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Enhancing Rice Crop Resilience: Leveraging Image Processing Techniques in Deep Learning Models to Predict Salinity Stress of Rice during the Seedling Stage

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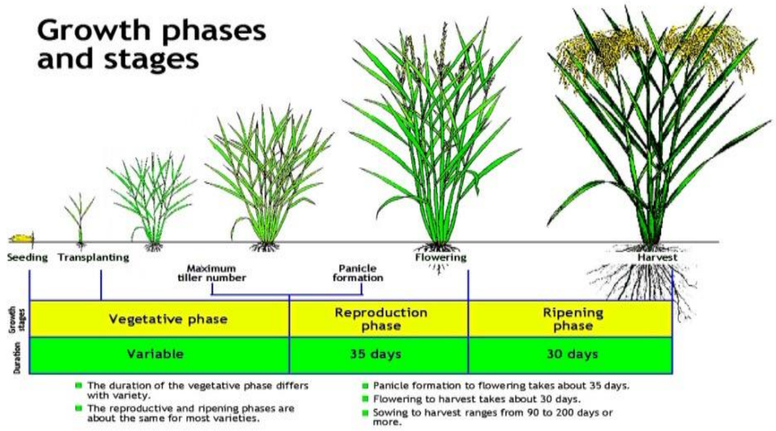
Abstract:
One of the most significant staple crops in the world is rice. Rice seedlings are particularly susceptible to salt stress during the seedling stage, which can negatively affect crop quality and yield. Traditional approaches for assessing the susceptibility of rice crops to salt stress during the seedling stage are deemed inadequate and time consuming. The study emphasizes the necessity of employing a deep learning model instead of traditional methods to identify and classify salinity stress in rice seedlings using field images. To predict salinity stress in rice crops, this research examines the significance of image processing methods employed in deep learning models. To enhance the clarity and visual representation of salinity-induced stress symptoms, we explore several image enhancement techniques, such as noise reduction, contrast augmentation, and image normalization. To further capture and quantify the distinct visual features related to salinity stress, feature extraction techniques such as texture analysis, shape analysis, and color-based segmentation are used. We employ a deep learning model such as VGG16 and VGG19 models to use these extracted features as input to effectively classify the severity of salinity stress in rice seedlings as 1,3,5,7,9 scores. A comprehensive set of rice seedling images from field taken under various salinity stress conditions is used to assess the suggested method. The effectiveness of image processing techniques in improving the discriminatory power of deep learning models for salinity stress prediction is demonstrated by experimental results with 99.40%. The combination of image enhancement and feature extraction methods significantly improves the overall accuracy and reliability of the predictions, enabling farmers to make informed decisions regarding crop management and potential interventions to mitigate salinity stress.

Keywords: Rice seedlings, Image Processing, Deep Learning, Salinity Stress

1. INTRODUCTION

About half of the world's population, especially in Asia and Africa, rely on rice, a popular complex carbohydrate, to meet their nutritional needs. To support the expanding human population, attempts have been made to increase rice production in response to the rising demand for the grain. In many nations, rice is regarded as a key crop, with India set to become the world's top producer in 2021–2022. Small-scale farmers who significantly rely on rice as their main source of income cultivate a sizeable amount of the country's rice. In addition, the economic value of rice as a staple meal and a source of income for farmers highlight how important it is to increase rice production to keep up with the growing demand.
Further discussing salinity, it is essential to understand the stages of rice. The growth of rice is shown in Figure 1 and divided into several stages, each characterized by specific physiological and morphological changes [1].

Figure 1: Stages of Rice growth,



Source: International Rice Research Institute (IRRI)

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The radicle (the embryonic root) and coleoptile (the protective sheath) emerge as the seed begins to take up water and swell in Germination stage. When the seed sprouts, the radical lengthens to form the first root system; Seedling stage: At this stage, the coleoptiles produce its first genuine leaf. To grow and perform photosynthesis, the seedling develops roots, branches, and leaves. It is a time where environmental stressors might affect the development; Tillering stage:
During this phase, the rice plant begins to produce a number of tillers, which are also referred to as secondary shoots or stems. These tillers appear at the main shoot's base. Tillering affects the number of grains produced by increasing the potential for panicles (flowering structures); Vegetative stage: The rice plant continues to grow additional tillers, stems, and leaves during this stage. The buildup of biomass and vegetative growth are the main points of attention. To help it absorbs nutrients and water, the plant develops a strong root system; Reproductive stage: This phase is where growth shifts from vegetative to reproductive. Panicle development on the rice plant produces the flowers that will eventually give rise to grains. Pollination and fertilization are steps in the flowering process that result in grain production; the stage of grain filling: After fertilization, the grains start to fill with carbohydrates and other nutrients. The outcome of this phase will determine the rice crop's ultimate output. The plant devotes resources to the growth of the grain, which gradually reaches its maximum size; Harvesting and grain maturation: The plant begins to senesce when the grain reaches maturity, changing from green to yellow or brown. The plant is getting close to maturity when the leaves and stems start to dry out. When the grains have the ideal amount of moisture for storage or consumption, harvesting begins.

1.1 Effect of Salinity in Rice

Salinity, or the excessive concentration of salt in soil or water, can have a big effect on rice yield and production [2]. Reduced growth and yield, ion toxicity, oxidative stress, changed physiological processes, changes in plant shape, and increased vulnerability to pests and diseases are just a few of the detrimental effects salinity can have on rice plants. The detrimental effects of salinity on rice production can be reduced, and sustainable rice agriculture can be achieved in saline-affected areas, with the support of good management practices such the adoption of salt-tolerant rice cultivars, improved irrigation systems, and soil amelioration strategies.

Here are some key points that highlight the effects of salinity on rice especially at seedling stage:

i. Salinity can limit the growth and development of rice plants, which can result in decreased yields. Rice plants' ability to absorb water and vital nutrients can be hampered by high salt concentrations in irrigation or soil, which can result in nutritional imbalance, reduced biomass buildup, and water stress. Reduced tillering, fewer grains per panicle, stunted growth, and ultimately poorer rice yields can all be effects of this.
ii. Ion toxicity: Excessive soil salt concentrations can cause hazardous ions like sodium (Na+) and chloride (Cl-) to build up in plant tissues disrupting normal cellular processes and leading to ion toxicity. Since Na+ ions can prevent the uptake of important minerals like potassium (K+), nutritional imbalances and decreased plant growth can occur. "Cl- ions"
iii. Enhanced oxidative stress: Rice plants may experience oxidative stress because of salinity. This might result in the creation of reactive oxygen species (ROS), which can damage cellular structures and impair cellular functioning. Proteins, lipids, and DNA can sustain oxidative damage from ROS, which inhibits plant growth and development and lowers yields.
iv. Modified physiological processes: Rice plants' transpiration, respiration, photosynthesis, and uptake of water and nutrients can all be impacted by salinity. Affected plant growth and development, decreased energy generation, and changed plant metabolism are all possible effects of these disturbances. Changes in plant morphology: Salinity can also cause changes in the morphology and anatomy of rice plants. This may include reduced root growth, increased root hair density, changes in leaf morphology, and alterations in reproductive structures. These changes can affect plant water and nutrient uptake, and overall plant growth and productivity.
v. Increased vulnerability to pests and diseases: Due to compromised physiological processes and changed plant defenses, rice plants under salinity stress may be more susceptible to pests and diseases. This may cause further yield losses and have an adverse effect on rice output.

From the observations of field experts and surveys, it is clear that rice crops are particularly vulnerable to saline shocks during the seedling stage. Any significant stress encountered at this time can do the plants permanent harm, resulting in decreased yield. However, conventional screening techniques are time-consuming and difficult, particularly when working with a wide variety of genotypes. Computerized screening, on the other hand, has the potential to be a quick, repeatable, and reliable procedure in this situation. The difficult and extremely nonlinear prediction and classification problems that have persisted over the past few decades can now be addressed with the help of deep learning techniques.

As a result, field images are used to create a model that precisely predict the level of salt stress in rice fields at the seedling stage. A powerful deep learning framework that can accurately identify and categorize salinity stress in paddy plants is unquestionably required to do this. Such a framework would be a useful tool for recognizing various stress levels in paddy crops, such as stresses 1, 3, 5, 7, and 9. By putting this cutting-edge system in place, farmers and researchers can make knowledgeable choices and take the necessary steps to lessen the negative impacts of salinity stress on rice agriculture.

This paper discusses the previous related work in section 2 which provides the importance of the proposed method. Section 3 describes the proposed method with deep learning model that uses various image processing techniques to extract features that enhance the image quality and contributes for a better prediction result. In section 4, we have discussed the accuracy of the predicted results using the deep learning models that motivates us to use more and more deep learning models for better results.

2. LITERATURE SURVEY OF IMAGE PROCESSING FOR DEEP LEARNING MODELS

The traditional method of identifying rice scores through visual analysis was discussed in one of our previous works [4]. To brief it, the experts would go for a lab setup as shown in Figure 2. At the seedling stage, microplots will be used to test the salinity stress tolerance of landrace collections. Through oven treatment and subsequent germination, seeds are prepared by removing their dormancy. Up until the second leaf stage, seedlings will be initially grown in non-salinized water. They are subsequently subjected to rising salt levels gradually for 14–15 days. Until the salinity-sensitive check genotype perished [14], the salinity level was kept. The standard evaluation system (SES) [6] for rice was used to grade the samples on a scale of 1 to 9. The color, shape, and texture of the leaves on stressed rice seedlings exhibit apparent symptoms [13]. These micro-symptoms are challenging to detect and measure manually by visual inspection. The efficiency of the prediction of salinity and analysis is based on the experience of the agricultural experts, which may be time consuming and tedious as well.

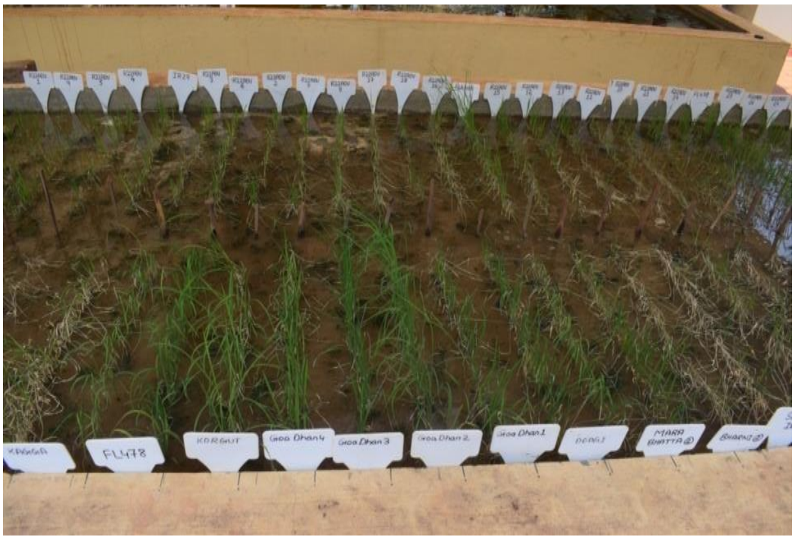

Figure 2: Experimental setup for Traditional method of identification of salinity stress in various genotypes of Rice seedlings

It is crucial to design an automated classification system for the prediction of salinity in rice seedlings for better rice yields. For agricultural researchers and scientists looking for innovative crop management methods, such a system would be of great value. Since none of the works are done on prediction of salinity in Rice at seedling stage, we are listing some of the related papers that combine image processing and deep learning for various image analysis and classification applications shown in Table 1.

Table 1: Survey of image processing for deep learning models

S. No	Title of the Paper	Year	Methods Used	Comparative Remarks with proposed Work
1	Rice Plant Disease Detection Using Image Processing and Probabilistic Neural Network. [11]	2022	Neural Networks	Rice Plant Disease Detection **But No salinity prediction was done**
2	Spectroscopy based novel spectral indices, PCA- and PLSR-coupled machine learning models for salinity stress phenotyping of rice [3]	2020	PLSR- and PCA-based machine learning models	Estimated Rice leaf nutritional content. **But No salinity prediction was done**
3	Rice disease leaf classification using CNN with Transfer Learning [13]	2020	CNN	Rice leaf disease Classification **But No salinity prediction was done**
4	Rice Grain Classification using Image Processing & Machine Learning Techniques [14]	2020	Deep learning	Rice Grain Classification **But No salinity prediction was done**
5	Rice Sample Segmentation and Classification Using Image Processing and Support Vector Machine [15]	2018	Local Binary Pattern (LBP) and Support Vector Machine (SVM).	Rice quality identification **But No salinity prediction was done**

3. PROPOSED METHOD

Deep learning-based salinity prediction has the potential to offer insightful information about salinity levels in rice-growing regions [5], assisting farmers and decision-makers in making well-informed choices about irrigation management, crop planning, and other agricultural practices to reduce the detrimental effects of salinity on rice production. Prior to deploying deep learning models in actual agricultural applications, it is crucial to apply image processing techniques to confirm the better accuracy and dependability using actual data and field tests.

In the proposed method shown in Figure 3, the rice seedling data samples collected are preprocessed to remove any noise, enhance contrast, and normalize the lighting. This will ensure that the images are of consistent quality and are suitable for analysis. Then the Image segmentation techniques are applied to identify and separate the objects or areas of interest within an image. Then the features are extracted from the segmented images, such as color, texture, and shape. These features will be used as inputs to the deep learning model to classify the images to the one of the relevant classes as Score1, Score3, Score5, Score7, and Score9.

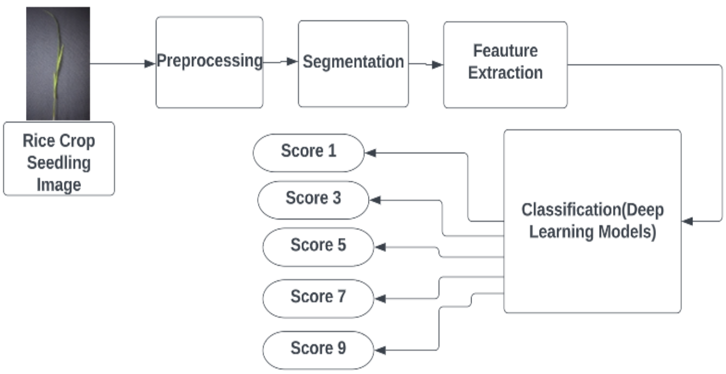

Figure 3: Workflow of proposed methodology

3.1Image Processing Techniques

Image processing techniques are used to identify salinity in rice through the analysis of digital rice seedling images taken directly from the rice fields. By analyzing these images, visual cues that indicate the presence of salinity would be identified, such as changes in color or texture of the rice plants. The segmentation and feature extraction algorithms are used to identify specific types of salinity stress on the rice seedling images. Salt stress can cause different types of damage to different parts of the plant, such as leaves, stems, or roots.

By analyzing images of the rice plants, which parts of the plants are most affected by salinity stress are identified.

3.1.1 Data Collection

We have consulted with domain experts from ICAR Goa, India and followed established scientific protocols to collect the images from the experimental setup carried out at ICAR Goa, India to ensure accurate and reliable results. Around 600 images of rice seedlings were taken by camera directly from an experimental field in various lighting situations and perspectives. The dataset includes the images of scoring levels such as Score 1, Score 3, Score 5, Score 7, Score 9 which are shown in Figure 4.

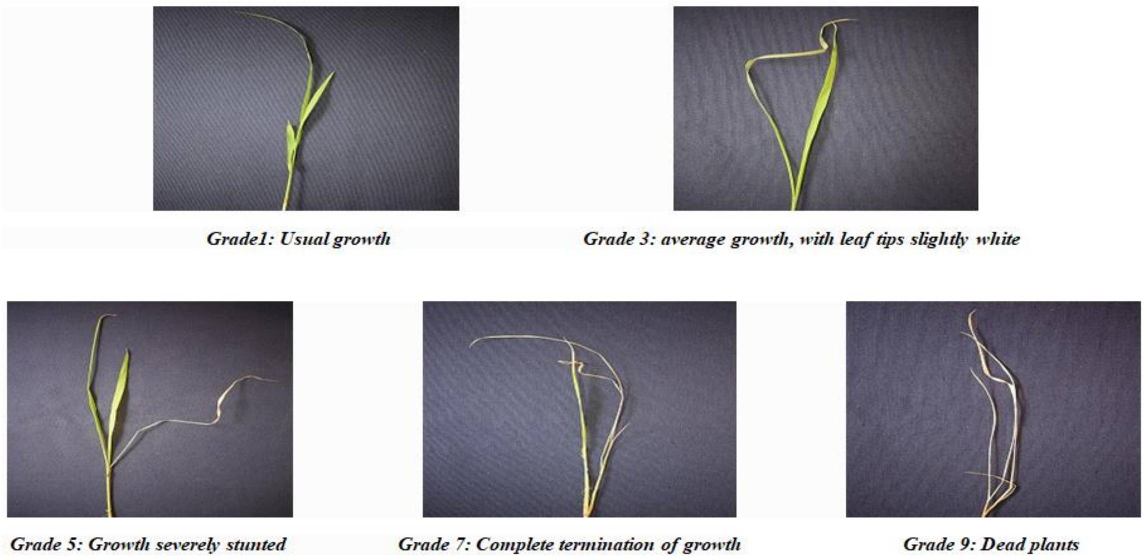

Figure 4. Rice Seedling samples for each grade were collected from Experimental Setup conducted at *ICAR,Goa,India*

Table 2 depicts the standard evaluation system used by the agricultural experts to label the rice seedling with salinity scores. A 1–9 scale was used to score the samples in accordance with the standard evaluation system (SES) for rice [6]. Scores of 1-2 indicate high tolerance, scores of 3 indicate tolerances, scores of 5 indicate moderate tolerance, scores of 7-8 indicate sensitivity, and scores of 9 indicate extreme sensitivity.

Table 2: Standard evaluation system for scoring of visual salt injury at seedling and reproductive stages in rice.

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

3.1.2 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.

It is also preferred over other methods such as bilinear interpolation for images because of the large amount of noise along the edges. When comparing the intensity of one pixel to the intensity of its neighbor's pixels, individually used a median filter to minimize the difference in brightness between the two pixels. To get the required results, all images are preprocessed using a median filter, edge detection, and binarization employing thresholding [7].

Here, the three-dimensional graphics are adjusted to be compatible with the Python programming language. The images are scaled, and the distortion produced by the non-uniform intensity of the magnetic field during that is eliminated. Noise is reduced by using a Median filter with three 3x3x3 filters. After scaling, the supplied image's dimensions are 120*120*77 pixels as shown in Figure 5.

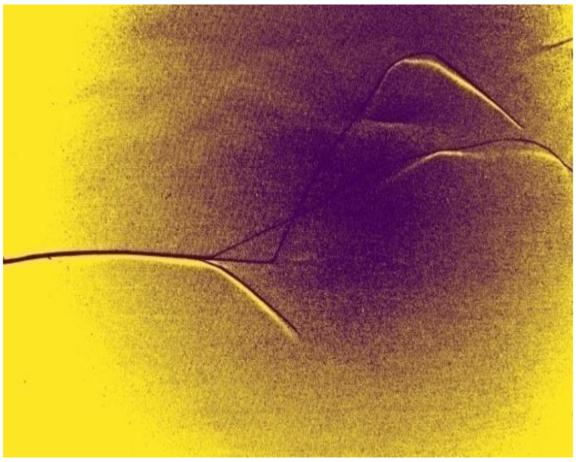

Figure 5: Preprocessed image of rice seedling sample

3.1.3 Resizing, Rescaling and Cropping

The trade-off between image quality and file size must be considered when rescaling an image. Loss of clarity and detail can occur when an image is enlarged, whereas loss of key details or information can occur when an image is reduced in size. Contrarily, cropping entails deleting a section of the image by trimming the edges. This method is used to get rid of distracting backgrounds and other undesired aspects from an image. When cropping an image, it is ensured that the important features and details are not lost in the process. Deep learning models typically require input images to be of a specific size and scale. As part of image processing steps, the images are resized and rescaled the images of rice seedlings to a standard size, such as 256x256 or 512x512 pixels. Resizing and rescaling the images as shown in Figure 6 are done using image processing libraries such as OpenCV or PIL. Resizing and rescaling will also help to reduce the computational cost of training the deep learning model.

Figure 6: Resized and Rescaled image of rice seedling sample

3.1.4 Normalization

The process of normalization involves converting the image's pixel values to a standard scale. This phase is crucial because it makes sure that there is no bias in the deep learning model towards any pixel intensity range. To normalize a dataset, we have subtracted the mean pixel value from each pixel and divided the result by the standard deviation. Scikit-learn libraries are used for normalization.

3.1.5 Labeling

The images of rice seedlings should also be annotated with the appropriate class or category. This stage is essential because it teaches the deep learning model which images belong to which classes and how to forecast outcomes correctly. First, as shown in Figure 1, the labeling procedure for the various scoring levels—including Score 1, Score 3, Score 5, Score 7, and Score 9 as shown in Figure 2 is supplied manually by field specialists from the ICAR Goa, India.

3.1.6 Data Augmentation

Several random adjustments were used to supplement the data to expand the dataset, enhance generalization, and reduce overfitting. These adjustments comprised a 15-degree rotation range, 0.1 height and width translation ranges, 0.1 height transformation ranges, 0.5 to 1.5 brightness ranges, and horizontal and vertical flips. The ability to analyze volumetric filed data using 2D deep learning techniques has been made possible by developments in neural network architectures, data augmentation methods, and top-tier GPUs. Image augmentation techniques were used because a portion of the dataset was not especially huge. By changing an existing dataset, image augmentation includes constructing an artificial dataset. It creates numerous clones of the original image, each with different dimensions, directions, locations, brightness levels, etc. Without adding fresh data, this method can improve the model's classification accuracy. For the constructed machine learning system in this work, two augmentation techniques rotation and horizontal flipping - were individually used to produce fresh training sets. Depending on the situation, the rotation procedure randomly rotates the input image by 90 degrees zero or more times. Each of the rotated photos was then given a horizontal flip.

It is advised to adjust the field images in the dataset to comparable widths and heights to get the best results. This is especially significant because the collection includes field images of various sizes. To match the input image dimensions of the pre-trained CNN models in this study, the photos were scaled to a size of 194x194 pixels. Five folds, each containing 1260 images, were created from the 600-image training dataset. A sample of the augmented images are shown in Figure 7.

3.1.7 ROI Extraction and Segmentation

Recognizing rice leaves before preprocessing involves region of interest extraction. The current method considers the leaf image, but because it can only partially eliminate background noise and ignores elements like finger location and shape, it is insufficient for achieving correct detection. We provide a more sophisticated method to deal with this problem by limiting the analysis to a particular area between two leaf image depressions as shown in Figure 8.

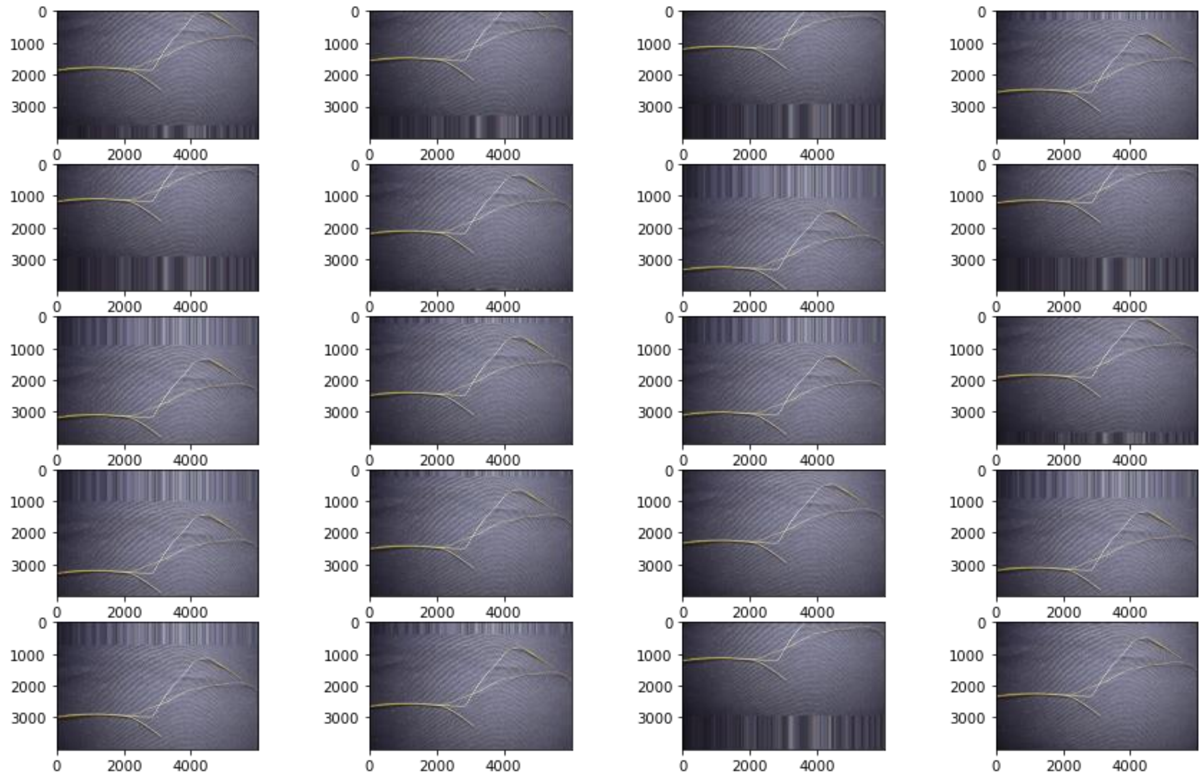

Figure 7: Data Augmentation

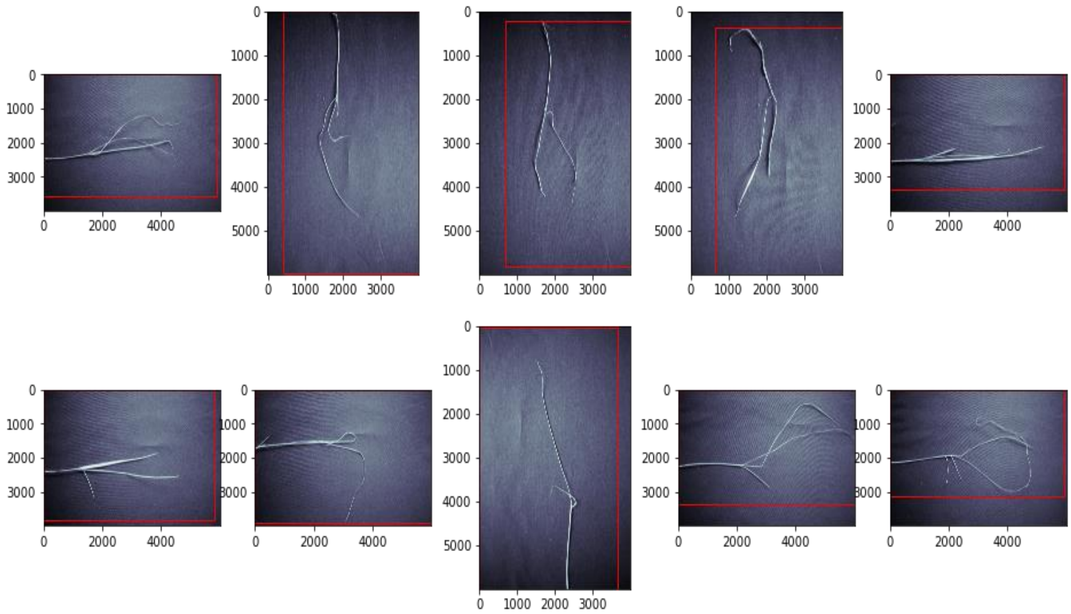

Figure 8: ROI Extraction performed on Rice seedling images

We deploy a brand-new ROI extraction technique and present a cutting-edge field slope operator designed specifically for this application. This technique overcomes the difficulty of precisely restricting the ROI in images with considerable gradient variations by scanning the target with a wide field of view, simulating human vision. Additionally, by averaging these conflicting elements over a greater range with a larger-sized operator, noise and uneven lighting in the image can be mitigated. The accuracy of subsequent matching and recognition operations is improved by this method.

Using a method called semantic segmentation is one popular method for segmenting images in which each pixel in an image is given a label designating which object or area of the image it belongs to. Here, salinity is predicted in images of rice seedlings by designating each pixel as either originating from the seedling or from the surrounding soil. With the labeled field images, the deep learning model for semantic segmentation is trained. Images of rice seedlings at various salinity levels, including Score 1, Score 3, Score 5, Score 7, and Score 9, are included in this dataset. The images are labeled at the pixel level to show what portions of the image represent the seedling and what portions represent the soil.

3.1.8 Feature Extraction

Once the image is segmented the feature extraction process is carried out, which is an important step. Salinity stress often leads to changes in the texture and color patterns of rice leaves or other plant parts. We have used local binary patterns to quantify and extract textural features that characterize salinity-induced changes in the image.

Here are some of the features that are extracted from rice seedling images for salinity prediction:
Leaf color: Salinity can have an impact on the color of leaves. The salinity level can be determined by taking the color values from the leaves.
Leaf area: Salinity can have an impact on how quickly leaves grow. The amount of salinity's impact on the growth of the rice seedling can be determined by counting the area of the leaves.
Leaf shape: Salinity can also have an impact on a leaf's shape. The length, width, and perimeter of the leaves, which are characteristics related to leaf shape, can be extracted to learn more about the impact of salinity.
Texture: The texture of the leaves can also be impacted by salinity. It can be helpful to extract texture-related variables including contrast, homogeneity, and energy to learn more about how salinity affects rice seedlings.
Chlorophyll content: Salinity can impact the amount of chlorophyll in the leaves. Knowing how much chlorophyll is present can help researchers understand how salt affects rice seedlings' ability to photosynthesize.
Stem thickness: Salinity may have an impact on how the stem grows. A useful indicator of how salinity affects the growth of the rice seedling is the stem thickness measurement.
Root length: Salinity may also have an impact on how fast roots grow. The amount to which salinity has an impact on the growth of the rice seedling can be determined by measuring the length of the roots.
Shoot length: Salinity can also have an impact on how the shoot grows. The length of the shoot can be used to measure the impact of salinity on the development of the rice seedling.
In contrast to feature extraction, which includes choosing pertinent characteristics to meaningfully represent the raw data, implicit processing refers to learning from raw data without actively extracting features. Deep learning models do not require explicit feature extraction or segmentation because the algorithm already takes care of these tasks. Due to their ability to learn complex and abstract features that are hard to extract using conventional feature extraction approaches, deep learning models have an advantage over feature-based methods. Therefore, using this method can make it much easier to identify and classify pests and illnesses that impact rice harvests. Convolutional neural network (CNN) models such as VGG16 and VGG19 that have already been trained can be reused, but they might need some modifications to better fit the job at hand. We shall train the CNN model with above mentioned extracted features which is discussed in the Results section.

3.2 VGG16 and VGG19 -Deep Learning Models for Salinity Prediction

For predicting salinity in rice, deep learning approaches are advantageous because they can manage complicated, high-dimensional data, adapt to changing environmental conditions, and produce accurate predictions. Depending on the unique needs of the task and the features of the data, a variety of deep learning methods such as VGG16 and VGG19are employed to estimate the salinity of rice.
We utilized the pre-trained VGG16 and VGG 19 models for the model architecture, which was trained on the image dataset. Karen Simonyan and Andrew Zisserman presented VGG in 2014 (Simonyan and Zisserman, 2015), and the acronym stands for the visual geometrical group at Oxford. The model's key improvement was the use of compact 3x3 convolutional filters. Max-pooling was used across a 2-by-2-pixel window with a 2-pixel strive to perform the pooling.

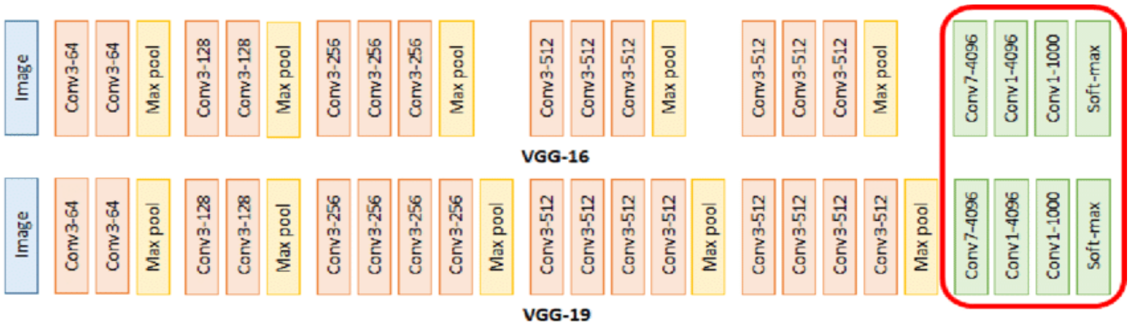

Figure 9: VGG Architecture

In these models, many convolutional layers are often stacked, followed by activation functions like ReLU and layer pooling to reduce spatial dimensions. To generate the salinity score predictions, the final layers include fully linked layers and a softmax or sigmoid activation function. Using the training dataset, we have trained the VGG16 and VGG 19 models. By minimizing a loss function during training, the model learns to optimize internal parameters like weights and biases. The difference between the true salinity scores and the anticipated salinity scores is quantified by the loss function. The gradients are computed, and the model parameters are updated in this case using adaptive optimization. The validation dataset was used to change the model's hyperparameters, including learning rate, batch size, and regularization methods. This helped to improve the model's performance and prevented overfitting.

Here, the initial layer weights are fixed, and we have used Python programming in the Jupyter Notebook Framework to tune the model's final layers for our application, as illustrated in Figure 10.

```
def VGG16_model():
    vgg16 = tf.keras.applications.VGG16(weights='imagenet',include_top=False, input_shape=[img_size,img_size,3])
    vgg16.trainable= True
    model = tf.keras.Sequential([
        vgg16,
        tf.keras.layers.GlobalAveragePooling2D(),
        tf.keras.layers.Dense(3, activation='softmax')
    ])

    model.compile(
        optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate),
        loss=tf.keras.losses.sparse_categorical_crossentropy,
        metrics=[tf.keras.metrics.sparse_categorical_accuracy]
    )

    return model
```

Figure 10. Sample piece of python code for training the model

The algorithms forecast the salinity scores for fresh, unused samples of rice when training is finished, and it has been fine-tuned. We run the trained model on an input image of a rice seedling, and it outputs a salinity score depending on the features that were learned. For fresh, unused rice seedling samples, this model is used to forecast the salinity scores. The trained model is then applied to the input image, and based on the ingested data, it produces a projected salinity score. Our input data for rice seedlings was slid over by several learnable filters or kernels in each layer of the VGG16 model, which produced feature maps by performing element-wise multiplications and summations. Within our data, these layers were able to identify the regional trends and spatial correlations. To inject non-linearity into the network, we have introduced a Rectified Linear Unit (ReLU) as an activation function after each convolutional layer. This activation function maintains positive values while setting negative values to zero. By lowering their spatial dimensions, pooling layers down samples the feature maps produced by convolutional layers. CNNs frequently employ the max pooling strategy, which keeps the maximum value from each pooling window while discarding the others. Pooling gives spatial invariance to minor input data translations and aids in lowering computing complexity.

We have added more fully connected layers after multiple convolutional and pooling layers. These layers link all the neurons in the layer below to the layer above. The global patterns and relationships in the learned characteristics are captured by fully connected layers. To avoid over fitting, we additionally employ a regularization method called Dropout that is frequently employed in CNNs. During training, it randomly changes a portion of the input units to zero, which aids in lowering neuronal dependencies and enhancing the network's generalization capacity. The feature maps are flattened into a 1-dimensional vector before being passed to the fully connected layers as the output of the convolutional and pooling layers. This transforms the spatial data into a format that the fully connected layers may use. The final layer of the CNN architecture is the output layer, which produced the salinity stress score predictions with 97.50 % accuracy.

4. RESULTS AND DISCUSSIONS

In our studies, we make use of pre-trained CNN models on the Imagenet dataset's one thousand classes. The initial and final layers of these models, including fully connected, convolutional, softmax, and classification output layers, are modified such that they are suitable for our intended use. Upper layers of pre-trained models often catch task-specific data whereas lower levels capture generic characteristics. The pre-trained model may be modified to new tasks by altering the higher layers, drawing on the information gained from the original work. Following this, once all models were trained with an identical set of hyperparameters. Training lasted 30 epochs, the number of which was established by comparing the models' training and validation results. Network training using the Adam optimizer and a learning rate of 0.0001. Several data partitioning strategies were used to assess the models' capacity to generalize to a larger testing set. We have used a 60/40 split between the dataset's training and validation sets.

Table.3: CNN Modelling Parameters

Model	Input Size	Parameters (in millions)	F1-Score	Accuracy
VGG19	224 × 224 × 3	148,568,120	0.752	0.994
VGG16	224 × 224 × 3	149,249,861	0.725	0.975

Table 3 shows the modelling parameters such as input size used, parameters for each model, F1 score and Accuracy for VGG 16 and VGG 19. Performance metrics for pre-trained deep learning models over 10 runs utilizing 60% of the data were provided in Table 3. The remaining 40% of the data was used to assess the accuracy of the models, and the results were tallied.

The F1 score balances accuracy and recalls into a single number. Precision measures how many positive observations were successfully predicted as a percentage of all positive observations predicted, whereas recall measures how many positive observations were accurately predicted as a percentage of all observations in the actual class. The most common indicator of a classification model's effectiveness is its accuracy. With an imbalanced dataset, however, accuracy in classification tasks is accompanied by a higher F1 score.

We could also observe the difference between the accuracy with feature extraction and without feature extraction as shown in Table 4. CNN resulted in improved accuracy when it's trained with extracted features. We make use of CNN models to find unexpected patterns in the data. CNNs are excellent at extracting distinguishing elements from images and have proven to be remarkably effective in spotting complicated patterns that are difficult to spot using traditional methods.

Table 4: Accuracy of classification based on feature extraction is measured.

Classifier	Accuracy (%) without features extraction	Accuracy (%) with features extraction
CNN-VGG19)	89.53 %	99.40 %

The confusion matrices, shown in Figure 11, also reveal the models' best and worst performances.

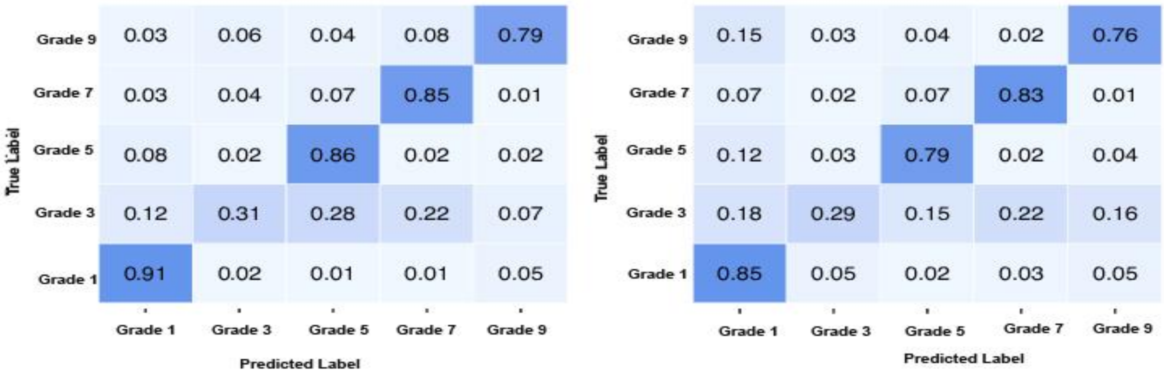

Figure11: Confusion matrix

Test accuracy measures the model's performance on unseen data. It indicates how well the model generalizes to new examples and predicts salinity levels accurately. Loss represents the error between the predicted salinity levels and the actual salinity levels in the training dataset. During training, the model tries to minimize the loss by adjusting its internal parameters. The Train, Test Accuracy, and Loss gained by the model are shown in Figure 12. Epochs refer to the number of times the model iterates over the entire training dataset during training. Each epoch consists of a forward pass (prediction), a backward pass (gradient calculation), and parameter updates. During each epoch, the model's performance is evaluated on the training dataset. Training accuracy measures how well the model predicts the salinity levels for the training examples. It indicates how well the model fits the training data. After training the model for the desired number of epochs, it is evaluated on the testing dataset.

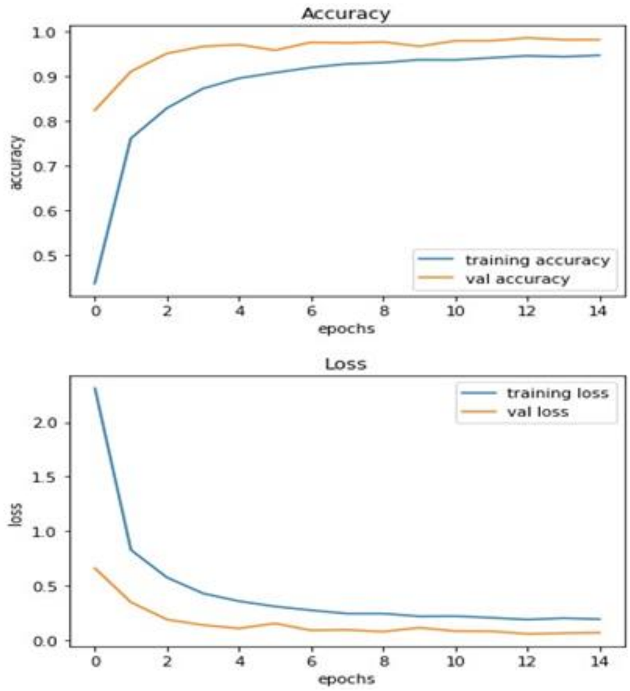

Figure 12: Train, Test Accuracy, and Loss

CONCLUSION

This study's goal was to automatically identify and classify rice seedlings based on salinity levels using photographs taken in the field. The usefulness of this strategy was effectively shown by using deep learning and image processing techniques. The photos were enhanced using a variety of image processing techniques, and the classification work was assessed using the two popular pre-trained deep learning models, VGG-16, and VGG-19. By training on a dataset of over 6800 images of diverse rice seedling varieties, the VGG-19 model achieved an impressive average stress classification accuracy of 99.4%. The research also highlighted the crucial role of image processing techniques in enhancing the accuracy of deep learning models for salinity level prediction in rice. These techniques effectively extracted relevant features from rice seedling images, resulting in a substantial improvement in accuracy from 89.53% to 99.4%.

The obtained results are encouraging, particularly due to the larger number of images considered in this work. However, there is still room for further improvement. As a future scope, the salinity stress classification performance of the VGG-16 model and VGG-19 can be compared with other state-of-the-art models such as ResNet, GoogLeNet, Inception-v3, and LeNet. The application of image processing techniques in conjunction with deep learning models offers a valuable tool for efficiently monitoring and managing salinity levels in rice cultivation, ultimately leading to improved crop yield and agricultural sustainability. This study bridges the gap between visual information derived from images and predictive models, empowering researchers, and practitioners in their efforts to optimize rice production.

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