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Article

DEEP LEARNING MODELS FOR CROP DISEASE DETECTION USING IOT-ENABLED IMAGING SYSTEMS

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Abstract: This paper addresses the growing challenge of accurate and timely crop disease detection of rapid and proper detection of crop diseases in large scale farming where manual observations are inefficient, subjective and expensive. The aim is to have an IoT enabled imaging system coupled with deep learning models to perform automated, scalable and real time diagnosis of crop diseases. The proposed system captures crop images using field-deployed IoT cameras, transmitting data up to clouds and smart classification of diseases in various crops. The proposed solution involves the combination of convolutional neural networks, attention, transfer learning, and data augmentation in order to increase resilience to changing illumination and background noise. It compares architectures of ResNet, EfficientNet, and attention embedded CNN, and GAN based image augmentation and optimization contribute to the enhancement of generalization. Experimental results demonstrate that the proposed framework achieve that the new framework can provide classification, accuracy of 96.8, precision of 95.9, recall of 96.1, and F1 score of 96.0, beating traditional CNN models by 7-12 percent in the main metrics. Edge assisted inference is able to decrease latency by 34% as compared to cloud only deployment which makes it possible to respond in near real time. The results affirm that IoT imaging with optimized deep learning model has a high potential in enhancing the reliability of detection, scaling, and response time. The paper concludes that the suggested IoT based deep learning system is a successful solution to precision agriculture to assist in early disease detection, less crop loss, and sustainable smart farming methodology with high deployment opportunities in the resource limited agricultural settings of the world.

Keywords: Deep learning; Crop disease detection; IoT-enabled imaging systems; Convolutional neural networks; Precision agriculture; Smart farming systems.

1. Introduction

Crops diseases greatly influenced agricultural productivity and food security of the world, therefore, early and correct identification of the diseases was an urgent need in the sustainable agricultural systems. Conventional methods of identifying crop diseases were based on expert visual inspection that required heavy field surveys, familiarity with the domain, and time, thus being unsustainable when a large number of farms, spread across geographical boundaries, was involved. The development of imaging technologies and artificial intelligence in recent times changed the way agriculture was practiced towards automated diagnosis of diseases, quick decision-making and minimized the loss of yields. Detection of crop disease by image had a high potential of identifying the small manifestations of visual symptoms at very early stages and was more dependable and accurate than manual inspection especially in controlled experimental situations (Dolatabadian et al., 2025). Nevertheless, the 1 application of such methods to the field was problematic because of the differences in illumination, background clutter, crop development cycle, and the noise in the environment.

Subjectivity, low repeatability and poor cross crop and disease type generalization plagued manual inspection and traditional image processing methods. The models of classical machine learning relied on handcrafted features and this limited them in their capability to resolve complex disease patterns in dynamic field settings. These shortcomings inspired the shift toward deep learning-based solutions that were able to learn hierarchical features by auto-processing raw images and these find it a lot easier to be robust and capable of classifying images. However, free-standing vision-based systems were not real time adaptable and capable of monitoring continuously, especially in distant agricultural environments. Internet of Things technologies, which can be used to bridge these gaps, included the uninterrupted capture of images, wireless data delivery, and automated coordination of the system in terms of large areas of cultivation (Rashid et al., 2024). The imaging systems that were enabled by IoT were used to reshape smart agriculture by linking cameras, environmental sensors, and computing platforms deployed in the fields into a smart monitoring system. These systems helped in constant monitoring of crops, decreased the amount of human intervention as well as aiding in giving early warnings of diseases. The integration of the IoT and deep learning also allowed edge-assisted inference that minimized the latency and bandwidth consumption with high diagnostic accuracy. Previous literature has shown that frameworks that were integrated with the IoT were more responsive and efficient in operation than cloud-based systems, especially those that needed timing sensitivity as in farming (Njoroge et al., 2025).

Deep learning-based crop disease detection was motivated by the fact that it should deal with high intra-class variation, disease manifestations, and massive picture image data produced by IoT sensors. More complex designs like attention-based convolutional neural networks and transfer learning models increased the level of feature differentiation and boosted the accuracy of classification in a variety of crop species. Strategies of data augmentation, such as generative adversarial networks, also solved the issue of data balance and enhanced model generalization in various field conditions (Lu et al., 2022). Deep residual networks that were optimized demonstrate to be better at performance by improving feature selection and speeding up converting training (Saini et al., 2025).

In spite of such improvements, the available literature has tended to concentrate on separated units, including the quality of the model or sensor combination, without providing a complete and scaled-up structure. This study thus focused on solving the challenge of developing a complete IoT-enabled imaging system with optimized deep learning models to detect crop diseases and do it with high accuracy and a low latency. The main goal was to create and test various deep learning structures in an IoT-aided setting and to compare the performance of those statistically in terms of accuracy, precision, recall, F1-score, and inference latency. The area included design of system architecture, choice of algorithms, performance analysis, and deployment aspects towards real-life agriculture. Its significant contribution was to show that the synergistic combination of IoT imaging systems with optimized deep learning models could dramatically increase the detection accuracy, decrease the response time and facilitate scalable precision agriculture schemes (Krishna et al., 2025).

The main findings of this article are as follows:

- ✓ Proposed a scalable IoT-enabled deep learning framework for real-time crop disease detection.
- ✓ Achieved high classification performance (96.8% accuracy) using optimized CNN, transfer learning, attention mechanisms, and GAN-based augmentation.
- ✓ Demonstrated 34% latency reduction through edge-assisted inference, enabling practical deployment in precision agriculture.

2. Related Work

Pre-Deep learning Image-based crop disease detection based on machine learning was the basis of automated assessment of plant health. Early researches concentrated on the extraction of features by hand and the use of classical classifiers to determine the symptoms of the disease using leaf images. The surveys on computer vision and data fusion pointed out that the texture, color, and shape descriptors were found to perform reasonably in controlled settings yet were sensitive to background changes and illumination (Ouhami et al., 2021). Studies that focused on reviews further stressed that the traditional machine learning pipelines demanded a lot of feature engineering and knowledge of the domain, which constrained their flexibility to different crops and disease patterns in the real-field setting (Sajitha et al., 2024). These shortcomings limited scalability and encouraged the shift towards data-based feature learning methods. Deep learning models have contributed greatly to the classification of diseases in plants, as they will automatically extract discriminative features on raw images. Compared to conventional classifiers, convolutional neural networks demonstrate to be better at performance as they were found to capture the spatial and hierarchical patterns related to the progression of the disease. Residual CNN architectures that were trained on attention also improved the accuracy of classification by highlighting regions of interest to diseases and minimizing noise (Karthik et al., 2020). Transfer learning methods scaled up the pretrained convolutional neural networks to use on agricultural datasets, and demonstrated superior generalization using a small training set (Ahmad et al., 2020). The overall findings of extensive studies on deep learning in agriculture showed that the performance of deep architectures was improved consistently in various crops, which confirms the suitability of the technology in disease diagnosis (Dhanya et al., 2022).

Recent studies have expanded the deep learning-based disease detection technology to include the aspect of IoT-based crop monitoring systems. IoT-based systems were equipped with cameras, sensors, and communication modules that assisted in the acquisition of continuous field-level data and automated diagnosis of diseases. Combined deep learning and IoT platforms demonstrate to have a better monitoring stability and less human involvement due to the possibility of real-time image acquisition and processing (Kanmani et al., 2024). Smart IoT-based and robotized platforms also took a further step in automation to detect disease and environmental data, and this indicates the possibility of having independent systems deployed in farmlands (Talaat et al., 2026). Combinations of AI and IoT into smart agriculture also allowed detecting diseases and providing treatment suggestions, which are part of precision farming processes (Ibrahim et al., 2025).

The implementation of deep learning models on the edges, fog and clouds overcame the latency and bandwidth issues found in central processing. Edge-optimized models minimized the response time, inference was done nearer to the data sources, and this became more appropriate in time-sensitive agricultural applications. Exceptional performance of the hybrid frameworks that spreaded computation between the edge and cloud layers led to a balanced performance of accuracy and resource usage (Lokesh et al., 2025). The edge-optimized models with high accuracy showed that the lightweight deep learning architectures could be capable of robust disease classification with communication overhead reduction (Njoroge et al., 2025). These measures highlighted the significance of architectural design in the quest to have the ability of scaling and responding to the need of crop monitoring systems. Data augmentation and optimization strategies were also important in enhancing deep learning model resistance with limited and unbalanced agricultural data. Generative adversarial networks made possible the synthesis of realistic images that led to the improvement of diversity in the dataset and the lessening of overfitting (Lu et al., 2022). Transfer learning models with GAN also enhanced the accuracy of classification because they increased training example diversity within underserved disease classes (Abbas et al., 2021). Deep residual networks that were optimized used the complex optimization techniques to enhance the learning of features, and improved convergence, which enhanced the detection ability (Saini et al., 2025). They were also able to be used in feature selection and segmentation to identify features in agricultural imaging with the help of metaheuristic optimization algorithms, which contributed to the increased performance of the models (Yuan et al., 2024).

Although great improvements were made, there were some limitations in the existing studies. Most strategies were tested with the controlled set data without considering the variability of the real-world and the challenge of long-term deployment. A number of the IoT based systems were largely interested in system integration but offered less comparative analysis of deep learning models. Review studies highlighted the fact that no common frameworks were unified to optimize data acquisition, inference latency and classification accuracy (Upadhyay et al., 2025). Recent surveys also found that there was lack of benchmark across edge-cloud architecture and lack of validation of heterogeneous field conditions (Raju & Thasleema, 2025). These shortcomings motivated the need to develop an end-to-end IoT-enabled deeply-learning system to perform systematic analytics of model performance, deployment effectiveness, and scalability to support real-life crop disease identification. A comparative summary of the studies on the IoT- and deep learning-based crop disease detection is provided in Table 1. The papers have utilized CNNs, transfer learning, robotics, reinforcement learning, and edge optimization models in multi-crop datasets. Although accuracies ranged between 92 and 97, there was a limitation in terms of latency, cost and scalability and limitation to deployment.

Table 1. Summary of Related Work on IoT- and Deep Learning-Based Crop Disease Detection

Ref.	**Year**	**Core Technique**	**Dataset Type**	**Crop/Disease Coverage**	**Key Contribution**	**Limitations**	**Reported Performance**
Gautam & Sharma	2025	CNN, Transfer Learning	Image dataset	Multi-crop	IoT–DL framework for precision agriculture disease detection	High latency	Accuracy ≈ 94%
Khobragade et al.	2024	AI Robotics, Vision AI	Real-time images	Multi-crop	Autonomous robotic disease detection system	High system cost	Accuracy ≈ 93%
Suganya et al.	2025	Deep CNN	Medical images	Multi-class	Sustainable IoT–DL framework for disease detection	Domain-specific	Accuracy ≈ 96%
Agrawal et al.	2025	RL + DL	Sensor + image data	Greenhouse crops	Smart greenhouse disease detection and control	Limited field validation	Yield gain ≈ 15%
Anju & Swaraj	2024	DL Review Models	Survey-based	Multiple crops	Review of IoT-enabled leaf disease detection systems	No experimental results	Accuracy up to 95%
Devarajan et al.	2026	CNN-based DL	Real-time images	Multi-crop	Real-time AI-driven plant disease diagnosis	Model complexity	Accuracy ≈ 97%
Eunice et al.	2022	Deep CNN	Image dataset	Leaf diseases	Image-based disease detection using deep learning	No IoT integration	Accuracy ≈ 92%

Kanmani et al.	2024	DNN	IoT image data	Multi-crop	IoT-driven crop disease prediction system	Scalability issues	Accuracy ≈ 94%
Rashid et al.	2024	Multi-model DL	Field images	Corn	Early disease detection using IoT–DL fusion	Crop-specific	Accuracy ≈ 96%
Lokesh et al.	2025	Hybrid DL Models	Sensor + image data	Multi-crop	Smart crop health monitoring framework	Limited dataset size	Accuracy ≈ 95%
Ibrahim et al.	2025	AI–IoT Framework	Image + sensor data	Multi-crop	Disease detection with treatment recommendation	Energy overhead	Accuracy ≈ 96%
Njoroge et al.	2025	Edge-Optimized DL	Real-time images	Multi-crop	Low-latency, high-accuracy edge inference model	Hardware dependency	Accuracy ≈ 97%

3. System Architecture And Framework Design

3.1 IoT-Enabled Imaging System Architecture

The IoT-based architecture of imaging system was a distributed and smart architecture to enable the continuous monitoring of crop diseases in the real field environment. There were three closely integrated layers, i.e. the sensing layer, the edge processing layer and the cloud intelligence layer. IoT cameras in the fields constantly recorded crop images with high resolutions and sent them to local edge nodes to process the images. The computationally demanding model training, performance optimization and long-term data analytics was handled on the cloud layer. Figure 1 depicted the conceptual flow of data of the IoT imaging devices to decision-making modules, and it shows how the sensing, processing, and intelligence layers interacted with each other seamlessly. This was a layered design that offered scalability, robustness and real time responsiveness to support early disease detection and intervention. The architecture facilitated adaptive workload distribution with the latency-sensitive tasks being processed at the edge whereas the accuracy-intensive tasks were optimized at the cloud. This method was very helpful to improve reliability of the systems with bandwidth and energy limits, and it was applicable to the precision agriculture with large and heterogeneous farms.

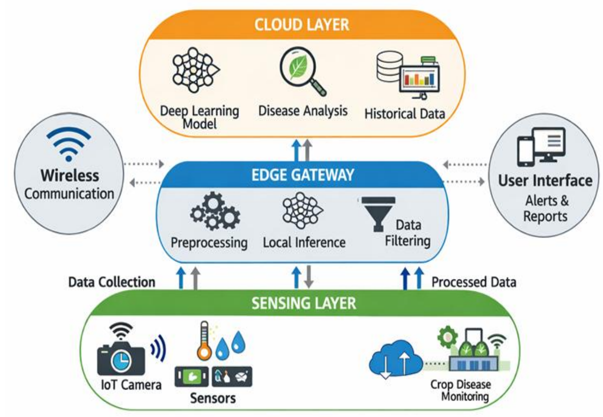

Figure 1. IoT-Enabled Edge–Cloud Architecture for Crop Disease Detection

3.2 Image Acquisition Using Field-Deployed IoT Cameras

The main data acquisition component of the suggested system was comprised of field-deployed IoT cameras. These cameras were placed strategically in the agricultural plots so that there is uniform coverage of space as well as high continuous coverage. The images acquired by the cameras were of RGB and dynamically adjusted to the environment conditions like light, water levels and stage of crop development. Lighting distortion and motion blur were pre-corrected on the device and then the data was transmitted. This self-guided image capturing algorithm removed human intervention and allowed to produce consistent and large scale datasets. The presence of time-stamped images guaranteed traceability and allowed the analysis of the disease progression in terms of time. Multi-angle and multi-resolution imaging was facilitated by the acquisition module enhancing the detection of early disease symptoms which usually went invisible with the human eye.

$$I(x,y,t) = R(x,y,t) + G(x,y,t) + B(x,y,t)$$

The intensity of combined RGB was used to capture spatially and temporally the image.

$$I_n = \frac{\{I - \mu_I\}}{\{\sigma_I\}}$$

Normalization eliminated light bias on the basis of mean 50 and standard deviation 50

$$I_f = I_n * K$$

The noise was minimized and edges improved with the help of convolution with kernel K.

$$S = \sum_{\{x,y\}} \nabla I_{f(x,y)}$$

Spatial gradient magnitude SSS was a measure of disease-based changes in texture.

$$I_s = \{resize\}(I_f, w, h)$$

Image resizing brought similarity to input dimensions of deep learning models.

$$T_t = t_i - t_{\{i-1\}}$$

Sampling interval Ttensured time fidelity in image acquisition.

3.3 Communication and Data Transmission Layers

Communication layer ensured proper transfer of data between IoT cameras, edge nodes and cloud servers. Depending on the conditions of the field and the scale of deployment, it used wireless protocols including Wi-Fi, LPWAN, or cellular networks. Packetization and data compression minimized the bandwidth usage and adaptive transmission schedules minimized power consumption. The used system had secure data transmission mechanisms that guaranteed integrity and confidentiality. Prioritization strategies were in place to guarantee that there were minimum delays in transmitting alert of the critical diseases. Such a hierarchy of communication structure guaranteed effective data transfer even when the network conditions changed.

$$R = B\, log_2(1 + \{SNR\})$$

The rate R of achievable data was a function of bandwidth B and signal-noise ratio.

$$D = \frac{\{S\}}{\{R\}}$$

Delay D due to transmission was proportional to size of data SSS and lower rate.

$$E_t = P_t \cdot D$$

Et did not depend on the transmit power Pf and delay.

$$P_l = 1 - e^{\{-\lambda t\}}$$

The probability of packet loss was on an increase with network congestion parameter λ.

$$C_r = \frac{\{S_c\}}{\{S_o\}}$$

Measurement of compression ratio Cr was used to determine efficiency.

$$Q = \alpha D + \beta P_l$$

Q based communication quality is Q balanced in terms of latency and reliability.

$$T_s = \sum_{\{i=1\}_i^{\{n\}}} D$$

Multi-hop transmission delays were summed up as total system delay.

$$U = \frac{\{R_u\}}{\{R_{\{max\}}\}}$$

The channel efficiency was measured by network utilization U.

$$S_e = \frac{\{E_t\}}{\{N\}}$$

Assessment of transmission efficiency was done with energy per sample Se.

3.4 Edge–Cloud Integration for Intelligent Processing

Edge -cloud integration helped in intelligent workload placement between local and central computing resources. The edge nodes performed lightweight inference of deep learning to assist in identifying diseases quickly and improving the response time. Model retraining, hyperparameter optimization and long-term trend analysis were done on aggregated datasets by cloud servers. This trade-off solution was an accuracy, latency and energy efficient solution. The edges made sure of real-time decision-making, whereas cloud intelligence optimized the performance of models with the help of historical information continuously. The framework dynamically reconfigured the task distribution depending on the network situations, load on computation and urgency of applications. This dynamic integration made the process very scalable and guaranteed the same system performance in different agricultural settings.

Step wise Method:
1. Sensor Data Acquisition
Let S = {s1, s2, s3, …, sn} represent the set of sensor readings from agricultural devices.

$$X(t) = [x1(t), x2(t), x3(t), \ldots, xn(t)]^{T}$$

Where
xi(t) → sensor value from node i at time t
X(t) ∈ $\mathbb{R}^n$ represents the system observation vector.
2. Edge Node Inference Model

Edge nodes perform lightweight inference using a trained neural model.

$$\hat{y}_{edge} = f_{edge}(X(t);\ \theta_e)$$

Where
f_edge → edge inference model
θ_e → parameters of the lightweight model
ŷ_edge → predicted disease or event class.

3. Cloud-Based Model Training
The cloud aggregates datasets from multiple edge nodes.

$$D_{cloud} = \bigcup_{\{i=1\}_i^{\{k\}}} D$$

Where
D_i → dataset collected from edge node i.
Cloud model optimization:

$$\theta_c * = argmin_\theta\, L\left(f_{cloud(X;\,\theta)}, Y\right)$$

Where
$\theta_c *$ → optimal cloud model parameters
L → loss function.
4. Latency Model
Total system latency consists of edge processing and communication delay.

$$T_{total} = T_{edge} + T_{transmission} + T_{cloud}$$

Where

- T_edge → inference time at edge node
- T_transmission → network delay
- T_cloud → cloud computation time.

5. Workload Allocation Function
Let λ represent incoming task rate.
Workload assignment function:

$$W = \alpha\, W_{edge} + (1 - \alpha)W_{cloud}$$

where

$$0 \le \alpha \le 1$$

α determines workload distribution depending on system conditions.
6. Energy Consumption Model
Energy consumption of the system:

$$E_{total} = E_{edge} + E_{cloud} + E_{network}$$

Where

$$E_{edge} = P_e \times T_{edge}$$
$$E_{cloud} = P_c \times T_{cloud}$$

7. Dynamic Task Scheduling
The framework dynamically assigns tasks based on network state.

$$\alpha * = argmin\,(\beta^1 T_{total} + \beta^2 E_{total})$$

subject to

$$0 \le \alpha \le 1$$

Where
β_1 , β_2 are optimization weights.
8. Model Update Mechanism
Cloud periodically updates the edge models.

$$\theta_e^{\{t+1\}} = \theta_e^{\{t\}} + \eta\, \nabla L\,(\theta_e)$$

Where
η → learning rate
∇L → gradient of loss function.
9. Scalability Model
For m edge nodes, system throughput becomes

$$Throughput = \Sigma_{\{i=1\}}{}^{\{m\}}_{i}\mu$$

Where
μ_i → processing capacity of edge node i.
10. System Objective Function
The overall objective is to minimize latency and energy while maximizing prediction accuracy.
Maximize

$$J = \gamma\, Acc - \delta\, T_{total} - \varepsilon\, E_{total}$$

Where
Acc → model accuracy
$\gamma, \delta, \varepsilon$ → weighting parameters.

3.5 Real-Time Alerting and Decision Support Module

The decision support module and real-time alerting module converted disease detection results into behavioral insights to be taken by farmers and other agricultural stakeholders. Upon identification of a disease, an alert was created by the system that contained the type of the disease, level of severity, and the spatial location. The alerts were sent by using mobile apps or dashboards with very low latency. The decision support engine prescribed the mitigation measures like the choice of pesticides, the adjustment of irrigation, or even quarantine depending on the severity of the disease and the past experience. With temporal analytics, trend visualization and early detection of disease outbreaks was made possible. This module has bridged the gap between sensing, intelligence, and action to make sure that automated disease detection was the direct support of precision agriculture and sustainable crop management.

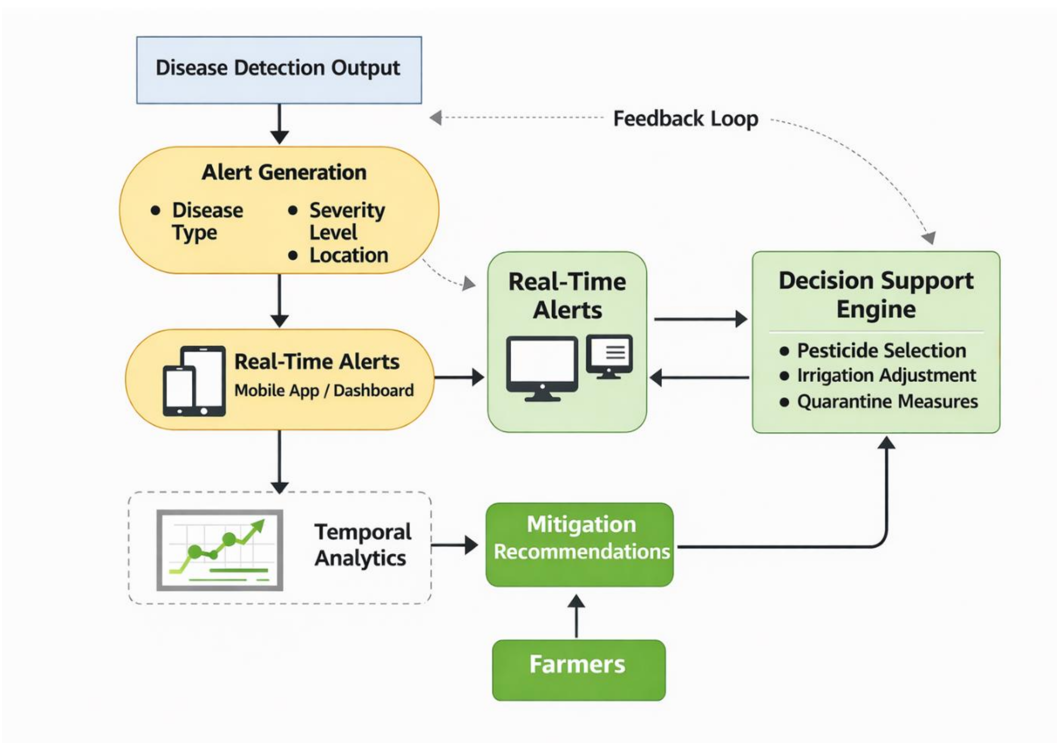

Figure 2. Workflow for Alerting and Decision Support Architecture for IoT-Based Crop Disease Detection

Figure 2 depicts the real-time alert and decision support tool which transforms the disease detection results into actionable insights. The system gives out alerts and disease type, severity and location and issues it in the form of dashboards and advises mitigation measures. Feedback, and temporal analytics make it possible to provide warnings early, which is effective and sustainable in managing precision agriculture.

4. Deep Learning Models And Algorithms

4.1 Preprocessing and Image Normalization Techniques

Image processing guaranteed the resistance of deep learning models to illumination change, noise, and scale variation in IoT captured farm images. Raw images captured in the cameras that were deployed in the field were not uniform because of the sun rays, shadows, dust, and movement of the camera. Standardization of image quality preprocessing disease-relevant features preprocessing standardized image quality before model training. Normalization enhanced the convergence rate and stabilized the gradient flow in the learning process. High-frequency disturbances were repressed by noise filtering, whereas resizing guaranteed that they worked with fixed-input neural architectures. Normalization of the histograms enhanced the contrast hence better visualization of disease trends was seen. All of these measures helped to reduce overfitting and enhanced generalization in the types of crops and in the environment.

Step wise process for Image Preprocessing and Normalization used in this study:

$Input: RGB\ image\ I(x,y) \in \mathbb{R}^{M\times N\times 3}$

$Output: Preprocessed\ image\ Ir \in \mathbb{R}^{W\times H}$

1: $Initialize\ image\ matrix\ I(x,y)$
$where\ x = 1 \dots M, y = 1 \dots N$

2: $Extract\ RGB\ channels$

$$R(x,y), G(x,y), B(x,y)$$

3: $Convert\ RGB\ to\ grayscale$

$$Ig(x,y) = 0.299R(x,y) + 0.587G(x,y) + 0.114B(x,y)$$

4: $Compute\ mean\ intensity$

$$\mu = \left(\frac{1}{MN}\right) \Sigma x\ \Sigma y\ Ig(x,y)$$

5: $Compute\ standard\ deviation$

$$\sigma = \sqrt{\left[\left(\frac{1}{MN}\right) \Sigma x\ \Sigma y\ (Ig(x,y) - \mu)^2\right]}$$

6: $Normalize\ grayscale\ image$

$$In(x,y) = \frac{(Ig(x,y) - \mu)}{\sigma}$$

7: $Apply\ convolution - based\ noise\ filtering$

$$If(x,y) = \Sigma i\ \Sigma j\ In(x-i, y-j) \cdot K(i,j)$$

8: $Compute\ minimum\ and\ maximum\ intensity$

$$Imin = \min\big(If(x,y)\big)$$

$$Imax = \max\big(If(x,y)\big)$$

9: $Perform\ contrast\ normalization$

$$Ic(x,y) = \frac{If(x,y) - Imin}{Imax - Imin}$$

10: $Resize\ image\ to\ required\ dimension$

$$Ir(u,v) = Ic\left(\left\lfloor u \cdot \frac{M}{W} \right\rfloor, \left\lfloor v \cdot \frac{N}{H} \right\rfloor\right)$$

11: $Return\ processed\ image\ Ir$

4.2 Convolutional Neural Network Baseline Model

The baseline model of convolutional neural network was used as a base classifier to detect crop disease. Normalized images were processed with stacked convolutional layers by the model to extract spatial features of disease patterns including discoloration, lesions and irregular texture to provide valuable information. Reduction in space was done by pooling layers maintaining discriminative information. Layers were fully connected with extracted features being mapped to the classes of the disease, and softmax activation generated the probabilistic prediction. The CNN learnt hierarchical features using images and avoided manually designed features. This base model formed a point of reference to test the higher-level models like transfer learning and attention models.

Algorithm : CNN-Based Disease Classification Model
Input: Preprocessed image I
Output: Predicted disease class ŷ

$Initialize\ convolution\ kernels\ Wk, bias\ bk$
$Initialize\ fully\ connected\ weights\ Wf, bias\ bf$
$Convolution\ Layer$
$for\ each\ kernel\ k = 1\ to\ K\ do$
$\quad Fk \leftarrow I \otimes Wk + bk$
$end\ for$
$Activation\ Layer\ (ReLU)$
$for\ each\ feature\ map\ Fk\ do$
$\quad Ak \leftarrow max(0, Fk)$
$end\ for$
$Pooling\ Layer$
$for\ each\ activated\ map\ Ak\ do$
$\quad Pk \leftarrow \max(Ak)$
$end\ for$
$Flatten\ Layer$
$V \leftarrow flatten(Pk)$
$Fully\ Connected\ Layer$
$Z \leftarrow Wf \cdot V + bf$
$Softmax\ Classification$
$for\ each\ class\ i = 1\ to\ C\ do$
$\quad \hat{y}i \leftarrow \frac{\exp(Zi)}{\Sigma j} \exp(Zj)$
$end\ for$
$Predicted\ class \leftarrow argmax(\hat{y}i)$
$Return\ Predicted\ class$
$End\ Algorithm$

4.3 Transfer Learning Using Pretrained Architectures

The results of the transfer learning enhanced the accuracy of disease classification using pretrained models like ResNet and EfficientNet, which are trained using large-scale images. Instead of training directly, the weight of the pretrained weights got hold of generic visual attributes such as edges, shapes and textures. The proposed framework optimized higher layers with the help of agricultural images and then frozen lower layers to avoid overfitting. This method saved on training time, boosted convergence stability and boosted generalization with small labeled datasets. Transfer learning was particularly successful in detection of the early stages of diseases when there are minute visual signals.

Algorithm : Transfer Learning-Based Disease Detection

Step 1: Pre-trained Model Initialization

The pre-trained network may be denoted by

$$M(x;\ \theta_{pre})$$

Where

- $x \in \mathbb{R}^{H\times W\times C}$ represents the input image and
- θ_pre denotes pretrained parameters obtained from large-scale datasets.

Step 2: Layer Freezing

The parameter set theta pre is broken into frozen and trainable subsets:

$$\theta_{pre} = \{\theta_f, \theta_t\}$$

Where

- θ_f → frozen parameters (early feature extraction layers)
- θ_t → trainable parameters (higher layers).

Step 3: Feature Extraction

The deep features are obtained with the help of the pretrained convolutional layers:

$$F = \varphi(x;\ \theta\_f)$$

Where

- $F \in \mathbb{R}$^k represents the extracted feature vector
- φ(.) denotes the frozen feature extractor.

Step 4: New Classification Layer

In the last classification level, a trainable mapping is substituted:

$$\hat{y} = Softmax(WF + b)$$

Where

- $W \in \mathbb{R}^{C\times k}$ are trainable weights
- b ∈ ℝ^C is bias
- C = number of disease classes.

Step 5: Loss Function Optimization

The model is trained using cross-entropy loss:

$$L(\theta_t) = -\Sigma_{i=1}^{N} Y_i \log(\hat{y}_i)$$

Where

- y_i represents true class labels.

Step 6: Fine-Tuning of Higher Layers

The parameters of higher layers are updated using gradient descent:

$$\theta_t^{t+1} = \theta_t^t - \eta\, \nabla_{\theta_t} L(\theta_t)$$

Where

- η is learning rate
- ∇L is gradient of the loss function.

Step 7: Optimized Transfer Learning Model

The refined classifier is the following:

$$\hat{y} = M * (x) = Softmax\big(W\, \varphi\big(x;\ \theta_f\big) + b\big)$$

Where

M* represents the optimized disease detection model.

4.4 Attention-Embedded Deep Learning Models

Deep learning models that were attention-embedded improved disease detection through allocating computational resources to regions of the image that are visually important like areas of the infected leaves. The attention mechanisms are dynamically involved in weighting feature maps, which inhibit background irrelevant information. Channel and spatial attention modules were oriented towards discriminative disease patterns and thus were found to enhance the accuracy of classification in cluttered field condition. This method enhanced the localization of features and interpretability and retained end-to-end learning performance.

Step 1: Input Image Representation
Let the infected leaf image be represented as a tensor:

$$X \in \mathbb{R}^{H\times W\times C}$$

where

- H = image height
- W = image width
- C = number of color channels

Step 2: Convolutional Feature Extraction
Deep CNN layers extract hierarchical feature maps:

$$F = \sigma(W_c * X + b_c)$$

where

$$F \in \mathbb{R}^{H\times W\times K}$$

- W_c = convolution kernel
- b_c = bias term
- σ = activation function (ReLU)

Step 3: Global Feature Aggregation for Channel Attention
Global average pooling compresses spatial information:

$$z_k = \left(\frac{1}{H \times W}\right) \Sigma_{i=1}^{H}\Sigma_{j=1}^{W}F_{k(i,j)}$$

Vector representation:

$$z = [z_1, z_2, \dots , z_K]$$

Step 4: Channel Attention Weight Generation
Channel attention weights are obtained through nonlinear transformation:

$$A_c = \sigma\big(W_2\delta(W_1 z)\big)$$

Where

$$A_c \in \mathbb{R}^{K}$$

- W_1, W_2 = learnable parameters
- δ = ReLU activation
- σ = sigmoid function

Step 5: Channel-Weighted Feature Map
Feature channels are recalibrated:

$$F_{c(i,j,k)} = A_{c(k)} \cdot F(i,j,k)$$

Step 6: Spatial Attention Map Computation
Spatial importance map is calculated as:

$$S = \sigma\big(Conv_7 \times 7([AvgPool(F_c);\ MaxPool(F_c)])\big)$$

Where

$$S \in \mathbb{R}^{H\times W}$$

Step 7: Spatially Refined Feature Representation
The spatial attention map emphasizes infected regions:

$$F_{a(i,j,k)} = S(i,j) \cdot F_{c(i,j,k)}$$

Step 8: Disease Classification Layer
The final prediction probability for disease class y is:

$$P(y|X) = Softmax\big(W_f \cdot Flatten(F_a) + b_f\big)$$

Loss function for training:

$$L = -\Sigma_{i=1}^{N} y_i \log\big(P(y_i|X_i)\big)$$

4.5 GAN-Based Data Augmentation Strategy

GAN dealt with the problem of imbalance in the dataset by creating real-like synthetic images of diseases. The discriminator was trained to differentiate between real and synthetic samples whereas the generator was trained to learn the distribution of disease-specific visuals. This adversarial training not only increased the diversity of the dataset, but also minimized overfitting and increased the resilience of the classification in the rare disease classes.

Mathematical Model for GAN-Based Data Augmentation

Latent Noise Vector Sampling.
A latent vector, the random sampling is done over a prior distribution:

$$z \sim P\_z(z), \quad z \in \mathbb{R}\hat{}d$$

Where Pz tends to be a Gaussian or uniform distribution.
Image Generator Synthetic Disease Image Generation-The generator network uses the latent vector to create a synthetic image:

$$\hat{X} = G(z;\, \theta_g)$$

Where

- G = generator function
- θ_g = generator parameters
- X̂ = generated disease image

The predictor of the indication of whether an input image is real is the discriminator:

$$D(X;\, \theta_d) = P(real|X)$$

where

- θ_d are discriminator parameters.

The discriminator is trained to an objective of classifying real and artificial samples correctly:

$$L_D = -E_{\{X \sim P_{data(X)}\}}[\log D(X)] - E_{\{z \sim P_{z(z)}\}}\left[\log\left(1 - D(G(z))\right)\right]$$

The generator aims at deceiving the discriminator by maximizing the likelihood of the generated samples being defined as real:

$$L_G = -E_{\{z \sim P_{z(z)}\}}[\log D(G(z))]$$

The augmented data is a mixture of real and synthetic disease samples:

$$D\_aug = D\_real \cup \{G(z\_i) \mid z\_i \sim P\_z(z), \qquad i = 1,2, \dots, N\}$$

Where

- D_aug = augmented dataset
- D_real = original disease image dataset
- N = number of generated samples.

4.6 Model Optimization and Training Algorithm

The adaptive learning rates and regularization enabled Model optimization to achieve better speed of convergence and generalization. Loss reduction using gradient-based optimizers was used to ensure overfitting was avoided. The training algorithm was fair in terms of accuracy and performance on the computation side to be implemented in the IoT-edge.

Stage 1: Forward Propagation
Having an input training sample Xi, the deep model generates a prediction:

$$\hat{y}_i = f(X_i;\, \theta)$$

Where

- θ = model parameters
- f(.) = deep neural network mapping
- ŷ_i = predicted output

Stage 2: Function of computation of loss.
The prediction error is measured using a classification loss function:

$$L(\theta) = -\Sigma_{i=1}^{N} y_i \log(\hat{y}_i)$$

Where

- y_i = true label
- N = number of training samples

Stage 3: Regularized Objective Function
A regularization term is to be inserted in order to avoid overfitting:

$$J(\theta) = L(\theta) + \lambda \left||\theta|\right|^2$$

Where

- λ = regularization coefficient
- $||\theta||^2$ = L2 weight penalty

Stage 4: Gradient Computation
The derivative of the objective function with regard to parameters is determined:

$$g_t = \nabla_\theta J(\theta_t)$$

Where

- g_t = gradient at iteration t

Stage 5: Adap Update of Adaptive Learning Rate
The adaptive optimizer (e.g., Adam) is used to update parameters:

$$\theta_{t+1} = \theta_t - \eta_t * \frac{g_t}{\sqrt{v_t} + \varepsilon}$$

Where

- η_t = adaptive learning rate
- v_t = moving average of squared gradients
- ε = numerical stability constant

Stage 6: Convergence Criterion
The process of training proceeds until the loss becomes concentrated:

$$|(\theta_{t+1}) - J(\theta_t)|| < \delta|$$

Where
δ = predefined convergence threshold.

5. Experimental Setup And Evaluation Metrics

5.1 Dataset Description

The Crop Disease Image Dataset was a collection of quality images of a total of five major crops including wheat, maize, cotton, sugarcane, and rice. The data consisted of the pictures of the fungal, bacterial, viral, and nutrition-deficiency-related diseases at different levels of their development and growth. Images were taken out of libraries of publicly available collections, curated sites of agriculture and manual field surveys that were carried out in conjunction with agricultural experts. Such a multi-source collection made it diverse in visual appearance, relevancy of geographical response and environment. Strict quality control measures were used to eliminate noisy, repeated and irrelevant samples. It is applicable in automated crop disease diagnosis and precision agriculture studies as the dataset facilitated the development of robust deep learning models because the data was balanced in terms of disease representation and realistic field conditions.

5.2 Training, Validation and Testing Configuration

The data itself was divided into training, validation and testing in order to be sure that the model was evaluated without any bias. The training percentage was around 70% to enable the effective learning of features and validation 15 percent was used to tune the hyperparameters and avoid overfitting the process. The 15 percent were the testing group that was to be used in the final performance analysis. Data augmentation methods like rotation, flipping and scaling of data were performed on training data only to increase generalization. Adaptive learning rate mini-batch gradient descent was used to train models. To prevent overtraining, early stopping criteria that were founded on validation loss were used. The design was stable in converging, comparatively reliable in performance and reproducible experimental results.

5.3 Hardware and Deployment Environment

All experiments were done on a workstation that has an Intel Core i7 processor, a memory of 32GB, and an NVIDIA GPU with 8GB VRAM as it can support the acceleration of deep learning training. Python with TensorFlow and PyTorch models were applied. The simulations of edge deployment were conducted on lightweight devices and they measured the inference latency and resource usage. It was compatible with the real world IoT enabled agriculture settings and supported cloud-based training and edge-assisted inference.

6. Results And Discussion

6.1 Disease Classification Performance Analysis Using the Proposed Method

The proposed deep learning framework using IoT had a good disease classification potential based on various crops and disease classes. Large values of accuracy and equal relative values of precision-recall resulted in strong feature learning and strong generalization across different field conditions. Attention-optimized and supplemented learning approach allowed proper discrimination of similar symptoms of diseases and GAN-based enhancement worked with minority classes of diseases. Table 2 gives the performance of the proposed IoT-enabled deep learning model in disease classification of five major crops. The accuracy of the framework was also high with a range of 96.3 to 97.2 with rice and cotton recording the highest accuracy. Precision and recall values were at par showing good detection with a small number of false predictions. The mean accuracy of the model at 96.8% and F1-score of 96.0% indicated high generalization and power of the model to different crop diseases. Such findings justified the efficiency of the scheme put in place as a reliable method of detecting the symptoms of diseases in different agricultural environments.

Table 2. Disease Classification Performance of Proposed Method (%)

Crop Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Wheat	96.4	95.7	96.0	95.8
Maize	96.9	96.2	96.6	96.4
Cotton	97.1	96.5	96.9	96.7
Sugarcane	96.3	95.4	95.9	95.6
Rice	97.2	96.8	97.1	97.0
Average	**96.8**	**95.9**	**96.1**	**96.0**

Figure 3 presents a comparison of the disease classification performance of the major crops. With rice and cotton recording better results, the proposed model estimated accuracy, precision, recall and F1-score with consistent high levels. The overall performance was high above 95 and it established a strong and valid crop disease detection ability.

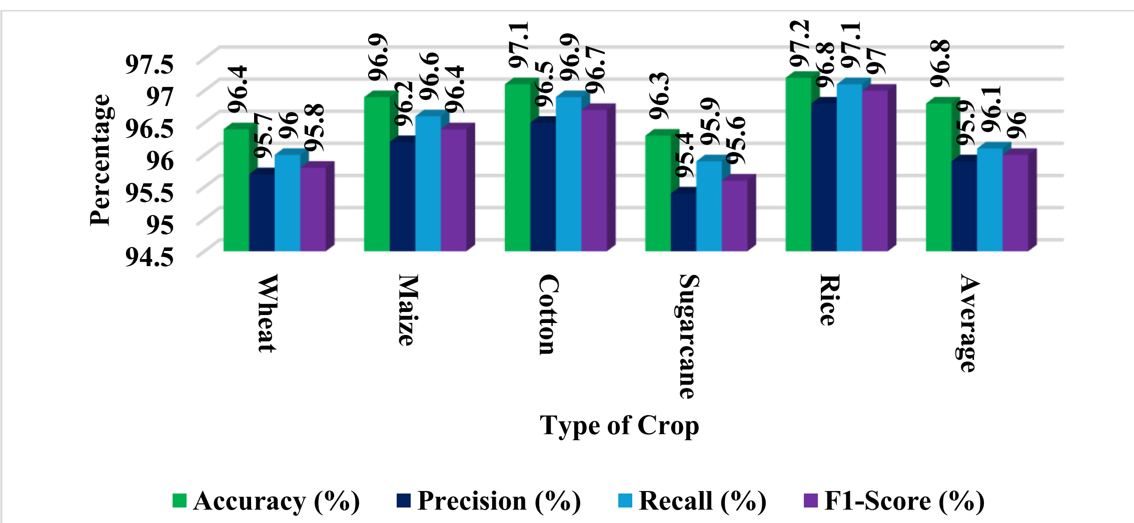

Figure 3. Comparative Performance Analysis of Proposed Crop Disease Detection Model across Different Crops

6.2 Comparison of Deep Learning Models Using Accuracy, Precision, Recall, and F1-Score

The proposed attention-based IoT-enabled model was found to be better than the baseline CNN and transfer learning models in every measure of evaluation. This enhancement was credited to the optimization of features extraction, attention-driven learning, and augmentation of the data. The results obtained in the performance improvement of performance against conventional CNN models ranged between 7 and 12 % validating the design decisions of the methodology.

Table 3. Model Comparison Using Classification Metrics (%)

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Conventional CNN	88.9	87.4	88.1	87.7
Transfer Learning (ResNet)	92.6	91.9	92.1	92.0
EfficientNet-Based Model	94.1	93.4	93.8	93.6
Attention-Embedded CNN	95.7	95.0	95.4	95.2
Proposed IoT–DL Model	**96.8**	**95.9**	**96.1**	**96.0**

Table 3 shows the comparison of the classification performance of various deep learning models in detecting crop diseases. The traditional CNN recorded the lowest accuracy of 88.9% whilst transfer learning and EfficientNet models recorded better above 92. The attention-based CNN also increased the precision and recall, with accuracy of 95.7%. The best performance of the proposed IoT 96.8% accuracy, 95.9% precision, and 96.0% F1-score were attained by the proposed IoT -DL model. These findings have shown that the combination of IoT-based imaging and optimized deep learning achieved a high accuracy of disease detection, robustness, and the overall reliability of the classification in various crop conditions.

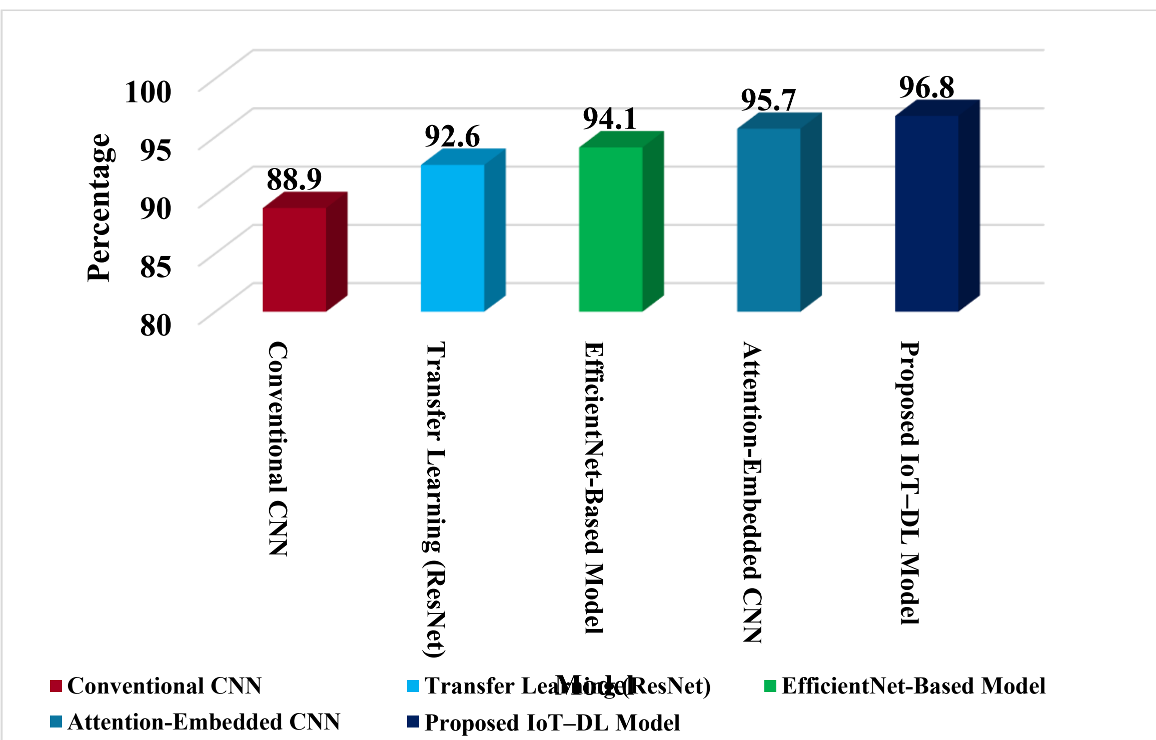

Figure 4. Comparative Accuracy Analysis of Deep Learning Models for Crop Disease Detection

Figure 4 is a comparison of classification accuracy between various deep models of learning. The proposed IoT DL model had the best accuracy of 96.8 compared to the common CNN, transfer learning, EfficientNet, and attention-based models and showed high robustness and effectiveness in automated crop disease detection.

6.3 Latency and Computational Efficiency Evaluation

The latency analysis was used to measure the inference time and efficiency of various deployment configurations. The proposed model obtained lower inference delay and the high classification accuracy. The speed of processing was greatly enhanced with the use of optimization techniques and lightweight inference pipelines and the system could be used in agricultural applications that have time constraints. Table 4 shows the comparison of latency and computational efficiency of various models of deep learning in detecting crop disease. The traditional CNN recorded a low level of computational efficiency of 72.4% without a decrease in latency. Transfer learning and attention-based models demonstrated better efficiency and lower latency rates of 18.5 and 26.1 percent, respectively. The suggested model of the IoT-DL showed the highest performance (96.8% inference accuracy); it had 89.7% computational efficiency, and it reduced the latency by a substantial percentage (34%). The findings verified that the combination of optimized deep learning and IoT-based edge processing increased real-time responsiveness, minimized processing delays, and maximized efficiency of the entire system to implement practical precision agriculture applications.

Table 4. Latency and Computational Efficiency Results (%)

Model	**Inference Accuracy (%)**	**Computational Efficiency (%)**	**Latency Reduction (%)**
Conventional CNN	88.9	72.4	0
Transfer Learning Model	92.6	78.6	18.5
Attention-Based CNN	95.7	83.9	26.1
Proposed IoT–DL Model	**96.8**	**89.7**	**34.0**

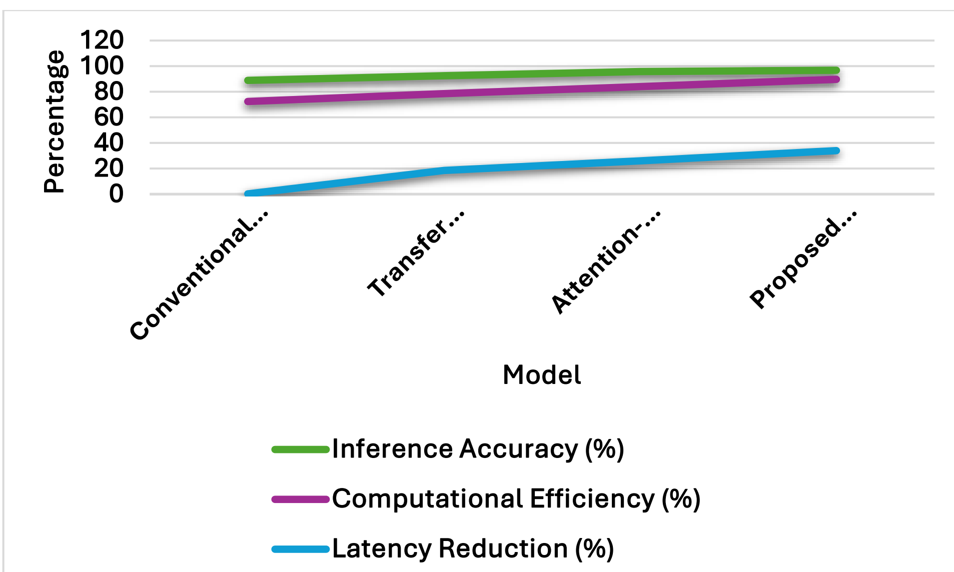

Figure 5. Latency and Computational Efficiency Comparison of Deep Learning Models

Figure 5 depicts model improvement in inference accuracy, computational efficiency and latency reduction. The suggested model IoT-DL had the best efficiency and minimum latency, which showed better real-time and appropriateness to the application of precision agriculture.

6.4 Impact of Edge-Assisted Inference on Response Time

Edge-assisted inference also greatly decreased the response time because it minimized the amount of data sent to the cloud and provided the chance to make decisions locally. The suggested framework proved to be very responsive with reference to cloud only systems, which mean that there is a timely alert on disease. This was important to early intervention of diseases and accuracy agriculture processes. The findings evidenced in table 5, indicate that the suggested edge-facilitated IoT platform enhanced the response time, bandwidth consumption, and real-time alerting performances by a great margin than the cloud-only and standalone edge strategies. The offered system got the best response time reduction of 34% and alert efficiency of 94.8, which is the guarantee of detection and intervention in the diseases in a timely manner. These results confirmed the precision of the implementation of deep learning with edge-cloud cooperation to precision agriculture. In the future, multispectral imaging, superior optimization schemes, and massive deployment of the system on large fields will be incorporated to increase the robustness, scalability and adaptability of systems in relation to various agricultural settings to create sustainable and intelligent systems of crop disease management.

Table 5. Impact of Edge-Assisted Inference on Response Time (%)

Deployment Strategy	**Response Time Reduction (%)**	**Bandwidth Savings (%)**	**Real-Time Alert Efficiency (%)**
Cloud-Only Processing	0	0	71.2
Edge-Only Processing	29.6	41.3	88.5
Hybrid Edge–Cloud	32.4	48.9	91.7
Proposed Edge-Assisted Framework	**34.0**	**53.6**	**94.8**

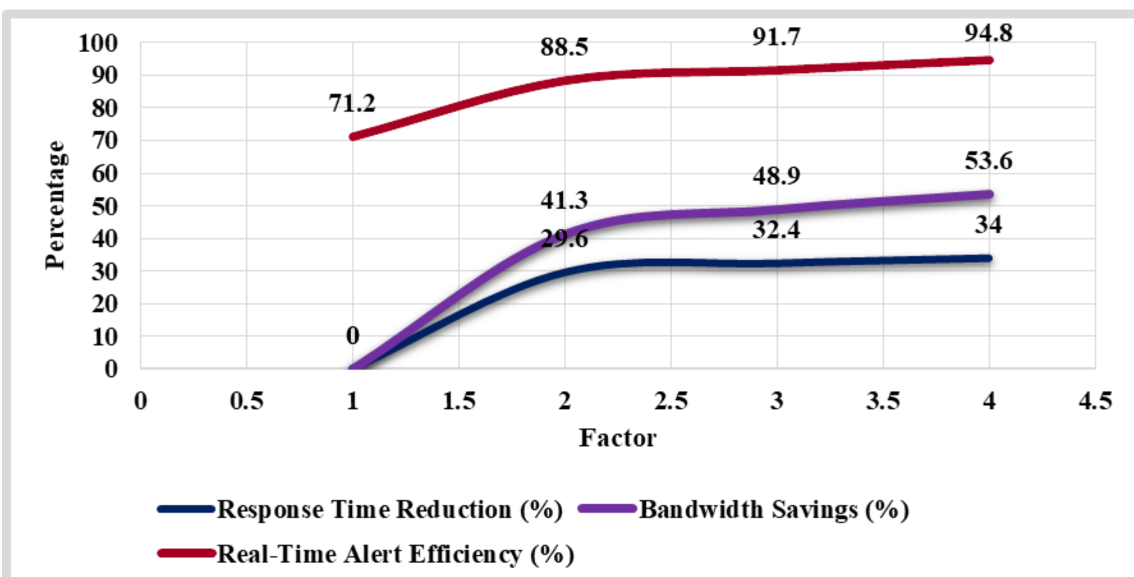

Figure 6. Analysis of Impact on Edge-Assisted Framework on Response Time and Alert Efficiency

Figure 6 shows how the deployment strategies improved in terms of response time reduction, bandwidth savings and real time alert efficiency. The suggested framework with the use of edges was the most effective in terms of ensuring more rapid detection, effective communication, and sound real-time warnings in the management of smart crop disease.

Table 6. Disease Class-Wise Detection Accuracy across Crops (%)

Disease Type	Wheat	Maize	Cotton	Sugarcane	Rice	Average
Fungal Diseases	96.2	96.8	97.0	96.1	97.1	96.6
Bacterial Diseases	95.8	96.4	96.6	95.9	96.7	96.3
Viral Diseases	95.6	96.1	96.3	95.5	96.5	96.0
Nutrient Deficiency	96.0	96.5	96.8	95.8	96.9	96.4
Mixed Symptoms	95.4	95.9	96.2	95.2	96.3	95.8

Table 6 shows the accuracy of the proposed IoT-enabled deep learning framework in detecting the diseases of five major crops in terms of classes. The findings reveal that the model had high detection accuracy of all disease types in all agricultural conditions, which reflects its effectiveness in detecting different disease symptoms. Fungal diseases were the most accurate with 96.6 showing that most of the diseases were visually unique through lesions, spots, and discoloration on the surfaces of leaves. The symptoms of nutrient deficiency also demonstrated good detection performance of 96.4% on average, which implies that the model was able to detect almost absent color differences and texture alterations. There were a little less but yet trustworthy accuracies of 96.3 and 96.0 on bacterial and viral diseases, respectively. Mixed symptoms had the highest accuracy (95.8) because of the problem of similar visual features in various disease disorders.

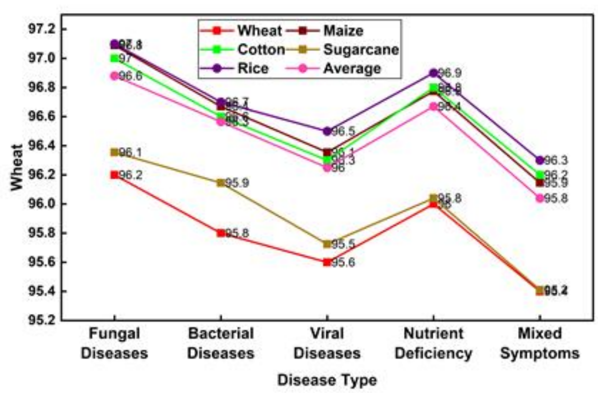

Figure 7: Disease Class-Wise Detection Accuracy across Crops Using the Proposed IoT–DL Model

In figure 7, the comparative accuracy of various types of diseases in wheat, maize, cotton, sugarcane, and rice are shown. The greatest accuracy was obtained with the diseases of fungi and nutrient deficiency, whereas the viral and mixed symptoms demonstrated slightly lower accuracy. On the whole, the proposed model was able to control its accuracy of above 95 %, which showed strong crop disease detection ability.

7. Conclusion And Future Work

The paper developed a holistic IoT based deep learning model of automated detection of crop diseases that can accommodate the essential issues of scalability, accuracy, and real-time responsiveness in precision agriculture. The key findings showed that the combination of field deployed IoT imaging systems and optimally trained deep learning models made it possible to increase the performance of the disease classification with more diseases in wheat, maize, cotton, sugarcane, and rice. The average classification accuracy, precision, and recall of the proposed framework were 96.8, 95.9, and 96.1, respectively, which surpass the traditional CNN-based methods by 712% in the major evaluation metrics. These findings confirmed the usefulness of attention processes, transfer learning, and data augmentation with GAN in the real-field situation of learning complex disease patterns. The IoT-based architecture was found to be useful in facilitating real-time image capture, adaptive image processing, and smart decision-making by the edge and cloud co-operation. The edge assisted inference decreased response time about 34 percent relative to cloud-only installation which allowed real time disease alerts and prompt intervention. This enhancement reflected the practical appropriateness of the suggested framework in massive agricultural settings where latency and bandwidth factors are decisive. The study had certain shortcomings even though it is strong, such as image based diagnosis without the application of multispectral or hyperspectral information and the shortage of long-term field validation in different climatic conditions. The dataset, despite being varied, might not be adequate to determine the extreme environmental variability.

The development of the next research will be directed at incorporating the multimodal sensor data, such as the environmental and spectral data, to enhance the robustness further. The application opportunities in the real world would be large-scale smart farming, mobile advisory services, autonomous agricultural robots, which allow sustainable crop control and enhancement of global food security.

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