

An Edge AI-Based IOT Framework for Real-Time Wheat Disease Detection and Precision Agriculture

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ABSTRACT: Accurate and early detection of crop diseases is essential for improving agricultural productivity and ensuring sustainable farming practices. Conventional manual wheat crop inspection takes a lot of time, is prone to mistakes, and necessitates specialized knowledge. This research describes a sophisticated Edge AI-based smart farming system that uses deep learning and an Internet of Things (IoT) framework to identify wheat illness in real time. The suggested system makes use of a Raspberry Pi-based acquisition unit with sensors to track environmental factors including temperature, humidity, and soil moisture as well as a camera to take pictures of wheat leaves. The suggested model, in contrast to traditional methods, is tailored for on-device inference using TensorFlow Lite, allowing deployment on an Android-based mobile application for offline and real-time disease prediction. Using a dataset of five thousand annotated photos, a deep convolutional neural network (CNN) model based on transfer learning is trained to categorize wheat diseases into five groups: Crown & Root Rot, Healthy, Leaf Rust, Stem Rust, and Wheat Loose Smut. With a 97% validation accuracy, a 98.8% training accuracy, and a minimal validation loss, the system performs well. Low latency, less reliance on cloud infrastructure, and effective field-level deployment are guaranteed by the combination of Edge AI, IoT, and mobile computing. The suggested solution increases crop productivity and supports precision agriculture by enabling farmers to diagnose diseases instantly and take prompt preventative action.

1. INTRODUCTION

Conventional wheat disease detection techniques mostly rely on manual examination, which is labor-intensive, time-consuming, and prone to human error, particularly in large-scale agricultural fields. To avoid yield loss and guarantee ongoing agricultural productivity, early and

precise detection of crop diseases is essential. Automated plant disease detection technologies have become effective and dependable substitutes for traditional methods because to the quick development of artificial intelligence (AI) and the Internet of Things (IoT) (Sharma et al., 2025; Nguyen et al., 2025).

Because deep learning methods, especially Convolutional Neural Networks (CNNs), can automatically extract complex and hierarchical features from raw input images, they have shown remarkable performance in image-based crop disease classification in recent years (Ahmed et al., 2025; Roumeliotis et al., 2025). Additionally, the contextual understanding of crop health has been improved by the incorporation of IoT-based environmental monitoring, such as temperature, humidity, and soil moisture, allowing for more reliable and accurate disease prediction systems (Chaturvedi et al., 2023; Takahashi et al., 2023).

Nevertheless, the majority of current systems rely on cloud-based processing, which limits real-time usability in rural farming contexts, adds latency, and necessitates constant internet connectivity. This study suggests an Edge AI-based smart farming system that enables real-time wheat disease diagnosis directly on local devices in order to address these issues. The suggested system combines environmental sensors with a Raspberry Pi-based image collecting unit and uses TensorFlow Lite to optimize a deep learning model for effective on-device inference.

Furthermore, an Android-based mobile application is created to give farmers an easy-to-use interface that allows for offline and real-time illness detection in the field. Images of wheat leaves are categorized by the system into four groups: Wheat Loose Smut, Crown & Root Rot, Healthy, and Brown Rust. An 80:20 training-testing split is used to train the model using a dataset of 5,000 annotated photos.

The suggested framework obtains a training accuracy of 98.8%, validation accuracy of 97%, and low validation loss, according to experimental results, suggesting good performance and generalization potential. The system eliminates latency, provides effective real-time deployment, and lessens reliance on cloud infrastructure by integrating Edge AI, IoT, and mobile computing. This method greatly improves early disease diagnosis, lowers crop losses, and advances smart farming and precision agriculture.

2. LITERATURE REVIEW

By enabling intelligent systems for crop monitoring and disease detection, the Internet of Things (IoT), Wireless Sensor Networks (WSN), and Artificial Intelligence (AI) have revolutionized modern agriculture (Sharma et al., 2025; Nguyen et al., 2025). Deep learning models, especially Convolutional Neural Networks (CNNs), have been widely adopted for image-based plant disease classification due to their ability to extract complex features and achieve high accuracy. These technologies have automated disease diagnosis by combining visual data with environmental sensing, increasing efficiency when compared to manual inspection methods.

In 2022 and 2023, a number of research (Chaturvedi et al., 2023; Takahashi et al., 2023) suggested IoT-enabled multimodal frameworks that combine CNN-based picture processing with environmental factors like temperature, humidity, and soil moisture. By adding contextual information, these systems showed enhanced performance, making them more appropriate for actual agricultural settings. However, their real-time usefulness in field settings was constrained by their reliance on centralized processing systems.

In order to solve issues including class imbalance, illumination variance, and leaf occlusion, research trends in 2024 and 2025 switched toward hybrid and advanced techniques, such as transformer-based topologies and transfer learning (Sharma et al., 2025; Patel et al., 2025). Edge AI-based solutions, where lightweight models optimized with TensorFlow Lite allow real-time, on-device inference through mobile applications, have garnered interest more lately. Despite these developments, unified systems that smoothly combine edge computing, mobile deployment, and IoT sensing are still lacking. By creating an Android-based smart farming system with Edge AI capabilities for effective and real-time wheat disease diagnosis, the proposed approach fills this gap.

3. METHODOLOGY

This study suggests a hybrid Edge AI-based wheat disease detection system that combines IoT sensing, deep learning, and multi-platform deployment via Web and Android interfaces. By providing real-time, offline-capable illness

detection at the field level, the system is intended to solve the drawbacks of conventional and cloud-dependent methods.

The design integrates environmental information gathered from Internet of Things (IoT) sensors, such as temperature, humidity, and soil moisture, with image-based disease categorization using a Convolutional Neural Network (CNN). There are two ways to use the trained model: TensorFlow Lite for edge deployment on Android devices Web-based implementation for centralized access, analytics, and monitoring For both farmers and agricultural specialists, this dual-system design guarantees adaptability, scalability, and accessibility.

3.1 System Overview

There are four main layers to the entire system

1. Data Acquisition Layer
2. Processing & AI Layer
3. Android-Based Edge System
4. Web-Based Monitoring System

Together, these layers create a smooth pathway from data gathering to insights that may be put to use.

3.1.1 Data Acquisition Layer

This layer is in charge of leveraging hardware components to gather field data in real time. High-resolution photos of wheat leaves are taken by a Raspberry Pi fitted with a camera module in a variety of environmental settings, including lighting, orientation, and disease stages .IoT sensors consist of: Temperature and Humidity (DHT22) Environmental parameters are continuously monitored by the Soil Moisture Sensor .By linking visual symptoms with environmental factors, each collected image is synchronized with sensor readings to provide a multimodal dataset that improves disease prediction. This method increases the system's resilience and guarantees that it operates efficiently in actual agricultural settings.

3.1.2 Processing Layer

Deep learning methods are applied to the gathered data in order to classify diseases. Images go through a number of preparation stages:

1. Changing the size to 224 x 224 pixels
2. Gaussian filtering for noise reduction
3. CLAHE contrast enhancement Data augmentation (rotation, flipping, brightness change)

These actions enhance the generalization and accuracy of the model.

3.1.3 Output & Alert Layer

After processing, the predictions and their probability scores are returned to the Raspberry Pi edge device. This layer provides farmers with real-time messages and visual feedback in the field, allowing them to make timely intervention decisions. To help with the long-term forecasting of potential disease outbreaks, the system also records environmental sensor readings and classification results for data tracking and trend analysis. Integrating edge-based deep learning with IoT devices ensures low latency, offline operation, and reduced dependency on high-bandwidth internet connections. As a result, the system is especially well-suited for remote or rural agricultural areas, where connectivity and processing power are often limited.

3.2 Dataset Collection



For any deep learning-based agricultural disease detection system to be reliable and effective, the dataset's quality, diversity, and comprehensiveness are essential. A carefully chosen and structured dataset was produced in order to train and assess the VGG19-based classification model for the proposed wheat disease detection framework. The dataset's objective is to record the visual traits of wheat leaves along with environmental elements

that collectively influence the onset and progression of disease.

3.2.1 Image Data Collection

High-resolution images of wheat leaves were captured using the Raspberry Pi Camera Module v2. It was set up at the perfect height to capture crisp, clear images in the field. The camera was positioned to capture images at various times of the day in order to guarantee lighting diversity and boost the model's resistance to shifting light levels and shadows. Several field sites were used to capture pictures of both healthy and sick plants at different phases of development.

To ensure fair representation, a total of approximately 5,000 high-quality photos were collected, with roughly 1,000 photos per class. Later, data augmentation techniques such as rotation, flipping, brightness adjustment, and Gaussian noise addition were employed to expand the dataset, improve model generalization, and prevent overfitting. This augmentation ensures that the trained CNN model can tolerate changes in camera angles, lighting, and leaf orientation.

3.2.2 Environmental Sensor Data

In addition to taking pictures, a network of Internet of Things (IoT)-based sensors was installed in the wheat field to gather important environmental data. These sensors included:

- **DHT22 Temperature and Humidity Sensor** – for measuring ambient temperature and relative humidity.
- **Soil Moisture Sensor (Capacitive Type)** – for detecting the volumetric water content in the soil.

Every image capture event was synchronized with a corresponding set of sensor values to produce a time-stamped multimodal dataset. This link allows the system to understand how specific environmental conditions correlate with the onset or severity of a particular disease. For example, high humidity and moderate temperatures are often linked to rust-type fungal infections, while excessively dry soil may be linked to root rot symptoms.

3.2.3 Data Annotation and Verification

Each image was subjected to a multi-phase annotation process after data collection. To personally review and confirm disease classifications, knowledgeable plant pathologists used reference images from agricultural research databases such as PlantVillage and CIMMYT's wheat pathology library. The annotation approach ensured label accuracy above 95%, which is crucial for training

supervised deep learning models. Duplicate and fuzzy images were also removed using automated Python scripts that used image quality metrics like Laplacian variance and histogram analysis. The dataset was refined during this preprocessing step, which also made sure that only high-quality, information-rich samples were kept.

3.3 VGG19 MODEL DESCRIPTION

The VGG19 model, a 19-layer CNN, is employed in this work to classify wheat diseases because of its robust feature extraction capabilities, tiny 3x3 filters, and straightforward structure. To identify disease-specific patterns, the top layers are refined on wheat leaf pictures while the lower layers are frozen using ImageNet pretrained weights. Softmax classification, Adam optimization, batch normalization, and dropout all contribute to increased stability and decreased overfitting. Five classes are identified by the model: Crown & Root Rot, Leaf Rust, Stem Rust, Loose Smut, and Healthy. Because it strikes a balance between accuracy, interpretability, and computing performance, VGG19 is favored for real-time application on edge devices such as Raspberry Pi. Overall, in a variety of field situations, the enhanced VGG19 framework offers accurate and dependable wheat disease detection.

3.4 Android-Based Edge System

In order to identify wheat disease in the field in real time and offline, an Android-based edge system is essential. This system uses on-device intelligence to guarantee quick and accurate forecasts without requiring constant internet connectivity, in contrast to conventional cloud-dependent methods. The Android application incorporates a TensorFlow Lite (TFLite) model for effective execution on mobile devices and is created using Java and XML in Android Studio. A camera interface for taking leaf photos, an image preprocessing module for preparing the input data, a TFLite inference engine for carrying out classification, and a user interface for showing results make up the application architecture. While preserving computational efficiency, its modular design guarantees seamless communication between hardware and software components.

When the user takes a picture of a wheat leaf with the built-in camera or chooses one from the device gallery, the Android system starts to function. In order to meet the input criteria of the trained CNN model, the taken image is then preprocessed on the device, including scaling, normalization, and enhancement. The TFLite model receives the preprocessed image, performs real-time classification, and predicts the disease category with a confidence score. Farmers are able to make prompt and well-informed decisions because the outcome is instantly shown on the screen in an understandable way.

This real-time inference feature guarantees instantaneous feedback in field situations and drastically lowers latency.

The Android-based system has a number of important benefits, such as full offline functionality, reduced latency, and an intuitive UI made especially for farmers. It is ideal for rural and isolated agricultural areas because it is scalable, portable, and does not require high-bandwidth internet connectivity.

This method removes reliance on cloud infrastructure and improves the usefulness of smart agricultural solutions by bringing intelligence right to the edge.



Figure 2: Android-Based System

3.5 Web-Based Monitoring System

A web-based monitoring platform is created in addition to the Android-based edge system to offer centralized access to data, analytics, and long-term monitoring features. By providing a thorough understanding of disease trends and environmental circumstances, the web system is intended to assist researchers, agricultural specialists, and farm managers. Modern web technologies, such as HTML, CSS, JavaScript (or React), and backend services like Firebase or Node.js for data processing and storage, are used in its construction. To provide safe and scalable data management, collected photos, sensor readings, and prediction results are stored in a cloud database.

The web platform offers a number of features that improve the system's general usefulness. It has an interactive dashboard that makes data interpretation simple by displaying disease statistics and categorization findings in graphical formats. Charts and graphs are used to illustrate environmental factors that affect crop health, such as temperature, humidity, and soil moisture. The system also keeps track of past data, which enables users to monitor disease trends over time and do trend analysis for forecasting insights. The online platform is a vital tool for

extensive agricultural monitoring and research applications because of these qualities.



Figure 3 : Web-Based Monitoring System

Centralized monitoring and decision-making are made possible in large part by the web system. It enables specialists to assess model performance, examine disease trends, and offer crop management suggestions. Additionally, it facilitates scalability by allowing numerous people to access and monitor data from various locations, which makes it appropriate for extensive agricultural installations.

3.6 Hardware Implementation

The suggested wheat disease detection system's hardware implementation is made to enable low-power operation, real-time monitoring, and field deployment in agricultural settings. In remote locations with potentially poor internet access, the system's compact edge-computing architecture allows for effective data collection, processing, and communication. The Raspberry Pi 4 Model B, which serves as the main processing unit in charge of picture acquisition, sensor data collecting, and deep learning model execution, is the central component of the hardware configuration.

The device incorporates a Raspberry Pi Camera Module v2 to take high-resolution pictures of wheat leaves in the field. To guarantee correct alignment, focus, and coverage across various crop heights and orientations, the camera is mounted on an adjustable support structure. This configuration increases the resilience of the detection process by enabling the device to take pictures in a variety of lighting and illness phases. Depending on system load and connectivity availability, captured photos are either temporarily stored for batch processing or processed locally on the Raspberry Pi for real-time inference.

The system integrates several IoT-based environmental sensors to improve the accuracy of disease prediction. The ambient temperature and humidity are measured by a

DHT22 sensor, and the water content of the soil is tracked by a capacitive soil moisture sensor. GPIO ports are used to interface these sensors with the Raspberry Pi, allowing for the synchronized collection of visual and environmental data. Multimodal analysis is made easier by the integration of sensor data with picture inputs, which enables the system to associate environmental factors with the onset and course of disease.

For deployment in rural agricultural areas, low latency and offline capabilities are essential, and the Raspberry Pi handles the majority of the computational work locally. Wireless communication for data transfer, remote monitoring, and system updates is made possible by its integrated Wi-Fi and Bluetooth modules. The gathered data, which includes photos, sensor readings, and prediction outcomes, can be sent to a centralized server or cloud platform for additional analysis, visualization, and model retraining when network connectivity is available.

All things considered, the suggested hardware configuration successfully integrates edge computing, Internet of Things sensing, and real-time picture processing into a single system. It is very ideal for real-world applications in smart farming because it is affordable, energy-efficient, and simple to implement. With this approach, farmers can decrease crop loss and increase agricultural productivity by continually monitoring crop health, early disease detection, and prompt remedial action.



Figure 3 : Hardware Setup of Wheat Disease Detection System

3.6 Performance Experiments and Results

In order to evaluate the accuracy, robustness, and real-time feasibility of the proposed wheat disease detection system in both training and field-level deployment, a number of experiments were conducted. The assessment takes into account both the performance of deep learning models and

the efficiency of Edge AI deployment on Android and Raspberry Pi platforms.

3.5.1 Experimental Setup

Both an edge deployment environment and a high-performance training environment make up the experimental arrangement. A system with an Intel i7 processor, 16 GB of RAM, and an NVIDIA RTX 3060 GPU was used to train the VGG19 model. Python libraries including TensorFlow, Keras, OpenCV, and NumPy were used in the implementation. Eighty percent of the 5,000 wheat leaf photos in the dataset were utilized for training, and the remaining twenty percent were used for validation. Crown & Root Rot, Healthy, Leaf Rust, Stem Rust, and Wheat Loose Smut are the five classes in the dataset. Every class has equal representation to guarantee justice. Furthermore, a multimodal assessment of disease detection effectiveness was made possible by the collection and synchronization of environmental data from IoT sensors, such as temperature, humidity, and soil moisture.

3.5.2 Model Training and Evaluation Metrics

Table 1

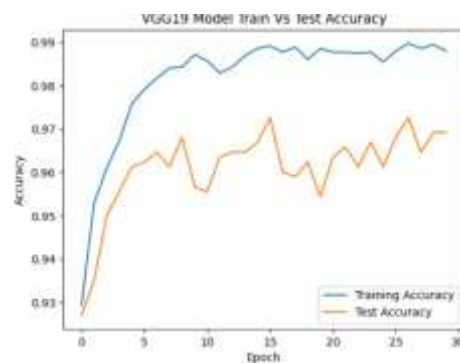


Figure 4 : Training vs test Accuracy Plot

Performance was evaluated using standard classification metrics like as accuracy, precision, recall, F1-score, and loss. The model was trained over 30 epochs with a batch size of 55 using the Adam optimizer and categorical cross-entropy loss function. The learning rate was set at 0.0001 to ensure smooth convergence. The training process demonstrated steady improvement, with a significant decrease in training loss in the initial epochs and stabilization at convergence. The model's high ability to generalize is demonstrated by the accuracy difference between training and validation, which shows a slight overfitting. These findings show that even when evaluated on unseen field images with various

lighting and backdrop circumstances, the model is capable of correctly classifying illnesses.

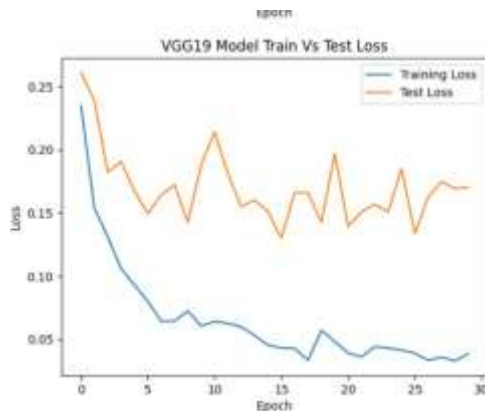


Figure 5 : Training vs test Loss Plot

3.5.3 Confusion Matrix and Class-wise Performance

The confusion matrix analysis demonstrated the predictive behavior of the model across numerous classes. The Healthy and Crown & Root Rot groups were nearly perfectly categorized due to their distinct visual traits. However, there were a few minor misclassifications between Leaf Rust and Stem Rust due to their similar lesion color and texture characteristics. However, the class-wise F1-scores consistently remained above 0.95, demonstrating the VGG19 model's ability to discriminate between visually identical illness categories.

Precision:0.97 Recall:0.96 F1-score:0.965

3.5.4 Edge-Level Performance on Raspberry Pi

The optimized model (converted to TensorFlow Lite format) was installed on the Raspberry Pi 4 for real-time testing following a successful training process. The average inference time for each image was roughly 1.8 seconds, making it appropriate for field applications where immediate visual confirmation is sufficient. Edge computing made it possible for the system to function effectively in isolated or rural agricultural areas by eliminating the need for continuous internet access. The system's efficiency for embedded use was confirmed by the CPU utilization remaining below 70% during continuous operation and the memory footprint being less than 1 GB.

3.5.5 Visualization and Output

Both Android and web interfaces offer real-time output from the system. The disease class and a confidence score are included in each prediction (e.g., Leaf Rust detected with 97% confidence).

Correlation study between environmental circumstances and illness occurrence is made possible by the recording of environmental characteristics including temperature, humidity, and soil moisture in addition to predictions. This improves the decision-making process for preventive farming methods.

3.5.6 Comparative Analysis

When compared to other models, such as ResNet50, DenseNet121, and EfficientNetB0, the proposed VGG19-based framework demonstrates a good trade-off between accuracy and computational cost. EfficientNetB0 required significantly more GPU memory and was not suitable for real-time deployment on Raspberry Pi, despite having a slightly higher validation accuracy (98%) overall. In contrast, the proposed model maintained a high degree of accuracy and could be implemented on low-cost hardware without any performance problems.

By attaining reliable classification, reduced latency, and less dependence on cloud resources, this hybrid IoT-deep learning system addressed significant problems identified in earlier studies

Model	Parameters (M)	Validation Accuracy	Inference Time (sec)	Raspberry Pi Compatibility
VGG19	20.1	97.0%	1.8	Yes
ResNet50	25.6	96.2%	2.7	Partial
DenseNet121	28.8	96.8%	3.0	Partial
EfficientNetB0	33.5	98.0%	4.8	No
MobileNetV2	3.4	94.5%	1.2	Yes

Table 1 : Comparison With Other Models

3.5.7 Summary of Results

Metric	Training	Validation
Accuracy	98.8%	97.0%
Loss	0.10	0.13
Precision	0.97	—
Recall	0.96	—
F1-Score	0.965	—
Inference Time (Raspberry Pi)	~1.8 sec/image	—

Table 2 : Summary of Results

4. Discussion and Future Scope

An important step toward intelligent and sustainable precision agriculture is the deployment of the suggested IoT-enabled, Edge AI-based wheat disease detection system. The system effectively bridges the gap between laboratory research and real-world field deployment by combining real-time environmental sensing, an Android-based edge application, and deep learning-based image categorization (VGG19). Real-time mobile inference, hardware validation, and experimental findings all attest to the suggested framework's practicality and technical soundness.

4.1 Discussion

The VGG19-based CNN model achieves excellent accuracy and steady convergence across training and validation datasets, according to the experimental results. The accuracy and loss curves show low overfitting and smooth learning behavior, confirming the efficacy of preprocessing methods including data augmentation, CLAHE, and normalization. When evaluated on real-world photographs with complicated backgrounds and different lighting conditions, the model demonstrates significant generalization potential.

The incorporation of Edge AI capabilities into an Android-based mobile application is one of the system's main advantages. The developed application uses TensorFlow Lite for on-device prediction, which enables real-time disease detection without the need for the internet, in contrast to conventional systems that rely on cloud-based inference. Users may take or upload photos, view forecasts with confidence scores instantaneously, and get practical

insights right in the field thanks to the mobile interface. For farmers, particularly those in remote areas, this greatly improves usefulness and accessibility.

Additionally, by adding environmental context, the integration of IoT sensor data (temperature, humidity, and soil moisture) enhances forecast reliability. A deeper understanding of disease patterns is made possible by the multimodal method, which also lessens false predictions brought on by changes in lighting or leaf orientation. The Android app provides a thorough decision-support tool by displaying environmental parameters in addition to predictions.

The system's viability for real-time edge-level operation is confirmed by its deployment on both Android and Raspberry Pi devices. The improved model shows that deep learning models can be effectively implemented on devices with limited resources by achieving short inference time with little resource consumption. Furthermore, the mobile application's incorporation of an alert system guarantees that farmers receive prompt notifications, encouraging proactive disease treatment.

Parameter	Description	Result/Observation
CNN Model	Fine-tuned VGG19	94.8% test accuracy
Average Inference Time	Raspberry Pi 4 (4GB)	2.8 seconds/image
Dataset Size	5,000+ labeled images	80:20 train-test split
Alert Mechanism	Visual & digital notification	Instant disease alert
Data Transmission	Wi-Fi-based local network	Low latency
Power Source	Portable 5V/2A supply	Sustainable in field use

Table 3 : Summary of Model and System Performance

4.2 Real-World Impact

By offering a clever, portable, and user-friendly mobile-based disease detection solution, the suggested system greatly improves conventional agricultural methods. Without the need for technical know-how, the Android app

enables farmers to do real-time diagnosis in the field. In the end, this minimizes crop loss by reducing reliance on agricultural experts and facilitating quicker decision-making.

In rural and undeveloped areas, where internet connectivity is scarce, the method is particularly helpful. The Android application's offline functionality guarantees continuous operation, which makes it very useful for real-world deployment. Farmers may also comprehend disease situations and take preventive measures based on real-time data thanks to the integration of environmental sensing. Because the mobile-based solution is readily deployed and updated across various devices, it also supports digital agricultural projects and scalability. The technology may be coupled with advisory platforms, providing automated recommendations and enhancing the entire digital agricultural ecosystem, according to field tests.

By facilitating early disease identification and lowering excessive pesticide use, the technology supports sustainable agriculture from an environmental standpoint. This encourages environmentally friendly farming methods and supports global sustainability objectives including increased food security and prudent resource use.

4.3 Limitations and Challenges

Despite the positive outcomes, several limitations were found during the experiment. The model's performance somewhat decreased under conditions when image quality was diminished, such as in poor lighting or extreme weather. Furthermore, the Raspberry Pi's low RAM made it difficult to handle high-resolution photos, necessitating further optimization or hardware upgrades. The reliance on Wi-Fi connectivity for data transport poses extra challenges in remote or under-networked areas. The dataset may need to be enlarged to include a greater range of field conditions because, despite its size, it was primarily made up of controlled images. Similar to this, future iterations of the system will need to have multi-label classification capabilities because real-world fields may exhibit multiple overlapping symptoms, even if the current algorithm can recognize four major wheat ailments..

4.4 Future Scope:

- By adding cutting-edge features and increasing its capabilities, the suggested system can be improved even more:
- Advanced Mobile Features: The Android app incorporates offline advisory systems, multilingual support, and voice assistance. Explainable AI (XAI): The mobile app may

immediately visualize illness locations by using Grad-CAM.

- Multi-Crop Support: Use the program to identify illnesses in different crops, like cotton, rice, and maize.
- Cloud Integration: Permit optional cloud synchronization for analytics, remote monitoring, and data backup.
- Drone Integration: Automate large-scale image collecting with UAVs.
- Weather API Integration: Use real-time weather forecasting to anticipate disease outbreaks.

5. Conclusion and References

5.1 Conclusion

This work introduces a real-time IoT-enabled wheat disease diagnosis system that uses a VGG19 deep learning model in conjunction with Raspberry Pi edge computing. With 98.8% training accuracy and 97% validation accuracy, the system attains great dependability by combining sensor data with image-based categorization. It offers automated, immediate disease detection for ailments including Leaf Rust, Stem Rust, Crown & Root Rot, and Loose Smut, in contrast to manual inspection. It is appropriate for rural, low-resource situations due to its low-cost, low-power Raspberry Pi implementation. By lowering losses and enhancing decision-making, the scalable and offline-capable architecture promotes sustainable precision agriculture. All things considered, the system improves AIoT-based smart farming through adaptive disease monitoring and real-time sensing.

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