IIIT Allahabad

Minor Project Presentation C3 23'

ML BASED RICE LEAF DISEASE DETECTION MOBILE APP

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Introduction

1. Rice is a critical crop and primary food source for many in the Indian subcontinent.
2. Rice leaf diseases can cause significant yield losses, lower grain quality, and crop failure.
3. Prompt diagnosis and treatment of rice leaf diseases are vital for sustainable agriculture and food security.
4. Convolutional neural networks (CNNs) have the ability to automate the identification of plant diseases.
5. A CNN-based model is suggested for identifying rice leaf diseases using digital photographs of leaves.
6. The model is trained using a large dataset of labeled rice leaf images affected with various diseases.
7. The model uses fully connected layers to categorize leaves into illness groups and convolutional layers to extract characteristics from input photos.
8. Using digital photographs for disease detection has several benefits, including non-invasive method and early detection of diseases to minimize yield losses.

Literature Survey

Author	Year	Title of Paper	Key Findings
Coulibaly, S., Kamsu-Foguem, B., Kamissoko, D., and Traore, D.	2019	Deep neural networks with transfer learning in millet crop images	• In Deep neural networks with transfer learning in millet crop images demonstrated that transfer learning in CNN can be used in plant leaf disease identification. • The classification accuracy has been 95% on pretrained based on feature extraction.
Y. Lu, S. Yi, N. Zeng, Y. Liu, Y. Zhang	2017	Identification of rice diseases using deep convolutional neural networks	• The study has categorized 10 classes of rice diseases on 500 images of infected rice and stems. • The experience has shown that the CNN gives a better result than to traditional techniques of identifying diseases on rice with an accuracy of 95%, by using pattern recognition bases and machine learning.

Author	Year	Title of Paper	Key Findings
Rangarajan, A.K., Purushothaman, R., Prabhakar, M. and Szczepański, C.	2023	Crop identification and disease classification using traditional machine learning and deep learning approaches	• It used two pre-trained deep learning models, AlexNet and VGG16 to classify all different types of crops then further clasiffy it into a defective and a healthy class of the crop from the image dataset. • The classification accuracy has been 99.24% for VGG16 and 96.51% for AlexNet.
Amara, J., Bouaziz, B. & Algergawy, A.	2017	A Deep Learning-based Approach for Banana Leaf Diseases Classification	• The authors use LeNet architecture as a deep convolutional neural network to classify banana sigatoka and speckle. • They obtain 98.61% of accuracy with color images and 94.44% for gray images.
Gong, A., Yu, J., He, Y., and Qiu, Z	2013	Citrus yield estimation based on images processed by an Android	• The authors use LeNet architecture as a deep convolutional neural network and get about 98% accuracy. • They discuss about various problems on out of lab implementation and encorporating such problems in an ai model

PROBLEM STATEMENT

The problem statements of the project is “Detection of Rice Leaf Disease using Machine learning Techniques”

The main focus of doing this project is to provide a high accuracy model to predict the rice leaf disease and help farmers in early detecting the rice leaf disease and increase the crop yield. This is implemented in an android application which can be used by farmers even with access to slow internet connection.

DATASET

- The data set used contains 5932 number images includes four kinds of Rice leaf diseases i.e. Bacterial blight, Blast, Brown Spot and Tungro.
- Later the dataset was divided into 80:20 ratio for train and test dataset
- Citation: Sethy, P. K., Barpanda, N. K., Rath, A. K., & Behera, S. K. (2020). Deep feature based rice leaf disease identification using support vector machine. Computers and Electronics in Agriculture, 175, 105527. doi:10.1016/j.compag.2020.105527.

METHODOLOGY

Methodology

Fig : Summary of primary 3 layer model

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 222, 222, 16)      448
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 111, 111, 16)      0
_________________________________________________________________
dropout (Dropout)            (None, 111, 111, 16)      0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 109, 109, 32)      4640
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 54, 54, 32)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 54, 54, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 93312)             0
_________________________________________________________________
dense (Dense)                (None, 30)                2799390
_________________________________________________________________
dense_1 (Dense)              (None, 10)                310
_________________________________________________________________
dense_2 (Dense)              (None, 100)               1100
_________________________________________________________________
dense_3 (Dense)              (None, 133)               13433
_________________________________________________________________
dense_4 (Dense)              (None, 4)                 536
=================================================================
Total params: 2,819,857
Trainable params: 2,819,857
Non-trainable params: 0
```

Methodology

Fig : Summary of primary 3 layer model with added another layer of dimension and dropout

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 16)	448
max_pooling2d (MaxPooling2D)	(None, 111, 111, 16)	0
conv2d_1 (Conv2D)	(None, 109, 109, 32)	4640
max_pooling2d_1 (MaxPooling2	(None, 54, 54, 32)	0
conv2d_2 (Conv2D)	(None, 52, 52, 32)	9248
max_pooling2d_2 (MaxPooling2	(None, 26, 26, 32)	0
conv2d_3 (Conv2D)	(None, 24, 24, 32)	9248
max_pooling2d_3 (MaxPooling2	(None, 12, 12, 32)	0
flatten (Flatten)	(None, 4608)	0
dense (Dense)	(None, 30)	138270
dense_1 (Dense)	(None, 10)	310
dense_2 (Dense)	(None, 100)	1100
dense_3 (Dense)	(None, 133)	13433
dense_4 (Dense)	(None, 4)	536

Total params: 177,233
Trainable params: 177,233
Non-trainable params: 0

Methodology

Fig : Summary of primary 6 layer model with added another layer of dimension and dropout

Model: "sequential_2"

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(32, 256, 256, 3)	0
conv2d (Conv2D)	(32, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(32, 127, 127, 32)	0
conv2d_1 (Conv2D)	(32, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling2	(32, 62, 62, 64)	0
conv2d_2 (Conv2D)	(32, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling2	(32, 30, 30, 64)	0
conv2d_3 (Conv2D)	(32, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling2	(32, 14, 14, 64)	0
conv2d_4 (Conv2D)	(32, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling2	(32, 6, 6, 64)	0
conv2d_5 (Conv2D)	(32, 4, 4, 64)	36928
max_pooling2d_5 (MaxPooling2	(32, 2, 2, 64)	0
flatten (Flatten)	(32, 256)	0
dense (Dense)	(32, 64)	16448
dense_1 (Dense)	(32, 4)	260

Total params: 183,812
Trainable params: 183,812
Non-trainable params: 0

RESULTS

Results

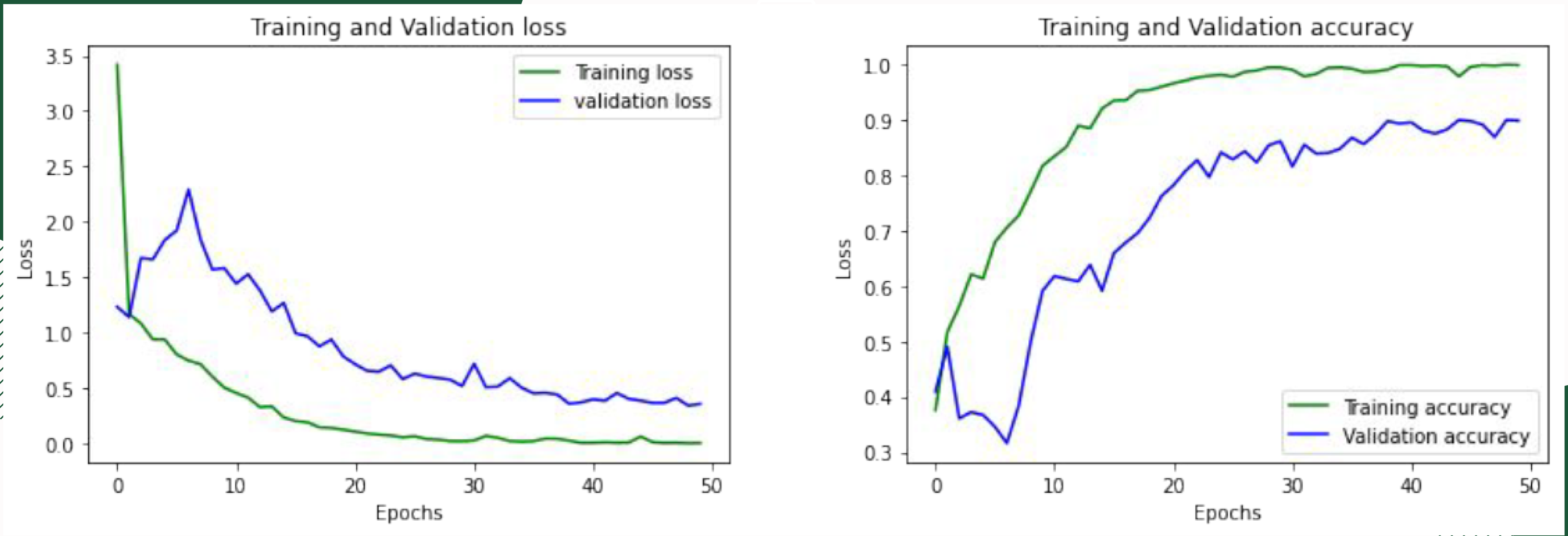

Fig. Graph of Loss vs Epoch and Accuracy vs Epoch on training and validation data of primary three layer model.

Results

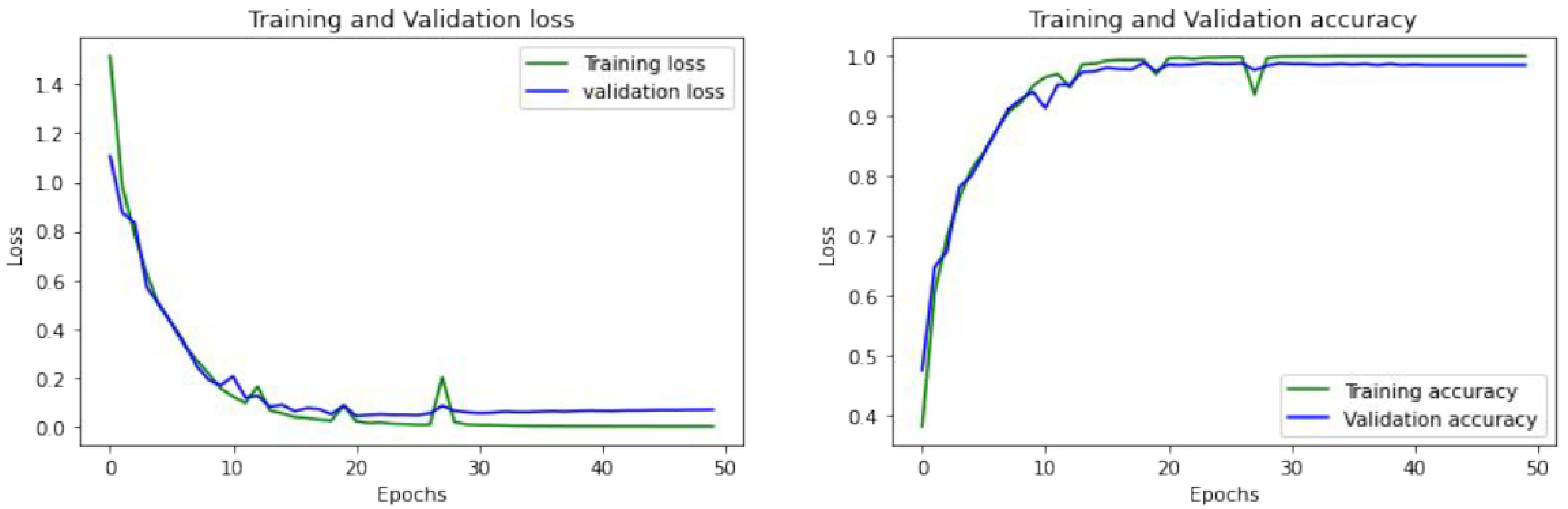

Fig. Graph of Loss vs Epoch and Accuracy vs Epoch on training and validation data of primary three layer model with added another layer of same dimension and dropout

Results

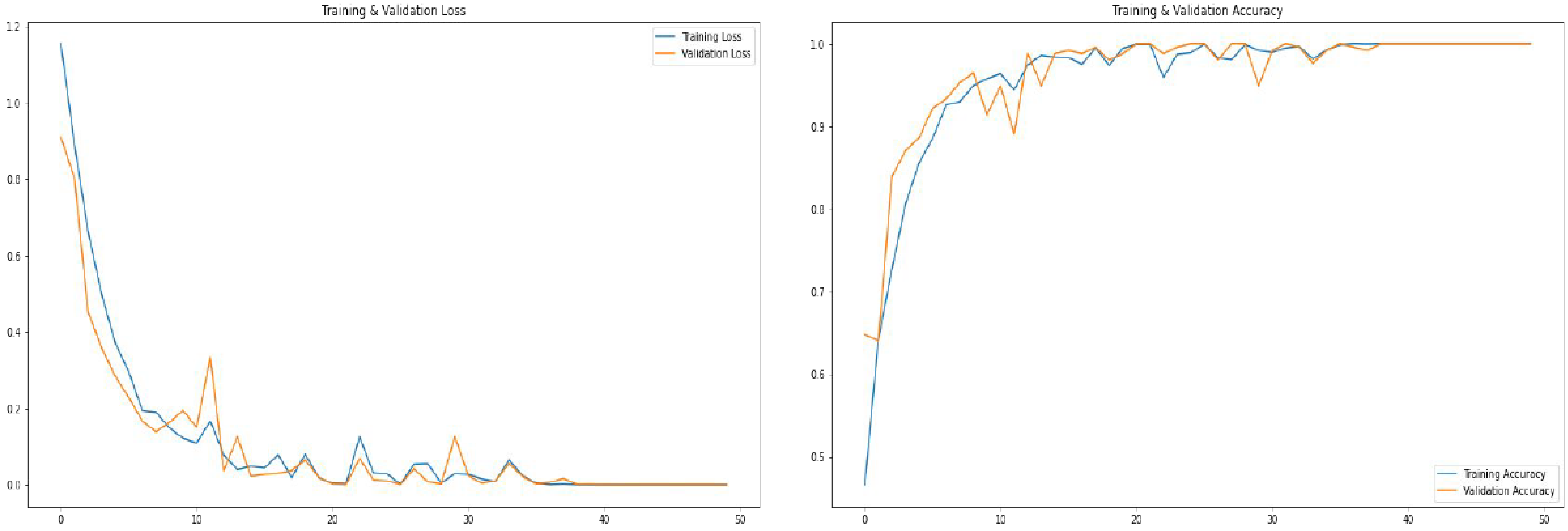

Fig. Graph of Loss vs Epoch and Accuracy vs Epoch on training and validation data of primary three layer model with added another layer of same dimension and dropout

DEPLOYMENT OF ANDROID APP

- The model is deployed in an android model
- The application doesn’t require high speed internet connection and works offline so that the application can be used with places having slow internet connection.
- The application is easy to use

Android Application

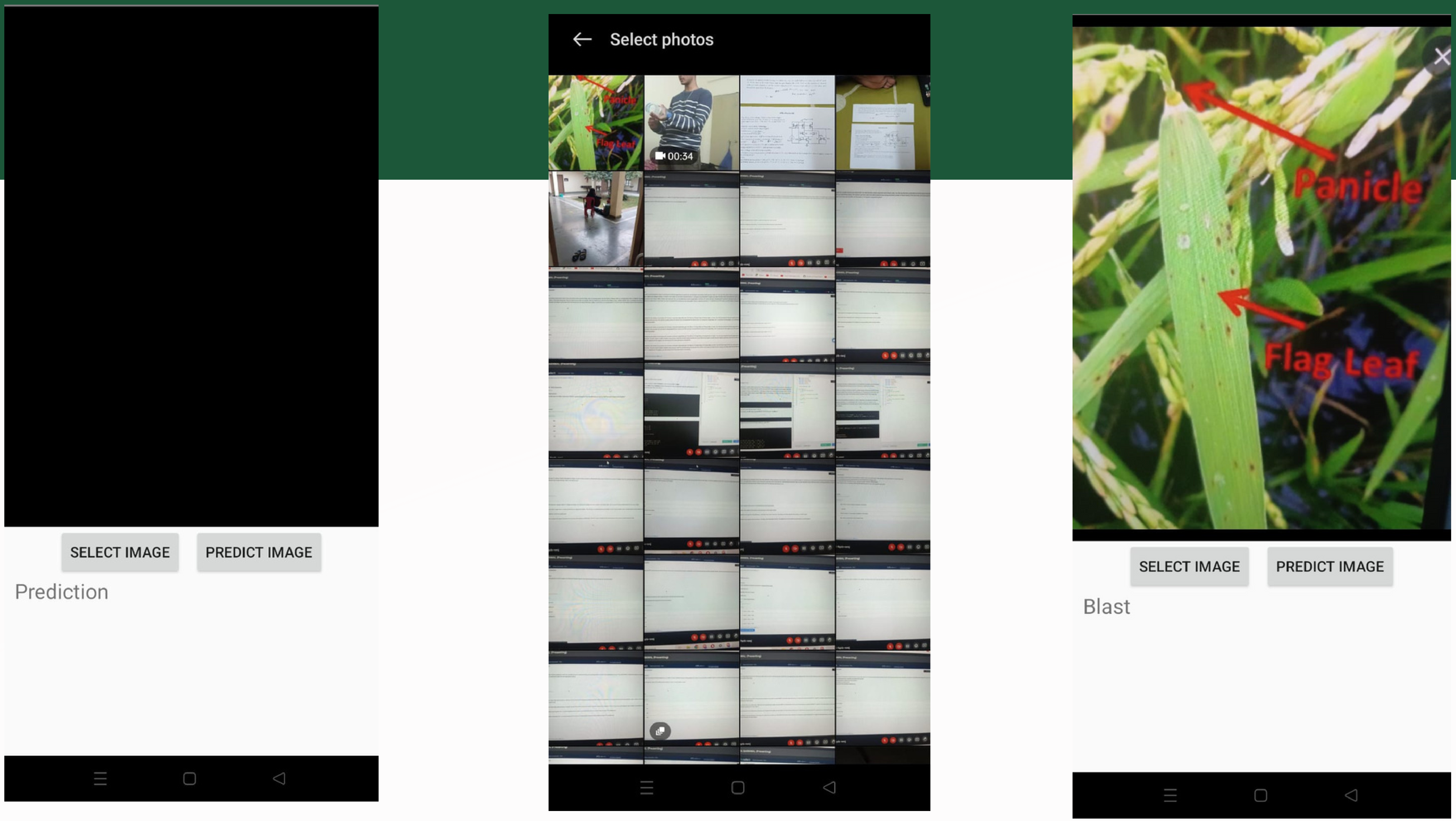

Fig : App launched from homescreen -- select image from gallery -- the result is shown

Conclusion

- A deep learning-based approach using CNNs was proposed for the detection of rice leaf diseases.
- A model was developed and trained on a large dataset of labeled rice leaf images with an accuracy of 96% and above.
- An android application was implemented for farmers to detect rice leaf diseases quickly and easily.
- The use of digital images for disease detection has several advantages over traditional methods, including early detection and non-invasive techniques.
- The android application can improve rice production and reduce yield losses, while the model can be utilized by researchers and agricultural experts.
- The proposed model and application offer a valuable contribution to the field of deep learning and agriculture.
- This thesis provides a reliable and efficient tool for the detection of rice leaf diseases, potentially contributing to sustainable agriculture and food security in the Indian subcontinent.

FUTURE SCOPE

- A larger and more diverse dataset can be used having images with high resolution images can be used and the model’s performance can be optimized using hyperparameter tuning and use of transfer learning model like VGG16 and VGG19
- Integrating the model with other technologies like IoT sensors or drones can provide more accurate and real-time data for disease detection and management for mechanized farming over large farm fields.

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THANK YOU