RESEARCH ARTICLE Agricultural Science Digest, Volume 46 Issue 5: 883-890 (October 2026)

Identification of Diseases in Tea Crops using a Computational Convolutional Neural Network Model for Enhanced Crop Production

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10.18805/ag.DF-714

ABSTRACT

Background: A major challenge to agricultural productivity in the tea industry is disease. that affects the quantity and quality of tea leaves produced. The extensive development of computational methods for treating diseases has been widely used due to fast and accurate detection.

Methods: The proposed method uses sequential Convolutional Neural Network (CNN) computations with many hidden layers to classify diseased and healthy tea leaves into multiple groups. By enhancing feature identification, this structure increases the criteria for accurate disease detection. The data having 5 diseased and one healthy category is obtained from the Kaggle database. After preprocessing the data, it is split into 80:20 ratios for training and testing steps. CNN is constructed using the Keras Sequential API in Jupiter notebook using Anaconda environment.

Result: The total accuracy of the ML neural network training for classification was 98.52%. After 50 epochs of training, the model performed well, achieving high accuracy on training and validation datasets. The examination of the confusion matrix showed that several tea leaf diseases may be identified with high accuracy and few misclassifications. In general, the model demonstrated remarkable precision in differentiating between unhealthy and undamaged tea leaves.

Key words: Classification, Keras API, Neural network computations, Sequential convolutional neural network.

INTRODUCTION

Tea is the second most consumed beverage in the world after water (Deka and Goswami, 2020). The global tea market is growing rapidly and is expected to reach USD 73 billion by 2024, up from about USD 50 billion in 2017. This growth is mainly driven by increasing demand in countries such as China, India, Sri Lanka, Kenya, Indonesia, Vietnam and Turkey (Deka and Goswami, 2020). Black tea accounts for most of the global production and consumption. However, demand for green tea and specialty teas is rising quickly.

China remains the top tea producer, with over 2.5 million tonnes annually. India ranks as the second-largest producer, contributing about 23% of global tea production, with over 1.2 billion kilograms annually (Tea Board of India, 2023). The tea industry supports millions of smallholders and workers and generates significant foreign exchange, with exports valued at around USD 250 million per year (Ministry of Commerce, 2023). In 2024, despite a 7.8% decrease in production due to climatic challenges, India produced approximately 1,284.78 million kilograms of tea and maintained its position as the world's second-largest producer (Reuters, 2024). The industry plays a crucial role in India's economy, providing employment to millions and supporting rural development. In 2024, North India exported 154.81 million kilograms of tea, generating revenue of INR 4,833.12 crores, while South India exported 99.86 million kilograms, earning INR 2,278.31 crores (Tea Board of India, 2024).

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How to cite this article: Annapoorna, B.R., Shravya, A.R., Sagar, K.R. and Poornima, N. (2026). Identification of Diseases in Tea Crops using a Computational Convolutional Neural Network Model for Enhanced Crop Production. *Agricultural Science Digest.* **46(5):** 883-890. doi: 10.18805/ag.DF-714.

Submitted: 17-01-2025 **Accepted:** 23-02-2026 **Online:** 16-03-2026

India has several famous tea-growing regions. Each region produces tea with unique flavors because of its climate and soil. Assam, in northeastern India, is the largest tea-producing state. It produces over half of India's tea

(Deka and Goswami, 2020). Assam's tropical climate and heavy rainfall help grow strong, malty black teas. Darjeeling is in the foothills of the Himalayas, West Bengal (Subba *et al*., 2024; Hai and Duong, 2024). It is known for delicate, floral teas with a special muscatel aroma. This is due to its high altitude and cooler climate. The Nilgiri region is in Tamil Nadu and Kerala in southern India. It produces brisk and fragrant teas, supported by its cool climate and hilly terrain. Kerala has lush landscapes and a tropical climate. Its tea gardens produce bright and brisk teas. Ooty is located in the Nilgiri hills (Ghuriani *et al*., 2023; Al-Sharqi *et al*., 2025; Alshahrani, 2024). The cool climate and red loamy soil there help produce mild-flavored teas. Tea is important for India's economy. It supports millions of people, especially in rural areas. However, tea plants face many diseases. The common diseases that affect tea leaves are algal spots, brown blight and root rot. Healthy tea leaves are vital for good-quality tea. They look bright green and uniform when free of diseases and pests. Proper irrigation, nitrogen and pest control keep tea plants healthy. This helps reduce diseases like algal spots, brown blight and gray blight.

Algal spots are caused by algae such as *Cephaleuros virescens* (red rust). These grow on leaf surfaces in moist, poorly drained, or humid areas. They form greenish patches on leaves. While they do not directly harm the plant, they reduce leaf quality and affect tea processing.

Brown blight is mainly caused by the fungus *Pestalotiopsis theae* (tea gray blight fungus). It creates brown lesions on leaves. This disease reduces photosynthesis, causing leaves to discolor and fall. It spreads fast in hot, humid weather and threatens tea yield and quality.

Gray blight is caused by fungi like *Botrytis cinerea* (gray mold). It produces fuzzy gray patches and kills leaf tissue. This lowers photosynthesis and weakens the plant, often reducing tea production.

Helopeltis spp. (capsid bugs or mosquito bugs) are insect pests, not pathogens. They feed on young stems and leaves, causing discoloration, distortion and early leaf fall. Effective pest control is needed to manage them.

Red spot disease is caused by fungi such as *Colletotrichum camelliae* and *Colletotrichum theaesinensis* (anthracnose fungi). It causes reddish-brown lesions on leaves. Environmental stress and poor nutrition can worsen symptoms. Good disease management and nutrition help protect tea leaves.

Machine learning (ML) methods in disease identification are widely applied in several disciplines such as finance, medicine, animal research, agriculture sectors, *etc*. (AlZubi and Al-Zu'bi, 2023; Cho *et al*., 2024; Kim and Kim, 2023; Kumar *et al*., 2023; Villasante and Zaib, 2024; Min *et al*., 2024; Kim and AlZubi; 2024). A low-shot learning method was reported for identifying diseases in tea leaves using SVM and C-DCGAN (Hu *et al*., 2019). The method uses color and texture features to segment disease spots, generating augmented images for training a VGG16 deep learning model (Maltare *et al*., 2023; Bagga *et al*., 2024). The model achieves an average accuracy of 90%, surpassing traditional low-shot learning methods. Yashodha and Shalini (2021) discussed ML techniques for identifying plant diseases using IoT and ecological sensing in their review article. They highlighted how this technology revolutionizes plant health monitoring, allowing farmers to monitor plants early and maximize production yields. The real-time feedback provides valuable insights for timely interventions. Jayapal and Poruran (2023) present a deep learning-based disease identification model for tea plants, enhancing image retrieval efficiency. The model, called Deep Hashing with Integrated Autoencoders, prioritizes prominent features in input data and is a hybrid model for hashing and image retrieval. This approach is also useful and appropriate for real-world situations with limited data availability.

In the presented work, tea leaf diseases that occurred due to various infections are considered for identification using the sequential CNN model. The dataset, after preprocessing, is divided into 80:20 for training and testing. In computational CNN methods, several convolutional and max-pooling segments are stacked for feature extraction without overfitting problems. The classification metrics and a confusion matrix are generated as the outputs. The following are the main contributions of the study that was presented:

- The creation of a CNN computational model to classify and diagnose tea leaf diseases that provides an effective means of identifying and treating several infections, thereby lowering losses in production.
- Using a large-scale dataset from Kaggle that shows the presence of disease on tea leaves. That provides an increment in the precision of disease categorization.
- A simple method for extracting features that combines the SoftMax classifier and CNN computations.

MATERIALS AND METHODS

System configuration and software environment for model training and dataset description

The tea leaf disease classification model was implemented in Python 3.11 using Jupyter Notebook within the Anaconda distribution for efficient environment and dependency management. The model was built and trained using TensorFlow 2.x and its high-level Keras API. Training was conducted on a workstation with 16 GB RAM and access to a TPU v3-8 (8-core Tensor Processing Unit), ensuring rapid training cycles and computational efficiency.

This dataset includes images of tea leaves affected by common diseases, along with healthy samples. The disease classes are: (1) Algal leaf spot, (2) Brown blight (3) Gray blight, (4) Helopeltis and (5) Red spot. Healthy leaves are also included as a separate class. The images were collected from the Johnstone Boiyon farm, Koiwa location, Bomet County, using tea clone 1510. The natural appearance of healthy and diseased tea leaves is presented in Fig 1.

The dataset is publicly available on Kaggle and is suitable for training machine learning models using transfer learning techniques. The data was organized into labeled folders and loaded using Keras's Image Data Generator.flow_from _directory() with shuffle enabled.

The distribution of images across different classes in the dataset is plotted in Fig 2. Using this dataset, the prediction of tea leaf disease can be done by transfer learning of ML computational models.

Preprocessing

Since images of the infected tea leaves were taken at various harvesting locations and under various conditions, noise in the images is to be expected. Noise can degrade image quality and lower the model's recognition ability. The input image is subjected to various preprocessing steps, including image scaling, normalisation and noise filtering, in order to reduce the influence of noise, before being fed into the model. The main objective of these preprocessing steps is to reduce the influence of noise, which will eventually enhance the model's prediction capability. A common deep learning method involves data augmentation, which produces additional variation in the training dataset to improve the model's capacity to extrapolate to new, unobserved data. Pixel values can be rescaled, random rotations (up to 20 degrees), random width and height shifts (up to 20% of the image size), shearing, zooming (20% up to 20%) and horizontal flipping belong to the specified augmentation techniques. The batch size is set to 32 and the rescaled image size is set to (224, 224). The dataset is divided between training and validation sets using an 80-20 split. There are 711 images in the training set that correspond to 8 classes and 174 images in the validation set that also belong to the same 8 classes. The procedure followed for classification by CNN is depicted in Fig 3.

Model summary

The Keras Sequential API is used to build a convolutional neural network (CNN). The model has a conventional CNN architecture for image classification applications (Fig 4).

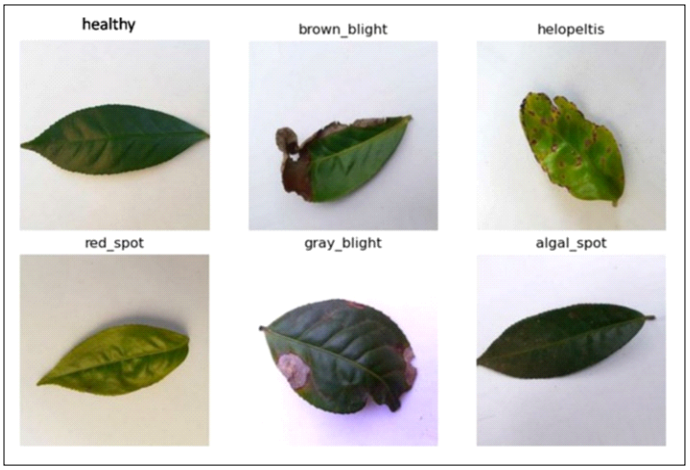

Fig 1: Tea leaves with healthy and diseased classes.

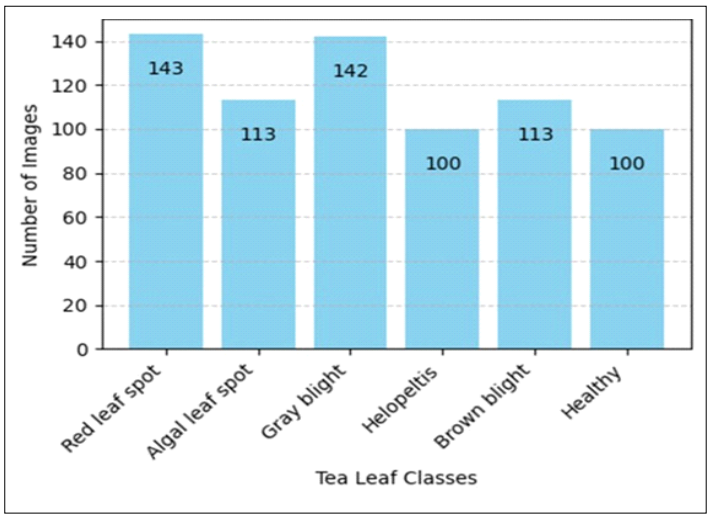

Fig 2: Number of images per class.

It is divided into multiple layers, each of which has a distinct function in the feature extraction and classification process. Using the ReLU activation function and a 3×3 kernel, it starts with a Conv2D layer that has 32 filters and a specified input shape of (224, 224, 3) for colored pictures. Then, to reduce the spatial dimensions, a MaxPooling2D layer with a 2×2 pool size is added. With increasing filter sizes (64, 128 and 256) and matching max-pooling layers, this pattern is repeated. The convolutional layers aim to extract structural features from the input data. A flatten layer is added after the convolutional layers to transform the 3D tensor into a 1D array. Three dense (fully connected) layers with 256, 128 and 8 neurons each are then fed the flattened output.

Filters, or kernels, are used in convolution processes to navigate through an input image or feature map. Each step involves extracting information from overlapping portions. Multiplying filter elements by input image components, summarizing the findings and performing mathematical operations are all part of the process. The input image (I) and kernel (K) for a two-dimensional convolution process are expressed as follows:

$$S_{(i,j)} = \sum_{p=0}^{m-1} \sum_{q=0}^{n-1} I_{(i+p,j+q/)} K_{(p,q)}$$

Where the image (I) coordinates are represented by i and j and the kernel (K) coordinates by m and n. A max pooling layer in the model lowers the risk of overfitting and computational complexity. Images are classified by the Fully Connected Layer using patterns it has learned from previous layers. The Fully Connected Layer uses a Softmax function to forecast and assign probability to classes, ensuring accurate and comprehensible input data classification. The preceding layer's neuronal numerical values, y_1, y_2, $y_3 \ldots y_n$, are converted into probabilities, P_1, P_2, $P_3 \ldots P_n$, given n *via* the softmax function.

$$P_k = \frac{e^{y_k}}{\sum_{j=1}^{n} e^{y_i}}$$

Where

P_k = Likelihood of class k application of softmax.

y_k = Numerical value of the jth neuron in the layer before the input is flattened into a one-dimensional array.

Softmax classifier

The SoftMax classifier is used in the computational model to determine the rate of correlation with the predicted label of tea leaf diseases. The SoftMax classifier uses correlation rates for different classes to identify images. When all probabilities add up to one, it generates output values between 0 and 1 (Ho and Wookey, 2019). It has advantages such as fast training and prediction times and easy-to-specify output probability ranges. It easily accepts the output from the last completely linked layer. In the end, SoftMax effectively divides images of tea leaf into six groups that are connected to healthy and diseased ones. The model was compiled with the Adam optimizer, using a categorical crossentropy loss function and categorical accuracy as the primary metric (Kingma and Ba, 2014). Training was conducted using model. fit () for 50 epochs, with a batch

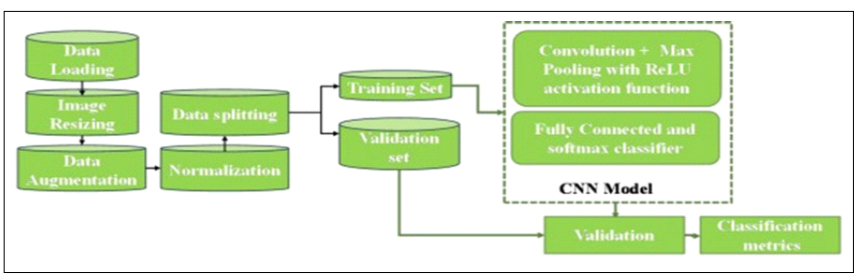

Fig 3: Flow chart of the model adopted in classification.

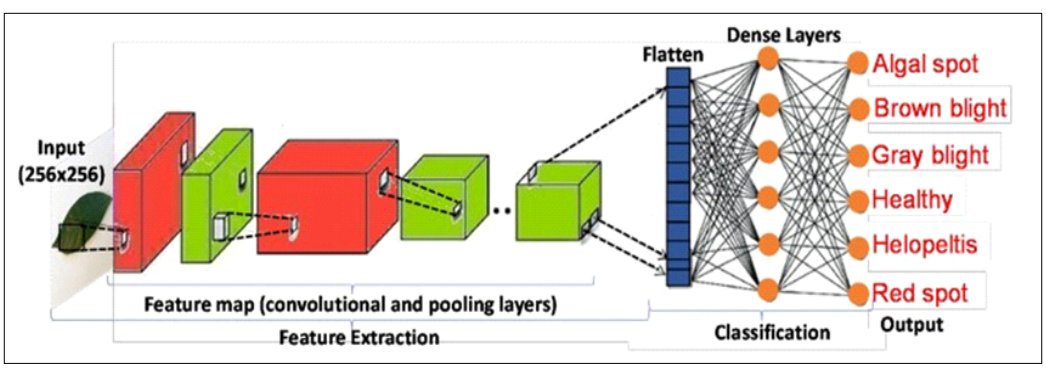

Fig 4: Architecture of CNN method.

size of 32. The model used early stopping and Model Check point callbacks to prevent overfitting and retain the best-performing model. The hyperparameters used for model execution is summarized in Table 1.

Evaluation parameters

To assess the classification performance of the proposed CNN model, several standard evaluation metrics were computed using the confusion matrix. The confusion matrix consists of four core components: True positive (TP), false positive (FP), false negative (FN), true negative (TN). based on these components, the following evaluation metrics were derived.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

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

$$\text{Specificity} = \frac{TN}{TN + FP}$$

These metrics collectively provide a comprehensive evaluation of the model's capability in identifying and classifying tea leaf diseases accurately.

RESULTS AND DISCUSSION

This section presents and discusses the experimental outcomes obtained from training and evaluating the proposed Convolutional Neural Network (CNN) model for tea leaf disease classification. The model was repeatedly iterated over the entire training dataset over 50 epochs to enhance performance (Fig 5). The average difference between the model's predictions and the actual labels in the training data is shown by the reported training loss of 0.0673. In contrast, a model's ability to accurately identify incoming data with a 97.65% accuracy on the training dataset is indicated by an accuracy score of 0.9765. The model's ability to generalise to new data is shown by the validation loss, which is much less at 0.0426 when determined on a different validation set.

Comparably, the model's ability to correctly predict the class of input data from the validation set 98.26% of the time is shown by the validation accuracy of 0.9826. When taken as a whole, these measures show the model's excellent performance, minimal loss and high accuracy on training and validation datasets, indicating that it can effectively understand underlying patterns and make correct predictions on previously unknown samples.

In the next section, the performance of the trained model for each kind of disease was carefully evaluated. It was able to determine the real, predicted classes with a confidence score. For example, a real healthy class is predicted as healthy by the model with a 99.94% confidence score (Fig 6). There are 3-widely-known measurement metrics that are utilised to evaluate the performance of the computational model: 1) accuracy 2) precision and 3) recall. In addition, a confusion matrix is a credible method that displays a classifier's prediction results for each class (Powers, 2020). It gives a visual depiction by comparing the true class labels with the predicted class labels.

Table 1: Summary of the hyperparameters used in CNN model.

Parameter	Value
Input image size	224 × 224 pixels
Color mode	RGB (3 channels)
Batch size	32
Number of epochs	50
Optimizer	Adam
Learning rate	0.001
Loss function	Categorical crossentropy
Activation function	ReLU (hidden layers), Softmax (output)
Pooling type	Maxpooling2D (2×2)
Data augmentation	Rotation (±20°), Shift (±20%), Zoom (±20%), Shear (±20%), Horizontal flip
Dropout	0.5
Dataset split	80% Training / 20% Validation

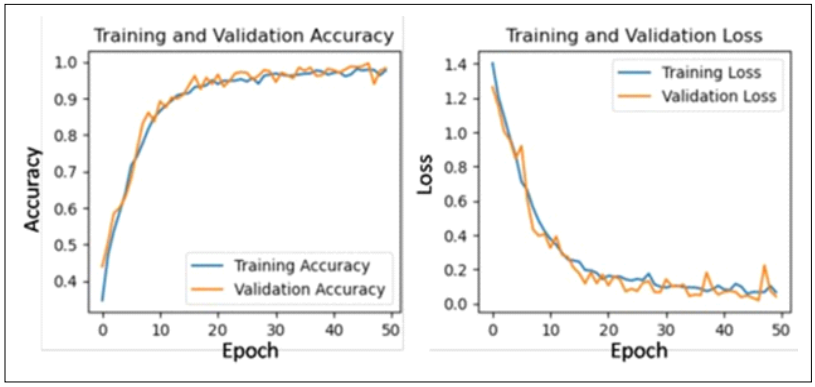

Fig 5: Accuracy and loss measurements over epochs.

The effectiveness of the model for each class is mapped out by the confusion matrix (Fig 7). In the algal spots class, 117 cases are correctly identified, while the number of misclassifications is zero. Additionally, all 82 cases of brown blight were effectively identified by the model. Out of 99 events, 3 cases of grey blight were incorrectly categorised as brown blight class and 1 incident was mistakenly classified as helopeltis. Two instances were mistakenly labelled as belonging to helopeltis and 110 instances of the Healthy category were correctly recognised. Ninety-eight instances of the helopeltis class were identified correctly. The red spot group identified ninety-three cases accurately. Whereas two cases were incorrectly classified as helopeltis. Finally, it can be seen that the confusion matrix shows the specific locations of misclassifications and offers a thorough summary of the ability of the method in data classification.

Table 2 summarizes the classification performance of the proposed CNN model across six disease categories of tea leaves. The model demonstrated excellent performance, with Algal Spot achieving perfect scores in all three metrics (1.0000), indicating flawless classification without any misclassifications. Brown Blight also performed strongly, achieving a precision of 0.9647, perfect recall of 1.0000 and an F1-score of 0.9820, suggesting that while a few false positives occurred, the model identified all actual cases accurately. Gray Blight reached a precision of 1.0000, but with a slightly lower recall of 0.9612, resulting in an F1-score of 0.9802-indicating a small number of missed cases. The Healthy class was classified with high accuracy, showing a precision of 1.0000, recall of 0.9735 and an F1-score of 0.9865. In the case of Helopeltis, the model achieved a precision of 0.9515 and recall of 1.0000, yielding an F1-score of 0.9751, which implies that all true Helopeltis cases were detected, though some false positives were present. Red Spot also showed a high classification capability with a precision of 0.9894, recall of 0.9789 and F1-score of 0.9841. Overall, the model achieved an impressive accuracy of 98.52%. The macro-averaged precision, recall and F1-score were 0.9843, 0.9856 and 0.9847 respectively, while the weighted averages for these metrics were also high at 0.9858, 0.9852 and 0.9852. These results confirm the model's robustness and reliability across complex multiclass classification tasks involving real-world tea leaf disease data.

The performance of the proposed CNN model was compared with existing studies, as shown in Fig 8. This model achieved an accuracy of 98.52%, which is higher than several previous approaches. Bao *et al*. (2022) developed the AX-RetinaNet model using images taken in natural scenes. It included an attention module and X-module to improve feature detection. The model achieved a F1-score of 0.954 and mAP of 93.83%, even with a small dataset. Lanjewar and Panchbhai (2022) created a CNN-based real-time system on a PaaS cloud platform. It allowed users to upload images for disease detection. They reported 100% accuracy, although this may reflect ideal or limited testing conditions. Datta and Gupta (2023) built a Deep CNN model trained on multiple crop datasets. It reached 96.56% accuracy and was designed for real-world use with IoT systems. Chen *et al*. (2019) introduced LeafNet and compared it with SVM and MLP classifiers. LeafNet achieved 90.16% accuracy. Hu *et al*. (2019) applied a deep CNN method and reported 92.5% accuracy, along with faster convergence and fewer parameters.

Compared to these models, the present CNN model performs better in terms of accuracy. It also maintains high precision, recall and F1-scores across all six disease classes.

Table 2: Classification parameters achieved after model execution.

Class	Precision	Recall	F1-score	Support
Algal spot	1.0000	1.0000	1.0000	117
Brown blight	0.9647	1.0000	0.9820	82
Gray blight	1.0000	0.9612	0.9802	103
Healthy	1.0000	0.9735	0.9865	113
Helopeltis	0.9515	1.0000	0.9751	98
Red spot	0.9894	0.9789	0.9841	95
Accuracy			98.52%	608
Macro avg	0.9843	0.9856	0.9847	608
Weighted avg	0.9858	0.9852	0.9852	608

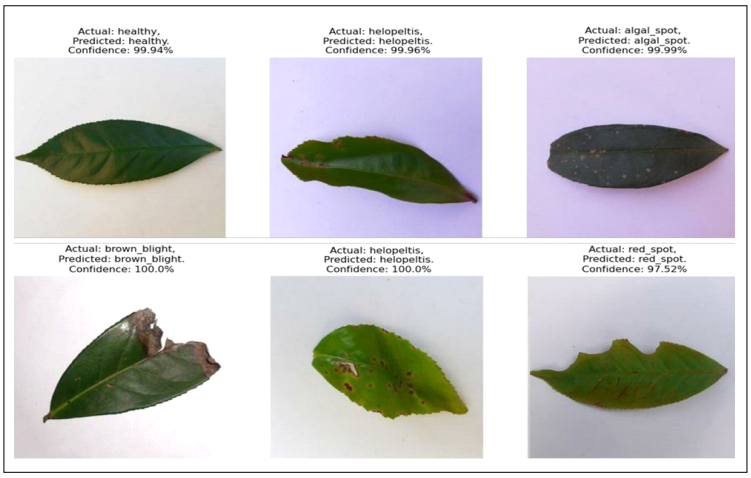

Fig 6: Results of actual, predicted classes with the rate of confidence.

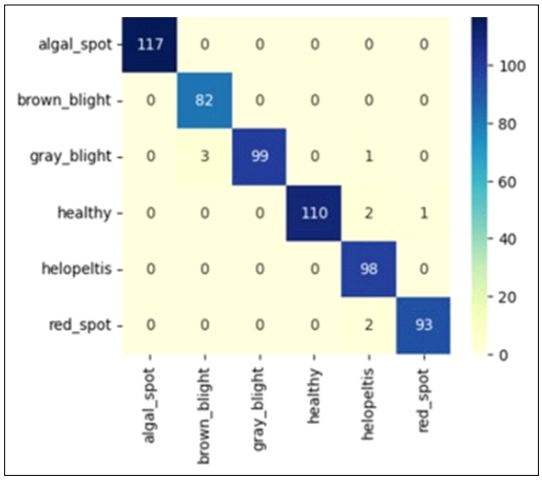

Fig 7: Display of true and false events by a confusion matrix.

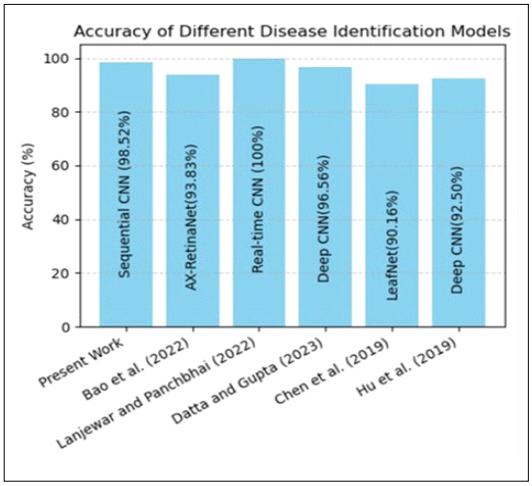

Fig 8: Comparison of accuracy of CNN model with existing literature.

These results confirm its robustness and ability to generalize across complex, real-world datasets. This makes the model suitable for practical deployment in agriculture, especially in field conditions where reliable detection is crucial.

CONCLUSION

The proposed CNN model for tea leaf disease classification demonstrated high performance, achieving an overall accuracy of 98.52% and strong precision, recall and F1-scores across all six disease categories. The results highlight the model's ability to generalize effectively and make accurate predictions, confirming its suitability for real-world agricultural applications. Algal Spot and Brown Blight were classified with near-perfect accuracy, while other classes such as Gray Blight, Helopeltis and Red Spot also showed excellent classification performance. However, the study is not without limitations. The dataset used, while effective, lacked diversity in terms of lighting conditions, leaf orientations and environmental variations, which may impact the model's generalization in outdoor scenarios. Moreover, the model was developed and evaluated in an offline setup, limiting its direct deployment in real-time field conditions. Future research should focus on expanding the dataset with field images collected under varied conditions to enhance robustness. Integrating the model with real-time platforms such as IoT devices or mobile applications could allow for on-site disease diagnosis. Furthermore, exploring hybrid architectures like CNN-LSTM or attention-based networks may improve the model's capacity to capture complex spatial and temporal features.

ACKNOWLEDGEMENT

Funding details

This research received no external funding.

Disclaimers

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Authors' contributions

All authors contributed toward data analysis, drafting and revising the paper and agreed to be responsible for all the aspects of this work.

Data availability

The data analysed/generated in the present study will be made available from corresponding authors upon reasonable request.

Availability of data and materials

Not applicable.

Use of artificial intelligence

Not applicable.

Declarations

Authors declare that all works are original and this manuscript has not been published in any other journal.

Conflict of interest

Authors declare that they have no conflict of interest.

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