Literature Review: Enhancing Plant Disease Detection with Deep Learning Models: A Case Study on Maize and Cassava Species

**CHAPTER TWO**

**LITERATURE REVIEW**

* 1. **Introduction**

Plant diseases pose a significant threat to global food security, causing substantial yield losses and economic hardship for farmers. Traditional methods of disease detection, relying on visual inspection and laboratory analysis, are often time-consuming, subjective, and require specialized expertise (Agrios, 2005). The need for rapid, accurate, and scalable disease detection methods has driven research into advanced technologies, including deep learning.

Machine learning (ML) is a subset of Artificial Intelligence (AI) that can automatically acquire, integrate, and develop knowledge from large-scale data. It enables predictive analysis and decision-making without being explicitly programmed. Deep Learning (DL), a subset of ML, has shown great promise in solving complex problems, including plant disease detection. Convolutional Neural Networks (CNNs), as a part of DL, are widely used in image classification tasks due to their ability to extract hierarchical features from images.

Deep learning, a subfield of machine learning, has emerged as a powerful tool for image recognition and classification tasks (LeCun et al., 2015). Convolutional Neural Networks (CNNs) have shown remarkable success in analysing visual data and identifying complex patterns, making them well-suited for plant disease detection. CNNs can automatically learn relevant features from images, eliminating the need for manual feature extraction and enabling more accurate and efficient disease diagnosis (Krizhevsky et al., 2012).

This section reviews existing research on deep learning applications for plant disease detection, specifically in maize and cassava species. It covers various deep learning architectures, dataset characteristics, and the challenges of real-world deployment before identifying research gaps.

* 1. **Deep Learning Algorithms for Plant Disease Detection**
     1. **Model Architectures and Performance**

Several studies have explored different deep learning architectures for plant disease detection. These studies have utilized a range of CNN architectures, including:

* **CNN-Based Models:** CNNs are commonly used for image-based plant disease classification. Ramcharan et al. (2017) employed an Inception v3 model with transfer learning to detect cassava diseases, achieving high accuracy in controlled environments.
* **EfficientNet Models**: EfficientNet, optimized for computational efficiency, has demonstrated high accuracy for plant disease detection. Studies by Riaz et al. (2022) reported >90% accuracy in controlled settings.
* **Transformer-Based Models:** Recent studies have explored Vision Transformers, which leverage self-attention mechanisms to capture long-range dependencies in images. However, practical applications of Vision Transformers for plant disease detection remain an emerging area of research.
* **Deep Learning predictions:** The review of Dharani et al. (2021) on crop yield prediction with the use of Deep Learning, showed that hybrid networks and the RNN-LSTM networks outperform all other networks. The reason for the high performance of RNN and LSTM stands on their storage and feedback loop. They resulted that those networks are more capable of making accurate predictions since they can deal with time-series data of crop yield.
* **Ensemble Learning Approaches:** Combining multiple deep learning models improves classification accuracy. Krishnamoorthy et al. (2021) compared Inception-ResNet-v2 with EfficientNet for rice leaf disease classification and demonstrated superior performance with an accuracy of 95.67% using ensemble methods.
* **AlexNet:** One of the pioneering CNN architectures that demonstrated the power of deep learning for image classification (Krizhevsky et al., 2012).AlexNet was developed in 2012 by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. AlexNet has been effectively utilized in plant disease detection tasks. For instance, a study achieved a test accuracy of 91.3% using AlexNet to classify 38 different plant diseases.
* **VGGNet:** Known for its deep architecture with small convolutional filters, VGGNet achieved state-of-the-art performance on image recognition tasks (Simonyan and Zisserman, 2014). The VGG architecture was introduced in 2014 by the Visual Geometry Group at the University of Oxford. VGG models, particularly VGG16 and VGG19, have been employed in detecting plant lesions. A comparative analysis demonstrated that VGG16 achieved notable accuracy in identifying plant diseases (Arora et al., 2024).
* **GoogLeNet (Inception):** Introduced the concept of inception modules, which allow for parallel processing of information at different scales (Szegedy et al., 2015).
* **ResNet:** Introduced residual connections to address the vanishing gradient problem, enabling the training of very deep networks (He et al., 2016).ResNet architectures, such as ResNet50, have been utilized to enhance feature extraction in plant disease detection. Studies have shown that ResNet50 can achieve high accuracy in identifying various plant diseases (Arora et al., 2024).
* **MobileNet:** Designed for mobile and embedded devices, MobileNet utilizes depthwise separable convolutions to reduce computational complexity (Howard et al., 2017).
* **Inception-V3**: Inception-v3 has been applied to identify maize diseases. A study reported an accuracy of 97.2% in classifying maize leaf diseases using this architecture (Qian et al., 2022).
  + 1. **Advanced Techniques**
* **YOLOv3 with Spatial Pyramid Pooling**: This approach has been employed to improve the detection of small agricultural pests. A study reported an average identification accuracy of 88.07% using this method (Shoaib et al., 2023).
* **Mask R-CNN**: Mask R-CNN excels at object segmentation, making it particularly useful for precise identification of affected areas in plant pest detection. Research has demonstrated its effectiveness in segmenting diseased regions in plant images (Shoaib et al., 2023).
* **Lightweight Models**: Recent trends focus on developing smaller, more efficient models that maintain high accuracy while reducing computational requirements. For example, MobileNet and EfficientNet have been explored for plant disease detection tasks (Adiga et al., 2024).
  + 1. **Performance and Applications**
* **Accuracy Rates**: Convolutional Neural Network (CNN) models have achieved accuracy rates between 91% and 98% in plant disease detection tasks. For instance, an EfficientNetB7 model achieved an accuracy of 98.77% in classifying maize leaf diseases (Bachhal et al., 2023).
* **Real-Time Disease Diagnosis**: The integration of CNN models into portable devices like smartphones and drones has facilitated real-time disease diagnosis. These advancements enable on-the-spot identification of plant diseases, aiding in timely intervention (Shoaib et al., 2023).
* **Transfer Learning Techniques**: Transfer learning has been successfully applied to improve model performance across different crop types and diseases. By leveraging pre-trained models, researchers can adapt existing architectures to specific agricultural applications with limited data (Shoaib et al., 2023).

These CNN architectures have been adapted and fine-tuned for plant disease detection, achieving impressive results on various datasets. These deep learning approaches demonstrate significant potential for enhancing crop health monitoring and disease management in agriculture.

* 1. **Deep Learning in Agriculture**
* Various deep learning models have been applied to agricultural challenges, including disease detection, yield prediction, and real-time monitoring.
* Disease Detection: Lottes et al. (2018) proposed a crop-weed classification system using a fully convolutional network with an encoder-decoder structure. The model achieved 96.1% recall and 96.6% precision.
* Yield Prediction: Khaki & Wang (2019) developed a Deep Neural Network model for crop yield prediction, outperforming regression-based models.
* Mobile and Edge Deployment: Ramcharan et al. (2019) implemented a CNN-based model for mobile devices using the Single Shot Multibox Detector (SSD) with MobileNet, achieving inference times between 50–200ms.
  1. **Case Study:** 
     1. **Maize Disease Detection with Deep Learning**

Maize (Zea mays L.) is one of the most important staple crops worldwide. Maize production is threatened by various diseases, including grey leaf spot, northern corn leaf blight, and common rust (Wise, 2010). Deep learning has been applied to detect and classify these diseases from images of maize leaves and plants.

* **Specific maize diseases targeted:** Identifying which diseases the study focused on (e.g., Gray Leaf Spot, Northern Corn Leaf Blight, Common Rust).
* **CNN architecture used:** Which CNN model was employed (e.g., AlexNet, VGGNet, ResNet, Inception).
* **Dataset details:** Size and source of the maize disease image dataset. If it includes field images, or only lab images.
* **Performance metrics:** Reporting accuracy, precision, recall, and F1-score of the model.
* **Comparison to other methods:** Comparing the performance of the deep learning model to traditional image processing techniques or machine learning algorithms.

Key challenges in maize disease detection include:

* **Variability in Symptoms:** The appearance of disease symptoms can vary depending on the stage of infection, environmental conditions, and maize variety.
* **Overlapping Symptoms:** Some diseases can exhibit similar symptoms, making it difficult to distinguish between them.
* **Real-world conditions:** Images captured in the field can be affected by variations in lighting, background, and image quality.
  + 1. **Cassava Disease Detection with Deep Learning**

Cassava (Manihot esculenta Crantz) is a staple crop in many tropical and subtropical regions, particularly in Africa, where it provides food security for millions of people. Cassava production is severely affected by diseases such as Cassava Mosaic Disease (CMD) and Cassava Brown Streak Disease (CBSD) (Legg et al., 2011).

Deep learning has emerged as a promising tool for cassava disease detection, enabling rapid and accurate diagnosis of these diseases. Based on your file titles, and general trends, aspects covered in the files might include:

* **Mobile-based solutions:** Developing mobile apps for on-site cassava disease diagnosis. This addresses the need for accessible and affordable disease detection tools in resource-constrained settings.
* **Fast and parallelizable methods:** Exploring techniques for accelerating deep learning inference, enabling real-time or near-real-time disease detection on cassava farms.
* **Specific CNN architectures for cassava:** Exploring CNNs tailored for cassava disease identification.
* **Challenges of cassava disease diagnosis:** Dealing with limited datasets, variations in symptom appearance, and the need for robust models that can generalize to different environmental conditions.
* **Comparison with traditional methods:** Assessing the performance of deep learning models against conventional methods of cassava disease diagnosis.
  1. **Challenges in Real-World Deployment**

Despite high accuracies in controlled environments, practical field applications face several challenges:

* Environmental Variability: Studies report a significant drop in accuracy when models are tested under real-world conditions. Ramcharan et al. (2018) observed a 32% decrease in F1 score when transitioning from laboratory to field environments.
* Disease Severity and Background Complexity: Models struggle to differentiate mild disease symptoms from healthy plants. Ramcharan et al. (2019) found that classification accuracy dropped from 80.6% to 43.2% for mild symptoms. Ramcharan et al. (2019) conducted a study on cassava disease detection using deep learning models and found that:

Classification accuracy was high (80.6%) for pronounced symptoms also Accuracy dropped significantly (43.2%) when detecting mild symptoms, indicating that the model struggled with subtle disease variations. This suggests that deep learning models face challenges in real-world applications due to environmental variability, mild disease symptoms, and background complexity.

* Limited Reporting of Deployment Metrics: Few studies provide insights into processing speed, resource consumption, and memory requirements, which are critical for real-time applications.
* **Domain Adaptation:** Models trained on one dataset may not generalize well to other datasets or real-world conditions.
* **Computational Complexity:** Deep learning models can be computationally intensive, requiring significant resources for training and deployment.
* **Explainability:** Understanding why a deep learning model makes a particular prediction can be challenging, hindering trust and acceptance.
  1. **Research Gaps and Future Directions**
     1. **Enhancing Model Generalization**
* Future studies should incorporate more diverse datasets that account for real-world variations in lighting, disease severity, and plant phenotypes.
* Domain adaptation techniques, such as adversarial learning, can be explored to improve robustness against environmental changes.
  + 1. **Lightweight and Efficient Models**
* Optimizing deep learning models for edge computing and mobile deployment remains a key area of research.
* Quantization and pruning techniques should be investigated to reduce computational costs while maintaining accuracy.
  + 1. **Modelling and Evaluation**
* **Data Augmentation Techniques:** Developing advanced data augmentation techniques to increase the size and diversity of training datasets.
* **Transfer Learning:** Leveraging pre-trained models on large datasets to improve the performance of models trained on smaller plant disease datasets.
* **Model Compression:** Exploring model compression techniques to reduce the size and computational complexity of deep learning models.
* **Explainable AI (XAI):** Developing methods to interpret and explain the decisions made by deep learning models.
* **Integration with IoT and Drone Technology:** Combining deep learning with Internet of Things (IoT) sensors and drone imagery for automated plant health monitoring and disease detection.
  + 1. **Explainability and Interpretability**

Understanding model decisions is critical for farmer adoption. Attention mechanisms and saliency maps can be integrated to provide visual explanations for disease classifications.

* 1. **Conclusion**

Deep learning has demonstrated great potential in automating plant disease detection, particularly for maize and cassava species. CNNs, EfficientNet, and Vision Transformers have shown high accuracy in controlled settings but require improvements in real-world adaptability. Key challenges include environmental variability, disease severity differentiation, and mobile deployment constraints. Addressing these gaps through improved datasets, lightweight models, and explainable AI techniques will be crucial for advancing practical applications in agriculture.

This chapter provides a comprehensive review of the literature on the application of deep learning models for plant disease detection, focusing on maize and cassava as specific case studies. The review explores the advancements, challenges, and future directions of using deep learning to improve crop health and productivity. Continued research and development in this area will pave the way for more effective and sustainable agricultural practices.

**Deep Learning for Crop Pest and Disease Detection in Ghana: Leveraging a Novel Multi-Crop Dataset**

Deep learning has emerged as a powerful tool for crop pest and disease detection, offering the potential to improve agricultural productivity and food security in developing countries like Ghana (Kamilaris & Prenafeta-Boldú, 2018). This literature review examines recent advancements in deep learning for crop pest and disease detection, with a focus on leveraging the novel "Dataset for Crop Pest and Disease Detection" from Ghana. The "Dataset for Crop Pest and Disease Detection" (Mensah Kwabena et al., 2023) is a valuable resource for developing AI models tailored to Ghanaian agriculture. Key characteristics include:

The "Dataset for Crop Pest and Disease Detection" (Mensah Kwabena et al., 2023) is a valuable resource for developing AI models tailored to Ghanaian agriculture. Key characteristics include:

* Multi-crop coverage: Images of cashew, cassava, maize, and tomato
* Size: 24,881 raw images and 102,976 augmented images
* Classification: 22 classes covering various diseases and pest infestations
* Validation: Expert plant virologists validated all images
* Accessibility: Freely available for research use

This dataset addresses the need for geographically relevant data to develop models suited to local agricultural conditions in Ghana.

Recent studies have explored various CNN architectures for crop disease detection:

* An enhanced ResNet34 model (ESA-ResNet34) demonstrated improved performance for crop pest and disease detection (Yuan and Zhang et al., 2024).
* Depth wise separable convolutions have been used to reduce computational complexity while maintaining accuracy (Yuan and Zhang et al., 2024).

Developing effective deep learning models for crop pest and disease detection in Ghana faces several challenges:

* Small and irregularly shaped fields: In Ghana, 77% of farms have an area of less than 1.2 ha, 16% of farms have an area of less than 1.2 to 2 hectares while about 7% have more than 2 hectares creating a highly heterogeneous landscape according to the Ministry of Food and Agriculture (MOFA, 2010).

This indicates that a significant majority of farms in the Eastern Region are smaller than 1.2 hectares. However, this data is specific to the Eastern Region in Ghana and may not represent the entire country.

* Limited Training Data: The relatively small size of local datasets can impact model performance. To address this, researchers have developed the "CCMT: Dataset for Crop Pest and Disease Detection," which comprises 24,881 raw images of cashew, cassava, maize, and tomato plants affected by various pests and diseases (Mensah Kwabena et al., 2023). This dataset aims to support the development of models tailored to Ghanaian agriculture.
* **Cloud Coverage**: Frequent cloud cover in tropical regions can affect image quality and complicate satellite-based monitoring.

To advance crop pest and disease detection in Ghana, future research should focus on:

* Leveraging Local Datasets: Utilizing datasets like the "CCMT: Dataset for Crop Pest and Disease Detection" to develop models tailored to Ghanaian agriculture.
* Exploring Transfer Learning: Applying transfer learning techniques to address limited data availability by leveraging pre-trained models.
* Investigating Multi-Modal Approaches: Combining satellite imagery with ground-level images to enhance detection accuracy.
* Developing Generalizable Models: Creating models that can generalize across multiple crop types and diseases to improve robustness.

By addressing these challenges and leveraging novel datasets, deep learning has the potential to significantly improve crop pest and disease detection, ultimately enhancing agricultural productivity and food security in the region.

**The "Dataset for Crop Pest and Disease Detection" (Mensah Kwabena et al., 2023)**

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* Accessibility: Freely available for use by the research community

The dataset aims to address challenges in developing countries' agricultural sectors, such as disease and pest infestation, knowledge gaps between farmers and technology, and lack of storage facilities. The images were captured under various conditions and with different backgrounds, including white, dark, illuminated, and real backgrounds (Mensah Kwabena et al., 2023). This dataset represents a significant contribution to AI applications in agriculture, particularly for crop pest and disease management in Ghana, and has the potential to improve crop yield, control crop pests/diseases, and reduce costs.

Human society needs to increase food production by an estimated 75% by 2050 to feed an expected population size that is predicted to be over 9.7 billion people [15,16]. Currently, infectious diseases and pests reduce yield by an average of 38% with many farmers in the developing world experiencing yield losses as high as 99%. The increase in the usage of smartphones and internet technologies among crop farmers around the world with an expected 5.3 billion smartphones by 2025 offers the potential of turning smartphones and the web into a valuable tool for diverse communities growing food. Potential application is the development of web and mobile pest and disease diagnostics through artificial intelligence based-machine learning (Mensah Kwabena et al., 2023).

**Conceptual Review**

Agricultural productivity is negatively impacted by plant diseases and pests. Food insecurity can typically rise because of delayed detection of plant pests and diseases. Generally, there is a visible pattern that can be used to diagnose any abnormalities of each pest and disease condition. One of the primary sources of identifying plant pests and diseases is the plant leaves, where symptoms of the pest/disease begin to appear (Ebrahim et al., 2017). Plant diseases and pests can be prevented and controlled with early diagnosis, which is also crucial for agricultural production management and decision-making. Diseased or pest-infected plants exhibit lesions or markings on their leaves, stems, flowers, or fruits. Detecting crop pests and diseases has become a critical issue in recent years, and academics are becoming increasingly interested in this area. This is partially since farmers depend on Extension agents to diagnose illnesses and pests using their expertise and training. In addition to being subjective, this human intervention is arduous, time-consuming, ineffective, and prone to mistakes. Inexperienced extension agents could make incorrect diagnoses and ultimately suggest inappropriate mitigation strategies that could harm the environment. The use of image processing techniques for automatic crop pest and disease detection has gained popularity as a means of addressing these issues.

In 2017, Halil et al. suggested designing a real-time detection robot with deep learning techniques. The goal of the project was to utilize a robot that could move around a field or greenhouse and autonomously identify plant illnesses. Additionally, using sensors installed in the greenhouse, the robot can identify diseases from close-up photos of plants (Durmus et al., 2017).

Muammer et al. (2019), assessed the effectiveness of nine deep learning architectures for the detection of plant diseases. They employed a deep learning model, transfer learning, and deep feature extraction in their study to identify the disease (Turkoglu & Hanbay, 2019).

Mensah et. al., 2020, proposed a Gabor capsule network with max-pooling for the detection of plant disease on tomato and citrus datasets. When compared to the most advanced techniques, the suggested approach showed superior plant disease identification. A Gabor capsule network was suggested in 2020 for the detection of plant diseases Using 48 × 48 and 68 × 68 image sizes, respectively, the experiment conducted for the paper's tomato and citrus datasets yielded overall accuracy of 98.12% and 98.93%, (Kwabena et al., 2020). Additionally, utilizing 48 × 48 and 68 × 68 image sizes, the approach yielded overall accuracy of 93.33% and 92.85%, respectively, on the citrus dataset. To enhance the model's functionality.

A survey of the development of deep learning methods in the field of crop lead disease detection in recent years was carried out by Lili et al., (2021). The study discussed the latest developments and difficulties in applying deep learning and cutting-edge imaging techniques to the detection of plant lead disease.

Kwabena et al (2022). suggested replacing CNN, SoftMax, and dynamic routing in the original capsule network presented and proposed in 2017 with an effective texture descriptor (Local Binary Pattern, or LBP), sigmoid function, and k-means routing (Sabour et al., 2917). Citrus, maize, and tomato datasets were used to test the suggested approach. In 2021, a citrus dataset and tomato and maize subsets of the Plant Village dataset were used to identify plant diseases using a capsule network with K-Means routing. Using the tomato, maize, and citrus datasets, the routing algorithm obtained accuracy rates of 98.80%, 97.99%, and 98.21%, respectively (Mensah et al., 2021).

**Empirical Review**

The raw and enhanced photos are the two formats in which the Cashew, Cassava, Maize, and Tomato (CCMT) dataset is displayed. Raw Data.zip, a 1.22 GB zip file, contains the raw photographs. The four (4) folders—Cashew, Cassava, Maize, and Tomato—are in the CCMT Dataset subdirectory of the Raw Data folder after it has been unzipped. In the meantime, CCMT Dataset.zip, a 6.81 GB zip file, contains the expanded dataset. Following unzipping, the four (4) folders—Cashew, Cassava, Maize, and Tomato—are in the main folder, CCMT. There are subfolders inside each folder. Anthracnose, Gummosis, Healthy, Leaf miner, and Red Russet are the five (5) subfolders that make up the first subdirectory, Cashew. There are five (5) folders in the second category, Cassava, including Bacterial Blight, Mosaic, Healthy, Brown Spot, and Green Mite. Seven (7) subfolders, including Fall armyworm, Grasshopper, Healthy, Leaf beetle, Leaf blight, Leaf spot, and Streak virus, are also found within the Maize subfolder. There are five (5) subfolders in the Tomato subfolder: Septoria leaf spot, Verticillium wilt, Leaf blight, Leaf curl, and Healthy (Mensah Kwabena et al., 2023). To this project, I will be focusing on cassava and maize plant.

**Data Collection**

Using a high-resolution camera system, pictures of plant pests and diseases were gathered. The data format where raw and annotated. A high-resolution camera was used to gather the crop pest and disease datasets. The initial JPEG files came in a variety of sizes, including 400 x 400, 487 x 1080, 1080 x 518, 3024 x 4032, and 4032 x 3024.The total number of classes is 22. Anthracnose, gummosis, healthy, leaf miner, and red rust are the five classifications of cashew. There are five types of cassava: mosaic, green mite, brown spot, bacterial blight, and healthy. Fall armyworm, grasshopper, healthy, leaf beetle, leaf blight, leaf spot, and stripe virus are the seven classes of maize. There are five types of tomatoes as well: septoria leaf spot, leaf curl, leaf blight, healthy, and verticillium wilt. The photographs were taken in a variety of settings and with a range of backgrounds, including genuine, dark, white, and lighted. Also, the data source location where the images were captured was in:

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