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Implementation of Deep Convolution Neuro-Fuzzy Network to Plant Disease Detection, Risk Assessment, and Classification

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Abstract— Indian agriculture drives the economy. Sickness is common in plants exposed to several environmental conditions. This lowers crop quality. Due to recent weather changes, farmers' biggest issue is maximizing output quality and quantity. Diagnosing and treating crop diseases quickly maximizes agricultural productivity. Illnesses can reduce tomato crop yields, lowering farmers' income. To treat and control tomato leaf diseases, proper identification is crucial. Deep learning improved recognition accuracy. Artificial intelligence incorporates deep learning. Due to its self-directed learning and feature extraction benefits, academic and industry circles have been discussing it recently. Learning-based methods in plant leaf disease detection can speed up research, improve feature extraction, and loosen disease spot feature selection. To improve identification accuracy, deep learning now uses fuzzy rules to represent and manage fuzzy information. Using a deep neuro-fuzzy neural network, we classify rice plant illnesses. To extract complex features, the neuro-fuzzy network uses a fuzzy inference layer and a fuzzy pooling layer. Then classify them in the fully linked layer. A huge dataset of 8 types of infected and uninfected rice plant photos yielded a 96.9% identification accuracy for the moa del. Three performance indicators were also used. The trials show the benefits of employing NFNHDL to diagnose rice diseases.

Keywords—rice plant, Deep learning, fuzzy rules, neuro-fuzzy, fuzzy inference layer.

I. INTRODUCTION

Rice is an important grain that provides nourishment for billions of people all over the globe [1]. It is the principal source of nutrition in the countries of India, and Indonesia. Anything that affects the rice crop, both in terms of superiority and measure, has a global impact. As a result, regular illness monitoring and identification are very necessary in order to effectively combat the problem. Diseases may have a severe impact on production if they are not treated in a timely manner [2]. A multitude of diseases and pests have contributed to the degradation of rice crops in recent years. Without proper surveillance and management, these attacks may cause severe disruption on farms, and the problem has only gotten worse in recent years. In addition, the early and accurate identification of problems in plants saves rice from dangerous diseases and significantly lessens the amount of money lost. The treatment of these disorders is supportive of our efforts to assure healthy agriculture [1].

The ability to automatically identify plant illnesses based on plant leaves is a major step forward in the agricultural sector. The efficiency and quality of harvests may be improved via early and correct diagnosis of plant leaf diseases. In order to maximize crop superiority, it is crucial to prevent the spread of disease throughout the farm. Diseases may be contained if their symptoms are recognized, their causes for proliferation are investigated, and control measures are put into place. Plant diseases may cause problems for plants at all stages of their life cycle.

Plants that are unwell will often have discolored, wilted leaves. Generally speaking, it is possible to recognize abnormalities in the visual presentation of a disease by looking for its characteristic pattern. The leaves of a plant are usually the first to show signs of disease, making them an excellent resource for diagnosing plant ailments [3]. Semantic segmentation and picture identification are only two areas where deep learning techniques have been effectively used recently. As an added bonus, this technique has been used to diagnose a wide range of plant diseases [4-6]. When discussing "Deep Learning," the term "Deep" denotes to the number of transformational layers over which data is passed, each of which extracts increasingly subtle features from the input. Layers of nodes make up the Deep Learning algorithm, which may be broken down into the input layer, the hidden layer, and the output layer. By learning additional complex data properties of the leaf, it performs an excellent classification procedure. The raw picture data serves as input to the convolutional neural network, and the model's learned classification serves as an output, making the neural network a full-stack solution. In the center, where learning occurs, neither human input nor well-crafted algorithms are necessary. However, this network has significant difficulties when dealing with ambiguous data. Some aspects of the training set, for instance, are often ambiguous or even noisy [7-9]. The incapacity of this neural network to produce fuzzy values for the feature map pixels has a detrimental effect on the detection accuracy of tomato leaf diseases. [10].

In order to interpret hazy, ambiguous, and erroneous data input, models might benefit from the utilization of fuzzy sets and fuzzy reasoning rules [11]. Human language is able to be used to represent ambiguous and hazy information thanks to the invention of fuzzy sets. As a measure of how fuzzy and uncertain a set is, the membership degree may be calculated using the fuzzy set concept's membership function. The goal of using fuzzy inference rules is to retrieve information that is ambiguous, fuzzy, or imprecise. To achieve this, image-processing algorithms that mimic human decision-making have been included.

As digital image processing and identification technology advances, it is now feasible to quickly and easily identify ailing crops and classify the specific disease that has afflicted them [12,13]. However, AI and ML alone will not be adequate; thus, some academics have proposed using surveillance drones, the Internet of Things, and cloud services, among other things, to create a holistic system that can effectively aid farmers in getting good outcomes and decreasing expenses [14]. Nevertheless, the most important element would be a machine learning algorithm, method, or process that is both extremely effective and capable of detecting and precisely diagnosing rice illness. As a result, researchers are still looking for the most effective machine-learning solution for the diagnostics of plant diseases. Although a recent study has been conducted in this area, the ideal and most precise answer is still an open research issue, and scholars are continually working near achieving this objective.

Jang et al. [15] first proposed the concept of a neuro-fuzzy inference system that could adapt to new information. To do this, the system uses a neural network-based inference mechanism to calculate the parameters of a TSK fuzzy model. The elevated method is by far the most common kind of neuro-fuzzy modeling, although its structure is somewhat simplistic because it only models a single rule set of a fuzzy system.

It is proposed here to use a deep neuro-fuzzy network trained with fuzzy reasoning rubrics to detect illnesses in tomato leaves. Fuzzy systems and deep learning are brought together in the deep neuro-fuzzy network through the use of fuzzy implication rules introduced within a deep framework. The fuzzy inference layer and the fuzzy pooling layer represent the two novel operations—fuzzy inference and fuzzy pooling, respectively—used by this network. Since this network with two operations can yield both clear and fuzzy values, more information may be extracted from the tomato leaf picture through the request of fuzzy inference and fuzzy pooling, allowing for higher recognition accuracy. For better performance and generalization, this end-to-end network employs a deep neuro-fuzzy network instead of a shallow one to process images of tomato leaves and extract the corresponding information from the input layer using several hidden layers.

II. MATERIALS AND METHOD

This section details how a robust method based on Hybrid Deep Learning with a neuro-fuzzy neural network was designed and developed for detecting and classifying rice leaves. First, input data is gathered from a database in which two datasets are combined to produce a third dataset.

A. *Proposed framework*

In this paper, we describe the steps we took to recognize and categorize rice leaves using a cutting-edge technique called Neuro-Fuzzy Network-based Hybrid Deep Learning (NFNHDL). The starting point is an image database where two datasets are combined into one. The pre-processing is done on the input images. Subsequently, suitable areas are segmented using Deep Fuzzy Gathering. After the partitioning is finished, the features are extracted so they may be processed further. All necessary characteristics, such as those based on statistics, the Convolutional Neural Network (CNN), and textures, are successfully recovered here.

Enhancing data by means of transformations like rotation, cropping, and zooming helps in the categorization process. Also, Neuro-Fuzzy Network is used for diagnosing whether or not a rice plant's leaf is healthy or diseased. Disease classification in rice leaf tissue is completed using a Deep neural network. If a diseased leaf is discovered, the plant is classified as having BLB, blast, or brown spot. Figure 1 is a high-level diagram of the proposed Hybrid Deep Learning technique for identifying Rice Disease.

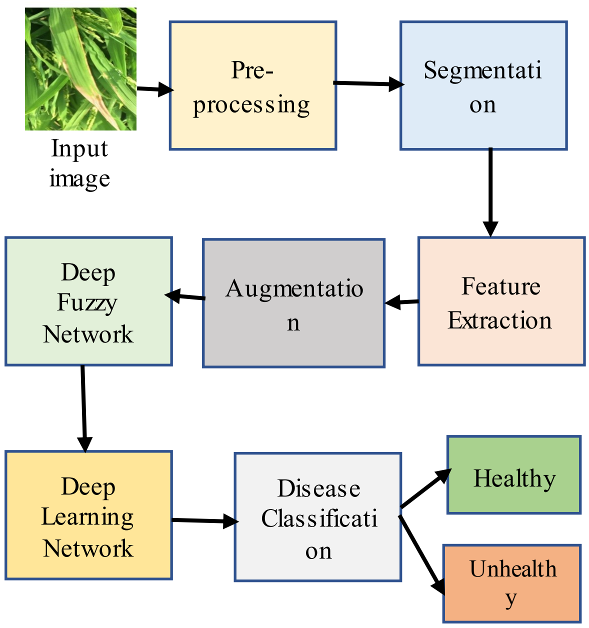

Fig. 1. proposed NFNHDL technique for recognizing Rice Disease

B. *Pre-processing of dataset*

From the dataset D with x input photos, which can be written as,

$$D = \{d_1, d_2, d_3, \ldots d_g \ldots d_x\} \quad (1)$$

where D represents the collection of data, the set of input photos as a whole, and d_g the image at the g^{th} index that is sent into the preprocessing phase. The input picture is cleaned of any manipulations using the Region of Interest (RoI) technique during preprocessing. In this case, the RoI is successfully identified from the input photos to reduce the amount of background noise and so improve the image's overall quality to the human eye. The output before dispensation is signified by the symbol D^*. Once the pre-processed picture D^* has been obtained, the afflicted regions may be extracted with DFC. As a result of using the DFC algorithm, the procedure is more reliable and productive.

The data augmentation procedure raises the characteristics' dimensionality to better facilitate detection and categorization. Modifications such as cropping, zooming, and rotation are used to bolster the data. When utilizing the cropping tool, the required portion of the original photo is extracted while the image is rotated to the chosen angle. In a similar vein, you may zoom in on an image or out to see more detail. At last, the rice leaf detection algorithm is applied to the augmented data result D^*.

C. *Neuro-Fuzzy Network*

An integral aspect of fuzzy logic is the notions of fuzzy sets and fuzzy reasoning rules. Membership functions that translate items of a domain of discourse (Y) to the interval [0,1] are what we mean when we talk about fuzzy sets.

$$X{:}\,Y \rightarrow [0,1] \quad (2)$$

Conventionally, such a system relies on a set of fuzzy rules for making judgements. An effective tool for functional approximation tasks like classification, this system employs if-then rules to create rules in fuzzy systems and achieves good approximation results.

If l_1 is X_{x1} and l_2 is X_{x2} and l_3 is X_{x3} and l_n is X_{xn} then

$$V_x = f_x(X) \quad (3)$$

where X_i is the ith input variable, and V_i is the xth rule output $(x = 1, 2, 3, \ldots)$. And is a fuzzy conjunction operator, where N is the total quantity of fuzzy if-then rules. In the illustration, there is a pattern for each fuzzy rule. The following is a definition of what the fuzzy rules of single input and multiple output are:

$$\begin{pmatrix} f_{x1}(X) \\ f_{x2}(X) \\ f_{x3}(X) \\ \cdot \\ \cdot \\ f_{mn}(X) \end{pmatrix}, then \;\; (x = 1, 2, 3, \ldots m) \quad (4)$$

The following formula, a nonlinear function, can be used to calculate the output of this system.

$$v = \frac{\sum_{x=1}^{M} D_m(X).f_x(X)}{\sum_{x=1}^{M} D_m(X)} \quad (5)$$

$$v = \sum_{x=1}^{M} \overline{(D_m(X))} \, . \, f_x(X) \quad (6)$$

$$D_m(X) = \prod_{j=1}^{n} D_{x_{jn}}(X_j) \quad (7)$$

the result of the mth rule, denoted by $f_x(X)$. An input's membership grade, or $D_{x_{jn}}(X_j)$, quantifies the degree to which x_{jn} and X_j, $D_m(X)$ are comparable to one another while also capturing the degree of uncertainty involved. The value denotes the mth rule firing strength, whereas $\overline{(D_m(X))}$ is the normalised operation on firing strength.

D. *Architecture of NFNHDL Network*

Fuzzy logic and the deep neural network model are brought together to create the NFNHDL classifier. A deep neural network is used for the first of two activities in NFNHDL. The initials NFNHDL stand for the deep neural feedforward network. In contrast, the second procedure uses fuzzy logic to estimate the system's aims. There are three distinct levels inside this framework: the input layer, the concealed layer, and the output layer. The value of the fuzzy logic system, along with a few additional input attributes, is needed to set up the input layer. In addition, three separate layers—the normalization layer, the rule layer, and the output defuzzification layer—are employed here. The deep neural network's ability to distinguish between premises and results is also crucial.

In conclusion, the output that was identified is denoted as M_o, and this indicates whether or not the rice leaf sickness is healthy or unhealthy. The NFNHDL algorithm's pseudo-code is described in Algorithm 1, which may be found here.

Algorithm 1 : Pseudocode of NFNHDL model

Step1. **Initialize** $D = \{d_1, d_2, d_3, \dots d_g \dots d_x\}$

Step2. **Calculate** Fitness

$$\propto = \frac{1}{\delta} \sum_{x=1}^{\delta} [T - M_o]^2$$

Step3. **While** D<limit **do**

Step4. **For** each result **do**

Step5. **Update** result

Step6. **End** for

Step7. **Increment** D by 1

Step8. **End** While

Step9. **Return** best result

Illustration of the proposed deep neural network design. For those curious, the input has a 224 by 224 matrix. 3. The model employs a total of 4 convolutional layers. To prevent overfitting, we employ a dropout value of 5.

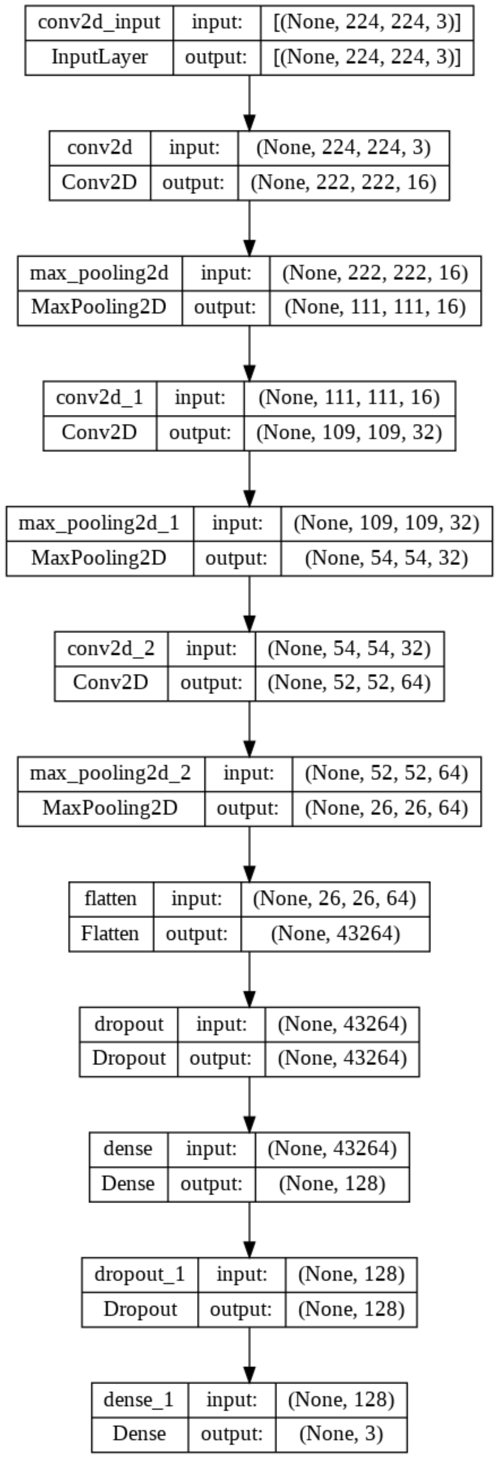

Fig. 2. The proposed NFNHDL model architecture

III. EXPERIMENTAL SETUP

Python, a computer with 2 gigabytes of random-access memory, the Windows 10 operating system, and an Intel i3 core processor are used to carry out the execution of the strategy that has been conceived.

A. Dataset

Compounding the Rice plant dataset [16] with the Rice disease dataset [17] allows for the successful use of the developed technique. There are a total of 1006 photos of both healthy and diseased rice seeds in the rice plant dataset [16]. Images of BLB, brown spots, and blasts may be seen in the rice disease dataset [17]. Images representative of those in the sample dataset are displayed in Figure 3.

(a) Healthy Rice Images from Rice plant dataset

(b) unhealthy Rice Images from Rice plant dataset

(c) Bacterial leaf blight – images from RiceDiseases-DataSet

Fig. 3. Sample healthy and unhealthy rice images from the dataset

IV. PERFORMANCE EVALUATION

The percentage of correctly predicted classes by a trained model of a deep neurofuzzy network is dependent on the training rate and the training batch size. Selecting a range of values for the initial learning rate and batch size and comparing the ensuing shifts in the learning rate allows one to zero in on the best possible combination of these two parameters. The goal is to find the optimal "learning rate" and "batch size" combinations. We started by varying the learning rate from 0.00001 to 0.0001, then to 0.001, and eventually to 0.002. When the initial learning rate is set at 0.00001, the recognition accuracy will vary depending on which of the four possible batch sizes is used. Regardless of any other adjustments, this will always happen. We trained the neural network with the identical settings we had used for the deep neuro-fuzzy network. Next, we use the trained model to generate predictions about the class of the test set, and our identification accuracy improves to 96.9%.

The accuracy of the model is calculated using

$$Accuracy(A) = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \quad (8)$$

To what extent are tests showing favorable results is what these metric measures (T_{pos}), or cases that have been correctly classified, and the equation for it is as follows:

$$sensitivity\ (S) = \frac{T_{pos}}{T_{pos}+F_{neg}} \quad (9)$$

The precision of these two different networks is contrasted in Fig.4 and 5, respectively.

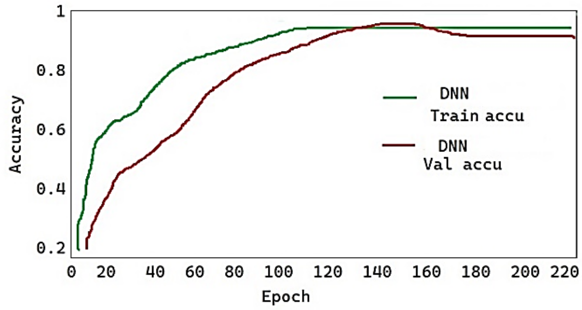

Fig..4. Accuracy of the DNN model

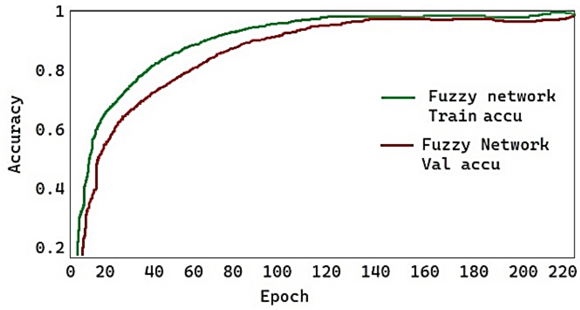

Fig.5. Accuracy of the model with fuzzy logic

The proposed model along with the fuzzy neural network is compared with the other baseline model. When compared to alternative baseline models, the suggested model performs better. Table 1 presents the comparison of the planned model with other models. Table 1 provides a comparison of the newly proposed method to previously used techniques by taking into account several performance indicators such as the testing accuracy, precision, and F1Score.

TABLE I

USING PERFORMANCE METRICS, WE COMPARED OUR PROPOSED NETWORK TO OTHER MODELS.

Model	Precision	Accuracy	F1 Score
LSTM	0.75	0.72	0.76
SVM	0.56	0.54	0.52
CNN	0.85	0.86	0.85
DenseNet	0.89	0.87	0.88
AlexNet	0.90	0.92	0.90
GoogleNet	0.93	0.94	0.94
Proposed model	0.96	0.97	0.96

The fig.6 shows the comparison graph with other baseline models. The proposed model produces the highest accuracy rate compared with other models.

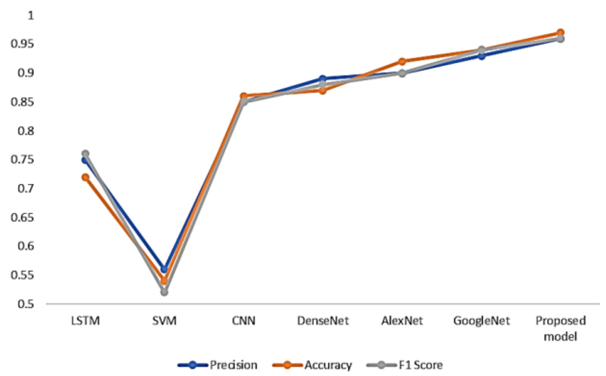

Fig. 6. Comparison chart of the proposed model

V. CONCLUSION

This study details the effective method for disease detection and classification in rice plant leaves; the method is called NFNHDL-based Deep Learning. The authors of this study created the method described in the paper. Here, the RoI extraction method is used in the pre-processing unit to get rid of any unwanted noise or distortion in the input image. When this is done, the algorithm isolates the broken areas from the pre-processed output. After that, features including statistical features, CNN features, and textual features are extracted using a procedure called feature extraction, and then data augmentation is performed. The next step in the rice leaf disease identification process is running the picture through a Deep Fuzzy neural network, which classifies it as either healthy or sick depending on its findings. In the last step, the NFNHDL classifier applies its knowledge of rice leaf illnesses to the unhealthy photos in order to categorize the rice leaf diseases as BLB, blast, or brown spot. We determined the value accuracy, recall, and F1-score for each category in order to evaluate the effectiveness of this network in detecting rice plant illnesses. To prove the benefits of this network in identifying illnesses that can harm rice plants, we conducted tests to examine the impact of the deep structure, fuzzy inference layer, and the network's structure on recognition accuracy. And we looked for the best approach to combine the learning rate and the batch size to get the maximum possible recognition accuracy, keeping both factors in mind. In a nutshell, deploying a deep neuro-fuzzy network as a diagnostic tool for rice plant illnesses is not only a workable, dependable, and outstanding approach, but it also yields a high level of accuracy.

In addition, the NFNHDL -based Deep Learning approach that was created exhibited greater performance in terms of testing accuracy, sensitivity, and specificity with higher values of 0.96, 0.97, and 0.96 respectively. In the next investigations, effective optimization strategies will be utilized with the goal of improving classification results. Additionally, in future the performance of the suggested technique will be evaluated by making use of big datasets, and other disorders will also be taken into consideration.

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