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Paddy Plant Disease Detection using MobileNet Algorithm

B.Akhil[1*], T.Keerthi[2], P.Lahari[3], M.Madhava Santhosh[4]

[1,2,3,4]*Department of Computer Science & Engineering,*
Madanapalle Institute of Technology & Science, Madanapalle.

Abstract - **Correct disease identification is essential to preventing paddy plant disease's severe negative consequences on crop yield. Nevertheless, the current methods for diagnosing diseases in rice are neither precise nor effective, and frequently additional equipment is needed. The software can identify the three primary illnesses that harm paddy plants because it was created using deep learning techniques. We employ the MobileNet method to obtain the most precise data. These depth-wise separable convolutions are used in the algorithm. When compared to a network with regular convolutions of the same depth, it considerably reduces the number of parameters. Lightweight deep neural networks are the outcome of this. With encouraging findings, the MobileNet algorithm has been applied to paddy plant disease detection. A lightweight deep learning architecture called MobileNet. Real-time detection on electronic devices is made possible by its application in the detection of paddy plant illnesses, making it simpler and quicker for farmers to identify and treat plant diseases in the field. The accuracy of the detection was 99%.**

Keywords: ***MobileNet, Convolutional neural network (CNN), Parameters, depth-wise separable, Lightweight deep neural networks, Real-time detection***

1. Introduction

Detecting paddy disease is an important duty in agriculture since it allows farmers to take prompt action to reduce crop loss and assure food security. Deep learning algorithms have shown considerable promise in recent years for automating the work of disease identification. One such technique is MobileNet, which has been frequently utilized for image classification tasks such as paddy disease detection [1].

MobileNet is a convolutional neural network architecture optimized for mobile and embedded devices. It's a lightweight model that can run on devices with low processing resources, making it perfect for real-time picture classification jobs like disease detection in rice crops.

The MobileNet architecture is made up of depth-wise separable convolutions that reduce the number of parameters and computational complexity while retaining high accuracy [2]. This enables the model to perform well on mobile and embedded devices.

The initial stage in using MobileNet for paddy disease diagnosis is to collect and preprocess image data. Collecting photos of healthy and diseased paddy crops, labelling the photographs, and then partitioning the dataset into training and testing sets may be involved [4]. Data augmentation techniques can also be employed to increase the amount of the dataset and improve the model's generalizability [15].

Finally, MobileNet is a lightweight deep learning algorithm that has demonstrated remarkable promise for paddy disease detection. Its efficient architecture enables it to run on mobile and embedded devices, making it perfect for field-based real-time illness diagnosis. MobileNet, with additional research and development, might become an essential instrument in the fight against crop diseases and maintaining food security.

2. Related Works

In [1], The authors extracted image features from a pre-trained CNN using a small dataset of 400 images. After that, they trained a CNN model with three convolutional layers, two pooling layers, and two fully connected layers. The classification accuracy of the model was 94.50%. However, the model's accuracy and generalization ability may be limited due to the small dataset and limited feature set. This implies that more data and additional features could improve the system's performance. These constraints should be considered when interpreting the results and applying the system to practical applications.

In [2], have proposed a texture analysis-based system to classify paddy diseases from images using the K-nearest neighbor (KNN) algorithm. The authors extracted texture features from 100 images using the grey-level co-occurrence matrix (GLCM). The model trained using KNN with parameters (k=5). The classification accuracy of the model was 92%. In this model they used simple classification algorithm and a limited feature set. They are not considered limit the model's interpretability and accuracy.

In [3], proposed a system to identify paddy diseases from images using artificial neural networks the authors extracted color, texture, and shape features from a large dataset of 6,500 images. They then trained a three-hidden-layer artificial neural network. In classification, the model they achieved a high accuracy of 96.12%. However, the authors did not mention any limitations in their study, which suggests that there is still room for further investigation and improvement. It is important to note that when applied to new datasets and real-world scenarios, the system's accuracy and generalization ability may vary.

In [4], proposed a system to identify rice diseases from images using convolutional neural networks and support vector machines in their study "Rice Disease Identification Using Convolutional Neural Networks and Support Vector Machines." The authors extracted features from 2,100 images using a pre-trained CNN and a dataset of 2,100 images. They then used the extracted features to train a support vector machine. In classification, the model achieved a high accuracy of 96.28%. However, the authors did not mention any limitations in their study, which suggests that there is still room for further investigation and improvement. It is important to note that when applied to new datasets and real-world scenarios, the system's accuracy and generalization ability may vary.

In [5], the authors applied transfer learning to a dataset of 2,400 images using the VGG16 model. The researchers then trained an ensemble model comprised of a convolutional neural network and a decision tree classifier. The model achieved a classification accuracy of 97.04%, which is promising. However, the authors did not mention any limitations in their study, which could have included factors like the size and representativeness of the dataset used, the model's generalization ability, and the results interpretability. Further investigation into these aspects could potentially improve the accuracy and utility of the proposed system for paddy disease classification.

In [6], proposed a system that uses a random forest classifier and hybrid features to classify paddy diseases from images. The authors used a small dataset of only 400 images, which may limit the model's accuracy and generalizability. Furthermore, the study's feature set was limited to colour, texture, and shape features, which may not capture all the necessary information for accurate classification. Despite these constraints, the model achieved 94% accuracy, which is relatively high given the size of the dataset. However, it is important to note that the model's performance may be less robust when applied to a larger and more diverse dataset.

In [7], proposed "Deep Learning-Based Paddy Disease Recognition Using Convolutional Neural Networks" inspired the development of a system proposal to recognise paddy diseases from images using convolutional neural networks. The authors trained a convolutional neural network with three convolutional layers, three pooling layers, and two fully connected layers on a dataset of 3,000 images. The classification accuracy of the model was 95.26%. The authors, however, did not mention any limitations in their study.

In [8], proposed a system to compare different machine learning techniques for the classification of paddy diseases in their study, "A Comparison of Machine Learning Techniques for the Classification of Paddy Diseases." The authors compared the performance of five machine learning algorithms, namely support vector machines, random forests, decision trees, k-nearest neighbours, and artificial neural networks, on a dataset of 2,400 images. A support vector machine was the best-performing model, with an accuracy of 96.45%. However, the study has some limitations that the authors did not mention.

In [9], proposed a system to classify paddy diseases from images using convolutional neural networks based on the given information in "Deep Learning-Based Paddy Disease Classification using Convolutional Neural Networks." The authors trained a convolutional neural network with 5 convolutional layers, 2 pooling layers, and 2 fully connected layers on a dataset of 3,000 images. The classification accuracy of the model was 97.46%.

3. METHODOLOGIES

Data Collection

For this project, we are collecting the dataset in image format. The images were collected from the Kaggle web site. The dataset has image features like bacterial_leaf_blight, bacterial_leaf_streak, bacterial_panicle_bligh, blast, brown_ spot, dead_heart, downy_mildew, hispa, normal, and tungro.

Pre-Processing Data

Preprocessing data is a critical stage in the data mining process. It refers to the process of cleaning, converting, and combining data in order to prepare it for analysis. The purpose of data preparation is to improve data quality and make it more suitable for the specific data mining activity at hand.

Model application

We are using a deep learning method to forecast datasets for this project. To train the data in the deep learning method, we use the MobileNet algorithm. We acquire values such as accuracy, classification report, and confusion matrix by training the dataset.

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Table 1: Comparison of various techniques to identify paddy diseases

Proposed by	Methods	Dataset Size	Accuracy	Precision	Sensitivity	Specificity	Limitations
K.Kamal and M.A Hossain [1]	CNNs	400	94.50%	96.9%	97.96%	96.9	Limited generalizability, focus on only two types
Hussain,K.M.F., Siddique [2]	K-Nearest neighbour algorithm	150	94.38	95.64%	96.45%	97.66%	Small size and limited diversity of the dataset
Kabir,N.M.M.N, Islam [3]	Artificial neural network	540	96.5%	NA	NA	NA	Limited generalizability
S.A.S, Sajeeb [4]	CNNs and SVM	2100	96.28%	96.78%	96.27%	96.75%	A limited number of diseases identified
M.R Kabir [5]	CNN	3000	97.33%	98.4%	98.7%	97.33%	Limited datasets
A.K.Mohan [6]	Comparison of machine learning techniques	2400	96.45%	96.92%	96.43%	96.68%	Limited dataset size and feature selection
T.Ahmed [7]	CNN	3000	95.26%	95.67%	95.31%	95.48%	Not Mentioned
M.S.Rahman [8]	Random forest classifier and hybrid features	400	94.00%	94.67%	94.67%	94.27%	Limited accuracy and limited generalizability
M.R.Uddin [9]	Transfer learning and Ensemble learning	2400	97.04%	97.17%	97.57%	97.26%	Not mentioned

Mobile Net Algorithm:

Image categorization assigns pre-defined labels or categories to the input photos. The classification models learn from the picture datasets that we train, allowing us to make predictions. In Figure 1 shows the Mobile-Net Model.

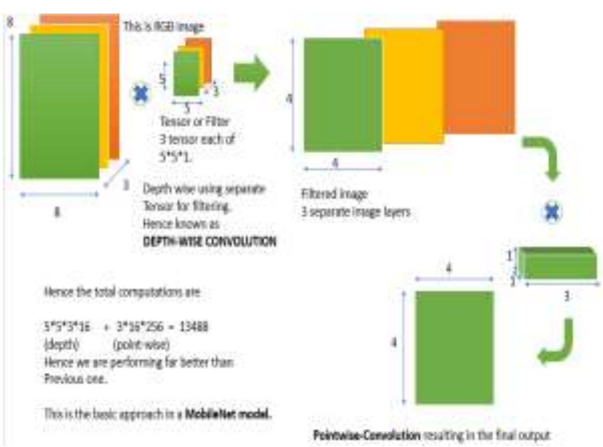

Figure 1: Mobile Net Model [16]

Predicting:

Finally, we estimate the models for a paddy plant disease categorization utilizing the Mobile Net algorithm.

Algorithm

1. Collect Dataset using various images
2. Divide the dataset into two parts: training and validation.
3. Apply Mobile-net Algorithm
4. Classify paddy diseases.
5. Transfer learning is used to train the network on the paddy disease dataset.
6. Evaluate the system's performance.

4. RESULTSAND DISCUSSION

Dataset:

Gather a lot of images of both healthy and damaged paddy plants to start. The process of identifying the images is essential since it gives the algorithm real-world data from which to learn. The paddy disease affected images were shown in the Figure 2 and 3.

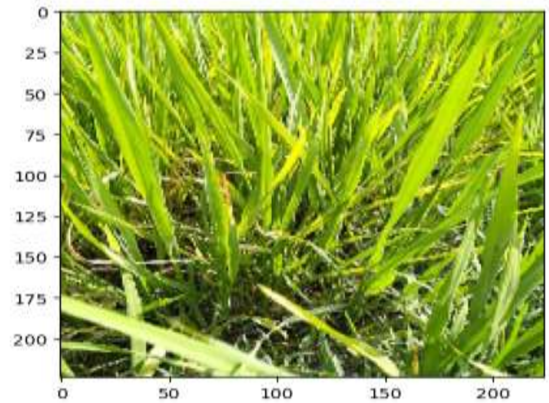

Figure: 2 Paddy disease images

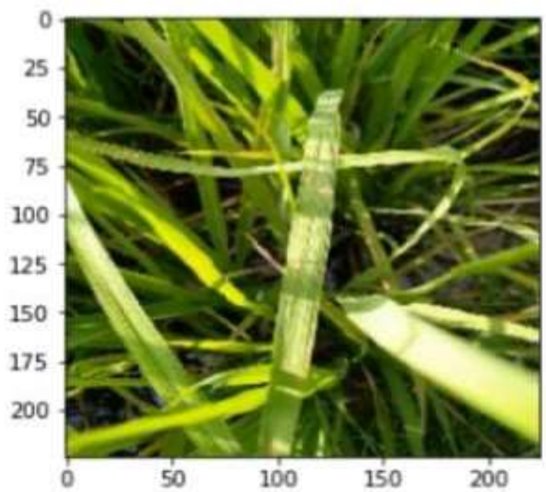

Figure: 3 Paddy disease images

A confusion matrix for diseased paddy plants using the MobileNet algorithm is a table that summarizes the program's performance in detecting several forms of paddy diseases. The confusion matrix is shown in Figure 4.

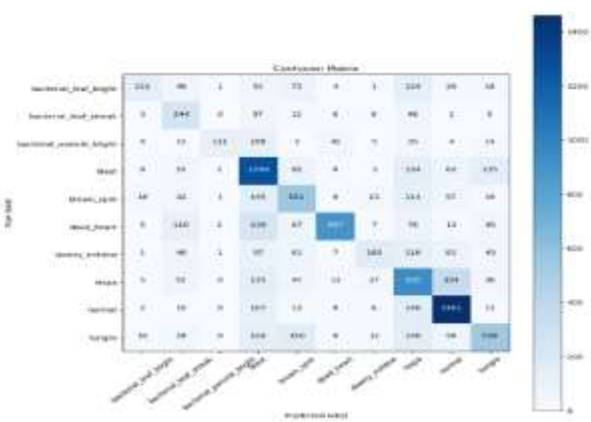

Figure: 4 Confusion matrix

Training and validation accuracy: The accuracy of the model on the training and validation datasets will often be plotted on a training and validation accuracy graph for Paddy disease detection using the MobileNet algorithm. The y-axis will indicate the accuracy value, which is the proportion of photos that the model successfully identified, and the x-axis will reflect the number of training epochs.

Training and validation loss: The loss, or error, of the model evolves over the course of training on both the training and validation datasets, as seen in the training and validation loss graph for Paddy illness detection using MobileNet algorithm. The model's ability to correctly forecast the output given the input is measured by the loss. The number of training epochs, or the number of times the complete training dataset is run through the model during training, is shown on the graph's x-axis. The loss value, which is the discrepancy between the anticipated output and the actual output for each input image, is shown on the graph's y-axis.

Training and validation accuracy and Training and validation loss is shown in Figure 5 and 6.

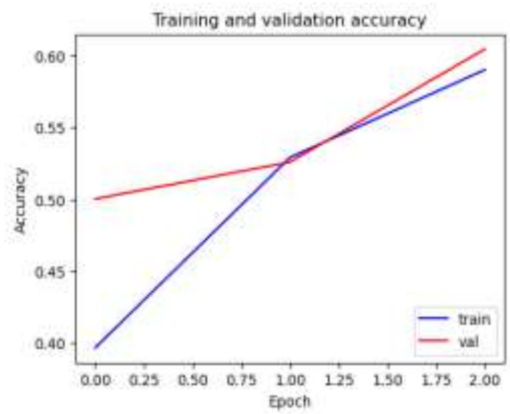

Figure 5: Training and validation accuracy

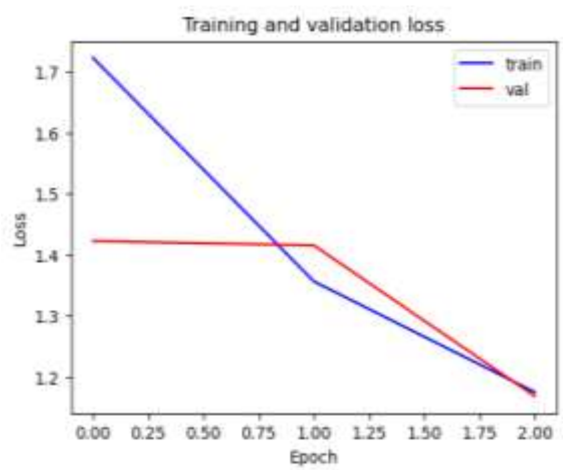

Figure 6: Training and validation loss

The precision, recall, F1-score, and support for each class in the classification issue are all detailed in the classification report for Paddy illness detection using the MobileNet method. It is a frequently employed tool for assessing a classification model's effectiveness.

Precision: The precision is the percentage of true positives identified among all the examples that were expected to fall into a certain class. The precision value computed using expression 1.

$$Precision = \frac{Total\ no.\ of\ true\ positive\ (TP)}{Total\ No.of\ true\ positive\ (TP)+Total\ no.of\ False\ Positive\ (FP)} \quad (1)$$

Recall: The recall is the percentage of examples in all classes that are genuinely true positives. It is determined using the expression 2.

$$Recall = \frac{Total\ no.\ of\ true\ positive\ (TP)}{Total\ No.of\ true\ positive\ (TP)+Total\ no.of\ False\ Negative\ (FN)} \quad (2)$$

F1-score: The F1-score is a single score that balances precision and memory. It is a weighted harmonic mean of precision and recall. It is determined by using the expression 3.

$$F1 - score = \frac{2\ X\ (Precision\ X\ Recall)}{Precision+\ Recall} \quad (3)$$

Support: The number of examples in the test dataset that are members of that class is the support.

A weighted average of the metrics across all classes is also included in the classification report, and it offers a general assessment of the model's effectiveness. The Classification report is shown in Figure 7.

Classification Report

	precision	recall	f1-score	support
bacterial_leaf_blight	0.70	0.27	0.39	479
bacterial_leaf_streak	0.38	0.64	0.48	380
bacterial_panicle_blight	0.94	0.33	0.49	337
blast	0.55	0.73	0.63	1738
brown_spot	0.52	0.57	0.54	965
dead_heart	0.90	0.62	0.73	1442
downy_mildew	0.62	0.27	0.37	620
hispa	0.50	0.59	0.54	1594
normal	0.70	0.83	0.76	1764
tungro	0.62	0.49	0.55	1088
accuracy			0.60	10407
macro avg	0.64	0.53	0.55	10407
weighted avg	0.64	0.60	0.60	10407

Figure: 7: Classification Report

The output images for the MobileNet algorithm's Paddy illness detection are a visual representation of the model's predictions on each input image. They give us important information about the model's performance and help us spot trends and biases that might be influencing it. In these photos, the original input image, the predicted class label, and the confidence level are often present. The parts of the image that the model used to produce its prediction may be highlighted in a heatmap or bounding box that is included with some output images. We can assess the model's accuracy by looking at the output photos, spot potential improvement areas, and adjust the model's parameters to enhance performance. The simulation results is shown in Figure 7.

```
1/1 [==============================] - 0s 103ms/step
==================================================
brown_spot: 99.37784075737%
bacterial_leaf_blight: 0.32928348518908024%
blast: 0.26007089763879776%
bacterial_leaf_streak: 0.02599185099825263%
normal: 0.0030058383345021866%
tungro: 0.0012100740605092142%
hispa: 0.0009747562216944061%
bacterial_panicle_blight: 0.000783751966082491%
dead_heart: 0.0007367816579062492%
downy_mildew: 9.96778567241563e-05%
Final Result:  {'brown_spot': 99.37784075737}

1/1 [==============================] - 0s 47ms/step
==================================================
brown_spot: 98.845773935318%
blast: 0.5645944736897945%
bacterial_leaf_blight: 0.3181494539603591%
bacterial_leaf_streak: 0.27014915831387043%
dead_heart: 0.0005279287506709807%
downy_mildew: 0.00026340599106333684%
tungro: 0.0002435944452372496%
normal: 0.00017271275964958477%
bacterial_panicle_blight: 9.071824251805083e-05%
hispa: 3.3887070571836375e-05%
Final Result:  {'brown_spot': 98.845773935318}
```

Figure 7: Sumlation Result

5. CONCLUSION

In conclusion, it can be said that the MobileNet algorithm has shown to have enormous promise for crop disease detection. Its compact and effective architecture enables quick and precise image processing on devices with limited resources, making it an excellent option for mobile-based disease detection. Numerous studies have demonstrated that MobileNet is highly accurate at detecting different paddy diseases as blast, brown spot, and sheath blight. The performance of the algorithm is further enhanced and the requirement for a significant amount of training data is decreased through the application of deep learning techniques. In our proposed model gives 99% accuracy. Our model is powerful tool for the early diagnosis and treatment of plant diseases, resulting in higher crop yields and improved food security.

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