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# Artificial intelligence and deep learning based technologies for emerging disease recognition and pest prediction in beans (phaseolus vulgaris l.): A systematic review

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**Artificial Intelligence (AI) and deep learning have the capacity to reduce losses in crop production, such as low crop yields, food insecurity, and the negative impacts on a country's economy caused by crop infections. This study aims to find the knowledge and technological gaps associated with the application of AI-based technologies for plant disease detection and pest prediction at an early stage and recommend suitable curative measures. An evidence-based framework known as the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) methodology was used to conduct systematic reviews of the state-of-the-art of AI and deep learning techniques for crop disease identification and pest prediction in developing countries. The results demonstrate that conventional methods for plant disease management face some challenges, such as being costly in terms of labour, having low detection and prediction accuracy, and some are not environmentally friendly. Also, the rapid increase in data-intensive and computational-intensive tasks needed for plant disease classification using traditional machine learning methods poses challenges such as high processing time and storage capacity. Consequently, this paper recommends a deep learning and AI-based strategy to enhance the detection, prediction and prevention of crop diseases. These recommendations will be the starting point for future research.**

**Key words:** Plant diseases detection, pest prediction, pesticide recommendation, artificial intelligence, machine learning.

## INTRODUCTION

The common bean (*Phaseolus vulgaris* L.) is considered to be the potential grain legume used as food as well as the key source of important micronutrients needed by millions of people worldwide, including in sub-Saharan Africa (Said and Taher, 2020). In Tanzania, consumption of common bean dry seeds with cereal-based food guarantees access to a balanced diet and supplementary nutrients that help alleviate malnutrition and prevent

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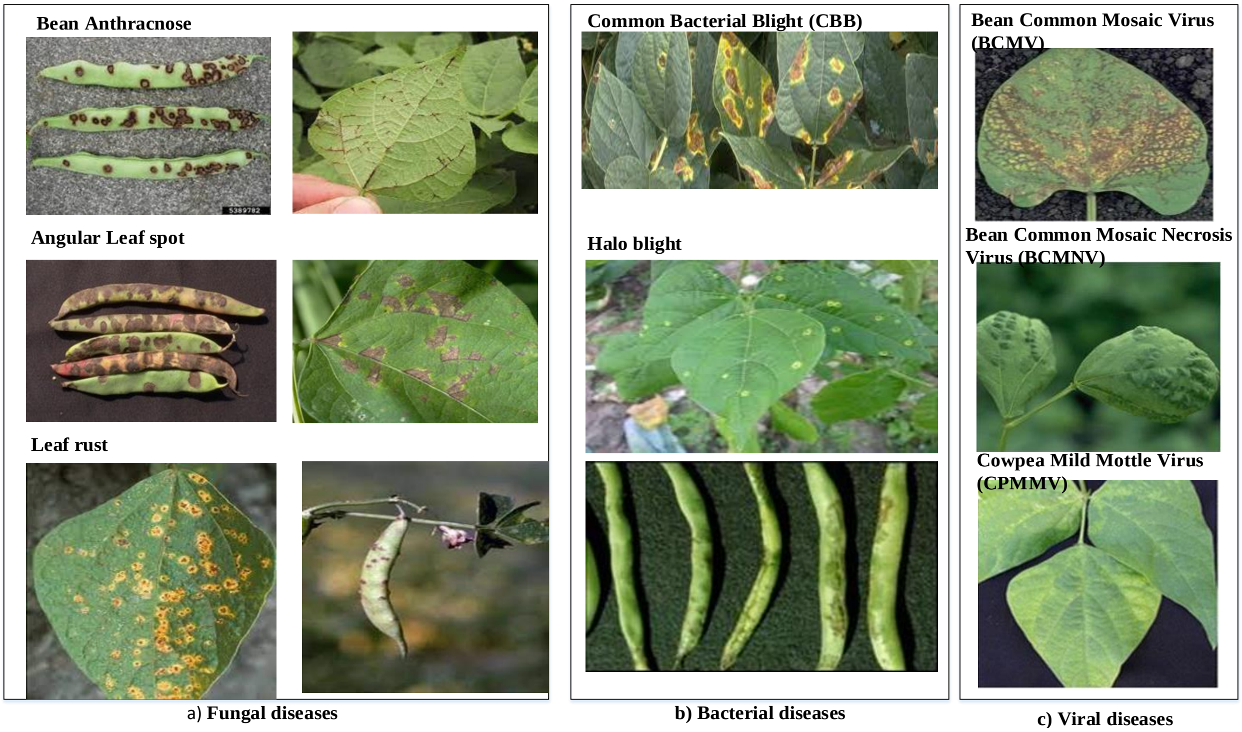


**Figure 1.** An overview of symptoms of common bean diseases.
Source: Hughes and Salathé (2015)

various diseases such as cardiovascular, certain types of cancer, and diabetes (Muimui, 2010; Hangen and Benink, 2003). In 2019, about 28.9 million tons of common beans were produced, with tropical low-income countries producing three-quarters of the total (FAOSTAT, 2016). Latin America is the leading bean producer worldwide, with Brazil being a leading country for both bean production and consumer (Rezende et al., 2018). In Africa, Tanzania is the prevalent producer of beans, followed by Uganda and Kenya (Philipo et al., 2020). In Tanzania, the main bean production areas are the northern region, the Great-lakes zone and the southern highlands, where more than 90% are produced by small-scale farmers on farms ranging from 0.5 to 2 ha in size (Ndakidemi et al., 2006). Unfortunately, the importance of the crop cannot be adequately measured due to numerous biotic and abiotic constraints. Biotic constraints refers to the numerous infections caused by bacteria, fungi, viruses, and nematodes (Markell et al., 2012; Pamela et al., 2014; Chilagane et al., 2016; Mpeguzi et al., 2020). Numerous infectious diseases are posing major limitations to bean productivity in Tanzania and worldwide (Hillocks et al., 2006). This in turn threatens the economy of many countries by affecting the production and quality of agricultural products and ultimately reducing food security. Other limiting factors include varieties with low genetic potential for yield; poor soil fertility; weather conditions; drought; insect pests and diseases (Hillocks et al., 2006). Some crop diseases common in Tanzania include Angular Leaf Spot (ALS) (*Phaeoisariopsis griseola*), root rots (a complex of pathogens), common bacterial blight (CBB) (*Xanthomonas campestris* pv. *phaseoli*), and anthracnose (*Colletotrichum lindemuthianum)*. Other essential diseases include halo blight (*Pseudomonas phaseolicola*), leaf rust (*Uromyces phaseoli*), *bean common mosaic necrosis virus* (BCMNV), and *bean common mosaic virus* (BCMV) (Mwaipopo et al., 2017). These diseases are prominent in Tanzania, occur in all bean-growing areas and emanates a yield loss of up-to 100% subject to the environment and variety grown (Tryphone et al., 2013). Recently, anthracnose has emerged as a major problem in Tanzania, as observed while conducting a comprehensive survey of common bean viruses in 2016/2017. Moreover, these diseases reduce the quality of harvested-seeds, germination capacity, and market significance, and some can be seed-borne, thereby threatening the seed supply (Degu et al., 2020). Figure 1 displays a synopsis of the symptoms of various diseases in common beans. Bean anthracnose is among the serious infection of beans in Tanzania triggered by the fungal-pathogen called *Colletotrichum lindemuthianum* (Mpeguzi et al., 2020). If the disease is not well controlled, would cause yield losses of upto 100% (Markell et al., 2012). The infection affects leaves, seeds, pods, and stems of beans. The infected seeds initiate and disperse the disease to the plant (Mudawi et al., 2009). The main symptoms of anthracnose disease in common beans are: growth dark and collapse of veins on the leaf underside; sunken lesions on pods displaying spore creation at the centers; and seed discoloration. Diseased plants may dry and crack, showing seeds inside the pods. Seed formed beneath pod lesions does not show the signs of infection (Padder et al., 2017). In Tanzania, few studies on anthracnose have been indicated regardless of the presence of the disease, such as Padder et al. (2017), Ndee (2013), Shao and Teri (1981). The ALS is the major damaging fungal disease affecting beans (*Phaseolus vulgaris* L.) spreading in tropical and subtropical areas, causing up-to 80% harvest losses in a given area (Muthomi et al., 2011). The infection is prominent in Eastern and Central African countries, including Tanzania (Pamela et al., 2014; Chilagane et al., 2016). Considering Tanzania as an example, the symptoms has been testified to spread from low to high altitudes above sea level where the common beans are grown (Hillocks et al., 2006) which covers the northern zone, the lake zone, the western regions and the southern regions. ALS has been extensively studied in various previous studies (Wani et al., 2022; Tryphone et al., 2015; Mongi et al., 2016; Mongi, 2018; Chilagane, 2017). Common bean rust is one of the major diseases in the common bean growing areas caused by the fungus called *Uromyces appendiculatus* (Fromme, 1924; Stavely and Pastor-Corrales, 1989). Leaf rust has been studied in detail by Mmbaga et al. (1996); Liebenberg and Pretorius (2010); Aylor (1990); and Hillock (2006).

The diseases caused by bacteria such as CBB and halo blight are also common worldwide with more cases reported in the USA, Asia, and Africa (Muimui et al., 2011; Chen et al., 2021b; Noble et al., 2019). CBB causes up to 75% of harvest losses (Allen et al., 1996; Muimui et al., 2011). In Tanzania, CBB is very common in all areas that produce beans, especially in the southern highlands of Tanzania. Symptoms of CBB appear on seedlings, foliage, stems, pods, and seeds of common bean plants (Chen et al., 2021b; Wohleb, 2011). CBB and halo blight diseases have been extensively studied to identify symptoms, factors triggering the incidence of disease, and curative measures (Chen et al., 2021a; Tugume et al., 2019; Chen et al., 2021a; Noble et al., 2019; Mwamahonje, 2018; McGrath, 2021). Moreover, common beans are infected with various viral diseases such as BCMV, BCMNV, and Bean Yellow Mosaic Virus (BYMV). In Tanzania, the above-mentioned viruses were discovered in bean samples using the next-generation sequencing method. More studies are needed to address their incidence, distribution, and severity, to complement few reported viruses (Mwaipopo et al., 2018). BCMV and BCMNV are the most common viruses that affect beans globally, where the beans are produced (Worrall et al., 2015). This in return causes up-to 80% harvest losses (Drijfhout, 1991). Consequently, various published articles investigated efficient mechanisms to detect viruses causing bean mosaic disease from the 1980s to date in Tanzania (Mwaipopo et al., 2017; Mwaipopo et al., 2018). Plant disease detection and prediction of harmful emerging pests is a challenging task due to the lack or inadequate tools for efficient surveillance, prediction, and prevention. Traditional methods based on scouting in combination with various diagnostic tools are labour and time-intensive. The use of deep learning and emerging artificial intelligence (AI)-based technologies to detect plant diseases and predict harmful pests is an interesting research area that needs to be explored.

This paper contributes to the implementation of the second Sustainable Development Goal (SDG), which focuses on eradicating hunger, guaranteeing food security and sustainable agriculture by 2030. It also addresses the goal of the 3rd SDG, which targets to safeguard healthy lives and stimulate well-being by 2030. Likewise, the aim of the target of the fourth goal is to ensure a well-educated and actively learning society, for which this paper leverages innovative emerging AI-based tools to propose a framework that can detect, classify, and disseminate knowledge on plant disease and pest control measures to ensure food security. This paper reviews new and novel AI-based tools for plant disease detection and prediction of harmful pests at an early stage and to recommend cost-efficient solutions to minimize damage to crop production.

## RESEARCH METHODOLOGY

This study applied the well-known evidence-based framework namely PRISMA to support standard reporting and conduction of systematic reviews (Moher et al., 2009; McKenzie et al., 2021). Four key steps were followed to conduct this study which includes identification of data-sources and search plan, article screening, quality evaluation, and data extraction and analysis. Figure 2 presents the PRISMA workflow for systematic review of the AI-based solutions in crop disease detection and harmful pest prediction.

### Identification of data-sources and search strategy

During the period from April 2022 to June 2022, we conducted an extensive literature search in well-known online databases such as Scopus, Science Citation Index (SCI), and other related databases indexing journals such as IEEE, Springer, Elsevier, ACM, and IGI Global Publishers. The keywords considered for searching cut across crop disease management and the application of AI-based technology in agriculture, such as “crop disease classification”, “pest management”, “artificial intelligence”, “Internet-of-Things”, “machine learning” and crop disease management. We considered various sources of information such as articles and reports published in English between 2006 and 2022. Therefore, the search query guiding information retrieval from the databases was (“crop disease classification” OR “crop disease management” OR “pest management” OR “plant disease identification”) AND (“artificial intelligence” OR “Internet-of-Things” OR “machine learning”) AND “precision agriculture”).

### Article screening

Initially, the total number of identified records based on the guiding

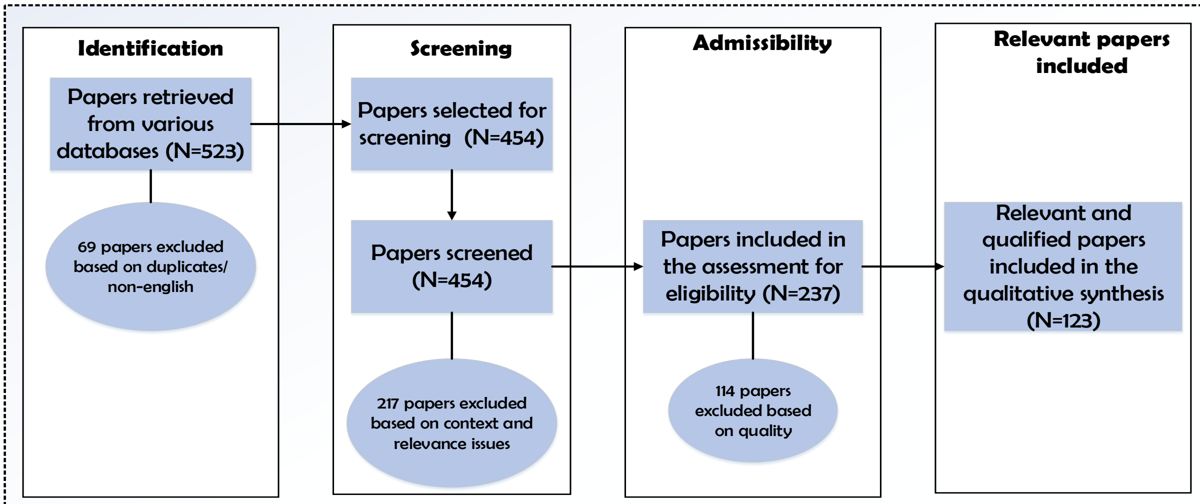


**Figure 2.** The PRISMA workflow for systematic review of the AI-based solutions in crop disease detection and harmful pest prediction.
Source: Adapted from McKenzie et al. (2021).

search query was 523 records. We conducted a manual evaluation of the retrieved records, considering analysis of various criteria such as title, abstract, index terms, publication language, and duplication. The initial evaluation process identified 69 records to be omitted for exclusion in the screening phase. The remaining 454 records were thoroughly screened based on their context and relevance to our study. The results of the screening process excluded 217 records that were found out of context and irrelevant to our study.

### Quality evaluation

The remaining 237 records were considered in the assessment for eligibility to be selected as relevant records. Based on the exclusion criteria, 114 records were found to be irrelevant and were therefore excluded based on the quality issues.

### Data extraction and analysis

Finally, 123 records were found relevant and qualified for inclusion in the qualitative synthesis as a sample for this study. A summary of the qualified papers was prepared using Microsoft excel 2013 and refined to filter information such as publication details, techniques used, performance evaluation indicators, dataset used for machine learning, and performance accuracy achieved for each technique. The summarized data were analyzed and reported on the basis of PRISMA checklist (Moher et al., 2009; McKenzie et al., 2021).

## RESULTS AND DISCUSSION

In Tanzania, agriculture is the backbone of the national economy with 80% of Tanzanians considering agriculture as their source of revenue (FAO, 2016). Also, Tanzania is considered to be among the leading countries in producing beans. The area under common bean production has increased from 1961 to 2016, thereby increasing total production. The increased bean production emanates from the growth of the total production fields rather than productivity. Low productivity is due to many diseases, as discussed earlier in this document. The source of diseases and how severely they damage common bean fields are influenced by a number of factors such as host resistance, the vectors, pathogen genetics, and the environment. For example, many crops are threatened by plant-viruses because it is challenging to control viruses because of inadequacy and economically sustainable methods for large production areas (Thresh, 2003). The pot viruses are particularly problematic because they are readily transmitted in seeds, so they may move over long distances in this form without being spread in the immediate environment by insect vectors. This leads to difficulties in their management (Galves and Molares, 1989; Shukla and Ward, 1989). Some fungal and bacterial diseases are transmitted in and on seeds, and all may be harboured in plant debris and spread by rainfall splashes. These varied modes of transmission make it difficult to control these diseases. Often, an understanding of the seasonal cycles of hostplants, pathogens, and vectors is needed in order to devise proper control measures for a disease. Different strategies can be used to minimize infections of common beans by plant pathogens depending on the nature of the disease, as described in the following section.

### Conventional plant disease management methods

Conventional plant disease management methods include various strategies such as Integrated Pest Management (IPM), cultural, physical, chemical, and biological controls, and host plant resistance. IPM is an active and environmentally sensitive approach to pest management that involves a combination of common- sense practices. IPM plans use up-to-date, comprehensive evidence on pest life cycles and their interactions or relationships with the environment. This information is used in combination with available pest control methods to manage pest damage by the most economical means and with the least possible hazard to people, property, and the environment. Disease control is the most effective method through the use of IPM; crop rotation; controlling of weeds; destroying of old crops; avoiding planting of new crops on diseased plantings; and rouging are very important (Persley et al., 2010; Munir, 2017). However, the IPM method is labour-intensive, as reported by Jørs et al. (2017). The cultural method is the method of controlling bean diseases by removing or burying infected plant debris after harvest to reduce overwinter survival of the pathogen (Mohammed, 2013b). It also includes two to three years of crop rotation with non-host plants to break the disease cycle and minimise the chances of pathogen survival (Coyne et al., 2003). Weekly scouting of the field for disease symptoms can assist in such a way that infected plants can be uprooted and removed. Additional cultural controls may include adequate plant spacing and removal of weeds to allow air circulation and foliar drying, as cool, humid conditions can promote certain diseases (McGee, 1995). Overhead irrigation should be avoided because it can cause the leaves to be wet, resulting in pathogen proliferation and sporulation on the foliage. Alternatively, drip irrigation that supplies water to the plant at the root zone (Buruchara et al., 2010) does not wet the leaves and can reduce disease incidence. Moreover, sanitation is another cultural method that has been implemented through the use of certified disease-free seeds and use of IPM. Physical methods include heat treatment through soil solarization with a plastic sheet over the plot about a month before planting, which reduces the incidence of pathogens such as anthracnose on beans. Apart from physical methods, there are biological methods that involve some fungi and bacteria producing bioactive volatile organic compounds that inhibit the growth of pathogens. For example, Mota et al. (2021) reported using endophytic fungi belonging to the genus *Induratia spp*. to control anthracnose, angular leaf spot, and white mould in beans. The effectiveness of bioagents against bean-causing disease pathogens was also supported by Abdel-Fattah et al. (2011), who revealed that the use of arbuscular mycorrhizal fungi as bioagents in common bean reduced the incidence and severity of *Rhizoctonia* root rot. Therefore, from these studies, it shows that different bioagents can be used as biological controls against bean disease-causing pathogens and they can offer a promising control of the diseases, although physical and biological methods still have weaknesses by Btryon (2022). Chemical methods comprise specific pesticides and have been proven to offer control of bean disease pathogens. Pesticides that are effective against *Pythium* spp have been reported by Abawi et al. (2006).

Also, the list of chemicals that are effective in reducing the severity and incidence of bean anthracnose, resulting in increased yield, has been reported (Mohammed et al., 2013a; Beshir, 2003). Moreover, phosphoric acid, benzoic acid, Bion, and pyrocatechol applications offered good control of *Uromyces appendiculatus*, a pathogen causing bean rust (Mansour et al., 2016). Lemessa et al. (2011) recommended spraying Benomyl for effective management of angular leaf spot.

Furthermore, various chemicals such as copper sulphate, copper hydroxide, and potassium methy-dithiocarbamate have been reported to control foliage infection of bean common bacterial blight (Karavina et al., 2011). Apart from other methods, host plant resistance is the most efficient and potentially durable disease management strategy for both resource-poor farmers and medium-sized small-holder farmers in Africa. Breeding for resistance is the most affordable method for these resource-poor farmers as they use it to retain their seeds for subsequent cropping cycles. Different cultivars with resistance to different diseases have been screened and developed by breeders as a long-term control of plant diseases. This is the most effective method of controlling viral diseases (Kelly et al., 1995). For example, it has been reported that the dominant *I* gene and the *bc-3* recessive gene together in the same variety of common bean give complete resistance to BCMV and BCMNV (Drijfhout, 1978; Vallejos et al., 2006; Naderpour et al., 2010). Anthracnose and angular leaf spot resistance were explained by Gonçalves-Vidigal et al. (2020). CBB resistance (Miklas et al., 2000), ALS (Oblessuc et al., 2012; Caixeta et al., 2005). Wasonga et al. (2010) developed snap bean lines with broad spectrum rust resistance and heat tolerance for tropical agroecosystems. Offering resistance to beans is crucial in minimising the diseases, though the challenge is to breed the varieties with resistance that is effective, stable, and broad–spectrum (Nelson et al., 2018). Palloix et al. (2009) also reported that resistance breakdown is obvious, and sometimes there is a negative correlation between yield and disease resistance variables, whereby the durability of plant major resistance genes to pathogens depends on the genetic background, experimental evidence, and consequences for breeding strategies. For instance, the wheat rust resistance gene reduces grain yield by 5%. Apart from that, since the resistance involves multiple gene introgression, the planning needs greater effort than single gene resistance. Lastly, horizontal resistance is durable but difficult to relate to an accurate and reliable assessment of the level of resistance.

**Research trends on plant disease management using artificial intelligence and deep learning based technologies**

Sensing technology, Unmanned Aerial Vehicle (UAV), Internet of Things (IoT), machine learning techniques and Mobile Cloud Computing (MCC) are driving smart farming and innovative disease management strategies. The following subsection discusses the cost-efficient innovative technologies for efficient management of plant diseases.

### *Low-cost sensors*

Rapid advances in sensor technology have aided in the detection of plant diseases and pests, overcoming the limitations of traditional methods and the reliance on human experts. For example, Huang et al. (2014) analysed the detection of Maize Chlorotic Mottle Virus (MCMV) using a bio-sensor implemented on the basis of Quartz Crystal Microbalance (QCM), which achieved high detection accuracy. Jócsák et al. (2019) investigated the application of Electrochemical Impedance Spectroscopy (EIS) sensors to detect viruses or pathogens that threaten plants. The EIS proved useful, especially for in-field investigations due to its portability and capability to deliver quick feedback. Khater et al. (2019) reported an innovative sensor to detect Citrus Tristeza Virus (CTV) in multiple infections, which is a common scenario for planted crops. Also, wearable sensors play a great role in real-time monitoring of plants' health. For example, Nassar et al. (2018) described wearable sensors that were configured to monitor plants' health. The sensors gathered data such as temperature, strain, and humidity that were used to investigate the influence of environmental conditions on the health of plants. Wearable sensors are also widely used in precision agriculture to observe variations in solute content in plants and keep records of water usage in plants (Coppedè et al., 2017).

### *Unmanned aerial vehicle*

The advancement in sensing technology such as Hyperspectral Imaging Sensors (HIS) is augmenting the traditional tools used for capturing airborne and satellite images. Analysing airborne or satellite-based data is expensive and time-consuming (Behmann et al., 2018). Hyperspectral sensing technology such as Unmanned Aerial Vehicles (UAVs) can guarantee a cost-efficient and effective way of acquiring imagery data from the field. UAVs can collect imagery data at a small aerospace attitude and provide an efficient platform for hyperspectral imaging, which is more suitable and cost-effective than traditional methods (Ishengoma et al., 2022). Moreover, UAVs contribute largely to supporting precision farming. For instance, UAVs are widely used in soil and field analysis to improve crop yield prediction through the implementation of data-driven techniques while improving fertilizer and pesticide utilisation (Peña et al., 2013; Torres-Sanchez et al., 2013). Also, crop and spot spraying is another application area of the UAVs that has been reported to be efficient in terms of cost and time (Yallappa et al., 2017; Hentschke et al., 2018; Xiongkui et al., 2017). Furthermore, Guo et al. (2012) demonstrated the applicability of UAVs in crop monitoring to assist farmers in tracking crop status and identifying areas that require immediate intervention to improve crop conditions. This study uses the advanced capabilities of UAV-based data to propose an innovative and smart platform for crop disease detection and prediction of harmful pests.

### *Internet of things technologies*

Advances in the Internet of Things (IoT) are transforming many sectors, including agriculture, to provide modern technologies in the agricultural production value chain such as precision farming, automated production processes, yield prediction, remote monitoring of plant diseases and pests, etc. In supporting smart farming, modern and innovative technologies such as IoT, remote sensing, wireless communication, and cloud computing have the potential to achieve real-time monitoring of plant health and the conditions necessary for plant growth (Maksimovic et al., 2017; Bastiaanssen et al., 2000; Hashem et al., 2015; Weber and Romana, 2010). Furthermore, the IoT and UAVs are widely used to track the occurrence of plant diseases and harmful pests. IoT equipment can collect real-time data such as weather data and plant growth by using cost-efficient sensor nodes, while UAVs could take field/farm and crop images that can be analysed to detect the prevalence of crop diseases and harmful pests. For instance, Gao et al. (2020) proposed a framework established on the basis of IoT and UAV to monitor pests and crop diseases. The proposed framework, in particular, considered the relationship between weather and the occurrence of pests and crop diseases.

### *Machine learning techniques*

Over the years, Machine Learning (ML) techniques have been considered important for crop disease detection. Traditional ML methods are widely used for disease detection; for instance, Support Vector Machine (SVM) and random forest in tomato (Govardhan and Veena, 2019; Mokhtar et al., 2015) and K-Nearest-Neighbors (KNN) in soybean (Shrivastava et al., 2017). An image segmentation algorithm established based on the Genetic Algorithm (GA) has been proposed to detect plant leaf diseases and classify them into appropriate classes (Singh and Misra, 2017). The proposed method used the K-means clustering technique with the lowest distance condition, followed by SVM classification. This, in turn,

**Table 1.** Deep learning techniques for plant disease detection and classification.

| Serial # | Technique | Evaluation Metrix | Dataset | Performance accuracy (%) | Reference |
|---|---|---|---|---|---|
| 1 | Convolution Neural Network (CNN) | Accuracy | PlantVillage dataset | 96.50 | Meen, 2019 |
| 2 | Hybrid Convolution Neural Network (HCNN) model, VGG16 and InceptionV3 | Accuracy, training time | Field dataset of maize leaves | 96.98 | Ishengoma et al. (2021) |
| 3 | ResNet 50 | Accuracy | PlantVillage dataset | 97 | Nithish et al. (2020) |
| 4 | CNN models: VGG16, VGG19,ResNet,Inception V3 | Precision, Accuracy, FI-Score, recall | Field dataset of tomato leaves | 93.6 | Ahmad et al. (2020) |
| 5 | CNN(4 hidden layers) | Accuracy, precision, recall, FI-score | PlantVillage dataset | 91.2 | Agarwal et al. (2020) |
| 6 | Improved ANN and CNN | Accuracy, FI-score | PlantVillage dataset | 93.75 | Chen et al. (2021) |
| 7 | CNN with fuzzy C-means segmentation | Accuracy, sensitivity | Field dataset of banana leaves | 93.45 | Krishnan et al (2022) |
| 8 | CNN-AlexNet | Accuracy | PlantVillage dataset | 99.16 | Singh et al. (2022) |
| 9 | CNN-AlexNet with PSO optimization | Accuracy, FI-score, precision | Field dataset of various crop leaves (corn, wheat, cotton,etc) | 98.83 | Elaraby et al. (2022) |
| 10 | CNN integrated with attention strategy | Accuracy | PlantVillage dataset | 98 | Karthik et al. (2020) |
| 11 | Principal Component Analysis(PCA) with Whale optimization and Deep Neural Network (DNN) | Accuracy, loss rate | PlantVillage dataset | 86 | Gadekallu et al. (2021) |
| 12 | CNN-AlexNet, Inception V3, SVM | Accuracy, recall, FI-score | PlantVillage dataset | 93.40 | Verma et al. (2020) |
| 13 | ResNet 50 (using contextual information) | Accuracy | Field dataset of various crop leaves (corn, wheat, rice,etc) | 98.0 | Picon et al. ( 2019) |

Source: Author

improved classification accuracy by 9.17%. Nevertheless, traditional ML approaches still face some challenges that need to be addressed, such as being highly dependent on feature extraction needed to train the models, which consumes a lot of time, and ML models are suitable for some specific environments, especially when used to process images (Nigam and Jain, 2020; Shrivastava and Pradhan, 2021). To address the aforementioned challenges, deep learning algorithms with automated feature extraction are promising solutions for crop disease detection and classification (Agarwal et al., 2020; Kamilaris and Prenafeta, 2018). Table 1 summarizes research trends on deep learning techniques for crop disease detection.

***Mobile cloud computing***

Mobile Cloud Computing (MCC) technology has the potential to implement an integrated and collaborative solution for automated crop disease detection, tracking, and prediction. Farmers can instantly and precisely detect the prevalence of diseases and acquire recommendations for curative actions with the help of a cloud-based-mobile application such as a real-world mobile-cloud based plant disease diagnosis system. However, the emerging trends of big data have brought substantial challenges in terms of processing time and cost (Hashem et al., 2015; Skourletopoulos et al., 2017; Pallis, 2017). This is due to the advancement of technologies for collecting data from fields such as sensors, UAVs, and mobile devices. To efficiently process this data, in line with meeting Quality of Experience (QoE) the combined and collaborative capabilities of Mobile Edge Computing and Cloud Computing technologies need to be explored. According to the findings of this study, artificial intelligence (AI) and deep learning algorithms are suitable for processing large amounts of data using cloud-based image processing techniques.

## Research gap

Analysis of reviewed papers demonstrates that conventional plant disease management strategies such as IPM are considered to be a tool kit approach to crop protection. However, the methods prove to be labour-intensive and not easily disseminated to farmers (Jørs et al., 2017). Btryon (2022) and Nzungize et al. (2012) also reported that biological methods of controlling pests or diseases can sometimes fail in their specificity when the predator used a bio-control agent may switch to a different target. It was further reported that the biological methods are slow and do not destroy the pest, only reduce the pathogen. Generally, the application of chemicals in controlling pathogens causing bean diseases has been an efficient method. However there are environmental concerns about their use and some are no longer available. Chemical treatments for large-scale farmers could contaminate soil and water, whereas small-scale, poor-resource farmers cannot afford to apply chemical control and face health risks associated with handling chemical pesticides due to a lack of education in handling chemical pesticides to the farmer community. Consequently, smart crop disease detection and pest prediction technologies are considered as important worldwide. However, developing countries face numerous challenges in implementing automated systems for crop disease identification and pest prediction. Such challenges include inefficient internet connectivity, high costs for purchasing equipment and deploying smart technology on farms, and a shortage of experts on smart farming technology. Several previous studies proposed ML-based techniques to address the challenges related to plant disease identification, classification, and prediction. However, traditional ML techniques face challenges due to overwhelming progress in resource-intensive and data-driven tasks such as large datasets of images originating in the field. For instance, traditional ML relies heavily on feature extraction for model training, which consumes significant processing time and memory when processing large image datasets (Nigam and Jain, 2020; Shrivastava and Pradhan, 2021). To address this technological gap, this study reviewed various deep learning and AI-based models with automated feature extraction suitable for implementing cost-effective crop disease detection, classification, and prediction solutions. According to the results of the systematic review of this study, the combined strategies of machine learning, recommendation systems, WebGIS and image processing techniques have not been sufficiently explored to implement an AI-based solution for joint disease detection and prediction

## Theoretical framework

Figure 3 shows the main building block of the deep learning and AI-based framework for detecting crop diseases and predicting harmful pests. The white-labelled rectangles indicate the existing machine learning strategies, and the directed arrows indicate information workflow from one machine learning task to another. The coloured rectangles indicate innovative tasks proposed by this study for crop disease identification and harmful pest prediction strategies. For instance, the orange-rectangles represent the proposed improvement of the machine learning tasks to predict harmful pests related to the detected disease, while the green-rectangle represents the proposed task that will be implemented in the system recommendation module to recommend possible solutions for the farmer to take curative actions. The proposed framework is expected to be applied by private and government agencies at district, regional, and national levels to monitor the plant's health at various stages of growth. The trained crop disease detection and harmful pest prediction models map the locations where crops are planted and deploy the AI-based models to detect diseases, predict harmful pests, and recommend possible curative measures. Moreover, this study helps to fill the policy research gap by combining existing and emerging technologies for predicting harmful pests and detecting plant diseases using artificial intelligence technologies in collaboration with crop disease management centers at the community, district, and regional level. Also, the demonstration of the real-world applications at department level, university management level, government officials, private sectors, media, and social media will serve as evidence to engage policymakers. In collaboration with other stakeholders, it is crucial to develop and implement an interactive and social mobilisation strategy to influence decision makers and other stakeholders to mobilise resources needed to deploy the technology in the real work environment. Therefore, a collaborative strategy guarantees public awareness and consent. This, in turn, will ensure the social commitment among all stakeholders in fighting against prevalence of plant diseases and harmful pests in Tanzania.

# CONCLUSION AND FUTURE WORKS

This paper presents a systematic review of the state-of-the-art of artificial intelligence and deep learning techniques for crop disease detection and harmful pest prediction. Initially, the paper presented an overview of the current situation and symptoms of various diseases, specifically fungal diseases, bacterial diseases, and viral diseases affecting crops, particularly common beans. Then, we reviewed various articles on conventional plant disease management strategies to identify areas of

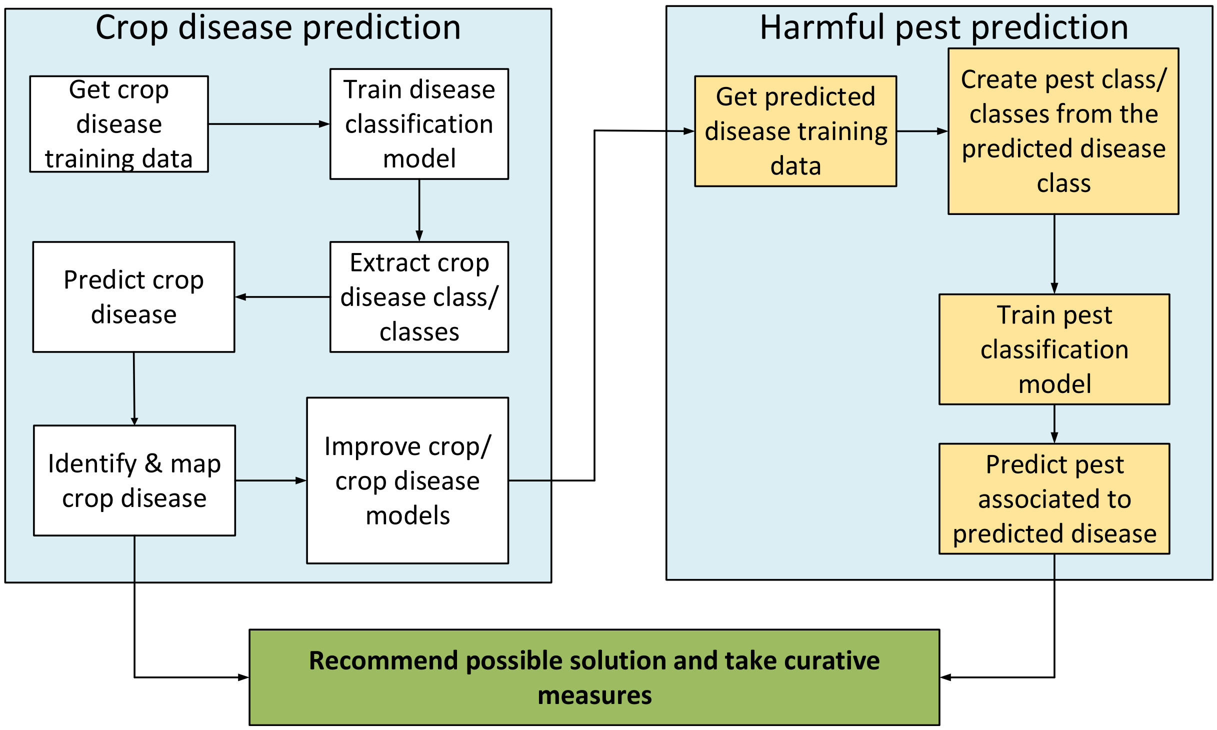


**Figure 3.** Main building block of deep learning and an AI-based framework for crop disease detection and harmful pest prediction.
Source: Author

improvement. The analysis of the reviewed articles reveals that conventional plant disease management strategies such as IPM are commonly used to minimise the prevalence of plant diseases. However, the review results further identified some challenges related to conventional methods, such as being costly in terms of labour, having low identification and prediction accuracy, and some not being environmentally friendly. Other identified challenges for implementing automated systems for crop disease identification and pest prediction, particularly in developing countries, include inefficient internet connectivity, high costs of acquiring equipment and deploying smart technology in farms, and a shortage of experts in smart farming technology. Previous studies also revealed that machine learning-based techniques were commonly used to process and handle real-time data captured to detect crop diseases. However, in recent years, the rapid increase in data-intensive and computational-intensive demands has posed challenges to traditional machine learning-based methods in terms of server capacity and performance, which should be addressed through complementary technologies capable of processing massive amounts of data, such as cloud computing, mobile cloud computing, edge computing, and big data processing architectures. Therefore, this systematic review recommends a deep learning and AI-based technique with automated feature extraction suitable for implementing cost-efficient crop disease detection, classification, and prediction. Moreover, this paper presents the theoretical framework describing the main components of deep learning and AI-based strategies for crop disease identification and harmful pest prediction. Future work may consider extending and implementing deep learning and AI-based models for crop disease identification and pest prediction in real-working environments. Furthermore, another significant future research direction could be to conduct rigorous usability assessment and design requirements for implementing the solution in the real-working environment of Mobile Edge Computing (MEC) to enable service delivery proximate to users.

## CONFLICT OF INTERESTS

The author has not declared any conflict of interests.

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