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Rohit Thanki · Ajay Kumar (Eds.)

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Iot and Machine Learning-Based Sugarcane Leaf Disease Classification

S. Akhil[1] and R. Durga[2(✉)]

[1] Department of Computer Science, VISTAS, Chennai, India
[2] Department of Advanced Computing and Analytics, VISTAS, Chennai, India
drrdurgaresearch@gmail.com

Abstract. Leaf infections have a significant impact on sugarcane production, a valuable cash crop, and can result in substantial financial losses. Traditional methods of identifying illnesses are time-consuming and need specific expertise. In this research, we propose a machine learning (ML) technique based on quantum-behavior particle swarm optimization (QPSO) and image processing techniques for accurate disease detection, aiming to provide IoT-integrated sugarcane leaf disease prediction. Furthermore, the IoT sensors are connected to the camera modules to collect environmental data (temperature, humidity, and soil moisture) and gather images of sugarcane leaves. A Contrast-Limited Adaptive Histogram Equalization (CLAHE) algorithm is used in pre-processing to enhance contrast. After that, leaf segmentation is performed using a watershed algorithm to isolate the affected areas. The use of a lightweight deep learning model, DenseNet, for feature extraction is optimized for edge computing. Furthermore, the optimal hyperparameter selection can be done by classifying using a convolutional neural network (CNN) and a support vector machine (SVM), with improved performance through QPSO based on extracted features. Additionally, the implemented results are sent to a cloud-based or edge computing platform, allowing farmers to access disease predictions through a mobile or web-based dashboard. Furthermore, it provides alerts and preventive measures to reduce crop losses. This system offers a cost-effective, scalable, and efficient solution for precision agriculture.

Keywords: quantum-behavioural particle swarm optimization · support vector machine · machine learning

1 Introduction

An important agricultural crop that plays a big part in the world economy is sugarcane, which is used to make biofuels and sugar, among other goods. Sugarcane farming has difficulties, particularly concerning diseases that might impair output and quality. Fungal, bacterial, viral, and phytoplasmic diseases are common in sugarcane and can result in significant financial losses. Traditional illness detection techniques are time-consuming and sometimes imprecise since they frequently depend on eye inspection. Furthermore, certain illnesses are asymptomatic, which makes early identification challenging and calls for more sophisticated and trustworthy techniques [1]. As previously stated, the

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crop contributes significantly to the country's economy and supplies unprocessed or raw materials for sugar production.

Additionally, sugarcane is the sole source of raw materials for more than 25 major industries, including producing alcohol, paper, chemicals, cattle feed, pharmaceuticals, and ethanol for biofuel production [2]. Sugarcane buds must be trimmed precisely to guarantee their viability and good germination. Automation is necessary since the existing hand-cutting method may be laborious and error-prone. Creating specialized seedling translators emphasizes even more how crucial accuracy and effectiveness are when planting bud chip seedlings [3]. Predicting sugarcane illnesses early and accurately is essential for prompt intervention and can lessen these difficulties, improving sustainable farming methods and stimulating the economy. However, high-quality datasets are frequently necessary for successful prediction, particularly when machine learning and other predictive modelling approaches are used [4].

This difficulty has prompted the introduction of several creative technology solutions. Utilizing chemical agents and macerating plants are two traditional methods for diagnosing plant diseases; however, both processes require expert evaluation in specialized labs, which increases the process's time and cost. To overcome these limitations, non-invasive plant disease monitoring and diagnosis techniques have been developed, such as image processing, spectral imaging, remote sensing, and computer-aided detection [5]. Unfortunately, the emergence of diseases poses a third threat to this crop's widespread cultivation, mostly brought on by a lack of pathology services. Additionally, most farming occurs in rural regions, where farmers usually neglect to identify diseases promptly, which eventually harms the produce. Fortunately, this problem can be solved if we have a trustworthy way to identify the condition quickly [6].

A. **Objectives**

To Create and implement an IOT-based system for categorising and monitoring of sugarcane leaf diseases. Utilize sophisticated gadgets and sensors to gather crisp photos of sugarcane leaves.

Use Contrast Limited Adaptive Histogram Equalization to increase feature extraction and picture contrast. Improve disease-related characteristics and reduce noise to improve classification accuracy.

Use quantum-behavioural particle swarm optimization (QBPSO) for hyperparameter tweaking and ML model optimization. SVM parameters can be adjusted to increase classification accuracy.

B. **Organization of the paper**

The remainder of the paper is divided into important sections that explain current IOT and machine learning research. Section 2 lists the Sugarcane Leaf Disease Classifications completed by different writers. Section 3 describes the steps of the suggested methodology, and Sect. 4 explains the results and performance comparison of the suggested model. Finally, Sect. 5 concludes the article.

C. **Motivation of the research**

- The research aims to develop an IoT-based system that leverages smart sensors to capture clear images of sugarcane leaves in real-time, thereby enabling more efficient disease identification.

- To improve the quality of these images, we use a technique called CLAHE, which increases the contrast of the images, makes disease features easier to identify, and reduces unwanted noise. Once a clear picture is available, the next step is to use machine learning to accurately classify diseases.
- To improve the accuracy of ML models, especially SVMs, we propose a technique known as QPBSO.
- The aim is to develop an automated system that can quickly and accurately diagnose sugarcane leaf diseases so that farmers can manage their crops more effectively.

D. Scope of the research

This research focuses on developing an IoT-based system to monitor and identify leaf diseases of sugarcane. The coverage includes:

- Advanced sensors and cameras are used to capture high-quality images of sugarcane leaves
- Utilize CLAHE to enhance image quality, facilitating the detection of disease features.
- Disease classification using ML models, especially SVM, is used to classify various sugarcane leaf diseases automatically.
- Improve the model performance by fine-tuning the model using QBPSO to improve accuracy.

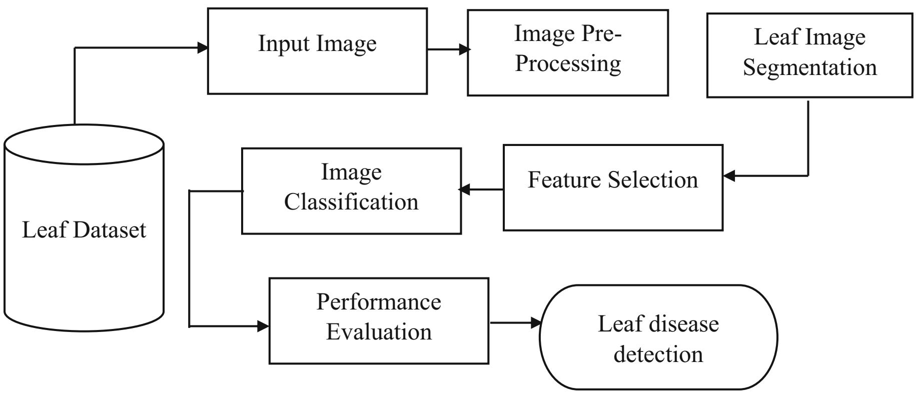

Fig. 1. Sugarcane Leaf Disease Basic Diagram

Figure 1 shows the basic process of diagnosing sugarcane leaf disease. The system starts with a leaf dataset, from which the input images are obtained. Images are pre-processed to improve quality and remove noise, and then segmented to isolate leaf regions. Then, feature selection is used to extract essential features such as color, texture, and shape. These features are used in image classification to categorize leaves as healthy or diseased. Finally, the computer performs a performance evaluation to measure accuracy and efficiency before moving on to the leaf disease detection.

2 Related Work

To enhance sugarcane disease prediction, this work offers a creative and efficient assessment of DL models that use the benefits of many DL classifiers, including Alex Net, ResNet18, and Densenet201 with VGG19. Red rust, red rot, mosaic, and yellow leaf disease are some diseases. Our approach first categorizes sugarcane pictures using individual classifiers and then identifies and compares the best-performing classifiers. This article used photographs of sugarcane leaves in 1990 to classify leaf illnesses into normal, red rust, red rot, and bacterial blight. VGG19 exhibited the highest sensitivity (96.33%), accuracy (98.82%), and precision (96.77%) across the four class classifications (Little Lion et al., (2024)). Using 20,000 images of sugarcane, both healthy and sick or diseased, from a database of sugarcane pictures, this study proposes many deep-learning models. The training models used in deep learning were used in the inquiry. The model with the most training will be the most accurate of all the trained models. The trained models do this task by recognizing and classifying images of healthy and diseased sugarcane leaves based on a pattern of defects and healthy leaves. If sugarcane illnesses are detected early on using deep learning algorithms, farmers can preserve their crops and revenue streams (Patil et al., (2024)). A channel and spatial attention are used for saliency detection to combine characteristics from lower to higher levels. On a custom database, the model outperformed cutting-edge models like VGG19, ResNet50, XceptionNet, and EfficientNet_B7, achieving an accuracy of 86.53%. The results demonstrate the importance of all-level features in picture classification and how they may boost output even in small datasets. The proposed design may facilitate early plant disease diagnosis and detection, allowing for quick mitigation of crop harm (Daphal et al., (2024)). A unique DenseNet-support vector machine: explainable artificial intelligence interpretation that combines a DenseNet and support vector machine with a local interpretable model-agnostic explanation interpretation. A picture's properties are extracted using a convolution network called DenseNet before SVM is used to assess if the image is healthy or not (Ethiraj et al., (2024)).

Device studying and deep studying techniques have surfaced as viable ways to automatically recognize and categorize plant diseases using image analysis in response to these challenging circumstances. This summary document thoroughly analyses image-based plant disease detection systems that focus on several areas, such as the kinds and resources of plant datasets, the variety of ML and DL algorithms employed, and how well they work in real-world applications. We look at a successful case study and highlight significant developments in the field, highlighting how these technologies have improved the precision and effectiveness of illness identification (Chakravarty, et al., (2024)). Transfer learning achieves remarkable accuracy on a dataset of images devoid of noise. However, their performance drastically declines on datasets containing photos with intricate natural backgrounds. This study outlines a group of binary classifiers based on transfer learning that use a binary classification tree to identify certain sugarcane leaf diseases. With an outstanding overall validation accuracy of 98.12%, macro-average precision of 97.75%, recall of 97.93%, and F1-score of 97.84%, our model was able to accurately classify five different sugarcane leaf diseases (Das, et al., (2024)). In automated opinion photographs, the neural network armature recognises complex patterns indicative of sugarcane instantiations. The algorithm achieves exceptional delicacy by learning to distinguish small characteristics linked to automatic opinion through an iterative training approach. The outcomes of the trial validate the effectiveness of our suggested approach. It examines the profit and drawbacks of the various CNN infrastructures used for manufacturing complaint finding, such as AlexNet, VGGNet, ResNet, InceptionNet, and DenseNet (Angamuthu et al., (2024)). The suggested model combines seven specially designed and LASSO-regularized pre-trained models into an optimal weighted average ensemble, specifically InceptionV3, InceptionResNetV2, DenseNet201, DenseNet169, Xception, and ResNet152V2. The greatest results for identifying sugarcane illnesses were obtained by this refined "sugarcane Net" model, which had F1 scores of 100%, 100%, 100%, and 99.67% for accuracy, precision, and recall, respectively (Talukder et al., (2024)). Specifically, the publicly available Sugarcane Leaf Dataset was utilized for training and evaluation using popular Vision Transformer topologies such as DeiT3-Small and DeiT-Tiny. There are 11 different disease categories and 6748 images in this collection. Additionally, these models were compared to popular CNN models. The results of the investigation demonstrate that, with a 90.96% F1-score, 91.27% precision, and 93.79% accuracy, the DeiT3-Small model performed the best out of the 12 models evaluated (Paçal et al., (2024)).

Vector Auto-Regressive Moving-Average model is applied to each modality of categorizing illnesses into distinct groups. This study represents a breakthrough in predicting and detecting sugarcane diseases. A comparative analysis demonstrates a significant improvement over current models, with improvements of 4.5% in accuracy, 3.5% in precision, 3.9% in recall, 4.3% in Area under Curve, and 3.4% in specificity. Additionally, the model reduced the latency by 2.9% by speeding up processing. The VARMA model's predictive precision showed improvements of 1.9%, 2.5%, 2.4%, 3.5%, and 1.5% in terms of precision, accuracy, recall, and specificity, as well as a 2.4% decrease in delay levels (Reddy et al., (2025)). The red, green, and blue channel values' output PW was recorded using three different colour types for hand-coloured nodes (black, red, and blue), three different feeding system speeds (7.5, 5, and 4.3 m/min), three different RGB colour sensor installation heights (2.0, 3.0, and 4.0 cm), and three different coloured line widths (10.0 mm, 7.0 mm, and 3.0 mm). The recognition rate for hand-coloured sugarcane nodes was 95% to 100% in laboratory tests, and the average scanning duration was between 1.0 and 1.75 s (Yang et al., (2024)). Explored the possibilities of machine learning in conjunction with visible-shortwave near-infrared spectroscopy for this categorization problem. Several preprocessing methods were used to improve spectral characteristics after spectral information from the Khon Kaen 3 sugarcane cultivar was obtained at various locations. The classification performance of three machine learning algorithms, artificial neural networks-Nearest Neighbors, and linear discriminate analysis was assessed. The results demonstrated exceptional accuracy across all models, with ANN and derivative preprocessing achieving an F1-score of 0.93 on the calibration and validation datasets and 0.92 on an independent test set (Veerasakulwat et al., (2024)).

Each polygon was classified as sugarcane or another land cover using machine learning techniques. 19 Principal Components accounted for 94.61% of the cumulative explained variance ratio. RF (78.51%) was the most accurate strategy, followed by

DT (72.30%), LR-L (69.64%), LR-R (69.64%), and LR (69.52%) using a testing sample of 20% of the data. The data collected for this study was divided into over 46,000 polygons (observations) and spanned an area of more than 306,000 hectares in the Brazilian state of São Paulo. Over 17 months, 102 variables were created by observing six spectral bands and vegetation indicators (Silva et al., (2024)). To assess four deep learning models' ability to identify betel leaf diseases: VGG19, a Vision Transform model, DenseNet201, and ResNet152V2. The VIT and ResNet152V2 models achieved testing accuracies of 97.83% and 98.42%, respectively. At 91% testing accuracy, the VGG19 model was somewhat less accurate. All things considered, these deep learning models demonstrated encouraging outcomes in identifying betel leaf illnesses. With a testing accuracy of 98.77%, the DenseNet201 model fared better than the others (Kusuma et al., (2024)).

Table 1. Comparison of literatures

Author Name	Dataset	Algorithms Used	Results Achieved
Amarasingam et al., (2022)	YOLOv5 Dataset	Deep Learning	precision = 0.50% recall = 0.95%
Kai et al., (2022)	Data Augmentation	machine learning, Support Vector Machine	Accuracy of 99.48%. Precision of 99.55%
Huang, et al., (2022)	DCGAN augmentation	deep learning, MobileNetV3-large	Accuracy of 99%
Eunice, et al., (2022)	Resnet-50	deep learning, transfer learning, convolution neural network	Accuracy = 99.81%
Lozano-Garzon et al., (2022)	Data Augmentation	machine learning, K-nearest Neighbours	F1-score of 98%
Xuechen et al., (2023)	SLD10k dataset	Lightweight model, convolution neural network, Vision Transformer	accuracy of 1.87%
Muthusamy, et al., (2022)	sugarcane leaf disease dataset	InceptionV3, ResNET50, Inception ResNET, and DenseNET201	accuracy of 88.7%
Daphal SD et al., (2024)	sugarcane leaf disease	XceptionNet, VGG19, and EfficientNet_B7ResNet50,	accuracy = 86.53%
Ismail Kunduracioglu at el., (2024)	Sugarcane Leaf Dataset	InceptionV and EfficientNet-b6	Accuracy rates of 93.39% and 93.10%
Anas Ansari,at el., (2024)	Data Augmentation	Convolution Neural Networks, Deep Learning	Accuracy of 95%

Table 1 is the comparison of various previous methods. It briefly describes the data type used, the algorithm employed, and the findings that their studies have revealed. This comparison helps in understanding the viability and effectiveness of different methods used to identify leaf diseases.

3 Proposed Methodology

The proposed IoT and machine learning-based sugarcane leaf disease classification system methodology involves multiple stages to ensure accurate disease detection. Initially, IoT sensors gather vital environmental information like soil moisture, temperature, and humidity.

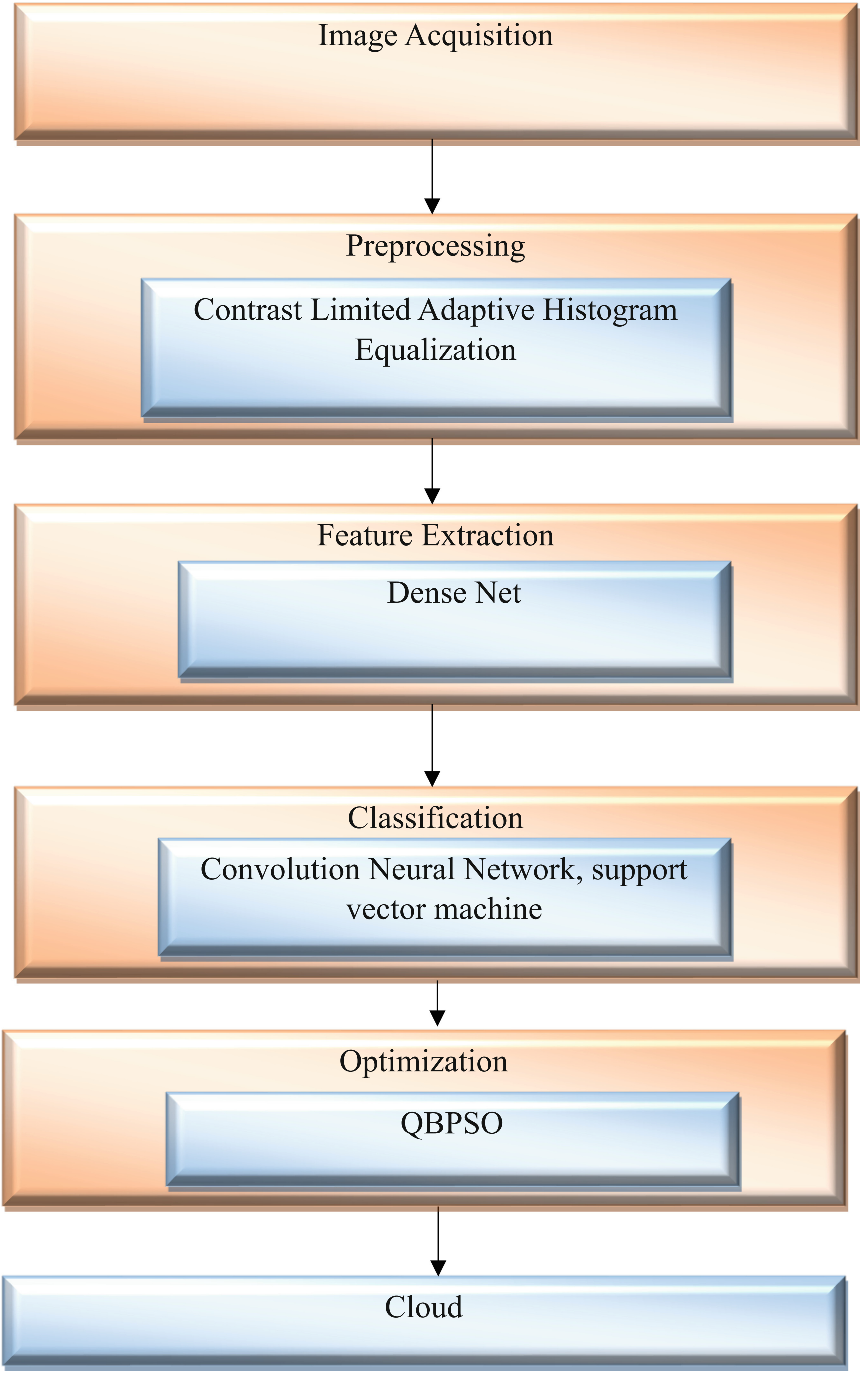

Fig. 2. Proposed Methodology of sugarcane leaf disease

As shown in Fig. 2, camera modules capture high-resolution images of sugarcane leave. The collected images undergo preprocessing, where CLAHE is applied to enhance contrast, and a median filter is used to reduce noise. The watershed algorithm is employed for leaf segmentation to identify diseased regions, isolating affected areas from the background. Feature extraction is performed using Squeeze Net, a lightweight deep learning model optimized for edge computing, ensuring efficient processing on low-power devices. The extracted features are then classified using a Support Vector Machine model, whose performance is improved through Quantum-Behavioral Particle Swarm Optimization for optimal hyperparameter tuning. The final classification results are transmitted to a cloud-based or edge computing platform, allowing farmers to access disease predictions via a mobile or web-based dashboard. The system provides preventive measures to help mitigate crop losses. By integrating IoT, machine learning, and optimization techniques, the proposed system offers a cost-effective, scalable, and automated solution for precision agriculture, reducing the dependence on manual disease detection methods while improving productivity and sustainability in sugarcane farming.

3.1 Dataset Collection

In this section, the collected image dataset of sugarcane leaf diseases mainly consists of five major categories: healthy, mosaic, red rot, rust, and yellow disease. The dataset was captured using smartphones with different configurations to maintain diversity. The database comprises a total of 2,569 images from all categories, collected from the state of Maharashtra, India.

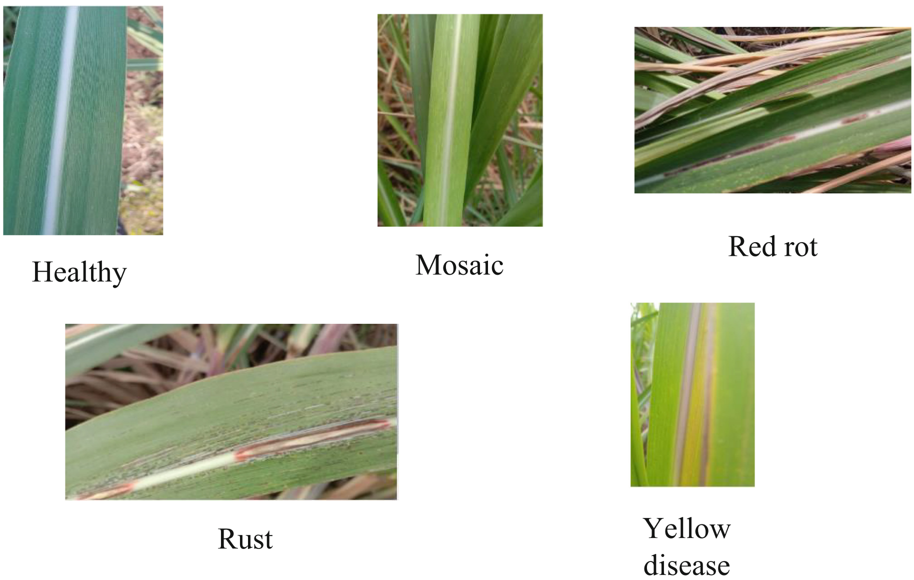

Fig. 3. Dataset Image Collection

The proposed accuracy improved by using the sugarcane leaf dataset, whose image collection includes healthy (522), mosaic (452), red rat (518), rust (514), and yellow disease (505) files, as shown in Fig. 3. This website utilizes the sugarcane dataset available at https://www.kaggle.com/datasets/nirmalsankalana/sugarcane-leaf-disease-dataset.

3.2 Contrast Limited Adaptive Histogram Equalization

Contrast-limited adaptive equalization is a modification of adaptive histogram equalization. This method gives each neighbour an improvement function. Pixel to produce the transformation function. Because of its contrast constraint, this is not the same as AHE.

CLAHE Algorithm.

- Step 1: obtaining an ambiguous image.
- Step 2: Independently obtain the transform function, distribution parameter type, clip limit, dynamic range, and any additional input variables required for the improvement process, as well as the number of regions in the row and column directions.
- Step 3: Divide the original image into a specified region to preprocess these inputs.
- Step 4: Use the tile to apply the procedure.
- Step 5: Create a clipped histogram and a grey-level mapping. Since each grey level's pixels are uniformly distributed, a contextual region's average pixel count is Gray. This can be expressed in the following fashion, as shown in Eq. 1.

$$N_{avg} = \frac{N_{cr-xp} * N_{cr-yp}}{N_{gray}} \tag{1}$$

Were,
V_{avg} = Pixel Average.
N_{gray} = The quantity of gray levels in the surrounding area.
N_{cr-xp} = The quantity of pixels in the contextual region's x direction.
N_{cr-yp} = Determine the real clip limit by counting the number of pixels in the y direct of the contextual area.

After that, calculate the actual clip limit as shown in Eq. 2.

$$N_{CL} = N_{CLIP} * N_{Avg} \tag{2}$$

- Step 6: Use grey level mapping interpolation to get a better image. In this procedure, four-pixel clusters are used, mapping is done, and each mapping tile partially overlaps the picture region. One pixel is then removed and goes through four mappings. Repeat over a picture and interpolate between the results to obtain an enhanced pixel.

3.3 Feature Extraction: DenseNet

Each DenseNet deep learning neural network design layer is linked to every other layer, allowing information to flow through the network completely and effectively. This feature allows the DenseNet network to learn and comprehend an image's features and structure more effectively. Because of the DenseNet's extensive interconnectedness, the network makes feature reuse possible, which enhances the method's learning efficiency and feature representation. Furthermore, the gradient vanishing issue that frequently arises in neural network models is resolved by the DenseNet network structure's simplicity and low parameter count (Fig. 4).

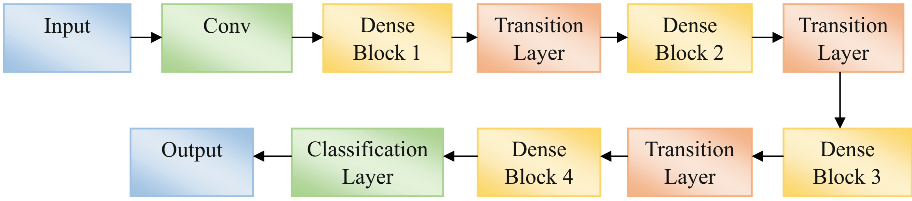

Fig. 4. Dense Net Architecture

The perfect itself is not learning the individuality mapping. To enable gradient values to be transmitted via the network's fast connections, DesNet incorporates rapid connections into the network model, drawing inspiration from this idea. Reusing features is another way that DenseNet reduces model parameters.

Equation 3 displays the output expression of a DenseNet layer, where X_o the neural network is the input. H_l is an acronym for nonlinear transformation, which includes activation functions, convolution, and more. X_l Denotes the network l layer's output.

$$X_l = H_l(x_0, x_1, x_2 \ldots) \tag{3}$$

The bottleneck layer, conversion layer, classifier, and dense connection module are the four components that makeup DenseNet. The feature map goes through a dimensionality reduction procedure through the CNN's pooling layer, which cuts the feature map's size in half.

$$k_l = k_0 + (l - 1) \tag{4}$$

Equation (4) displays the number of characteristic maps of the l layer, where k is a hyperparameter that denotes the number of growth rate-related characteristic maps of the bottleneck layer.

3.4 Convolution Neural Network (CNN)

Each neuron functions as a convolution kernel, forming the convolution layer that may extract different characteristics from discrete small portions of the input data. Three dimensions are present in every convolution kernel: depth, width, and length. Convolution kernel size is a synthetic kernel, which is the breadth and length of the convolution in a CNN's convolution layer L × W. CNN models are essentially composed of an input layer, one or more fully connected layers, activation functions, alternating degrees of convolution and pooling layers, and an output layer at the end. However, there are many variations.

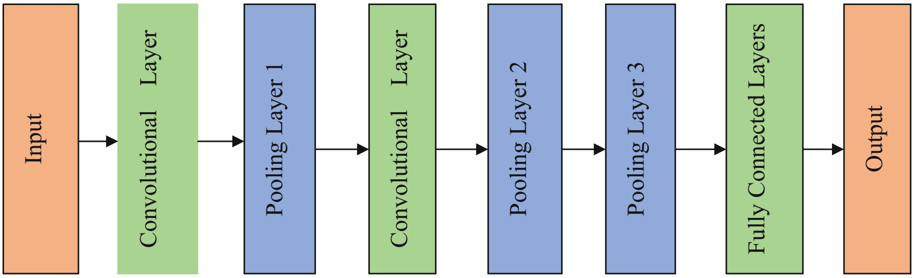

Fig. 5. Convolution Neural Network

Several convolution and pooling layers are layered alternatively in the first half of the network to create a feature extractor, which makes it possible to transform previously processed raw input data into a higher-level, more abstract feature representation. Activation functions and fully connected layers perform operations on the recovered features, such as classification or regression, as shown in Fig. 5.

A classifier known as a Support Vector Machine may be used to divide data into linear and nonlinear categories. If you have more than one group, support vector machine analysis can assist you in constructing a hyperplane that optimizes the distances between them. To find the total number of hyperplanes, multiply the number of features by the number of classes. The precise location and orientation of the hyper planes may be determined by examining the points that make up the supports vector. These support vectors make it possible to enhance the margins of the hyperplanes.

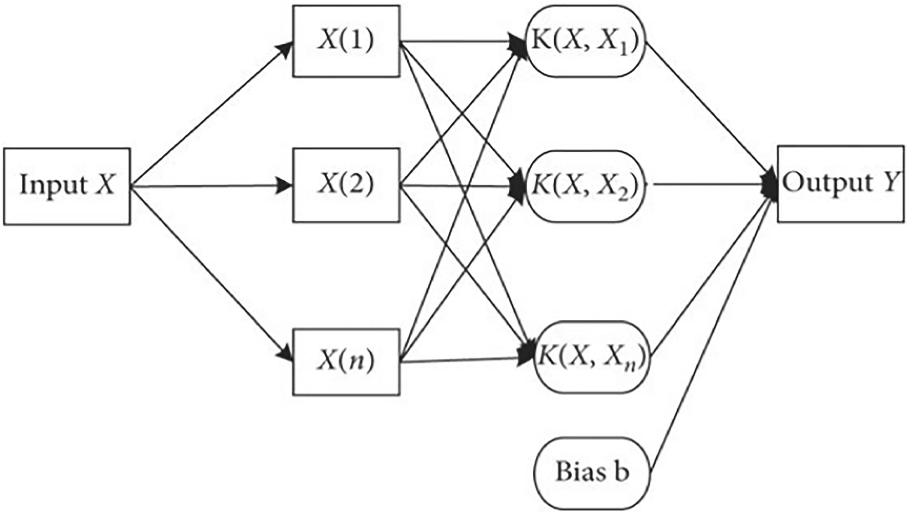

Fig. 6. Support Vector Machine Architecture

Mathematical functions called kernels make up support vector machines or SVMs for short, as shown in Fig. 6. These kernels receive data as input and output it in the proper format. There are several different types of SVM kernels, including sigmoidal, polynomial, linear, and radial basis functions. The inclusion of these kernels is based on how the data is distributed. While conducting this study, we used radial basis functions to create a support vector machine classification model. “IoT Cloud” describes a cloud computing platform that facilitates Internet of Things applications. It makes it possible to gather, process, store, and analyze data produced by linked devices. Wireless protocols like MQTT, HTTP, and CoAP offer a scalable and secure infrastructure that enables communication between Internet of Things devices, such as sensors, smart appliances, and cloud servers.

Fig. 7. IoT Cloud

As shown in Fig. 7, IoT Cloud platforms, such as AWS IoT, Google Cloud IoT, and Blynk, offer data processing, analytics, remote device management, and AI and machine learning integration for intelligent automation. These platforms enhance efficiency by allowing users to monitor, control, and automate IoT-based systems from anywhere through web or mobile applications. Additionally, the IoT Cloud ensures data security with authentication protocols and encryption, making it an essential component for applications in smart homes, healthcare, industrial automation, and smart cities.

As shown in Eq. 5, the input image is processed through convolutional and pooling layers to extract the high-level features. Let’s assume W− convolution kernel, b− bias, $*$− convolution operation, f− activation function, F− extracted feature vector.

$$\mathrm{F} = \mathrm{CNN(I)} = \mathrm{f(W} * \mathrm{I} + \mathrm{b)} \tag{5}$$

As shown in Eq. 6, the optimal hyperplane is identified in the CNN feature vector that the SVM classifier uses to separate classes. Let’s assume α_i− Lagrange multipliers, y_i− class labels, $K(F, F_i)$− kernel function, b− bias term.

$$f(x) = sign\left(\sum\nolimits_{i=1}^{n} \alpha_i y_i K(F, F_i)\right) + b \tag{6}$$

As shown in Eq. 7, the predicted release classes detect leaf diseases. Let’s assume $\hat{y}$− disease category

$$\hat{y} = \mathrm{argmax\ f(x)} \tag{7}$$

A CNN automatically extracts deep features from leaf images, and an SVM classifier accurately discriminates whether a leaf is healthy or diseased.

4 Result and Discussion

The proposed sugarcane leaf disease prediction system uses a hybrid CNN-SVM classification approach enhanced by quantum-behaved particle swarm optimization to improve prediction accuracy. CLAHE is used in the pre-processing step to improve picture contrast and successfully draw attention to illness patterns. Feature extraction uses DenseNet, which captures deep spatial and texture features from leaf images, ensuring efficient gradient descent and feature reuse. The extracted features are then classified using a Support Vector Machine, known for its strong generalization ability. The most discriminating features are chosen, and the hyperparameters are adjusted using QBPSO to enhance classification performance further. Users may upload photos of sugarcane leaves and receive leaf disease forecasts thanks to the system's Python implementation and web application deployment. Key performance metrics, including accuracy, precision, recall, and F1-score, are used to evaluate the model's performance to ensure a thorough evaluation of classification performance.

Table 2. Simulation Parameter

Simulation	Variable
Dataset Name	Sugarcane leaf dataset
Number of Dataset	2521
Language	Python
Tool	Jupyter
Training	1789
Testing	732

Simulation parameters used in the experiments are listed in Table 2. A sugarcane leaf dataset with a total of 2521 images was used, of which 1789 samples were used for training and 732 samples were used for testing. The implementation was carried out in Python language using the Jupyter tooling environment for model development and evaluation.

The proposed sugarcane leaf blight prediction system uses a hybrid CNN-SVM classification approach enhanced by quantum-behaved particle swarm optimization to improve prediction accuracy. The preprocessing stage uses CLAHE to enhance image contrast and effectively highlight disease patterns. Image enhancement using the CLAHE algorithm enhances images of sugarcane leaf diseases, including mosaic, red rot, rust and yellowing, as shown in Fig. 8.

Fig. 8. Image enhancement CLAHE algorithm

Fig. 9. Feature map values

Figure 9 illustrates the visualization and analysis of feature map values for extracted features. A support vector machine, known for its powerful generalization capabilities, is then used to classify the retrieved features.

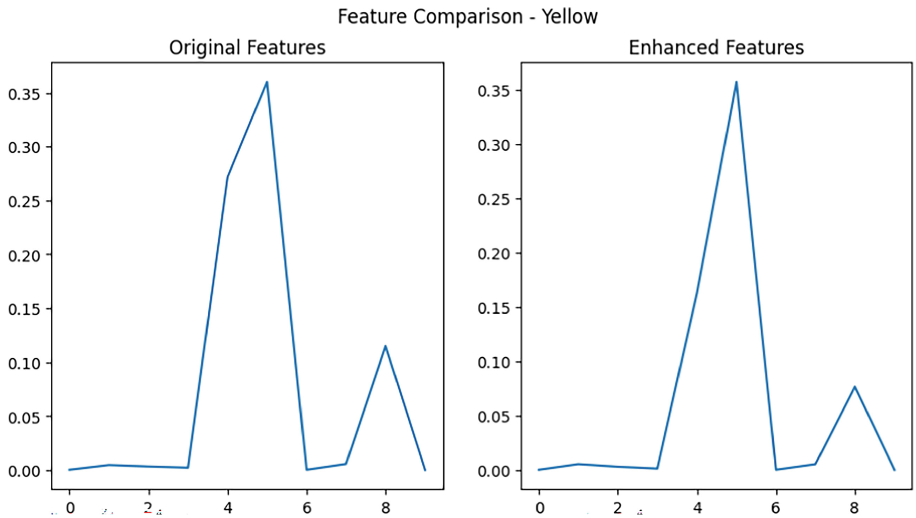

Fig. 10. Feature-enhanced images

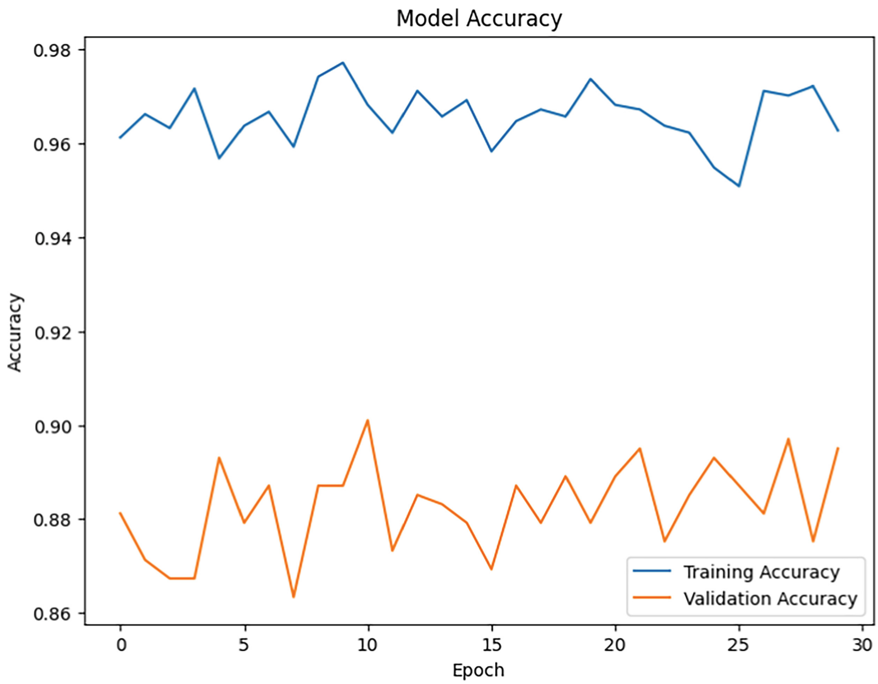

Fig. 11. Model accuracy for training and testing

Furthermore, the features enhance the original image and produce an enhanced image, improving disease visibility, as illustrated in Fig. 10. The mined features are classified using an SVM, which is known for its strong generalization ability.

The accuracy of the training and testing values used to train the sugarcane leaf dataset using the CNN-SVM model is based on the number of sugarcane leaf images, as shown in Fig. 11.

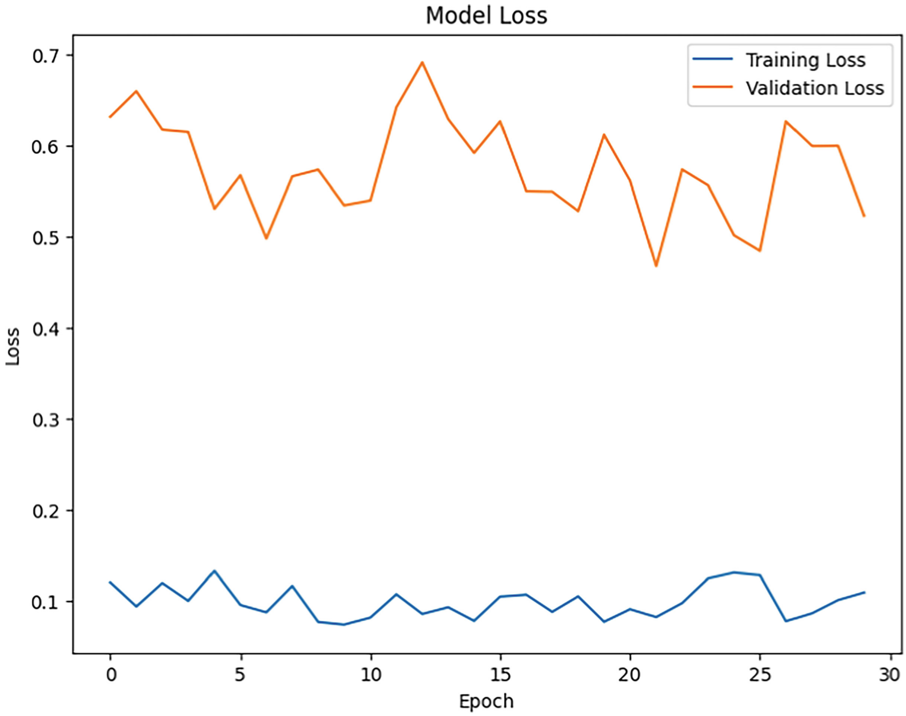

Fig. 12. Losses on training and validation loss

Figure 12 displays the CNN-SVM algorithm's training losses for the sugarcane leaf disease classification model. The number of epochs and the number of images of the losses are measured using sugarcane leaf diseases such as mosaic, red rot, rust, and yellowing.

The precision, F1-score, recall, and accuracy of the sugarcane leaf disease classification model, with 0.96% highest accuracy scores, were evaluated using the CNN-SVM model, as shown in Fig. 13.

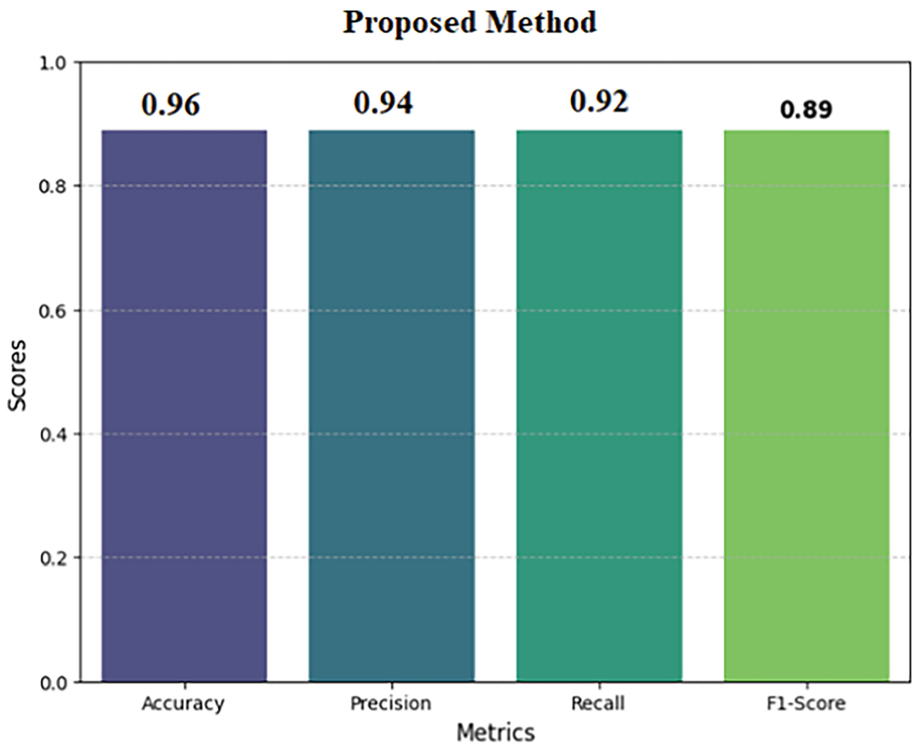

Fig. 13. Performance metrics

Figure 14 shows the classification results for evaluating the dataset on sugarcane leaf disease. Based on a single image input, it divides the entire dataset into categories like Red Rot, Rust, Mosaic, Yellow, and Healthy.

As seen in Fig. 15, the categorization findings are updated to the IoT Adafruit cloud and are categorized as Red Rot, Rust, Healthy, Mosaic, and Yellow.

Fig. 14. classification result

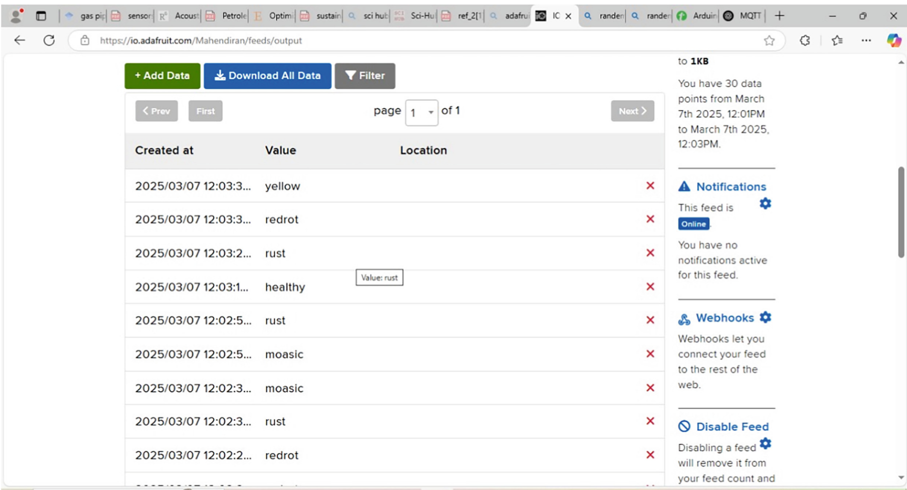

Fig. 15. IoT result

5 Conclusion

In conclusion, IoT and machine learning-based sugarcane leaf disease classification system presents an innovative, efficient, and cost-effective approach to leaf disease detection in sugarcane crops. The system ensures continuous crop health monitoring by integrating IoT sensors for environmental data collection and camera modules for image acquisition. Advanced image processing techniques, such as CLAHE and median filtering, enhance image quality, while the watershed algorithm enables precise leaf segmentation. Furthermore, implementing Squeeze Net for feature extraction and SVM for organization ensures high accuracy in disease identification. The system's performance is further optimized through Quantum-Behavioral Particle Swarm Optimization, which enhances hyperparameter tuning for improved classification results. Farmers can conveniently access disease predictions through mobile or web-based dashboards by leveraging cloud-based or edge computing platforms, enabling them to take timely preventive actions. Overall, this system provides a scalable and intelligent solution for precision agriculture, reducing reliance on manual disease detection methods and mitigating potential crop losses. By empowering farmers with leaf alerts and actionable insights, this research contributes to increased agricultural productivity, sustainability, and economic benefits in the sugarcane farming industry. The sugarcane foliar disease classification model is enduring a thorough evaluation process to determine its validity. Key performance measures, including precision, F1 score, recall, and precision, were carefully evaluated. The results of this evaluation indicate that the model performs well across these key metrics, achieving a score of 0.96%. Future enhancements include integrating deep learning models, expanded disease classification capabilities, and further optimization for real-world deployment.

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