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An Efficient Deep Neural Network for Disease Detection in Rice Plant Using XGBOOST Ensemble Learning Framework

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Abstract:

Rice disease has a substantial impact on agriculture production, and accurate rice disease diagnosis is more significant for farmers' economic development. Deep learning algorithms have made a massive impression in the context of agricultural disease identification in past few years. However, there are a number of detection techniques available, some of which may not be quite as effective as they might be. Timely detection and identification of specific disease help significantly in disease control and management. In this regard, deep learning-based convolution neural network model is developed to equip the diagnosis process for early detection. The proposed prototype is introduced by integrating XGBOOST ensemble learning model with Keras Inception ResNet V2 Framework for solving various tasks like classification of input images, object segmentation and image feature extraction. Initially, rice plant images undergo pre-processing stage for rotating, flipping, cropping and scaling to enhance image quality for the process of training and classification. The Adam optimizer is used to further optimize the proposed framework by making the learning and training process more efficient. The proposed model is applied to the augmented dataset and establishes a benchmark performance in terms of accuracy, precision, and recall. The findings of this investigation will help to increase the practice of deep learning technology in agriculture for earlier plant disease diagnosis and prevention.

Keywords: *Rice Leaf; XGBOSST Ensemble learning; Disease detection; Feature Extraction;*

1. Introduction

Agriculture has now a significant impact on the economic development and society whereas it is the cornerstone for most nations' long-term development. The diagnosis of plant diseases is greatly aided by a continuous plant monitoring strategy. With agriculture accounting for 66.5 percent in rural India, plant conservation seems to have become a major priority. In general, the agricultural industry contributes roughly 19.9% of the total gross domestic output [1]. In India, rice is one of the most widely consumed grains. Diseases impair the social progress and better standards of rice plants, lowering the revenue of the cultivation. Various illnesses can affect specific rice crops, making it difficult for farmers with inadequate expertise to detect them. Some automatic data processing expert schemes are essential for this accurate and preliminary detection of plant disease analysis which makes good and healthy development in the field of agriculture. Rice agriculture faces a number of problems, including pest-induced yield reductions, poor resource management, inconsistent nutrient consumption, and environmental degradation [2].

Plant pathology is a good investigational study for identifying illnesses in rice leaves. The visual patterns of the plants are the target of this study [3]. Monitoring the health and disease of plants is critical to successful crop production. Plant disease inspection and analysis were once carried out manually by a competent individual. This operation has a heavier workload and takes a very long time to complete [4].Image processing technologies were among the most extensively utilized approaches for detecting plant disease. The disease's signs seem to be most apparent on the stems, fruits, and leaves. One of the most significant aspects of disease detection is the plant leaf, that aids in the identification of clinical manifestations [5].

Numerous tasks can be performed as key to sustainable agriculture by utilizing technology to automate disease screening. Pathogen production, host genetic modification, and disease globalization have all resulted in the creation of numerous remedies. Precision farming's core issue is that it brings several issues related to data gathering, analysis, and expert interpretation [6]. Earlier, the sole method for diagnosing rice illness was naked-

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eye inspection. This technique necessitates ongoing agricultural field observation by a disease expert for accurate disease estimation. The visual process model is expensive, time-consuming, and inconvenient for vast regions of plants because it involves regular human monitoring [7]. The exponentially rising population rapidly alters the need for food crop availability. Such a condition requires society to consider adopting technological advancements to estimate disease early and accurately so that remedial measures can be implemented at the appropriate time. Image processing techniques have shown to be among the most accurate and cost-effective methods for determining the factors associated with different plant diseases [8]. To interpret the data in the cultivated field, precision farming can be incorporated using image processing and computer vision technology. Disease identification, weed recognition, analyzing the signs of disease, and subsequent grading of the yield output have all been solved using image processing [9].

In the standard approach, the disease is detected visually by a skilled individual with the capacity to detect slight differences in plant color. To determine the infection proportion, scouts and plant canopy are monitored. Precision farming was created with the goal of reducing the usage of costly chemical-based farming practices [10]. Mobile robots, wireless sensor systems, and UAVs are utilized in this style of farming to deliver regulated and measurable quantities of treatment to sick plant areas. Hence, it is critical to accurately and quickly identify plant diseases. It is common knowledge that many ML models have indeed been engaged and selected for the diagnosis and categorization of sick plants, nevertheless advances in technology have enabled the research domain more accurate and precise [11].Rice crops take 3–6 months to cultivate and go through three periods of development: vegetal, reproduction, and maturing. Aside from such three phases, germination is another one from the lateral root to the plumule form of the seed. Plantlets or seedlings develop from the seed after the embryos have germinated [12]. Table 1 depicts the disorders that developed at various stages of development and its remedial measures to control the disease and Fig 1 shows the variation on the healthy leaf and type of diseases considered in this research.

Disease	Signs and symptoms	Remedial Measures
Bacterial blight	Infected seedlings become grey-green and folded. The leaves turn yellow to straw-coloured and wilt as the disease spreads, causing the seedlings to run dry and perish.	Use a healthy balance of nutrient elements, particularly nitrogen. Keep the fields tidy. Plow beneath weed hosts can act as bacterium hosts.
Bacterial Leaf Streak	Tiny, water-soaked diagonal lesions form between leaf veins is the first indication. These streaks start off a dark green and gradually lighten to a yellow-grey colour. A copper-based disinfectant sprayed at the heading can indeed be beneficial in controlling the disease in cases of serious infection wherein yield may be compromised.	Eliminate plant hosts and plow under rice straw, ratoons, and spontaneous seedlings to maintain fields clean.
False Smut	Isolated rice grains have been turned into spore balls on plants infected with fake smut. When these spore balls mature, orange to a green to black colour. After harvesting, remove any diseased seeds, panicles, or plant residues.	Utilize authorized seeds and appropriate nitrate levels. Over 10 minutes, heat the seeds to 52°C.
Red Stripe	The lesions start off small and yellow-green to bright orange in appearance. Older lesions have an upward streak and appear orange. It becomes necrotic and aggregated on the leaves, causing a blight. Apply nitrogen according to the crop's needs.	Ensure that the sowing rate is optimal and that the planting is broader. Seeds should be treated with benzimidazole fungicides.
Sheath Blight	The centre of the patches turns greyish white when they get bigger, while the edge is an erratic blackish brown or	Minimize sheath blight outbreaks by improving canopy architecture by sowing drainage rice paddies at a lower

	purple brown colour. The higher portions of plants develop lesions that spread quickly, coalescing with one another to cover entire plantlets from the water's surface to the leaf blade.	rate earlier in the farming period.
Sheath Rot	While sheath rot could be seen as a separate illness on the rice sheathing in the field, this is more usually seen as half of the complexity of grain and leaf sheath discoloration in rainy season rice.	Reduce the number of insects in the rice field. Use the most appropriate plant spacing. As foliar application, use fungicides like benomyl and copper hydroxide.

Table 1. Disorders and remedial measures of Rice Leaf Diseases

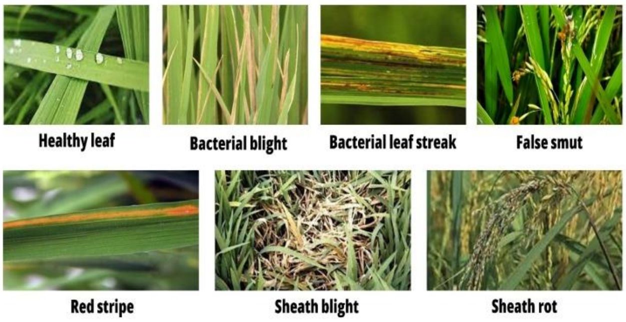

Figure1. Diseases of Rice Plants

Deep learning's robust method has been applied to agriculture to solve many challenges such as weed and seed identification, plant pathogens categorization, fruit enumeration, root slicing, and so forth. Deep learning is a computational intelligence breakthrough that effectively trains large volumes of information and dynamically acquires the attributes of the input and generates the output based on decision criteria [13]. The visual imagery is processed well by CNN. This artificial neural system includes three layers: an input layer, hidden units, and an output vector. The convolutional layer, pooling layer, normalizing layer, and fully connected layer make up the hidden layer, which has a set of automatically trainable parameters that allow it to understand the geometric distribution of the input data and accomplish a multiclass classification [14,40]. Transfer learning could be used to apply a previously trained convolutional network to a different issue. Transfer learning can be used to create a classifier model that can be utilized as a specific feature representation by discarding the final fully connected layers or fine-tuning the final few levels which will function more precisely for the relevant dataset [15,41].

Research Objective

In summation, deep learning is a suitable technique for disease identification in a variety of crops with high precision. This study aims to identify diseases in rice leaves using deep learning architectures. The proposed model is exhibited in this scenario by combining the XGBOOST ensemble learning model with the Keras Inception ResNet V2 Framework to solve numerous tasks, including object segmentation, visual feature extraction, and image categorization. Furthermore, the Adam optimizer is utilized to stabilize the proposed framework by speeding up the learning and training process.

Research Report Flow

- *Literature Review:*The literature review for past research in this subject is detailed in depth in Section 2.
- *Proposed Model Design:*Section 3 provides the motivation of the proposed methodology and working functionality of XGBOOST ensemble learning model with Keras Inception ResNet V2 Framework. It also provides a concise overview of how research work is carried out.
- *Result and Evaluation:*Section 4 discusses the performance measures that are assessed during the work's implementation.
- *Conclusion:*In Section 5, an executive summary of the research effort is provided, along with future scope.

2. Literature Review:

The research has been made and investigated to categorize the leaf disease is discussed in this section. It also gives background information and analysis of previous studies on the various technologies and methods prevalent in this research area. The previous studies of disease detection are explained in this part, which includes pre-processing, segmentation, and feature extraction.

Agriculture is indeed necessary for the increasing population and a vital source of energy. Plant diseases, on the other side has an influence on the amount and quality of crops grown for agricultural purposes. As a result, diagnosing plant diseases in their early stage is critical for avoiding and controlling them. The conventional technique developed for plant disease detection is physical observation by experts but it involves a lot of time and effort [16]. An intelligent plant disease detection model was created to address these concerns. Deep learning (DL) has been successfully employed in numerous tasks in conventional image processing techniques, including object recognition, disease diagnosis, and pattern classification. With DL, artificial intelligence is modeled as a neural network with multiple hidden layers and a lot of data from the training phase. It is based on information transfer learning and identified as artificial intelligence [17,42].

For evaluating and predicting water supplies, ANNs are becoming extremely prevalent. The advantage of ANNs over traditional techniques is that they require less knowledge about the complicated structure of the underlying mechanism in order to reveal complicated visual features from raw data and automatically generate features [18,19]. DL techniques' excellent learning ability further allows them to execute a wide range of issues very well, as well as to adapt easily to a wide range of highly complicated problems. The eight machine learning approaches used to diagnose plant diseases are shown in this literature along with their limitations [43].

Nanehkaran et al., [20] describes that the Plant Species disease detection categorization which is a computer vision challenge that involves interpreting the information and layout of a digital image. Computer vision research concentrates on developing approaches that allow computers to perceive. Thomos et al. [21] explored the benefits of using hyper-spectral photography for agricultural crops. This review discusses the many types of hyper-spectral detectors and hyper-spectral metrics. The high computation cost of using multi-spectral and hyper-spectral imaging technology is the main drawback.

Ashourloo al., [22] reveal that even though it is possible to examine canopies with a low degree of land cover. One of the major drawbacks of using digital cameras is that the only three spectral bands are evaluated which correspond to the three primary colours, but spectrometers have several spectral bands, enabling a more complete multivariate model, that has been shown to improve findings. Raza et al., [23] examined how machine vision technology is being used in the agricultural industry for things like natural resource evaluation, precision agriculture, post-harvest food safety and quality monitoring, categorization, grouping and intelligent systems. They emphasized agricultural inspection using multi-spectral and hyper spectral images.

Iftikhar et al., [24] announced about MLR, ANN and ANFIS models for grassland biomass prediction were constructed to predict grassland yield. It works well as an input to a system for grassland control and reporting using hyper temporal time series of satellite data.Su et al., [25] suggested that Unmanned air vehicles (UAV) are commonly used to take hyper spectral and multi-spectral photos, which is the time taken to process and even costly.

Kumar et al., [26]discussed that the fruit pictures' histogram equalization is combined with wavelet de-noising. This technique has the benefit of accounting for data leakage in addition to equating the histogram. Pre-processing is important when it comes to imagery scenes taken at night. Jia et al., [27] says that because of the effects of lighting, heat, moisture and other factors, the workplace environment at night-time is highly complicated, limiting the harvesting robot's efficiency and productivity. The best artificial light source for night time apple-gathering drone operations is the incandescent light bulb, and the type of noise visible in apples night vision images is Gaussian noise mixed with some salted and speckle noise. Deisy et al. [28] described various segmentation methods utilized in a leaf investigative method. Using several segmentation approaches, the researchers conducted experiments on infested leaf samples. Vani et al., [29] proffered that the time-sensitive images are initially pre-processed with a median filter, and afterward classified using the k means clustering approach to achieve the necessary image component. Gray Scale Co-occurrence Matrix (GSCM) is used to capture textural features, which are then compared to a healthy cotton leaf image.

Pujari et al, [30] presented a Discrete wavelet transform (DWT) which is used to automatically extract, which are then minimized using Principal component analysis (PCA). After the reduction of features, the attributes are then utilized as sources for classifiers, and PNN classifiers are used to categorize image samples. Sapkal et al., [31] developed a precise and sensible diagnosis of diseases and insects in rice seedlings can assist farmers in administering immediate care to the plants, reducing economic damage significantly. Wide scale designs like VGG16 and InceptionV3 have also been implemented and improved for the identification and recognition of rice diseases and parasites.

Krishnaswamy et al., [32] propounded the GoogleNet design relies heavily on inception modules. The inception module captures a variety of capabilities simultaneously by using parallel convolutions and a max-pooling layer concurrently. Hassan et al., [33] developed the VGG-16 design for CNN to identify plant illnesses and increase agricultural productivity to take immediate action to remedy them. Considering that we used a huge dataset and numerous harvests in our model which outperformed previous investigations in terms of accuracy.

Ashwin et al., [34] reviewed that binary Logistic Regression, Multilayer Perceptron with Gradient Tree Boosting (GBT), Random Forest, Adam optimisation and SVM Classifier are six various machine learning methods with ten-fold cross-validation. Confusion matrix, F1-score, precision and other metrics are used to evaluate these machine learning algorithms. GBT was the most successful among the six methods.

Xian et al., [35] used Extreme Learning Machine (ELM) for achieving a good accuracy. When compared to the Decision Tree model to identify the presence or absence of tomato illnesses, ELM obtains greater overall levels of accuracy throughout all 10 classes and achieves 84 % from 78% accordingly. Meanwhile, SVM is slightly more accurate (91.43%) than ELM model.

Bedi et al., [36] proposed the hybrid system that includes a convolutional auto-encoder "CAE" and a CNN. The CAE model will be learned, and compressed domain depictions of leaf pictures will be obtained, from which a Convolution layer would be trained. The suggested system was evaluated using the Adam optimizer and binary cross-entropy with variables, such as NRMSE loss and reliability measures.

Anwar et al., [37] presented a new way of detecting rice illnesses based on deep CNN methodologies. They made use of a dataset of 500 real photos of injured and healthy rice leaves and roots that were collected from a field trial with ten different rice diseases. The presented CNNs-based model outperforms a 95.48 percent accuracy using a 10-fold cross-validation technique.

Lamba et al., [38] offered a framework for plant disease that uses DL as a classifier with unique activation functions and the Auto-Color Correlogram as an image filter. Fifteen algorithms were examined from the viewpoint of learning algorithms, including Bayes network, random forest, and iterative optimum classifier. Different activation functions, such as SoftMax, Softsign, ReLu and others were utilized in the deep learning process. DL integrate with Softsign is the finest of the series, while Softmax is excellent for multi-class classification. Kishore et al., [39] used convolutional network approach that uses filtering of images using median filtering in the Preprocessing. AdaBoostSVM Classifier is used for multiclass diseases diagnosis while the DWT approach is used for extracting features. The outcome is achieved with high accuracy, but still the classification process's learning rate is deficient while avoiding overfitting.

In summary, relevant literature has been emphasized. While deep learning methods have a significant impact on the diagnosis of agricultural diseases, still some improvements in the diagnosis process and computation time are needed. Thus, we propose XGBOOST ensemble learning model framework to optimize the classification task and achieve high accuracy.

3. Proposed Model Design:

This research provides a new CNN architecture that focuses on the problem of detecting infestations in rice plant leaves. The focus of this research is to develop a disease detection learning approach that is both computationally cheap and reliable. The proposed architecture incorporates residual learning on top of feed-forward convolution layers and is trained with Keras Inception ResNetV2 training model with the augmented dataset. The proposed model frame work and the operational workflow for diagnosis process is illustrated in Figure 2.

The structure of constructed neural network is simple and comprised of aggregated 12 layers and hyper parameters in which four convolution layers, four down sampling layers, one dropout layer, and two fully connected layers following the final output. The input images are set to 224x224x3 pixels in size. The extracted features are made up of a sequence of convolution, activation and pooling layers. Therefore, improving the image quality begins with this pre-processing step. Convolutional layers are crucial to Deep CNN models because they extract feature information from input images. An important building block of Deep CNN is the convolutional layer. An input data set is processed using 12 layers of deep convolutional neural networks where four layers are convolution processors.

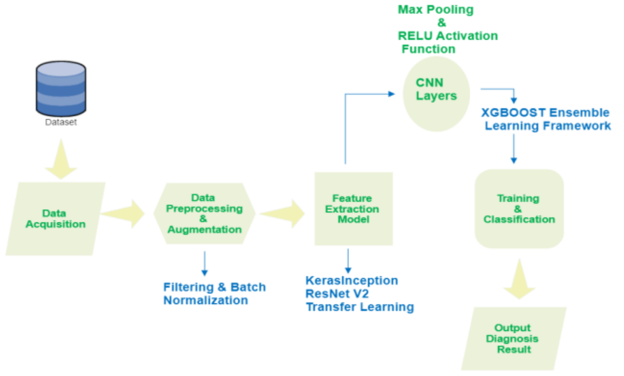

Figure2. Process Workflow of Proposed Framework

Individual convolutions are performed as with a single filter, and then the convolutions are stacked to generate an output vector with a 3D representation of the set of parameters. It's being used to extract attributes from an input image using filters with a set of automatically trainable parameters known as weights. The model's performance is enhanced by using the ReLU activation function, which is an unbalanced activation function that outperforms saturated activation models. Max pooling layers operate on inputs feature map using a 3x3 pooling window with a stride ratio of 2 and a down sampling process. As a result of this pooling process, the most significant element from the feature map range is specified by the filter selected.

3.1 Data Acquisition:

An online dataset of rice leaf diseases has been acquired using Kaggle.com. Images were captured against a white background in bright sunlight. Farmers also exchanged information on illnesses that harm rice leaves. The photographs subsequently sorted into six groups based on the illnesses. Bacterial blight, Bacterial leaf streak, False smut, Red stripe, Sheath blight and Sheath rot are some of categories. For every category, the data set have been further separated into training and testing sets. The dataset was retrieved with the goal of studying rice leaf diseases which can be used to recognize and categorize disorders.

The image acquisition process has been completed using this data selection method. The data is saved in the repository after the images have been acquired. We will be able to use this information in the next stage of the process.

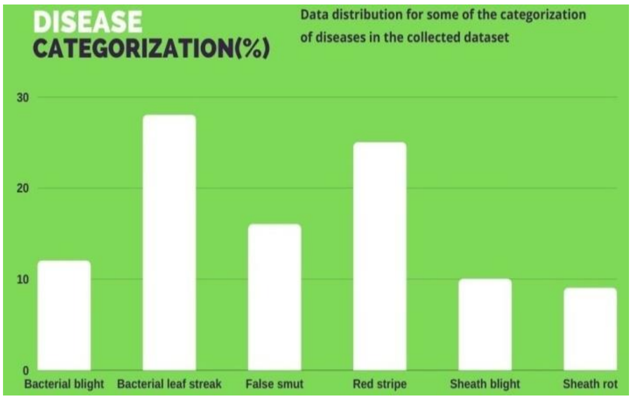

Figure 3. Data categorization for disease types

3.2 Data Pre-processing:

Weiner filtering can be considered of as a local image generator that identifies the interconnections among pixels in an input image in order to obtain the most effective and relevant high-level data to improve a CNN model's classification performance. Additionally, down sampling and weight sharing can significantly reduce the amount of training samples and also increasing training efficiency. The model's inputs are comprised of the original colour images from the training dataset. An image data generator function was used to dynamically resize the source images dimension. The wiener filters attempt to replicate the pixel in order to decrease the measure of noises in the image and may evaluate this to the intended noise image by assessing it. The basic purpose of the wiener filter is to remove noise from a signal that has been broken. It provides high-frequency border preservation and other image segmentation, although it takes longer to compute than others.

$$W(I1, I2) = \frac{H(F1,F2)Pxx(S1,S2)}{H(F1,F2)Pxx(S1,S2)+Pyy(S1,S2)} \quad (1)$$

where,

Pxx(S1,S2) and Pyy(S1, S2) are the source image's power spectral and additive noise respectively, while H(F1,F2) is the blurring filter. This not only conducts deconvolution using inverse filtration, but also reduces noise using a compression operation, such as low pass filtration.

Figure3. Transformation in Weiner Filter

The sample batches are represented by a high-dimensional input, while the task objective is frequently represented by a low-level input. Batch normalization performs the pre-processing action in the network model levels in the centre. Furthermore, the preceding layer's input is normalized before entering the network's succeeding level, that can effectively eliminate gradient dispersion and speed up the network's training phase. Sample of batch-size were acquired for training throughout every training. A neuron is considered as a feature in the batch normalization layer. The batch-size samples will also have batch-size data within every neuron dimension, followed by batch-size numbers in each feature dimension. Formulas are used to compare the average and variance of such samples, and then parameterization and linear mapping are utilized to control the output vector of each neuron.

3.3 Feature extraction:

Convolutional layer:

It is among the most significant layers in CNN's framework. Convolution is a linear, translation-invariant procedure that involves applying a local weighted sequence to the input data. Various aspects of the inputs will be shown based on number of specified weights. In the frequency response, the modulating factor is however associated to the point spread function, which determines how phase-shifting and scaling modify the input frequency component. As a result, selecting the appropriate kernel is crucial for extracting the much more important and meaningful information from the input signal source enabling the model to make superior predictions about the information signal's contents.

Activation layer:

The activation layer manages of trying to turn on the particular diagnosis that the convolutional layer has retrieved. Because the convolution process performs a linear conversion on the input image and the convolution kernel, an activation layer must be implemented to create non-linear mapping. Relu, also known as linear rectifier, is the most widely utilized activation function used here.

Pooling layer:

The resultant feature map is nevertheless relatively large if the pooling fields viewpoint or filter is comparably tiny and the stride is also very modest as the input data travels over the convolution layers. The pooling layer could also execute a high-dimensionality reduction in size procedure for each feature space. In addition, the pooling layer features a pooling field view that scans the matrices of the feature map and calculates the column values. As a result, there are two techniques of calculation as follows:

Average pooling:

It uses the pooling view matrix's average value. As part of the operative procedure, the scanning step stride is also incorporated. The scan and convolutional layering processes are identical. Once you're done scanning, move the fabric length down, then back to the left. As a final step, three 2424 feature maps could be downscaled into three 2424 feature vectors.

Max pooling:

In the pooling view matrix, the maximum value is taken. In general, the pooling layer's merits include immutability, which focuses on whether or not particular characteristics exist instead of their precise location. It's like putting a strong before to the learned features, allowing them to withstand some alterations. The number of computations and parameters is minimized by lowering the preceding layer's input size. Producing an output with a set length. For instance, in text categorization, the inputs size may be variable and the output can be consistent length which can effectively deter over-fitting or under-fitting.

Fully connected layer and output layer:

The fully connected layer is a continuous pattern mappings procedure that maps multi-dimensional characteristic inputs to two-dimensional feature outputs. The sample batch is represented by a high-dimensional input, while the work goal is frequently represented by a low-level input. The fully connected layer is solely accountable for enhancing the features in order to prevent characteristic data redundancy, whereas the output layer is mostly responsible for generating the ultimate target outcome.

3.4 XGBoost Ensemble Learning Framework:

Extreme gradient boosting or XGBoost is a technique that has been extended from decision tree algorithm. This outperforms conventional supervised learning algorithms such as original gradients boosting tree approach by a significant margin.

The objective function is specified by (2).

$$Obj(\theta) = L(\theta) + \Omega(\theta) \qquad (2)$$

In the above equation, $L(\theta)$ and $\Omega(\theta)$ signifies training loss and regularization. Weak learners are grouped together by the classifier. The procedure starts by creating a feature-based tree. It builds a new tree using the objective function that increases on the prior tree's faults or latent variables. The error or residual is estimated and reduced via gradient descent during the construction of a new tree. Tree pruning is performed in a greedy manner based on every split's accuracy gains. The decision tree construction process is boosted by depth-first tree pruning and gradient loss reduction, resulting in faster implementation and higher accuracy.

Classification Algorithm with XGBoost Classifier

Input: Data samples taken from the dataset.
Output: Classified images
Start
N denotes no. of Images and P← i x j Pixels in it
While (N > 0)
Start
G(P)= $\frac{1}{\sqrt{2\pi\sigma}} C^{X^2}_{2\sigma^2}$
σ= difference (Pi,j-1 $- Pi-1,J$)
End
Define centroid mid $\{X1, X2, \ldots \ldots \ldots \ldots, Xn\}$
While (mid > 0)
Start
GW ← Centroid
G∝ ← G(P)
$G\beta$ ← N
$G\delta$← P
Get the updated weights

$$W^{n+1} = \frac{W_0 G_\propto + \sum GW}{G_\propto + G_\beta + G_\delta}$$

End
End

We utilised a Max pooling layer just after convolution layer to substitute the fully connected layer and batch normalization. Following the extraction, the features are passed into the XGBoost ensemble learning machine learning classification. The prediction accuracy and reduced computation time are the reasons for supporting this classification. It makes a judgement by combining the output of all trees and reducing the overfitting. Furthermore, XGBoost incorporates combined LASSO (L1) and Ridge (L2) regularisation approaches to avoid overfitting the models.

XGBoost is an ensemble learning method based on decision trees that is mostly used to solve classification and regression problems. It makes use of such a framework for gradient boosting. It excels all other classification algorithms in the prediction of unstructured information and large dataset.Based on the Inception series, keras Inception ResNet v2 incorporates residual connectivity from the convolutional neural system. This method returns a Keras image classifier model, which can be preloaded with pre-trained matching weights if needed.

Procedure:

Create a base model with pre-trained weights initially and is to be freeze. On top of that, create a new model. New data should be used to train a model. After the system has accumulated on the updated information, one can seek to unfreeze all or a portion of the underlying system and train up the entire design from beginning to end with extremely low learning rates. This is an elective final step that may provide you with additional gains. It also has the potentially lead to rapid overfitting.

The central aspect of CNN is the convolutional layer, which collects features from the input pictures using various resulting solution. The convolutional operation's output of each sample can be calculated as:

$X_j = \mathrm{I} * W_j + b_j$ where j=1, 2, ….,F. (3)

The output feature of each sample X_j corresponds to the j^{th} convolution filter, the weight W_j resembles to the bias b_j and the number of filters F, corresponds to how many filters there are.

The Pooling layer diminishes the size of the input vectors and prevents overfitting in the outputs. It also decreases the model's computational effort and the output is evaluated as follows:

X_i^k = down ($X_i^{k-1,}$ s) (4)

where down () represents a down sample, X_i^{k-1} seems to be the feature vector of the preceding layer, and s is indeed the pool size. Maximum pooling and averaging pooling are still the most prominent pooling procedures.

Following the convolutional and pooling layers, there are various fully connected layers that turn the preceding layer's output into a single row vector. For multi-class prediction, the ReLu activation method is frequently deployed. To reduce neuron size and avoid over-fitting, LASSO (L1) regularisation method is implemented.

In contrast to the convolution layers, each layer also incorporates a batch-normalization mechanism and a ReLU activation function. In the Keras Inception ResNet V2 learning, there has been one residual connection between the input and output layers. The residual network aims to learn previously learned features, but those that aren't relevant to decision-making are eliminated. The complexity of computations and variables can be reduced using this approach.

Predictions of the output can be expressed as follows:

$\mathrm{Y_i} = \varphi\ (\mathrm{X_i}) \sum_{k=1} K\ \sum_{K=1}^{K} f_k(X_i),\ f_k \epsilon\ \mathrm{F}$ (5)

In this case, X_i represents the training set and Y_i. represents the corresponding class labels. F is a set of all K scores for all regression trees and f_k is the node score for the kth tree. A regularization algorithm is used in XGBoost to improve the results.

$\mathrm{L}(\varphi) = \sum_i l\ (\text{\"{}}\mathrm{Y_i}, \mathrm{Y_i}) + \sum_k \Omega\ (\mathrm{f_k})$ (6)

where,the predicted output is ‶Y_i and actual output is Y_i.

As for the term Ω, it represents regularization, which measures how complex the tree is by optimizing regularization, we avoid over fitting and encourage generalized simpler models.

$\Omega(\mathrm{f}) = \sqrt{T} + \frac{1}{2}\lambda \sum_{j=1}^{T} W_j^2$ (7)

There are two parameters used in regularization. T is the number of nodes in j^{th} tree, W represents their weight, and λ is a constant that determines the degree of regularization.

Fine-tuning entails unfreezing the entire model built and retraining this with a very modest learning rate upon updated information. By continually modifying the pre - trained models features to the fresh data, this has the capability to gain considerable developments. Generally, all weights are trainable weights. The Batch Normalization level is the unique built-in layer with non-trainable parameters. During training, it keeps a record of the mean and variance of its inputs using non-trainable weights. This workflow has the benefit of constantly running the base model once on your data, instead of once per training epoch. As a result, this is a considerably faster and less expensive. Adam is a computational optimal scheduling method for the Neural Network algorithm that takes minimal storage and is perfectly suited for problems with a lot of data, variables, or even both. Adam is a common stochastic gradient extension.

4. Result and Discussion

In order to determine how Convolutional networks may access to training of the various classes assessed, visualization techniques are frequently utilized to even further interpret the CNN image features due to the restricted explanatory nature of deep learning. The system also supports to further understand the differences between feature maps that were derived from photos of rice leaves with various illnesses, including bacterial leaf streak, false smut, red stripe, sheath blight, and sheath rot. A sample of a diseased leaf is taken from the dataset, which is then used to analyse 53,656 images of rice leaf tissue and attribute labels to the specified leaf illnesses.For a 60-40 distribution, the allocation of the training data set and the testing data is subjected and evaluated respectively. Every one of these 50 experiments lasts for a maximum of 20 epochs, where an epoch denotes the number of training iterations that individual neural network has finished to traverse the whole training dataset. The decision to use 20 epochs was based on observational finding as learning consistently converged within this time frame in these experiments. The KerasInceptionResNetv2 framework was used and carried out in a Python 3 environment. For the datasets, tests were carried out on a Ryzen 2700X CPU and GeForce GTX 1660 Ti GPU.Figure 4 displays the comparison outcome of the various dropouts throughout the training phase of the twelve-layer deep neural network model.

Hyperparameters	**Options**
Batch size	20
Epochs	1000
Dropout	0.2
Optimizer	ADAM

Table2. Training Variables and Parameters

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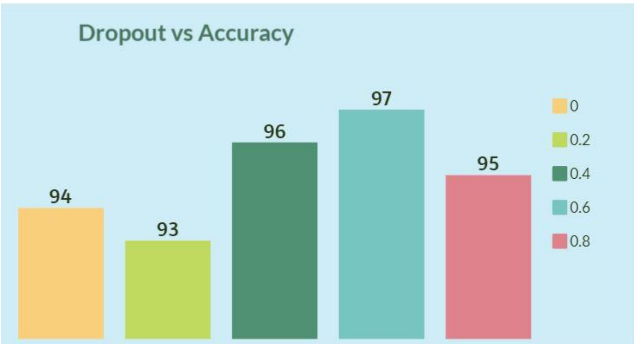

Figure 4. Dropout Classification.

A selection of existing detection algorithms was evaluated to see how well the proposed model performed. The effects of the disease prediction were divided into four categories for each network model: true positive (TP), which specifies that the disease category was accurately predicted; false positive (FP), which signifies that other types of diseases were anticipated instead of original; true negative (TN), which specifies that the other types of diseases also weren't predicted for the exact disease; and false negative (FN), which indicates that another type of disease was anticipated for that disease. Accuracy, precision, recall rate, and F1 score are the performance measures that were determined using the outputs. The other variables were analysed for a single type of disease, while the performance metrics were evaluated for all sorts of disorders.

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

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

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

$$\text{F1} = 2 \text{ X } \frac{Precision\ X\ Recall}{recision+\ Recall}$$

where, A represents accuracy, P stands for precision, R is recall rate and F1 signifies the score. Additional metric for assessing the algorithms is the loss value. Loss assesses the degree of fit of the training set rather than the test set. Even during the training phase, the model's fitting condition can be approximately inferred from changes in loss, though it can also describe the model's performance explicitly. As compared to other models, the loss value was relatively low following training and fine-tuning where the learning rate ranges between 0 and 0.00. We adjust the test set for training set ratio to resolve the problem of over-fitting and find that the approach provides an overall accuracy of 99.3 percent even in the intense circumstance of training only on 20% of the testing data in the trained model on the remaining 80% of the data.

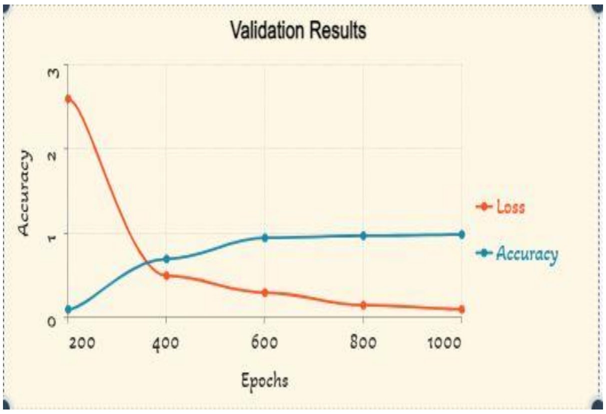

Figure 5. Validation of Results for Loss and Accuracy

In addition to learning well about connection weights of the neural network during training, the XGBOOST ensemble learning model with Keras Inception ResNet V2 architecture is used, which lowers the loss function. The batch size or number of training sets is calculated by the XGBOOST algorithm at randomly. The batch size is set to 1, with a fixed total of 53,656 iterations. Although very modest, the learning rate is considered at 0.001 which leads to more accurate findings. The traversing speed is tuned to 0.9, and it serves as an extra determinant of how efficiently the XGBOOST algorithm accumulates to the optimum value. The research seeks to minimize function loss and lowering errors. Each learning algorithm does this, repeating computations repeatedly until the loss reaches a threshold. When the learning rate is set at 0.001, it is important to consider how to reduce the loss function.

As seen in the figure 6 and table 3, the test accuracies of various pre-networks (Alexnet, ResNet, VGG16, and AdaBoost SVM) are compared using an accuracy graph. The accuracy of the Alexnet networks is lower while convergence rate is faster. Comparing the Keras Inception ResNet V2 model to certain other pre-trained models, it is clear from the image that this really exhibits high accuracy and precision.

Disease Type	Alexnet	ResNet	VGG 16	AdaBoost SVM	Proposed Framework
Bacterial leaf streak	0.987	0.956	0.965	0.995	0.996
False smut	0.965	0.967	0.968	0.995	0.995
Red stripe	0.984	0.967	0.965	0.986	0.990
Sheath blight	0.931	0.988	0.979	0.989	0.993
Sheath rot	0.932	0.965	0.963	0.991	0.993

Table 3. Comparative table of Disease classification accuracy

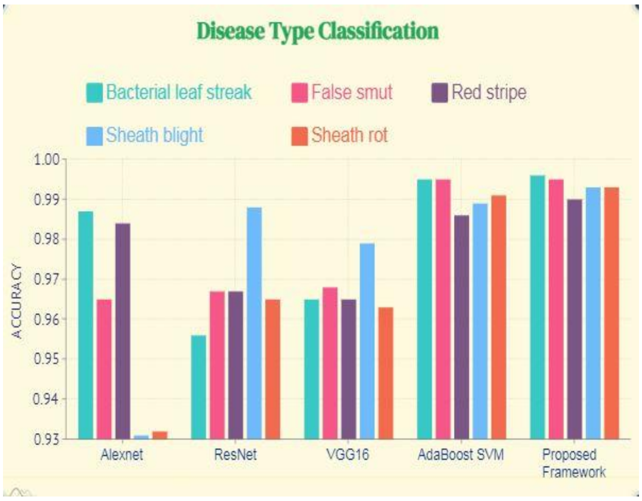

Figure 6. Graphical Analysis of proposed and existing models for 6 disease classifications

Detection Models	Performance metrics			
	Precision	Accuracy	recall	F1Score
SVM	0.52	52.6	0.97	0.65
Decision Tree	0.76	71.2	0.99	0.73
Logistic Regression	0.77	77	0.99	0.89
K-Nearest Neighbors, BPNN	0.85	81.8	0.99	0.85
Random Forest	0.82	82.6	0.96	0.85
AlexNet	0.8	84.5	0.95	0.87
ResNet	0.83	89.9	0.95	0.88
VGG16	0.84	90.2	0.95	0.89
Inception-v3	0.87	91.7	0.95	0.91
AdaBoost SVM	0.95	98.8	0.94	0.94
Proposed Framework	0.965	99.4	0.93	0.95

Table 4. Performance Measures Evaluation of the Proposed and Existing Techniques

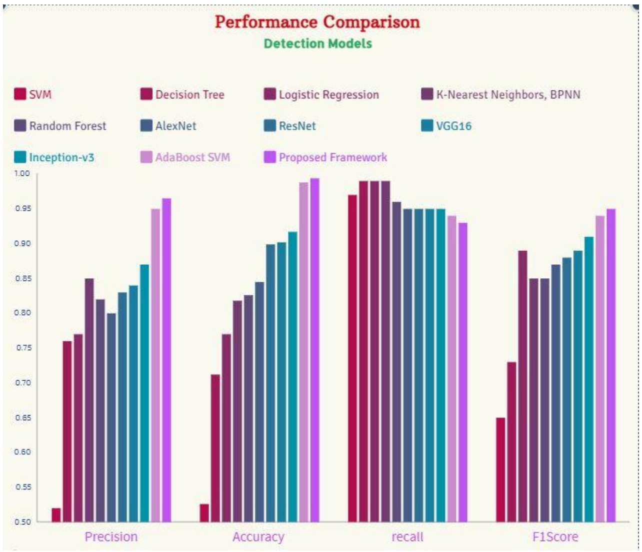

Figure 7. Graphical Comparison of the Proposed and Existing Techniques

In the graphic illustration, existing models also were assessed and a comparison of all performance indicators is shown in Figure 7. Our suggested method is thus preferable to other relevant approaches for identifying rice leaf diseases in past studies in case of strong dataset and real-time disease detection capability.

Uncertainties:

Even though the suggested model outperforms cutting-edge techniques for detecting rice leaf illnesses, significant limitations are however recognized. The following are some study constraints with potential solutions to these problems:

- The network scans the entire image, focusing on different areas of it sequentially rather than all at once. As a result, the method requires numerous passes, which takes time, to identify all objects from a single image. To solve this problem, a network that can identify an image's objects in a single iteration ought to be suggested.
- The geometrical feature similarity amongst the diseases may be the cause of the classification problems. More datasets with equivalent geometric parameters should be used to train the system in order to solve this challenge. Additionally, it recommended adopting a deeper learning algorithm that is more effective and can classify diseases with slight feature differences.

- The high volume of images produced by the data augmentation method during training allows the proposed model to keep a lot of irrelevant features. LASSO regularization aids in minimizing the overfitting issue and enhancing performance.

Conclusion:

Nowadays researchers are being inspired to conduct comprehensive studies on the detection of plant diseases using techniques for leaf image analysis by the development of computer vision technology. The benefits of an automated method for detecting rice diseases can be very beneficial to producers and agricultural organizations. The goal of this study was to identify rice diseases quickly and accurately by merging the XGBOOST ensemble learning model with the Keras Inception ResNet V2 Framework. The Adam optimizer is also used to improve the proposed framework by accelerating the knowledge and training process. A dataset with 53,656 photos of six different forms of rice illnesses was created for this investigation. Based on such trained and tested visuals, the conceptual approach outperformed conventional monitoring models with over 99% accuracy, 0.95 F1 score, 0.96 precision, and 0.93 recall. The proposed findings of this study provide extremely positive evidence for accurately identifying healthy leaves as well as various sick leaf types in both lab-based and field photos. As a result, more research needs to be done to build a dynamical mechanism to detect widespread rice leaf diseases. This system might be helpful to modernize the farming sector, might be thought up of a various mobile processor and to implement agricultural Internet of Things probably.

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