PREDICTING DIFFERENT TYPES OF PADDY LEAF DISEASES USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

In most of the world's are agriculturally dependent countries, paddy farming is the primary source of income. Automated detection of paddy diseases is widely needed in the field of agriculture. Early detection of paddy-related diseases is necessary to protect paddy crops as they can harm the entire farm land. The area of agricultural disease identification has greatly benefited from the recent advances in deep learning approaches. In this study present a unique deep convolutional neural network-based approach for diagnosing three Paddy illnesses such as paddy bacterial leaf blight, paddy blast and paddy brown spot. CNNs are trained to recognize these three rice illnesses by using a dataset of 500 naturally occurring images of damaged and good paddy leaves are taken from a paddy experimental area. The suggested CNNs-based approach obtains an average accuracy for predicting the paddy leaf disease is 0.76 percent. Compared to other standard machine learning models, this effectiveness is significantly greater. The simulated outcomes for identifying paddy illnesses demonstrate the viability and efficiency of the suggested approach.

Keyword: *Agriculture, Paddy leaf illness, Diagnosis, Deep learning, Convolution neural network*

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1. INTRODUCTION

In agricultural, paddy is a crucial crop, on the other hand crop diseases can drastically lower crop productivity and quality, posing a serious danger to global food supplies. So, prevention of disease is essential for the production of rice. Accurate and prompt illness diagnosis is essential for effective disease management because it enables timely implementation of pesticide control strategies. Presently, manual diagnosis based on illness appearance is the technique most frequently employed to identify diseases in rice crops [1].The main source of energy for both humans and animals is plants and fruits. Due to their therapeutic properties, the leaves of many plants and herbs are beneficial to humans. Asia and Africa are two regions where more than 50% of the population depends on agriculture for employment, food security and export earnings[2]. According to estimates, crops are lost along the production system at a rate of 30 to 40 percent annually[3]. With an overall demand of 493.13 million metric tons in

2019-2020 and 486.62 million in the previous year, rice is one of the most popular foods globally [4]. Whenever compared to the metric tons consumed over the years, this indicates an increase in rice consumption. Rising production levels are expected to coincide with rising rice demand. Moreover, the lack of or improper supervision of farms frequently led to the destruction of a significant volume of rice as an outcome of disease-related issues. The main cause of significant economic losses is the common occurrence of certain illnesses in the rice farming industry. Additionally, the extensive use of pesticides such as bactericides, fungicides and nematicides to control plant pathogens has had negative consequences on the agro-ecosystem [5].

In the majority of nations, farmers are accustomed to spotting pests with their naked eyes. This method necessitates constant surveillance of the crop leaves and stems that is a challenging, imprecise, and costly operation for big farms. A relatively small number of sick leaves can transmit the infection to the entire batch of vegetables and fruits, which has an impact on future storage and sales of agricultural commodities. As a result, early diagnosis of plant diseases is crucial. Plant diseases have a tremendously damaging effect, depressing many farmers to the point that some have given up on crop farming [6]. Early or advanced detection and treatment of these diseases is essential to reduce damage and to increase agricultural production. The goal of agricultural development is to investigate crop productivity and the quality while minimizing costs and maximizing output. In order to successfully regulate the elements affecting the crop's yield and quality, the illness must be diagnosed quickly and any potential remedies must be put into practice as soon as feasible. Manual diagnosis is a laborious process since it incorporates many different criteria. Therefore, it is mandated that automation processes be implemented in way to attain farmers and aid them in the enhanced accuracy of earlier disease identification. The process of illness categorization during this stage heavily relies on cutting-edge machine learning algorithms [7].

Deep convolutional neural networks have been successfully applied in a variety of domains over the past decade, such as video classification, image classification, human action detection and traffic sign recognition among others. To build a deep convolutional network model for rapid and precise automated detection utilizing images of paddy illnesses. Paddy false smut, blast, bakanae disease, brown spot, sheath rot, sheath blight, bacterial sheath rot, bacterial leaf blight, bacterial wilt and seeding blight are the most common disease of the rice which is shown in figure 1.The study presents a brand-new deep convolutional neural network-based technique for diagnosing rice illnesses. The suggested CNNs-based model is capable of achieving greater classification ratios. The photos of the paddy leaves totaling 650 are pre-processed before being utilized to train CNNs. This CNNs approach can outperform the traditional model in terms of recognition rate and fast convergence when training the CNNs' variables. The main driver for the creation of the deep convolutional network modeling for paddy illness was to give farmers a simple method for spotting early-stage illnesses using a standard digital camera. Secondly, it is crucial yet difficult to extract beneficial properties for diagnosing paddy illnesses, and CNNs are supposed to be automatic feature learners from the raw inputs in a methodical manner. The learned features are considered as a high-level representation of low-resolution source images of rice disease through deep modeling. CNNs are considered to be one of the best classifiers for cognitive tasks due to their improved detection performance. Therefore, in this study develop a deep convolutional neural network model for rice disease detection.

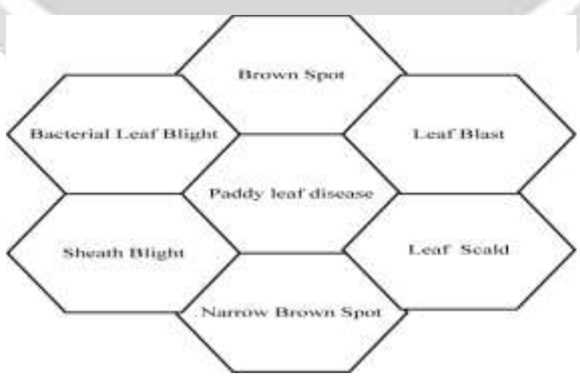

Fig -1: Various kinds of paddy diseases

This study presents a brand-new approach for identifying rice illnesses that is based on deep convolutional neural networks. The suggested CNNs-based approach is capable of achieving greater classification ratios. The gradient-descent approach may be used to train CNNs based on an understanding of their structure and variables.

The images of the rice leaves and stems, totaling 650 are pre-processed before being utilized to train CNNs. This CNNs approach can outperform the traditional model in terms of recognition rate and fast convergence when training the CNNs' specifications. This paper's primary contribution mostly consists of two parts. The first problem to which convolutional neural network is used is that of disease detection in paddy. It should be noted that the suggested approach may accurately and successfully identify the 10 prevalent paddy illnesses. The outcomes of the experiments demonstrate that the CNNs approach not only accelerates converging but also achieves a greater recognition rate than other models such as support vector machine, particle swarm optimization, K-means clustering and the decision tree approach algorithm.

1.1 PROBLEM IDENTIFICATION

In agriculture sector, the farmers are using the traditional methods that is they are predicting diseases of paddy leaf by human way of analysis but sometimes it's not so accurate, due to this the farmers loss the entire farm land paddy cultivation which cause great loss in economy. If the diseases are identified in initial time of paddy leaf diseases the production loss can be minimized.

1.2 OBJECTIVE

- To find the types of paddy diseases in initial stage
- To help the farmers to protect the farm land
- To stop spreading the paddy diseases, from one paddy to other

2. RELATED WORK

Investigate various foliar diseases in a prescribed setting using image processing detection and classification techniques. Initially, various rice leaves are photographed using digital technology. Subsequently, the RGB model is converted to HSV model for image segmentation and k-means clustering for image resizing. PCA technique is used to retrieve specific characteristics. Additionally, the BFO-DNN approach and extracted features were used to classify paddy leaf illnesses. The detection performance and entropy losses are both improved by this classification technique. The ability to recognize or identify an image of a sickness using a variety of options is extremely effective (sheath rot, Bacteria light, Normal and Brown spot etc.). To determine performance metrics like accuracy, TPR, TNR, FDR, Cross Entropy, and FPR, experimental investigation is used. The next step is to evaluate and contrast the old variables with the new variables. Hybrid BFOA-DNN accuracy ratio is 97 and DNN accuracy value is 93.50 percent, recommended system performance rating is 98 percent The key benefit of the study software system is that it can be easily modified to add additional leaves. But the system performance is slow compared to other methods [8].

A fast R-CNN and FCM-KM fusion method is developed to solve many problems of rice disease images including noise, blurred image edges, significant background interference and low detection rate. Initially, a fast two-dimensional Otsu threshold segmentation algorithm (fast 2D-Otsu) is used to identify the target blade in the image to reduce the interference from the complex background. The method uses a weighted multilevel median filter combined with a two-dimensional filtering mask to reduce noise. Then, K-Means clustering algorithm (FCM-KM) is improved using dynamic population firefly algorithm, based on chaos theory and maximum and minimum threshold algorithms, to find the best clustering class k value. FCM-KM analysis is combined with R-CNN algorithm for detecting rice diseases to find different sizes of target frame for faster R-CNN. According to the application results of 3010 images, rice blast, bacterial blight and blight detection accuracies and times were 96.71 percent/0.65 seconds, 97.53 percent/0.82 seconds and 98.26 percent/0.53 seconds, respectively. It clearly shows that this technique can detect rice disease and improve the detection performance of the speedier R-CNN algorithm. This method is not appropriate for dynamic identification of large-scale paddy cultivation monitoring and disease [9].

In the Internet of Things (IoT) farming applications, many pathogen prediction algorithms are created, although correctly anticipating the illness generates significant environmental difficulties. In order to anticipate the illness in the rice cultivation, the Sunflower Earth Worm (S-EWA) optimization technique is established. The sensing nodes are deployed at random across the suggested Sunflower Earth Worm optimization algorithm's IoT network of farm areas. These sensor networks gather agricultural data from the rice cultivation and send it to the base station (BS) via the best route. The route utilizing the best path is made possible by the regenerating, replication, and dynamic characteristics of the optimization technique. Depending on where the earthworms are the optimization algorithm determines the best route using the fitness value. There at base station, the Deep Regression Neural Network predicts paddy leaf illness using artificial neurons. By adjusting the learning percentage and the number of hidden layers, the suggested S-EWA-based DBN achieved superior results in terms of accuracy, sensitivities, and specificity with values of 95.2, 95.51, and 94.89, correspondingly[10].

Epidemics of crop diseases can lead to significant losses in agriculture production and have a negative impact on food security, particularly in Nepal and south Asian nations where rice is a year-round mainstay. The suggested method seeks to provide a prototype system for paddy pathogen detection in order to accomplish automated identification of plant diseases. Twin Support Vector Machine (TSVM) technology will be used to categorize the paddy disease and image analysis techniques to improve the picture quality will be used for disease detection. The approach includes picture collecting, pre-processing, rice illness assessment, and categorization. Before moving on to the binary conversions, the RGB computation will be applied to all of the rice instance images. The specimen is dynamically classified as regular if it falls within the range of typical rice RGB. Then, before moving on to the TSVM for training and validation, the entire segmentation paddy illness specimen will be turned into binary information in the database. The suggested system is to produce improved identification outcomes[11].

Identify and classify rice leaf pathogens using optimal deep neural network and Jaya algorithm. Imaging of rice plant leaves is taken directly from the farm field to collect images for healthy, bacterial leaf blight, brown spot, sheath rot and blast diseases. In pre-processing, the RGB images are converted to HSV images to remove the background, and then the binary images separate the diseased and healthy regions based on hue and saturation. A clustered approach is utilized to separate the sick region from the normal portion and the backdrop. The Optimizing Deep Neural Network with Jaya Optimization Algorithm (DNN JOA) is used to classify disorders. In the post-processing stage, a feedback loop is created in order to precisely measure the sustainability of this technique. Evaluation and comparison of the experimental findings using ANN, DAE and DNN are performed. The suggested approach produced results with high accuracy, including 98.9% for the impacted blast, 95.78% for the bacterial blight, 92.0% for sheath rot, 94.0% for the brown spot, and 90.57% for the healthy leaf images. This approach has low classification efficiency[12].

2.1 THREE TYPES OF DISEASE IN PADDY LEAF

Paddy Bacterial leaf blight

A pathogenic illness called bacterial leaf blight is brought on by Xanthomonas oryzae, which is present on rice leaf. It generally makes seedlings droop and turn their leaves yellow and dried out. Disease-affected leaves become wrinkly and greenish-gray in color. As the illness progresses, the leaves become yellow to a crumb-colored shade and droop, making the entire seedling to dry up and perish. The yield loss will be reduced the faster the disease can be found. Whenever crops are impacted in the early phases, bacterial blight will not impede the harvest, but it will result in low-quality grains and a significant amount of infected seeds. Figure 2 depicts the bacterial leaf blight disease in the paddy leaf.

Fig -2: Paddy leaf disease of bacterial leaf blight

Paddy blast

Fungus Magnaporthe oryzae is the paddy disease family of Blast. Main symptom of paddy blast has leaf collar, leaf node, collar node and neck parts of the panicle will be affected by Blast diseases. Blast can occur in paddy in all growth stages, wherever the Blast spores are present. Normally it is present in low soil moisture, rain shower and cooled temperature. Initially appear as gray green spot with dark green border. Later lession became elliptical with gray center and brownish border. Then it gets enlarged and killing the entire leaves. Figure 3 depicts blast disease in the paddy leaf.

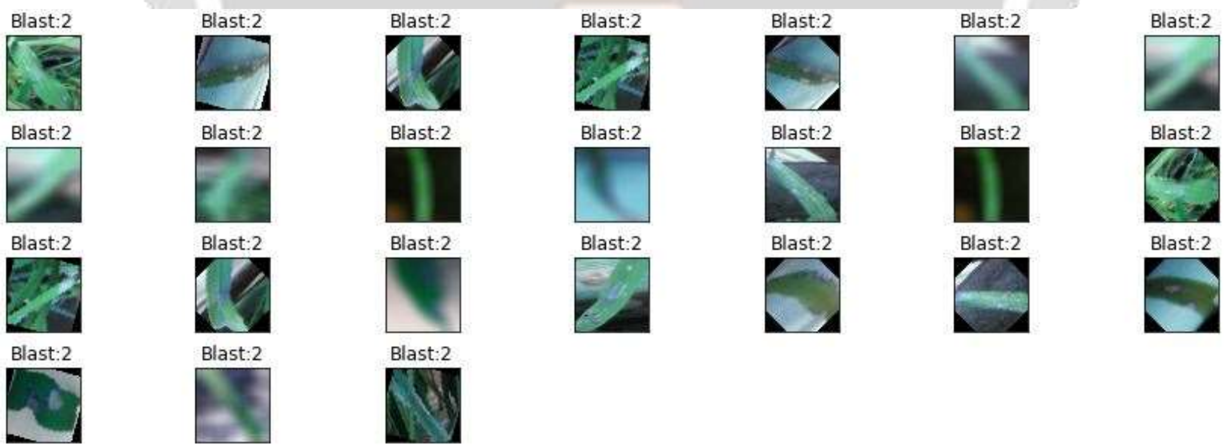

Fig -3: Paddy leaf disease of blast

Paddy Brown spot

The protecting layer covering the leaves, leaf, branches, leaf sheath and outer husk encircling the grain are all impacted by the fungal infection known as brown spot. Smaller, round, yellow-brown or dark-brown patches may harm the coleoptiles and destroy the entire leaf on disease-infected leaves. Decrease of both amounts and uniformity is being brought on by brown spot. Although brown spot infections can appear at any stage of crop development they are most dangerous when the crop is fully mature. Figure 4 depicts the brown spot disease in the paddy leaf.

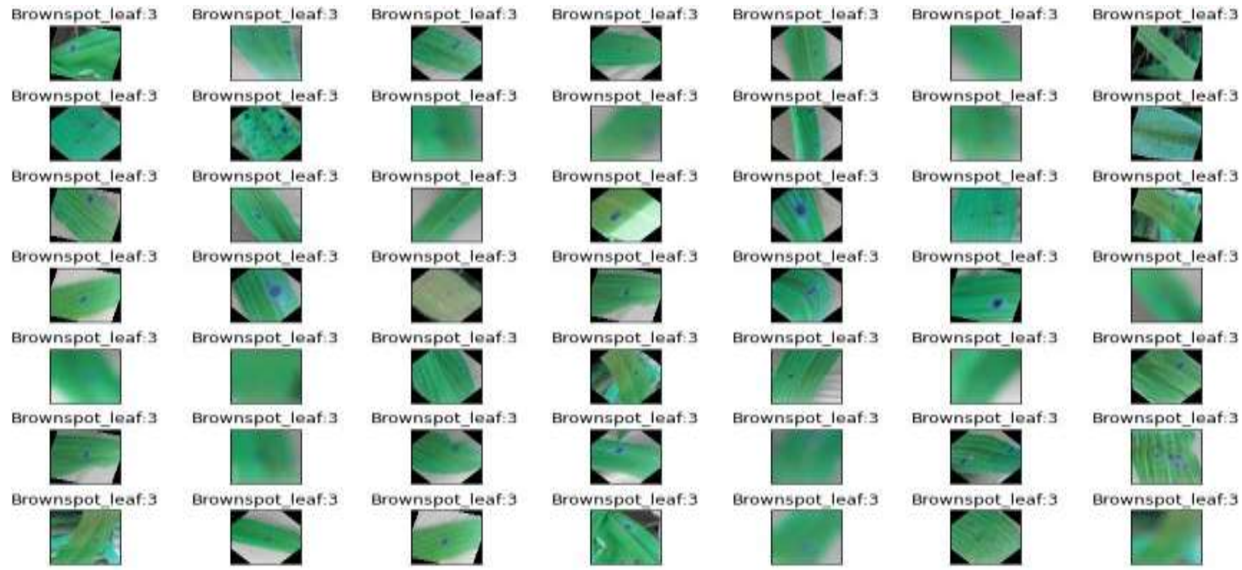

Fig -4: Paddy leaf disease of brown spot

3. METHODOLOGY

The suggested method is described in the part that follows. It was utilized in this work to categories three types of rice leaf diseases such as paddy bacterial leaf blight, paddy blast and paddy brown spot using datasets that were gathered both before and after balanced. Convolution neural network-based architecture for rice disease classification is the main accomplishment of this study. Convolution layer, softmax layer and stochastic pooling layer are all components of CNN based architecture.

Paddy disease detection approach

Gathering datasets for database is often the first step. Images for the dataset were taken from the UCI machine learning library. It is made possible by the creation of a database with 500 images of paddy illnesses. The 450 images of a prevalent paddy illness are selected from the database. Three classifications make up the dataset's specimen images. There are 50 healthy paddy leaf images per class, 150 images for bacterial leaf blight, 180 for paddy blast and 120 for paddy brown spot. The gathered images are offered for pre-processing to separate the diseased area from the affected region. The chosen images dimension for the paddy illness is 5760×3840 pixels. Utilizing Matlab R2021a software's digital image processing toolbox and Stanford dl ex-master CNNs toolbox, the images are analyzed and evaluated. Figure 5 represent the paddy diseases detection methodology in the form of flow chart.

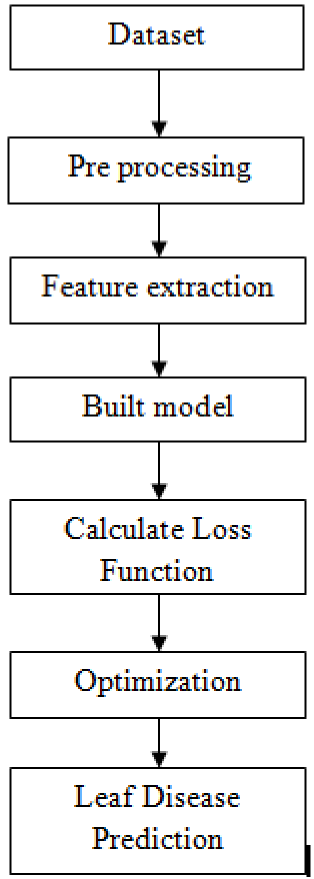

Fig -5: flow chart

The input of paddy image's dimension range is 224 × 224 × 3. In the direction of depths, it is divided into several pieces of images. The quantity of neurons in a piece may be thought of as the convolutional network, which is a square filtering with dimensions like 16×16, 9×9 and 5×5.These neurons each relate to a certain local region in the image, and the characteristic of the region is extracted using these neurons. Assuming that the input paddy image is X pixels in shape, the convolution kernel is C_f pixels in size, the mobile stride of the convolution kernel is C_s pixels, which is typically $C_s = 2$, and padding P pixels, which is typically P = 0, is being used to complete in the boundary of the input data, the image size after convolution is represented by equation 1. The resulting tensor is then obtained.

$$R = \left(\frac{X - C_f + 2P}{C_s + 1} \right) \tag{1}$$

Paddy Disease Image Processing

The size of the images for the paddy illness is reduced from 5760×3840 to 512×512 in order to shorten the duration of the Matlab program. CNN is not a fully linked networks; it is just partially linked. The number of variables that must be trained will increase significantly and the training process will lengthen in a fully connected network, if all nodes in the input layer link to all the nodes in the hidden layer. In a partial network connection, the hidden layer networks connect a portion of the input layer nodes. By simulating the visual system in the human cerebral cortex, this technique only affects the local area at various positions. Because natural images are steady, or that a section of an image's statistics traits are comparable to those of other areas of the image, the qualities of the sections the study learn also apply to other sections. Additionally, since all of the images of paddy illnesses are in color, the stationary condition does not hold across color information. As a result, this study rescales the information to the range [0, 1] use PCA and whitening to get the trained attribute and evaluating attribute. Figure 6 depicts the pre-processing method of paddy images.

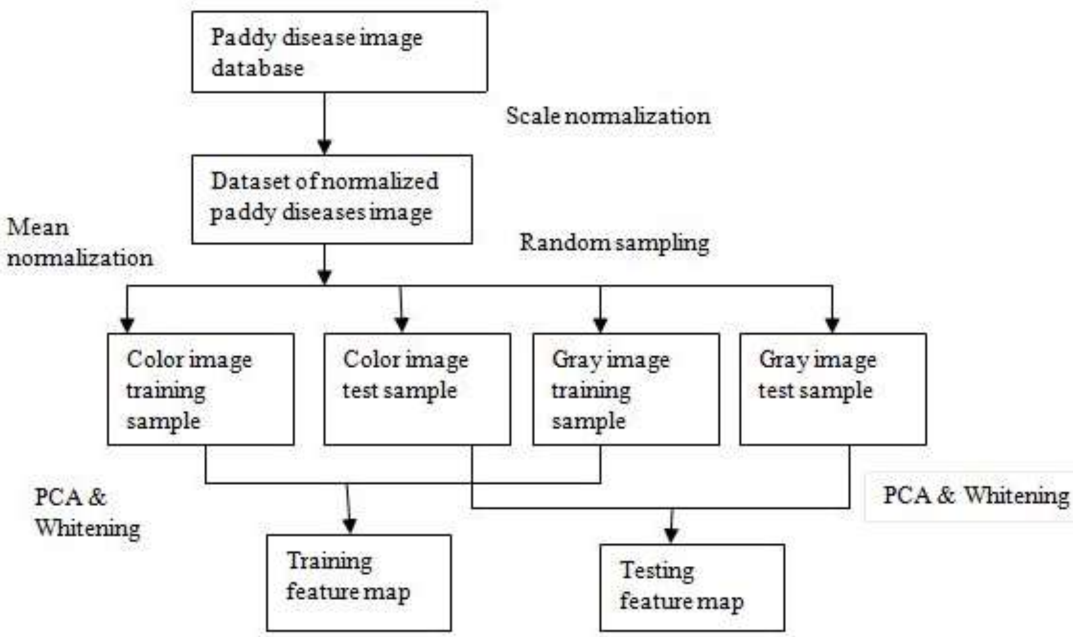

Fig -6: Paddy image processing technique

Proposed Convolution Neural Network

Three convolutional layers are present in the suggested CNNs that have a hierarchical design. Corners, lines, and other low-level characteristics from the input images are extracted using the first convolutional layer. The other two are eligible for additional features. The design of CNN network is represented in figure 7.

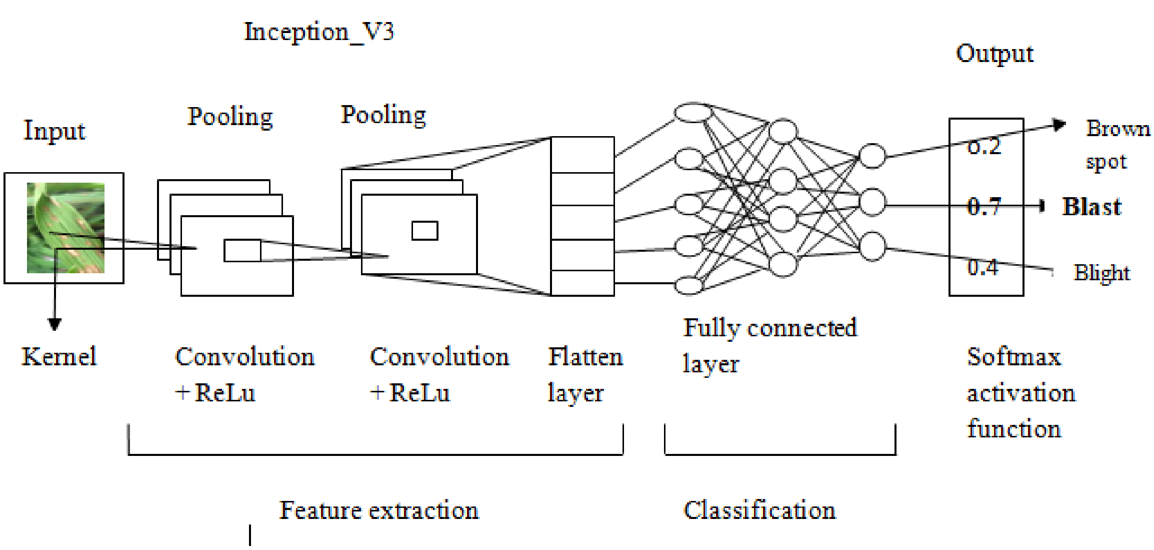

Fig -7: Design of convolutional neural network model

Every outputs map characteristic applies convolutions to merge several input maps. Typically, the following equation 2 can be used to indicate the outcome.

$$Y_i^k = h\left(\sum_{j\in N_i} Y_i^{k-1} \times l_{ji}^{\ k} + a_i^{\ k}\right) \tag{2}$$

Where, k stands for the k^{th} layers, k_{ij} for the convolution kernels, a_i for bias, and N_i for a collection of input maps.

Pooling layers

In CNNs, the study replaces the sub-sampling layer with a stochastic-pooling layer. Stochastic-pooling layer may calculate the maximum value of a specific attribute over an area of the image and it is used to minimize variability. Even if the image characteristics have minor translating the outcome will still be the same. In addition to combining the benefits of meaning and max pooling, stochastic pooling also guards against over-fitting. It is crucial for the categorization and identification of paddy illnesses. The probability p for each area j in stochastic pooling must first be determined using equation 3.

$$P_j = \left(\frac{\beta_j}{\sum_{l\in A_i} \beta_l}\right) \tag{3}$$

Where, i is the index of each element inside it, and A_i is the region's pooling area in the feature map F_c.

Softmax regression

When dealing with a multi-class classification issue, softmax regression is used. The form is taken by the hypotheses functional is calculated by using equation 4.

$$H_\theta(k) = \left(\frac{1}{1+e^{(-\theta^t k)}}\right) \tag{4}$$

An approach for supervised learning is employed to teach the network how to train. The similarity between training instances is reflected in the internal state. For the purpose of identifying paddy diseases, the study creates ten classes. The maximal activity neuron reflects the detected paddy sickness in order to understand the feature representation that the deep convolutional neural network has acquired. Finally, by averaged image patches associated with neurons in a higher layer that have stochastic responses, the study shows the image characteristics.

Learning algorithm

Additionally, the work trains CNNs using a back gradient-descent technique. Two steps of feed forward passing and back propagation pass are included. This study takes into account a multiclass issue with c classes and N trained sample during the feed forward passes phase. The formula for the squared-error value is given by equation 5.

$$S_e^{\ n} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(T_j^{\ i} - Y_j^{\ i}\right)^2}{2} \tag{5}$$

Where Y_j^i is the values of the j^{th} output layer unit in responding to the i^{th} input pattern, and T_j^i is the j^{th} dimensions of the n^{th} pattern's associated label.

4. RESULTS AND DISCUSSION

On 500 data set specimens of healthy and diseased paddy leaves taken from the preserved specimens of the paddy leaf disease repositories, then perform the pre-processing technique and Figure 8,9 & 10 represents the image pre-processing of paddy leaf disease such as bacterial leaf blight, paddy blast and paddy brown spot. The learning and validation of the proposed technique were done .65 percent of certain data set images were used to create training samples, while the other 35 percent were used for testing. When accuracy is computed for every illness category and for images of healthy leaves, paddy bacterial leaf blight illness, paddy blast illness, paddy brown spot illness, and normal leaves all score 0.74 percent, 0.78 percent, 0.76 percent and 0.77 percent, respectively. The dataset's training and validation samples are compared using the CNN prediction model to determine how similar they are. It identifies the dataset to which illness type it belongs by comparing every one of the acquired feature values of the training images with the tested images. Lastly, employing the CNN technique, the total accuracy for identifying paddy leaf disease is 0.76 percent. Figure 11 & 12 depicts the training, validation sets of proposed system accuracy and losses.

Fig -8: Paddy bacterial leaf blight disease image processing

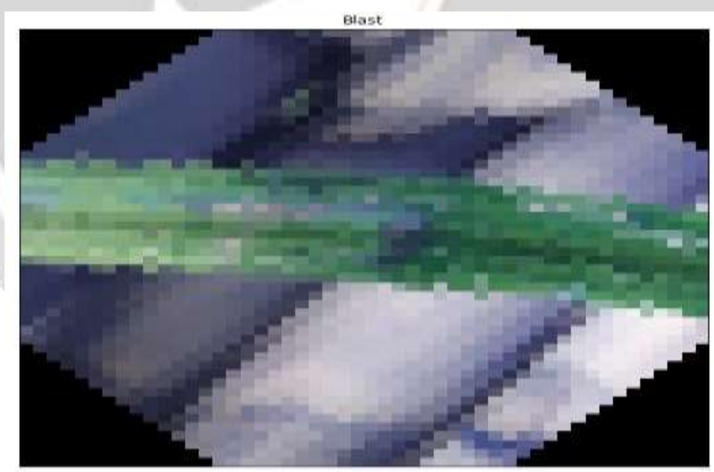

Fig -9: Paddy blast disease image processing

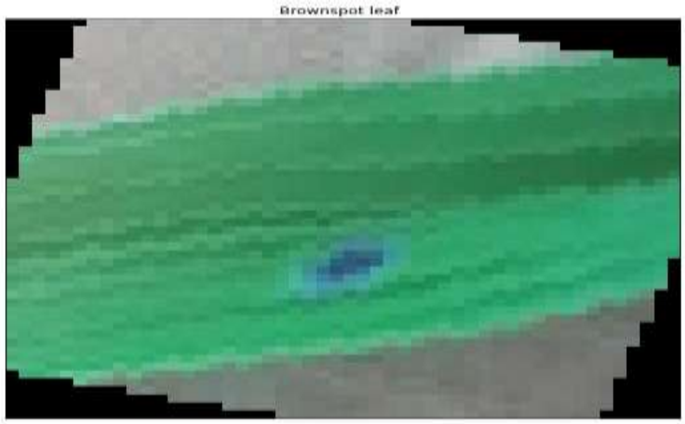

Fig -10: Paddy brown spot disease image processing

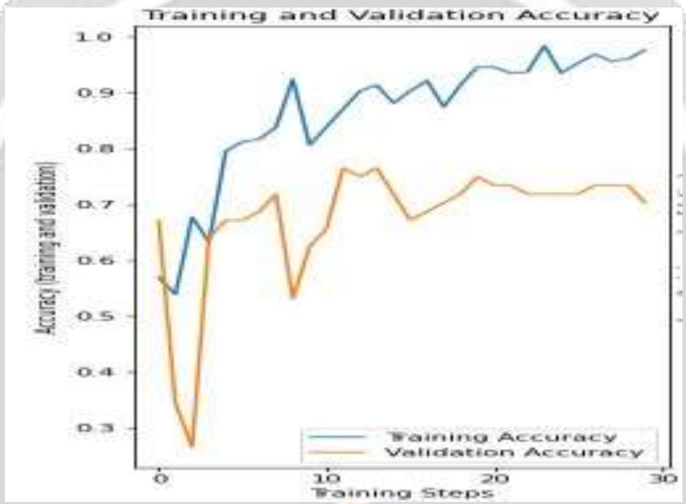

Fig -11: Training and validation accuracy of proposed system

Fig -12: Training and validation loss of proposed system

The following table 1 displays the comparison results of proposed CNN with the support vector machine (SVM) approach, K-means clustering (KNN), Decision tree approach (DTA), and particle swarm optimization (PSO) and its performance evaluation is represented in chart 1.

Table -1: Various methods compared with suggested approach

Methods	**False rate**	**Average accuracy**
SVM	0.95	0.72
KNN	0.89	0.68
DTA	0.77	0.65
PSO	0.82	0.69
Proposed CNN	0.53	0.76

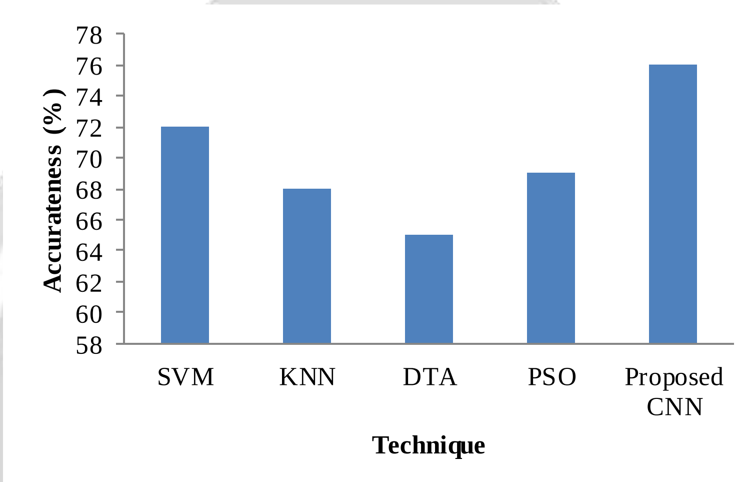

Chart -1: Performance evaluation of suggested CNN technique with other approaches

5. CONCLUSION

An original method for improving CNNs' capacity for deep learning was presented. Three common paddy illnesses may be successfully classified using the suggested CNNs-based approach using image pre-processing and transfer learning. The method to the detection of paddy illnesses demonstrates that the suggested CNNs model can accurately and successfully predict the paddy illness like bacterial leaf blight, brown spot and paddy blast. The suggested technique performs better during learning, converges more quickly and has superior identification capabilities than the other approach. Future research might expand on the study's findings to address distributed state estimation issues for nonlinear time-varying systems and sensing devices. Need to increase more paddy diseases dataset and need to use various new hybrid algorithms to increase the accuracy rate.

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