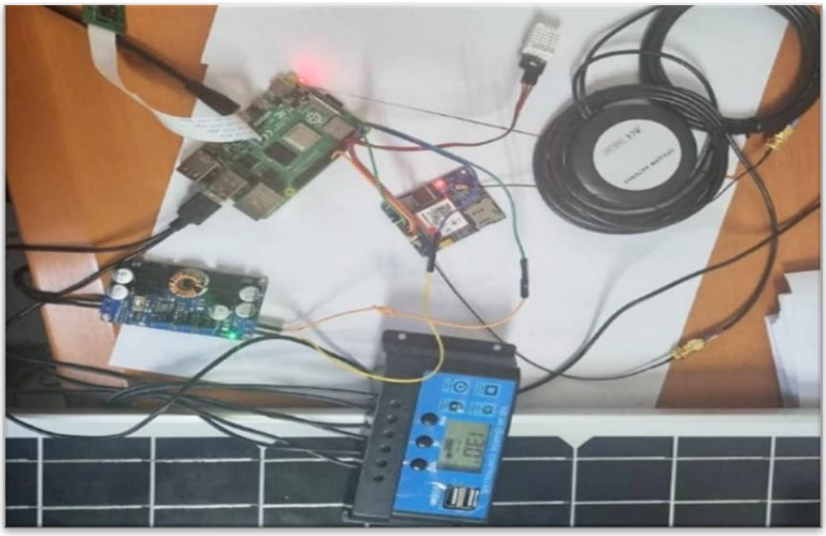


Figure 18:Low Cost IoT

In the second iteration of our DSRM process, we focused on refining the AI-driven locust identification system after initial field testing highlighted several areas for improvement. This phase began with a redesign of the algorithm to enhance its accuracy in identifying locust species under varied environmental conditions. The revised algorithm incorporated additional training data collected from the first deployment, which included a wider range of locust images capturing different times of day and weather conditions. Subsequently, the improved system was deployed for a second round of field experiments where IoT devices were installed at key locations known for frequent locust activity within the Sikaunzwe area.

4.4 Chapter Summary

This chapter encapsulates the comprehensive methodologies applied to address the challenges in managing locust invasions, particularly focusing on the inadequacies of existing early warning systems. The chapter begins with an introduction that outlines the scope and objectives of the research. A significant portion of the chapter is devoted to exploring the interplay between locust infestations and mobile phone technology. This includes a detailed examination of the study's design, the specific area and population involved, the methods employed for data collection along with ethical considerations, and the procedures used for data analysis. Furthermore, the chapter delves into the innovative application of Artificial Intelligence, the Internet of Things (IoT), and cloud computing in detecting locust invasions, marking a shift towards technologically advanced solutions. This section meticulously outlines the steps involved in creating the dataset, the processes of data pre-processing, and the intricacies of training the AI model.

Finally, the chapter introduces a cutting-edge IoT deep learning embedded model, suggesting a novel approach for locust invasion management. This model represents a pivotal part of the research, showcasing the integration of deep learning with IoT technology for real-time, efficient locust invasion detection and management.

CHAPTER 5: RESULTS

5.1 Introduction

This chapter unfolds the comprehensive findings from the research study titled "A Framework for an Early Warning System for the Management of the Spread of Locust Invasion Based on Artificial Intelligence Technologies." Aimed at systematically reporting and analysing results in line with the defined research objectives, this chapter probes into addressing key aspects of locust invasion management. It begins by shedding light on the challenges faced in controlling African Migratory Locust (AML) and Red Locust (RL) invasions, drawing on data gathered through surveys, interviews, and field observations. This analysis provides a deep understanding of the current difficulties encountered by farmers and government entities, highlighting existing gaps in locust management and underscoring the necessity for innovative AI-driven approaches.

The chapter then transitions into exploring the potential applications of Artificial Intelligence in detecting AML and RL invasions. The findings from these experiments offer valuable insights into the capabilities of AI, significantly enhancing the detection and prediction of locust invasions.

Central to the study is the development of an AI-based early warning system framework, which is comprehensively outlined in this chapter. This framework, which integrates AI with other emerging technological innovations such as the Internet of Things (IoT) and cloud computing, is presented in detail, emphasizing its architectural design, usability, scalability, and how it dovetails with existing locust control strategies. The results presented underscore the comprehensive nature of the framework, establishing its potential as a transformative tool in locust management.

Furthermore, the chapter focuses on the validation of this early warning system framework, highlighting the rigorous testing and evaluation methodologies employed to gauge its effectiveness in real-world scenarios. The presentation of results from these evaluations provides a clear depiction of the framework's efficacy in accurately predicting and managing locust invasions.

In synthesizing these findings, the chapter not only reflects on the achievement of the research objectives but also imparts critical insights into the applicability and impact of AI technologies in ecological and agricultural management. The results demonstrate a notable progression in locust control strategies, moving from traditional reactive methods to a more proactive, technologically-advanced approach. The implications of these findings for farmers, governmental bodies, and the broader pest control field are discussed, paving the way for future innovations in this crucial area of study. This introduction thus sets the stage for a detailed presentation of the research results, meticulously linking each section to the specific study objectives and underscoring the significant contributions of this research in advancing locust invasion management through AI technologies.

5.2 Challenges in Locust Control

The FGD yielded the following results.

5.2.1 Challenge in Identifying Correct Locust Species

The FGD revealed a significant challenge faced by staff in accurately identifying locust species. This issue is critical as incorrect identification can lead to inefficient management and control measures. Similar findings were echoed in the works of [133] and [134], who highlighted the difficulties and inaccuracies associated with manual identification of various locust instars and monitoring practices. Such inefficiencies often result in the transmission of erroneous or alarmist information to the Locust Control Center, operated by the Food and Agriculture Organization (FAO).

A key aspect discussed during the FGD was the capability of the eLocust3 application in addressing this identification challenge. Participants noted that while the early warning system is a significant step forward in locust management, it currently lacks a feature that would enable automatic recognition of locust species. This limitation suggests a gap in the application's functionality, underscoring the need for enhanced features that can aid field staff and the local community in accurately identifying locust species, especially in situations of uncertainty.

5.2.2 Proposed Technological Solution- Development of an AI-Enhanced Mobile Application for Locust Identification

In response to the challenges identified in locust species identification, the research team has conceptualized the development of an innovative Mobile Application. This application is designed to facilitate the automatic identification of pest species, specifically focusing on African Migratory Locust (AML) and Red Locust, utilizing Artificial Intelligence (AI) technology. The foundation of this application is a custom-made dataset, meticulously compiled to include extensive and diverse images of both AML and Red Locust in various stages of their life cycle. This dataset is crucial for training the AI model to recognize and distinguish between these locust species with high accuracy.

5.2.3 Alignment with Existing AI Research in Pest Identification

This proposed solution aligns with the emerging trend of employing AI in entomological research, particularly in pest identification. The work of [133] serves as a significant precedent in this domain. Their research successfully applied AI techniques to automatically identify migratory locust species in East Asia, demonstrating the feasibility and effectiveness of AI in this field. Moreover, the study by [135] further reinforces the growing interest and potential of AI applications in grasshopper and locust research, highlighting the transformative impact AI can have in pest control and management strategies.

5.2.4 Collaborative Opportunities with FAO

A pivotal aspect of this proposal involves exploring collaborative opportunities with the Food and Agriculture Organization (FAO). The Focus Group Discussion (FGD) highlighted the potential integration of this AI Application with the existing eLocust3 system. eLocust3, primarily used on Tablets by field staff for locust monitoring, could be significantly enhanced by incorporating the AI capability for locust identification. This integration could streamline the process of species identification, making it more efficient and accurate, thereby improving the overall effectiveness of locust management efforts. Engaging with FAO to discuss the feasibility of installing this AI application on eLocust3-installed Tablets could mark a substantial step forward in advancing technology for ecological monitoring and pest control.

5.3 Challenge of Limited Field Staff

A significant challenge in managing locust invasions, as identified in this research, is the scarcity of field personnel. The current situation in agricultural camps is such that there is typically only one trained locust expert per camp. This limitation severely hampers the ability to monitor and respond to locust invasions effectively, as the geographical areas to be covered are vast and the manpower is insufficient.

5.3.1 Technological Innovation as a Solution

In response to the challenge of limited field staff, this project proposes a novel early warning system designed to manage the spread of locust invasions. This system leverages a combination of advanced technologies including Artificial Intelligence (AI), the Internet of Things (IoT), Geospatial technology, and Cloud Computing. The integration of these technologies aims to enhance the efficiency and effectiveness of locust monitoring and control strategies.

5.3.2 Components and Functionality of the Early Warning System

The cornerstone of this system is a specialized trap, equipped with a camera to capture targeted insects. Addressing the issue of energy dependency, the trap is powered by a battery, which is charged using solar energy, thus ensuring continuous operation. The incorporation of a Raspberry Pi 4B microcomputer, linked with a Pi camera and various sensors, forms the crux of the proposed IoT node within this system. This setup enables the automatic daily capture of images of the pests caught in the trap.

Additionally, a suite of environmental sensors was deployed to collect local weather data, including temperature, and humidity. This data is crucial in understanding and identifying the environmental conditions favorable for the proliferation of the African Migratory Locust (AML) and Red Locust (RL).

5.3.3 Data Collection and Transmission

To facilitate seamless data gathering and transmission, the system is equipped with integrated GPRS and 3G/4G connectivity. Moreover, a Global Positioning System (GPS) module, connected serially to the Raspberry Pi, provides accurate location data for the trap, thereby enabling the collection of valuable geospatial data. The data captured by these devices will be transmitted to the cloud service, which allows for efficient data visualization and analysis.

5.3.4 Integration with Machine Learning

A significant feature of this system is the integration of a machine learning model, which has been designed and discussed in section 5.2 of this dissertation. This model, embedded within the trap system, analyzes the captured images and environmental data, thereby reducing the need for frequent field visits and enabling more effective monitoring and prediction of locust activities.

5.3.5 Supporting Research and Expected Impact

This approach aligns with the findings of [5]Salim et al. (2021), who developed an IoT solution for monitoring agricultural activities. The proposed system is expected to significantly mitigate the challenges posed by limited field staff. It promises a more proactive and data-driven approach to locust invasion management, transforming the current practices and leading to more efficient and effective control strategies.

5.4 Challenge of Inaccessibility in Infested Areas

A critical challenge encountered in managing locust invasions is the inaccessibility of infested areas, particularly during flooding seasons. The terrain, often characterized by tall grass and flooded plains, poses significant difficulties for on-ground monitoring and control activities. The use of locally made canoes for navigation through these areas is not feasible, thereby severely limiting the ability to assess and respond to locust outbreaks in such regions effectively.

5.4.1 Innovative Use of AI-Powered Drones as a Solution

In response to the challenge of inaccessible infested areas, this research proposes the adoption of low-cost, AI-powered drones. Drones, or unmanned aerial vehicles (UAVs), offer a versatile and efficient solution for surveying and monitoring locust activities in areas that are otherwise difficult to reach. The integration of AI technology with drones enhances their capability to not only capture images and videos of vast areas but also to analyze the data intelligently for locust detection and monitoring.

The use of AI-powered drones in agriculture, especially in pest control and monitoring, is gaining traction, as evidenced by the work of [136]. Their research supports the feasibility and effectiveness of using drones in agricultural settings. In the context of locust management, drones can cover large areas quickly, providing real-time data that is critical for early detection and rapid response to locust invasions. This technology, therefore, presents a significant advantage in terms of speed, coverage, and data accuracy.

Furthermore, the work of [137] illustrates the practical application of drones in identifying locust concentrations in areas prone to invasion. Their findings underscore the potential of drones not just in surveillance but also in precise locust population estimation, which is essential for targeted control measures. Integrating drone technology into the existing locust control strategies could revolutionize how these invasions are managed, especially in challenging terrains. The use of AI enhances the drones' capabilities, allowing for automated processing and analysis of the captured data, leading to more informed and timely decision-making. This approach aligns with the trend towards precision agriculture, where technology is used to optimize field-level management regarding crop farming and pest control.

5.5 Locust infestation and Digital Tools (Mobile Phones)

This segment of the study reveals the empirical results derived from both descriptive and Chi-square analyses. The descriptive statistics offer a snapshot of the sample, helping to elucidate the extent of awareness and knowledge regarding locusts among the participants.

5.5.1 Description of the sample

The descriptive analysis characterizes the participants by their gender, age, marital status, educational attainment, type of employment, and household income levels. As depicted in Figure 1.1, males constituted 62.5% of the study's participants. About 64% of the participants were married. Age-wise, 21.74% of the respondents were either between the ages of 26 to 30 years or over 40 years, while the 31 to 35 years age group included only 17% of the respondents. Educationally, the largest group, comprising around 32% of the sample, had completed primary education. Conversely, a mere 1.56% had achieved a diploma or a higher qualification. Occupation-wise, the vast majority, about 84%, were farmers, and a small fraction, only 2%, were employed by the government. In terms of household income, the predominant portion (88%) of households earned below K5000 per month, placing them in the low-income bracket.

Table 1:Sample Characteristics

Variable	n	Percent
Sex		
Male	160	62.5
Female	96	37.5
Marital Status		
Married	158	64.23
Single	46	18.7
Divorced	21	8.54
Widowed	21	8.54
Age		
Years 21-25	52	20.55
Years 26-30	55	21.74
Years 31-35	43	17
Years 36-40	48	18.97
Years above 41	55	21.74
Education level		
Primary	82	32.03
School Leaver	81	31.64
Certificate	55	21.48
Diploma or more	4	1.56
Never been to school	34	13.28
Occupation type		
Farming	213	83.86
Trading	33	12.99
Government worker	6	2.36
Others (specify)	2	0.79
Household income		
below 5000	219	87.95
6000-10000	23	9.24
11000-20000	6	2.41
26000 and above	1	0.4

The research explored the understanding and incidence of locusts in Sikaunzwe. As shown in Table 1.2, more than half of the participants (58.47%) received notifications about locusts on their mobile devices. A significant majority (78%) observed that locusts predominantly impacted agricultural fields rather than grazing areas. Only a small fraction (8%) had undergone training in managing locust infestations. A substantial majority (72.44%) reported experiencing locusts in the year before the survey was conducted. Concerning the types of locusts prevalent in the region, 80% of the respondents identified red locusts as the most common, while migratory locusts were noted by just 11%. Furthermore, around 70% mentioned that they received locust-related information from governmental sources. A majority could identify the signs of locust presence, with 56% noticing crop or grass damage and 35% spotting flying swarms. In terms of locust prevention and control, 75% of those surveyed used chemical sprays, and about 11% employed burning techniques to manage infestations. Additionally, more than half (57%) of the respondents believed they could anticipate locust outbreaks.

Table 2:Knowledge of locusts, management and control

Variable	N	Percent
Locust alert on phone		
Yes	107	58.47
No	76	41.53
Locust effect		
Grazing land	55	22
Crop fields	195	78
Locust management training		
Yes	17	8.17
No	191	91.83
Last experienced locust		
This year	45	17.72
Last year	184	72.44
2 years ago	16	6.3
every year	9	3.54
Knowledge of types of locusts		
Migratory locust	28	11.02
Red locust	203	79.92
Others(specify)	23	9.06
Signs of locusts outbreak		
Presence of a flying swam	89	34.77
Eaten crops/grass	144	56.25
Presence of locusts on the ground	21	8.2
others(specify)	2	0.78
Government provide locust information		
Yes	176	69.57
No	77	30.43
Prevention measures		
Burning affected areas	28	10.98
Spraying chemicals	192	75.29
Harvesting for food	2	0.78

Beating drums	17	6.67
Others (specify)	16	6.27
Contacts with local control team		
Yes	172	68.25
No	80	31.75
Ability to Predict locust		
Yes	146	57.03
No	110	42.97

5.5.2 Association between mobile phone ownership and locust information access

To explore the link between ownership of mobile phones and the accessibility of locust-related information, this research utilized cross-tabulation and the Pearson-Chi Square Test. Results, detailed in Table 2, show that about 64% of individuals owning mobile phones received locust updates through their devices. In a similar vein, approximately 65% of mobile phone owners used their devices to report on locust sightings, whereas 92% of those without mobile phones had to physically go to locust reporting centers to relay such information. Additionally, just over half (55%) of the mobile phone users accessed agricultural information via their devices.

Table 3:Ownership of mobile phone and access to locust information

	Own mobile phone				
	Yes		**No**		
	n	**Percent**	**n**	**Percent**	**p-value**
Alerts on locusts on mobile					
Yes	97	63.82	10	33.33	0.002
No	55	36.18	20	66.67	
Agric related information on phone					
Yes	84	54.55	9	29.03	0.010
No	70	45.45	22	70.97	
Report locust information					
Mobile phone	86	65.15	5	6.76	0.000
Walk to locust camp	36	27.27	68	91.89	
Cycle to the locust c	9	6.82	1	1.35	
Drive to the locust c	1	0.76	0		

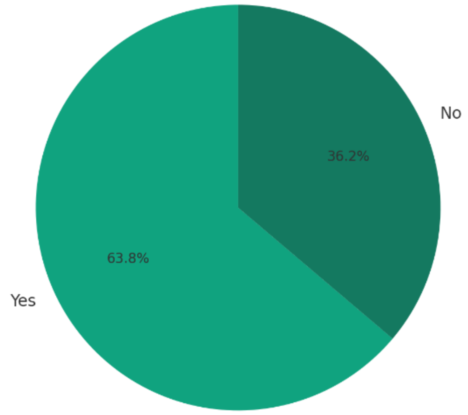


Figure 19:Alerts on locusts on mobile

Figure 19 shows the percentage of individuals who receive alerts about locusts on their mobile phones.

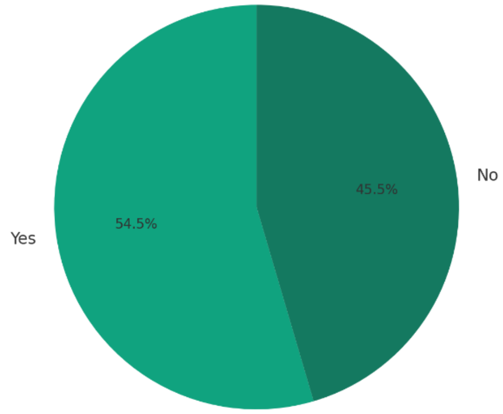


Figure 20:Agriculture-Related Information on Phone

This chart, figure 20, illustrates the distribution of individuals who access agriculture-related information on their mobile phones.

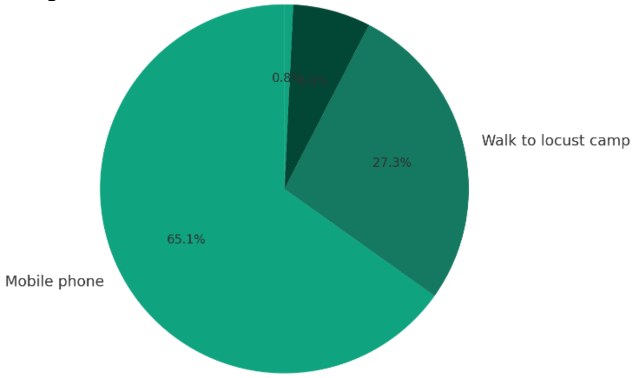


Figure 21:Report Locust Information Methods

Figure 21 displays the different methods used by individuals to report locust information, including using a mobile phone, walking, cycling, or driving to the locust camp.

Table 4:Mobile Phone Ownership and Alerts on Locusts

	Receives Locust Alerts (Yes)	Receives Locust Alerts (No)	Total
Owns Mobile Phone (Yes)	97	55	152
Owns Mobile Phone (No)	10	20	30
Total	107	75	182

Chi-Square Test

Hypotheses:

- **Null Hypothesis (H0):** There is no association between mobile phone ownership and access to locust information.
- **Alternative Hypothesis (H1):** There is an association between mobile phone ownership and access to locust information.

The Chi-square test conducted to examine the association between owning a mobile phone and receiving alerts on locusts yielded significant results. The calculated Chi-square statistic stood at 8.3923, which is indicative of a notable difference between the observed and the expected frequencies in these two categorical variables. More crucially, the p-value obtained from the test was approximately 0.0038. This value is significantly lower than the standard alpha level of 0.05, strongly suggesting that the observed association is not merely due to chance but is statistically significant.

With 1 degree of freedom, applicable in a 2x2 contingency table format, the test's significance is both clear and robust. The expected frequencies—89.36 individuals owning mobile phones receiving alerts and 62.64 not receiving, against 17.64 individuals not owning mobile phones receiving alerts and 12.36 not receiving, further corroborate this finding.

Based on the Chi-square test results, we reject the null hypothesis, thereby affirming that there is a statistically significant association between owning a mobile phone and receiving alerts about locusts. This implies that the ownership of a mobile phone is likely linked to the increased likelihood of receiving timely information about locust alerts. It's important to note, however, that these findings, while statistically significant, do not imply causation but rather a strong association between the two variables under consideration.

5.6 Architecting the Early Warning System Framework

5.6.1 Results of the Early Warning System Development

The development and testing of the AI-embedded, low-cost IoT model for locust invasion management yielded significant insights, with each component undergoing rigorous evaluation.

5.6.2 GPRS Module Functionality and Integration

The initial component evaluated was the General Packet Radio Service (GPRS) module, which is essential for wireless data communication across cellular networks using GPRS technology. This module supported packet-based data transfer, enabling uninterrupted data flow between the DHT22 Sensor, Pi Camera, and the microcomputer through the internet via a cellular link. The SIM800 GPRS module, produced by SIMCom, was incorporated into the setup. It featured a cellular modem and antenna, and it included the necessary protocols to establish a data connection with the mtn cellular network. This connectivity was crucial for the remote transmission of data from the field locations to the central monitoring system

5.7 Raspberry Pi Camera and AI Model Efficacy

The low-cost AI-integrated IoT model underwent individual component testing. Initially, the General Packet Radio Service (GPRS) module was assessed. This module facilitates wireless data communication across cellular networks using GPRS technology, supporting packet-based data exchanges. It enabled the microcomputer to transmit and receive data from the DHT22 Sensor and Pi Camera over the internet through a cellular link. The SIM800, a widely-used GPRS module by SIMCom, connects via a serial interface and features a cellular modem, antenna, and communication protocols necessary for linking with an Airtel cellular network.

The second component evaluated was the Raspberry Pi Camera's ability to capture images of locusts in real-time, coupled with the AI model’s capability to identify locust species. The camera module, equipped with a 5-megapixel sensor, successfully captured high-definition images of locusts collected during the study. These images were crucial for the object detection testing phase. The system was configured to only upload images to the web server that met a minimum classification accuracy of 80%.

The second aspect evaluated was the capability of the Raspberry Pi Camera in conjunction with the AI model for locust detection. The camera, equipped with a 5-megapixel sensor, demonstrated its ability to capture high-quality images of locusts, crucial for the object detection phase. Real locust specimens collected from the study area were used in this phase. The AI model effectively analysed these images, discerning the type of locust present. Figure 19 and Figure 20 shows identified images of ALM and RL respectively.

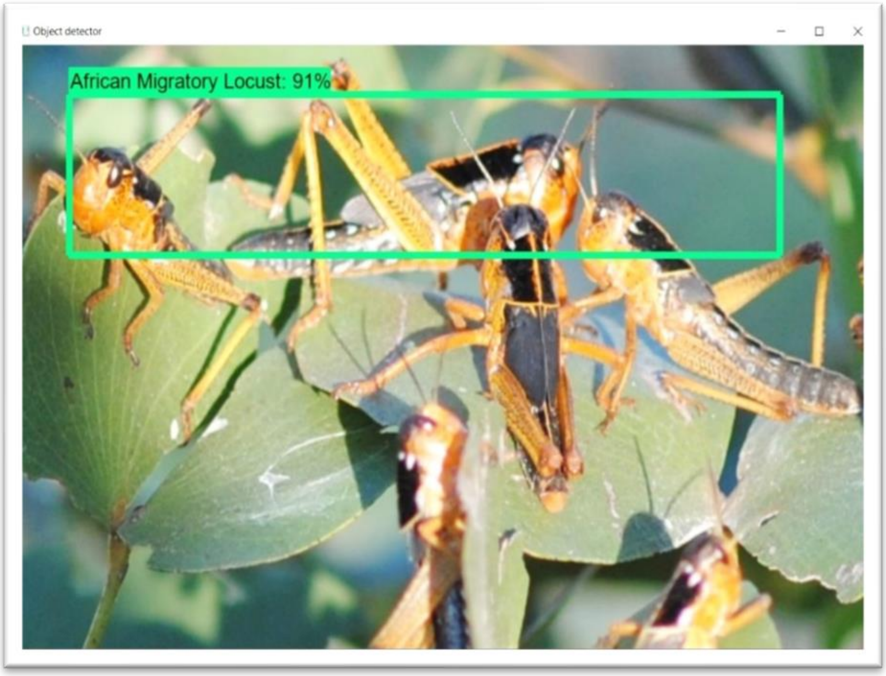


Figure 22: AML Image Detection

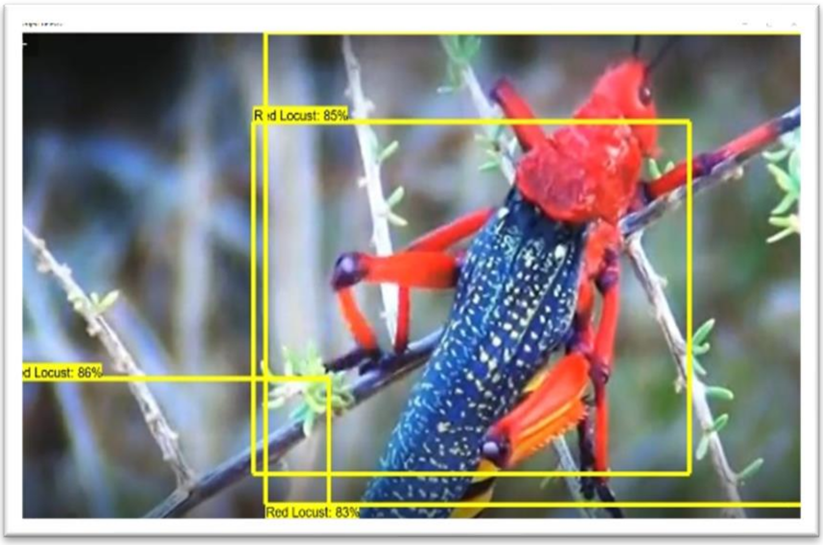


Figure 23:Red Locust image detection

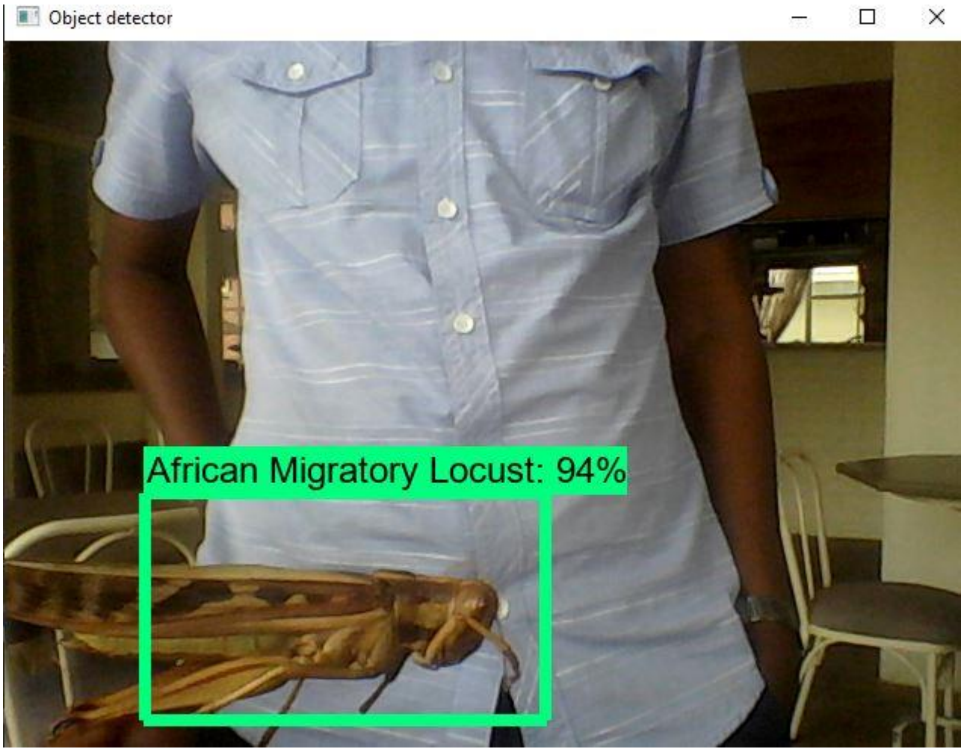


Figure 24:Red Locust image detection

The model's effectiveness was also confirmed through analysis of video footage captured in December 2020, during an African Migratory Locust (AML) invasion in the study area, where it achieved an average accuracy of 91% (Figure 25). Additionally, video results from a Red Locust invasion depicted an average model accuracy of 92%, as illustrated in Figure 23.

Figure 25:AML detection on the video

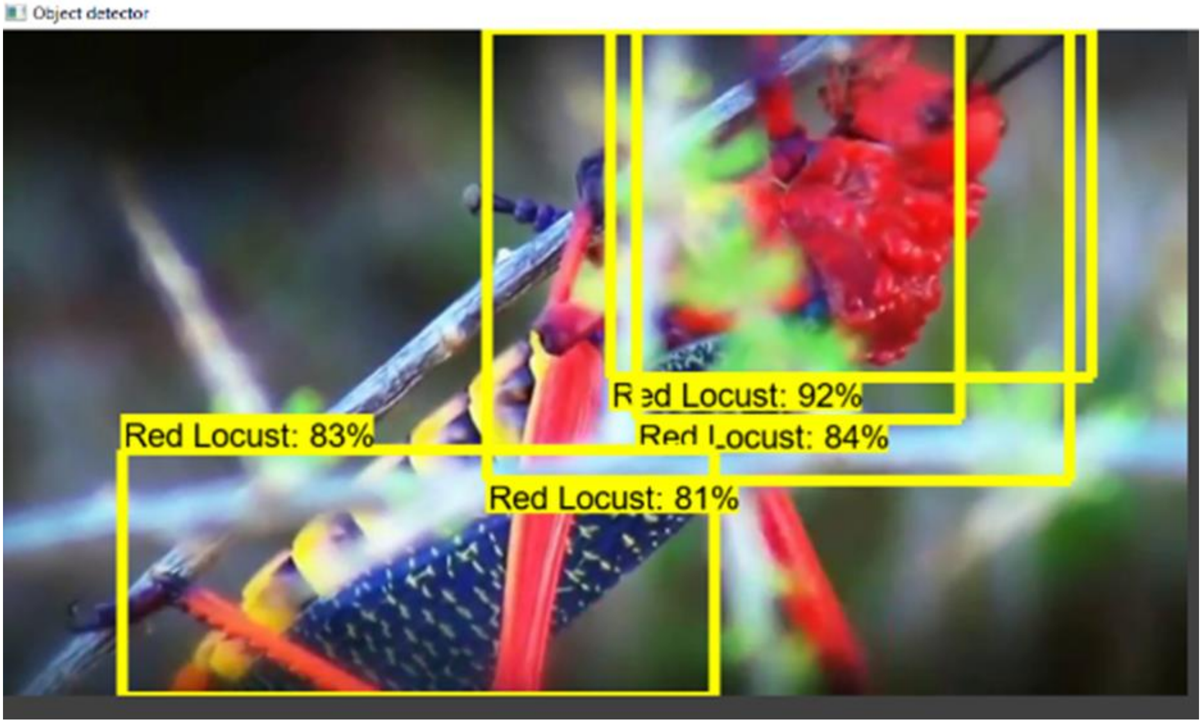


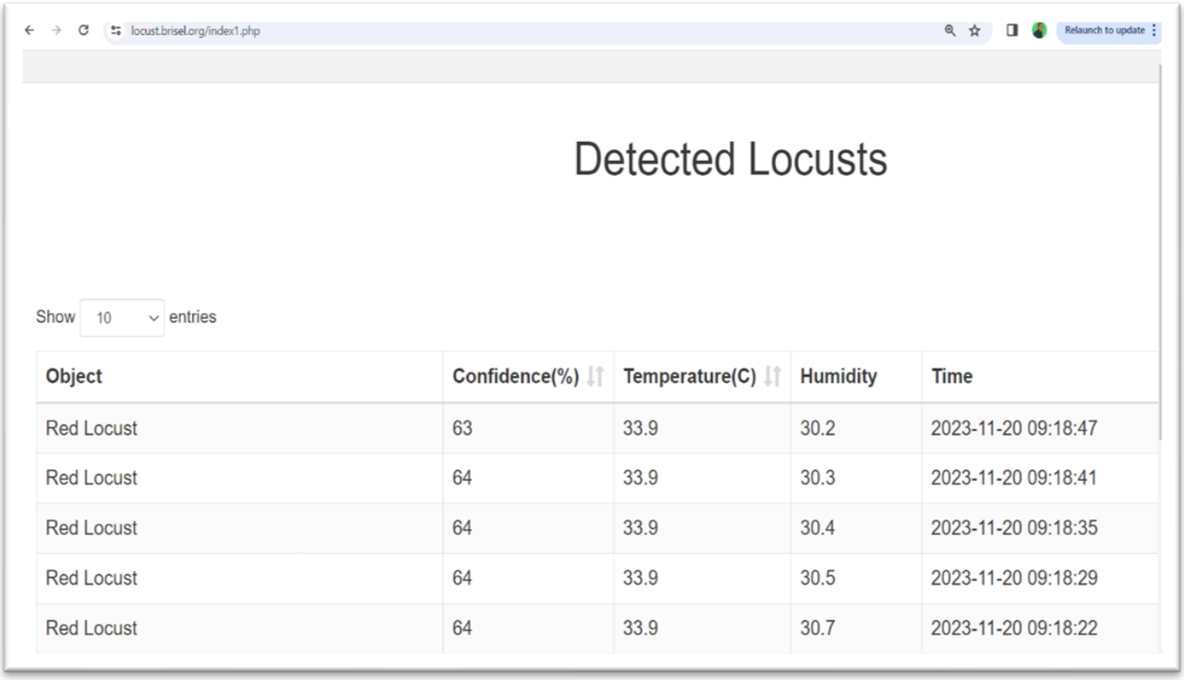
Figure 26:Red Locust detection on the video

5.7.1 Integration and Data Output from DHT22 Sensor

Testing the integration of the DHT22 sensor was a crucial part of assessing the system. Attached to the Raspberry Pi, this sensor tracked environmental metrics like temperature and humidity during image acquisition. The setup involved connecting the DHT22 VCC to the Raspberry Pi's 5V power, the DHT22 GND to the Raspberry Pi's ground, and the DHT22 DATA to the Raspberry Pi GPIO 4. The environmental data captured by the DHT22 sensor enriched the locust images with critical context, enhancing the analysis of the environmental conditions favorable for locust activity.

5.7.2 Web-Based Data Visualization and System Consistency

The output from each IoT component was systematically organized and displayed via a web interface (Figure 27), aligning with the research objectives. This web-based visualization allowed for easy interpretation and analysis of the collected data, making the system user-friendly and accessible to stakeholders.



Detected Locusts

Show 10 entries

Object	Confidence(%)	Temperature(C)	Humidity	Time
Red Locust	63	33.9	30.2	2023-11-20 09:18:47
Red Locust	64	33.9	30.3	2023-11-20 09:18:41
Red Locust	64	33.9	30.4	2023-11-20 09:18:35
Red Locust	64	33.9	30.5	2023-11-20 09:18:29
Red Locust	64	33.9	30.7	2023-11-20 09:18:22

Figure 27: Detection details (www.locust.brisel.org)

5.7.3 Evaluation of Research and System Innovativeness

The research's evaluation stage concentrated on the importance of the identified issue and the practicality of the suggested solution. As noted by [4], addressing this problem was crucial for overcoming the obstacles encountered by locust specialists in the field. The early warning system's innovative design introduced a new method for tracking locust invasions with reduced human involvement. This system merged the precision of locust detection with environmental data gathered by the DHT22 sensor, offering essential insights into the relationship between locust behavior and environmental factors. Such integration marks a critical advancement in enhancing locust detection and management strategies.

5.7.4 User Perspective and Data Dissemination

From the user perspective, the system was found to be straightforward, consistent in data collection, and easy to use, with potential for further expansion. This versatility makes it a robust innovation in the field of pest management. The efficiency and effectiveness of the model in real-time monitoring of locust invasions were evident, reducing the need for manual monitoring and data collection. The system's capability to disseminate data effortlessly to users further underscores its practicality and relevance in addressing the challenges of locust invasion management.

5.8 Validating the Efficacy of the Framework

The analysis of the image datasets for African Migratory Locust (AML) and Red Locust (RL) yielded insightful results. For the AML dataset, which comprised 1135 images, 193 were used for validation. In this subset, 175 images were correctly identified as true positives, while 18 were false negatives. The model achieved an accuracy of 91%, a notable level of precision in identifying the African Migratory Locust. This high accuracy suggests that the model is quite effective in distinguishing AML instances in the images. On the other hand, the RL dataset consisted of 565 images, with 97 used for validation purposes. Of these, 85 were true positives, and 12 were false negatives. The model's accuracy for the RL dataset stood at 85%. Although slightly lower than the AML's performance, this still represents a substantial accuracy, indicating that the model is relatively effective at identifying the Red Locust in the provided images.

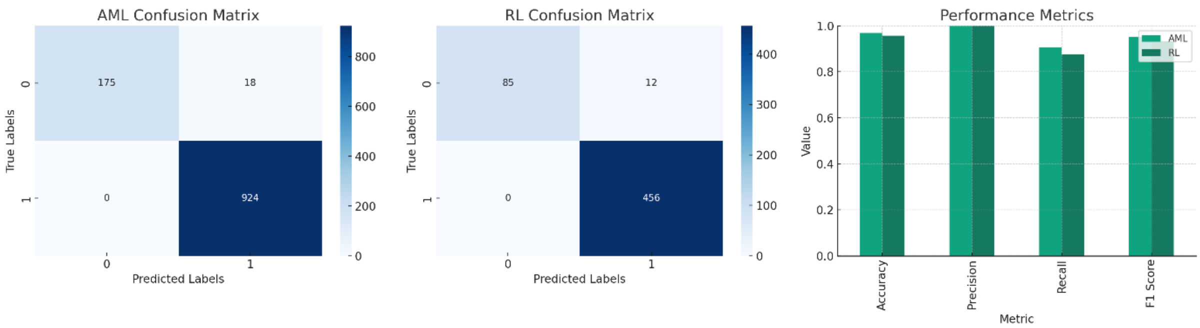


Figure 28:Confusion Matrix and Performance Metrics

Both datasets exhibited robust performance metrics, with the AML model slightly outperforming the RL model in terms of accuracy. The results demonstrate the models' capabilities in locust identification, which is crucial for pest control strategies.

The assessment of this study focused on the significance of the identified issue and the practicality of solving it. As outlined by [4], addressing this problem was vital for alleviating the challenges faced by locust experts in the field. Thus, an innovative solution was necessary to develop a system that could monitor locust invasions efficiently with minimal manual intervention. Integrating temperature and humidity data from the DHT22 sensor with the accuracy of locust detection provided valuable insights into how environmental conditions influence locust activity. Figure 29 illustrates the solar-powered trap that was set up in the study area

Figure 29: Solar Powered Trap

Additionally, it is now feasible to discern trends or connections between temperature, humidity, and locust behavior, which could inform the creation of more advanced locust detection and management techniques. This straightforward approach offers clear benefits from the user's viewpoint, with consistent data collection. The system is user-friendly and designed for potential scalability, enhancing its robustness as an innovation. The model crafted allows for efficient and effective real-time monitoring of locust invasions with minimal manual intervention. Data from the model is smoothly relayed to usersFigure 30 shows the AI embedded IoT housed in a shelter in the study area.

Figure 30:AI embedded IoT

5.9 Chapter Summary

This summary encapsulates the key findings and implications of the research conducted in Chapter 5, providing a concise overview of the results and their significance in the context of locust invasion management and agricultural technology. The results are a culmination of extensive research, experiments, and evaluations that align with the stated objectives of the study. These objectives included identifying challenges in controlling locust invasions, investigating the potential application of AI in locust detection, architecting an AI and IoT-based early warning system, and validating the efficacy of this system. The research identified significant challenges in the current approaches to locust control, particularly highlighting the issues of limited field staff and inaccessibility of infested areas. The findings underscored the need for technological innovations to augment human efforts in monitoring and controlling locust invasions.

The study explored the use of AI for detecting locust invasions, demonstrating the technology's potential in accurately identifying locust species and predicting invasion patterns. The AI models tested showed promising results in enhancing the precision and efficiency of locust detection.

A significant achievement of this research was the development of an integrated early warning system, combining AI, IoT, geospatial technology, and cloud computing. This system was designed to address the identified challenges, improve data collection and analysis, and enable real-time monitoring of locust activity.

The efficacy of the early warning system was rigorously tested under various conditions. The system demonstrated high accuracy in locust detection, effective data transmission via GPRS, and valuable insights from the integration of environmental data. The results confirmed the system's potential in revolutionizing locust invasion management.

The findings from this study have significant implications for the management of locust invasions. The development and validation of the AI-powered early warning system represent a substantial advancement in pest control strategies. This system not only enhances the capability to monitor and respond to locust invasions but also reduces the reliance on extensive field staff and addresses accessibility issues in infested areas.

CHAPTER 6: DISCUSSION AND CONCLUSIONS

6.0 Introduction

This chapter discusses the findings and offers recommendations based on the results of the study. It aims to contextualize the research within the broader field of locust management and technological innovation.

6.1 Discussion

This section discusses the finding to answer the research questions developed in the first chapter.

6.1.1 Challenges in Current Locust Management Practices

The study identified key challenges in the current locust management strategies employed by the Ministry of Agriculture in Zambia. These challenges include the misidentification of locust species, the scarcity of field staff, and difficulties in accessing affected areas. Such limitations hinder the effectiveness of existing early warning systems and locust control measures, leading to delays in response and potential crop damage.

6.1.2 Technological Solutions to Enhance Locust Management

To address these challenges, the research proposed innovative technological solutions. These encompass the utilization of automated data collection methods and the implementation of advanced monitoring systems. The Ministry can enhance the accuracy of locust detection, streamline data dissemination, and improve the overall efficacy of locust management efforts.

6.1.3 Role of Mobile Technology in Locust Information Dissemination

In the study on the ownership of mobile phones and access to locust information, the Unified Theory of Acceptance and Use of Technology (UTAUT) model provides a valuable framework to understand the underlying factors influencing technology adoption among farmers. Performance Expectancy is a critical factor, focusing on how farmers perceive the effectiveness of mobile phones in receiving locust alerts. A high level of Performance Expectancy is evident if farmers believe that these alerts significantly improve their ability to manage locust threats. Effort Expectancy, which addresses the perceived ease of use of the technology, is also significant. The study's indication that farmers find mobile phones convenient for accessing agricultural-related information and reporting locust sightings suggests that mobile phones are seen as user-friendly, enhancing their likelihood of adoption. Social Influence is another important aspect, highlighting the impact of peers and advisors on farmers' technology use. If farmers perceive that their peers or agricultural advisors endorse the use of mobile phones for locust-related activities, they are more inclined to adopt this technology. Facilitating Conditions, encompassing the availability of the necessary organizational and technical infrastructure, play a crucial role. This include the availability of mobile network coverage, locust-related information tailored for mobile delivery, or support from agricultural bodies in the form of mobile phone provisions or subsidies.

The study underscored the importance of mobile technology in disseminating locust-related information. Given the widespread ownership of mobile phones, these devices can be instrumental in providing timely warnings and crucial information to farmers. Developing mobile-based applications and SMS services could significantly improve the reach and effectiveness of locust management strategies.

6.1.4 Importance of Training in Locust Management

There is a clear need for comprehensive training programs in locust management. The study revealed a low proportion of trained individuals in this area, suggesting an opportunity for governmental and non-governmental organizations to invest in educational initiatives. Workshops and extension services could effectively equip farmers and field staff with essential skills for managing locust invasions.

6.1.5 Safe and Sustainable Locust Control Measures

While chemical sprays are commonly used for locust control, their impact on the environment and human health cannot be overlooked. The research advocates for the development of guidelines for the safe use of chemical sprays and the promotion of sustainable alternatives like biological control methods.

6.1.6 Community Involvement in Locust Management

The study also highlights the crucial role of community involvement in locust management. Encouraging farmers to participate in decision-making and implementation can enhance the effectiveness of control measures and foster a sense of responsibility and accountability.

6.2 Summary of Research Findings

The research successfully designed a CNN model using MobileNet v2 quantized for the detection of Locusta migratoria and Nomadacris septemfasciata in the Sikaunzwe agricultural camp plains. The model demonstrated high precision in identifying these species, outperforming other methods reviewed in the study.

6.2.1 Contributions of the Study

This study contributes significantly by fine-tuning a CNN model capable of detecting locusts both in stationary and real-time scenarios. Optimized for standard mobile devices, the model presents a practical tool for locust detection in the studied area. Additionally, the creation of a new dataset provides a valuable resource for future research in this field.

6.2.2 Implications for Locust Management in Zambia

The findings of this study have substantial implications for locust management in Zambia. By facilitating early detection and accurate identification of locust species, the model can aid in timely and effective control measures, potentially reducing crop damage and economic losses.

6.2.3 Future Research Directions

Future research can build upon this study by developing algorithms for image augmentation to expand the dataset further. A more detailed classification of locust growth stages would also enhance the model's utility.

6.2.4 Benefits of Implementing IoT-based Locust Monitoring System

Deploying a budget-friendly IoT-enabled locust surveillance system in Kazungula brings several benefits. It provides capabilities for real-time observation, prompt identification of locust swarms, and critical data insights essential for agricultural strategy. Such a system would be especially advantageous for small-scale farmers who do not have access to sophisticated monitoring technologies.

6.2.5 Potential Impact on Local Agriculture

Overall, the introduction of an IoT-based automated locust monitoring system in Kazungula could revolutionize the local agricultural sector. It provides a scalable and efficient solution to a pressing challenge, setting a precedent for other regions facing similar issues.

6.3 Recommendations and Future Works

The comprehensive discussions and evaluations in this chapter lead to a series of recommendations and future directions aimed at refining locust invasion management strategies and enhancing the application of AI and related technologies in this field.

6.3.1 Recommendations

For African Migratory Locust (AML) and Red Locust (RL) invasion management, it's crucial to strengthen the collaboration between farmers and government entities. This involves developing robust communication channels and frameworks that enhance response times and the effectiveness of locust control measures. Additionally, there's a need for comprehensive training and awareness programs targeted at farmers and local communities. These programs should focus on early detection methods and effective response strategies to better equip those on the frontline of locust invasions.

In terms of policy development and resource allocation, it's essential to advocate for the creation of robust policies and the allocation of sufficient resources by government bodies. This should focus not only on immediate response mechanisms but also on long-term prevention strategies. Moreover, promoting research and the adoption of sustainable and ecofriendly locust control measures is necessary to balance effectiveness with ecological preservation.

Regarding the application of AI in locust management, continuous development and enhancement of AI technologies are recommended. This includes improving the accuracy and reliability of locust detection and prediction models. Expanding the range of data sources, such as satellite imagery and IoT sensor networks, and enhancing their integration can significantly improve the early warning system's comprehensiveness and accuracy. Additionally, there's a need to design AI tools and interfaces that are accessible and user-friendly for non-technical users, particularly in rural farming communities, to ensure broad usability and adoption.

For AI-integrated early warning systems, focusing on scalability and adaptability is key. The system should be capable of adjusting to different regions and environmental conditions, ensuring its applicability across diverse geographic areas. Lastly, fostering public-private partnerships is crucial. These partnerships, involving governments, technology companies, research institutions, and NGOs, can pool resources, knowledge, and expertise, leading to the development of more advanced and effective early warning systems.

6.3.2 Future Works

Several avenues of research and development stand out as critical for advancing the management of African Migratory Locust (AML) and Red Locust (RL) invasions. One key area is conducting longitudinal studies and impact assessments. These long-term studies are essential to evaluate the enduring impact of AI-integrated systems on locust invasion management and agricultural practices. Understanding the long-term effectiveness of these systems will be crucial in continuously improving and adapting them to changing conditions and challenges.

Another vital area for future work is global collaboration and knowledge sharing. Establishing international collaborations for knowledge exchange and joint research initiatives can significantly enhance the effectiveness of locust management strategies. By pooling resources and expertise on a global scale, the farming community worldwide can benefit from the advances in AI and locust management techniques. This approach not only fosters innovation but also ensures that solutions are adapted to diverse agricultural contexts.

Exploring new technologies is also a promising direction. Investigating the potential of emerging technologies, such as blockchain for enhancing data security and drones for real-time monitoring, could further revolutionize early warning and response systems. These technologies have the potential to provide more secure, efficient, and accurate tools for managing locust invasions, offering significant improvements over current methods.

Additionally, policy research and advocacy will play a crucial role in the integration of advanced technological interventions in agriculture. Engaging in research to understand the broader implications of these technologies is necessary. Advocating for policies that support technological integration, while ensuring sustainability and equity, will be key to the successful implementation of these innovations. Policies need to be carefully crafted to support the adoption of advanced technologies in agriculture, ensuring that they benefit all stakeholders, particularly small-scale farmers and local communities.

6.4 Limitations

Like any complex technological system, the proposed AI-based framework has limitations that must be acknowledged and managed. One such limitation is the dependency on the quality and reliability of image data captured by IoT devices. Factors such as poor lighting, lens occlusion, or movement blur can affect image quality, potentially leading to inaccurate locust detection. Additionally, the effectiveness of the IoT devices is contingent upon network connectivity and signal strength, which can be variable in remote or rural areas where locust invasions typically occur. Network downtime or interruptions can delay the transmission of critical data, impacting the system's ability to provide timely alerts.

To address these limitations, future iterations of the system could explore the use of more advanced imaging technologies that are less susceptible to environmental interferences and improvements in data transmission technologies to enhance network reliability. Additionally, incorporating redundancy in data transmission methods or local processing capabilities on the IoT devices could mitigate some of the risks associated with network issues.

6.5 Chapter Summary

Chapter Six synthesizes and integrates the comprehensive findings from the exploration of the AI-integrated early warning system designed to manage African Migratory Locust (AML) and Red Locust (RL) invasions. This chapter connects the detailed discussions and extensive research presented in preceding chapters, culminating in a robust understanding of the complexities of locust management and the transformative role of emerging technologies.

In addressing the challenges, this chapter looked into the real-world struggles faced by agricultural frontline workers and the logistical hurdles encountered by government bodies. For instance, during the field studies, farmers expressed significant concerns about the timely receipt of locust invasion alerts. One farmer in the Kazungula district noted, "We often get warnings too late, which doesn't give us enough time to react effectively." This highlights the critical need for real-time data, which our AI-driven system aims to provide.

The evolution of AI technologies has been pivotal, not just in agricultural contexts but across various environmental monitoring applications. The system represents a significant leap forward, utilizing deep learning algorithms capable of processing complex environmental data rapidly. When compared with systems employed in East Africa, which primarily rely on satellite imagery, our model offers ground-level precision and faster processing times, enhancing early detection capabilities significantly.

The AI-integrated early warning system features a multi-layered architecture that includes data acquisition via IoT devices, data processing in the cloud, and user interface delivery through a mobile application. A block diagram included in this research illustrates how environmental data and image captures are seamlessly integrated and processed through our fine tuned convolutional neural network, ensuring efficient and accurate locust detection.

The system's accuracy and efficiency have been evaluated through field deployment, showing a consistent performance improvement over conventional locust monitoring techniques, significantly reducing the response time and associated costs.

In this study, specific actionable steps were identified for each key stakeholder group to maximize the impact of our findings. For farmers, we propose the implementation of community-based training sessions designed to enhance their familiarity with our AI-driven technology. This initiative aims to empower farmers with the knowledge and tools needed to respond more effectively to locust threats. For policymakers, we recommend the development of supportive policies that facilitate the integration of AI technologies into national pest management strategies. Such policies could provide the necessary framework for widespread adoption and effective utilization of these innovative tools.

Tech developers are encouraged to follow guidelines for the next iteration of AI models, which should include adaptive learning capabilities to handle dynamic environmental conditions effectively. This advancement will ensure that our AI systems remain at the cutting edge of technology and are capable of responding to changing pest behaviors and environmental variables. Moreover, we advocate for the formation of a global consortium to foster international collaboration on pest management innovations. This consortium would help standardize approaches to locust management globally and ensure that best practices are shared and implemented across borders. We propose that our AI model serve as a template for these international standards, showcasing its effectiveness and adaptability.

In conclusion, this research not only validates the effectiveness of an advanced AI-driven approach to locust management but also sets the stage for future innovations in environmental monitoring. Looking to the horizon, the continued refinement and global adoption of AI and IoT technologies hold the promise to revolutionize locust management and introduce new paradigms for addressing a wide range of agricultural pests worldwide. This progress is essential for enhancing food security and sustainability in an increasingly unpredictable global climate.

REFERENCES

[1] Gorospe, J., Mulero, R., Arbelaitz, O., Muguerza, J., & Antón, M. Á. (2021). A Generalization Performance Study Using Deep Learning Networks in Embedded Systems. Sensors, 21(4), 1031.

[2] Butt, U. A., et al. (2020). A review of machine learning algorithms for cloud computing security. Electronics, 9(9), 1379.

[3] Klein, I., Uereyen, S., Eisfelder, C., Pankov, V., Oppelt, N., & Kuenzer, C. (2023). Application of geospatial and remote sensing data to support locust management. International Journal of Applied Earth Observation and Geoinformation, 117, 103212.

[4] Halubanza, B., Phiri, J., Nyirenda, M., Nkunika, P.O.Y., & Kunda, D. (2022). Detection of Locusta migratoria and Nomadacris septemfasciata (Orthoptera: Acrididae) Using MobileNet V2 Quantized Convolution Neural Network, Kazungula, Zambia. In: Silhavy, R. (eds) Cybernetics Perspectives in Systems. CSOC 2022. Lecture Notes in Networks and Systems, vol 503. Springer, Cham. https://doi.org/10.1007/978-3-031-09073-8_43

[5] Salim, S. A., Amin, M. R., Rahman, M. S., Arafat, M. Y., & Khan, R. (2021, September). An IoT-based smart agriculture system with locust prevention and data prediction. In 2021 8th International Conference on Information Technology, Computer and Electrical Engineering (ICITACEE) (pp. 201-206). IEEE.

[6] Kamil Usmani, M., & Usmani, S. (2018). Locusts. *Pests and Their Management*, 825-869.

[7] Le Gall, M., Overson, R., & Cease, A. (2019). A global review on locusts (Orthoptera: Acrididae) and their interactions with livestock grazing practices. Frontiers in Ecology and Evolution, 7, 263.

[8] Ceccato, P., Cressman, K., Giannini, A., & Trzaska, S. (2007). The desert locust upsurge in West Africa (2003–2005): Information on the desert locust early warning system and the prospects for seasonal climate forecasting. International Journal of Pest Management, 53(1), 7-13.

[9] Cressman, K. (2013). Role of remote sensing in desert locust early warning. *Journal of Applied Remote Sensing*, *7*(1), 075098-075098.

[10] FAO. (2019). Desert locust crisis appeal: FAO's response. Retrieved from http://www.fao.org/3/ca5185en/ca5185en.pdf

[11] Topaz, C. M., D'Orsogna, M. R., Edelstein-Keshet, L., & Bernoff, A. J. (2012). Locust dynamics: behavioral phase change and swarming.

[12] Thomson, A., & Miers, H. E. N. R. I. E. T. T. A. (2002). Assessment of the socio-economic impact of desert locusts and their control. *UK Department for International Development: London, UK*, 37.

[13] Riaz, U., & Hakeem, K. R. (Eds.). (2023). *Locust Outbreaks: Management and the World Economy*. CRC Press.

[14] Brader, L., Djibo, H., Faye, F. G., Ghaout, S., Lazar, M., Luzietoso, P. N., & Babah, M. O. (2006). Towards a more effective response to desert locusts and their impacts on food security, livelihoods and poverty. *Multilateral evaluation of the 2003–05 Desert locust campaign. Food and Agriculture Organisation, Rome,* 1-86.

[15] De Vreyer, P., Guilbert, N., & Mesplé-Somps, S. (2012). *The 1987-89 Locust plague in Mali: Evidences of the heterogeneous impact of income shocks on education outcomes*. DIAL.

[16] Latchininsky, A., Piou, C., Franc, A., & Soti, V. (2016). Applications of remote sensing to locust management. In *Land surface remote sensing* (pp. 263-293). Elsevier.

[17] Union, A. (2006, January). Status of food security and prospects for agricultural development in Africa. In *Mali: AU Ministerial Conference of Ministers and Agriculture*.

[18] Kausar, M. A. (2018). A review on Respiratory allergy caused by insects. *Bioinformation*, *14*(9), 540.

[19] Halubanza, B., Phiri, J., Nyirenda, M., Nkunika, P., Kunda, D., & Mulenga, J. (2023). Locust Infestations and Mobile Phones: Exploring the Potential of Digital Tools to Enhance Early Warning Systems and Response Mechanisms. *Zambia ICT Journal*, *7*(2), 10-16.

[20] Klein, I., Oppelt, N., & Kuenzer, C. (2021). Application of remote sensing data for locust research and management—A review. *Insects*, *12*(3), 233.

[21] Van Huis, A., Cressman, K., & Magor, J. I. (2007). Preventing desert locust plagues: optimizing management interventions. *Entomologia Experimentalis et Applicata*, *122*(3), 191-214.

[22] De Groote, H., Douro-Kpindou, O. K., Ouambama, Z., Gbongboui, C., Müller, D., Attignon, S., & Lomer, C. (2001). Assessing the feasibility of biological control of locusts and grasshoppers in West Africa: Incorporating the farmers' perspective. *Agriculture and Human Values*, *18*(4), 413-428.

[23] Lecoq, M., & Cease, A. (2022). What Have We Learned after Millennia of Locust Invasions? Agronomy, 12(2), 472.

[24] Khan, I., Ullah, W., Karami, A., Qazi, I., & Ahamad, I. (2023). Analyze The Socioeconomic Consequences of Locust Outbreaks on Agriculture, Rural Communities, And Food Security. *Indus Journal of Animal and Plant Sciences*, *1*(01), 14-20.

[25] Sharma, A. (2014). Locust control management: moving from traditional to new technologies–an empirical analysis. *Entomol. Ornithol. Herpetol*, *4*(141), 2161-0983.

[26] Farrow, R. A. (1975). The African migratory locust in its main outbreak area of the Middle Niger: Quantitative studies of solitary populations in relation to environmental factors. (11).

[27] Lecoq, M. (2023). Locusta migratoria (Migratory locust). *Crop Protection Compendium. Wallingford, UK: CAB International. https://doi. org/10.1079/cabicompendium*, *31151*.

[28] Therville, C., et al. (2021). Locusts and people: Integrating the social sciences in sustainable locust management. Agronomy, 11(5), 951.

[29] Showler, A. T., et al. (2022). Desert Locust Episode in Pakistan, 2018–2021, and the Current Status of Integrated Desert Locust Management. Journal of Integrated Pest Management, 13(1), 1.

[30] Showler, A. T., & Lecoq, M. (2021). Incidence and ramifications of armed conflict in countries with major desert locust breeding areas. *Agronomy*, *11*(1), 114.

[31] Mmari, M. W., Kinyuru, J. N., Laswai, H. S., & Okoth, J. K. (2017). Traditions, beliefs and indigenous technologies in connection with the edible longhorn grasshopper Ruspolia differens (Serville 1838) in Tanzania. *Journal of ethnobiology and ethnomedicine*, *13*, 1-11.

[32] Githae, E. W., & Kuria, E. K. (2021). Biological control of desert locust (Schistocerca gregaria Forskål). *CABI Reviews*, (2021).

[33] Zimba, R., et al. (2020). Impact of locust invasion on crop production and food security in Zambia. International Journal of Agricultural Science and Food Technology, 6(2), 61-68.

[34] Sakala, G., et al. (2019). Species composition and abundance of locusts in Luangwa Valley, Zambia. Journal of Agricultural Extension and Rural Development, 11(5), 80-86.

[35] Chitala, M., et al. (2015). Locusts and grasshoppers control in Zambia: A review of progress made, gaps and future prospects. International Journal of Agricultural Research, Innovation and Technology, 5(2), 39-45.

[36] Tadele, T., Emana, G., & Tafesse, T. (2020). Knowledge and management practices of Ethiopian farmers towards desert locust invasion. Journal of Agriculture and Environmental Sciences, 9(2), 175-182.

[37] Ibrahim, A. M., Mohamed, E. A., & Abdelrahman, A. H. (2021). Awareness and knowledge of desert locust among smallholder farmers in North Kordofan, Sudan. Sudan Journal of Agricultural Research, 5(1), 41-48.

[38] Mumo, M., Gichuki, N., Mulinge, W., Mwachala, G., Opiyo, P., Ng'ang'a, K., & Wambugu, S. (2021). Knowledge, attitudes, and practices of farmers in Kenya regarding desert locust control. Journal of Agricultural and Environmental Sciences, 10(1), 27-36.

[39] Njoroge, S. M., Muthee, J. K., & Waturu, C. N. (2019). Farmers' knowledge and practices on the control of desert locust in Laikipia County, Kenya. Journal of Agricultural Extension and Rural Development, 11(6), 95-103.

[40] Gebremedhin, B., Swinton, S. M., & Lulseged, T. (2014). Farmers' perceptions of and coping strategies to crop damage by forest pests in Ethiopia. Environment, Development and Sustainability, 16(6), 1279-1298.

[41] Ndiaye, M., Ba, M. N., Ba, A. T., & Diarra, K. (2011). Perceptions and knowledge of farmers about the desert locust and its control in the Sahel. International Journal of Pest Management, 57(4), 317-322. Khalidi, M., Bouharroud, R., El Haddad, M., & Douaik, A. (2018). Contribution of mobile technology in locust monitoring in Morocco. Journal of Agricultural Extension and Rural Development, 10(3), 47-53.

[42] Chewe, D., Chikha, M. M., & Haankuku, C. (2020). The role of mobile phones in enhancing farmers' knowledge and preparedness in locust control in the Kazungula district of Zambia. Journal of Applied Science and Agriculture, 15(6), 84-91.

[43] Mutungi, C., Irungu, P., & Wambugu, S. (2016). Using mobile phone technology to enhance locust monitoring and management in Kenya. International Journal of Computer Applications, 148(9), 32-38.

[44] Kirwa, H., Mutanga, O., & Karanja, D. (2014). Improving locust surveillance and control in Tanzania using mobile phone-based reporting. International Journal of Computer Science and Information Security, 12(7), 72-78.

[45] Negussie, H., Beshir, T., & Emana, G. (2013). Mobile phone-based reporting of locust outbreak in Ethiopia: challenges and prospects. International Journal of Computer Applications, 68(19), 19-24.

[46] Khalidi, M., Bouharroud, R., El Haddad, M., & Douaik, A. (2018). Contribution of mobile technology in locust monitoring in Morocco. Journal of Agricultural Extension and Rural Development, 10(3), 47-53.

[47] Daka, J. N., Njobvu, C. A., & Mubanga, J. (2020). The use of mobile phones for monitoring and reporting desert locusts in Zambia. African Journal of Agricultural Research, 15(6), 130-138.

[48] Sichali, S., Phiri, E., & Jere, S. (2019). Use of mobile phones for early warning and response to desert locusts in Zambia. International Journal of Agriculture and Biology, 21(6), 1326-1330.

[49] Russell, S. J., & Norvig, P. (2010). Artificial Intelligence: A Modern Approach (3rd ed.). Pearson Education.

[50] Jurafsky, D., & Martin, J. H. (2019). Speech and Language Processing (3rd ed.). Pearson.

[51] Bengio, Y., Goodfellow, I. J., & Courville, A. (2021). Deep Learning. MIT Press.

[52] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

[53] Bostrom, N., & Yudkowsky, E. (2014). The ethics of artificial intelligence. In K. Frankish & W. M. Ramsey (Eds.), The Cambridge Handbook of Artificial Intelligence (pp. 316-334). Cambridge University Press.

[54] Bishop, C. M. (2006). Pattern Recognition and Machine Learning. Springer.

[55] Alpaydin, E. (2020). Introduction to Machine Learning (4th ed.). MIT Press.

[56] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444. https://doi.org/10.1038/nature14539

[57] Makinde, F. A., Ako, C. T., Orodu, O. D., & Asuquo, I. U. (2012). Prediction of crude oil viscosity using feed-forward back-propagation neural network (FFBPNN). Petroleum & Coal, 54(2).

[58] Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. *Heliyon*, *4*(11).

[59] Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A., & Arshad, H. (2018). State-of-the-art in artificial neural network applications: A survey. Heliyon, 4(11).

[60] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780.

[61] Pan, S. J., & Yang, Q. (2009). A survey on transfer learning. IEEE Transactions on Knowledge and Data Engineering, 22(10), 1345-1359.

[62] Howard, A., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., Andreetto, M., & Adam, H. (2017). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. arXiv:1704.04861.

[63] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. (2018). Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510-4520).

[64] Kaur, S., & Kulkarni, N. (2023). FERFM: An Enhanced Facial Emotion Recognition System Using Fine-tuned MobileNetV2 Architecture. *IETE Journal of Research*, 1-15.

[65] Habeeb, Z. Q., Vuksanovic, B., & Al-Zaydi, I. Q. (2023). Breast cancer detection using image processing and machine learning. *Journal of Image and Graphics*, *11*(1).

[66] Sik-Ho Tsang (2019). MobileNetV2: The Next Generation of On-Device Computer Vision Networks. Google AI Blog. https://ai.googleblog.com/2018/04/mobilenetv2-next-generation-of-on.html [Last accessed 2022, February 28].

[67] Li, M., Zhou, J. T., IHPC, A., STAR, S., & Goh, R. S. M. (2021). Evolutionary Multi-Objective Model Compression for Deep Neural Networks.

[68] Patel, R., & Chaware, A. (2021, March). Quantizing MobileNet Models for Classification Problem. In 2021 8th International Conference on Computing for Sustainable Global Development (INDIACom) (pp. 348-351). IEEE.

[69] Ghosh, S. and Pathak, S. (2019). Real-time object detection on Raspberry Pi using Deep Learning. Procedia Computer Science, 165, pp.621-630. https://doi.org/10.1016/j.procs.2019.12.220.

[70] Popescu, D., Zilberman, N., & Moore, A. (2017). Characterizing the impact of network latency on cloud-based applications' performance.

[71] Shukla, S., Hassan, M., Tran, D. C., Akbar, R., Paputungan, I. V., & Khan, M. K. (2021). Improving latency in Internet-of-Things and cloud computing for real-time data transmission: a systematic literature review (SLR). Cluster Computing, 1-24.

[72] Ma, H., Qiu, H., Gao, Y., Zhang, Z., Abuadbba, A., Fu, A., Al-Sarawi, S., & Abbott, D. (2021). Quantization Backdoors to Deep Learning Models. arXiv preprint arXiv:2108.09187.

[73] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Identity mappings in deep residual networks. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part IV 14* (pp. 630-645). Springer International Publishing.

[74] Borawar, L., & Kaur, R. (2023, March). ResNet: Solving Vanishing Gradient in Deep Networks. In *Proceedings of International Conference on Recent Trends in Computing: ICRTC 2022* (pp. 235-247). Singapore: Springer Nature Singapore.

[75] Mhapsekar, M., Mhapsekar, P., Mhatre, A., & Sawant, V. (2020). Implementation of residual network (ResNet) for devanagari handwritten character recognition. In *Advanced Computing Technologies and Applications: Proceedings of 2nd International Conference on Advanced Computing Technologies and Applications—ICACTA 2020* (pp. 137-148). Springer Singapore.

[76] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

[77] Tan, W., Liu, P., Li, X., Liu, Y., Zhou, Q., Chen, C., ... & Zhang, Y. (2021). Classification of COVID-19 pneumonia from chest CT images based on reconstructed super-resolution images and VGG neural network. *Health Information Science and Systems*, *9*, 1-12.

[78] Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., ... & Kudlur, M. (2016). TensorFlow: A System for Large-Scale Machine Learning. In 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16) (pp. 265-283).

[79] Chollet, F. et al. (2015). Keras. Retrieved from https://keras.io

[80] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., ... & Chintala, S. (2019). PyTorch: An Imperative Style, High-Performance Deep Learning Library. In Advances in Neural Information Processing Systems (pp. 8024-8035).

[81] Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., ... & Darrell, T. (2014). Caffe: Convolutional Architecture for Fast Feature Embedding. In Proceedings of the 22nd ACM international conference on Multimedia (pp. 675-678).

[82] Zhong, Y., Gao, J., Lei, Q., & Zhou, Y. (2018). A vision-based counting and recognition system for flying insects in intelligent agriculture. Sensors, 18(5), 1489.

[83] Neha, H. C., & Munavalli, J. R. (2020)

[84] Chudzik, P., Mitchell, A., Alkaseem, M., Wu, Y., Fang, S., Hudaib, T., ... & Al-Diri, B. (2020). Mobile real-time grasshopper detection and data aggregation framework. *Scientific reports*, *10*(1), 1150.

[85] Xia, D., Chen, P., Wang, B., Zhang, J., & Xie, C. (2018). Insect detection and classification based on an improved convolutional neural network. Sensors, 18(12), 4169.

[86] Kumar, K. S., & Abdul Rahman, A. (2020). Early detection of locust swarms using deep learning. In *Advances in Machine Learning and Computational Intelligence: Proceedings of ICMLCI 2019* (pp. 303-310). Singapore: Springer Singapore.

[87] Samil, H. M. O. A., Martin, A., Jain, A. K., Amin, S., & Kahou, S. E. (2020). Predicting regional locust swarm distribution with recurrent neural networks. *arXiv preprint arXiv:2011.14371*.

[88] Shuhan, L. U., & YE, S. J. (2020). Using an image segmentation and support vector machine method for identifying two locust species and instars. *Journal of Integrative Agriculture*, *19*(5), 1301-1313.

[89] Gubbi, J., Buyya, R., Kavitha, S., & Lyengar, S. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. Future generation computer systems, 29(7), 1645-1669.

[90] Ashton, K. (2009). That ‘internet of things’ thing. RFID journal, 22(7), 97-114.

[91] Evans, D. (2011). The Internet of Things: How the Next Evolution of the Internet Will Change Everything. Cisco IBSG.

[92] García, C. G., Meana-Llorián, D., G-Bustelo, B. C. P., Lovelle, J. M. C., & Garcia-Fernandez, N. (2017). Midgar: Detection of people through computer vision in the Internet of Things scenarios to improve the security in Smart Cities, Smart Towns, and Smart Homes. *Future Generation Computer Systems*, *76*, 301-313.

[93] Shih, H.-J., et al. (2007). A Smart Home System Based on ZigBee Wireless Sensor Network. International Journal of Sensor Networks, 4(3-4), 284-292.

[94] Khan, A. R., et al. (2013). An Energy-Efficient Real-Time Home Automation System. International Journal of Hybrid Information Technology, 6(4), 373-384.

[95] Sazonov, E., et al. (2014). Wearable health monitoring systems: A review. Expert Systems with Applications, 41(13), 5230-5263.

[96] Mauldin, T. R., Canby, M. E., Metsis, V., Ngu, A. H., & Rivera, C. C. (2018). SmartFall: A smartwatch-based fall detection system using deep learning. Sensors, 18(10), 3363.

[97] Harding, J., Powell, G., Yoon, R., Fikentscher, J., Doyle, C., Sade, D., Lukuc, M., Simons, J., & Wang, J. (2014). Vehicle-to-Vehicle Communications: Readiness of V2V Technology for Application. IEEE Communications Magazine.

[98] Hartenstein, H., et al. (2010). Connected vehicles: A review of the enabling technologies and applications. IEEE Intelligent Transportation Systems Magazine, 4(1), 17-28.

[99] Rathore, D. M., et al. (2016). Smart cities: A survey. Journal of the Institution of Engineers (India): Series B, 97(4), 589-600.

[100] Xu, L. D., et al. (2016). Industrial Internet of Things: A survey of enabling technologies, standards, and model. IEEE Transactions on Industrial Informatics, 14(2), 752-761.

[101] Lee, J., et al. (2015). The Industrial Internet of Things: A vision on architecture, challenges, and opportunities. IEEE Systems Journal, 4(4), 334-346.

[102] C. -J. Chen, Y. -Y. Huang, Y. -S. Li, C. -Y. Chang and Y. -M. Huang, "An AIoT Based Smart Agricultural System for Pests Detection," in IEEE Access, vol. 8, pp. 180750-180761, 2020, doi: 10.1109/ACCESS.2020.3024891.

[103] Zheng, J., Zhang, Y., Gao, L., & Wang, Y. (2019). Locust detection based on IoT and machine learning. In IEEE International Conference on Computer and Communications (ICCC), pp. 1411-1416. https://doi.org/10.1109/ICCC.2019.8793388

[104] Dong, Yingying, Longlong Zhao, and Wenjiang Huang. *Monitoring of Desert Locust in Africa and Asia*. Springer Nature, 2023.

[105] Liu, R., Li, G., Li, Y., Wang, Y., Li, C., & Li, H. (2020). Smart Pest Control System for Locusts Based on Raspberry Pi. International Journal of Distributed Sensor Networks, 16(8), 1550147720947432.

[106] Amilan, S., & Aparna, K. (2023). Factors influencing the adoption of cashless transactions: toward a unified view. South Asian Journal of Marketing, (ahead-of-print).

[107] Mir, S. A., & Padma, T. (2020). Integrated technology Acceptance Model for the evaluation of agricultural decision support systems. Journal of Global Information Technology Management, 23(2), 138-164.

[108] Holden, H., & Rada, R. (2011). Understanding the influence of perceived usability and technology self-efficacy on teachers' technology acceptance. Journal of research on technology in education, 43(4), 343-367.

[109] Bajunaied, K., Hussin, N., & Kamarudin, S. (2023). Behavioral intention to adopt FinTech services: An extension of unified theory of acceptance and use of technology. Journal of Open Innovation: Technology, Market, and Complexity, 9(1), 100010.

[110] Soehnchen, C., Weirauch, V., Schmook, R., Henningsen, M., & Meister, S. (2023). An acceptance analysis of a sexual health education digital tool in resource-poor regions of Kenya: an UTAUT based survey study. BMC Women's Health, 23(1), 1-19.

[111] Márquez, L., Henríquez, V., Chevreux, H., Scheihing, E., & Guerra, J. (2023). Adoption of learning analytics in higher education institutions: A systematic literature review. British Journal of Educational Technology.

[112] Abbad, M. M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. Education and Information Technologies, 26(6), 7205-7224.

[113] Liu, D., & Wu, X. (2023, June). Research on the Use Behavior of Agricultural Big Data in the Era of Intelligent Agriculture Based on UTAUT Model. In Proceedings of the 3rd International Conference on Big Data Economy and Information Management, BDEIM 2022, December 2-3, 2022, Zhengzhou, China.

[114] Jain, M., Soni, G., Verma, D., Baraiya, R., & Ramtiyal, B. (2023). Selection of technology acceptance model for adoption of industry 4.0 technologies in agri-fresh supply chain. Sustainability, 15(6), 4821.

[115] Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. MIS Quarterly, 28(1), 75-105.

[116] Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A design science research methodology for information systems research. Journal of Management Information Systems, 24(3), 45-77.

[117] Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. MIS Quarterly, 37(1), 337-355.

[118] Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A framework for evaluation in design science research. European Journal of Information Systems, 25(1), 77-89.

[119] Hevner, A., & Chatterjee, S. (2010). Design research in information systems: Theory and practice. Springer Science & Business Media.

[120] Gregor, S., & Jones, D. (2007). The anatomy of a design theory. Journal of the Association for Information Systems, 8(5), 312-335.

[121] Vaishnavi, V., & Kuechler, W. (2015). Design science research methods and patterns: Innovating information and communication technology. CRC Press. International Journal of Applied Earth Observation and Geoinformation, 117, 103212.

[122] Kozma, D., Varga, P., & Larrinaga, F. (2021). System of systems lifecycle management—a new concept based on process engineering methodologies. Applied Sciences, 11(8), 3386.

[123] Brocke, J., Budde, L., & Schenk, T. (2020). Design Science Research. In T. M. Durand & J. J. Grodal (Eds.), The Palgrave Encyclopedia of Strategic Management. Palgrave Macmillan UK. https://doi.org/10.1007/978-3-030-02006-0_84-1

[124] Zimmermann, R., Mora, D., Cirqueira, D., Helfert, M., Bezbradica, M., Werth, D., ... & Auinger, A. (2023). Enhancing brick-and-mortar store shopping experience with an augmented reality shopping assistant application using personalized recommendations and explainable artificial intelligence. Journal of Research in Interactive Marketing, 17(2), 273-298.

[125] Sottile, F., Foglietti, J., Pastrone, C., Spirito, M. A., Defina, A., Eisenhauer, M., ... & Rosengren, P. (2022). IoT solutions for large open-air events. In Internet of Things–The Call of the Edge (pp. 207-253). River Publishers.

[126] Sutton, S. G., & Arnold, V. (2013). Focus group methods: Using interactive and nominal groups to explore emerging technology-driven phenomena in accounting and information systems. *International Journal of Accounting Information Systems*, *14*(2), 81-88.

[127] Pajankar, A. (2021). Introduction to Raspberry Pi. In Practical Linux with Raspberry Pi OS (pp. 1-34). Apress, Berkeley, CA.

[128] Islam, F. B., Nwakanma, C. I., Kim, D. S., & Lee, J. M. (2020, October). IoT-based HVAC monitoring system for smart factory. In 2020 International Conference on

Information and Communication Technology Convergence (ICTC) (pp. 701-704). IEEE.

[129] Ali, B., Khalid, H., & Rao, M. (2022). Self-sustainable non-toxic locust control using electric field & real-time remote monitoring using Android application. Journal of Independent Studies and Research Computing, 20(1), 31-38.

[130] Chiwamba, S. H., Phiri, J., Nkunika, P. O. Y., Sikasote, C., Kabemba, M. M., & Moonga, M. N. (2019). Automated fall armyworm (Spodoptera frugiperda, JE Smith) pheromone trap based on machine learning. Journal of Computational Science, 15(12), 1759-1779.

[131] Sahin, M., Ozdemir, E., & Kose, E. (2020). Design and implementation of a solar-powered Raspberry Pi system for IoT applications. Journal of Ambient Intelligence and Humanized Computing, 11(10), 4283-4293. doi:10.1007/s12652-019-01432-8

[132] Deka, D., Baruah, P., & Sarma, K. B. (2019, December). Design of a standalone solar powered Raspberry Pi based monitoring system for agriculture. In 2019 IEEE International Conference on Sustainable Energy Technologies and Systems (ICSETS) (pp. 548-552). IEEE. doi: 10.1109/ICSETS48194.2019.9069360.

[133] Ye, S., Lu, S., Bai, X., & Gu, J. (2020). ResNet-locust-BN network-based automatic identification of east asian migratory locust species and instars from RGB images. *Insects*, *11*(8), 458.

[134] Zhao, L., Li, H., Huang, W., Dong, Y., Geng, Y., Ma, H., & Chen, J. (2023). Outbreak Mechanism of Locust Plagues under Dynamic Drought and Flood Environments Based on Time Series Remote Sensing Data: Implication for Identifying Potential High-Risk Locust Areas. *Remote Sensing*, *15*(21), 5206.

[135] Alhady, S. S. N., & Xin Yong Kai. (2018). Butterfly species recognition using artificial neural network. In Intelligent manufacturing & mechatronics (pp. 449-457). Springer, Singapore.

[136] Suwandej, N., et al. (2022). The efficiency of using drones to reduce farming costs and yields. Journal of Positive School Psychology, 1412-1424.

[137] Matthews, G. A. (2021). New technology for desert locust control. Agronomy, 11(6), 1052.

APPENDICES

Appendix 1 - Questionnaire

QUESTIONNAIRE

Dear Respondent,

I am Brian Halubanza, a student pursuing a PhD degree in Computer Science at the University of Zambia (UNZA). I am carrying out a research study entitled *A framework for an early warning system for the management of the spread locust invasion in Zambia; based on Artificial Intelligence Technologies*. You are among the respondents selected to answer the questions. The information given will be treated with utmost confidence and for academic purposes only.

Personal and Demographic information

Name of interviewer		
Time of interview		
Date		
Name of Community		
Number of houses within the community		
Estimated number of households[1]		
Name of interviewee		
Sex of interviewee		
Name of the village head		
Sex of the village head		

SECTION 1: DEMOGRAPHIC DATA

		Grade Point (1,2,3,4 and 5)				
		1	**2**	**3**	**4**	**5**

	Are you a famer? 1= Yes, 2= No					
	Please tick your Gender Male Female					
	Marital Status Married Single Divorced Widowed					
	Please select your Age range Years 21-25 Years26-30 Years31-35 Years36-40 Years Above 41 Years					
	What is your qualification? 1= Primary, 2=School leaver, 3= Certificate, 4= Diploma or more, 5 = Never been to school					
	Do you have children? 1=yes, 2=No					
	How many children do you have? 1=1-3, 2=3-6, 3=6 and above					
	How many of them go to school? 1=2; 2=3; 3=all of them					
	How many members are in your household? 1=1-3 2=3-6, 3=6 and above					
	Who works in the farm in your household? 1=Husbands, 2=wives, 3=children, 4=others (specify)					
	What is your source of drinking water? 1=Shallow well, 2= River, 3= Borehole					
		1	**2**	**3**	**4**	**5**
	When members of your household fall sick what form of treatment do you access? 1= clinic; 2=hospital; 3=herbalists 4=others (specify)					
	How far is the distance to a nearby Health Facility? 1=1-2 Kilometers, 2= 2-3 Kilometers, 3=3 and above Kilometers					
	SECTION 2: AGRICULTURAL PRACTICES					
	What crops do you grow yearly?					

	1=Maize, rice, 2-Millet, 3=Sorghum, groundnuts, 4=vegetables, 5=all of the above					
	How many years have you been farming the crop? 1= 1-2 years, 2= 2 or More					
	What tools do you use in land cultivation? 1=Hoe, 2= Oxen Plough, 3= Tractors					
	How many acres do you cultivate annually? 1= less than 1 ha, 2=2 – 3 ha, 3 = 4 to 6ha,5= more than 6ha					
	Do you use fertilizers in your crop cultivation? 1=yes 2=no (if yes, go to next question)					
	Where do you access fertilizer from? 1=Government, 2= Dealers 3=others (specify)					
	If purchased, how much does a bag of fertilizer costs? 1=500, 2=600, 3=650, 4=above 650					
	As a farmer, are you part of any cooperative? 1=yes, 2=No (if yes, go to Q36. If no, skip next question)					
	How many members do you have in the cooperative? 1=5, 2=10, 3=15,4=20 or more					
	SECTION 3: INCOME GENERATED FROM AGRICULTURE					
	What is your household major source of income?1=farming, 2= trading, 3=teaching 4=Government worker, 4=others (specify)					
	What is your household estimated monthly income from all sources? 1= below 5000; 2=6,000 -10,000, 3=11000 – 20000, 4=21,000-25000, 5=26,000 and above					
	What does your household spends on with money generated from farm produced? 1=daily feeding, 2=paying school fees, 3=supporting family members, 4=paying medical bills 5=all of the above					

	Do you have any other sources of income? 1=yes 2=no (if yes, go to next question)					
	What are some of these other sources of income for the household? 1=trading, 2=Charcoal, 3=fishing 4=tailoring 5=others (specify)					
	SECTION 4: LOCUST KNOWLEDGE					
	What types of Locusts are in your area? 1=African Migratory Locust,2= Red Locust, 3= Others (Specify)					
	How frequency do they occur? 1=Yearly, 2= Between 1 and 2 Years, 3= After 3 Years,4= Others specify					
	In which year did you recently experience locust? 1=This Year, 2= Last Year, 3= Two Years ago, 4= Every Year					
	How much area was affected? 1=Less than 1Ha, 2= Between 2ha and 5ha,3=more than 5 ha					
		1	**2**	**3**	**4**	**5**
	What was most affected? 1=Grazing land, 2= Crop Fields					
	What was mostly impacted by locust? 1=Humans, 2=Animals, 3=Bees					
	What are the signs of locust invasion in your area? 1=Presence of a flying swam, 2= Eaten Crops/grass, 3= Presence of hopping locusts on the ground, 4=Other(s) (specify)					
	What whether condition favours locusts? 1=Rain Season, 2= Cold Season, 3=Hot Season, 4=Dry Season,5=Others(Specify)					
	SECTION 5: LOCUST CONTROL MEASURES					
	Are you able to predict when locusts will be present in a particular year? 1=Yes, 2= No. If no, go to the next question					

	Does government provide warning information on the likelihood of locust invasion? 1=Yes, 2= No					
	What prevention or control measures did you put in place during the invasion? 1=Burning affected areas, 2= Spraying Chemicals, 3=Harvesting for food, 4= Beating drums, 5= others(specify)					
	What challenges do you face during an outbreak of Locusts? 1=Lack of Chemicals, 2= Lack of Manpower to control the invasion, 3= Lack of transport, 4=Lack of training, 5= Others (Specify)					
	Have you ever had training in locust management? 1=Yes,2= No. If yes, go to the next question.					
	Which forms of training have you done? 1=locust breeding, 2=locust harvesting, 3=locust elimination, 4=Early locust identification, 5=all of the above.					
	Who was conducting these trainings in your community? (1=government 2=Non-Governmental Organizations/Community Based Organizations, 3=Religious groups, 4=others (specify)					
	Do you have contacts for local locust control team where to report locust invasion? 1=Yes, 2 = No					

	SECTION 6: USE OF MOBILE PHONES					
		1	**2**	**3**	**4**	**5**
45	**If yes to question 44, what do you use to report locust related information? 1= Mobile phone, 2= walk to locust camp, 3= cycle to the locust camp, 4= drive to the locust camp, 5= others(specify)**					
46	**Do you Own a mobile phone? 1=Yes, 2= No. If no**					
47	**If No to question 46, why don't you own a mobile phone? 1= its costly, 2=there is no network in my area, 3=I don't know how to use it, 4= others(specify)**					
48	**If yes to question 46, does your phone access internet? 1- Yes, 2= No**					
49	**If no to question 48, why doesn't your mobile phone access internet? 1=Its not a smart phone, 2=Data bundles are**					

	expensive, 3= the network is not good, 4=there is no network, 5=others (Specify)					
50	**If yes to question 46, how easy is it to buy a phone? 1= easy, 2= difficulty, 3= not sure, 4= others (Specify)**					
51	**If yes to question 46, how do you find the use of a mobile phone? 1= Easy, 2= Difficult, 3= not sure, 4= others (Specify)**					
52	**If yes to question 46, how secure is data on your phone? 1=secure, 2= not secure, 3= not sure, 4= others(specify)**					
53	**Do you have access to agricultural related information using your mobile phone? 1=Yes, 2= No**					
54	**If yes to question 53, do you have access to information about buying and selling products? Yes, 2= No**					
55	**Do you have access or receive alerts about locust on your phone? 1=Yes, 2= No**					

Thank you for your participation

Appendix 3: Publications

1. Halubanza, B., Phiri, J., Nyirenda, M., Nkunika, P.O.Y., Kunda, D. (2023). Low Cost IoT-Based Automated Locust Monitoring System, Kazungula, Zambia. In: Silhavy, R., Silhavy, P. (eds) Networks and Systems in Cybernetics. CSOC 2023. Lecture Notes in Networks and Systems, vol 723. Springer, Cham. https://doi.org/10.1007/978-3-031-35317-8_59

2. Halubanza, B., Phiri, J., O.Y Nkunika, P., Nyirenda, M., & Kunda, D. (2022). Toward Locust Management: Challenges and Technological opportunities, Sikaunzwe, Zambia. Zambia ICT Journal, 6(1), 61–65. https://doi.org/10.33260/zictjournal.v6i1.152

3. Halubanza, B., Phiri, J., Nyirenda, M., Nkunika, P.O.Y., Kunda, D. (2022). Detection of Locusta migratoria and Nomadacris septemfasciata (Orthoptera: Acrididae) Using MobileNet V2 Quantized Convolution Neural Network, Kazungula, Zambia. In: Silhavy, R. (eds) Cybernetics Perspectives in Systems. CSOC 2022. Lecture Notes in Networks and Systems, vol 503. Springer, Cham. https://doi.org/10.1007/978-3-031-09073-8_43

4. Halubanza, B., Phiri, J., Nyirenda, M., Nkunika , P., Kunda, D., & Mulenga, J. (2023). Locust Infestations and Mobile Phones: Exploring the Potential of Digital Tools to Enhance Early Warning Systems and Response Mechanisms . Zambia ICT Journal, 7(2), 10–16. https://doi.org/10.33260/zictjournal.v7i2.266