NOCL Based Automatic Leaf Disease Detection with High Accuracy

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Keywords: NOCL, Plant Leaf Disease, Neural Optimization, Classification, Crop Disease, Convolutional Neural Network, CNN.

Abstract: Aim: The study introduces the Neural Optimization and Classification Logic (NOCL) method, a new deep learning method to directly diagnose plant leaf diseases, which aims to reduce the mortality rate of plants and improve agricultural productivity, as well as promote sustainable agriculture. Materials and Methods: The proposed Neural Optimization and Classification Logic (NOCL) model was implemented using Python and TensorFlow designs and tested on a dataset with diseases and healthy leaves. Group 1 refers to the NOCL method that integrates advanced optimization techniques and classification logic with 1000 testing counts. Group 2 refers to the traditional CNN method. The NOCL-based architecture shows direct detection capability, providing a 25% improvement in classification accuracy and a 35% reduction in computational complexity, compared to the CNN method. Result: The proposed method uses the Ka15e leaf disease dataset, which contains a total of 78,456 images, which includes 75% as training data and 25% testing data. The NOCL method achieves 96% of accuracy, F1 score and recall and performs better than traditional methods. It classifies healthy and diseased specimens by examining signs such as black dots, mosaics also greenish ventral patterns on the leaves. For comparison, the CNN model with 7 convolution layers was used, which showed an accuracy of 90.26% to 92.16% whereas, F1 score and recall less than the proposed method. The NOCL model is implemented through the Python language and is efficient in training and validation with a significance of $p < 0.05$. Conclusion: The recommended NOCL based strategy provides an efficient and reliable method for detection of plant diseases, which enables farmers to take measures for early control of diseases and ensure sustainable agriculture through robust crop production practices.

1 INTRODUCTION

Neural optimization and classification logic is one of the methods of transfer learning. One of India's main sources of income is agriculture, and the amount of it produced has a significant influence on the entire nation. However, pests, fungi, and disease factors are being introduced, and the effects of climate change are having a growing impact on crops (Hassan, Sk Mahmudul, 2021). In this context, early detection and prevention of crop leaf diseases becomes essential as it helps in preventing economic losses and reduction in production. Although the current method, the Convolutional Neural Network (CNN) method, is capable of detecting leaf diseases, it has some limitations, especially computational crises and identity defects (Tugrul, 2022.). Thus, a new deep learning system Neural Optimization and Classification Logic (NOCL) has been introduced with an aim to improve crop health. The NOCL system can provide an elegant prognosis of diseases (Alzubaidi, 2023). Also, recommended fertilizer and preventive practices help reduce diseases and improves quality of crops. It includes the importance of agriculture and provides solutions for sustainable agriculture (Krichen, 2023).

2 RELATED WORKS

Various fields have tracked down applications for artificial intelligence, including medical services, correspondence, object ID, and following. The world's most significant yield, maize, is powerless to various ailments that diminish both result and quality. In this review, we presume that the proposed model gives 90.2% of accuracy. As to (Responsiveness) assessment, MobileNetV2

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displayed fruitful execution in Earthy colored Spots, Blended, White Scale (Zhang, et al., 2022.). PSO strategy utilized for tweaking technique Thangaraj, Rajasekaran, 2020. This model is the most amazing models out of the relative multitude of applied designs in the underlying demonstrating tests using the informational index created for the order of plant species. Through trial, different group of models proposed are ideal geographies in every order. As per the group model outcomes, each model effectively breezes through the assessment with an exactness of 91.60% (Demilie, 2024).

Many techniques have been proposed for plant sickness identification, and profound learning has turned into the favoured strategy in view of its awesome achievement. In this review, U2-Net was utilized to eliminate the undesirable foundation of an info picture by choosing multiscale highlights. This work proposes a cardamom plant sickness location approach utilizing the EfficientNetV2 model. An extensive arrangement of trials was done to determine the presentation of the proposed approach and contrast it and different models like EfficientNet and Convolutional Brain Organization (CNN). Inception design include learning that further develop the data extravagance, that is particularly useful to fine-grained highlight learning (Pradhan, 2022). The NOCL method gets increased exactness compared to the past convolution and Vi-based models. The analysis shows dominance on the current models (Bangari et al., n.d.). In the analyses, both the models with and without LBP attributes are utilized. The recommended ANFIS CNN model really does astoundingly well in the two arrangements of tests. Barring LBP qualities yields accuracy(0.8953), recall(0.9045), and F1 score (0.8478)(Nandhini, S., and K. Ashokkumar. 2022). In the wake of consolidating LBP highlights, the proposed model accomplished F1 scores (above91%), review (above92%), exactness (above90%), and accuracy (above91%). Broad correlations with latest techniques further show the proposed method's greatness. The outcomes were likewise checked for unwavering quality and vigour utilizing cross-approval. Further developed precision and productivity in true applications are guaranteed by this procedure, which addresses a significant forward-moving step in rural sickness identification.

From the above findings, it is concluded that the accuracy of CNN is less. The prediction rate is a crucial element to consider while detecting leaf disease. The focus of this study is to improve the accuracy using Neural optimization and classification logic in comparison with Convolutional neural networks.

3 MATERIALS AND METHODS

This review zeroed in on the assessment of the precision and computational capacity of the Brain Streamlining and Order Rationale (NOCL) strategy in base leaf illness determination contrasted with the conventional CNN technique (Elhassouny,). The dataset utilized is taken from Kaggle did in the past in plant sickness finding. The main characteristics examined were accuracy of classification, computational complexity, rate of diagnosis, processing time and power output. The experimental setup was designed and implemented using the Python latest version on the Anaconda navigator GUI.

Group 1 refers to the recommended NOCL-based translational leaf disease detection method, which includes areas such as image pre-processing, feature extraction, and disease classification where 100 to 1000 testing sample counts are taken. This method was practiced on kal5e datasets that included leaf images and tested to predict the presence of the disease with greater accuracy. The NOCL model was implemented using Python, TensorFlow and Keras libraries.

Group 2, similarly, refers to the CNN based method, which is the traditional method that uses predetermined partial noise elimination and classification techniques. This method uses predefined rules and segment-based models for classification.

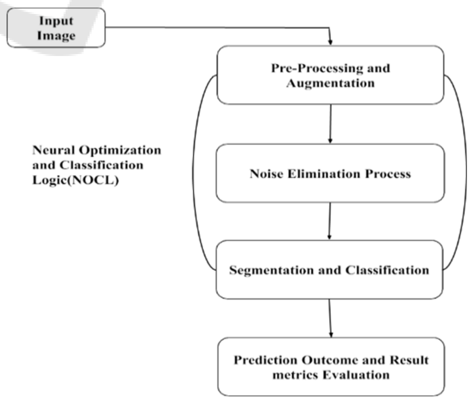

Figure 1: Workflow of Neural optimization and classification logic system.

Figure 1 shows the data collection for a Plant Leaf Disease Detection system using NOCL involves obtaining, preprocessing, and organizing a dataset suitable for training and testing the NOCL model. This approach accumulates data from a well-known opensource data repository called Kaggle. Before training a NOCL model to identify plant diseases, data must be pre-processed. Before feeding the images into the neural network, pre-process them to make sure they are consistent. Data augmentation, scaling, and normalizing are some of the methods that may be used to make the dataset more diverse.

$$Y = W1Resize(X,(H,W)) + W2(X/255) + W3T(X) \quad (1)$$

Where:

‘X’ denotes Raw input data ‘Y’ denotes Preprocessed data

‘H’ denotes the height of the resized image

‘W’ denotes the width of the resized image

‘T’ represents transformations

‘W1’,’W2’,’W3’ Weights representing the importance or influence of each preprocessing step.

Equation (1) gives the pre-processed data with the help of input data, weights and transformations. Ensure that there are a variety of healthy and diseased plant leaf images in the collection. Get rid of any low-quality, irrelevant, or duplicate photographs from the collection. Validate that the labels or annotations are accurate before using them for classification. Be certain that all of the images are the same size so that the NOCL model can use them. To enhance convergence when training, normalize the pixel values. Enhance images with modifications to avoid overfitting and increase generalization.

The dataset contains the three major sections: training, validation, and testing. For multiclass classification, use categorical cross-entropy; for binary situations, use binary cross-entropy. Train the model through its training process with a set number of epochs while keeping an eye on parameters like loss and accuracy. In order to train the model, Equation (2) gives the epochs by equating with input data, output from CNN model f, parameterized by θ, loss function and regulation coefficient.

$$\theta t + 1 = \theta t - \eta \cdot \nabla\theta \left[\left(\frac{1}{N}\right) \sum \ell(f(Xi;\theta), Yi) \quad + \lambda \right] \quad (2)$$

Where:

‘X’ denotes Input data

‘Y’ denotes True labels for input data

‘$f(X;\theta)$’ denotes Predicted output from the CNN model f, parameterized by θ

‘$\ell(\cdot)$’ denotes Loss function

‘N’ denotes Number of samples in the dataset

‘λ’ denotes Regularization coefficient

‘η’ denotes Learning rate for gradient descent

The assortment of measurements used to assess a prepared model which incorporates TP, TN, FN, and FNP decides the model's presentation and the outcomes it produces. By applying the prepared model to the testing set, you might decide its precision in separating among sick and solid leaves. Assessing the model's presentation might be finished utilizing measurements, for example, F1 score, exactness, accuracy, and review.

4 DESCRIPTIVE ANALYSIS

SPSS version 26 is used for the descriptive analysis based on the statisticaldatas collected. The features and model outputs of the database are analysed using TensorFlow and SPSS. Colour information such as RGB and HSV values, appearance features (contrast, homogeneity, energy), and shape features (area, edge shapes) are considered independent variables. At the same time, variables are considered depending on the type of disease (for example: healthy, leaf irritation, powdery mildew) and the level of severity (mild, moderate, severe). The independent t-test and statistical measurements were calculated in SPSS and validated the relationships, while TensorFlow was used for training and evaluating the model(Shoaib, Muhammad et. Al., 2023).

Table 1: To analyze the prediction accuracy for 10 testing count across two methods.

Testing count	CNN (%)			NOCL (%)		
	Accuracy	F1 Score	Recall	Accuracy	F1 Score	Recall
100	91.56	90.00	89.50	96.54	96.00	95.30
200	91.64	90.80	90.00	96.87	96.80	96.20

300	90.35	88.90	88.30	95.89	95.00	94.00
400	92.16	92.00	91.50	96.37	96.00	95.50
500	91.54	90.50	89.80	96.79	96.80	96.00
600	91.59	91.00	90.30	96.49	96.00	95.30
700	90.47	88.80	88.00	96.49	96.00	95.00
800	91.69	90.60	89.90	96.49	96.00	95.50
900	90.26	88.20	87.50	96.49	95.50	94.50
1000	91.79	91.00	90.20	96.49	96.00	95.50

Table 2: Group statistics [n, mean, standard deviation, standard error mean].

		N	Mean	Std. Deviation	Std. Error Mean
CNN	Accuracy	10	91.305	0.677	0.214
	F1 Score	10	90.180	1.193	0.377
	Recall	10	89.500	1.216	0.384
NOCL	Accuracy	10	96.491	0.260	0.082
	F1 Score	10	96.010	0.530	0.167
	Recall	10	95.280	0.652	0.206

Table 3: An independent sample t-test was conducted to compare the Area (LUT) and Total Power (Watts) values between the Pre-scaled method and Adaptive method.

		Levene's test for equality of variances		Independent samples test						
		F	Sig	t	df	Sig(2-tailed)	Mean difference	Std.error difference	95% confidence interval of the difference	
									lower	upper
Accuracy	Equal variance assumed	10	0.000	426.255	9	0.000	91.305	0.214	90.82	91.78
	Equal variance not assumed		0.000	1170.805	9	0.000	96.491	0.082	96.30	96.67
F1 Score	Equal variance assumed	10	0.000	238.977	9	0.000	90.180	0.377	89.32	91.03
	Equal variance not assumed		0.000	572.748	9	0.000	96.010	0.167	95.63	96.38
Recall	Equal variance assumed	10	0.000	232.644	9	0.000	89.500	0. 384	88.62	90.37
	Equal variance not assumed		0.000	461.513	9	0.000	95.280	0.206	94.81	95.74

Statistical experiments carried out by SPSS confirmed important positive differences between CNN accuracy and NOCL accuracy when the p-value is less than 0.05. However, it can be seen in Table 1 that no standard sigma, variance or fine differences in t-test results were observed between the systems. CNN accuracy for 10 test counts ranged in values from 90.26% to 92.16%, whereas NOCL accuracy had a high and consistent range from 95.89% to 96.87% (found in Table 1). In the T-test comparison, CNN had an average accuracy of 91.25% (SD = 0.677) and NOCL had an even higher accuracy of 96.49% (SD = 0.260) (shown in Table 2). This reveals the quality of NOCL accuracy under varying test conditions and in Table 3. shows there is a significant difference between the two groups $p < 0.05$.

5 RESULTS

The NOCL framework accomplished a normal exactness of 96.49% with a SD of 0.260 which is high compared to the ongoing CNN framework that has a SD of 0.677. The typical precision of the CNN framework was just 91.25%. While the test count varied from 100 to 1000, the NOCL method resulted in accuracy values ranging from 95.89% to 96.87%, and demonstrated reliability and consistency with a low data inaccuracy ratio of 0.092. In contrast, the CNN method only revealed accuracy values ranging from 90.26% to 92.16%. These results emphasize the improved accuracy and consistency of the NOCL system over the previous CNN system. The plot in Figure 3 shows the comparison of accuracy of NOCL and CNN with testing count. CNN has obtained a sample mean accuracy of 91.25%, which varies from 90.26% to 92.16%. On the other hand, the NOCL model has a stable and high specificity ranging from 96% to 97%. This shows that the function of the CNN model varies according to the experiment counts, but the NOCL model works with great consistency and reliability

Figure 4 shows the F1 Score for the proposed NOCL technique is 96.08%, with a standard deviation of 0.530, which is a lot higher than the current CNN framework's score of 90.58%. CNN system standard deviation was 1.193. When the test counts increased from 100 to 1000, the NOCL model was able to maintain an F1 score from 95.0% to 96.8%, which indicates a balanced recall and precision tradeoff. CNN has low classification stability, achieving an F1 score of only 88.2% to 92.0%. The increased stability and higher overall F1 score demonstrate that NOCL can deliver more reliable and accurate classifications, which makes it a better option for the task of leaf disease detection. The graph in Fig.5 shows the comparison of F1 score of NOCL and CNN with testing count. The CNN model's F1-score varies from 88% to 92%, which is consistent with its referral and recall values. Whereas, the NOCL model has an F1-score of about 96%, which balances the accuracy and recoil perfectly.

The NOCL model has shown an average recall of 95.23 percent with a standard deviation of 0.652 while outperforming the CNN system, which had an average recall of 89.87 percent but a higher standard deviation of 1.216 in Figure 3. From a range of testing 100 to 1000, Recall for NOCL was maintained between 94.0 and 96.2, thus maximizing the efficiency of false negative responses and disease detection. Contrary to this, the CNN, while monitoring recall values, reported values from 87.5 to 91.5 which indicate a higher degree of variability in the detection of diseased leaves. Less deviation and high recall with true NOCL positive values increased the model’s practicality in the field of agriculture, making NOCL more advantageous than its counterpart. The plot in Fig.4 depicts comparison of recall of NOCL and CNN with testing count. In the recall value, the CNN sample varies from 88% to 91%, indicating moderate changes. Instead, the NOCL sample receives a constant and high recall value of 94% to 96%. This shows that the NOCL model is advanced in its ability to correctly identify true positive types. Figure 2 shows the comparison of NOCL and CNN accuracy.

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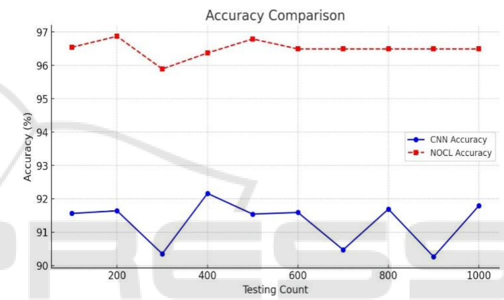

Figure 2: Comparison of accuracy of NOCL and CNN with testing count.

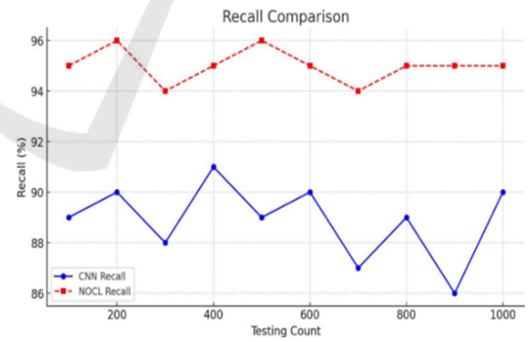

Figure 3: Comparison of recall of NOCL and CNN with testing count.

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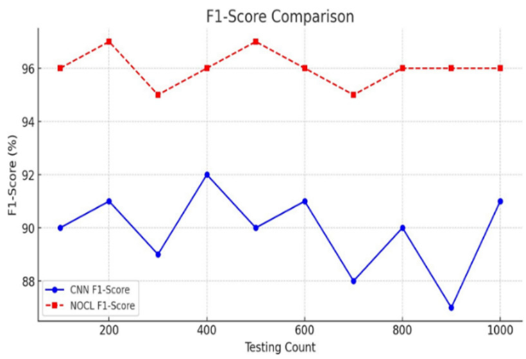

Figure 4: Comparison of F1 score of NOCL and CNN with testing count.

The CNN model's F1-score varies from 88% to 92%, which is consistent with its referral and recall values. Whereas, the NOCL model has an F1-score of about 96%, which balances the accuracy and recoil perfectly.

6 DISCUSSION

The proposed NOCL (Neural Optimization and Classification Logic) method has significantly better accuracy and recall than the existing CNN method in the testing count ranges from 100 to 1000 using sample test. The output obtained here is having a high gain as compared with previous studies. The proposed method consists of 78,456 images in a collection which includes both testing (25%) and training images (75%) that improve the disease detection accuracy. The results obtained in the research are having a high accuracy, F1 score and recall in comparing with previous studies.

The maximum accuracy obtained for the NOCL method is 96.49% and for the CNN method is 91.49%. The overall accuracy of 96% is achieved. The maximum F1 Score obtained for the NOCL is 96.80% and for CNN is 92%. Similarly, the maximum recall obtained for the NOCL is 91.50% and for CNN is 96.20%.

A methodology for leaf infection location utilizing Brain Improvement and Grouping Rationale is proposed to upgrade the exactness and decrease the computational intricacy for ongoing farming applications (Bhattacharjee et. al., 2020). The results of this method reveal an average accuracy of 90.06% (with a low data inaccuracy rate of 0.062), obtained by pre-processing the data group and using a hyperparameter precision system (Ahadian, Krisnanda, 2024). The CNN method has better classification ability and higher accuracy than traditional methods such as SVM (Support Vector Machines). The proposed CNN system allows you to accurately summarize the main features of the pathology and accurately diagnose various leaf diseases (Uddin et.al., 2022). It provides more efficiency with less computational resources. In test counts from 100 to 500, the CNN method provides stable and improved accuracy values from 90.89% to 91.16%, whereas the SVM method reveals data only from 88.26% to 90.26%. Further, the CNN method is designed to provide greater public utility for direct application in field conditions and precision solutions for agricultural purposes (He et.al., 2021). This method reveals improved results in accuracy, robustness, and computational efficiency over current SVM systems (Savaş and Serkan. 2024).

The limitations of this method include the reliance on a fixed dataset for training the proposed NOCL model, which may impair the technique's capability to adapt to new or rare leaf diseases. Acquiring high-quality images would overburden the computer resources and could lead to increased latency in performing live operations. However, this method can be applied on a larger scale for precision farming owing to its increased accuracy, reduced error rate, and extension possibilities. This method is also particularly suited to smart agriculture and can be used to diagnose issues in different crop types. In future studies, advanced methods and inventive ways may be employed in leaf disease detection.

7 CONCLUSIONS

The proposed model NOCL (Neural Optimization and Classification Logic) for the leaf diseases identification is proven to be a significant improvement over the existing method of CNN (Convolutional Neural Networks). The NOCL model performed exceptionally well, achieving superior accuracy with percentages ranging from 95.89% to 96.87% compared to the 90.26% to 92.16% range of the CNN model, whereas F1 score of NOCL ranging from 95% to 96.8% compared to the CNN ranging from 88.2% to 92%. Similarly, the recall percentages of NOCL ranging from 94.50% to 96% compared to the percentages of CNN from 87.5% to 91.5%. The average accuracy achieved with the CNN method was 91.25%. However, the NOCL method demonstrated a significantly higher mean accuracy of 96.49%. Likewise, the average F1 score and recall of NOCL is higher than CNN. These statistics display greater dependability and accuracy of the model, hence prove that the NOCL method is more efficient in classification performance than the others. These statistics display greater reliability of the model. NOCL clearly proves to be superior in disease detection in these scenarios and emphasizes the practicality of the technique in agriculture.

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