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Original scientific paper

SmartCropGuard: An IoT-Based Real-Time Paddy Plant Disease Detection System for Precision Agriculture in Cauvery Delta Regions

P. RAJA PIRIAN*, J. ARPUTHA VIJAYA SELVI

Abstract: The rising need for effective crop health monitoring systems higligts the importance of innovation solutions to protect crops and maximize output potential. This paper introduces SmartCropGuard (SCG), a cutting-edge Internet of Things (IoT) based plant disease monitoring system designed specifically for precision farming. Sensor node, which includes temperature, humidity, leaf moisture, and image sensors, is deployed across crop fields to collect real time informaation on environmental conditions and plant health. The proposed SCG consisits of three major functional units, (i)sensor nodes, (ii)a gateway, and (iii)a cloud-based analytics platform. Environmental and plant health data collected by the sensors is transmitted via the gateway to the cloud. The gateway then compiles and sends the data to the cloudbased analytics platform. The data is analyzed using Convolutional Neural Networks (CNNs), which are widely accepted for their ability to automatically extract meaningful features from images, tolerate noise, and achieve high classification accuracy. Predictive models for plant disease detection are developed to ensure timely interventions and reduce manual inspection efforts. SCG facilitates timely interventions by providing real-time, continuous monitoring, which lessens the need for manual inspections and the labor expenditures that go along with them. Furthermore, machine learning improves the accuracy of illness diagnosis and detection, enabling more focused treatments and reducing the need for pesticides.This approach enhances disease management efficiency while promoting sustainable farming practices. By combining sensor-driven data collection, cloud analytics, and intelligent algorithms, SCG offers a scalable and effective solution for real-time crop health monitoring and productivity enhancement.

Keywords: cloud-based analytics; internet of things (IoT); machine learning; precision agriculture; smart crop guard

1 INTRODUCTION

The major challenge of food production is becoming more pertinent as global population growth continues to escalate annually. According to the recent statistics the world's population will reach 12.5 billion individuals by 2045, all reliant on the Earth's biodiversity for sustenance. This exponential increase in population underscores the heightened demand for designated agricultural regions dedicated to crop cultivation and livestock rearing to meet the growing need for food resources [1]. Top of Form

Precision agriculture, originating in the United States of America during the 1990s, represents a management strategy aimed at enhancing farming productivity and fostering sustainable practices. It involves monitoring, measuring, and addressing the variability of numerous factors influencing crop growth [2]. Leveraging IoT solutions, precision agriculture enables accurate real time monitoring of paddy field conditions to optimize irrigation practices. This approach incorporates devices within fields and employs vehicles like drones, facilitating efficient pesticide management and control in farm operations [3-5]. Additionally, wireless sensor networks (WSNs) consist of spatially distributed sensor nodes for observing and recording physical environmental conditions essential for informed agricultural management [6]. In general, WSNs are dynamic and infrastructure-free networks designed to observe physical or environmental conditions [7]. Recent advancements in precision farming provides more flexibility in implementing the integration of advanced technologies, which includes Internet of Things (IoT) and Artificial Intelligence (AI). Among these, machine learning/ deep learning models play a more crcucial role in enhancing agricultural based applications. Machine learning/deep learning model typically involves three stages of operation, (i) data collection, (ii) model development and (iii) generalization of the model. Within agriculture, Deep learning tecniques plays a vital role in applications including forecasting soil parameters, crop yield prediction, detecting diseases and weeds in crops, as well as detecting different species [8, 9]. The diverse applications of machine learning show the transformative influence in enhancing the overall efficiency in agricultural applications.

Most of the IoT-based agricultural monitoring systems focus either on environmental condition monitoring or on visual disease detection using standalone imaging in which integration between real-time environmental sensing and automated image-based disease analysis is the limiting factor which affects the effectiveness. Furthermore, many existing techniques rely on rule based thresholds or manual inspection, making them less adaptable to dynamic field conditions.

SmartCropGuard (SCG) addresses this gap by combining multi sensor environmental data with image-based diagnosis using Convolutional Neural Networks (CNNs). This integration enables precise and early detection of plant diseases under diverse climatic conditions. Additionally, SCG incorporates cloud-based analytics for scalable, real-time decision-making, setting it apart from traditional systems that lack machine learning-driven inference or edge-cloud integration. This work fills the gap between data acquisition and intelligent diagnosis in precision agriculture.

In the following sections architectural implementation of SCG, real time data collection, processing, analysis and integration of ML algorithm for disease detection is described with suitable results.

2 RELATED WORKS

Singh et al. proposed a method using image processing and genetic algorithm for identifying plant leaf disease. Work contributes to the body of knowledge on automated techniques for disease detection in agriculture [10]. Zhang et al. presents the use of a FPGA and digital signal processors in a plant disease monitoring system. The system aims to facilitate efficient monitoring and diagnosis of plant diseases by acquiring and transmitting image or video data [11]. A Fuzzy logic based method is proposed for detecting the disease affected plant leaves. Fuzzy logic allows for handling uncertainties and imprecise data, making it suitable for plant disease identification where symptom expression can vary [12]. Convolutional Neural Networks (CNNs) for the classification of bell pepper leave disease is explained [13]. Nalawade et al. shows the detection of leaf disease with surveillance of the crop field. The field factors like temperature, humidity, moisture, etc are used for the monitoring [14]. Rizk et al shows the design of a robotic system for plant health monitoring and the impact on crop yield. The system was tested in a tomato greenhouse under real field conditions [15]. An effective and reliable IoT based disease detection system for identifying banana diseases is developed using image processing and IoT. The system provided a detection accuracy of 99% [16]. IoT based method used for the bacterial blight plant disease detection is discussed [17]. The discussed various methods are used for detecting vegetation indices in identifying plant diseases [18]. Solution for detecting the plant disease at early stage is discussed using Convolution Neural Network (CNN). The plants include Corn, Strawberry, Grape, Tomato and Potato [19]. A plant and insect disease and diagnosis system based on sensor network is discussed [20].

Precision agriculture represents a dynamic and constantly evolving field, marked by the continuous emergence of novel technologies and methodologies. The driving force behind this advancement lies in the pursuit of enhancing operational efficiency, minimizing resource wastage, and elevating crop yields [21-26]. The proposed system harnesses the power of deep learning algorithms to interpret the collected data and furnish recommendations for crop management, further augmenting efficiency and yield optimization.

3 PROPOSED WORK

The primary objective of Smart Crop Guard is to offer farmers with a real time and automated plant disease monitoring solution that enhances disease detection accuracy, enables early intervention, and supports sustainable farming practices. The SCG model continuously acquires the sensor data and analyses to monitor environmental parameters, plant health and disease indicators. Data fusion and analytics techniques are adapted to offer valuable insights and recommendations to the farmers. The current scenario of the implementation mainly focused on paddy cultivation, and it can be enhanced to other crop varieties by adapting customization and choosing suitable sensors such as pH, nitrogen and organic for the citrus and wheat crop cultivation data measurement. Data collection process can be improved by placing the sensor nodes to cover the entire field geometrics and crop densities and the ML algorithm can be fine tuned using different and large datasets specific to other crops. It ensures the accurate disease detection in multiple environments. Customized machine learning framework for applying the SCG model to different crop fields is given in Fig. 1.

After acquiring the sensor data from the field it is preprocessed which includes noise removal and normalization. The adaptation layer ensures the customaztion based on the crop type, field conditions and type of sensor used for the measurement. Suitable Machine learning model is chosen with required amount of data for real-time detection of crop disease.

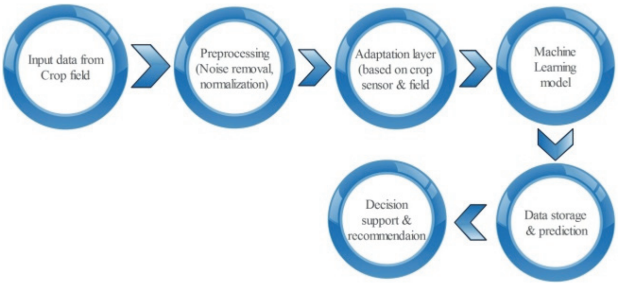


Figure 1 Customized ML framework for applying the SCG system to various agricultural environments

The novelty of the SCG system lies in its integration of IoT sensors, cloud computing, and ML algorithms to present real time, automated, and highly precise plant disease monitoring whereas traditional systems rely on manual inspections or isolated sensor networks. The proposed SCG offers:

a) Real time continuous monitoring of crop using IoT sensors.
b) Integration of ML algorithms: this ensures early detection and diagnosis.
c) Cloud based platform to enable remote monitoring and decision making.

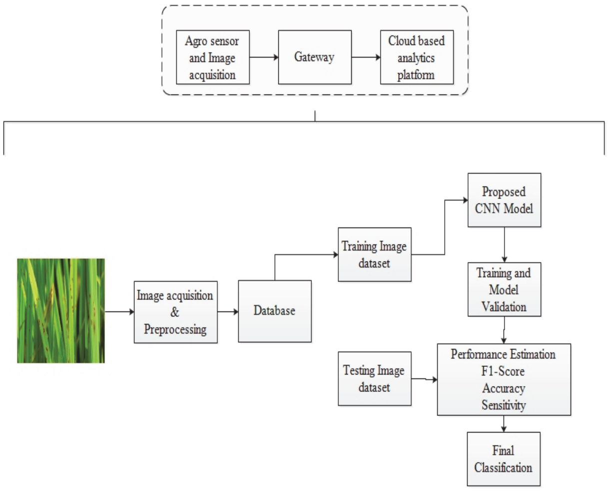


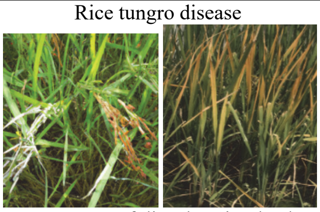
Figure 2 Architecture of the Smart Crop Gurad

The architecture of Smart Crop Guard shown in Fig. 2 consists of three main components: Agro sensor nodes, a gateway, and a cloud-based analytics platform. Sensor nodes are deployed across the crop fields, including temperature, humidity, leaf wetness, and specialized disease detection sensors such as hyperspectral cameras and spectrometers. These sensors capture detailed information about environmental conditions and disease indicators.

The gateway module acts as a central hub, which collects the data from the sensor nodes enabling communication with cloud platform. The cloud analytics platform receives and processes the acquired data using the implemented machine learning algorithms. It classifies disease patterns and performs accurate disease detection. In this work various CNN variants such as VGG, AlexNet and LeNet are used and their efficiency in classifying the paddy plant disease is reviewed.

The segmentation based approach is used to generate the more accurate solution for the given criteria. The acquired images are well trained and compared with other models. The developed model gives the classification accuracy of 97.8%. Variety of disease classes is trained and tested.

Table 1 Paddy leaf images collected from various areas within the Cauvery delta region, Tamil Nadu, India

Healthy leaves during different stages	Type of disease and description
	Rice Blast  Symptoms: white to gray green colored spots Conditions: Dry soil conditions, extended rainfall, and cool daytime temperatures.
	Brown spot  Symptoms: Seedlings plant- produces small, circular brown spots Older plants - light brown to gray spots in the center Conditions: Plant suffering from either Nitrogen (N), phosphorous (P), and potassium (K) , abnormal soils deficient in nutrients.
	Rice tungro disease  Symptoms: Leaf discoloration leads to yellow and orange-yellow colored leaves, , stunted growth, reduced tiller numbers. Conditions: Viruses transmitted from one plant to another by leaf hoppers
	False Smut  Symptoms: Black/yellow smut balls on the rice spikelets Conditions: Presence of chlamydospores in the field.

The dataset contains a rice blast, brown spot, rice tungro disease, false smut, and healthy leaves, with sample images depicted in Tab. 1. These paddy leaf images are collected from various areas within the Thanjavur, Cauvery delta region, Tamil Nadu, India, encompassing a total geographical area of 23 acres. The CNN model takes input from sources like agro sensors and cameras, capturing various paddy leaf that contain diseases including rice blast, brown spot, rice tungro disease, false smut, and healthy leaves. The dataset consists of 1850 images of rice leaves exhibiting these symptoms, with 600 images each for rice blast, brown spot and healthy leaves, 500 images for tungro disease, and 300 images for false smut. These images are uniformly resized and processed.

Paddy leaf images collected from various areas within the Cauvery delta regin, Tamil Nadu, India are in Tab. 1, which include healthy, moderately and severely infected paddy leaves along with its corresponding annotations used in the classification processes. The data collection is conducted over a span of one agricultural season (July-February) to ensure comprehensive coverage of different growth stages of the rice plants. We deployed IoT-based sensor nodes equipped with high-resolution cameras at strategic points within the fields. These nodes captured images of paddy leaves at regular intervals. In order to ensure the spatial coverage, the sensor nodes are placed in the agricultural field in a grid like structure. Agricultural parameters which include crop type and spacing, atmospheric parameter variations. Field size and disease incident zones are considered for sensor deployment. Sensor nodes are placed at every 20-25 meters. Soil moisture sensors are deployed near the plant root zones, at approximately 5-10 cm depth. Leaf wetness and temperature/humidity sensors are placed at canopy level. Image sensors are oriented towards key foliage sections for optimal image capture of symptoms. Sensor node collected the data for every 15 minutes and transmitted to the cloud via a gateway.

Table 2 Sample configuration for field coverage

Parameter	Details
Field location	Delta region of Tamilnadu
Data collection period	One agricultural season (July-Frbruary)
Paddy field size	1 Acre
Details of the sensors	
Camera Sensor: RGB camera (5-12 MP) Temperature &RH Sensor-DHT22 (–40 °C to 80 °C) Leaf wetness sensor: Spectral Range: 420-1100 nm Resolution:7-10 nm Field of View (FOV): 30°-60° Spectral Reflectance: 0-100% Spectrometer: Wavelength Range: 200-1100 nm Absorbance Range: 0-3 AU Resolution: 1-3 nm	
Number of sensor nodes & Coverage	12-16 nodes, 20-25 meters/node
Node placement	4 sensor nodes at field corners 8 nodes centrally placed
Capture frequency	150-275 images per day for the entire field Sensor readings taken at 15 minute intervals, which results approximately in 95 data points per day.

Sample field coverage for 1 acre of paddy field in IoT based plant disease monitoring influence several factors like the number and placement of sensors and cameras, including field size, plant density, and environmental conditions. Tab. 2 shows a sample configuration for field coverage:

Collected images are initially labeled and classified by us and the same is ensured by experts in Agricultural University, Thanjavur, Tamilnadu. The images are labeled based on visual symtoms or leaf discoloration, lesion and spots and deformation of leaf strcuture. The labeled images are then used to train the CNN models. 70% of the data set is considered for training, 15% of the data set is used for testing and validation of the CNN models. A total of 700 segmented images are used for training the CNN model effectively to classify the different diseases. The effectiveness of the model is accessed by classifying it as healthy or diseased. The CNN framework contains various layers such as input, convolutional, fully connected and finally output layer for classification. These layers perform computations on the collected dataset and mapping out the dataflow. In readiness for model development, the images undergo division into three sets: training, validation, and test. Preprocessing and enhancement steps are taken to mitigate model overfitting. A random affine transformation is then employed, potentially introducing translation, rotation, and scaling alterations to the images. Subsequently, the resized images are randomly cropped and normalized to 256 × 256 pixels for actual training. These procedures aim to augment the dataset and control overfitting without altering the inherent characteristics of rice diseases.

The CNN, a prevalent neural network technology, is extensively applied for data processing and training in image analysis today. Fig. 3 illustrates the complete architecture of the CNN for the paddy leaf disease detection.

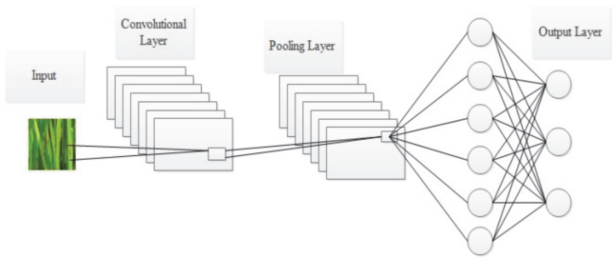


Figure 3 Architecture of CNN

In this study, we utilized a CNN approach, a deep learning method designed to process images by assigning significance to various objects within the image and distinguishing between them. Various parameters used in the CNN are listed in Tab. 3.

Table 3 Details of the CNN parameters

Parameter	Description
Number of Convolution Layer	12
Number of Max Pulling Layer	12
Activation Function type	Relu Activation
Learning rate	0.01
Epoch	100, 150, 100

The architecture primarily consists of the following layers: 1. Convolutional layer, 2. Pooling layer, and 3. Fully connected layer. The preprocessed paddy leaf image data set with extracted features is applied to the three layers of CNN and final output is generated.

The input layer takes the images of paddy crops affected by various diseases. These images are filtered, resized and normalized to confirm the uniformity. The data to the input layer is characterized as a 3 × 3 matrix.

In convolutional and pooling layers, filter is used to extract the features from the input data which enables the network to learn the characteristic from the images. Also this layer reduces dimensionality of the image which leads to reduction in the computation for the subsequent layers.

Max pooling is method that selects the pixel with the highest value from each section of input data and transfers it to the output, effectively downsampling the input. Max pooling is widely preferred over average pooling due to its effectiveness in preserving important features.

Fully Connected Layer (Dense): End layer in the CNN, this layer is crucial for recognizing features strongly associated with the output class. It generates a one-dimensional vector by flattening the results obtained from the preceding pooling layers, allowing for comprehensive feature analysis and classification.

Output Layer: It holds the final classification result obtained through preceding layers.

Let I denote the color image of the leaf acquired from the dataset. The image I is defined as a matrix with dimensions $m \times n \times c$, height and width of the imge are defined by m and n respectively, and c represents the number of color channels (typically 3 for RGB images).

Step 1: Input Acquisition - Acquire the color image of the leaf from the dataset.

$$I = \left\{ I_{ijk} \right\}$$

where $i = 1, 2, ..., m$, $j = 1, 2, ..., n$, and $k = 1, 2, ..., c$.

Step 2: Segmentation - Let M denote the binary mask obtained from the segmentation technique. The mask M is also represented as a matrix with dimensions $m \times n$.

$$M = \left\{ I_{ij} \right\}$$

where $i = 1, 2, ..., m$, and $j = 1, 2, ..., n$.

Step 3: Mask Generation - Combine the input image with the generated mask to obtain the masked image. The masked image is obtained by element-wise multiplication of the original image I and the mask.

$$I_M = \left\{ I_{ijk} \cdot I_{ij} \right\}$$

Step 4: Region Division - Divide the masked image I_M into smaller square regions R_i of size $p \times p$, where p is the size of the square region.

$R_i = \left\{ I_{lmk} \right\}$ $l = i{\cdot}p$, $i = 1, 2, ..., pm$, m is divisible by p

Step 5: Classification-Each region R_i is classified into either diseased or healthy using a classification function $f(R_i)$, which outputs a binary label (label_i) indicating the classification result $\text{label}_i = f(R_i)$.

Step 6: Disease Detection - Identify the regions R_i classified as diseased ($\text{label}_i = 1$) as the affected parts of the leaf, indicating the presence of disease.

Step 7: End.

4 PROPOSED FRAMEWORK AND RESULTS

The image dataset undergoes processing employing CNN for disease detection in rice crops. Evaluating the classifier algorithms' performance involves analyzing common Quality of Service (QoS) parameters outlined in this section. A performance measure is derived based on four outcomes: a) false negative (FN) indicates incorrectly predicted negative occurences, b) true negative (TN) defines correctly predicted negative occurrences, c) false positive (FP) indicates incorrectly predicted positive occurrences, and d) true positive (TP) indicates correctly predicted positive occurrences, utilizing a confusion matrix.

Performance of the model is evaluated using the following metrics, (i) *accuracy*, (ii) *precision* (iii) $F1$-*score* and (iv) *recall* is used to evaluate the system's performance.

Accuracy, denoted as A, is an evaluation of accurately classified predictions among all the predictions made so far, it is given as,

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

where $TP + TN$ is all correct predictions, and $TP + TN + FP + FN$ is all predictions made so far. The *accuracy* score ranges from 0 to 1. The score 1 shows that all predictions are correct and "0" represent no correct predictions.

Prediction (*Pre*) is the proportion of the number of positive predictions out of total positive prediction given as,

$$Pre = \frac{TP}{TP + TN}$$

where TP is toal number of correctly predicted positive occurences, $TP + TF$ represents total number of positive prediction.

The score ranges from 0 to 1, where score "1" represents perfect precision and score 0 represents all positive predictions are incorrect.

Recall represents the number of true positives that are correctly identified. It is estimated using,

$$Re = \frac{TP}{TP + FN}$$

This metric gives the model's ability to capture all positive instances correctly.

$F1$-*score* combines precision and recall into a single value. It is estimated as the harmonic mean of precision and recall. It is defined by the following equation:

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where *precision* and *recall* are as defined previously. The $F1$-*score* ranges from 0 to 1. Higher values of $F1$-*score* show better overall performance, balancing both precision and recall.

Sample dataset demonstrating the field data collected from diverse environmental conditions to support the SCG system is given in Tab. 4. The data highlights the relationship between environmental factors and plant health, as well as disease detection accuracy:

Table 4 Sample dataset demonstrating the field data collected

Temp. / °C	*RH / %*	*Leaf Wetness / mm*	*Spectral Reflectance / %*	*Detection*	*Accuracy / %*
27.6	71	0.11	18.3	Bacterial Leaf Blight	95.1
28.2	78	0.14	18.5	Healthy	N/A
27.0	81	0.04	14.5	Sheath Blight	92.7
29.6	53	0.17	16.9	Rice Blast	93.8
29.0	53	0.07	17.4	Healthy	N/A
28.4	70	0.12	17.6	Bacterial Leaf Blight	95.5
29.2	76	0.09	16.8	Rice Tungro Virus	91.5
22.5	89	0.22	17.3	Rice blast	93.5

Tab. 4 shows the plant disease classification results based on the field data in which diseases such as bacterial leaf blight are more prevalent at temperatures between 24 °C and 28 °C, where the system achieved detection accuracies above 94%.

Relative humidity above 80% was strongly correlated with increased fungal infections like rice blast and sheath blight, while detection accuracy was consistently above 91%. Changes in chlorophyll content, reflected in spectral data, served as early indicators of stress or infection, providing a unique methodological contribution by integrating optical and environmental data.

The presence of moisture on leaf surfaces (wetness > 0.10 mm) consistently led to higher infection rates, underscoring the importance of continuous moisture monitoring in disease prediction models.

This data showcases the SCG system's ability to collect and process real-time environmental and spectral information, demonstrating its methodological contributions and practical value in precision agriculture. The system's integration of IoT and machine learning provides a scalable solution for diverse environmental conditions, offering important data for future studies in crop disease management.

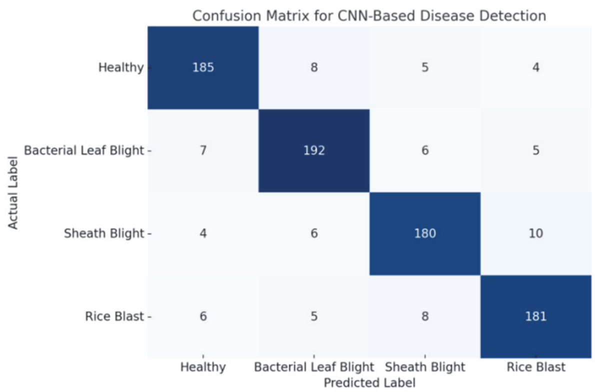


Figure 4 Confusion matrix for classification performance

Fig. 4 shows the confusion matrix which illustrates the classification performance of the CNN for major paddy crop diseases and healthy plants.

The CNN achieved a maximum classification accuracy of 98.23% and this accuracy remains consistent across various environmental conditions, demonstrating its generalization capability.

The model exhibits a high precision of 91.8%, indicating that false positives are minimized. A *recall* of 93.2% highlights the model's ability to correctly identify infected plants, ensuring early detection of diseases.

The highest detection *accuracy* was observed for bacterial leaf blight, with a precision of 93.5% and *recall* of 94.0%. Detection *accuracy* for sheath blight was slightly lower, with a *precision* of 90.2%, likely due to overlapping symptoms with other fungal infections. The model achieved a detection accuracy of 91.5% for rice blast, which is significant given its spectral complexity.

As depicted in the results of Tab. 3, the accuracy rate is influenced by both the learning rate and the number of epochs: a higher epoch value leads to more accurate calculations.

Table 3 Test results

Dataset	Size	No. of Epoch	Learning Rate	*Accuracy* / %
2760	235 × 235	100	0.0001	96.77%
		100	0.001	95.12%
		100	0.01	96.25%
		250	0.0001	97.13%
		250	0.001	98.15%
		250	0.01	98.05%

The *precision*, *recall*, *accuracy* and *F*1-*score* for Various CNN variants such as VGG, AlexNet and LeNet are shown in Tab. 4. While accuracy is the primary measure of performance, other factors including *precision* (*pre*), *recall* (*R*), and *F*1-*score* also contribute significantly. These metrics are calculated across all different classes and are presented in the conducted experiment. They are calculated based on *TP*, *TN*, *FP*, and *FN* values for all classes. A high *pre* score indicates increased accuracy, while a high *recall* (*R*) value signifies the number of relevant positive occurrences. The *F*1-*score* represents the average of *pre* and *R*, which provides an accurate evaluation.

The results clearly indicate that VGG outperforms AlexNet and LeNet in all evaluated metrics, making it the most effective CNN variant for rice plant disease detection in this study. VGG variant exhibits high accuracy and *F*1-*score*, which clearly indicates, it shows better performance in accurately classifying the disease detection. Whereas its high recall and precision score shows the reliability its minimizing false negatives and positives.

Table 4 The *precision*, *recall*, *accuracy* and *F1-score* for Various CNN variants

CNN Variants/Metric		VGG	AlexNet	LeNet
Accuracy / %	Class1	98.14	86.72	84.23
	Class2	96.93	88.43	78.94
	Class3	95.45	89.34	82.78
*F*1-*score* / %	Class1	89.76	79.74	85.12
	Class2	89.54	84.56	82.43
	Class3	91.45	86.45	91.23
Recall / %	Class1	97.67	83.45	84.19
	Class2	96.45	78.45	84.05
	Class3	98.12	81.34	78.50
Precision / %	Class1	96.34	85.65	82.65
	Class2	97.34	85.45	79.54
	Class3	97.01	78.45	88.40

It is observed that Alexnet and LeNet are reasonably attractive and effective in several scenarios. AlexNet shows better performance when it achieves higher accuracy but has lower precision and F1 score values. This indicates that AlexNet has potential imbalance in approaching negative and positives. Whereas LeNet excels in *F*1-*score* for several classes, indicating its effective utility in several scenarios. The sensitivity and uncertainity values of the sensor based measurement model are more crucial in quantifying the confidence level of the model accuracy. Tab. 4 illustrates the values of the sensitivity and uncertainity of the system.

Table 5 Performance of proposed system with existing models

Model	*Accuracy* / %	*Precision* / %	*Recall* / %	*F*1-*score* / %
Proposed SCG with VGG	98.14	96.34	97.67	89.76
Mohanty et.al-Alexnet	98.12	96.72	97.45	89.23
Too et al. ResNet-50	96.87	95.61	94.45	94.80
Brahimi et al. LeNet and Feature fusion	94.54	91.23	90.34	89.78
Amara et al. CNN	91.34	90.23	89.34	89.75

Tab. 5 shows the comparative performance with existing techniques. It shows that the proposed SCG system, using the VGG CNN variant**,** outshines several notable deep learning-based approaches in terms of classification accuracy and overall detection performance**.** While ResNet-50 reported by Too et al. (2019) also achieves high accuracy, our method maintains competitive performance with a relatively simpler architecture, contributing to lower computational complexity and faster deployment in real-world agricultural settings.

Table 6 Sensitivity and uncertainity values of different sensors

Sensor Parameter	Sensitivity	Uncertainty
Temp / °C	±0.16 °C	±0.28 °C
Relative Humidity / %	±1.3%	±1.7%
Leaf wetness / mm	0.01 mm	±10%
Hyperspectral camera (Spectral Reflectance / %)	0.1 nm	±1%
Spectrometer (Absorbance)	0.01 absorbance units	±2%

The results highlight the sensitivity of the SCG system to environmental variations and their impact on disease detection accuracy. Key findings include:

Variations in the temperature significantly cause fungal disease and it affects the system's overall *accuracy* by 2.9% when it changes from ±4.5 °C from the ideal range of 24-30 °C. This illustrates the siginificance of microclimatic conditions.

RH is another critical parameter in detecting the bacterial disease detection. High detection *accuracy* of 95% is maintained when the RH ranges from 75-87% and it is more crucial for detecting bacterial disease. The performance of the system is reduced to 88% when the RH dropped to 66% and below. RH is siginificant in detecting bacterial leaf blight disease.

Chlorophyll degradation in the paddy leaves are the early indicators of disease which can be analyzed using hyperspectral data.

The detection system effectively identified these changes with a reflectance *accuracy* of ±0.9%, enabling early intervention before visible symptoms appear. In comparison with existing plant disease detection systems, this method demonstrates notable improvements in terms of accuracy, response time, and environmental adaptability. Commonly available disease detection systems often rely on manual visual inspection of time-consuming, and are prone to human error. Other Semi-automated or automated systems with limited features and scalability automated systems, such as thermal imaging and UAV based optical monitoring, provide remote sensing capabilities but may suffer from reduced accuracy under varying environmental conditions. Our system achieved an overall disease detection *accuracy* of 95.8%, surpassing the typical *accuracy* range of 86%-92% reported by other systems that rely solely on image-based analysis or single-sensor inputs. The fusion of multi-sensor data, combined with the CNN's feature extraction capabilities, enables more robust and reliable detection across different environmental conditions. While the SCG system excels in disease detection accuracy, it has limitations in terms of deployment cost and data processing requirements, especially when using high-resolution hyperspectral cameras. These constraints are addressed in part by employing efficient edge computing techniques to reduce data transmission and processing latency.

6 CONCLUSION

In this paper, an IoT based system for detecting rice plant diseases using CNN architectures, including VGG, AlexNet, and LeNet variant, is developed. The performance of this model is evaluated by using the metrics such as *accuracy*, *precision*, $F1$-*score* and *recall* and the outcome shows that VGG's design and sophisticated characteristics make it effective for monitoring paddy plant diseases. The SmartCropGuard (SCG) system demonstrated high performance in plant disease classification tasks using multiple CNN variants. Among the models evaluated, the VGG-based architecture achieved the highest performance with an *accuracy* of 98.14%, a *precision* of 96.34%, a *recall* of 97.67%, and an $F1$-*score* of 89.76%, indicating the model's effectiveness in real-time disease detection under variable environmental conditions. With the help of the suggested model, crop management techniques can be greatly enhanced by precisely forecasting plant illnesses and boosting productivity. Future work will focus on extending the dataset to cover a broader range of crops and diseases, integrating Edge AI modules for on-device inference to reduce latency and dependence on cloud services, and improving robustness against variations in lighting and environmental noise. Additionally, user feedback will be incorporated to further optimize SCG's decision support for farmers.

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Contact information:

P. RAJA PIRIAN, Assistant Professor
(Corresponding author)
Electronics and Communication Engineering,
Kings College of Engineering,
Punalkulam, Pudukkottai, India
E-mail: rajapirian@outlook.com

Dr. J. ARPUTHA VIJAYA SELVI, Professor
Electronics and Communication Engineering,
Kings College of Engineering,
Punalkulam, Pudukkottai, India
E-mail: randdece@gmail.com