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Research Article

Multimodal CNN–LSTM Framework for Real-Time Maize Disease Detection

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ABSTRACT

Maize diseases present a major challenge to agricultural productivity and food security, particularly in low-resource settings in sub-Saharan Africa. Timely detection plays an important role in reducing yield losses and enabling effective farm management. This research introduces and validates a multimodal machine learning–based system for real-time maize disease detection in Bomet County, Kenya. The system integrates maize leaf image data, environmental sensor data, and farmer-reported observations to develop a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) model designed to automatically identify and categorize maize diseases. A mixed-methods research design was adopted, combining machine learning experiments with surveys and interviews involving farmers and agricultural officers. The findings revealed that Maize Lethal Necrosis (MLN) was the most prevalent disease (41%), followed by Gray Leaf Spot (33%) and Northern Leaf Blight (26%). Environmental variables such as humidity and temperature demonstrated strong associations with disease occurrence. The proposed multimodal CNN–LSTM framework integrates maize leaf images, environmental sensor data, and farmer observations, achieving an accuracy of 94.2%, which outperforms conventional image-only CNN models (87.5%) and environmental-data-based LSTM models (81.3%). Additionally, 78% of farmers reported faster disease diagnosis using the developed system. The findings demonstrate that the proposed system supports real-time maize disease detection through an edge-enabled architecture, enabling deployment on mobile devices and facilitating practical intelligent system integration in agricultural environments.

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1. INTRODUCTION

Maize farming plays a critical role in supporting livelihoods and food security in Bomet County, Kenya, where smallholder farmers depend heavily on crop production for income and sustenance. However, maize productivity in the region is frequently constrained by diseases such as Maize Lethal Necrosis (MLN), Gray Leaf Spot (GLS), and Northern Leaf Blight (NLB), which significantly reduce yield when not detected early [1][2]. In most rural settings, disease identification relies on visual inspection by farmers or agricultural officers. While this approach is accessible, it is often inconsistent due to overlapping disease symptoms and limited technical expertise. Delayed or inaccurate diagnosis can allow infections to spread, resulting in substantial crop losses [3].

Recent advances in deep learning have enabled automated plant disease detection using image-based approaches, particularly convolutional neural networks (CNNs) [4]. These models have demonstrated strong performance in identifying visual disease symptoms such as lesions, discoloration, and texture variations. However, unimodal image-based systems often fail to capture environmental dynamics that influence disease progression, including temperature, humidity, and soil moisture. Although multimodal learning has been proposed to address these limitations, most existing studies remain confined to controlled datasets and lack real-world deployment considerations [5-10].

Recent studies published in Aviation Electronics, Information Technology, Telecommunications, Electricals, and Controls (AVITEC) have highlighted the growing application of artificial intelligence and datadriven approaches in real-time system monitoring and optimization. For example, intelligent system design and performance optimization techniques have been applied in dynamic environments to support efficient and adaptive decision-making [11]. In addition, computer vision approaches such as CNNs have been successfully applied in plant disease detection tasks, demonstrating the effectiveness of AI in agricultural applications [12]. Building on these developments, this study proposes a multimodal CNN–LSTM framework that integrates visual and environmental data for real-time maize disease detection.

Despite the strong performance of image-based disease detection models, many existing systems rely exclusively on visual data obtained from plant leaf images. In real agricultural environments, disease development is influenced by environmental factors such as temperature, humidity, rainfall, and soil moisture. For instance, fungal diseases like Gray Leaf Spot thrive under high humidity conditions, while temperature variations influence viral disease progression. Consequently, reliance on image-only data limits the robustness and generalizability of disease detection systems [1][13][14].

To address these limitations, recent studies have explored multimodal machine learning approaches that integrate image data with environmental variables to enhance predictive performance [15][16]. Multimodal frameworks enable models to capture complementary spatial and temporal patterns associated with disease development. However, most existing implementations are evaluated using controlled datasets and lack validation in real agricultural environments, limiting their practical applicability [17][18].

Many existing systems rely on cloud-based processing, which requires stable internet connectivity and limits usability in rural agricultural settings. Edge computing offers an alternative by enabling real-time disease detection directly on local devices such as smartphones, reducing latency and improving system accessibility in resource-constrained environments [13][19].

Despite these advancements, there remains limited research focusing on multimodal systems validated in real agricultural environments, particularly in smallholder farming contexts in developing countries. In addition, many existing models rely on controlled datasets and lack practical deployment considerations. While our previous study provided a systematic review of multimodal machine learning approaches for maize disease detection, the present study focuses on the experimental development, implementation, and real-world validation of a multimodal CNN–LSTM framework using field-acquired data. The proposed framework integrates image data, environmental measurements, and farmer-reported observations and is designed for edge-enabled deployment, thereby bridging the gap between theoretical model development and practical agricultural implementation [18]. Unlike existing studies that primarily focus on model accuracy using controlled datasets, this research emphasizes real-world deployment, edge-enabled inference, and field validation using data collected directly from smallholder farms.

To overcome these challenges, this research introduces a multimodal learning approach that combines maize leaf images, environmental sensor measurements, and farmer-reported data to enhance disease detection accuracy. The proposed system integrates a CNN for extracting visual features with an LSTM model to capture temporal patterns in environmental data. The key contributions of this study are positioned toward practical implementation and real-world applicability and include:

1. The development of a multimodal CNN–LSTM architecture integrating image, environmental, and farmer-reported data for maize disease detection.
2. The design and implementation of a real-time disease detection system capable of operating under field conditions.
3. The validation of the proposed model using field-acquired agricultural data collected from smallholder farms in Bomet County, Kenya.
4. The development of an edge-enabled mobile detection system that supports real-time inference in resource-constrained environments.

This study focuses on maize farms in Bomet County, Kenya, where maize production represents a major agricultural activity and source of livelihood for smallholder farmers. To support the development of a practical disease detection system, data were collected from 398 farmers and 66 agricultural officers, including maize leaf images, environmental sensor measurements (temperature, humidity, and soil moisture), and farmer-reported observations. These datasets were used to develop and evaluate the proposed multimodal CNN–LSTM model, with the aim of improving the accuracy and reliability of maize disease detection in real agricultural environments. In addition, the system is designed as an integrated intelligent framework that combines sensing, data processing, and real-time decision support, aligning with modern embedded and real-time system applications emphasized in AVITEC. The specific objectives of the study were:

1. To identify the most common maize diseases affecting farmers in Bomet County.
2. To determine environmental factors associated with maize disease infestation.
3. To design and develop a multimodal machine learning model for maize disease detection.
4. To evaluate the effectiveness of the developed system in real-world agricultural settings.

The remaining sections of this paper are organized as follows. Section 2 provides a review of related work on machine learning applications in crop disease detection. Section 3 outlines the research methodology and presents the proposed multimodal approach. Section 4 reports the experimental results and evaluates model performance. Section 5 discusses the findings in relation to existing studies. Finally, Section 6 concludes the paper and suggests directions for future research

2. RELATED WORK

Unlike the previous review study, which analyzed existing multimodal approaches, this section focuses on positioning the proposed system within current implementation-based research.

Recent advances in machine learning have greatly improved agricultural monitoring, particularly in crop disease detection. Automated diagnostic systems are increasingly adopted to support farmers in the early identification of crop diseases and to improve overall crop productivity. Studies have demonstrated that deep learning approaches outperform conventional machine learning methods in detecting plant diseases from leaf images [5][20].

2.1 Deep Learning Approaches for Plant Disease Detection

Deep learning approaches, particularly convolutional neural networks (CNNs), have been widely applied in plant disease detection and have demonstrated strong performance in classifying leaf-based disease symptoms [21]. Similarly, Ref. [5] demonstrated that deep learning models developed using large-scale plant image datasets can effectively identify multiple plant diseases across different crop species. Other studies have also explored transfer learning approaches to improve model performance when training datasets are limited. Ref. [22] applied transfer learning using pretrained CNN architectures and achieved high classification accuracy in crop disease detection tasks. However, most existing studies rely on image-only datasets and do not incorporate environmental variables that influence disease development.

Recent studies have explored mobile-based CNN models for real-time disease detection, achieving high classification accuracy under controlled conditions [23-25] . Similarly, Ref. [26] conducted a comparative evaluation of different CNN architectures and reported that deeper networks such as ResNet and DenseNet achieve better performance in plant disease recognition under field conditions. However, these approaches remain limited by their reliance on visual data alone and lack integration with environmental factors.

Other researchers have also investigated hybrid deep learning architectures. Ref. [27] proposed a hybrid CNN–Vision Transformer (ViT) architecture that improves feature extraction and enhances classification performance in maize leaf disease detection. Similar approaches combining CNN and transformer architectures have also been utilized for plant disease detection tasks [28-30].

Despite these advances, most existing plant disease detection systems rely solely on visual data obtained from leaf images. However, plant diseases are influenced by multiple environmental factors that cannot be captured through image analysis alone.

2.2 Environmental Monitoring and Time-Series Analysis in Agriculture

Environmental variables such as temperature, humidity, and soil moisture play a significant role in plant disease development. Recent studies have shown that integrating environmental data with machine learning models improves disease prediction and monitoring in agricultural systems [31][32] .

For example, Ref. [33] developed an (IoT)-based environmental monitoring framework for agricultural applications. The system enables the collection of real-time environmental data that can be utilized to monitor crop health conditions. Similarly, Ref. [34] proposed a CNN–LSTM hybrid deep learning model for early crop disease detection by integrating spatial and temporal features.

The use of sensor technologies in agriculture has significantly improved the ability to monitor environmental conditions affecting crop health. Ref. [19] reviewed the application of IoT and artificial intelligence technologies in smart agriculture and reported that environmental sensing systems are important in modern precision farming systems.

2.3 Multimodal Machine Learning in Crop Disease Detection

To address the limitations of unimodal systems, recent research has explored multimodal machine learning approaches that integrate image data with environmental variables. These approaches have demonstrated improved predictive performance by combining complementary spatial and temporal features [17] [18]. Similarly, [35] investigated multimodal deep learning architectures for crop disease detection and demonstrated that integrating environmental sensor data with image-based CNN models improves classification accuracy. These findings are supported by recent review studies that emphasize the importance of multimodal data integration in agricultural monitoring systems [36].

In addition, several systematic reviews have highlighted the growing role of artificial intelligence in agricultural disease detection. Ref. [37] provided an early overview of deep learning applications in agriculture, while more recent studies by Ref. [3] and Ref. [5] analyzed the rapid growth of machine learning approaches in plant disease detection.

2.4 Edge Computing in Precision Agriculture

Edge computing enables machine learning models to perform real-time inference directly on local devices such as smartphones and embedded systems. This approach reduces latency and eliminates dependence on continuous internet connectivity, making it suitable for agricultural applications in rural environments [38-41].

Edge-based crop monitoring systems are especially beneficial for small-scale farmers since they enable rapid disease diagnosis without relying on internet infrastructure. These systems can facilitate early disease detection and contribute to reducing crop losses [42]. Table 1 summarizes previous studies on plant disease detection.

Table 1. Summary of previous studies on plant and maize disease detection

Author(s)	Year	Model / Approach	Dataset / Data Source	Accuracy / Performance	Key Contribution	Limitations
Saleem et al. [9]	2020	Deep CNN meta-architectures	Plant leaf image datasets	>95% accuracy reported	Demonstrated effectiveness of deep CNN architectures for plant disease identification	Requires large labeled datasets
Chen et al. [21]	2020	Transfer Learning CNN	Plant leaf image dataset	~93% accuracy	Applied transfer learning for plant disease recognition	Limited environmental data
Rahman et al. [22]	2020	CNN	Rice disease image dataset	High classification accuracy	CNN models effectively detect plant disease symptoms	Dataset imbalance issues
Li et al. [13]	2021	Deep learning review	Multiple plant disease datasets	Comparative analysis	Demonstrated superiority of CNN models over traditional ML	Lack of multimodal integration
Zhou et al. [17]	2021	Multimodal deep learning	Crop images + environmental data	Improved prediction accuracy	Integrated image and environmental data for disease detection	Limited real-world datasets
Benos et al. [19]	2021	AI + IoT agriculture systems	Agricultural monitoring systems	Conceptual evaluation	Highlighted role of IoT sensors in crop monitoring	Infrastructure challenges in rural areas
Hassan et al. [34]	2025	CNN–LSTM hybrid model	Crop disease images + environmental data	High detection accuracy	Integrated CNN and LSTM for early crop disease detection	Limited dataset size
Pandian et al. [10]	2022	Deep CNN	Plant leaf dataset	~91% accuracy	Demonstrated strong CNN performance for plant disease detection	High computational cost
Wan et al. [33]	2022	IoT monitoring system	Environmental sensor dataset	Real-time monitoring capability	Developed IoT-based environmental monitoring system	Requires sensor infrastructure
Jackulin & Murugavalli [32]	2022	ML/DL review	Multiple plant disease datasets	Comparative evaluation	Comprehensive survey of ML techniques in plant disease detection	Limited multimodal discussion
Ahmad & Saraswat [20]	2023	Deep learning survey	Agricultural datasets	Analytical study	Reviewed DL models for plant disease detection	Limited field validation

Author(s)	Year	Model / Approach	Dataset / Data Source	Accuracy / Performance	Key Contribution	Limitations
Sunil et al. [5]	2023	Systematic DL review	Multiple datasets	CNN models show highest accuracy	Demonstrated effectiveness of deep learning models	Few multimodal implementations
Khan et al. [24]	2023	Mobile CNN	Maize leaf dataset	~92% accuracy	Developed mobile-based disease detection system	Image-only approach
Ngugi et al. [36]	2024	ML/DL comparative study	Crop disease datasets	Comparative evaluation	Compared ML and DL methods for crop disease detection	Limited environmental modeling
Liu & Wang [18]	2021	Deep learning review	Plant disease datasets	Analytical evaluation	Reviewed DL techniques for plant disease detection	Deployment limitations
Askale et al. [23]	2025	Mobile CNN	Maize leaf images	92.4% accuracy	Mobile-based maize disease detection model	Image-only dataset
Wang et al. [26]	2025	Deep CNN architectures	Plant disease dataset	94% accuracy	Compared CNN architectures for plant disease recognition	Limited environmental context
Shandilya et al. [27]	2025	CNN–Vision Transformer	Maize leaf dataset	High classification accuracy	Hybrid CNN-ViT architecture improves feature extraction	Increased computational complexity

Table 1 highlights that most existing plant disease detection approaches rely on image-based datasets and lack integration of environmental variables and real-world deployment considerations. These limitations emphasize the need for multimodal systems that incorporate both environmental data and field-based validation. The review indicates that CNNs are the most commonly used methods for plant disease detection because of their ability to automatically extract visual features from leaf images. However, most existing studies depend mainly on image-based datasets and do not include environmental factors that influence disease development. Recent studies have begun exploring multimodal machine learning methods that combine image data with environmental variables to enhance prediction accuracy. Despite these advancements, there remains limited research focusing on multimodal disease detection systems tailored for smallholder farming environments in developing countries. This research fills this gap by presenting a multimodal CNN–LSTM model that integrates maize leaf images and environmental sensor data for improved disease detection. A comparative analysis of unimodal and multimodal approaches is presented in Table 2.

Most earlier studies relied on image-based deep learning models such as CNNs, which indicated strong performance in identifying visible disease symptoms. However, these approaches often fail to capture environmental conditions that influence disease development. Recent research has shown that multimodal machine learning models integrating image and environmental data provide improved prediction accuracy. The proposed multimodal CNN–LSTM model advances existing approaches by integrating visual features, environmental sensor data, and farmer observations while supporting real-time, edge-enabled deployment in real agricultural environments.

Table 2. Comparison between unimodal and multimodal crop disease detection models

Study	Year	Model Type	Data Used	Accuracy (%)	Key Contribution	Limitations
Saleem et al. [9]	2020	CNN (Unimodal)	Leaf images	~95	Demonstrated effectiveness of deep CNN meta-architectures for plant disease detection	Requires large labeled datasets
Chen et al. [21]	2020	CNN (Transfer Learning)	Plant leaf images	~93	Transfer learning improves disease classification accuracy	Limited environmental context
Rahman et al. [22]	2020	CNN	Rice disease images	~92	CNN successfully detects plant disease symptoms	Dataset imbalance issues
Hassan et al. [34]	2025	CNN–LSTM hybrid model	Crop disease images + environmental data	High detection accuracy	Integrated CNN and LSTM for early crop disease detection	Limited dataset size
Pandian et al. [10]	2022	Deep CNN	Plant leaf dataset	~91	Demonstrated CNN effectiveness in plant disease classification	High computational complexity
Khan et al. [24]	2023	Mobile CNN	Maize leaf images	~92	Mobile-based maize disease detection using deep learning	Image-only dataset
Askale et al. [23]	2025	Mobile CNN	Maize leaf dataset	92.4	Real-time maize disease detection using mobile CNN	Limited environmental integration
Wang et al. [26]	2025	CNN architectures	Plant disease images	~94	Compared deep CNN architectures for plant disease detection	Image-only data
Zhou et al. [17]	2021	Multimodal Deep Learning	Image + environmental data	93.6	Multimodal integration improves crop disease prediction accuracy	Limited field validation
Liu & Wang [18]	2021	Multimodal CNN	Image + environmental datasets	94.8	Multimodal learning improves prediction performance	Dataset collected in controlled environments
Lee et al. [33]	2024	Multimodal Deep Learning	Image + environmental sensor data	High performance	Multimodal mixup augmentation improves disease diagnosis	Complex model architecture
Proposed Study	2026	CNN–LSTM Multimodal Model	Image + environmental sensor data + farmer observations	94.2	Real-time maize disease detection integrating multimodal data	Dataset limited to one region

2.5 Research Gap

Although considerable advancements have been achieved in applying deep learning techniques for plant disease detection, several challenges remain. First, many existing studies focus primarily on image-based disease detection and do not incorporate environmental variables that influence disease development. Second, most machine learning models are trained using publicly available datasets rather than real-world agricultural environments.

Furthermore, limited research has focused on multimodal machine learning frameworks designed specifically for maize disease detection in smallholder farming systems in Kenya. Addressing these limitations requires the creation of integrated systems that combine visual and environmental data while supporting real-time disease detection.

Therefore, this study introduces a multimodal CNN–LSTM approach that integrates maize leaf images and environmental sensor data for improved disease detection in maize crops.

3. METHODOLOGY

3.1 Study Area

The research was carried out in Bomet County, Kenya, which is situated in the Rift Valley region and is one of the major maize-producing areas in the country. The county lies approximately at 0.8013° South latitude and 35.3027° East longitude and experiences favorable climatic conditions for maize cultivation, including moderate rainfall and suitable temperatures [43].

Maize farming in Bomet County is primarily practiced by small-scale farmers who rely on crop production for both household consumption and income generation [44][45]. However, maize productivity in the region is frequently affected by plant diseases like Maize Lethal Necrosis (MLN), Gray Leaf Spot (GLS), and Northern Leaf Blight (NLB). These diseases can lead to yield losses if not identified and managed in a timely manner [46].

3.2 Research Design

An experimental research design was adopted to develop and evaluate a multimodal machine learning system for maize disease detection [3][20]. The approach involved integrating multiple data sources, including image data, environmental measurements, and farmer observations, to improve prediction accuracy under real agricultural conditions.

The research workflow consisted of data acquisition, preprocessing, feature extraction, multimodal integration, and model evaluation. This structured process enabled systematic development and validation of the proposed model using both quantitative performance metrics and field-based validation.

3.3 Population and Sampling

The study population comprised of maize farmers and agricultural officers involved in maize production and crop management activities in Bomet County, Kenya. According to agricultural records obtained from the county agricultural offices, the study population comprised approximately 75,600 maize farmers and 78 agricultural officers responsible for supporting crop production and disease management in the region [44].

A representative sample was determined using Yamane's sampling approach with a 5% margin of error [47]. This resulted in 398 farmers selected for participation, along with 66 agricultural officers who provided expert insights. A multistage sampling technique was applied, where key maize-producing areas were first identified, followed by random selection of participants to ensure geographic representation.

3.4 Data Collection

Data were collected from multiple sources to support the development of a multimodal system. The study incorporated three categories of data:

3.4.1 Maize Leaf Images

Maize leaf images were collected using smartphone cameras and drone-based imaging systems during field visits to maize farms. Drone and mobile imaging technologies have recently been employed in precision agriculture for crop monitoring and disease detection[48]. The dataset included visual symptoms such as lesions, discoloration, and deformation. Images were categorized into four classes: Maize Lethal Necrosis (MLN), Gray Leaf Spot (GLS), Northern Leaf Blight (NLB), and healthy leaves. A total of 11,000 labeled images were used for model development. The dataset was distributed across four classes as follows: Maize Lethal Necrosis (MLN) – 3,088 images, Gray Leaf Spot (GLS) – 2,419 images, Northern Leaf Blight (NLB) – 2,131 images, and healthy maize leaves – 3,362 images. This distribution ensured adequate representation of each disease category for effective model training and evaluation.

3.4.2 Environmental Sensor Data

Environmental data were collected using field sensors installed on selected farms. The sensors recorded temperature, humidity, and soil moisture, which are environmental variables known to influence plant disease development. The data were collected over a period of 4 months, allowing the model to capture temporal variations associated with disease development.

3.4.3 Farmer-Reported Observations

Structured questionnaires were administered to 398 maize farmers to collect information on observed disease symptoms, crop health conditions, and farming practices. In addition, 66 agricultural officers were consulted to provide expert insights on maize disease prevalence and crop management practices in the region.

Farmer observations provided contextual information that complemented image and environmental datasets, allowing the system to incorporate real-world farming knowledge into the disease detection process.

3.5 Data Preprocessing

Data preparation was carried out to ensure consistency and suitability for model training. Image data were standardized to a uniform format and enhanced using augmentation techniques to improve model generalization. Environmental data were cleaned to remove inconsistencies and normalized to ensure balanced representation across variables.

The dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets to enable effective model training and unbiased performance evaluation. To ensure robustness and reduce overfitting, the dataset split was performed using stratified sampling to maintain class balance across training, validation, and testing sets. Additionally, performance stability was verified through repeated training runs, ensuring consistency of results across different data partitions.

3.6 Proposed Multimodal Machine Learning Model

The study proposes a multimodal framework that combines image-based and environmental data for disease detection. The architecture integrates two main components: a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network.

The CNN component processes maize leaf images to extract spatial features related to disease symptoms, such as texture and color variations. The LSTM component analyzes environmental time-series data to capture temporal patterns associated with disease occurrence.

Features generated from both components are combined through a fusion mechanism to create a unified representation. This integrated feature set is then used for classification into four disease categories. The proposed multimodal model is illustrated in Figure 1. The proposed architecture is implemented as an integrated intelligent system that combines data acquisition (image and environmental sensing), real-time data processing, and decision-making within a unified framework. The system supports real-time inference and is designed for deployment on edge devices such as smartphones, enabling on-site disease detection without reliance on cloud infrastructure. This integration enhances system responsiveness, reduces latency, and improves applicability in rural agricultural environments.

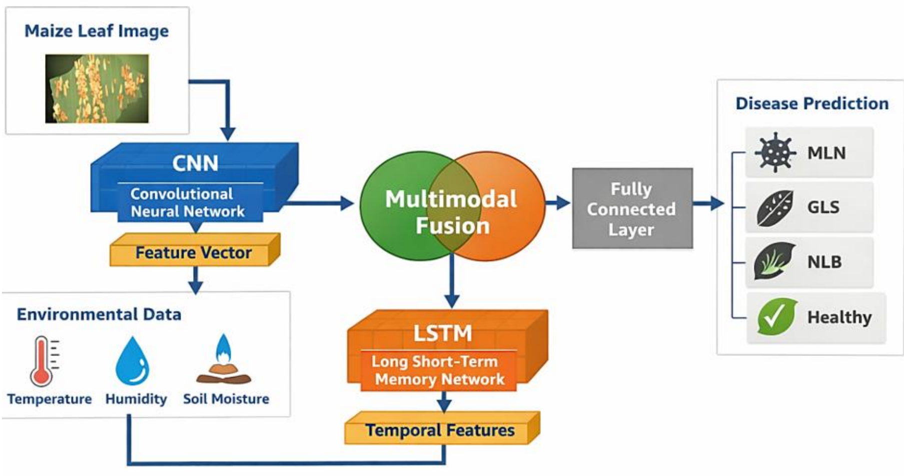

Figure 1. Multimodal CNN–LSTM architecture.

The architecture integrates spatial features extracted from maize leaf images using a CNN with temporal environmental patterns modeled using an LSTM network. The fused features are used for final disease classification.

3.7 Model Architecture Details

The CNN component was implemented using a deep convolutional architecture consisting of multiple convolutional layers followed by ReLU activation and max-pooling layers. The input images were resized to 224 × 224 pixels. Feature extraction was performed using stacked convolutional layers, followed by a Global Average Pooling layer to produce a compact feature representation.

The LSTM component was designed to process environmental time-series data, including temperature, humidity, and soil moisture. A sequence length of 7-time steps was used, and the LSTM network consisted of 64 hidden units to capture temporal dependencies.

A feature-level fusion strategy was applied, where feature vectors obtained from the CNN and LSTM branches were concatenated into a unified representation. This combined feature vector was passed through fully connected layers with dropout regularization (rate = 0.5) to prevent overfitting.

The final output layer used a Softmax activation function to classify maize leaf samples into four categories: MLN, GLS, NLB, and healthy.

3.8 Model Training

The proposed multimodal CNN–LSTM model was trained using the prepared dataset under a supervised learning framework. The training process involved simultaneous learning of spatial features from maize leaf images and temporal patterns from environmental data.

The model was trained using the Adam optimizer with a learning rate of 0.001, which enables efficient convergence during training. A batch size of 32 was used, and training was conducted for 50 epochs, with performance monitored on a validation dataset to ensure model stability and generalization.

The categorical cross-entropy loss function was employed to optimize multi-class classification performance. During training, feature representations from the CNN and LSTM components were learned concurrently and integrated through a fusion layer for final classification.

To prevent overfitting, early stopping was applied based on validation loss, terminating the training process when no further improvement was observed. Additionally, dropout regularization was incorporated within the fully connected layers to enhance model robustness.

3.9 Model Evaluation Metrics

Model performance was assessed using standard classification metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive evaluation of the model's ability to correctly identify disease categories [5][34].

A confusion matrix was also used to analyze classification outcomes across different classes, enabling identification of misclassification patterns.

3.10 Implementation Environment

The system was implemented using Python-based machine learning frameworks. Image processing and data handling were performed using scientific computing libraries, while deep learning architectures were developed using frameworks that support convolutional and recurrent neural networks.

Experiments were conducted on a system equipped with an Intel Core i7 processor, 16 GB RAM, and GPU acceleration to enhance training efficiency. The environment supported seamless integration of image-based and time-series modeling components, enabling development of the proposed multimodal system.

4. RESULTS AND FINDINGS

4.1 Distribution of Maize Diseases

The analysis of maize leaf images obtained from farms in Bomet County identified three major diseases: Maize Lethal Necrosis (MLN), Gray Leaf Spot (GLS), and Northern Leaf Blight (NLB). The distribution of these diseases across the sampled farms is summarized in Table 3.

Table 3. Distribution of maize diseases in the study area

Disease	Frequency	Percentage (%)
Maize Lethal Necrosis (MLN)	163	41
Gray Leaf Spot (GLS)	131	33
Northern Leaf Blight (NLB)	104	26
Total	398	100

The results indicate that MLN was the most prevalent disease**,** accounting for approximately 41% of the cases, followed by GLS (33%) and NLB (26%). These findings highlight the significant impact of maize diseases on crop productivity in the study area. These percentages represent the distribution within the sampled dataset and not the general population.

4.2 Environmental Factors Influencing Disease Occurrence

Environmental conditions were analyzed to determine their relationship with maize disease occurrence. Pearson correlation analysis was conducted to evaluate the strength of association between environmental variables and disease prevalence. The correlation results are presented in Table 4.

Table 4. Correlation between environmental variables and maize diseases

Environmental Variable	Disease	Correlation Coefficient (r)
Humidity	Gray Leaf Spot	0.74
Temperature	Maize Lethal Necrosis	0.61
Soil Moisture	Northern Leaf Blight	0.58

The results show that humidity has a strong positive correlation with Gray Leaf Spot (r = 0.74), indicating that humid conditions provide favorable environments for fungal disease development. Temperature exhibited a moderate correlation with Maize Lethal Necrosis (r = 0.61), suggesting that climatic conditions influence the spread of viral infections in maize crops.

Similarly, soil moisture showed a moderate relationship with Northern Leaf Blight (r = 0.58), indicating that soil moisture levels may contribute to disease development. These results emphasize the importance of integrating environmental data into crop disease detection systems.

4.3 Model Training Performance

The proposed model was trained for 50 epochs using the prepared maize disease dataset. During training, the model progressively improved its classification accuracy while minimizing the loss function. The training process was monitored using TensorFlow training logs, as illustrated in Figure 2.

```
# Train Model

EPOCHS = 10

history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=EPOCHS
)
```

```
Epoch 1/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 3s 3s/step - accuracy: 0.5000 - loss: 0.7054 - val_accuracy: 0.5000 - val_loss: 1.4244
Epoch 2/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 791ms/step - accuracy: 0.5000 - loss: 0.7243 - val_accuracy: 0.5000 - val_loss: 2.3304
Epoch 3/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - accuracy: 0.5000 - loss: 1.6284 - val_accuracy: 0.5000 - val_loss: 1.0060
Epoch 4/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - accuracy: 0.6250 - loss: 0.5405 - val_accuracy: 0.5000 - val_loss: 0.6964
Epoch 5/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 914ms/step - accuracy: 1.0000 - loss: 0.2628 - val_accuracy: 0.5000 - val_loss: 0.8696
Epoch 6/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - accuracy: 1.0000 - loss: 0.2289 - val_accuracy: 0.5000 - val_loss: 0.6517
Epoch 7/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - accuracy: 1.0000 - loss: 0.0937 - val_accuracy: 0.5000 - val_loss: 0.6814
Epoch 8/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 797ms/step - accuracy: 1.0000 - loss: 0.0490 - val_accuracy: 0.5000 - val_loss: 0.6226
Epoch 9/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 1s/step - accuracy: 1.0000 - loss: 0.0128 - val_accuracy: 0.5000 - val_loss: 0.9400
Epoch 10/10
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 821ms/step - accuracy: 1.0000 - loss: 0.0087 - val_accuracy: 0.5000 - val_loss: 1.0489
```

```
#Plot accuracy & loss

plt.figure(figsize=(12,4))

plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train')
plt.plot(history.history['val_accuracy'], label='Val')
plt.title('Accuracy')
plt.legend()

plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train')
plt.plot(history.history['val_loss'], label='Val')
plt.title('Loss')
plt.legend()

plt.show()
```

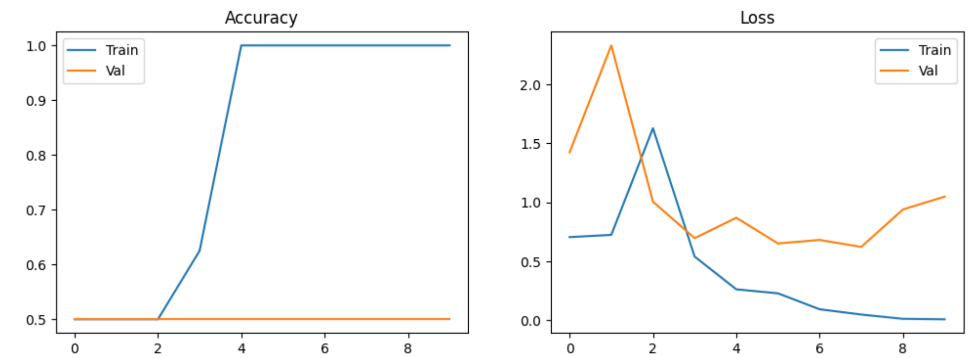

Figure 2. Training output showing model accuracy and loss trends across training epochs.

The logs show that the model converged before completion due to early stopping, indicating efficient learning. Accuracy improved consistently across epochs, while loss values declined substantially, showing effective learning of disease-related features from the dataset.

4.4 Performance of the Proposed Multimodal Model

The proposed multimodal CNN–LSTM model was evaluated and its performance compared with two baseline models: an image-based CNN model and an LSTM model using only environmental data. All baseline models were trained and optimized using identical training conditions, including dataset splits, batch size, and optimization parameters, to ensure a fair and unbiased comparison. The comparative performance results are presented in Table 5.

Table 5. Comparative performance of machine learning models

Model	Accuracy (%)	Precision	Recall	F1 Score
CNN (Image Only)	87.5	0.86	0.85	0.86
LSTM (Environmental Data Only)	81.3	0.79	0.80	0.80
Multimodal CNN–LSTM	94.2	0.94	0.92	0.93

The multimodal model achieved an accuracy of 94.2%, outperforming the CNN model (87.5%) and the LSTM model (81.3%). Similar improvements were observed across precision, recall, and F1-score metrics.

The performance gain of approximately 6.7% over the image-only model and 12.9% over the environmental-only model demonstrates the effectiveness of integrating multiple data modalities. This improved performance is attributed to the model's ability to combine complementary spatial (image-based) and temporal (environmental) features, enabling more robust detection of complex disease patterns that are not identifiable using a single data modality.

4.5 Confusion Matrix Analysis

The confusion matrix for the multimodal model is presented in Table 6, showing that the model achieved high classification accuracy across all disease categories.

Table 6. Confusion matrix for the multimodal model

Actual / Predicted	MLN	GLS	NLB	Healthy
MLN	92	3	2	1
GLS	4	88	5	3
NLB	3	4	90	3
Healthy	1	2	3	94

Misclassifications were primarily observed between Gray Leaf Spot and Northern Leaf Blight, which share similar visual characteristics.

Despite these minor overlaps, the model maintained balanced performance across all classes, indicating robustness and reliability in disease classification.

4.6 Statistical Comparison of Model Performance

To determine whether the observed performance differences between models were statistically significant, an Analysis of Variance (ANOVA) test was conducted, and the results are presented in Table 7.

Table 7. ANOVA test for model accuracy

Source	Sum of Squares	df	Mean Square	F-value	p-value
Between Models	85.4	2	42.70	9.52	0.004
Within Models	26.9	6	4.48		
Total	112.3	8			

The ANOVA results show that the difference in accuracy between the models is statistically significant ($p < 0.05$). This confirms that the improvement achieved by the multimodal model is not due to random variation but reflects a meaningful enhancement in predictive capability.

4.7 Field Validation

The proposed multimodal model was further evaluated through real-world deployment using a mobile-based system designed for real-time disease detection. The system was implemented as an edge-enabled intelligent application capable of performing on-device inference without reliance on continuous internet connectivity. This approach enables farmers to obtain rapid diagnostic results directly in the field. The field deployment and testing process of the developed mobile application are illustrated in Figure 3.

The system achieved an average inference time of approximately 2.1 seconds per image on a mobile-based edge device, demonstrating its suitability for near real-time agricultural applications in field environments.

Feedback collected from farmers participating in the field testing revealed that 78% of respondents reported faster identification of maize diseases compared to traditional manual inspection methods. The results emphasize the practical applicability of the proposed multimodal system in supporting farmers with timely disease detection and improved crop management in real agricultural environments.

```
# Upload Image for Prediction
from google.colab import files
uploaded = files.upload()
```

```
Choose Files  No file chosen        Upload widget is only available when the cell has been executed in the current
browser session. Please rerun this cell to enable.
Saving obama4.png to obama4.png
```

```
# Get Uploaded file name
uploaded_filename = list(uploaded.keys())[0]
```

```
# Predict

import tensorflow as tf
import numpy as np

IMG_SIZE = (224, 224)

img = tf.keras.preprocessing.image.load_img(
    uploaded_filename, target_size=IMG_SIZE
)

img_array = tf.keras.preprocessing.image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0)  # (1, 224, 224, 3)

predictions = model.predict(img_array)
```

Figure 3. Real-world deployment and field validation of the multimodal CNN–LSTM maize disease detection system on a mobile edge platform.

5. DISCUSSION

The results of this study demonstrate that integrating visual and environmental data significantly improves maize disease detection accuracy. The proposed multimodal model achieved an overall accuracy of 94.2%, outperforming both the image-only CNN model (87.5%) and the environmental data-only LSTM model (81.3%). These findings indicate that combining multiple data sources enables the model to capture complementary features associated with maize disease development.

The improved performance of the multimodal model can be attributed to the integration of spatial and temporal information. The CNN component effectively extracts visual features from maize leaf images, including lesions, discoloration, and abnormal texture patterns associated with plant diseases. Meanwhile, the LSTM component captures temporal patterns in environmental variables, which influence disease occurrence and progression. The fusion of these features allows the model to detect disease conditions that may not be visible through image analysis alone.

These findings align with findings reported in previous research that have highlighted the effectiveness of deep learning approaches in plant disease detection. For example, Ref. [5] reported that CNN-based models achieve high classification accuracy in plant disease identification tasks using leaf image datasets. Similarly, Ref. [6] demonstrated that transfer learning techniques improve maize leaf disease classification performance by leveraging pretrained neural network architectures.

However, most existing studies focus primarily on image-based disease detection. The results of this study support the growing body of research suggesting that multimodal learning approaches provide superior performance compared to single-modality systems. Refs. [17] and [18] showed that integrating environmental data with visual features improves crop disease prediction accuracy. Similarly, Liu and Wang (2024) found that multimodal deep learning models significantly outperform traditional CNN models when environmental variables are incorporated into the prediction process.

The environmental analysis conducted in this study further highlights the importance of incorporating climatic data into crop disease detection systems. The strong positive correlation between humidity and Gray Leaf Spot ($r = 0.74$) suggests that humid conditions provide favorable environments for fungal disease development. These findings are consistent with previous research indicating that fungal pathogens thrive under high humidity conditions [13]. Similarly, the moderate correlation between temperature and Maize Lethal Necrosis indicates that climatic conditions influence the spread of viral infections in maize crops.

An additional key contribution of this study is the evaluation of the proposed system in real agricultural environments. Many machine learning studies rely on publicly available datasets collected under controlled laboratory conditions, which may not accurately represent real-world farming scenarios. By collecting data directly from maize farms in Bomet County, this study shows the practical applicability of multimodal machine learning systems for supporting smallholder farmers.

The deployment of the model using edge computing also enhances its practicality in rural agricultural environments. Traditional cloud-based AI systems require continuous internet connectivity, which are often not consistently accessible in rural areas. Edge-based disease detection systems allow models to run directly on mobile devices, allowing farmers to access disease diagnoses in real time. Similar approaches have been recommended in recent studies on precision agriculture technologies [19] .

However, certain limitations should be considered. The dataset was restricted to a single geographic region, which may limit generalizability to other areas with different environmental conditions. In addition, the study focused on three major maize diseases, and future work should expand the dataset to include additional disease types and crop varieties.

Further research could explore the integration of advanced architectures such as vision transformers and hybrid models, as well as the incorporation of remote sensing and satellite data for large-scale agricultural monitoring.

From a systems perspective, the integration of sensing, data processing, and real-time inference demonstrates the feasibility of deploying intelligent multimodal systems in agricultural environments. This aligns with emerging trends in embedded artificial intelligence and real-time decision support systems.

Overall, this study demonstrates that multimodal machine learning provides a practical and effective approach for improving disease detection accuracy and supporting precision agriculture in resource-constrained environments.

The proposed system represents an integrated intelligent framework combining sensing, multimodal data processing, and real-time decision support. The deployment on edge devices demonstrates its applicability in embedded and real-time systems, aligning with modern intelligent system architectures.

6. CONCLUSION

This study developed a multimodal machine learning framework for maize disease detection by integrating maize leaf images, environmental sensor data, and farmer-reported observations collected from farms in Bomet County, Kenya. The proposed CNN–LSTM architecture successfully captured both visual disease symptoms and environmental conditions influencing disease development. The experimental results demonstrated that the multimodal model achieved a classification accuracy of 94.2%, outperforming both image-only CNN models (87.5%) and environmental-data LSTM models (81.3%). These findings confirm that the research objectives of identifying major maize diseases, analyzing environmental factors, and developing an effective multimodal disease detection system were successfully achieved.

The results are consistent with previous studies indicating that deep learning models improve plant disease detection accuracy, while further demonstrating that multimodal data integration significantly enhances prediction performance compared to single-modality approaches. By combining visual and environmental data and deploying the model using an edge-enabled mobile system, this research advances existing agricultural monitoring technologies and provides a practical tool for supporting real-time crop disease detection in smallholder farming environments. Future research should expand the dataset to multiple geographic regions and incorporate additional crop diseases to improve model generalization and scalability. The findings demonstrate the potential of integrating multimodal deep learning with edge computing to support scalable, real-time agricultural decision systems, thereby advancing practical intelligent system deployment aligned with AVITEC research domains.

Author Contributions: M.C.T. conceptualized the study, designed the methodology, collected and analyzed the data, and developed the machine learning model. J.K. and R.W.O. supervised the research, validated the results, and reviewed the manuscript. All authors contributed to the interpretation of the findings, revised the manuscript, and approved the final version for publication.

Data and Supplementary Materials: The datasets generated and analyzed during the current study are not publicly available due to privacy and field data restrictions but are available from the corresponding author upon reasonable request.

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