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UTILIZING PERFORMANCE ANALYSIS OF DEEP LEARNING MODELS FOR EARLY PREDICTION OF SALINITY TOLERANCE IN RICE SEEDLINGS

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Abstract: Rice is one of the most widely cultivated food crops in the world. However, there is a significant probability that high amounts of salt, especially at the seedling stage, would have a detrimental effect on rice growth. To prevent a decrease in rice productivity, it is crucial to quickly discover and develop salinity-tolerant rice crop types, particularly at the seedling stage. Expertise from humans is required for the classification of visual signals and the conventional way of a standard assessment system for identifying rice crop salt stress. It's not only time-consuming, but it often leads to mistakes that lead to inaccurate classification. The research shows the need for a deep learning developed model over the conventional approach of measuring rice crop sensitivity to salt stress during the seedling stage to detect and classify salinity stress in rice seedlings using field images. Therefore, we employ pre-trained deep learning approaches, such as VGG 16, VGG 19 to develop the classification model. These techniques are developed in Jupyter Notebook using Python programming. The model can classify images of rice seedlings into scores of 1, 3, 5, 7, and 9, demonstrating the critical need for a computer-based classification system for salinity prediction that could be used as a tool for automating the classification process for rice development to aid researchers and farmers in the rice crop management system.

Index Terms **-** Salinity, Deep Learning, Rice Seedling

[1] INTRODUCTION

Rice remains an important staple meal for tens of millions of humans round the sector and has been a part of cultural and culinary heritage for hundreds of years. It is a staple meal for over half of the world's populace, and within the global, it's far an important source of energy and vitamins. Rice offers a low-cost and abundant supply of meals, that's crucial for food protection in countries where in poverty and hunger are widely wide-spread. According to the Food and Agriculture Organization of the United Nations (FAO), the arena's general rice production in 2020 became approximately 495.9 million metric lots (MT). The pinnacle 5 rice-producing international locations within the global are China, India, Indonesia, Bangladesh, and Vietnam. Asia is the most important rice-generating area, accounting for approximately 90% of the arena's overall rice production. The common yield of rice global is approximately 4.6 MT in line with hectare; however this varies appreciably via United States and location type.
Salinity is a serious issue that has an impact on rice production in a number of nations worldwide. Rice crops' growth and production are negatively impacted by salinity, which is the term used to describe the presence of high quantities of salt in the soil and water. Making salt-tolerant rice varieties, enhancing irrigation and drainage systems, and putting good water management practices in place are all ways to lessen the effects of salinity on rice farming. Additionally, salt concerns and improving the resilience of rice crops are two goals of research and development in sustainable agricultural practices.
Rice plants may be less able to absorb water and nutrients from the soil if it contains a lot of salt, which may lead to stunted development and a reduced yield. Salinity may decrease the number of tillers and spikelet per panicle, lowering grain output. Salinity's effect on grain quality results in smaller, lighter rice grains. Salinity can change the physiological constitution of rice plants, affecting their ability to absorb nutrients, perform photosynthesis, and produce chlorophyll. Salinity can harm rice plants, making them more vulnerable to pests and diseases and decreasing yield. High salt concentrations in the soil can negatively affect nutrient cycling and soil health in addition to the diversity and abundance of soil microbial communities.
For a better understanding of salinity, it is crucial to examine the stages of rice. The rice seed first goes through the germination stage, during which it begins to produce roots and shoots. And then the seedling stage or the early vegetative stage, in which the rice plant grows quickly and makes leaves and stems. Early vegetative, active vegetative, and late vegetative stages make up this stage, which is followed by the reproductive stage, during which the rice plant begins to produce panicles, or flower clusters containing rice grains. Panicle initiation and heading can be separated into two sub-stages, which are followed by the grain filling stage. The rice grains begin to develop and fill with starch at this point. The two sub stages of this stage are the milk stage and the dough stage. The last stage of rice growth is called ripening, during which the rice grains reach complete maturity and the plant begins to dry out. The maturation stage is another name for this phase. In Figure 1, the stages of rice growth are depicted.

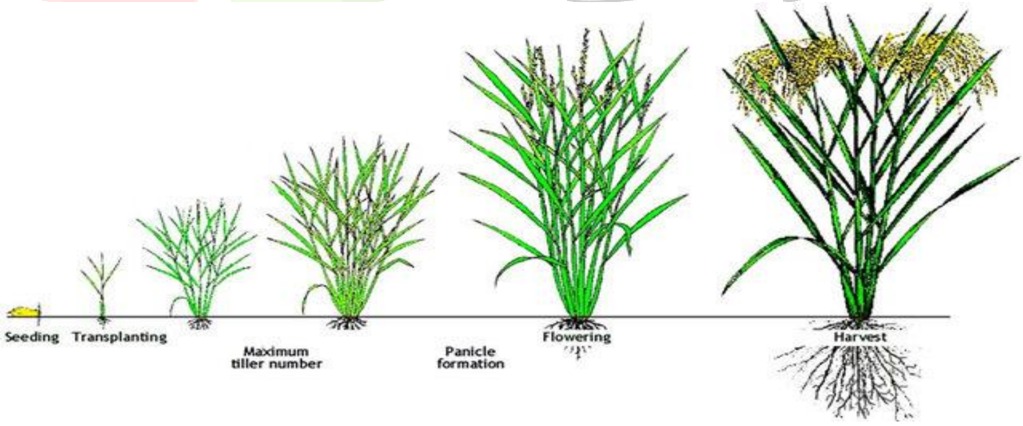

Figure 1: Rice crop stages. *Source: Image from the International Rice Research Institute (IRRI)-Rice Knowledge Bank.*

Rice crops are more vulnerable to saline shocks at the seedling stage, and severe stress at this period may cause irrecoverable damage to the plants, resulting in lower production, as learned from field specialists and the survey. Screening using traditional techniques takes a long time and might be complicated when dealing with a large population of genotypes. Computerized screening has the potential to be a quick, repeatable, and reliable procedure in this setting. Therefore, deep learning approaches play a crucial part in resolving highly nonlinear prediction and classification along with difficult issues during the last several decades. As a result, a model that could forecast the salt stress level in rice crops at the seedling stage using field photos is feasible to construct. In light of this, there is a need for a sophisticated deep learning framework for paddy plant salinity stress recognition and classification system that can be used as an efficient instrument in implementing the identification of various stresses in paddy crops, including stresses 1, 3, 5, 7, and 9.

[2] LITERATURE SURVEY

1. Survey on Traditional Method of Identification of Salinity Stress to Predict the Stress Level in Rice Seedlings:

One traditional method of identifying salinity stress in rice seedlings is by measuring the electrical conductivity (EC) of the soil or growing medium. Visual assessment is then performed by agricultural experts, looking for symptoms like leaf discoloration and wilting to estimate stress levels qualitatively. For this the experiment was conducted at ICAR Goa—Central Coastal Agricultural Research Institute research farms shown in Figure 2, following a randomized complete block design (RCBD). The research farm is situated at coordinates 15290 5500N latitude and 73540 5500E longitude, with an elevation of 10 meters above mean sea level (MSL).

Figure 2: Experiment Conducted at ICAR Goa, as a traditional method of identification of salinity stress in various genotypes of Rice seedlings

Each accession was grown in seven rows, each measuring 2 meters long. Throughout the whole cropping season, standard agronomic and plant protection procedures were employed, with a row spacing of 20 cm and a plant spacing of 15 cm between rows. The qualitative and quantitative descriptors were recorded using the Shobharani et al. [22] minimal descriptor technique. Five randomly selected sample plants from each accession were tagged for observational purposes.

The seedlings were examined using newly built micro plots at the seedling stage to gauge the landrace collections' susceptibility to saline stress. By placing the seeds in an oven for three days at 50 degrees Celsius, the seeds' dormancy was broken. The seeds were then immersed in a cotton bag to aid with germination. Pre-germinated seeds of all 18 accessions were used in two replications, coupled with a sensitive check (IR-29) and a tolerant check (FL-478)[ ], to sow 13 seedlings in each row.

The seedlings were grown in non-salinized water from germination through the second leaf stage (about 7-8 days after sowing). The seedlings were gradually subjected to salt stress, with an initial salinity of 4 dS/M. Experts had made a salt solution by combining table salt and distilled water. Until the electrical conductivity reached 12 dS/M (about 14–15 days after sowing), the salt of the irrigation water was raised by two units each day. The reference salinity-sensitive check genotype IR 29 was then lost, and the salinity level in the tank was kept constant at 12 dS/M.

Based on the standard evaluation system (SES) for rice [7], a 1–9 scale was used for scoring. Table 1 displays the score, with scores of 1-2 indicating high tolerance, 3 indicating tolerances, 5 indicating moderate tolerance, 7-8 indicating sensitivity, and 9 indicating extreme sensitivity.

By subjecting rice seedlings to significant amounts of salt and evaluating how they react, this evaluation system is used to determine how well-adapted seedlings are to salinity. Agricultural professionals can identify which seedling varieties are more salt-tolerant and better adapted for growth in saline settings by comparing the scores of various seedling varieties [ ]. The sample seedling images from each grading level, which are shown in Figure3, have been scaled by agricultural experts.

Table 1: Standard evaluation system for scoring of visual salt injury at seedling and reproductive stages

Score	Observation	Tolerance
Grade1	Normal growth, no leaf symptoms	Highly tolerant
Grade3	Nearly normal growth, but leaf tips or few leaves whitish & rolled	Tolerant
Grade 5	Growth is severely retarded; most leaves are rolled; few elongating	Moderately tolerant
Grade7	Complete cessation of growth; most leaves dry; some plants dying	Sensitive
Grade9	Almost all plants are dead or dying	Highly sensitive

in rice

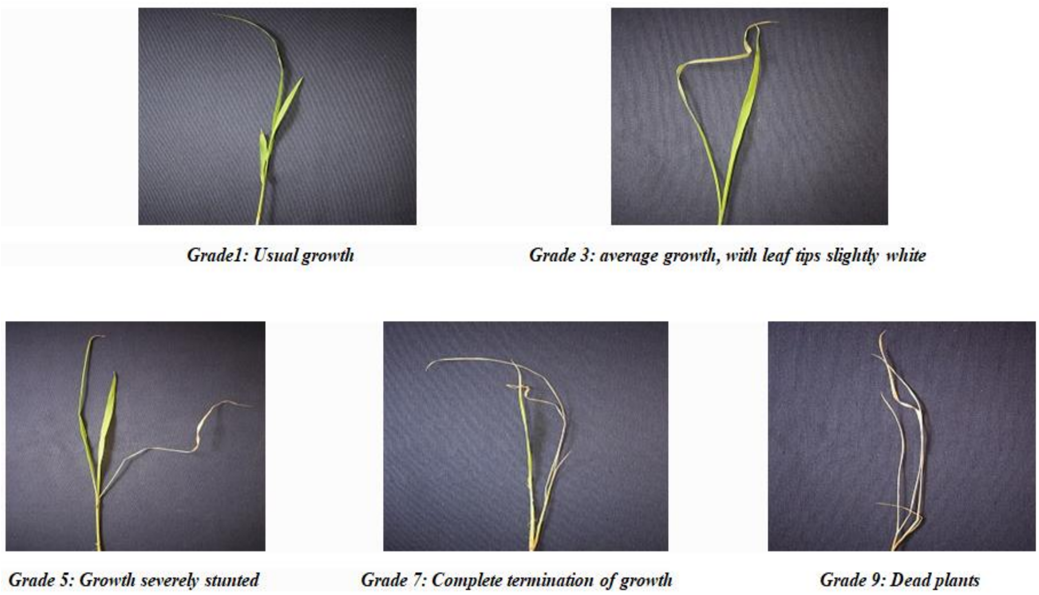

Figure 3. Rice Seedling samples for each grade were collected from Experimental Setup

2. Survey on Deep Learning Based Approach for Screening of Salinity Stress to Predict the Stress Level in Various Rice Seedlings

It is clear from looking at the studies carried out by different authors and shown in Table 2 that there is a research deficit in the area of rice development processes using Artificial Intelligence and Deep Learning approaches. While a lot of work has been put into classifying rice diseases, there hasn't been enough done to classify salinity scores for rice, especially at the seedling stage. To increase rice yields, it is crucial to consider this factor. The development of an automated prediction and classification system specifically for rice seedlings is thus highly motivated. A system like this would be very useful for agricultural researchers and scientists working on crop management techniques.

Table 2: Some of the studies that demonstrate the potential of deep learning models

S. No	Title of the Paper	Year	Methods Used	Comparative Remarks with proposed Work
1	Prediction of soil salinity parameters using machine learning models in an arid region of northwest China	2023	Machine learning models	predicting soil salinity parameters, evaluated the performances [REF10]
2	Comparative performance of four CNN-based deep learning variants in detecting Hispa pest, two fungal diseases, and NPK deficiency symptoms of rice (Oryza sativa)	2022	Deep learning	Evaluated the comparative performance of the (CNN) for automatic and rapid detections of Hispa, brown spot, leaf blast, and NPK deficiency symptoms from public and real field images.
3	An Automated Convolutional Neural Network Based Approach for Paddy Leaf Disease Detection [20]	2021	Deep learning	Paddy leaf disease detection
4	Rice disease leaf classification using CNN with Transfer Learning [14]	2020	CNN	Rice leaf disease Classification done
5	Spectroscopy based novel spectral indices, PCA- and PLSR-coupled machine learning models for salinity stress phenotyping of rice[2]	2020	PLSR- and PCA-based Machine learning models	Estimated Rice leaf nutritional content
6	Measurement of diseases verity of rice crop usingMachine learning and computational intelligence [13]	2017	Fuzzy Logic	Rice leaf disease Classification done

[3] DEEP LEARNING BASED APPROACH FOR SCREENING OF SALINITY STRESS TO PREDICT THE STRESS LEVEL IN VARIOUS RICE SEEDLINGS

It is crucial to provide a better way to create a type of device for the salinity stress of rice seedlings because agricultural scientists and researchers use it as an effective mechanism in the development of rice breeds. The construction of the image collection and the classification based on deep learning are the two key components of the proposed work. The block diagram outlines the steps of the suggested methodology in Figure 2 and illustrates them.

1. Materials and Methods

The two main parts of the proposed study are the compilation of the image collection and the classification using deep learning. Here the deep learning techniques are used to identify key visual patterns and indicators of salt stress in rice seedlings using large sets of field images and then utilize transfer learning to leverage pre-trained deep learning models, trained on diverse image datasets, as a starting point for training a model and then fine-tuned followed by adapting the generic visual features extracted by the pre-trained model for the prediction. Neural network architectures, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are used to capture complex patterns and temporal dependencies in the analysis of paddy crop salt stress. The block diagram demonstrates the steps of the proposed methodology shown in Figure 4.

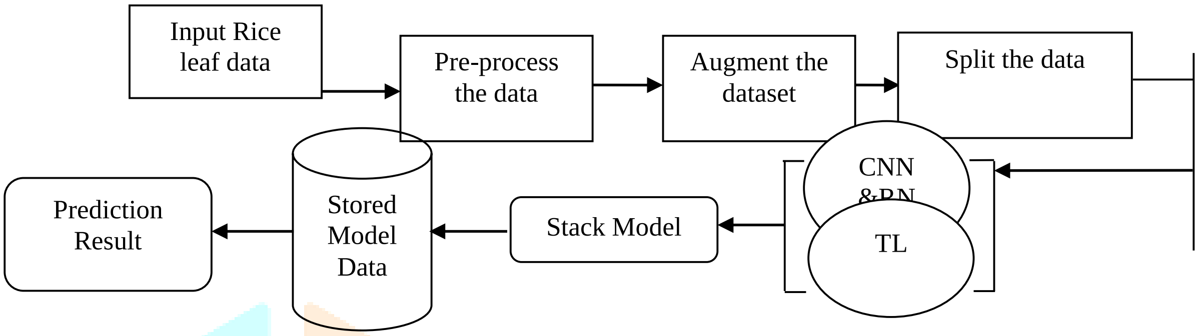

Figure 4: Proposed Architecture

2. Data Collection:

The experimental rice seedling samples were procured from the Experimental Setup shown in Figure 2 conducted at the farm of Central Coastal Agricultural Research Institute(ICAR) in Old Goa, India, in September 2022 .Images were taken in high resolution Camera from the scene. From the experimental setup, about 600 images were gathered. Images of rice seedlings have been labeled by scientists and specialists in agriculture at ICAR to make up the initial training data set. Image dimensions, the number of levels per pixel, the number of channels, and the number of images is the four most common image data input parameters. The image dataset includes the corresponding grades of 1, 3, 5, 7 and 9. The images are created by downsizing them to 224*224 pixels and then using the augmentation techniques for increasing the size of dataset.

3. Pre-Processing:

Import the original rice leaf images into the computer for pre-processing. Following that, individually do thresholding on the images to transform them into binary images. In addition, privately conduct the dilation and erosion procedures to eliminate noise from the images captured. After that, computed the four extreme points (extreme top, extreme bottom, extreme right, and extreme left) of the threshold images by selecting the contour with the greatest area of the threshold images and selecting the largest contour of the threshold images. Finally, crop the image based on the information provided by the contour and extreme point information. Figure 5 shows Bicubic interpolation is used to enlarge the salty images that have been clipped. This method is preferred over other interpolation methods such as bilinear interpolation because it produces a smoother curve than other methods such as bilinear interpolation.

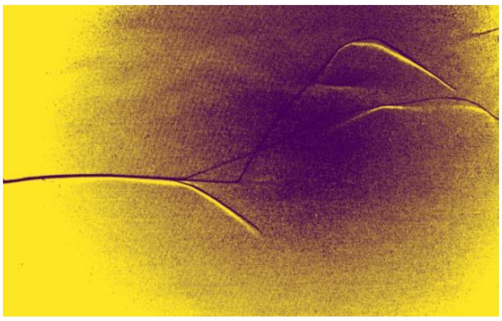

Figure 5: Preprocessed Image

Due to the significant amount of noise along the rims, it is also favored over other techniques such as bilinear interpolation for pictures. It has been used a mean filter was to reduce the difference in brightness between the two pixels when comparing the depth of one pixel to the depth of its neighbors' pixels. Every image is preprocessed using an average clear out, side detection, and binarization utilizing thresholding to achieve the desired results. The three-dimensional images in this case have been modified to work well with the Python programming language. The images are scaled, and the distortion caused by the magnetic subject's non-uniform intensity during that process is removed. The usage of a Median filter with three 3x3x3 filters reduces noise. The dimensions of the provided image as shown in Figure 6, after scaling, are 122*120*77 pixels.

Figure 6: resized image

4. Data Augmentation and Region of Interest (ROI) Extraction

By modifying an existing dataset, an image augmentation strategy can produce an artificial dataset. Different random alterations have expanded the data in order to increase the datasets 'size. By augmenting the data, over-fitting chances were reduced and the model's generalizability was improved. A 15 degree rotation range, 0.1 height and width translation and heightened transformation ranges, 0.5 to 1.5 brightness ranges, and horizontal and vertical flips are among the increment options. Due to the input image dimensions of pre-trained CNN models, this work requires images to be no larger than 194*194*50 pixels.

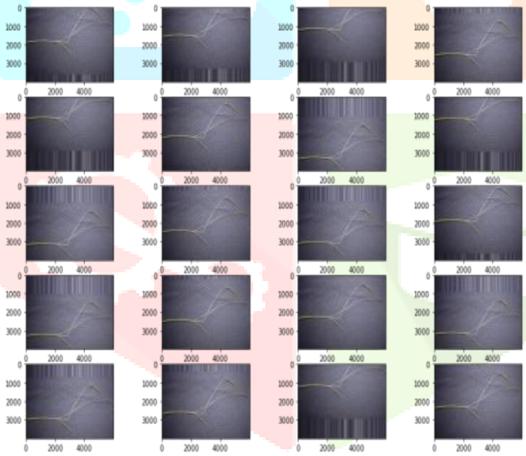

Figure 7: Data Augmentation

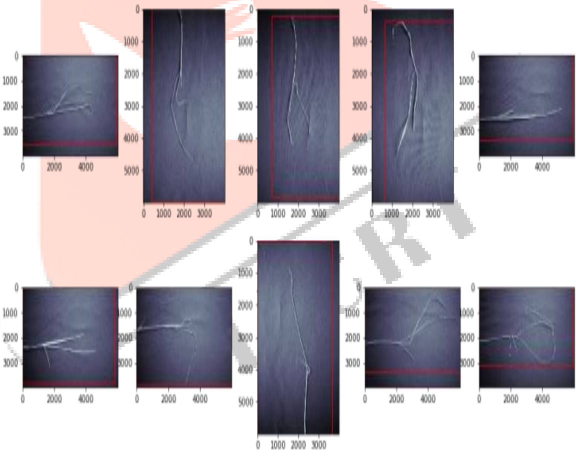

Figure 8: ROI Segmentation

The next step is to segment the image to identify the regions containing the rice plants. Canny edge detection [ ] is a widely used technique in image processing for detecting edges in an image. It used as a pre-processing step to extract edge information that may be useful in subsequent stages of analysis. The rice seedling image in Figure 8 uses the bounding boxes technique [ ] to extract its various features including color, shape, and pattern.

USE OF TRANSFER LEARNING IN PREDICTING THE SALINITY SCORE OF RICE SEEDLING

As an ensemble technique, model stacking combines a variety of classification models. Superior predictive performance can be achieved by stacking the predictions of different models. Some of the classification techniques used itself is ensemble approaches. For transfer learning classifiers, boosting ensembles are utilized, whereas CNN (Convolutional Neural Network) is an ensemble boosting method. CNN classifiers can improve accuracy and reduce overfitting by merging the forecasts of various decision-making bodies during training. On the other hand, by utilizing gradient increases, transfer learning classifiers can lessen distortion and boost accuracy.

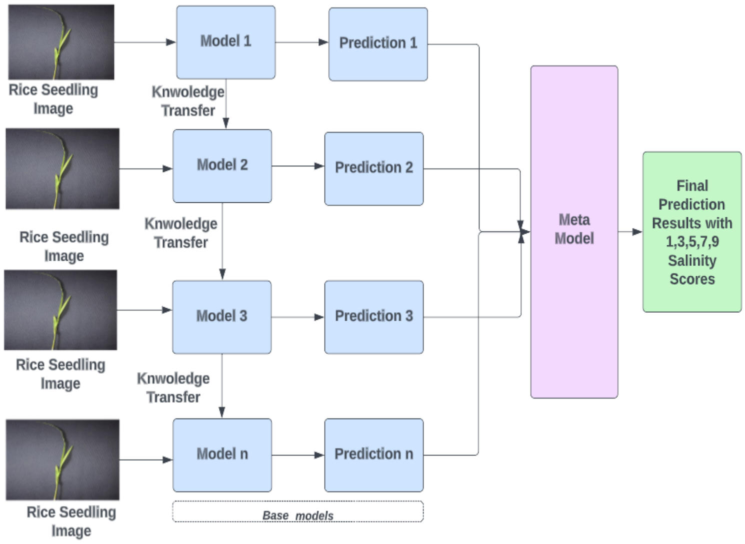

Figure.9: The workflow of Proposed Stacking Ensemble Model with Transfer learning

Stacking is a technique for combining several classifications or regression models into a single model. There are a variety of methods for putting together models. To investigate the space of alternative models for the same issue, stacking must be performed. The concept is that you may approach a learning issue using various kinds of models, each of which is capable of learning a portion of the problem but not the whole problem space. As a result, you may create many distinct learners, which you can then use to construct an intermediate prediction, with one prediction for each learned model created. Then you add a new model that learns from the intermediate predictions and learns the same goal as the previous model. Because this final model is piled on top of the others, it is given the term "stacked model." As a result, you may see an improvement in your overall performance, and you may even end up with a model that is superior to any particular intermediate model. Model stacking is the ensemble technique used to integrate a diverse group of classification algorithms. Through model stacking, several model predictions may be merged to achieve superior predictive performance. Some of the methods of classification employed are assemblies themselves. Transfer learning classifiers are bagging assemblies while CNN is an ensemble boosting. By training many decision-making bodies together and combining their forecasts, CNN classifiers can enhance their accuracy and avoid overfitting. On the other hand, Transfer learning classifiers can minimize distortion and increase accuracy by increasing the gradient.

The working of Transfer Learning goes as follows. First divide the training dataset into n equal-sized sections. A basic model (say, linear regression) is fitted on n-1 parts, and predictions for the nth component are produced using the results. For each of the n pieces in the train set, this process is repeated. The meta model is then fitted to the whole train dataset, which is the last step. This model will be used to predict the results of the test dataset. The same procedure is followed again with another base model, resulting in another set of predictions for the train and test datasets. To develop the new model, the predictions on the train data set are utilized as a feature. The predictions made on the test dataset are based on the final model that was developed.

5.1 Convolution Neural Networks

A common deep learning model for computer vision tasks like object detection and image classification is the convolutional neural network (CNN). It works very well when examining and removing features from images. Multiple convolutional layers, such as VGG, ResNet, or custom-designed models, are often stacked, then layers are pooled before being connected to fully connected layers for classification in order to create a CNN architecture that is appropriate for image classification. Here is how CNN operates. The input image is first put through a sequence of convolutional layers in a CNN. Each layer performs a convolution operation on the input image by applying a set of learnable filters (kernels). This procedure aids in removing important aspects from the image, such as edges, textures, or patterns. To add non-linearity to the network, an activation function (like ReLU) is applied element-wise after every convolutional layer. As a result, the retrieved traits can form more intricate associations, which the CNN can learn. Pooling layers are frequently used to downsample the spatial dimensions of the feature maps in between convolutional layers. Pooling makes the network less computationally difficult and more resilient to changes in the input image.Common pooling techniques include max pooling or average pooling.

The generated feature maps are flattened into a 1D vector and fed into fully connected layers after a number of convolutional and pooling layers. These layers, which aid in making predictions based on the retrieved features, are comparable to those in a conventional neural network. To get class probabilities, the output of the fully connected layers is often routed via a softmax activation function. Utilizing a sizable labeled dataset, CNNs are trained. Using optimization algorithms like gradient descent, the network's parameters (weights and biases) are iteratively changed during training. A loss function that measures the difference between expected and actual labels must be minimized. Gradients are calculated using backpropagation, and the parameters are updated one layer at a time.

An input image of a rice seedling must first be transformed into an array of pixels in order to expose its unique characteristics before CNNs can begin to function. Before the image reaches the fully connected layer, which utilises a "voting" mechanism to classify the image, it passes through layers such as convolution, ReLU activation, and pooling. This voting mechanism uses the data from the earlier levels to choose a categorization. The accuracy of the CNN classifier is demonstrated in Table 5.

The equation provided is a mathematical representation of the output (O) of CNN.

$$O_s = b_s + \sum_r W_{sr} \cdot X_r$$

Here $O_s$is the output of the neuron with index s. And b_s is the bias term for the neuron s. It is a learnable parameter that helps shift the activation of the neuron.W_{sr}represents the weight connecting the neuron s to the neuron r. W_{sr} is the strength of the connection between the two neurons, and it is also a learnable parameter.$X_r$is the output of the neuron r in the previous layer or the input layer, depending on the architecture of the neural network.

The equation calculates the output of the neuron s by summing the weighted inputs from all the neurons in the previous layer (or input layer), and then adding the bias term. The weights Wsr determine how strongly the inputs from the previous layer influence the output of the neuron s. The bias term bs helps introduce a shift or offset to the output.

5.2 VGG 16, 19, Inception and Resnet 50 and 100:

Convolutional neural network (CNN) architectures VGG16 and VGG19 are mainly employed for image classification tasks. In the 16-layer VGG16 CNN model, 13 convolutional layers and 3 fully linked layers are included. Max pooling layers employ a 2x2 filter with a stride of 2, while convolutional layers often use 3x3 filters with strides of 1 and paddings of 1. The final classification is carried out by the fully connected layers, which are stacked on top of the convolutional layers. With 19 layers, including 16 convolutional layers and 3 fully linked layers, VGG19 is an expansion of VGG16. VGG19's architecture resembles that of VGG16, but with more convolutional layers. Like VGG16, it also uses 3x3 filters, max pooling layers, and fully connected layers.

As feature extractors, we have employed the pre-trained VGG16 or VGG19 models. In order to get feature vectors, the top classification layers of the model were removed and the preprocessed images of rice seedlings were fed into the network. The learned representations of the rice photos are shown by these feature vectors. Versions of VGG16 and VGG19 that have already been trained are trained on sizable datasets like ImageNet. As feature extractors or as a place to start for transfer learning, these pre-trained models are employed. The training process is made simple by the dataset, which consists of class labels and the tuples linked to those labels.

We've initialised the Inception model with pre-trained weights from ImageNet in order to utilise it first. This enables the model to make use of the information gained from a variety of visual aspects. Additionally, the model was trained using rice images as the objective variable, and it was then fine-tuned using images of rice seedlings.

The Inception classification model assigns data to classes based on distance. This function determines the separation between a test illustration, X, and actual examples (y1, y2,..., yk). These distances are determined using the Resnet 50 and 100 classification algorithms.

The distance function can be implemented using several techniques, such as Euclidean, Manhattan, or Minkowski, depending on the situation. With continuous values, these techniques deliver the required results. The probability that sample X will be assigned to class C depends on the K number of neighbours that are taken into account. In other words, the chance is influenced by the allowed number of neighbours.

$$MinkowskiFunction: \left(\sum_{i=1}^{k} |x_i - y_i|^q\right)^{\frac{1}{q}}$$

Network (ResNet) architecture, a deep convolutional neural network (CNN). 50 layers make up ResNet-50, comprising convolutional, pooling, and fully linked layers. The residual block, which solves the vanishing gradient issue by providing skip connections, is the fundamental building block of ResNet-50. The model can learn residual mappings thanks to these skip connections, which facilitates deep network training.ResNet-50's architecture involves stacking numerous residual blocks, each of which has a distinct number of convolutional layers. ResNet-50 typically begins with a convolutional layer, followed by a max pooling layer, four sets of residual blocks, and filters in increasing order. The model ends with global average pooling and a fully connected layer for classification.

A 100-layer extension of ResNet-50 is known as ResNet-100. It features a more complex network architecture but adheres to the same fundamental concepts as ResNet-50. ResNet-100's additional layers enable the learning of more intricate representations, which could boost performance on difficult tasks.In comparison to ResNet-50, ResNet-100 has a greater number of residual blocks and filters within each block. Longer training times and greater processing resources are needed for this deeper design, but it may be able to detect more complex patterns in the data.Especially for image classification tasks, the ResNet-50 and ResNet-100 models have been widely used in a variety of computer vision applications. It's crucial to keep in mind that when working with these models, pre-trained versions that have been trained on sizable image datasets (like ImageNet) are frequently used. These pre-trained models are adjusted here to be used as feature extractors for transfer learning since we only have a small dataset.

5.3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS is a different model that we have employed in our work. In order to develop a potent modeling and control tool, it is a hybrid intelligent system that integrates the principles of neural networks and fuzzy logic. Numerous fields, including system identification, prediction, pattern recognition, control systems, and optimization, have effectively used ANFIS. ANFIS blends the fuzzy logic systems' ability to reason with neural networks' learning capabilities. Based on a predetermined set of input-output data, it utilizes a learning algorithm to modify the parameters of a fuzzy inference system. The inputs and outputs of the system are related in accordance with a set of fuzzy rules that make up the fuzzy inference system.

The input layer of the ANFIS architecture, which normally has five layers, is where the system's input variables are received. Additionally, the Fuzzification layer uses membership functions to transform the sharp input values into fuzzy sets. Then, by integrating the fuzzy sets from the preceding layer, the Rule layer determines the firing strength of each rule. The Defuzzification layer aggregates the rule outputs to form a crisp output, which is followed by the Output layer, which creates the ANFIS system's ultimate output.

In ANFIS, gradient descent and least squares estimation are frequently used as the learning algorithm. Based on the difference between the actual and expected outputs, the fuzzy inference system's parameters are adjusted. Forward propagation of the input data through the network, computation of the error, and backward propagation of the error to update the parameters are all steps in the learning process.It provides a versatile and adaptable modelling framework that can manage complicated and nonlinear interactions between inputs and outputs, combining the benefits of both fuzzy logic and neural networks.

IMPLEMENTATION:

From the keras, the VGG-16 is used. Here, the initial layer weights are frozen, and only the model's final layers are tuned for our application. The output of the feature extractor would be flattened before being followed by the output layer and the fully connected layer. The model must then be assembled using the optimizer. We employ the transfer learning technique, which describes a scenario in which what has been learned in one setting is used to improve generalization in another.

Given that the majority of real-world situations often do not contain thousands and thousands of categorized fact points to train such a neural network model, transfer learning offers the advantage of decreasing the training time for a neural network model. In transfer learning, the learned features are first applied to a base network that is trained on a base dataset and task, and then the learned features are transferred to a second target network that is trained on a target dataset and task. If the traits are general—that is, applicable to both the base task and the target task—rather than task-specific, this procedure is more likely to succeed. To categorize the images as Grade 1, Grade 3, Grade 5, Grade 7, and Grade 9 using our small dataset, it is needed to use the pre-trained VGGNet and exceptional adjustment done to it.

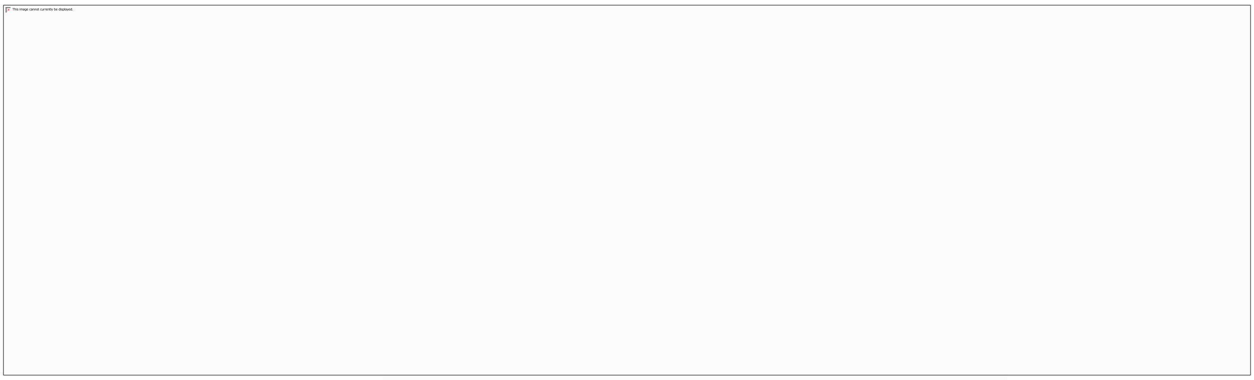

Figure 10. Python code for training the model

We utilize a pre-trained VGG16 model for the model architecture, which was trained on the image dataset. Here, the initial layer weights are fixed, and we only use Python programming in the Jupyter Notebook Framework to tune the model's final layers for our application, as illustrated in Figure 10. The model is then assembled by setting up model checkpoints to save the best model. The model is prepared to test the picture samples with the accuracy of classification score once it has been trained.

[4] RESULTS AND DISCUSSIONS

The proposed method conducts preprocessing, augmentation, segmentation, and classification in the same way as stack ensemble perception does, which results in identification of various images with different textures, contrast, brightness, and depth of the image in the same way that it does in stack ensemble perception. The Table4, Table5, Table6, Table7 shows the various results obtained by different classification models.

Table 4: Accuracy Table for Transfer Learning Classifier (Stack Ensemble)

Parameters	**Test Accuracy %**	**Sensitivity %**	**Specificity %**
Transfer Learning Algorithm	**98.33**	**97.5**	**76.54**

Table 5: Accuracy Table for CNN Classifier

Parameters	**Training Accuracy %**	**Sensitivity %**	**Specificity %**
CNN Algorithm	84.3	96.48	87.3

Table 6: Accuracy of classification based on feature extraction is measured

Classifiers	**Accuracy (%) without features extraction**	**Accuracy (%) with features extraction**
CNN	89.53	97.50
Stacked (TL)	90.54	98.33

Table 7: A comparison of the accuracy of various classifiers is shown

Parameters	**RNN**	**CNN**	**Stack Ensemble (TL)**	**ANFIS** [20]
False Positive	53	60	59	48.25
False Negative	53	57	59	46.25
Specificity (%)	78.5	87.3	76.54	79.74
Sensitivity (%)	92.3	96.48	97.5	96.72
Accuracy (%)	88.33	97.50	98.33	78.75

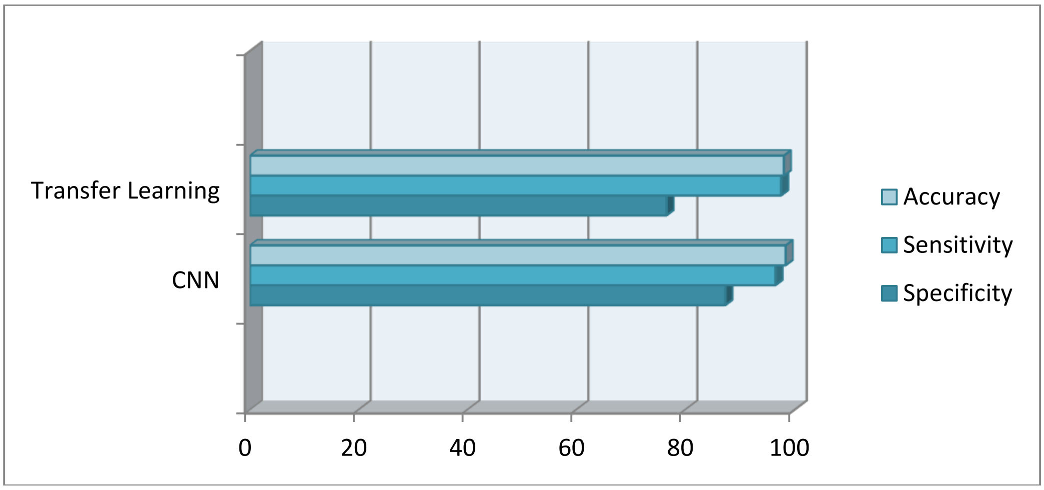

Figure 11: Accuracy Performance

According to the different assessment criteria, Table 7 and Figure 11 provide a summary of the classification analysis of the results of the suggested models. When looking at the table, it can be seen that the TL model has the lowest specificity (78.5 percent) and the highest sensitivity (92.3 percent). Furthermore, the Stacked Ensemble model outperformed the CNN model in terms of sensitivity (97.48 percent), specificity (76.54 percent), and accuracy (987.50 percent), all of which were greater than the TL model for all grades1,3,5,7,9.

The Ensemble Model has shown an acceptable classification result, with such sensitivity of 96.47 percent, a specificity of 87.3 percent, and an accuracy of 98.3 percent, despite its relatively small sample size. However, the Ensemble Model has shown superior performance, with the highest levels of sensitivity, specificity, and accuracy.

Test Accuracy TL = $\frac{\text{False Positive+False Negative}}{TotalTestDataset} X100 = \frac{106}{120}$ x100 = 88.33.

Test Accuracy Stacked Ensemble = $\frac{\text{False Positive+False Negative}}{TotalTestDataset} X100 = \frac{118}{120}$ x100 = 98.33.

Test Accuracy CNN = $\frac{\text{False Positive+False Negative}}{TotalTestDataset} X100 = \frac{117}{120}$ x100 = 97.50

The false positive would occur if the model predicts that a particular seedling is experiencing salinity stress when it is not. And a false negative would occur if the model predicts that a particular seedling is not experiencing salinity stress when it actually is. Here the sensitivity refers to how much the accuracy of the model changes as the hyper parameters or architecture of the transfer learning process is adjusted. The specificity refers to the ability of the model to accurately identify positive and negative instances of salinity stress in rice seedlings. The graphical representation of the above result is shown in Figure 11.
The Figure.12 shows the graphical representation of accuracy and loss. The loss function measures the difference between the predicted output of the model and the actual output. Epochs gives the number of times the entire training dataset is passed through the model during training. During each epoch, the model updates its weights based on the loss function and the optimizer, with the goal of improving the accuracy of the predictions.

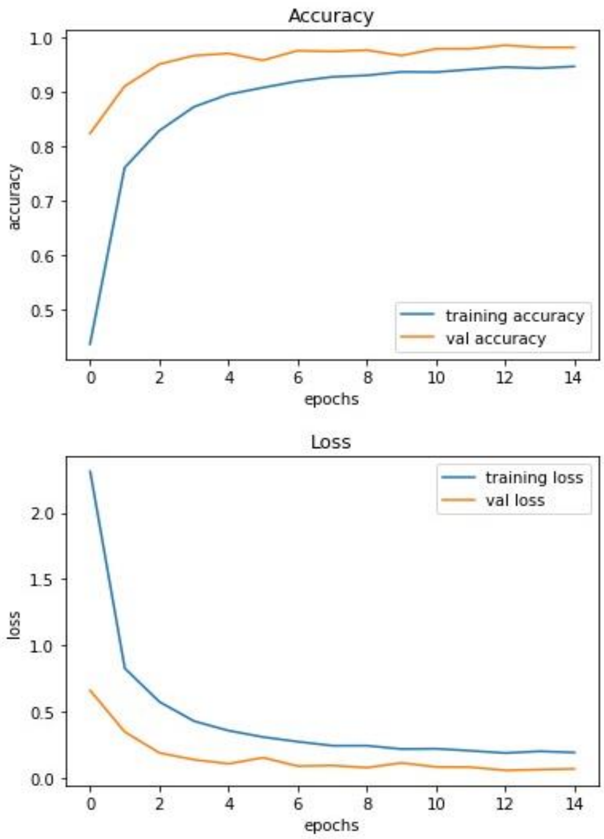

Figure 12: Train, Test Accuracy, and Loss

CONCLUSION:

Nowadays, artificial intelligence and machine learning frameworks can be used at all stages of agricultural food production. Since rice salt stress can result in a large loss in rice yield, these frameworks can be utilized to automatically identify and classify the various rice crops in the score evaluation process. The information gathered from this work may aid agricultural scientists and researchers in evaluating and accelerating breeding by selecting potential genotypes at early growth stages required for salinity tolerance tests, even though the images in the proposed work are insufficient to give each image a specific score. In this study, the use of ensemble approaches to improve the efficiency of individual classifiers in the essential task of multimodal classification—which is of paramount importance—was examined.

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