**Title Page 4**

# Tea leaf disease prediction by comparative analysis of convolutional neural networks (CNNs) with FNNs (feedforward neural networks) to improve accuracy

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**Keywords:** Tea Leaf Diseases,novel Neural Networks,Image Processing,Machine Learning,Optimization,ComputerVision,DiseaseDetection,agriculture,foodsecurity,novel Feedforward Neural Networks (FNN)

## ABSTRACT

**Aim:** In order to achieve accurate classification, this study focuses on automating detection of tea leaf illness using feedforward neural networks (FNN) and convolutional neural networks (CNN). The goal of the project is to include cutting-edge deep learning techniques to provide proactive solutions and real-time monitoring for maximising the health of tea crops in precision agriculture.
**Materials and Methods:** Convolutional neural networks (N = 20) and feedforward neural networks (FNN) (N = 20) are used to identify the tea leaf illness. Each of the two groups that

comprise the original data has a sample size of twenty. In this study, a G-power pretest of 80%, a threshold of 0.05%, and a confidence interval (CI) of 95% are used to calculate the final sample size. Because of its great accuracy, the Convolutional Neural Network Algorithm—a supervised machine learning and deep learning recognition technique—is essentially required for classification and recognition. Artificial Neural Networks (ANNs) use their ability to recognize patterns to identify diseases from photos of tea leaves with greater accuracy
**Results:** CNNs have a 94% accuracy rate in identifying tea leaf illness, while feedforward neural networks have a 58% accuracy rate. Convolutional neural network techniques (CNNs) and feedforward neural networks differ significantly (0.003 ($p<0.001$)).**Conclusion:** In the identification of tea leaf illness, convolutional neural networks (CNNs) appear to be more accurate than feedforward neural networks (FNNs).

**Keywords:** Tea Leaf Diseases,Neural Networks,Image Processing,Machine Learning,Data Set,Performance Metrics,Optimization,Computer Vision,Implementation,Disease Detection

## INTRODUCTION:

The diagnosis of illnesses that affect tea leaves is crucial to the management and cultivation of tea plants, and this has a direct bearing on the world tea market(Bao et al. 2022). Effective techniques for identifying and diagnosing these illnesses are becoming more and more important for sustainable tea production as the global demand for tea rises(Liu et al. 2020). Tea production is seriously threatened by agricultural diseases such as blister blight, grey blight, and brown blight, which result in lower yields and difficult financial situations for tea growers (Liu et al. 2020; Inoue, Fujikawa, and Takikawa 2021). To stop these illnesses from spreading and lessen their negative effects on tea production, early detection is essential(Heng, Yu, and Zhang 2024).

Approximately 456 papers have been uploaded to IEEE resources, and over the last 5 years, 58 papers have been uploaded to Google Updated Scholar. (Avula et al. 2015)have introduced a new model called a novel convolutional neural network model for tea leaf disease detection with an approximate success rate of around 90%. (Tew et al. 2022)used improvised models and random forest to detect diseases, yielding results that were more accurate than those of existing algorithms. found the dataset's hidden patterns using the random forest algorithm, which helped(Li et al. 2022) classify the data more quickly. The maximum accuracy achieved was nearly 89%. (Karunarathna et al. 2021)a pre-owned fuzzy method to identify tea leaf diseases. It combines support vector machines with innovative convolutional neural network methods, with a maximum accuracy of about 94%.

In terms of tea leaf disease detection, all of the deep learning and machine learning models that have been around for a while perform less accurately. In light of this, the current paper's goal is to identify actions using the novel convolutional neural network algorithm and feedforward neural network with significantly better and more accurate results. By altering the models and selecting a larger dataset with more parameters and more diverse results, these methods aid in the much better recognition of tea leaf diseases than did earlier models (Yang et al. 2019).The objective is to increase the accuracy rate of feedforward neural networks for tea leaf disease diagnosis by employing an improved novel convolutional neural network algorithm.

## MATERIALS AND METHODS

The proposed project's research environment is the Computer Vision Department of SIMATS, Saveetha School of Engineering, Chennai. Convolutional neural networks (CNNs) and feedforward neural networks (FNNs) are the two main groups in the project. The sample size was calculated using the Sample Size Calculator (clincalc.com) based on the findings of earlier research. Level 0.07, G capacity of 35%, and a certainty range of 99.0% were the parameters that were applied (Bengio, Simard, and Frasconi 1994).

The dataset that is currently being used is called TRAIN_DATASET, and it was obtained from kaggle.com. The dataset called TRAIN_DATASET was obtained from Kaggle.com and is now being used. The database contains 885 files that are arranged into 8 classes. 177 files were used in the validation process. Terms like "algal," "anthrone," "bird eye," "brown blight," "grey light," and "healthy" are among those that denote information about both healthy and diseased tea leaves. Here, a healthy leaf is the independent variable; the dependent variables are the algae, anthrone, and grey light

Windows 11 was the operating system used for the assessment. Six gigabytes of RAM and a Ryzen i5 processor were part of the gear setup. 64-bit system sorting was applied. The Python programming language was used to implement the code. In this case, the algae, anthrone, and grey light are the dependent factors, and a healthy leaf is the independent variable. To increase accuracy, both independent and dependent variables are incorporated into the analysis.

**Novel Neural Convolutional Network Technique**

A type of deep learning model called Convolutional Neural Networks (CNNs) is intended for image processing applications. They automatically extract hierarchical information from input photos by using convolutional layers, which allows them to capture spatial hierarchies. Layers for pooling keep important information while reducing spatial dimensions. Because CNNs share weight parameters, they are well-known for their efficiency in object detection, feature extraction, and picture classification. They are frequently used in computer vision applications because of their architecture, which makes translation-invariant recognition easier.

**Pseudocode**

Step 1: Set up the CNN model architecture initially
Step 2: Configure the learning rate, epochs, and batch_size hyperparameters.
Step 3: Divide the dataset into test, validation, and training groups.
4. Establish a loss function.
Step 5: Put the CNN model together using the optimizer and loss function of your choice.
To store training and validation losses for a later analysis, step six involves initialising empty lists.
Step 7: To add randomization, shuffle the training set.
Step 8: Extract labels and a batch of input photos.
Step 9: Move forward by passing via CNN
Step10: Update weights and biases by doing a backward pass (backpropagation).
Step 11: Determine the average training loss for the current period and record it.
Step12: Following each epoch, carry out validation:
Step 13: Assess the CNN model using the test set after training:
Step 14: Possibly save the trained CNN model parameters for future use.
Step 15: Deploy the trained CNN for tea leaf disease detection on new, unseen images
Step 16. Accuracy is achieved through the use of all classifiers.
Step 17. End.

## Feedforward Neural Networks (FNN)

Feedforward neural networks (FNNs), also called multilayer perceptrons, embody the basic architecture of artificial neural networks. FNNs are a straightforward yet effective structure for a variety of tasks, including regression and classification, because they don't include cycles or loops in their connections like recurrent neural networks do.

**Pseudocode**

1. Use pre-trained values or random initialization to set the FNN parameters (weights and biases).
2. Adjust the learning rate, batch size, and epoch hyperparameters.
3. Divide the dataset into test, validation, and training sets.
4. Describe the FNNs architecture, including the input size, hidden layer sizes, and output size.
5. Select an activation function (like ReLU) for the hidden layers and a sigmoid or softmax for the output layer (as in binary classification).
6. Specify the loss function.
7. Create initial blank lists to hold training and validation losses for examinations at a later time.
8. To add unpredictability, shuffle the training set of data.
9. Extract a group of labels and features from the input.
10. Proceed with a forward pass via the network:
11. Determine the average training loss for the current epoch and record it.
12. Validate each epoch once it has occurred:
13. Assess the model after training.
14. Deploy the trained FNN for tea leaf disease detection on new, unseen data:
15. End.

The Jupyter (Anaconda) programme was used to examine the techniques. The components included are an Intel Core i7-8th generation CPU with 8GB of RAM. The main software configuration of the system is 64-bit, Windows OS, a 64 bit processor, and an HDD of 2 TB.

**Statistical Analysis**

The study employs an independent sample T test analysis, with the models' mean accuracy being analyzed first, and the standard deviation and standard error noted after. The statistical analysis is performed using IBM SPSS 26.0.1 software for both the proposed model and the compared model, with the healthy tea leaf disease images in this dataset serving as independent variables and the algae, anthrone, and grey light serving as dependent factors.

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## RESULTS

Table 1 shows the description of analytics for precision for both algorithms. Convolutional Neural Networks (CNN) and Feedforward Neural Networks (FNN)

Table 2 shows a collective analysis that gives a precision average of 99.9% for the convolutional neural networks (CNN), which seems more precise in comparison to the feedforward neural networks (FNN), which have only 95.9%. The standard deviation and mean errors are calculated. The standard error mean for Convolutional Neural Networks (CNN) is 0.25 and for feedforward neural networks (FNN),

Table 3 indicates the significance of testing data findings at 0.003 (less than 0.005). The bar chart in Fig. 1 shows the mean accuracy between convolutional neural networks (CNN) and feedforward neural networks (FNN). From the results, it is clearly evident that the convolutional neural network (CNN) Algorithm is performing better when compared to the Neural Networks (FNN)

## DISCUSSION

In the current study, we observed that the deep learning, machine learning Convolutional Neural Networks (CNN) algorithm appears to have a higher success rate than the Feedforward Neural Networks (FNN) algorithm (p=0.001,stratified random analyst). The enhanced precision of this CNNT (mean precision =99.9900) than that of Feedforward Neural Networks (FNN) (mean precision =97.9490).

A number of techniques, including feedforward neural networks (FNN), convolutional neural networks (CNN), and others, are used in the study (Martini, Conte, and Tagliazucchi 2018). Convolutional neural networks (CNN) perform better than feedforward neural networks (FNN), according to a comparison of the two types of neural networks (FNN and CNN) (Nakamatsu et al. 2020). The accuracy of the convolutional neural network (CNN) algorithm is 94%, while feedforward neural networks (FNN) have 58% accuracy. (Zhou and Chen 2018). Additionally, we evaluated the CNN and Feedforward Neural Networks (FNN) algorithms; the findings indicate that Convolutional Neural Networks (CNN) outperform Feedforward Neural Networks (FNN). Additionally, it has produced outcomes that are comparable to our own (Wang et al. 2010). The study on the diagnosis of tea leaf disease using supervised pattern recognition and advanced analytics shows that convolutional neural network approaches perform better and have the highest accuracy among all other algorithms (Chatterjee et al. 2021). Furthermore, we can draw the conclusion that the convolutional neural network algorithm performs better than feedforward neural networks (FNN) and appears to be more accurate based on the aforementioned arguments and observations.

There are some limitations with the convolutional neural network, which consists of clusters of a large number of CNN classifiers and takes more time to execute compared to other machine learning, advanced analytics algorithms for tea leaf disease identification. In future work, this model will be improved with enhanced qualities, less execution duration, and more exact outcomes. This might have a better future, as the number of actions has been increasing every day.

## CONCLUSION

In this current paper, recognition of tea leaf disease detection is performed using two different algorithms, the convolutional Neural Network algorithm and Feedforward Neural Networks (FNN), which outperform the statistical method for tea leaf disease detection

## DECLARATIONS

### Conflicts of interests

**The manuscript has no conflicts of interest.**

### Authors Contribution

Author VM was involved in literature study, data collection, data analysis, and manuscript writing. The author, AK, is involved in data verification, validation, and review of the manuscript.

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**TABLES AND FIGURES**

## TABLES AND FIGURES

**Table 1.** Accuracy values of cnn and fnn

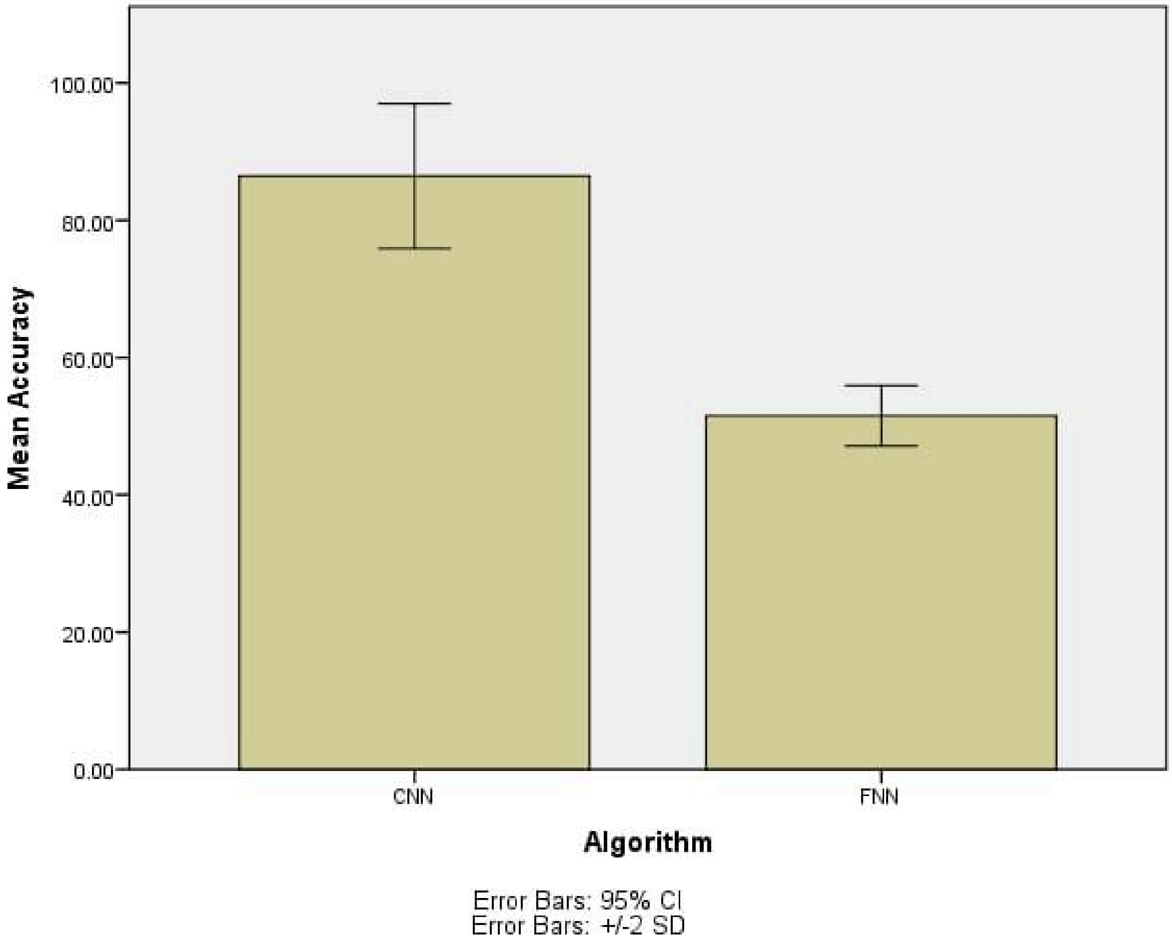
| S. No | CNN | FNN |
|---|---|---|
| 1 | 94.00 | 58.00 |
| 2 | 93.00 | 57.55 |
| 3 | 91.60 | 56.22 |
| 4 | 92.00 | 54.00 |
| 5 | 90.80 | 53.00 |
| 6 | 89.80 | 52.11 |
| 7 | 88.70 | 50.00 |
| `8 | 87.00 | 49.00 |
| 9 | 92.90 | 48.22 |
| 10 | 45.00 | 37.00 |

**Table 2.** Group Statistics results (Mean of Convolutional Neural Networks Algorithm is 99.9 is more compared to Feedforwarded neural networks 97.9 where Average variances for CNNs technique is 0.25 where Feedforward Neural Networks (FNN) is 0.16).

| | GROUPS | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| **ACCURACY** | CNNs | 10 | 86.4100 | 14.71873 | 4.65447 |
| | FNNs | 10 | 51.5100 | 6.14194 | 1.94225 |

**Table 3:** Individual Data Analysis to Determine Importance and Variance average. P rate is 0.003 (lower than 0.005) was determined to be statistical analysis, and a 95% certainty interval was considered.

| | | Levene's test for Equality of Variances | | T-test for equality of means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | F | Sig. | t | df | Sig.(2-tailed) | Mean Difference | Std. Error Difference | 95% Confidence interval of the difference | |
| | | | | | | | | | lower | Upper |
| Accuray | Equal variances assumed | .978 | .336 | 6.920 | 18 | .000 | 34.90000 | 5.04345 | 24.30409 | 45.49591 |
| | Equal variances not assumed | | | 6.920 | 12.042 | .000 | 34.90000 | 5.04345 | 23.91551 | 45.88449 |


100.00
80.00
60.00
40.00
20.00
0.00
Mean Accuracy
CNN
FNN
Algorithm
Error Bars: 95% CI
Error Bars: +/-2 SD