Deep Ensemble Mobile Application for Recommendation of Fertilizer Based on Nutrient Deficiency in Rice Plants Using Transfer Learning Models

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Abstract—India is an agricultural country, and farming is the most common occupation among Indians. Rice is a vital crop in the agricultural industry. Productivity has been declining for almost a decade. There are several causes for this, including fragmented land holdings, Indian farmer illiteracy, a lack of decision-making capacity in selecting excellent seeds, manure, and irrigational infrastructure. One of the major reasons for rice crop failure is due to malnutrition. Rice, maybe in particular, lacking in nutrients such as potassium, nitrogen, and phosphorus. Nutrient deficiency detection in crops is necessary to plan further actions to enhance yield. Most studies have relied on the use of transfer learning models for agricultural uses. Ensembling of different transfer learning techniques has the ability to greatly increase the predictive model's performance. Five transfer learning architectures InceptionV3, Xception, VGG16, Resnet50, and MobileNet are all taken into account, and their different ensemble models are used to perform deficiency detection in rice plants where ensembled models performs better when compared to individual models. The ensembled model i.e. InceptionV3 + Xception has achieved an accuracy of 98% when compared to other models and it can be utilized in real time situations. The mobile application was created as a user-friendly interface to assist farmers. The accurate diagnosis of these nutritional deficiencies like nitrogen, potassium, phosphorus and recommendation of fertilizer to corresponding nutrient deficiency with the help of mobile application could aid farmers in providing correct plant intervention and to keep track of crop growth.

Keywords—ensemble averaging, Inception V3, MobileNet, nutrient deficiency, transfer learning

1 Introduction

Rice is the most significant food crop in Asia, both culturally and economically. For almost 58% of India's population, agriculture is their primary source of income. There are multiple factors that influence agriculture production, one of them is malnutrition [1]. The plant receives an insufficient amount of necessary nutrients for growth due to nutrient deficiency. Nutrient deficiency has an impact on crop yield and quality in rice cultivation. The principal nutrients required in the soil for rice plant growth are nitrogen (N), magnesium (Mg), calcium (Ca), phosphorus (P), chlorine (Cl), zinc (Zn), potassium (K), and iron (Fe) [2].

Rice is produced all over the world and is one of the most significant cereal crops. According to 2021 data from the U.S Department of Agriculture (USDA) [2], China is the leading producer of rice, India and Indonesia came in second and third, respectively. Figure 1 illustrates the production of rice per country [3].

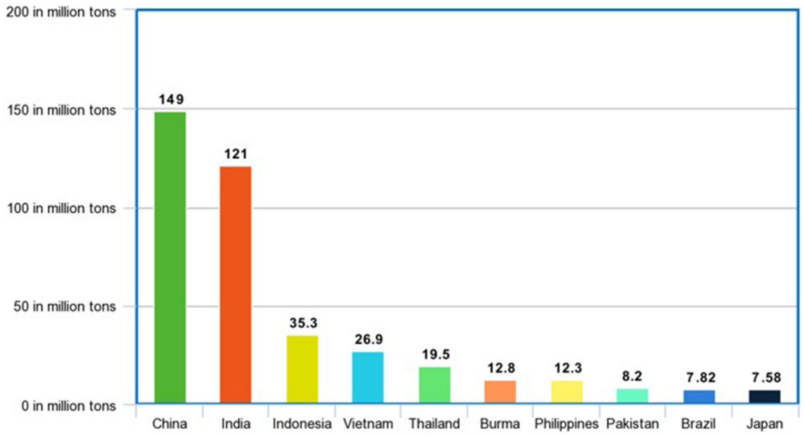

Fig. 1. Rice production in 2021

Nitrogen is particularly needed at two periods of rice crop development: early vegetative and panicle initiation. Phosphorus is very crucial in the early phases of plant development, as it promotes root development, tillering, and early flowering. Potassium aids in the resistance of plants to diseases, insect attacks, cold, and other stresses, and it is required for the formation of starch [4]. Calcium combines with pectin, an essential element of the cell wall. Zinc is required for the conversion of carbohydrates and regulates sugar consumption. Iron and magnesium are required for chlorophyll production. Chlorine controls rice diseases and increases resistance [5].

The nutrient deficiencies identification in crops is critical in order to plan future actions to improve yield and maintain crop growth. It is difficult for a human expert to diagnose nutrient deficiency since crop production regions are widespread and numerous nutrient deficiencies were dispersed throughout a vast area [6,7].

These deficiencies are generally only visible when the crop was already severely affected. With technological developments methods such as image processing and the internet of things, computer vision has been developed to help farmers detect nutrient deficiencies early enough. Nutrient deficiencies can be diagnosed using CNN-based Deep Learning approaches and transfer learning techniques [8,9]. Ensemble Averaging technique on several TL models, such as MobileNet, Inception, VGG16, Resnet, and Xception, which improves the performance of nutrient deficiency detection [10,11].

P. K. Sethy et al. [12] developed a CNN+SVM-based technique for rice nitrogen deficiency prediction. SVM (replacing the last layer of CNN) for higher accuracy and performance. CNN for training and testing. For nitrogen deficiency prediction, six top deep learning architectures are employed with SVM. DCNN was utilized by Zhe Xu et al. [13] to identify a nutrient deficiency. Removed the top layer and applied all DCNNs with ImageNet pretraining weight. The SoftMax function was used to classify the 11 categories. Four DCNNs, ResNet50, DenseNet121, Inception-v3, and NasNet-Large, were successfully fitted and utilized to identify different types of deficiencies in rice plants using image recognition.

On the photos of okra plants, L. A. Wulandhari et al. [14] developed an Inception-Resnet architecture and fine-tuning from a model that was previously trained using the ImageNet. The image augmentation method has been used to improve the dataset's variation. The fine-tuning technique delivers the best accuracy, with 96% for training and 86% for testing, according to the results obtained. S. M. Hassan et al. [15] used EfficientNetB0, InceptionResNetV2, MobileNetV2, and InceptionV3 to create models that accomplished disease-classification estimation satisfying accuracy, which was higher than the traditional based approach.

A transfer learning model was presented by J. Chen et al. [16]. To recognize rice plant diseases and label them as Brown spot, Leaf smut, and Bacterial leaf blight. DenseNet was pre-trained on ImageNet, and Inception was used as the network's technology. To improve the learning ability of the micro lesion characteristics, the network employs the Focal Loss function. M. Sharma et al. [17] investigate six TL architectures, namely Xception, VGG16, InceptionV3, VGG19, DenseNet, InceptionResNetV2, and ResNet152V2, and their distinct ensemble models are applied to perform deficient diagnosis in rice crop to determine NPK nutrient deficiency and nitrogen deficiency.

By designing a portable device that captures multispectral reflectance pictures and multicolor fluorescence concurrently, C. He et al. [18] identified an effective technique for identifying citrus HLB disease. The analysis indicated that utilizing the Navel orange dataset as input, the lightweight CNN model (MobileNetV3) can achieve an accuracy of 92.1% by integrating multispectral reflectance pictures with multicolor fluorescence. O.O. Abayomi-Alli et al. [19] proposed a deep learning model for determining Cassava diseases. In smart agriculture, enhancing deep learning techniques is necessary to detect plant diseases in the early-stage. Image-enhancing methods are employed to validate the proposed model. MobileNetV2 network showed substantial results in cassava disease recognition when compared to previous models.

Krishnamoorthy N et al. [20] recognized that brown spot, bacterial blight, and Leaf blast are three primary attacking diseases in rice plants. In order to recognize diseases in images of rice leaves, InceptionResNetV2 is used in combination with a transfer learning approach. The parameters were optimized for classification and it achieved an accuracy of 95.67%. Yogesh et al. [21] proposed a classifier called SVM to identify the defects and causes based on its stage. Fruits are divided into two classes throughout the classification process: defected and non-defective. The observed defected image was further divided into three stages: the first, second, and ultimate stages of fruit defect.

G. B. D. Cruz et al. [22] proposed architecture to detect the deficiency of nitrogen-based on the color of leaves in rice plants. An image preprocessing method was used to capture images digitally which are represented in RGB formats. The images are normalized and comparison is done by using the image/pixel subtraction strategy. The amount of fertilizer is also recommended by the mobile application. The Z statistic score is used to determine the accuracy of the procedures.

T. Tran et al. [23] uses a deep CNN for the identification of nutrient deficiency in tomato plants. Plants require specific vitamins and supplements to flourish at various phases of development, such as the blossoming stages of fruit production. A total of 571 instances of tomato fruits and leaves were used for training (461images) and testing (110 images).

D. O. Oyewola et al. [24] proposed a deep RCNN for cassava Mosaic Disease identification. African farmers use cassava both for local and business purposes. distinct block processing helps in incrementing the number of pictures. To improve the color separation, decorrelation and gamma correction are used. DRNN demonstrate outflanks the PCNN by an enormous edge of 9.25%. According to work done by Nurbaity Sabri et al. [25] an image processing technique is used for the identification of nutrient deficiency in maize plants which helps in removing human errors in the detection process. A combination of GLCM, color histogram and hu-histogram were used for parameters for classification. It also determines the type of nutrient deficiency. The random forest method achieves an accuracy of 78.35%.

2 Methods

2.1 Dataset

The images were collected from Kaggle, an online resource [26]. Color images (RGB) of rice plant nutrient deficiencies were considered. There are 1156 images in total in the existing dataset, which is divided into three categories: Nitrogen (N), Potassium (K), and Phosphorus (P). There are 440 photos of nitrogen, 333 images of potassium, and 383 images of phosphorus. Table 1 shows the data division of rice plant datset.

Table 1. Data division

Category	Number of Images
Nitrogen	440
Phosphorus	333
Potassium	384
Total	1157

2.2 Methodology

Data preprocessing and data augmentation. Most deep learning models' performance in determined on the terms of quality and quantity of training data they acquire. However, one of the most prevalent problems in applying machine learning is the limited data available. This is because that gathering such data can be costly and time-consuming in many circumstances. Including a variety of images with diverse attributes such as color, cropping, translation, orientation, etc can aid in the creation of a model that is robust using the data that is already available.

Data augmentation is a method of expanding the quantity of data available by integrating current data with newly created synthetic data in order to increase the sample space available for any model. The model must be trained on numerous instances of data in order to produce an accurate result. ImageDataGenerator's main feature is that it can generate batches of data that have been enhanced. The dataset was improved to 3005 images after data augmentation. The data was partitioned for computation, with 2686 images used for training, 335 images used for testing, and 335 images used for validation.

Pre-processing refers to the modifications made to the data before it is fed to the algorithm. The received data typically contains a significant amount of noise from various sources. A method for transforming messy data into a clear data set is data preprocessing. In order to get better results from the used model in deep learning algorithms, the data must be effectively organized.

Preprocessing is often used to improve image quality, reduce complexity, and thus increase the accuracy of the overall model. Rescaling and resizing were done in data pre-processing. Because neural networks only accept inputs of the same size, all photos must be scaled to the same size before being fed into the convolutional neural network. Each image is resized into 150*150 size. Rescaling real-valued numeric variables in the range of 0 and 1 are referred to as standardization.

Model definition and training. In smart agriculture, deep learning models play a pivotal role in identifying and classifying different plant diseases and nutritional deficiencies and help farmers with creative approaches. The rice plant dataset is used to fine-tune multiple transfer learning models, including InceptionV3, Resnet50, Vgg16, Mobilenet, and Xception. A dense layer, softmax layer, and pooling layer were added to the pre-trained model classification layer [27]. The models were trained using 30 epochs and a batch size of 32, cross-entropy, and Adam optimizer were used to test and validate each model.

To identify nutrient deficiencies in rice plant leaves, an ensemble of several transfer learning models is utilized. The rice plant dataset is taken from Kaggle and is subjected to data preprocessing and augmentation.Vgg16, Resnet 50, Inception v3, Xception, and Mobilenet are five deep learning-based transfer learning models that were trained separately on the dataset. To efficiently train neural networks, Adam optimizer and softmax activation function was used. The best-achieving transfer learning models are ensembled to produce ensemble classifiers. To pick the optimum model for a rice deficiency diagnosis, performance measures were used to evaluate all of the classifiers. Figure 2 illustrates proposed architecture of the model.

The Visual Geometry Group, or 'VGG,' has 16 convolutional layers and outperforms AlexNet. VGG16 is a deep learning image recognition system that is utilized in a variety of ways. VGG16 is frequently used in learning applications due to its benefits.

The Google product Xception stands for Extreme version of Inception. Using an improved feature extraction technique, it's even superior to Inception-v. It is 71 layers deep CNN. The Imagenet which has been trained on millions of images can be used here.

On the ImageNet dataset, Inception v3 has been achieved an accuracy of 78.1%. Dropouts, max pooling, Convolutions, and average pooling are some of the building elements that make up the model. The activation inputs are subjected to batch normalization, which is employed frequently throughout the model. Softmax is used to compute loss.

ResNet is an abbreviation for Residual Network. Convolutional neural networks with 50 layers, such as the ResNet-50 model, are deep residual networks. By using identity shortcut connections or skip connections that skip one or more layers, ResNet addresses the vanishing gradient problem. To improve the accuracy of the models, Resnet employs residual blocks.

MobileNets are low-power, low-latency models that have been parameterized to fit diverse use cases resource constraints. They can be used for classification, embedding, and segmentation, all while keeping in mind the restricted resources available for a device.

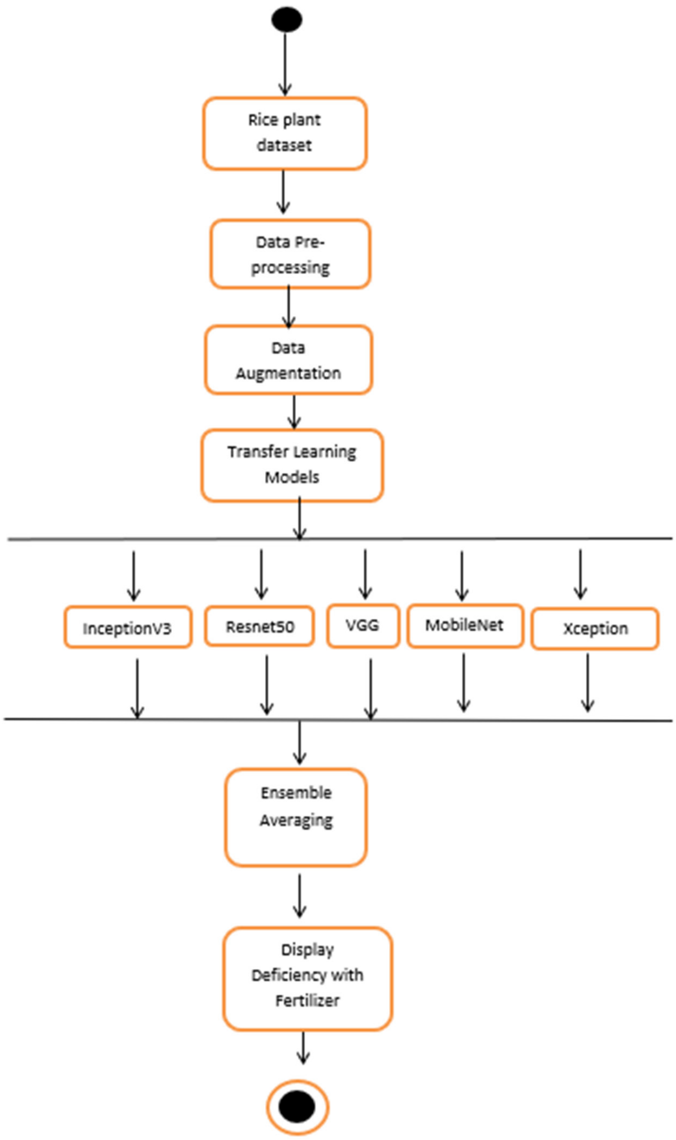

Fig. 2. Proposed architecture

Ensemble averaging is a way to integrate the predicted probabilities of various models. Ensemble learning aims to outperform any individual algorithm by combining numerous algorithms and merging the results with various voting practices. Inceptionv3, ResNet, Xception, MobileNet, and VGG16 are the basic models employed. Binary ensemble classifiers are built. Each ensemble classifier evaluates the dataset's prediction probability and averages it. After successful prediction of the class, fertilizer is recommended for the corresponding nutrient deficiency.

Mobile application. For a project with the best model to exhibit its performance, a medium is required. As a result, the development of a mobile application for the proposed system is necessary. Apart from developing an accurate CNN model for nutritional deficiency detection, it is also vital to provide an appealing interface for using it. The proposed idea is to create a mobile application that can predict nutrient deficiency and show the user the necessary fertilizer.

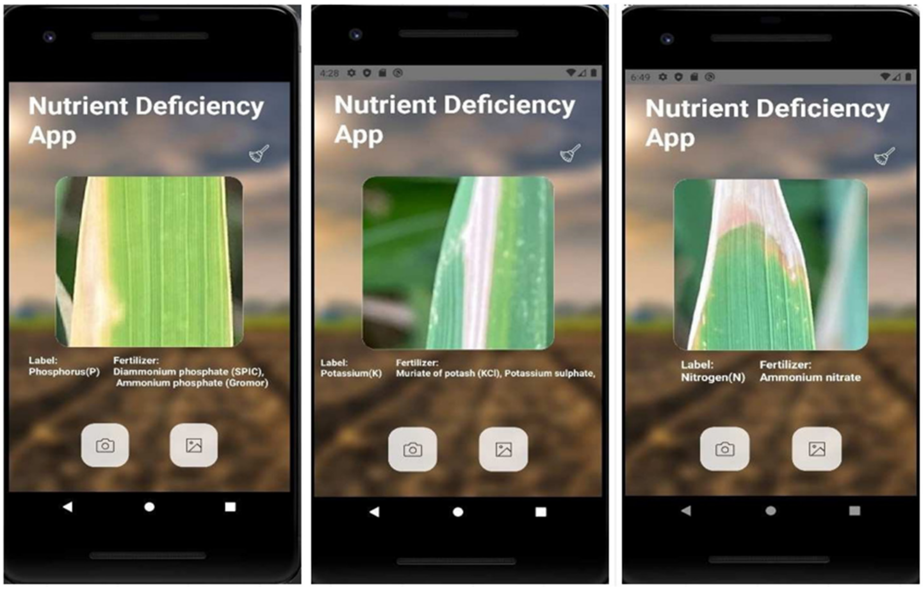

Fig. 3. Results of mobile application for types of nutrient deficiencies

The homepage is the initial step in creating a mobile application. The name of the system is displayed on the home page, along with a file for uploading images and a camera option for capturing images. The user can then upload the image and submit it for prediction.

The next step is connecting the front end to the model for the prediction of the output. It is challenging to integrate a trained model into a mobile application. We used react-native to accomplish this. The mobile application is developed with React Native and the trained model is deployed on the Google Cloud Platform (GCP). The most effective model is implemented during the deployment procedure. The image is provided to the model in the background after the user clicks the submit button, and the complete process runs within. Finally, the predicted nutrient deficiency and fertilizer are returned as output.

3 Results and discussions

The transfer learning model was obtained and its performance was checked over each epoch. The accuracy score of all the models was in the range of (87–98%). The Performance of the InceptionV3 and Xception is considered to be the highest compared to other models.

This demonstrates that the model has been learning new features with each epoch, and then using those features to predict the outcome. The increasing trend in accuracy indicates that the model has no problems with the data. The training images appear to be distinct enough to allow the model to be trained on all possible data.

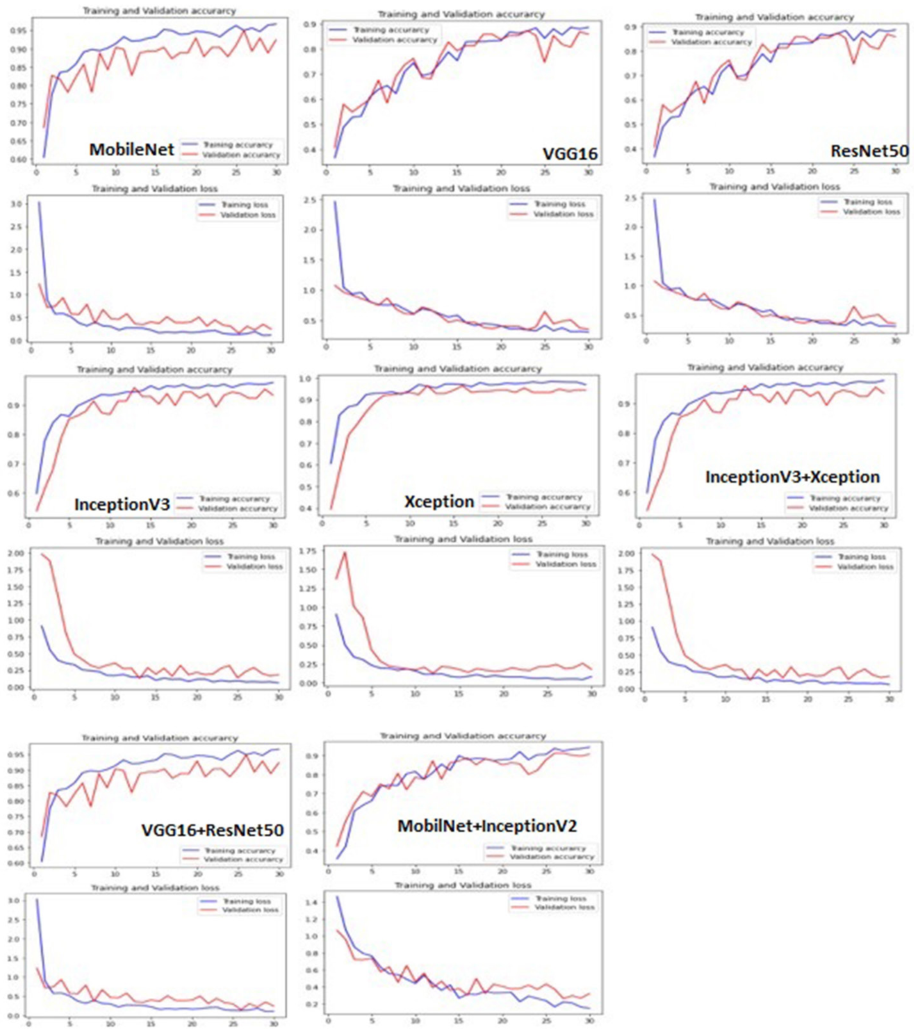

Fig. 4. Training and validation accuracy

As the epoch advanced, the model accuracy improved significantly. Over the course of each epoch, the model loss decreases. Each epoch's loss is backpropagated, and weights are adjusted correspondingly. This continuous learning over epochs helps in the reduction of loss. Over time, the number of misclassifications decreases.

For a certain number of epochs, the model is trained. The number of iterations the deep learning algorithm has made on the training dataset is stated as an epoch. The model is compared to the previous best model after each epoch, and if the current model outperforms the current best model, the current best model is updated to the present best model.

The image is transferred from the input state to the feature state and lastly to the neural network model that classifies the image in each iteration, which is called a forward pass. An iteration is a single movement from the initial to the end state. Model learning simply entails updating the weights. By backpropagating the model's errors, loss functions are utilized to retrain it. This tuning technique is enhanced by validation data. Table 2 shows the performance metrics for different transfer learning models and the proposed ensembled models.

Table 2. Performance metrics for transfer learning models and proposed ensembled models

Classifiers	Precision	Recall	F1-Score	Accuracy
MobileNetV2	92	92	92	93
VGG16	93	92	91	94
ResNet50	96	95	96	96
InceptionV3	97	95	96	97
Xception	96	97	95	97
InceptionV3 + Xception	97	96	96	98
VGG16 + ResNet50	95	94	95	96
MobileNet + Inception V3	95	94	93	95

The validation loss is for determining which model performs better. The reason for using validation loss is that it allows for a more thorough analysis of performance when compared to data other than training data. The best model is determined by having the lowest validation loss. We used the loss as the criterion for picking the best model since we needed fewer misclassifications rather than more accuracy. The loss and accuracy growth for each epoch can also be visualized for the best model.

We can determine the difference between the predicted and actual outputs by evaluating functional capabilities. This inference will aid us in developing a highly sophisticated model for nutrient deficiency detection. The elements employed in the evaluation metrics are False negative (FN), true positive (TP), false positive (FP), and True negative (TN). Accuracy, loss, confusion matrix, support, precision, f1-score, and recall are used for evaluating the model.

As a result, the final model had the best accuracy and the least loss. The model was evaluated with the dataset of 1156 photos to ensure that it was free of overfitting. The best transfer learning models are considered for the ensemble averaging model that outperformed with an accuracy of 97% and 95% for the Inception and Xception model and Resnet and MobileNet model respectively.

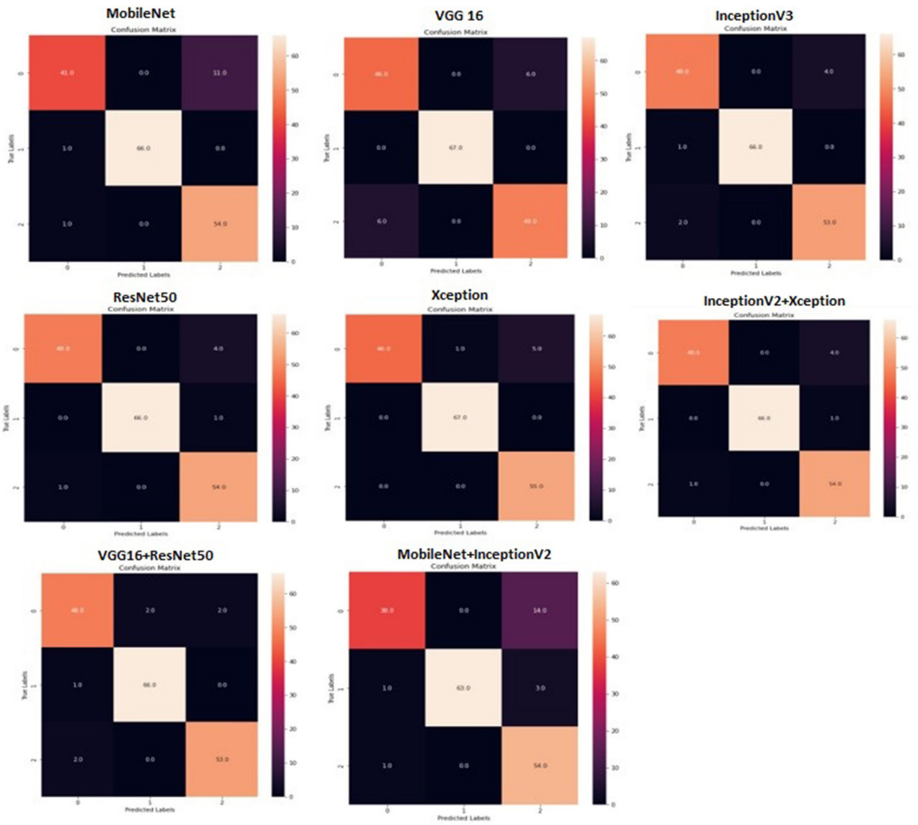

Fig. 5. Confusion matrix

The diagonal elements are more numerous, as may be observed. This is the total number of correct classifications. The number of misclassifications is represented by the sparse values in the other cells. The model identifies appropriate nutrient deficiencies and predicts the corresponding fertilizer.

Important measures including accuracy, f1-score, and support were calculated to visualize the model's performance. When the precision of the model is higher, it tends to work better. The model developed has a 98% accuracy rate. For the user to upload an image, an interactive mobile application was designed. The user can add a picture and submit it by clicking the submit button.

4 Conclusion

An ensemble averaging strategy is used for detecting rice plant nutrient deficiencies using transfer learning architectures. This was performed using five transfer learning architectures: Xception, InceptionV3, ResNet50, MobileNet, and VGG16. In the Kaggle dataset, the best results were attained with InceptionV3 (97%) and Xception (96%). When compared to individual models, the ensemble models perform significantly better i.e 98% accuracy. The average accuracy of the models improved after the ensemble approach was applied to the dataset. Accurately determining nutritional deficiencies at the proper time may assist farmers in planning future actions and covering up huge losses. As a result, serious crop damage and yield loss can be eliminated. A mobile application is developed for assisting farmers and fertilizer is recommended for corresponding nutrient deficiency present in rice plants can be applied in real time applications and severe damage to the rice plant can be avoided in early stages. The model may be taught for different crops in the future, such as cotton, chilly, and tomato plants, etc and the amount of fertilizer applied might be predicted.

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