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DETECTION AND PREVENTION OF RICE LEAF DISEASE USING DCNN_ RESNET50 TECHNIQUE

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Abstract- In the agricultural field, deep convolutional neural networks (DCNN) have been widely used for image categorization, object detection, and image segmentation. Deep DCNN is a deep convolutional neural network (DCNN) used for analysing visual imagery. These networks consist of multiple layers of convolutional filters that learn spatial hierarchies of features from input images. This research aims to assess deep convolutional neural networks with transfer learning to identify various diseases in rice plant leaves. The prediction of disease. The proposed ResNet50 Technique was used with transfer learning to reduce training time and enhance the functional capabilities of the neural networks. Machine learning plays a crucial role in addressing challenges in leaf disease identification. The paper presents a novel algorithm for detecting rice leaf diseases using machine learning techniques. The study uses various techniques to classify images of rice leaf diseases, with an accuracy of 81.8% using a Quadratic SVM classifier. The results met the required expectations and demonstrate the potential of deep learning in various industries. Our project achieved the highest disease accuracy rate of 98% using deep learning technique.

Keywords: Deep Convolutional network (DCNN), ResNet50 is Intercept

I.INTRODUCTION

Deep learning techniques have shown significant potential in image classification [1]. Especially analysing diseases of tea, apple, tomato, grapevine, peach, and pear. However, rice plants have unique challenges in disease detection due to their ability to affect both stem and grain, and the lack of significant colour contrast between healthy and affected areas. The study focuses on the study focuses on the detection utilizes deep convolutional neural networks to study rice diseases. (DCNNs): . Alex Net are being used to detect 10 distinct diseases in rice plants. Study on distinguishing between this research is the first to use the study utilizes the detection of rice diseases and pests. The study includes four diseases and three pests, aiming to build a deep DCNN capable of recognizing a rice plant's health and disease status. The model can differentiate between diseased and dead leaves and can detect diseases on any part of the plant, including leaves, stems, and grains. The study utilized Five different DCNN architectures are KNN, ResNet50, RNN, and ResNet16, InceptionV3, InceptionResNetV2, and Exception, and assessed their performance through This involves fine tuning, transfer learning, and training from scratch. VGG16 architecture consistently showed high accuracy on the test set. However, these models are characterized by a vast array of parameters. Making them unsuitable for remote areas with slow internet connectivity or poor internet speed. To address this issue, the researchers developed a DCNN model that is memory efficient and provides reasonably good classification accuracy. The Extreme Learning Machine (ELM) is a popular, simple, and generalized single-layer feedforward neural network used for classification with minimal input weight modifications. Rice plant disease identification and classification are achieved using traditional machine learning techniques [7] such as discriminant analysis, decision trees, neural networks, and support vector machine SVM[16].

II.RELATED WORK

ChowdhuryR.et.al., [1] Year: 2022 Deep learning is a method that uses machine learning techniques to predict patterns and trends method for identifying the text discusses the various diseases and pests that can affect rice plants through the use of images. The approach uses the advanced Large-scale architectures like VGG16 and InceptionV3 are being explored for their potential in various applications. Being utilized for real dataset detection and recognition. This approach can help farmers apply timely treatment and reduce economic losses. The paper's contribution lies in its ability to achieve the model achieved a 93.3% accuracy rate with a significantly smaller model size [13].

Md. Mafiul Hasan.et.al., [2] Year: 2021 The authors introduce a new method for segmenting studies using ensemble learning, the convolutional neural network-based method, which enhances the performance of neural networks. Architectures reduce computational complexity in retinal images. Entropy sampling is used to select informative points, which are then used the project aims to create a learning framework for convolutional filters that utilizes boosting techniques. The output is used as input for a SoftMax logistic classifier.

R. Salini A. Farzana [3**]** Year: 2021 Crop cultivation is crucial in agriculture, but infected crops are causing food loss and reduced production. The main challenge is to reduce pesticide usage and increase production quality. A system uses enhanced Machine Learning to predict leaf disease infected areas using a colour-based segmentation model. The system detects plant diseases through image processing techniques, this process involves various steps the strategy aims to reduce pesticide usage and improve production efficiency through various techniques

This process involves various steps such as image acquisition, pre-processing, segmentation, feature extraction, and classification [17].

Vimal K. et.al. [4] Year:2021 Researchers are developing Image-based automated systems are being developed to categorize diseases in rice plants to address the time-consuming and subjective methods used the purpose of this statement is to identify and categorize diseases. The study utilized colour features from A support vector machine classifier with a high accuracy of 94.65% was the study was conducted on a dataset of 619 real-life agricultural images, utilizing 14 distinct colour spaces [14].

Prabira Kumar Sethy et.al. [5] Year:2021 They uses 5932 on-field 1 deep feature-based CNN models to identify rice diseases in images, utilizing transfer learning and deep feature plus support vector machine techniquesThe deep feature model outperformed the transfer learning model.

III.PROPOSED WORK

The aim to evaluate the effectiveness of the study utilizes (DCNNs) with transfer learning to identify diseases in rice plant leaves. The proposed ResNet50 with DCNN is trained using transfer learning, a technique that reduces training time and enhances the functional capabilities of the neural networks, proving successful in image categorization, object detection, and segmentation (refer Fig 1) [8].

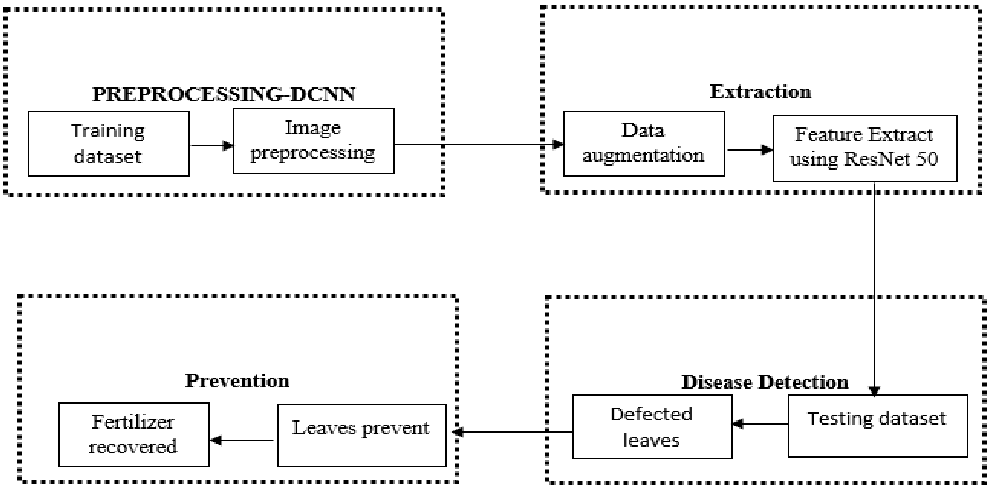

Fig 1: System Architecture

Preprocessing

Preprocessing for deep convolution nerual network(DCCN) involves several steps to process a data to give requried output .In this frist we train the dataset and image processing method. The training dataset refers to the collection of images utilized in training the DCNN model. Image preprocessing involves resizing images to a uniform size and converting them into a model-friendly format for training purposes.

Extraction

Data augmentation is a process that involves altering existing images to create more training data, such as cropping, rotating, or flipping, to prevent overfitting in the model. The DCNN performs feature extraction in the test images, identifying important characteristics for disease detection based on its learned characteristics.

ResNet-50

The vanishing gradient problem, a major obstacle in deep neural network training, inspired the creation of the DCNN design ResNet-50.

Diseases Detection

The model's ability to identify diseases and label healthy photos as sick is tested on a testing dataset, which is a collection of photographs.

B. DCNN_ResNet50

High-quality training data can significantly reduce bias in machine learning models by ensuring diversity, representation, and unbiased labelling processes. This reduces the risk of AI bias and ensures fair and accurate AI implementation can improve machine learning model [10] accuracy and fairness, emphasizing the significance of prioritizing high-quality training data for effective AI systems. The data augmentation technique artificially increases the training set by creating modified dataset copies. feature extraction is nothing but Load pretrained ResNet50 without fully connected layers and use it as feature extractor. Prepare images, extract features from them using pretrained ANN and store these features in NumPy arrays. Build small FC ANN and train it on these features. The ResNet50 mode can be improved by replacing the first FC layer with a set of FC layers, with the first layer having 2048 out-features and applying a probability of 0.5 for dropout. The second layer is identical to the first layer, and REL and dropout are applied with a probability of 0.5. Performance testing evaluates system responsiveness and stability under specific workloads, and results analysis helps understand student learning and performance in each syllabus area. vessels, optic disc, and surrounding structures from individuals including those with a history of rice leaf. The inclusion of images from diverse age groups, genders, and ethnic backgrounds minimizes biases and improves the model's applicability to a broader population [9]. Ethical considerations and rice leaf prioritized during the data collection process, with all data anonymized and protected by privacy regulations. The study adheres to established ethical guidelines and institutional review board approvals for transparent research practices.

Fig 2 : Dataset of rice leaf

Paddy diseases (Fig 2) pose significant challenges in agriculture, affecting crop quality and quantity. Traditionally, naked eye observation has been used to detect rice infections, but this can automatic detection of plant diseases is a significant area of focus, enabling image-based inspection [6], process control, and robot guidance using machine vision [7]. The Deep DCNN with ResNet50 system aims to distinguish faults in a paddy, minimizing early detection loss. The existing system supports small data sets and can now identify Bacterial leaf blight, brown spot, smut, and tango diseases are examples of bacterial leaf diseases [11].

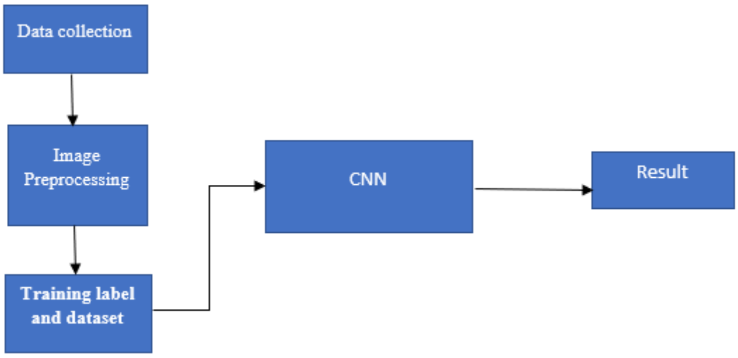

Fig 3: DCNN Model

IV.PERFORMANCE ANALYIS

The study investigates the efficacy of a model for predicting rice leaf diseases using images and Convolutional Neural Network (DCNN) (Fig 3), specifically ResNet 50 [6]. Key metrics Accuracy measures the model's overall correctness in predictions but it may not be sufficient in agricultural applications where imbalances between classes are prevalent. Precision and recall provide a more nuanced the model's performance is evaluated, revealing its strengths and weaknesses. Ability to make accurate positive predictions and identifying all actual positive instances. Balancing precision and recall is crucial in the medical domain to ensure sensitivity and specificity. The F1 score integrates recall and precision. is a method for consistently assessing a model's performance. Particularly useful when striving for a balanced trade-off The ROC curve is a statistical tool that evaluates.

	PRECISION	RECALL	F1-SCORE
BACTERIAL BLIGHT	100	100	100
BLAST	67	100	80
BROWN SPOT	100	75	86
TUNGRO	100	100	100
ACCURACY			98
MACRO_AVG	92	94	91
WEIGHTED_AVG	.94	92	92

Table 1: classification report

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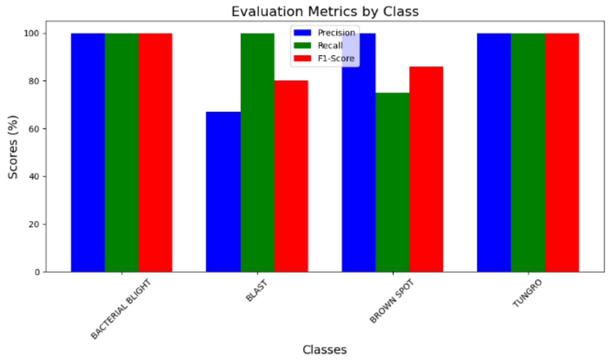

Fig 4: Evaluation Matrix

The (Fig 4) graph Evaluation Matrix is developed from Table 1 classification report**.** The confusion matrix can be determined by identifying the following parameters:

Accuracy: This refers to the percentage of the total number of correct predictions.

$$\textbf{Accuracy} = \frac{\text{True}_{\text{positive}}+\text{True}_{\text{negative}}}{\text{True}_{\text{positive}}+\text{True}_{\text{negative}}+\text{False}_{\text{positive}}+\text{False}_{\text{negative}}} \textbf{ x 100}$$

- The **Positive Predictive Value** or Precision refers to the percentage of positive cases correctly identified.
  - $$\textbf{Precision} = \frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}+\text{False}_{\text{positive}}}} \textbf{ x 100}$$
- **The Negative Predictive Value** refers to the percentage of negative cases correctly identified.
- **Sensitivity** or Recall is the percentage of correctly identified positive cases.
  - $$\textbf{Recall}=\frac{\text{True}_{\text{positive}}}{\text{True}_{\text{positive}+\text{False}_{\text{negative}}}} \textbf{ x 100}$$
  - $$\textbf{F1 }=2*\frac{precision*recall}{precision+recall}\textbf{x 100}$$
- **Specificity** refers to the percentage of accurately identified negative cases.

The confusion matrix, a key component in binary and multiclass classification problems, can be calculated using the Scikit-learn metrics module in Python. The four metrics accuracy, precision, and recall are discussed, with each defined based on multiple examples, and the learn. metrics module is utilized for calculation.

Models	Accuracy
DCNN with ResNet 50	98.4
RNN	95
KNN	93.3
SVM	81.3

Table 2: **Result analysis of DL Models**

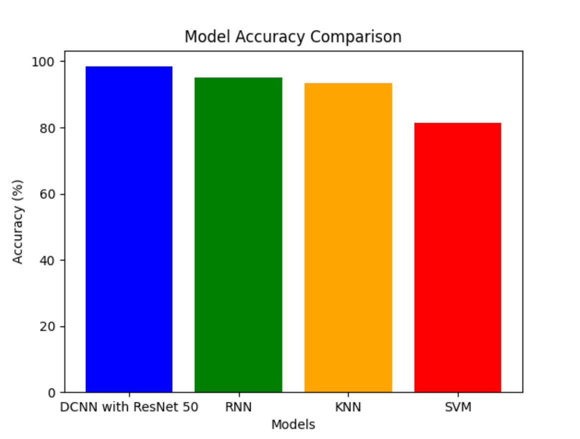

Fig 5: Result analysis of DL models

(Fig 5) The graph illustrates the result analysis of deep learning models, developed using Table 2, with input images labelled with stages of Rice leaf diseases, and the output being a set of labelled images (Fig 6)

A	Bacterialblight				
B	Blast				
C	Brownspot				
D	Tungro				

Fig 6: Output of model

ACCURACY:

We train our model through several batches by dividing the number of training sets into groups called Epoch. The accuracy at which our model predicts to each epoch is shown by using the following graph. The accuracy for 5 epochs is 98.14% shown below:

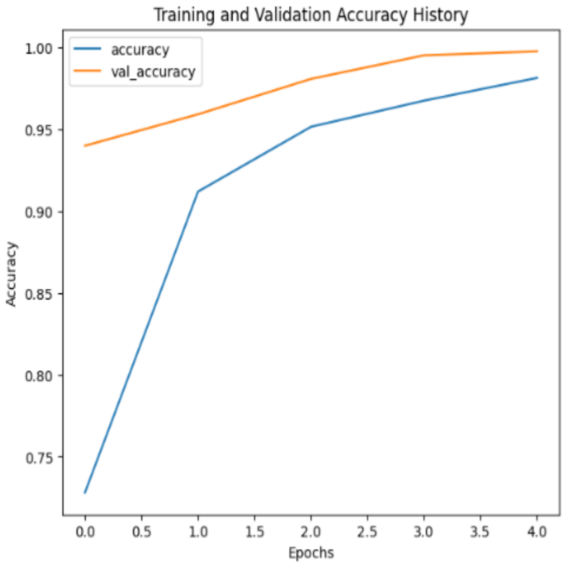

Fig 7: Accuracy

In the above graph (Fig 7) of Training and Validation accuracy history in which the Training involves adjusting neural network parameters to minimize cost function, while validation measures model accuracy on a specific data subset, ensuring the model's effectiveness. Increases accordingly to the epochs and the value accuracy increases from 0.94 to 1.00 accordingly to epochs.

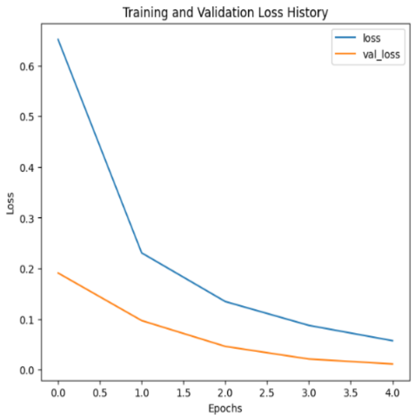

Fig 8: False positive

In graph (Fig 8) which defines A number indicates the poorness of the model's prediction on a single example. where the history denotes the loss decreases which epochs increases and the val_loss also parallelly to the loss from 0.2 to 0.0 accordingly to epochs.

V.CONCLUSION

The proposed system uses deep learning methods, specifically a 5-layer convolutional network (DCNN), to identify and classify leaf diseases in rice leaves using a 5-layer DCNN model. The model outperformed than the existing models by 6%. The system included nine classes of diseases, pests, and healthy plants. This proposed system experiment and analysis the leaf diseases earlier and recommend fertilizers to prevent from the damage earlier. The DCNN_Resnet50 achieves 98% of detection accuracy than the existing methods. The future enhancement has to integrate location, weather, and soil data that controls the plants automatically using robot.

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