DeepFruit: A Unified Deep Learning Framework for Fruit Classification and Quality Evaluation

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Abstract. The dual problem of classification and grading of fruits, a very important aspect in agricultural automation, is seldom pursued in the sphere of personal computer vision. Though several works are performed based on features regarding size, shape, and color using CNNs for classification, the current work will utilize transfer learning to leverage pre-trained deep learning models. This work classifies six categories of fruits namely banana, apple, orange, pomegranate, lime, and guava using the FruitNet Indian Fruits dataset comprising 19,400 images by implementing various architectures like MobileNetV2, EfficientNetV2, NASNet, DenseNet, VGG16, InceptionV3, and Xception. It is observed that pre-processing increased the model performance for classification and grading by a huge margin to enable MobileNetV2 to go as high as 99.7% accuracy. In this paper, a discussion will be made on the possibility of applying MobileNetV2 in fruit classification and grading for improvement towards developing agricultural automation.

Keywords: Deep Learning · Convolutional Neural Network · Transfer Learning · classification · Quality grading · Keras Integration · FruitNet Indian dataset

1 Introduction

Fruits are one of the most important foods for the body because of their contents of vitamins and minerals[1], and as such, they are indispensable in human nutrition. In the fruit quality traditional grading, much reliance has been placed on human inspection based on color, shape, size, ripeness, and cleanliness. However, new technologies have totally changed this situation in recent decades with computer vision and machine learning[2][3].Those tools enable the performance of certain human functions more quickly and with high precision, with a view to reducing production costs. Deep learning has become the primary methodology on which fruit classification and quality grading[4] have been based, mainly through techniques using CNNs. While there has been some progress, most works have focused on single types of fruits[5][6]. Our work deals with this shortcoming by proposing a flexible solution able to classify and grade different fruit types. We adopt the approach of transfer learning and benchmark our model based on the MobileNetV2 architecture. First, we train a model for fruit classification and then fine-tune it for quality estimation, using knowledge derived during the first training cycle.

A significant use case of MobileNetV2 would be to be deployed quickly on low power devices, such as crop health monitoring, pest detection, yield prediction in the pre-harvesting stages[2], and fruit grading and vegetable grading in the post-harvesting stages. This streamlined model brings faster assessments of the crops grown and can help farmers and agricultural technicians who make such decisions straight from the field by using data-driven inputs. From this analysis, it can be found that MobileNetV2 supports every single cycle at the agricultural level toward enhancing the decision-making capabilities and process automation. MobileNetV2 reduces human errors due to faster, yet constant assessments of quality. This paper proposes to demonstrate the applicability of MobileNetV2 in automating fruit classification and grading, thus pushing agriculture workflows toward efficiency and accuracy. Scaling technology-based approach allows practical agricultural[7]machine vision in order to enable holistic automation in multi-fruit variety classification and grading[4].

2 Related Work

Out of the remainder studies conducted,Lama A. Aldakhil And Aeshah A. Almutairi in 2024, EfficientNetV2 was quite accurate during the same-domain transfer learning for multi-fruit classification using the FruitNet dataset along with recommendations for the next steps on multiple task learning adoption[4]. In the year 2023, Sultanabanu Kazi and Kazi Kutubuddin were speaking at a discussion on the image processing techniques on grading and fruit detection of disease. This is how it can lead to improvement in the accuracy as well as effectiveness of crop quality and further issues pertaining to crop health[7].Another 2024 paper, Divya Arivalagan et al. used the FruitsGB dataset in the building of a transfer learning-based smart fruit classifier, in which they considered the potential of deep models and the urgent need to improve the accuracy[8].WEIWEI ZHANG in 2023 claims that YOLOv5 automatic grading and sorting fruits were carried out with dramatic depth with potential and other work on deep learning in proposed [9].

In the year 2023, Farsana Salim et al. have an exhaustive comparison of DenseNet201 and Xception networks for fruit segmentation, and it was observed that both models were effective in fruit segmentation [10].Non-Destructive Deep Learning Method for Classifying Fresh/Rotten Fruit: As per this paper,Surya kant pal et al. the researchers will get a scope to develop fruit detection based on hybrid designs[11].In another study undertaken in 2022 by Jin Wang et al. They conducted a cross domain fruit advanced classification[12] adopting lightweight attention networks and unsupervised domain adaptation, fulfilling the aim of persuading enhancement along with the aid of introducing a hybrid module.In 2023, Tej Bahadur Shahi et al.conducted the survey consists of a modified MobileNetV2 model for classifying fruit images, and achieves 99% accuracy using advanced deep learning techniques and data enhancement to prevent overfitting[13]. In 2023,The IPDC-HMODL model by Johnson Kolluri and Ranjita Das integrates YOLO-v5 and RetinaNet for pedestrian detection, using KELM for classification, with HSSO optimizing parameters for enhanced accuracy. This multimodal approach outperforms other detection models[14].

3 Methods and Materials

3.1 Dataset Preperation

We hired data set which is publicly available and mainly serves for model training and testing purposes; It has up to 19,400 high-resolution pictures[17] of various fruits comprising six classes of apples, bananas, pomegranates, guavas, oranges and limes.The incorporated class for each image includes good quality, bad quality, and mixed quality that supports multi-task learning[4].The images that are part of this dataset have been taken with a cell phone having high resolution camera in different backgrounds and lighting conditions. All images in this dataset are 256 x 256 pixels in size we reorganized these images into folders or directories specific to their classifications so as to suit our needs by dividing each fruit into classes based on their qualities. We used Python scripts to divide the data into an 80% training set and a 20% testing set.

Fig. 1. Good Quality Fruits

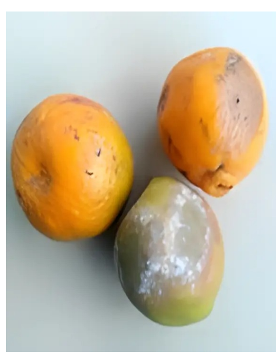


Fig. 2. Bad Quality Fruits

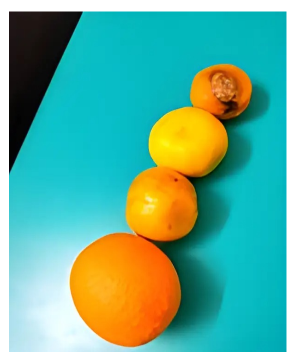


Fig. 3. Mixed Quality Fruits

3.2 Data Pre-processing

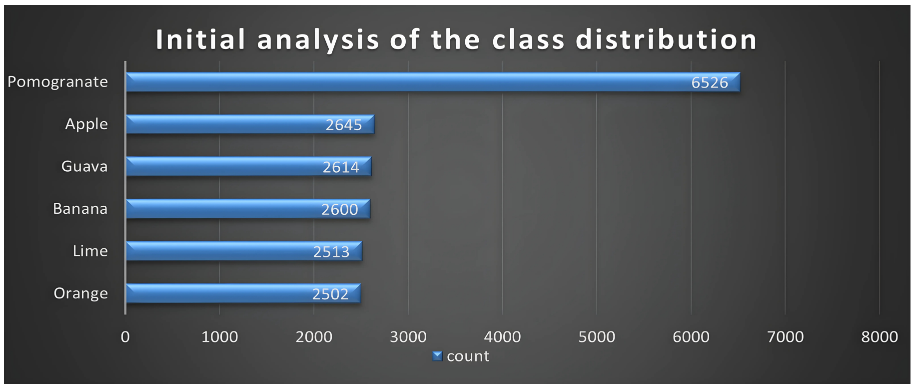


Fig. 4. Indicates an over-representation of the pomegranate class

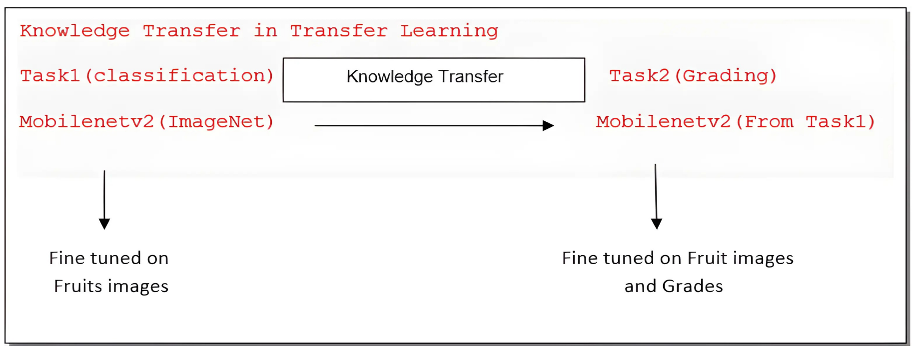
The Fig 4 was carried out as the first step in analyzing the class distribution of the training dataset, which showed that the pomegranate class is over represented. This is owing to the prior oversampling techniques used by the creators of the dataset. This therefore called for a pre-processing strategy which would offset this and reduce the possibility of model overfitting.

The raw harvest images must be converted into a formattable machine learning algorithms with data preprocessing[15]. Using libraries such as NumPy, TensorFlow, OpenCV, and scikit-learn, images are resized and normalized to enable better performance in a model. Libraries like NumPy provide fast arithmetic operations and handle large data sets, which form the backbones of these libraries[10]. Resizes image OpenCV also makes sure that images are converted from BGR to RGB, which is the format of a model. The 'train_test_split' function in Scikit-learn splits the data into an 80-20 training to testing split, then resized and converted RGB and stored as NumPy arrays, pixel values normalized between [0, 255] to [0,1],improve stability and accuracy of fruit grading and classification[16].

4 Overview of the MobileNetV2 Architecture

MobileNetV2 utilizes Conv2D for feature extractions including edges, textures; DepthwiseConv2D for higher performance at lower computational cost; Batch Normalization to stabilize the activations and speed up the convergence during training[13]. ReLU6 can improve the performance on small devices by bounding the upper value of activation. ZeroPadding2D keeps the size of a feature map in a convolutional layer. GlobalAveragePooling2D reduces the feature map in size, preventing overfitting, which also reduces the number of parameters. Dropout randomly turns off neurons to regularize overfitting. In MobilNetV2 transfer learning, it considers a pre-trained model from ImageNet and removes all fully connected layers and trains the convolutional base on particular features. The convolutional basis is followed by Global Average Pooling and dense layer of ReLU so nonlinearity is introduced. Further, this also includes an extra Dropout layer to prevent overfitting and then a classification layer tuned to the number of fruit varieties in the dataset.

4.1 How it works



The above diagram depicts how to use transfer learning within the MobileNetV2 architecture to allow for the transfer of knowledge between tasks. First, it trains a model on a large set of fruit images[17]. Task 1 is classifying different kinds of fruits and learning fruits based on their unique features. Then, the model is fine-tuned for grading fruits based on what it had learned in the knowledge classification process. That way, the process is much more efficient because features learned in Task 1 can then be applied immediately for grading and therefore an enormous amount of new training would not be necessary. This transfer learning will speed up training and hence improve the judgment ability of the model about fruit quality.

4.2 Model Analysis

Among the 4,793,546 total parameters within the MobileNetV2 architecture, there are 4,759,434 trainable parameters, which implies that almost the whole model could have been learned during training. This robust proportion of trainable parameters significantly contributed to how the features would be learnt by the model and equally to achieving very good results.The 34,112 non-trainable parameters remained to stabilize and regularize the model without excessive complexity added. This balance of trainable and non-trainable parameters made the model perform well but kept it efficient and lightweight to fit MobileNetV2 into real-time applications.

Layer (Type)	Output Shape	Param #
mobilenetv2_1.00_128	(None, 4, 4, 1280)	4,257,984
GlobalAveragePooling2D	(None, 1280)	0
dense	(None, 256)	527,936
dropout	(None, 256)	0
dense_1	(None, 18)	6,626

Table 1. Model: `sequential`

- **Total Params:** 4,793,546 (9.88 MB)
- **Trainable Params:** 4,759,434 (9.75 MB)
- **Non-Trainable Params:** 34,112 (133.25 KB)

5 Formulae related to MobileNetV2 Architecture

5.1 Depthwise Convolution

$$\text{ODepthwise} = \sum_{k=1}^{K} I_k * W_k \tag{1}$$

5.2 Pointwise Convolution

$$\text{OPointwise} = \sum_{C=1}^{C} D_C \cdot P_C \tag{2}$$

5.3 Inverted Residuals

$$\text{OInverted Residual} = \text{OPointwise} + I \tag{3}$$

5.4 Bottleneck Residual Block

$$\text{OBottleneck} = \text{OPointwise}_2 + I \tag{4}$$

5.5 Global Average Pooling Output

$$\text{OGAP} = \frac{1}{H \times W} \sum_{i=1}^{H} \sum_{j=1}^{W} x_{i,j} \tag{5}$$

6 Environmental Setup

The environmental setup changed into conducted on Google Colaboratory using a Colab Pro subscription. This cloud-based provider totally provides an interactive Jupyter Notebook surroundings, with computational sources inclusive of a T4 GPU, with RAM 12.7 GB, and with Disk Space 166.8 GB. The dataset is integrated through Google Drive for perfect access and management.

7 Evaluation Metrics

7.1 Evaluation on MobileNetV2

CLASS	Precision	Recall	F1-Score	Support
Lime_bad	0.98	0.99	0.99	204
Guava_bad	1.00	0.99	0.99	209
Orange_bad	0.99	0.98	0.99	244
Pomegranate_bad	1.00	0.99	1.00	252
Banana_bad	0.99	1.00	0.99	215
Apple_bad	1.00	0.99	0.98	237
Lime_good	0.99	1.00	0.99	222
Apple_good	1.00	0.99	0.98	232
Banana_good	0.99	1.00	0.99	220
Orange_good	0.98	0.99	0.97	223
Pomogranate_good	1.00	1.00	1.00	1241
Guava_good	0.99	0.99	0.99	216
Apple_mixed	1.00	1.00	1.00	20
Guava_mixed	1.00	1.00	1.00	17
Orange_mixed	1.00	0.97	0.98	27
Lemon_mixed	0.99	0.98	0.99	55
Banana_mixed	0.98	0.99	0.98	49
Pomogranate_mixed	1.00	0.98	0.98	23
Macro avg	0.99	0.99	0.99	3906
Weighted avg	0.99	0.99	0.99	3906
Accuracy		**0.99**		3906

Table 2. Evaluation metrics report for the fruit type model on the test set.

Fruit	Precision	Recall	F1-Score	Support
Bad_Quality	0.99	0.99	0.99	552
Good_Quality	1.00	0.99	1.00	908
Mixed_Quality	0.98	0.99	0.99	112
Macro avg	0.99	0.99	0.99	3906
Weighted avg	0.99	0.99	0.99	3906
Accuracy		**0.99**		3906

Table 3. Evaluation metrics report for the fruit quality model on the test set.

The above Table 2 and Table 3 presents evaluation metrics for the MobileNetV2 model in fruit classification based on kind and quality, respectively. Table 2 displays the model performing well on all fruit kinds with consistency in precision, recall, and F1-scores at an average accuracy of 99%. Table 3 is pretty much in the same scenario, having a great performance in the classification of fruit quality where bad and good quality classes have almost perfect metrics again with an accuracy of 99%.

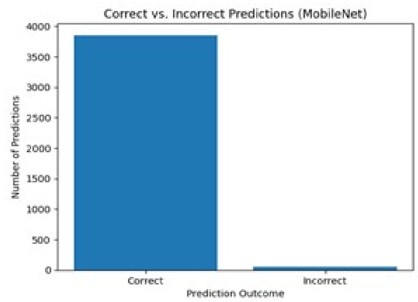


Fig. 5. Correct vs. Incorrect Predictions using MobileNet

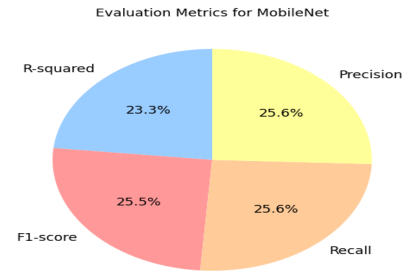


Fig. 6. Evaluation Metrics for MobileNet

8 Comparitive Analysis of other CNN Models

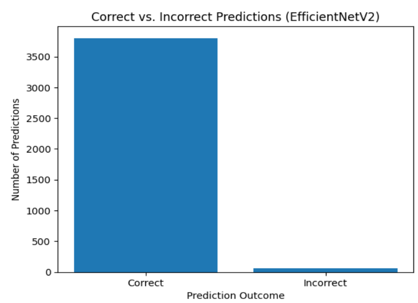


Fig. 7. Correct vs. Incorrect Predictions using EfficientNetV2

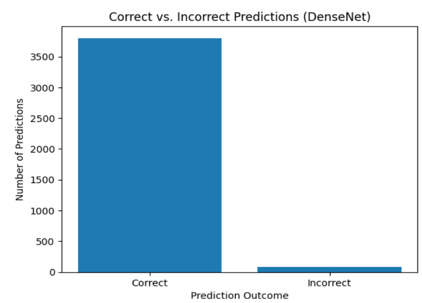


Fig. 8. Correct vs. Incorrect Predictions using DenseNet

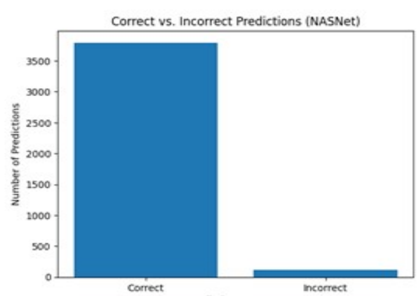


Fig. 9. Correct vs. Incorrect Predictions using NASNet

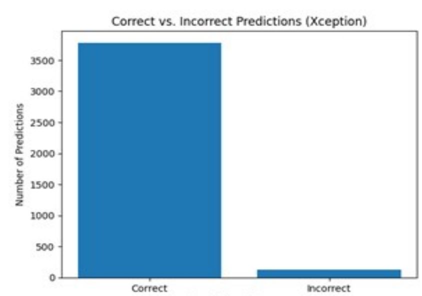


Fig. 10. Correct vs. Incorrect Predictions using Xception

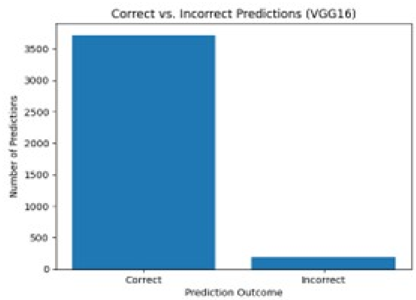


Fig. 11. Correct vs. Incorrect Predictions using VGG16

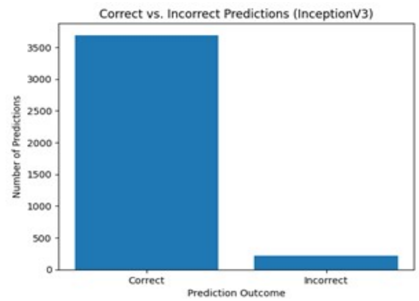


Fig. 12. Correct vs. Incorrect Predictions using InceptionV3

Model	**Precision**	**Recall**	**F1-Score**
EfficientNetv2	0.99	0.98	0.97
VGG16	0.95	0.93	0.94
InceptionV3	0.96	0.97	0.95
Densenet	0.98	0.98	0.96
Nasnet	0.97	0.98	0.99
Xception	0.98	0.99	0.95

Table 4. Evaluation metrics for other compared models regarding fruit type.

Model	**Precision**	**Recall**	**F1-Score**
EfficientNetv2	0.98	0.95	0.96
VGG16	0.98	0.92	0.91
InceptionV3	0.95	0.98	0.97
Densenet	0.97	0.97	0.97
Nasnet	0.96	0.98	0.98
Xception	0.97	0.97	0.95

Table 5. Evaluation metrics for other compared models regarding fruit quality.

Method	**Accuracy**
Mobilenetv2	99.7% (Proposed Approach) ✓
Efficientnetv2	99.5%
Densenet	98%
NASNET	97.6%
Xception	97%
VGG16	96%
Inceptionv3	95.75%

Table 6. Accuracy of all models

Among all the models tested for the variety and quality assessment of fruits, the highest accuracy achieved was 99.7% by MobileNetV2. More details in terms of precision, recall, and F1 scores about other models have been depicted above Table 4 and Table 5 and the overall performance in Table 6. The MobileNetV2 model has turned out to be the most effective of all the tasks performed. Precisely, MobileNetV2 had attained an accuracy of 99.7% at Table 6, while EfficientNetV2 reached 99.5% and DenseNet at 98%. This architecture's success demonstrates its suitability for efficient and high-performing applications in fruit classification and grading.

9 Evaluating Model Performance with Confusion Matrices

The confusion matrices analysis described MobileNetV2 to be the best based on the evaluation of various CNN architectures, which include MobileNetV2, EfficientNetV2, DenseNet, NASNet, Xception, VGG16, and InceptionV3. Excellent extracting features with very light computational operations, and could be termed very effective for fruit classification and grading use cases. The model achieved accurate results but with the assumption that reduced computational load required for the processing which suitable for real-time processing and scalability. Its performance gains over other models confirm that MobileNetV2 is optimized for applications that need precision and speed to come together. MobileNetV2 emerges as a practical and powerful model choice compared to all other architectures tested for this application.

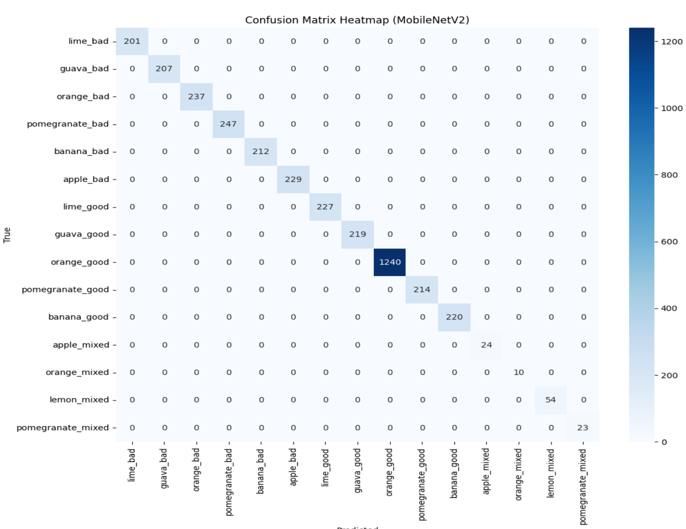


Fig. 13. MobileNetV2 Confusion Matrix

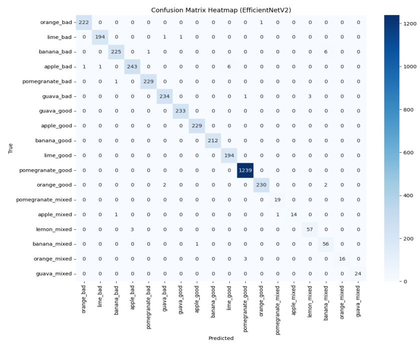


Fig. 14. EfficientNetV2 Confusion Matrix

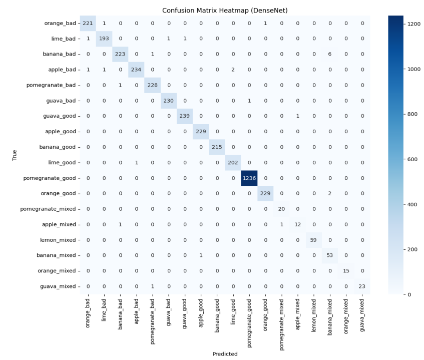


Fig. 15. DenseNet Confusion Matrix

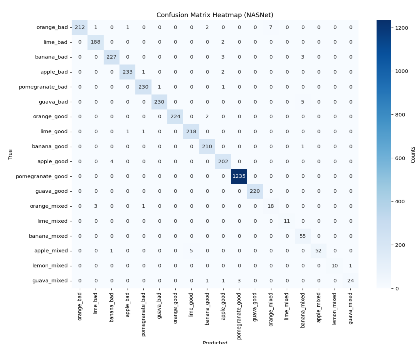


Fig. 16. NASNet Confusion Matrix

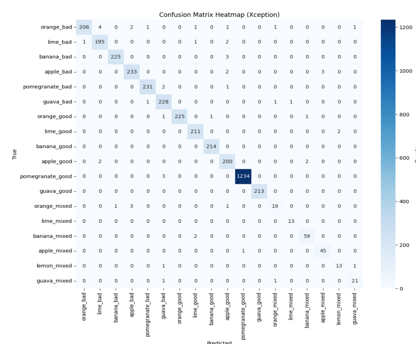


Fig. 17. Xception Confusion Matrix

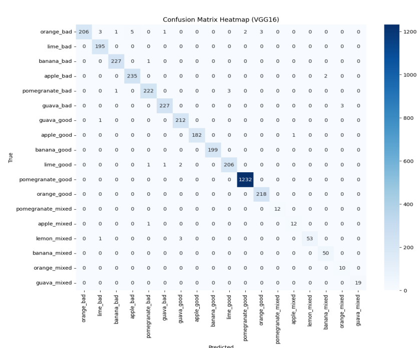


Fig. 18. VGG16 Confusion Matrix

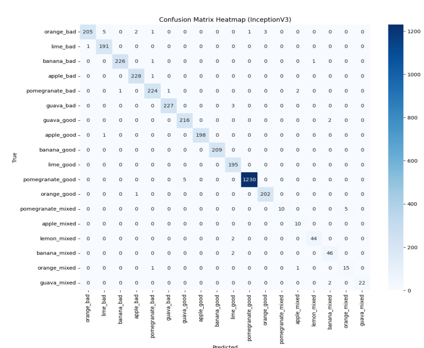


Fig. 19. InceptionV3 Confusion Matrix

10 Result

As explained in Table 6 and Section 9, the MobileNetV2 model outperformed other EfficientNetV2, DenseNet, Xception, VGG16, InceptionV3, and NASNet models on accuracy. This is further confirmed from the training and validation metrics represented in Figure 20 and 21.

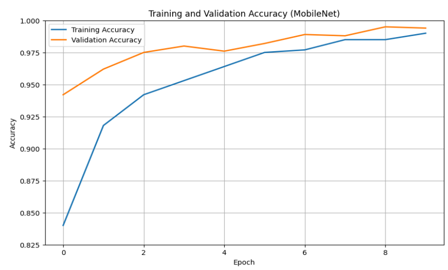


Fig. 20. Accuracy in training and for validation

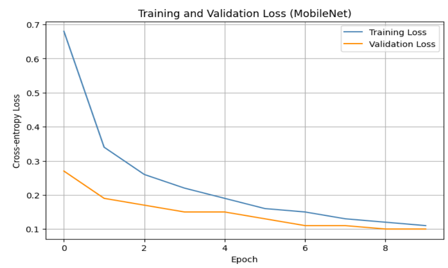


Fig. 21. Loss in training and for validation

– In fig20, it can be observed that the training and validation accuracies of MobileNet rise up to 99% in 10 epochs with closely aligned curves. It is a sign of good generalization without overfitting.
– In fig21, The overall reduction of training and validation losses signifies that the MobileNet model learns well, and both losses are converging to 0.1. Since always the loss for validation is less than that of training, this hints at good generalization and no signs of overfitting

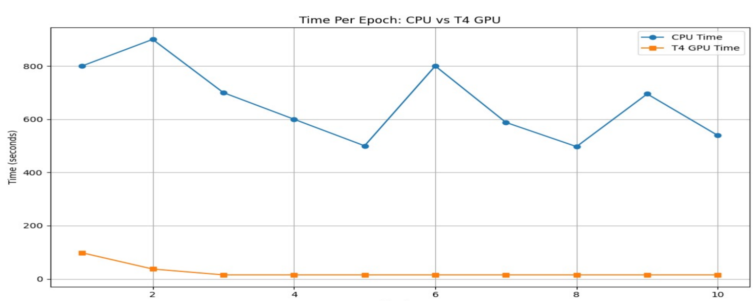


Fig. 22. Time per Epoch - CPU VS T4 GPU

The fig 22 depicts that, T4 GPU significantly reduces the training time per epoch compared to the CPU, speeding up model development and testing. This makes it important for high-performance machine learning experiments.

11 Conclusion

In conclusion, this paper demonstrates the application of MobileNetV2 with great potential uses in the agriculture practices to obtain optimization in automation and more efficient and scalable farming practices. EdgeML, EdgeAI, and IoT devices ensure setting up significant applications for development under agricultural conditions.It not only optimizes operational efficiency but also brings about innovative solutions to respond to changing agriculture challenges. At the end, this step is a full leap towards the transformation of farming practice into an automated and data-based business that can meet the challenging needs of a demanding people.

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