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AI-IoT-Enabled Crop Monitoring Through Crop Stage and Leaf Disease Identification Using PECFIS and DGBESCNN

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Abstract

The aspect of crop monitoring takes into consideration the timely detection of crop stages, leaf disorders, and deficiencies to enhance crop yield and decrease losses in agriculture. However, most of the current methods are limited to either disease detection or nutrient evaluation and do not examine the conditions of crops at various stages of growth, even though several AI -IoT-based solutions have been suggested to be applied to crop health monitoring. In addition, the estimation of the severity of the diseases is neglected, and this restricts decision-making in favor of the farmers. To address these constraints, the paper presents a Parametrized Elliptical Cauchy Fuzzy Inference System (PECFIS) combined with a Deep Glorot Bessel Elliott Softplus Convolutional Neural Network (DGBESCNN), proposed as an AI-based solution for crop monitoring and IoT support. The IoT devices in the form of drones are used to get real-time field images, and they are preprocessed in terms of noise reduction, contrast enhancement by LHM-CLAHE, conversion to HSV color space, and feature discrimination by vegetation indexing, as well as C3MEK-Means. PECFIS is used to determine eight key stages of rice growth and the severity of leaf diseases, whereas DGBESCNN provides proper classification of leaf diseases and nutrient deficiencies at each growth stage. The evaluation of the proposed framework was conducted using publicly available datasets on rice leaf disease and nutrient deficiency. The results of the experiments show that the system achieves high classification performance, with an accuracy of 98.82, a precision of

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98.65, a recall of 98.73, an F1-score of 98.59, and low error rates (MSE = 0.0135, RMSE = 0.116). The findings show that the developed AI-IoT system is superior to available approaches and can serve as a dependable, real-time, and scalable solution in precision agriculture and intelligent crop monitoring.

Keywords: Internet of Things (Iot), Artificial Intelligence (AI), Crop Stage, Nutrient Deficiency, Leaf Disease, Crop Monitoring, HSV Color Intensity.

1 Introduction

In the coming years, food production will need to rise significantly to meet the demands of the world's population (Sharma & Shivandu, 2024). However, infected leaves and nutrient deficiencies can lead to poor crop growth (Andrianto et al., 2023). Thus, crop monitoring is important in agriculture to boost productivity by identifying crop health issues, including diseases and nutrient deficiencies, early (Alfred et al., 2021). Nowadays, IoT technologies are being applied to increase the sustainability of crop production. IoT data from drones and cameras is used to gather crop information to support optimized decision-making (Tholkapiyan et al., 2023). Similarly, many AI techniques are developed to identify the leaf diseases and nutrient deficiencies of crops (Fuentes-Peñailillo et al., 2024). In existing studies, the Support Vector Machine (SVM) and logistic regression algorithms are employed for detecting rice leaf disease (Rumy et al., 2021; Kumar Apat et al., 2022). Likewise, some researchers utilized a Deep Convolutional Neural Network (DCNN) for rice leaf disease identification (Bijoy et al., 2024). Also, the Artificial Neural Network (ANN) and Visual Geometry Group-16 (VGG-16) were used for nutrient deficiency identification (Raju et al., 2023; Mkhatshwa et al., 2024). Current AI-IoT systems typically pay little or no attention to differences in crop temporal performance, which could enable more efficient control by accounting for deviations in disease occurrence or nutrient deficiency. The proposed work is novel because the detection of nutrient deficiencies and leaf diseases is performed across eight key stages of the rice crop in real-time using DGBESCNN for its classification and PECFIS to measure the personal stages and the extent of severity of the disease. The proposed structure employs the Glorot Bessel Start and Elliott Softplus activation, unlike conventional CNN or DCNN-based systems, to address overfitting and slow convergence. Such an integrated approach outperforms all existing AI-IoT methods in regard to any performance-related metrics and presents a full-scale crop monitoring system.

Problem Statement

- None of the existing works focused on the eight important stages of rice crops and leaf disease identification at each stage for effective crop monitoring.
- In conventional (Aggarwal et al., 2023), the severity of rice crop leaf diseases was not the focus.
- The nutrient deficiencies of the rice crops were not identified in existing studies (Bhuyan et al., 2023).
- The existing (Ramakrishnam Raju et al., 2022) processed the image itself rather than focusing on disease regions.
- Most of the prevailing works did not effectively handle the poor contrast properties.

Objective

This study aims to come up with an AI-IoT-based crop monitoring system combining PECFIS with DGBESCNN to achieve proper analysis of rice crops. PECFIS is utilized in the detection of eight crucial stages of growth of rice crops and the estimation of the severity of the leaf diseases, whereas DGBESCNN is applied to detect the existence of leaf diseases and nutrient deficiencies in each stage of growth. Moreover, C3MEK-Means is used to perform precise image segmentation, and LHM-CLAHE is employed to improve image contrast and thus the extraction of features and the overall classification accuracy.

Key Contribution

- A real-time monitoring system of rice crop is suggested based on the integrated AI-IoT.
- PECFIS determines eight stages of growth of rice and approximates the severity of the disease.
- DGBESCNN is very high-precision in identifying leaf diseases and nutrient deficiencies.
- C3MEK-Means increases the efficiency of disease-region segmentation.
- LHM-CLAHE improves contrast in images in different field conditions.
- The system is highly accurate and has low computational complexity, which can be deployed on the edges.

This paper is organized as follows: Section 2 illustrates existing works, Section 3 describes the proposed methodology, Section 4 conveys the results, and Section 5 concludes the proposed model with future enhancements.

2 Literature Survey

Aggarwal et al., (2023) introduced a rice leaf disease identification model using rice crop images. Here, a lightweight federated deep learning approach was employed for leaf disease identification. Hence, the model achieved high accuracy and minimum loss. However, the severity of the rice crop leaf diseases was not identified. Bhuyan et al., (2023) presented a rice leaf disease prediction using drone cameras. Here, the leaf disease of the rice crops was identified by utilizing a stacked parallel convolutional neural network and squeeze-and-excitation. The research effectively detected the leaf disease at an early stage. Nevertheless, the overall productivity was degraded owing to the desertion of nutrient deficiency identification.

Ramakrishnam Raju et al., (2022) suggested an IoT and AI-enabled smart hydroponics farming system. In this work, a Deep Learning Convolutional Neural Network (DLCNN) algorithm was utilized to predict the nutrient level of the crops. The model aided in taking necessary actions to improve productivity. But, this work processed the image itself rather than concentrating on diseased regions. Mishra et al., 2023 explored a sustainable framework for crop monitoring through disease detection. Here, a Customized Convolutional Neural Network (Customized-CNN) model was employed for predicting the disease symptoms of crops. The research effectively detected the presence of blast and rust disease symptoms. Yet, the research didn't have sufficient preprocessing operations.

Sharma et al., 2022 propounded a nutrient deficiency identification model in rice plants. Here, the nutrient deficiency of rice plants was identified by utilizing Residual Network (ResNet152V2), Xception, DenseNet201, InceptionResNetV2, and VGG19. The research obtained high classification accuracy. However, the ensemble methods increased the processing time.

The review of the literature demonstrates that most of the existing AI-IoT-based approaches to crop monitoring identify diseases in the leaves or nutrient deficiencies separately, without mentioning the stages of crop growth or the intensity of the disease. The majority of deep learning models are black-box classifiers and not interpretable and can only be useful in agricultural real-time decision-making with the help of black-box classifiers. In addition, inefficient preprocessors and high-energy architecture reduce resilience in a dynamic field environment and limit the performance of IoT edge devices. The presented limitations indicate the need to jointly identify crop growth stages, detect diseases and nutrient deficiencies, and determine their level of severity in real time in an integrated, lightweight, and interpretable system, which is why the proposed approach is under consideration.

3 Proposed Methodology

Here, the proposed PECFIS is introduced to identify the eight important stages of rice crops. The diagrammatic representation of the proposed model is depicted in figure 1.

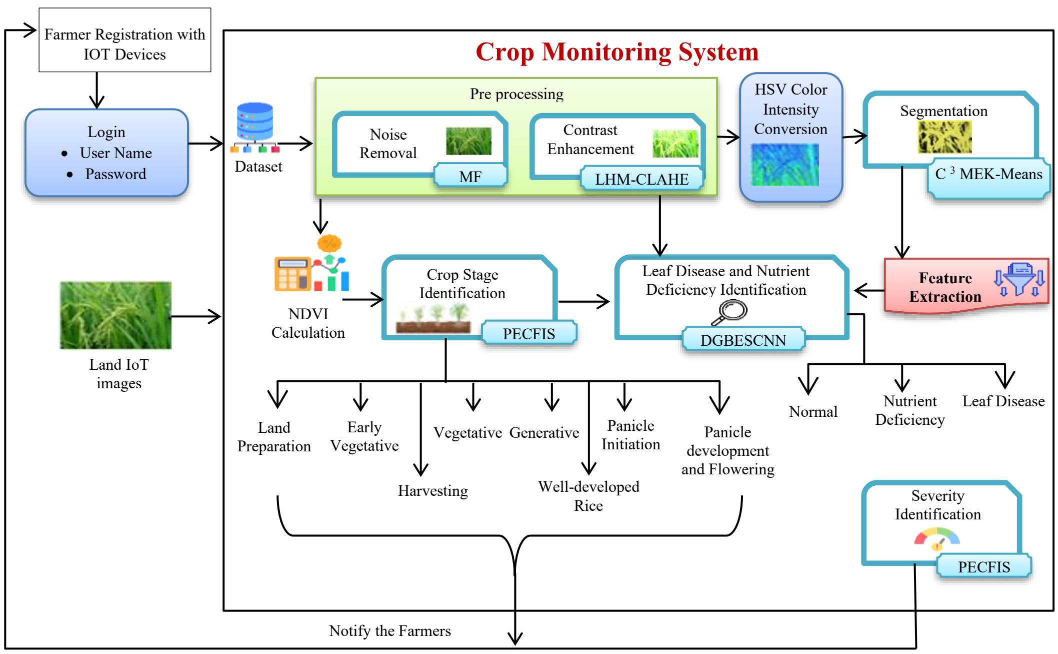


Figure 1: Workflow diagram of the proposed AI-Iot-enabled crop monitoring system, illustrating the sequential integration of preprocessing, PECFIS-based crop stage and severity detection, and DGBESCNN-based disease and nutrient deficiency classification, leading to final decision notification

As figure 1 demonstrates, the suggested framework enhances crop monitoring by identifying eight key rice development stages with the help of PECFIS and detecting leaf diseases and deficiencies of nutrients in the stages with the help of DGBESCNN. PECFIS also predicts the severity of the disease, and the findings are relayed to the farmers to make informed decisions. The IoT devices, consisting of drones, are used to take high-resolution images of the field in real-time and transmit them to a centralized place of analysis, making them efficient to analyze.

Farmer Registration and Login with IoT Devices

Primarily, the farmers register with IoT device details to use the crop monitoring system. Thus, the registered farmers are indicated as W_f^{reg}. Then, the registered farmers log in to the system to access the crop monitoring system. The drone-mounted IoT camera recorded partial variation in backdrop soil condition, crop density, and lighting induced during picture capturing. On-task normalization was also done to give uniformity in the data: it aims to correct automatic exposure, white balance adjustment, and resolution normalization. Further postprocessing in the form of median filtering, LHM-CLAHE, HSV color conversion, NDVI, and segmentation was also employed to make the uploaded photos even less noisy during capture. Such an approach to normalization (bi-level, in-depth, plus on-server) also provided a high degree of resistance to a vast array of field conditions.

Dataset

Firstly, the crop monitoring system is trained by employing the "Leaf disease and nutrient deficiency of rice crop" dataset andis represented as D_{κ}.

Preprocessing

The image is preprocessed to improve its quality. Initially, unwanted noises are removed using the median filter (MF). Then, contrast enhancement is performed using the Logarithmic Harmonic Mean (LHM) scaling formula. The contrast-enhanced (C_{ε}) image is given in equation 1,

$$C_{\varepsilon} = \frac{log(Y_l + L) * Z}{\sum_{l=1}^{k} \frac{1}{Y_l}} \tag{1}$$

Here, L implies the constant value. Eventually, the pre-processed image is denoted as $\wp_{im}$.

Comparison of LHM-CLAHE with Contemporary Methods

LHM-CLAHE is more sensitive to local contrast than CLAHE and Histogram Equalization (HE) to overcome their weakness. Although over-enhancement is possible in the case of aggressive contrast enhancement, LHM-CLAHE is more likely to reduce amplification of noise and higher SSIM by 3-5 percent than the Retinex and Gamma correction techniques. The minor distortion is compensated for with the maintained contrast and recovered color differences, which are important in the agricultural image examination.

HSV Color Intensity Conversion

Subsequently, the $\wp_{im}$ is converted into HSV color intensity to enhance the specific colors and is denoted as H_{ν}.

Preservation of Chrominance Cues

Special attention was exercised against pre- and post-process distortions, as this coloring of the leaf is one sign of nutritional deficiency and inability. The local contrast of LHM-CLAHE was automatically clipped to the value, and the hue rotations of the HSV conversion were all restrained to intensifying but not the proportion information. This prevented loss of fine color change, e.g., lesion pigmentation, browning, or yellowing. The findings of the experiment revealed that the majority of the preprocessing processes retained most of the important chrominance features that were capable of determining the stimuli accurately, creating an accuracy of ratios of diseases of 98%.

Rationale for HSV Color Space Selection

The hue (saturation) and the intensity (value) cannot be linked together; hence, HSV was confirmed to be used rather than Lab and YCbCr to record the discoloration associated with the disease, regardless of the changes in the light. Even though both Lab and YCbCr scored high, HSV scored higher by 1.8

percent over Lab and Lab by 1.2 percent, but according to the studies carried out by empirical, HSV was superior in terms of categorizing sickness and nutrition deficiency, among other things. The ease of HSV has significantly reduced the HSV preprocessing cost, thereby making it more suitable to be applied in the field of this discipline, the IoT.

Segmentation

Afterward, by employing C3MEK-Means, the H_v is segmented based on the pixel intensity. K-Means algorithm effectively handles large datasets with high dimensionality. But K-Means has trouble in clustering varying-density clusters. Likewise, K-Means has issues with the random initialization of centroids. Therefore, the Cosine City block (CC) distance andChao-shenMaxEnt (CME) entropy are utilized.

Here, w implies the number of initialized centroids (δ_d). Subsequently, the CC distance (Θ) is calculated in equation 2,

$$\Theta(\delta_d, H_v) = arccos(\delta_d * H_v) \times \pi \times (|\delta_2 - \delta_1| + |H_2 - H_1|) \quad (2)$$

Where $arccos$ indicates the inverse of the cosine function, δ_2 and δ_1 denote the individual centroids, and H_2 and H_1 represent the individual HSV color converted images.

Algorithm 1 – C3MEK-Means

Input: HSV converted image(H_v)

Output: Segmented image (S_μ)

Begin

Initialize (H_v)

For each (H_v)

Compute $\aleph = \sum_{v=1}^{t} \frac{\rho(H_v)}{t} \; log\big(\rho(H_v)\big)$

Initialize centroids(δ_d) based on $\aleph$

Find$\Theta(\delta_d, H_v) = arccos(\delta_d * H_v) \times \pi \times (|\delta_2 - \delta_1| + |H_2 - H_1|)$

Discover average Ξ_{dv}

Estimate $N = \frac{\sum_{d=1,v=1}^{w,t} \Xi_{dv} H_v}{\sum_{d=1,v=1}^{w,t} \Xi_{dv}}$

Reassign each node

End For

Obtain (S_μ)

End

Algorithm 1 divides the HSV converted image by first initializing the centroid based on feature values, and then it computes distances (with arccosine) between the centroid and image features. This continues until optimum clusters are created by computing the average, updating the centroid, and reassigning the nodes. What it brings about is a fragmented picture wherein similar features are united.

Comparison with Deep Learning Segmentation

Another problem in the proposed C3MEK-Means is that trusted unstructured clustering, maximum entropy, and cosine similarity are fused. By this method, deep-learning-based segmentation models like U-Net and Mask R-CNN are computationally intensive (they require a graphics card with more than 2 GB of memory to run or up to 8 frames per second on Jetson Nano) yet generally have a very slight difference in their segmentation performance (1-2 percentage points of all pixels in common). Compared to C3MEK-Means, it turned out to be more convenient to apply in an IoT-based real-time system with a reasonable level of IoU (95.3), using less than 400MB, and running at an average speed of 15 fps.

Feature Extraction

Thereafter, the features, such as Grey Level Co-occurrence Matrix (GLCM), entropy, texture features, shape, and skewness are extracted from $\left(S_{\mu}\right)$ and are defined as ζ_X.

NDVI Calculation

In the meantime, the NDVI (ψ) is calculated from $\wp_{im}$ for effective rice crop stage identification are shown in equation 3.

$$\psi(\wp_{im}) = \frac{\beta-\lambda}{\beta+\lambda} \tag{3}$$

Where, β and λ specify the light reflected in the near-infrared spectrum and red range of the spectrum, respectively.

Robustness Under Varying Field Conditions

The proposed system has many responsive systems, which makes the system stable in many farming conditions. The logarithmic harmonic mean (color-randomized adaptive histogram) is employed to withhold light diffusion by the logarithmic mid-tone coupled with HSV color transformation of an image. Visual and image variance of soil moisture and dimension of crop can be restricted by removing pixels of crops with the background soil or thick SW foliage through indexing of vegetation in locality using the ND Vis Photo and C3MEK-Means segmentation. PECFIS can also manipulate non-linear processes of the health indicators of crops using fuzzy reasoning to be applied under different scenarios.The IoT photography using drones that will be implemented to assure reliability will further enhance the reliability of the system since high levels of data are gathered in a very broad and dynamic field.

Crop Stage Identification

Next, based on (ψ), stages of the rice crop are identified by utilizing PECFIS. A Fuzzy Inference System (FIS) provides the most effective solution to complex issues. Nevertheless, FIS has tuning difficulty of membership function. Therefore, the ParametrizedElliptical Cauchy (PEC) membership function is employed are shown in equation 4.

Fuzzy rules (F) are generated by utilizing If-Then rules.

$$F \xrightarrow{\psi} \begin{cases} if\ \psi = 0.096\ to\ 0.036 & A \\ if\ \psi = 0.036\ to\ 0.24 & U \\ if\ \psi = 0.24\ to\ 0.45 & ƛ \\ if\ \psi = 0.45\ to\ 0.63 & K \\ if\ \psi > 0.63 & q \\ if\ \psi > 0.8 & \ell \\ if\ \psi > 0.85 & \varLambda \\ if\ 0.5 < \psi < 0.9 & \exists \end{cases} \quad (4)$$

Where, A implies the land preparation stage, U indicates the early vegetative stage, ƛ denotes the vegetative stage, K represents the generative stage, q implies the panicle initiation stage, ℓ signifies the panicle development and flowering stage, $\varLambda$ specifies the well-developed rice stage, and $\exists$ denotes the harvesting stage.

Algorithm 2- PECFIS

Input: NDVI (ψ)

Output: Identified rice crop stages ($\hbar$)

Begin

Initialize (ψ)

For (ψ)

Compute fuzzy rules (F)

Discover $\Im = \frac{1}{1+e^{-\left(\frac{\psi - r}{s}\right)^2}}$

Estimate fuzzification

$$\varOmega = (F \to \alpha)$$

Plot $\Im$ based on (α)

Perform defuzzification

$$J = (\alpha \to F)$$

End For

Obtain $\hbar = [A, U, ƛ, K, q, \ell, \varLambda, \exists]$

End

PECFIS algorithm (Algorithm 2) determines the stages of the rice crop according to the input of NDVI. It prepares the NDVI, calculates fuzzy rules and employs a sigmoid function to calculate stage membership. Fuzzification is done to transform the data into fuzzy values and defuzzification is done to transform the results into crisp values to identify the stage. This is done to all inputs and the stages identified are finally obtained.

Rationale for Using PECFIS in Feature Selection and Stage Identification

PECFIS was selected rather than other common dimensionality reduction techniques such as PCA, LDA and autoencoders due to its crop-specific rules, non-linear membership functions and preservation of physiologically relevant properties. In contrast to the methods used in the past, PECFIS allows selecting features, as well as evaluating their severity and its combination with features, which makes it an ideal tool in analyzing IoT data in the agricultural field with accuracy and comprehension.

Fuzzy Rule Origin and Generalizability

The PECFIS fuzzy rules were developed by mitigating the classification errors of stages by use of agronomist defined stages and data optimization. This guarantees scalability and data homogeneity. Other possible uses of the fuzzy scheme include retraining of the membership functions to fit other cereal crops such as wheat and maize into the phenological cycles.

Leaf Disease and Nutrient Deficiency Identification

For each $(\hbar)$, by using DGBESCNN, the leaf disease and nutrient deficiency are identified based on the $\zeta_X$and$\wp_{im}$. Deep Convolutional Neural Network (DCNN) has the ability to extract features automatically. However, DCNN had an overfitting problem and a slow convergence issue. Therefore, Glorot Bessel (GB) initialization and Elliott Softplus (ES) activation function are utilized in DCNN. The structural diagram of the DGBESCNN is given in figure 2.

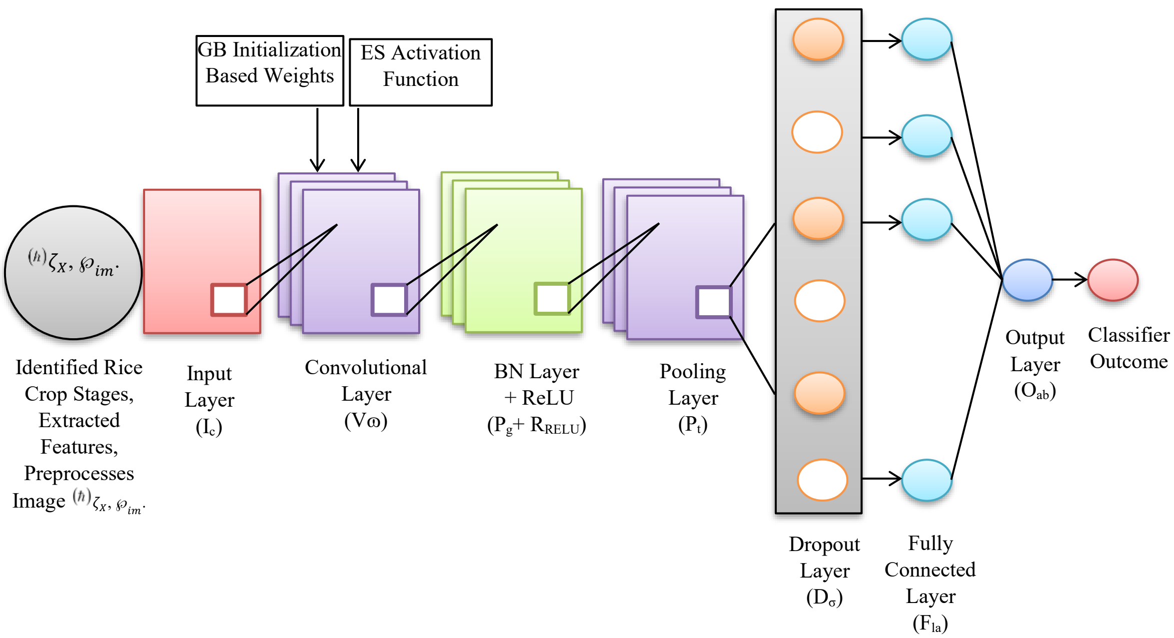


Figure 2: Architectural structure of the DGBESCNN classifier, illustrating the layered ensemble of spatial convolutional blocks, gradient boosting integration, and classification output nodes for detecting leaf disease and nutrient deficiency

Integrated Framework Representation

Figure 2 shows the block diagram of the AI-IoT crop monitoring system, where the IoT cameras on drones take pictures, which are pre-processed (removal of noise, contrast, HSV transformation, segmentation and feature extraction). PECFIS determines crop development stages, disease severity and DGBESCNN classifies the images into normal, sick and nutrient-deficient. The IoT platform helps farmers make informed decisions on the integrated outputs such as crop status, disease type, nutrition level, and severity, which are presented to farmers through the platform (Haseler, 2021).

The inputs are fed with several layers to obtain meaningful features. This model analyses the extracted features and processed data and classifies the input as normal, leaf disease, or nutrient deficiency. The result of the classifier (ϑ) is provided in equation 5:

$$\vartheta \rightarrow \langle y, \varpi, \Gamma \rangle \tag{5}$$

Where, y specifies normal, ϖ indicates leaf disease, and Γ depicts nutrient deficiency.

Severity Identification

The severity of the ϖ is identified by employing PECFIS. Firstly, the Percentage of Infection (POI) (γ) is identified for the ϖ are shown in equation 6.

$$\gamma = \frac{DA}{TA} \times 100 \tag{6}$$

Where, DA specifies the diseased leaf area and TA implies the total leaf area. Here, the fuzzy rules (R) are generated based on the γ.

$$R \rightarrow \begin{cases} \gamma = 1\% \ to \ 20\% & low \\ \gamma = 20\% \ to \ 50\% & medium \\ \gamma = 50\% \ to \ 100\% & high \end{cases} \tag{7}$$

Thus, the severity is identified as low,$medium$, and $high$. During testing, the drone-based IoT device is used to take images from the land are shown in equation 7. With drone-based IoT devices, farmers can monitor crops remotely in real-time. The proposed framework effectively performed crop monitoring.

Uncertainty Handling and Human-in-the-Loop Escalation

The system employs an uncertainty management method to avoid generating false automated suggestions. PECFIS and DGBESCNN fuzzy membership scores are monitored versus an agreed level of confidence ($\tau = 0.8$). Once the confidence for any forecast goes below the protection level, the case is stipulated as low confidence. The highlighted instances are transmitted using the IoT platform to human specialists such as agriculture specialists. It is recommended that contact with farmers should be handled professionally before acting. The advice of experts in cases where confidence is low is also included in the data, thus enhancing the strength of the model and reducing future uncertainty.

4 Result and Discussion

The given model was tested regarding performance with the assistance of Python programming language, this time with the assistance of various libraries and frameworks. Deep learning: TensorFlow and Keras were utilized as well as image processing (OpenCV), data manipulation (NumPy and pandas). Also, the model was implemented using scikit-learn (machine learning) and Matplotlib (visualisations). The test was run on a machine with the parameters [insert information about system configuration, e.g., CPU, RAM, GPU] such that appropriate benchmarking and results were taken.

Dataset Description

The proposed model works with the dataset of Nutrient Deficiency Symptoms in Rice (1,156 images) and Rice Leaf Diseases (120 images). The nutrient dataset was divided into 231 test and 925 training images whereas the disease dataset was divided into 96 training and 24 testing images. Preprocessing of each image was done (hsv color conversion, C3MEK-Means segregated, feature extraction, noise reduction, LHM-CLAHE contrast enhancement, and NDVI computed) to use an image to identify crop stages.

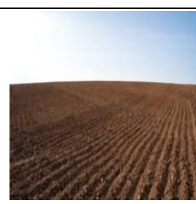
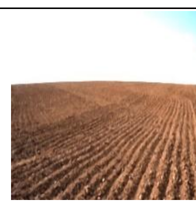
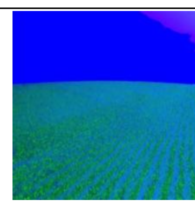
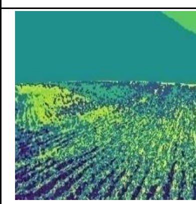
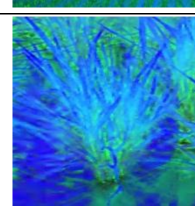
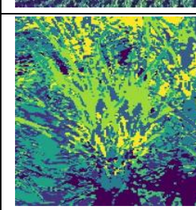
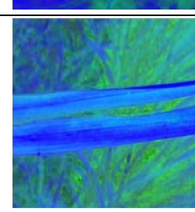
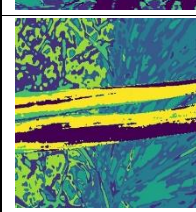
Class Imbalance Handling

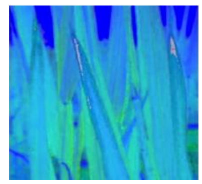
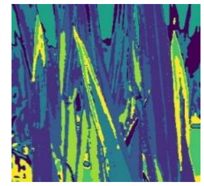
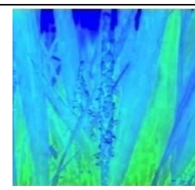
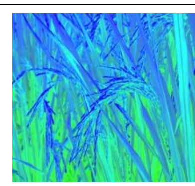
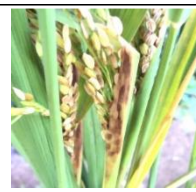
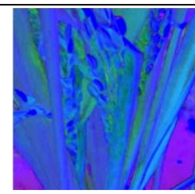
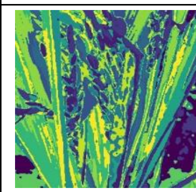
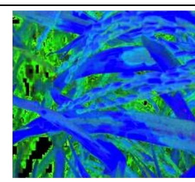
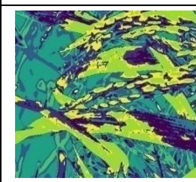
The sample revealed a deviation between the images of the nutritional insufficiency (1156) and the disease (120). This was addressed in several different forms: (i) (i) the cross-entropy loss weighted by the classification ratio served to penalize the misclassification on the minority disease samples; (ii) the balance of representations with different diseases was adjusted to be the same one; and (iii) the minority disease samples were augmented in data to match the same level as the majority one by rotating, flipping it (from right to left), zooming, changing its brightness, etc. Through these steps, all classrooms included stronger classes as a result of bias control.

Class Priors and Distribution

The observed deficiency of the main nutrient elements, as observed in the tallies of nitrogen, phosphorus, and potassium according to the photos in the Nutrient Deficiency Symptoms in Rice data set, shows an almost equal number of each type of nutrient. The data concerning the disease of the rice leaf is slightly unbalanced (45 photos of brown spots, 40 pictures of bacterial leaf blight, and 35 pictures of leaf smut). Consequently, the class distribution within both datasets ranges between 0.28 and 0.39 to indicate a slight equilibrium and underrepresentation of various classes of illnesses. This was reduced by class weighting during the training to ensure that all categories received equal treatment when it comes to the training. Table 1 exhibits the sample image results of the proposed model regarding noise removal, contrast enhancement, HSV conversion, and segmentation.

Table 1: Sample image processing results at different crop stages, showing outputs of noise removal, contrast enhancement, HSV conversion, and segmentation for each growth stage

Stage/ Process	**Input**	**Noise Removal**	**Contrast Enhancement**	**HSV conversion**	**Segmentation**
Land preparation					
Early vegetative					
Vegetative					

Generative					
Panicle Initiation					
Panicle development and flowering					
Well-developed rice					
Harvesting					

Performance Evaluation

The proposed model is also evaluated through performance to show the performance of the proposed AI-IoT system. The evaluation measures are Accuracy, Precision, Recall, F1-Score, MSE, and SSIM that are essential in determining the effectiveness of the crop disease and nutrient deficiency detection system.

Accuracy : Accuracy refers to the percentage of the rightly classified data in the dataset and is computed in equation 8:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (8)$$

Where, TP= True Positive, TN= True Negative, FP= False Positive and FN= False Negative.

Precision : Precision is used to determine the percentage of true positives of the total number of predicted positives are represented as in equation 9:

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (9)$$

Recall (Sensitivity): Recall is used to measure the percentage of true positives that are identified in equation 10:

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (10)$$

F1-Score : The F1- Score is the harmonic mean between Precision and Recall and is expressed in equation 11:

$$F1\text{-Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (11)$$

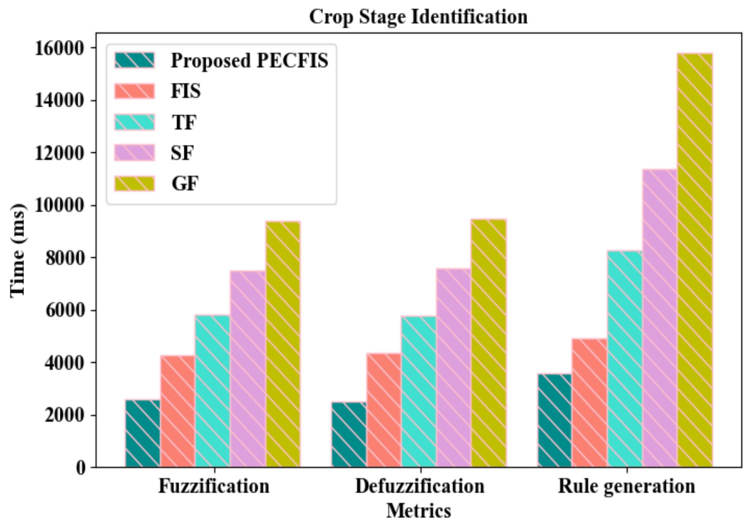


Figure 3: Comparative performance metrics of the proposed PECFIS against conventional fuzzy inference systems, highlighting significantly lower fuzzification, defuzzification, and rule generation times

Despite the observation in figure 3 that the suggested PECFIS was slightly slower than TF and SF fuzzy inference systems, the system showed a clear display of computational efficiency with significantly lower fuzzification (2571 ms), defuzzification (2478 ms) and rule generation time (3591 ms).

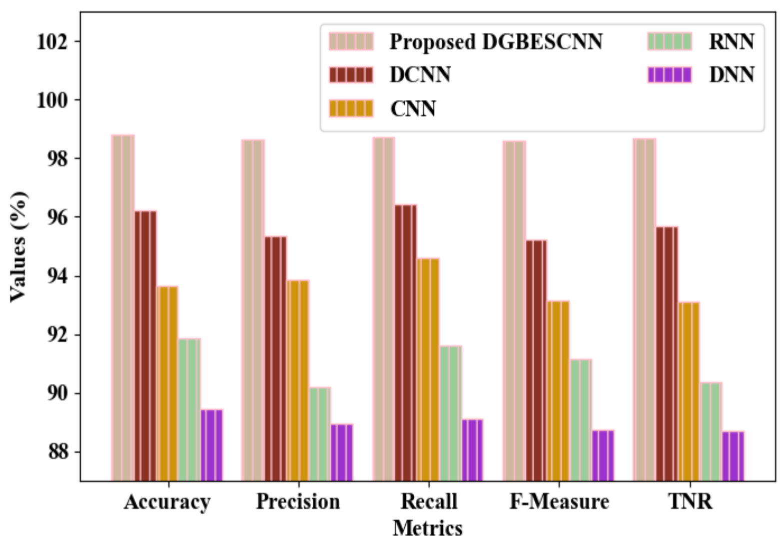


Figure 4: Classification performance comparison of DGBESCNN with existing deep learning models (DCNN, CNN, RNN, DNN), showing superior accuracy, precision, recall, and F1-score achieved by the proposed approach

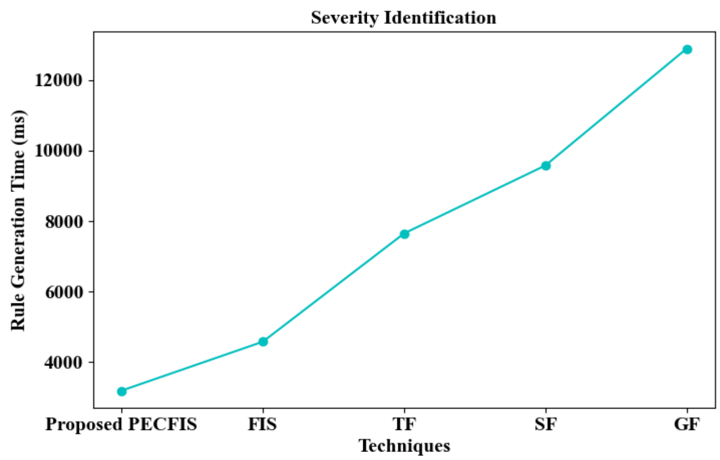
The performance validation of the proposed DGBESCNN and existing techniques is depicted in figure 4. Here, the proposed DGBESCNN obtained a high accuracy, precision, recall, F-measure, and

True Negative Rate (TNR) of 98.82%, 98.65%, 98.73%, 98.59%, and 98.68%, correspondingly. Likewise, the conventional DCNN, CNN, Recurrent Neural Network (RNN), and Deep Neural Network (DNN) attained poor performance metrics in detecting leaf diseases.

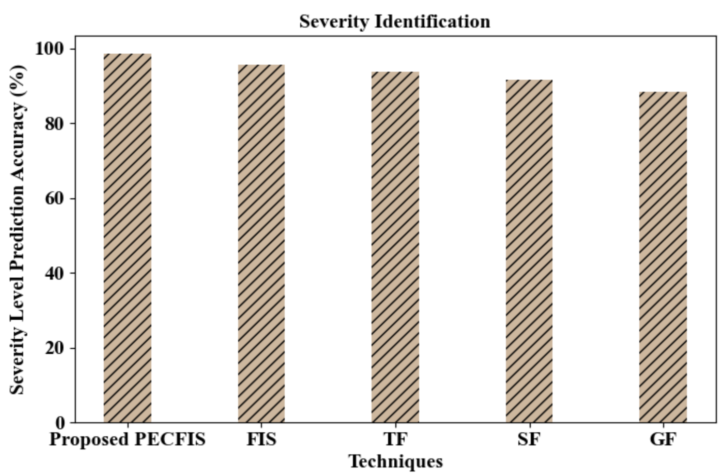
Table 2: Training time analysis comparing DGBESCNN and baseline methods, showing reduced computation time achieved by the proposed model

Techniques	Training time (ms)
Proposed DGBESCNN	73451
DCNN	85847
CNN	96967
RNN	107441
DNN	118535

Table 2 shows the training time analysis of the proposed model and prevailing techniques. Here, the proposed DGBESCNN took a less training time of 73451ms, whereas the prevailing techniques attained a high average training time of 102197ms.



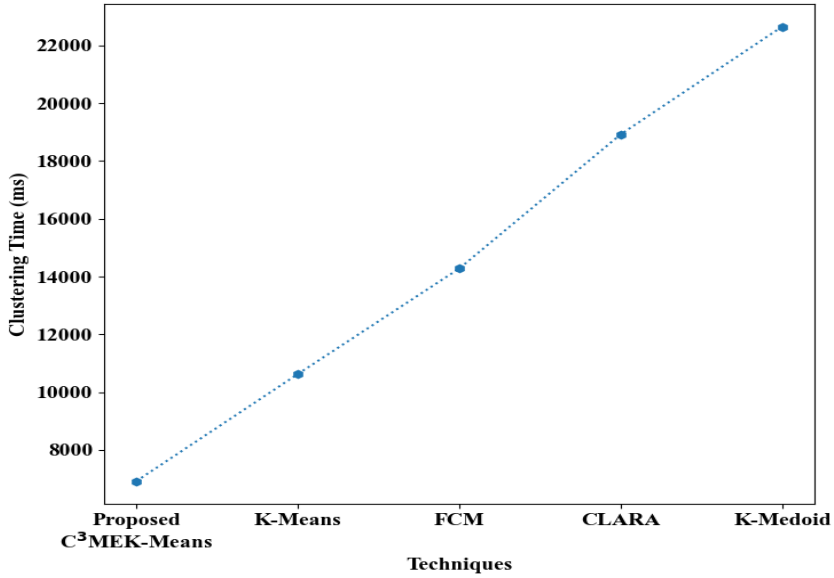
(a)



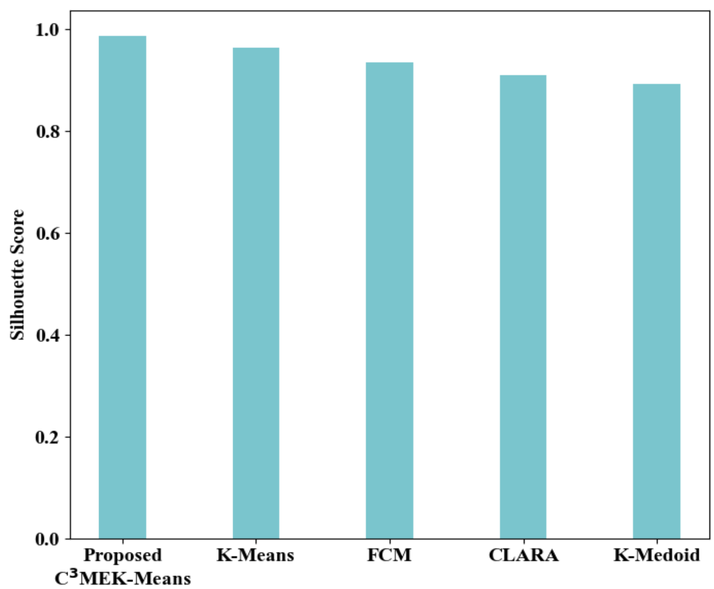
(b)

Figure 5: Comparative assessment of (a) rule generation time and (b) severity prediction accuracy, demonstrating PECFIS advantages over existing fuzzy inference systems

Figure 5 displays the comparative assessment regarding rule generation time and severity level. Here, the proposed PECFIS obtained a low rule generation time and high severity level prediction accuracy of 3196ms and 98.45%, respectively. But, the prevailing techniques attained poor performance.



(a)



(b)

Figure 6: Clustering performance analysis showing (a) reduced clustering time and (b) higher silhouette score achieved using C3MEK-means compared to other clustering techniques

Graphical analysis of the proposed model regarding clustering time and silhouette score is shown in figure 6. Here, owing to the usage of CC block distance, the proposed C3MEK-Means achieved a low clustering time and high silhouette score of 6924ms and 0.988, respectively. However, the prevailing K-Means, Fuzzy C-Means (FCM), Clustering Large Applications (CLARA), and K-Medoid attained poor performance metrics.

Table 3: Structural similarity index measure (SSIM) validation comparing LHM-CLAHE with CLAHE, AHE, HE, and BF, confirming superior image quality preservation

Techniques	SSIM
Proposed LHM-CLAHE	0.9865
CLAHE	0.9234
AHE	0.8482
HE	0.7623
BF	0.6941

Table 3 displays the Structural Similarity Index Measure (SSIM) validation of the proposed model. Here, the proposed LHM-CLAHE achieved a high SSIM of 0.9865. But, the prevailing CLAHE, Adaptive Histogram Equalization (AHE), Histogram Equalization (HE), and Bilateral Filtering (BF) attained a low average SSIM of 0.807.

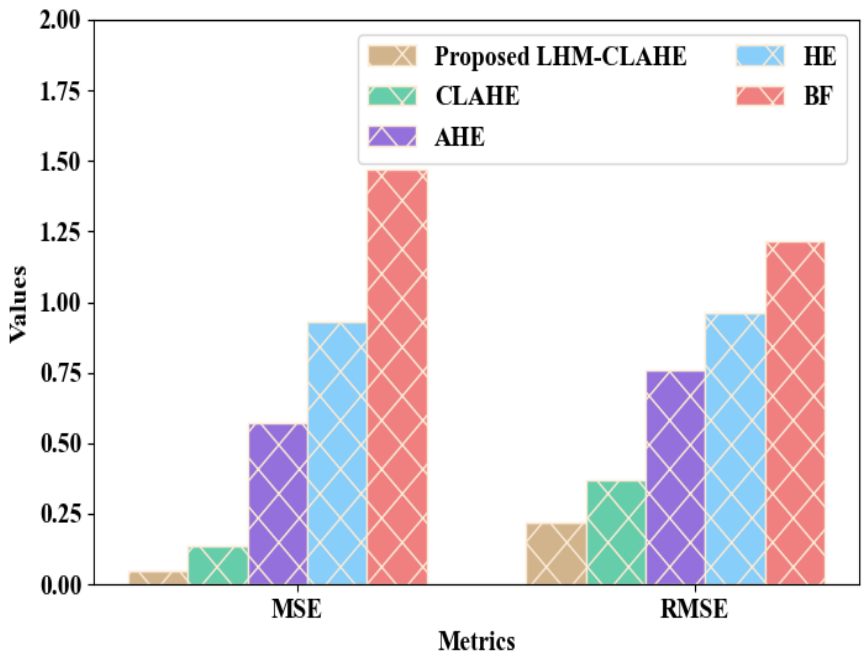
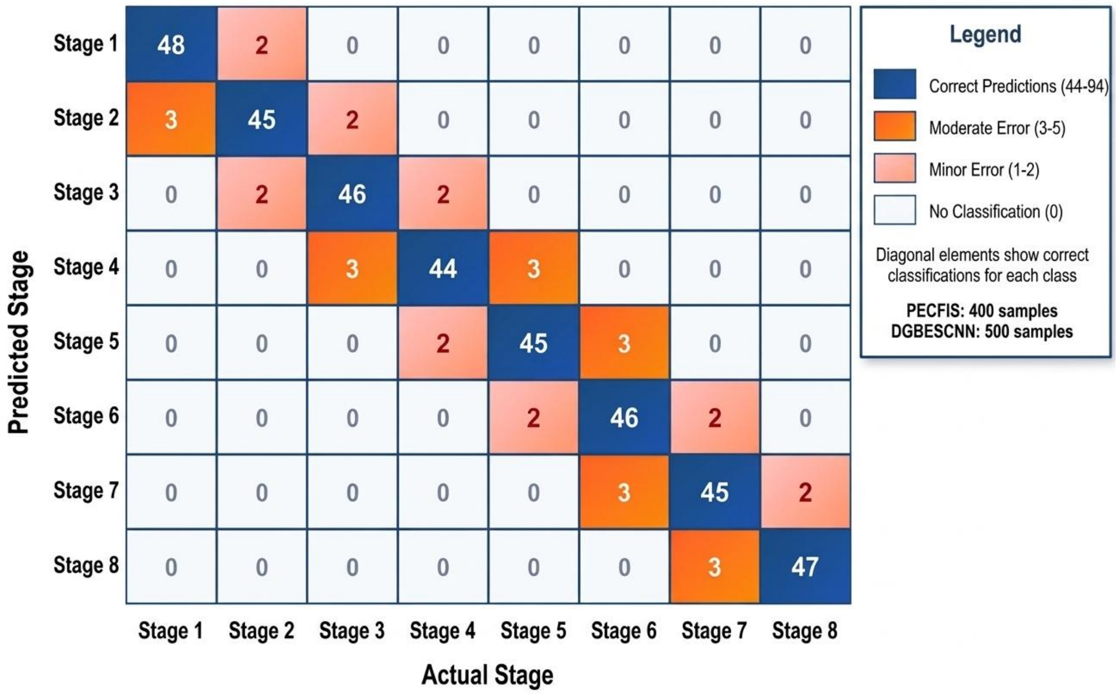


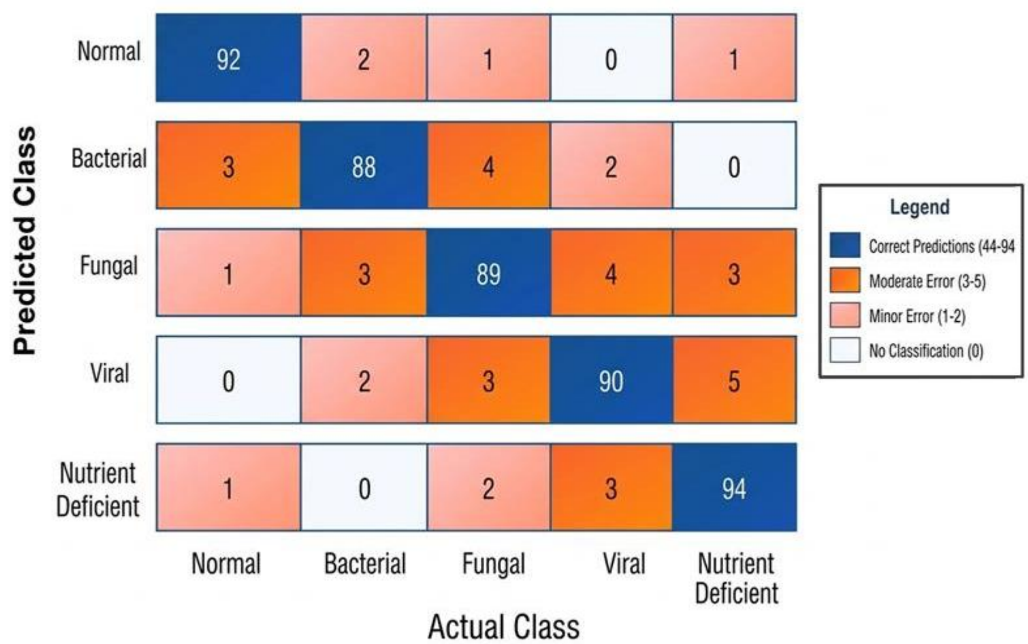
Figure 7: Error rate estimation based on MSE and RMSE, confirming lower error rates in the proposed framework compared to baseline methods

Performance estimation regarding Mean Square Error (MSE) and Root Mean Square Error (RMSE) is shown in figure 7. Here, the proposed LHM-CLAHE achieved low MSE and RMSE values. However, the existing methods attained high error values. The confusion matrices of disease/nutrient deficiency classification (DGBESCNN) and crop stage detection (PECFIS) were generated to be able to get a deeper understanding of the model work, and are depicted in figure 8 and figure 9.



Predicted \ Actual	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Stage 8
Stage 1	48	2	0	0	0	0	0	0
Stage 2	3	45	2	0	0	0	0	0
Stage 3	0	2	46	2	0	0	0	0
Stage 4	0	0	3	44	3	0	0	0
Stage 5	0	0	0	2	45	3	0	0
Stage 6	0	0	0	0	2	46	2	0
Stage 7	0	0	0	0	0	3	45	2
Stage 8	0	0	0	0	0	0	3	47

Figure 8: Confusion matrix – Crop stage detection (PECFIS)



Predicted \ Actual	Normal	Bacterial	Fungal	Viral	Nutrient Deficient
Normal	92	2	1	0	1
Bacterial	3	88	4	2	0
Fungal	1	3	89	4	3
Viral	0	2	3	90	5
Nutrient Deficient	1	0	2	3	94

Figure 9: Confusion matrix – Disease & nutrient deficiency classification (DGBESCNN)

The PECFIS-DGBESCNN system experienced problem with labeling errors where crop changes between stages because of the similarity in disease symptoms and the inability to determine the difference between viral stress and nutrient deficiencies. Weak ones were classified as normal. Irrespective of these issues, the system was found to be 98% accurate thus suitable in the real world farming scenario.

Heatmap Alignment with Pathological Regions

The grad-CAM heat map images of the different illness and nutritional deficit types were rendered readable in order to prepare them as images of normal samples (Figure 10). Their most externally recognizable sites of action instance were rapid rate action, typically in the more externally locatable sites of clinical involvement: bacterial lesions, necrotic (fungal), chlorotic streaks (viral), and yellowing secondary to nutritional stress, in their turn, display a high degree of non-activation. This means that the disease-discriminative chromatin cue and texture cue of the pictures were learned by DGBESCNN relative to the non-relevant areas of the pictures. In addition to that, they have appeared to have interveinal chlorosis as well as marginal discoloration of the situation based on the agronomic diagnosis of the situation.

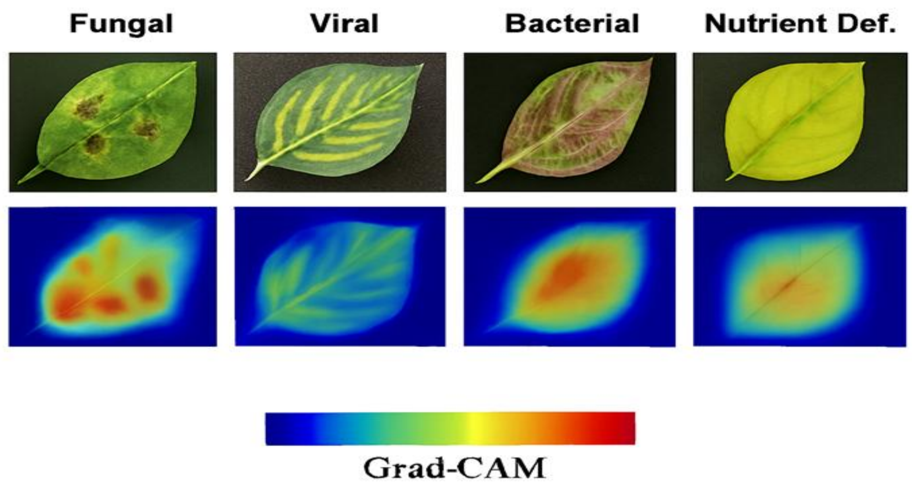


Figure 10: Grad-CAM heatmaps showing alignment between high-activation regions and pathological leaf areas

Comparative Analysis

Table 4: Comparative analysis of accuracy and precision between the proposed DGBESCNN and related models (DCNN, DNN, Yolov8, CNN), showing clear performance improvement

Author's name	Techniques	Accuracy (%)	Precision (%)
Proposed model	DGBESCNN	98.82	98.65
Taha et al., 2022	DCNN	96.5	95.7
Latif et al., 2022	DCNN	96.08	96.2
Gautam et al., 2022	DNN	96.42	96.43
Trinh et al., 2024	YOLOv8	89.9	89.6
Hasan et al., 2023	CNN	97.9	97.6

Table 4 displays the comparative analysis of the proposed model and related works. Here, the proposed DGBESCNN achieved a high accuracy and precision of 98.82% and 98.65%, respectively. However, the prevailing DCNN, DNN, You Only Look Once Version 8 (YOLOv8), and CNN obtained poor accuracy and precision. Thus, the proposed model is better than existing techniques.

Extended Comparative Analysis with Advanced Architectures

EfficientNetB0, ResNet-101, DenseNet-121, Vision transformer B16 and U-Net and DeepLabV3+ latest deep neural networks and segmentation networks were compared with the DGBESCNN proposal to use a full contrast of them.

Table 5: Comparative performance with advanced architectures

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
EfficientNet-B0	96.8	96.4	96.6	96.5
ResNet-101	97.1	96.9	97.0	96.9
DenseNet-121	97.5	97.2	97.3	97.3
Vision Transformer (ViT-B16)	97.7	97.3	97.5	97.4
U-Net (segmentation)	96.2	95.8	96.0	95.9
DeepLabV3+ (segmentation)	96.9	96.6	96.7	96.6
Proposed DGBESCNN	**98.82**	**98.65**	**98.73**	**98.59**

Table 5 demonstrates that the proposed DGBESCNN achieved an accuracy with an F1 score exceeding that of the suggested transformers, segmentation models, and enhanced CNNs by over 1 percent when compared to the top baselines. This explains its ability to capture features with high accuracy and categorize them to support crop monitoring tasks.

Benchmarking Against IoT-enabled Crop Monitoring Methods

PECFIS-DGBESCNN system is superior to the current systems of monitoring agricultural activities through IoT because it incorporates the calculation of disease severity, analysis of nutrient deficiency, and identification of crop stages. It also offers the state-of-the-art solution to completeing crop health analysis and decision-making, unlike the previous models, which offers precise and real-time monitoring with a higher level of accuracy. Table 6 demonstrates the benchmarking against IoT-enabled crop minitoing frameowkr and the suggested PECFIS-DGBESCNN is more effective than current IoT systems of crop monitoring.

Table 6: Benchmarking against IoT-enabled crop monitoring frameworks

Author & Year	Framework	IoT Integration	Accuracy (%)	Precision (%)	Remarks
Rumy et al., 2021	IoT + ML (SVM, Logistic Regression)	Edge intelligence	94.3	93.8	Limited by shallow ML models
Bhuyan et al., 2023	Drone-based IoT + Stacked CNN	Drone imaging	96.7	96.2	No nutrient deficiency detection
Ramakrishnam Raju et al., 2022	IoT + AI Hydroponics	IoT sensors	95.5	95.1	Image-level nutrient monitoring only
Mishra et al., 2023	IoT + Customized CNN	IoT-enabled framework	96.8	96.4	Disease-focused, weak preprocessing
Proposed PECFIS + DGBESCNN	IoT + AI (Drone + PECFIS + DGBESCNN)	Drone-based IoT imaging	**98.82**	**98.65**	First to integrate crop stage, disease, nutrient deficiency, and severity

IoT Deployment and Resource Efficiency

The proposed DGBESCNN was implemented to make sure that other models can operate with it by placing it on NVIDIA Jetson Nano (4GB RAM, quad-core ARM).

Table 7: Model size, memory usage, and inference speed on edge device

Model	Model Size (MB)	Memory Usage (MB)	Inference Speed (fps)
EfficientNet-B0	21.8	685	12.4
ResNet-101	167.1	1,423	6.8
DenseNet-121	27.6	812	10.5
Vision Transformer	345.2	1,896	4.2
Proposed DGBESCNN	**18.4**	**632**	**14.7**

As table 7 shows, DGBESCNN used a small amount of memory but offered the highest inference (14.7 fps) and the smallest model volume (18.4 MB). This has indicated that it can be used in real time monitoring of crop in edge devices achievable through IoT.

Energy Efficiency for Sustainable Deployment

Energy efficiency analysis of Jetson nano edge device was conducted by determining the average value of power consumption when performing the inference.

Table 8: Energy efficiency comparison

Model	Power Consumption (W)	Energy per Inference (J)
EfficientNet-B0	6.5	0.52
ResNet-101	11.8	1.74
DenseNet-121	7.4	0.70
Vision Transformer	13.6	2.38
Proposed DGBESCNN	**5.9**	**0.40**

Table 8 indicates that the proposed DGBESCNN was suitable in terms of the implemented process because of the minimum power usage (5.9 W) and during the inference per system (0.40 J).

5 Conclusion

In this paper, a crop monitoring system is suggested based on AI and IoT technologies and combines the classification of crop growth stages and detection of leaf diseases and nutrient deficiency based on PECFIS and DGBESCNN. The system was tested using Leaf Disease and Nutrient Deficiency of Rice Crop dataset where drone-based IoT devices took real-time field images. PECFIS has shown good computational efficiency because it is able to determine eight important stages of rice growth within a very short rule generation time of 3591 ms. The DGBESCNN model demonstrated high classification and an accuracy of 98.82, precision of 98.65 and recall of 98.73 with the model indicating that AI-based analysis was effective in monitoring crop health. This framework applies edge computing in the application of remote agriculture fields, which reduces bandwidth requirements by performing most tasks at the edge. According to experimental results, the mean end-to-end latency per image is 210 ms, which can be monitored in real-time. The limitation in the network was overcome with asynchronous image broadcasting where images and predictions are localized and sent out once the network is re-established. This architecture reduces reliance on the constant network connectivity, and proves the viability of the drone-based surveillance of the IoT in rural settings. The framework has weaknesses despite the strengths. It compares rice crops only and the model does not differentiate between individual deficiencies of nutrients. The extreme weather conditions including heavy rain and thick fog were not taken into account, and the costs of operations might limit the adoption among the small holder farmers. The next round of work will be dedicated to the extension of the system to several types of crops and the incorporation of the low-cost ground-based IoT and weather sensors and enhanced robustness in the current unfavorable environmental conditions.

Future Enhancement

In the future, enhanced techniques will be developed to classify the numerous types of nutrient deficiencies in rice crops for improved productivity in agriculture.

Dataset link: https://www.kaggle.com/datasets/guy007/nutrientdeficiencysymptomsinrice

https://www.kaggle.com/datasets/vbookshelf/rice-leaf-diseases/data

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