CHAPTER ONE

INTRODUCTION

1.1.Background of the Study

Agriculture is one of humanity's most crucial practices, essential for survival and growth on earth. The global population is expected to rise by nearly 2 billion by 2050 (Haque et al., 2023), necessitating sustainable food security. Corn, a major cereal crop globally, is considered a key contributor to the food supply chain (Kaur et al., 2020; Soto-Gómez & Pérez-Rodríguez, 2022). Maize is cultivated on approximately 197 million hectares of land in nearly 170 countries around the world, resulting in 5.82 t/ha of maize crop in 2020 (Food & Agriculture Organization of the United Nations, 2014).

Agriculture remains a cornerstone of Nigeria's economy, with maize playing a pivotal role in ensuring food security. The global demand for food is projected to escalate significantly by 2050, emphasizing the need for sustainable agricultural practices. Maize, a staple cereal crop, is crucial to Nigeria's food supply chain, providing a substantial portion of the population's caloric intake and supporting livestock and industrial sectors. Nigeria stands as a significant maize producer in Africa, cultivating this crop across vast expanses of land. However, despite its importance, the nation's average maize yield remains comparatively low, signaling opportunities for enhanced agricultural practices and technological interventions. Research has shown that global maize production has risen due to increased demand and technological advancements, and in Nigeria, maize supplies over 30% of caloric consumption (Akano et al., 2021; Erenstein et al., 2022).

Kaduna State emerges as a critical contributor to Nigeria's maize production, accounting for a notable percentage of the country's total output. As a strategic producer, the state's agricultural practices significantly influence national maize availability (Africa Exchange Commodities Limited, 2020). Socio-economic factors, including farmers' access to resources, education, and experience, play a crucial role in shaping maize production outcomes in Kaduna. However, farmers in the state encounter numerous challenges, including limited access to credit, high input costs, and the persistent threat of pests and diseases. Studies document constraints such as lack of capital, high cost of farm inputs, lack of credit facilities, inadequate storage facilities, inadequate processing facilities, incidence of pests and diseases infestation, poor road network and poor extension services. (Costs and Returns Analysis of Maize Production in Lere Local Government Area of Kaduna State, Nigeria, 2024).

Despite its high yield, maize is highly susceptible to a range of diseases during the growing season. To meet the growing demands of this massive population, long-term food security must be maintained or improved. This vulnerability results in significant yield losses and economic impacts, affecting farmers' livelihoods beyond just food production, including beverages and poultry, particularly for farmers in Ghana and West Africa (Rajeena PP et al., 2023). To combat these diseases and minimize their impacts, farmers in these regions must use a combination of methods to manage pests and disease-resistant maize varieties. Despite its high productivity, the maize crop is still prone to various pests and diseases that can significantly reduce yields during the growing or farming season.

Several diseases that impact maize crops have been identified in the literature to come from different regions of the world (Zhang et al., 2018; Haque et al., 2023). The most often observed diseases are grey leafspot, northern corn leaf blight, and southern corn rust. These diseases have the potential to drastically impair maize crop productivity. According to reports from (Oerke & Dehne, 2004), disease-causing bacteria ruined 4–14% of the total maize production. To tackle this phenomenon effectively, maize diseases must be characterized and identified as soon as possible before any crop management practices can be implemented.

Current methods for detecting and identifying maize crop diseases include visual inspection, laboratory experiments on damaged plant parts by experts, and plant DNA sequencing. These methods are time-consuming and costly (Demilie, 2024; Haque et al., 2022). Visual inspection often falls short because people’s eyes are naturally not trained to see the same way, in their early stages, diseases can present with similar symptoms, making it difficult to distinguish their specific characteristics. The traditional methods that involve laboratory experiments suffer from inherent limitations that are not feasible. These methods depend on exceptionally knowledgeable staff members and involve a considerable amount of time to complete the desired goal or tasks. As a result, an effective and exact disease detection strategy, as well as the development of innovative technologies and procedures, are critical for increasing agricultural efficiency and accuracy. So there is a need for more efficient and cost-effective disease detection techniques that can be easily implemented on a larger scale using a transfer learning method. Transfer learning is a method in which a deep learning model is developed on one task and the representation is used as the basis to find customary patterns on another task. These are possible by either using the trained model as a fixed feature extractor or altering the trained structure’s weights for the new task.

In recent years, the computer vision discipline of computer science has seen significant success with deep learning-based techniques, particularly convolutional neural networks (ConvNet). ConvNets have helped to automate picture recognition (LeCun et al., 2015). ConvNet can extract intrinsic and relevant features from a huge number of images and classify them into their appropriate classes. In recent years, image identification utilising deep learning algorithms has grown in favour in the agriculture industry (Kamilaris & Prenafeta-Boldú, 2018). In this context, detecting crop diseases through symptomatic images has become a major advancement in computer science. Consequently, Convolutional Neural Networks (ConvNets) are widely recognized as the leading framework for automating crop disease diagnosis using digital images. As a result, ConvNets are widely regarded as the cutting-edge framework for automated crop disease diagnosis utilising digital photos (Haque et al., 2021). In the current study, we created a unique transfer learning model based on the amalgamation of the Res-Net-9 and Efficient-Net-b4 models to diagnose, identify, and predict maize crop diseases.

1.2.Problem Statement

Maize cultivation is fundamental to Nigeria's food security and agricultural economy, yet it faces significant challenges from various leaf diseases and pests. These diseases, including Common Rust, Gray Leaf Spot, and Blight, can severely diminish crop yields, leading to substantial economic losses for farmers and threatening regional food supplies. Traditional methods of disease detection, such as visual inspection and laboratory analysis, are often time-consuming, costly, and prone to inaccuracies. Visual inspection, in particular, is subjective and may fail to identify diseases in their early stages, resulting in delayed interventions and increased damage. Furthermore, laboratory experiments require specialized expertise and resources, making them inaccessible to many smallholder farmers who form the backbone of Nigeria's agricultural sector.

There is, therefore, a pressing need for an automated, accurate, and accessible solution that can rapidly and reliably detect maize leaf diseases. Such a system would empower farmers with timely and precise information, enabling them to implement effective disease management strategies and minimize crop losses. An automated solution, leveraging advanced technologies like deep learning and mobile applications, has the potential to revolutionize disease detection, making it more efficient, cost-effective, and readily available to farmers across Nigeria, ultimately contributing to enhanced food security and improved livelihoods.

1.3. Aim and Objectives of the Study

The study aims to create a simple, accurate mobile tool that helps Nigerian maize farmers quickly find and treat leaf diseases, leading to better harvests.

The objectives include:

- to gather and organize clear pictures of healthy and sick maize leaves.
- to build a computer model that accurately identifies maize leaf diseases from pictures.
- to connect the model to a language tool that gives easy-to-understand treatment advice in English and Hausa.
- to create a user-friendly mobile app that farmers can use, even without the internet.
- to test the app with real farmers in Kaduna State to see how well it works.

1.4. Significance of the Study

This study holds significant potential for transforming maize farming practices in Nigeria, particularly in regions like Kaduna State, where maize is a vital crop. By developing an automated, accurate, and accessible mobile tool for the early detection of maize leaf diseases and pest infestations, this research addresses a critical need for efficient and timely agricultural interventions.

Firstly, the project's focus on leveraging deep learning for image recognition offers a substantial improvement over traditional, often unreliable, disease and pest detection methods. The mobile tool will empower farmers with rapid and precise diagnoses, enabling them to implement targeted treatments and pest control strategies, thereby minimizing crop losses and enhancing yields. This directly contributes to increased food security and improved livelihoods for farmers and their communities.

Secondly, the integration of a language model to provide treatment and pest control recommendations in both English and Hausa ensures that crucial information is readily accessible to a broader audience, including those with limited literacy or formal education. This linguistic inclusivity is essential for effective technology adoption and knowledge dissemination among Nigerian farmers.

Thirdly, the development of an offline-capable mobile application addresses the challenges of limited internet connectivity in rural agricultural areas. This ensures that the tool remains functional and beneficial, even in regions with poor infrastructure, promoting widespread adoption and sustained impact.

Finally, this study contributes to the growing body of research on the application of artificial intelligence in agriculture, specifically in the context of developing nations. It showcases the potential of advanced technologies to address real-world challenges faced by smallholder farmers, fostering sustainable agricultural practices and contributing to economic development. The results of this research can serve as a model for similar interventions in other agricultural sectors and regions facing comparable challenges, thereby promoting innovation and progress in agricultural technology.

CHAPTER TWO

REVIEW OF RELATED LITERATURE

Researchers worldwide have conducted studies to diagnose and detect plant diseases, particularly in maize crops, using deep learning methods. Haque et al. (2022) developed three Inception-V3 architectures (Inception-V3 flatten-fc, Inception-V3 GAP, and Inception-V3 GAP fc) for maize disease classification, focusing on Maydis Leaf Blight, Turcicum Leaf Blight, Banded Leaf and Sheath Blight, and healthy plants. Utilizing a dataset of 5,939 images from India, collected under diverse conditions, they employed data augmentation techniques like rotations and brightness adjustments to address class imbalance. While achieving a 95.99% accuracy, the Inception-V3 model's higher computational cost compared to other pre-trained models poses a challenge in resource-limited environments.

Rajeena PP et al. (2023) explored an EfficientNet architecture for detecting corn leaf diseases, including common rust, gray leaf spot, blight, and healthy plants, using 3,188 images from PlantVillage and PlantDoc. Applying preprocessing techniques such as grayscale conversion, smoothing, and segmentation, they achieved 98.85% accuracy through transfer learning, outperforming Inception V3, VGG16, and ResNet models. However, this study did not address the practical deployment in real-world agricultural settings, image quality variability, or the limited data sources, which restricts model effectiveness.

Mohanty et al. (2016) conducted a comprehensive study evaluating 60 configurations of datasets, architectures (GoogleNet and AlexNet), and train-test splits for crop and disease detection. Using a dataset of 54,306 leaf images from PlantVillage with 37 disease classes and homogeneous backgrounds, they observed model convergence after approximately 30 epochs. The best-performing configurations achieved 85.53% accuracy for AlexNet and 99.34% for GoogleNet.

However, the high accuracy was based on grayscale images with homogeneous backgrounds from a single source, limiting its applicability to diverse real-world conditions. Testing on external datasets resulted in a significantly lower accuracy of 31.60%.

Ubaidillah et al. (2022), in their research, utilized the Random Forest and Näive Bayes methods. The study employed a dataset consisting of 3500 images of maize plant leaves categorized into 4 classes. Their testing results indicated that the Neural Network method yielded the best outcomes, achieving an AUC of 90.09 %, classification accuracy of 74.44 %, an f1-score of 72.01 %, precision of 74.14 %, and a recall of 74.43 %.

In a study by Sandotra et al. (2023), a CNN architecture was employed, testing several models. The resulting model successfully classified 4 classes: Healthy, Blight, Gray Leaf Spot, and Common Rust, using a dataset of 4188 images. Evaluation metrics, including precision, recall, and F1-Score, revealed mean average precision values of 92.91 % for EfficientNet-b0, 89.95 % for InceptionNetV3, 88.53 % for VGG19, 91.08 % for VGG16, and 78.19 % for ResNet50 in model testing on the test dataset.

Yuliany and Nur Rachman (2022) identified overfitting issues with the CNN method in their research. To address this, the study proposed three types of data division between training and testing data, alongside various parameters. The evaluation indicated that the 90 %:10 % data split was most suitable for the dataset, with the architectures achieving training accuracies of 83.02 %, 78.30 %, and 81.13 %. Testing accuracy values for these three models were 69.33 %, 77.33 %, and 76 %.

Huda et al. (2021) showcased in their research the success of a web system utilizing Python and CNN, achieving good classification results. The best accuracy value reached 94.44 %. In another study by Irawan et al. (2021), validation results were presented for an application built using CNN and SqueezeNet architecture. The application demonstrated the ability to recognize Anthracnose, Ringspot Virus, and healthy papaya through leaves with 97 % accuracy, while accuracy through fruits reached 70 %.

The existing literature demonstrates the potential of deep learning for maize disease detection, yet significant challenges remain. Studies frequently report high accuracy under controlled conditions, often using limited or homogeneous datasets that fail to capture the variability of real-world agricultural environments. Furthermore, the computational demands of some high-performing models hinder their practical application in resource-constrained settings. Consequently, there is a critical need for research that develops robust, efficient, and deployable solutions. This study seeks to address these gaps by constructing a model that not only achieves high accuracy but also demonstrates adaptability to diverse field conditions, optimizes computational efficiency for practical deployment, and utilizes a comprehensive, representative dataset. By focusing on these key aspects, this research aims to bridge the gap between theoretical potential and real-world applicability, ultimately contributing a valuable tool for sustainable and efficient maize crop management.

CHAPTER THREE

METHODOLOGY

3.1. Data Collection and Preparation

This study employed a hybrid dataset, combining publicly available images from the Kaggle Maize Leaf Disease dataset with locally sourced images captured from maize fields. The Kaggle dataset provided a foundation of diverse maize leaf images, encompassing various disease states (e.g., Gray Leaf Spot, Common Rust, Northern Leaf Blight), pest infested leaves and healthy leaves. However, to enhance the model's robustness and generalizability to real-world conditions, locally sourced data will be incorporated.

3.1.1. Data Augmentation and Balancing

To mitigate overfitting and improve the model's ability to generalize to unseen data, a comprehensive data augmentation strategy will be implemented. This will involve applying a range of transformations to the images, including:

- **Geometric Transformations:** Rotations (e.g., 0-360 degrees), flips (horizontal and vertical), scaling, and translations.
- **Photometric Transformations:** Adjustments to brightness, contrast, saturation, and hue.
- **Noise Injection:** Adding Gaussian noise and salt-and-pepper noise to simulate sensor noise and environmental disturbances.
- **Cutout and Mixup:** Randomly masking portions of images and combining image pairs to increase data diversity.

Furthermore, to address potential class imbalance, which can bias model performance, SMOTE oversampling data balancing technique will be employed. This will ensure that each disease class and the healthy class were adequately represented in the training dataset, preventing the model from being biased towards the majority classes.

3.2. CNN Model Development

This study explored a range of Convolutional Neural Network (CNN) architectures to identify the most effective model for maize leaf disease detection. The architectures selected were chosen based on their performance in image classification tasks and their varying computational complexities.

- **TinyVGG:** Chosen for its lightweight architecture and efficiency, TinyVGG serves as a baseline model, suitable for deployment in resource-constrained environments.
- **ResNet (ResNet50, ResNet101):** Selected for their deep residual learning framework, ResNet models are known for their ability to handle complex image features and mitigate the vanishing gradient problem.
- **EfficientNet (EfficientNetB0, EfficientNetB3):** Selected for their compound scaling method, which balances network depth, width, and resolution, EfficientNet models offer high performance with improved efficiency.

3.2.2. Training Process

The training process will be conducted using PyTorch in agnostic mode to use GPU when available and CPU as the default. The following parameters and techniques were employed:

- **Optimization Algorithm:** Both SGD and Adam optimizers will be used for their adaptive learning rates and efficient convergences. This is so the best optimizer will be selected and used.
- **Loss Function:** Categorical cross-entropy loss will be utilized for multi-class classification tasks.
- **Learning Rate:** A learning rate of 0.01 will be initially set, with learning rate decay applied to prevent overfitting.
- **Batch Size:** A batch size of 32 will be used to balance memory constraints and training speed.
- **Epochs:** The models will be trained for 10 epochs, with early stopping implemented to prevent overfitting based on validation loss.
- **Transfer Learning:** Pre-trained weights from ImageNet will be used for ResNet and EfficientNet models to accelerate training and improve performance.
- **Fine-tuning:** The final layers of the pre-trained models will be fine-tuned on the maize leaf disease dataset.

3.2.3. Model Evaluation Metrics

To comprehensively evaluate the performance of the trained CNN models, the following metrics were used:

- **Accuracy:** The overall proportion of correctly classified images.

- **Precision:** The proportion of correctly predicted positive cases (disease presence) out of all predicted positive cases.
- **Recall (Sensitivity):** The proportion of correctly predicted positive cases out of all actual positive cases.
- **F1-Score:** The harmonic mean of precision and recall, providing a balanced measure of performance.
- **Area Under the ROC Curve (AUC):** A measure of the model's ability to distinguish between different classes.
- **Confusion Matrix:** A visualization of the model's classification performance, showing true positives, true negatives, false positives, and false negatives.

3.3. Language Model Integration

This study will integrate Google's Gemini language model to provide treatment recommendations based on the diagnosed maize leaf diseases. The integration aimed to leverage Gemini's ability to process and generate human-like text, providing practical and actionable advice to users. The integration was designed to be a post-processing step, triggered after the CNN model accurately identifies the disease present in the maize leaf image.

3.3.1. Prompt Engineering Strategy

To ensure Gemini delivers accurate and relevant treatment recommendations, a structured prompt engineering strategy will be employed. The prompts were carefully crafted to provide Gemini with the necessary context and constraints. The prompt structure was as follows:

1. **Disease Identification:** The output of the CNN model, specifying the diagnosed disease (e.g., "Gray Leaf Spot"), will be the initial input.
2. **Contextual Information:** Additional context will be provided, such as the severity level (if determined by the CNN), the stage of crop growth (if known), and any user-provided information about the growing conditions.
3. **Specific Request:** A clear request for treatment recommendations will be included, specifying the desired format and level of detail. For example: "Provide specific treatment recommendations for Gray Leaf Spot on maize, including recommended pesticides, application methods, and preventive measures. Please provide information suitable for a farmer with limited technical expertise."
4. **Output Format:** Specifying the desired output format, such as bullet points or a step-by-step guide, aided in making the information easily digestible for users.

3.4. User Interface Development

This study aims to develop a user-friendly interface to facilitate the practical application of the maize disease detection and treatment recommendation system. The development strategy will focus on creating an intuitive and accessible platform for farmers and agricultural professionals.

3.4.1. Streamlit Web Application

A Streamlit web application will be chosen for its rapid development capabilities and ease of deployment. Streamlit allows for the creation of interactive web applications using Python, which integrates seamlessly with the CNN models and Gemini API. The web-based format ensures accessibility across various devices, including smartphones, tablets, and computers.

3.4.2. Key Features

The user interface was designed to include the following core features:

- Image Upload: A simple interface for users to upload maize leaf images.
- Disease Diagnosis Display: Clear and concise presentation of the CNN model's disease diagnosis.
- Treatment Recommendations: Display of Gemini-generated treatment recommendations, formatted for easy comprehension.
- User Feedback Mechanism: A feature for users to provide feedback on the system's accuracy and usability.
- Visualisations: Where applicable, visualisations of the results will be displayed.

3.4.2. Accessibility and Ease of Use

To ensure accessibility and ease of use, the following design principles were implemented:

- **Intuitive Layout:** A clean and straightforward layout will be used to minimize cognitive load and facilitate easy navigation.
- **Clear Language:** Simple and concise language will be used throughout the interface, avoiding technical jargon where possible.
- **Responsive Design:** The interface will be designed to be responsive, adapting to various screen sizes and devices.
- **Visual Cues:** Visual cues, such as icons and color coding, will be used to enhance clarity and usability.
- **Error Handling:** Robust error handling will be implemented to guide users through potential issues, such as incorrect image formats or network errors.
- **Tutorial and Help Section:** a tutorial and a help section will be included to help new users to be able to use the application without any problems.

3.4.3. Multilanguage Support

To cater to a diverse user base, multilanguage support will be integrated into the application. The languages that will be supported will be English and Hausa

3.5. Testing Data and Evaluation Procedures

The performance of the developed system will be rigorously evaluated using a combination of controlled test datasets and real-world field testing.

- **Test Dataset:** A held-out test dataset, distinct from the training and validation sets, will be used to evaluate the model's generalization capabilities. This dataset will include images with varying degrees of disease severity, environmental conditions, and image quality.
- **Evaluation Metrics:** The performance of the CNN model will be evaluated using the metrics previously described: accuracy, precision, recall, F1-score, AUC, and confusion matrix. Additionally, the performance of the integrated Gemini language model was evaluated based on the relevance, accuracy, and clarity of the treatment recommendations.
- **User Interface Evaluation:** The user interface will be evaluated based on usability, accessibility, and user satisfaction through user testing and feedback collection.
- **Computational Efficiency:** The efficiency of the model will be measured, including inference time, model size, and resource consumption.

3.5.1. Field Testing with Farmers:

To assess the practical applicability and effectiveness of the system in real-world agricultural settings, field testing will be conducted with farmers in Kaduna State.

- **Pilot Study:** A pilot study will be conducted with a select group of farmers to evaluate the system's usability and effectiveness in diagnosing and managing maize diseases.
- **Data Collection:** Data will be collected on the system's accuracy in diagnosing diseases under field conditions, the usefulness of the treatment recommendations, and the overall user experience.

- **Feedback Collection:** Farmers were interviewed and surveyed to gather feedback on the system's strengths and weaknesses, as well as suggestions for improvement.
- **Iterative Refinement:** Based on the feedback collected from field testing, the system will be iteratively refined to improve its performance and usability.

CHAPTER FOUR

EXPECTED RESULTS

This study anticipates achieving significant advancements in the detection and management of maize leaf diseases through the integration of advanced CNN models and the Gemini language model. The following results are expected:

- A disease detection Application capable of detecting maize plant diseases and preferring solutions to farmers.
- **High Accuracy in Disease Detection:** The CNN models, particularly ResNet and EfficientNet, are expected to achieve high accuracy in detecting and classifying maize leaf diseases, surpassing the performance of baseline models like TinyVGG. The models are anticipated to demonstrate robust performance across diverse field conditions and image qualities, validated through rigorous testing on held-out datasets and field testing.
- **Effective Treatment Recommendations:** The integration of the Gemini language model is expected to provide accurate, relevant, and user-friendly treatment recommendations, tailored to the specific diagnosed diseases and field conditions.
- **Improved User Experience:** The Streamlit web application is expected to provide a user-friendly and accessible interface, facilitating easy disease diagnosis and treatment management. User feedback is anticipated to demonstrate high satisfaction with the system's usability, clarity, and effectiveness.
- **Multilingual support:** The application will be able to support Hausa and English for languages for now.

- **Positive Impact on Farmers:**
  - Field testing with farmers is expected to demonstrate the system's practical value and positive impact on their disease management practices.
  - The system is anticipated to empower farmers with timely and accurate information, enabling them to make informed decisions and improve their livelihoods.

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