TRANSFER LEARNING BASED AUTOMATED CROP ANALYSIS

A DISSERTATION REPORT

SUBMITTED IN THE PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF THE DEGREE

OF

MASTER OF TECHNOLOGY

IN

VLSI DESIGN & EMBEDDED SYSTEMS

Submitted by:

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May, 2022

UNDERTAKING

I declare that the work presented in this project titled "**Transfer Learning Based Automated Crop Analysis**", submitted to the **Department of Electronics & Communication Engineering, Delhi Technological University, Delhi** for the award of the **Master of Technology** degree in **VLSI Design & Embedded Systems** is my original work. I have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, I accept that my degree may be unconditionally withdrawn.

Date: 30/05/2022

Place: Delhi

Sachin Kumar (2K20/VLS/16)
M.Tech VLSI & Embedded Systems
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CERTIFICATE

This is to certify that the work contained in the project titled "**Transfer Learning Based Automated Crop Analysis",** submitted by **Sachin Kumar, Roll no. 2K20/VLS/16,** in the partial fulfillment of the requirement for the award of Master of Technology in VLSI & Embedded Systems to the Electronics & Communication Engineering Department, Delhi Technological University, Delhi, is a bonafide work of the students carried out under my supervision.

Place: Delhi

Date**:** May 30, 2022

Dr. Chhavi Dhiman

Supervisor

Department of ECE

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ABSTRACT

In our project work, we have implemented the notion of transfer learning for classification of fruits, crops and vegetables. Every year the quality of large amount of crops and fruits deteriorates because of the lack of essential nutrients provided to them. In many areas, more than one crop are harvested in a single field which makes it very difficult for the farmer to provide proper nutrients to each and every type of crops as every crop requires specific kind of nutrients. To overcome this scenario, we have implemented the method of transfer learning using pretrained models to segregate the crops based on the features like size, colour, quantity and so on. Two pretrained deep learning models namely ResNet50 and MobileNet are fine-tuned appropriately to evaluate the quality of fruits and crops. For the evaluation of these fine-tuned models, we collected datasets of 15 different classes of fruits and crops. The dataset of each class consists of approximately 500 images. Based on these datasets, both the models were evaluated. The result of the models shows that ResNet50 model achieved the higher test accuracy as compared to the MobileNet model. The hardware implementation of our project includes the deployment and testing of our model on the Jetson Nano Developer kit in real time. Also, it includes calculating how long it takes the setup to compute a single frame at the time of real time testing.

ACKNOWLEDGEMENT

I'd want to convey my deep heartfelt gratitude and devotion to our excellent and well recognized guide Dr. Chhavi Dhiman for recommending my project's theme and providing me with entire freedom and flexibility to work on it. She has been very encouraging and motivating and the intensity of encouragement and motivation has always increased with time. Without her constant support and guidance, I would not have been able to perform efficiently and learn from this project.

I am thankful to my cohorts and peers for giving me constant support and help whenever I asked for it. I also extend my sincere thanks to all my friends who have patiently helped us directly or indirectly in accomplishing this project successfully.

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NOMENCLATURE

Abbreviations

ResNet	Residual Network
MobileNet	Mobile Network
RNN	Recurrent Neural Network
ANN	Artificial Neural Network
AvgPool	Average Pooling
Conv	Convolution
MaxPool	Maximum Pooling
CNN	Convolutional Neural Network

CHAPTER 1

INTRODUCTION

Crops and fruits are one of the major sources of nutrition required by the human body. As a result, both crops and fruits are consumed in large amounts by human beings worldwide. However, while buying crops and fruits, humans tend to visually inspect the items from the market. Visual evaluation of crops and fruits is possible, but it is a difficult and subjective procedure that relies on an inconsistent set of criteria. The proposed framework utilised the appearance of the crops, its texture and the colour of the items. The quick recognition of various fruits, vegetables and crops using machine learning and improving the precision of fruit classification to improve farmer's multi-species cognition level is one of the main targets of research on algorithm of fruits and crops classification in real world. The application of our model could easily let a farmer know when the fruit is ripe or when the fruits start to rot. Also, any disease in our fruits and crops can be detected at early stages so that it could be cured timely, without human intervention. This kind of automation in the field of agriculture can bring lots of ease to the farmers in the field. We have two objectives for our crop analysis project. The first objective is the designing of a transfer-based learning algorithm for crop analysis or crop classification and the second objective is to deploy our model of the Jetson nano Developer kit so that we can produce the results in real time. The purpose of deploying the algorithm on the kit is that the models are defined but they are not producing results in real time as per our requirement. So, the aim is to develop a light model that can be deployed on a movable device with a limited computation capacity and still can perform a good monitoring solution.

The work is organized in five sections. The introduction of the research work is covered in the Chapter-1. In chapter 2, we have discussed about the literature survey in reference with our experiment. The steps required for the classification of fruits and crops are also covered. We have also talked about the method of transfer learning and data augmentation. We have also talked about how we have trained the datasets and finally the testing and validation of the model has been done. In Section-3, that is the proposed work, we have discussed about the collection of data and dataset, also the specifications of the framework used and hardware implementation of our project and the specifications of Jetson nano developer kit. In section-4, the experimentation results are reported and discussed. Finally, in section-5 Conclusion of our work and the future scope of our experiment is provided, followed by references.

CHAPTER 2

LITERATURE SURVEY

The literature survey provides the description of the process of image classification, which include creating database and the process of training of the model. The approach of transfer learning and data augmentation is also discussed with an example of data augmentation applied on an image.

2.1 Steps for Image Classification

Crop and fruit identification is used in a variety of settings. Identification in the retail industry and regions where the goal is to make harvesting easier from an agriculture standpoint are the most popular. Identification is typically done manually or via self-service technology in the market or in the retail industry. In the fields of agriculture and botany, classification is a fundamental scientific project. Thousands of different species have been discovered thus far. People will be perplexed since they are unfamiliar with fruit species. As a result, the creation of crops and fruits classifier will make people's life easier.

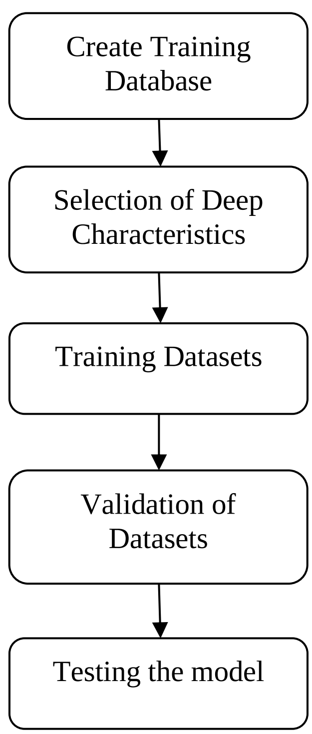


Figure 2.1 Stages of Image Classification

A classifier can be defined as an algorithm that employs a combination of attributes that characterise things to identify which class each object belongs to. Shape, colour, size, and other characteristics of crops and fruits are example of these characteristics. These properties are then used by the classifier to determine the crops and fruits. The steps used for image classification using transfer learning are shown in Figure 2.1.

Unsupervised and supervised classification [1] procedures are the two types of classification techniques. As we talk about supervised classification, a human would have established the category an object falls within, as well as provided multiple datasets that match with those classifications [1] [2]. The dataset used for training consists of generally recognised objects that are used by the classification system in order to understand the procedure of classification of things. Unsupervised categorization mostly works on the process of pixel-based analysis as there are no pre-determined classes or training datasets [2].

2.2 Transfer Learning and Data Augmentation

Collecting the millions of datasets for training different models that are required to construct a model for deep learning with high accuracy used for application purpose is tough. Therefore, transfer learning is regarded as a prompt approach of training customized deep learning frameworks [3]. Transfer learning can be referred to as a form of machine learning in which a model constructed for one job can be used again as the initial point for another task. The versatility [4] of characteristics inside the learning model is crucial to transfer learning. The output layer for categorization feeds the features disclosed by the deep learning network. Because these features may be reused, the trained network can be utilized for a new challenge in some way. In our paper, we have worked with two pre-trained models that are ResNet50 and MobileNet. ImageNet datasets were used as weights that can be used to classify up to 1000 classes [5].

In order to help our classifier model learn about the characteristics of specific crops and fruits, we have collected a dataset of 15 different classes. In total there are 14500 images of all the classes collectively. All the images used to train and test the model are collected over a period of 9 weeks so that we get the images of the crops and fruits when they start deteriorating as well.

In our experiment, training of both the fine-tuned models is included with data augmentation. In applications like image classification, object identification and segmentation, data augmentation can be utilised to train deep learning models. Depending on the nature of the application, data augmentation techniques such as photographs and text range from simple modifications to neural network generated data. Geometric changes such as flipping, rotation, translation, cropping and scaling, [6]as well as colour space transformations such as colour casting, varying brightness, and noise injection, are some of the simple alterations applied to the image. In our experiment, data augmentation has been done in such a manner that firstly, the images are mirrored randomly along the X-axis. After that, each image has been rotated along X-axis and Y-axis with an angle ranging from 1 degree to 35 degrees. The datasets have been divided into three parts which are 60% for training, 20% for validation and 20% for testing.

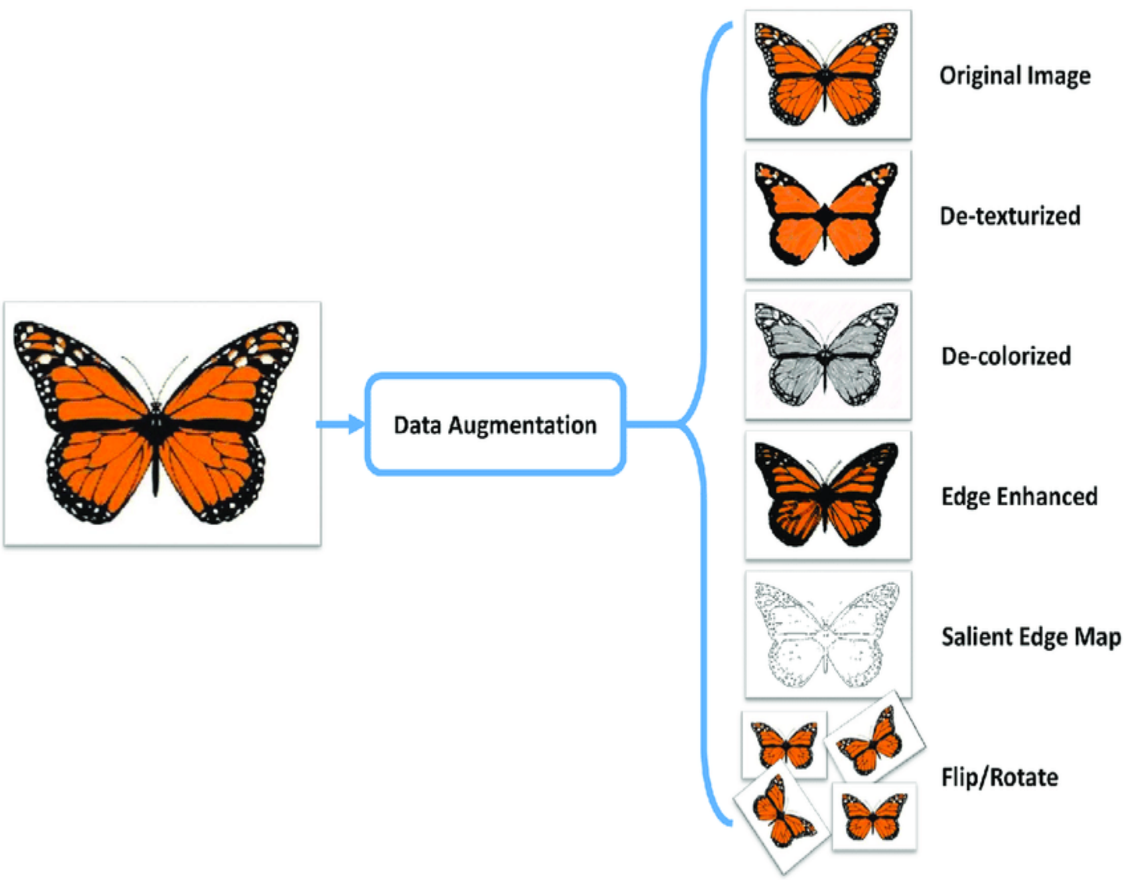


Figure 2.2 Example of Data Augmentation

CHAPTER 3

PROPOSED WORK

This section will describe the number of classes used and the number of images belonging to each class along with the sample image of each class. Also, this section includes the CNN models used for transfer learning. The specifications of the Jetson Nano developer kit have also been discussed.

3.1 Data collection

In this experiment, we have considered 15 different classes of crops, fruits and vegetables, which are mentioned in Table 3.1. A sample image of different classes is shown in Figure 3.1. We have collected 500 samples of each class and divided these samples such that 60% of the samples are used for training the model. From the remaining 40%, we have used 20% of the samples for validation of the model and rest 20% for testing the models.

We have performed our experiment with two different types of collected data samples. Firstly, we have collected the data samples of the 15 classes manually and secondly, we have collected the data samples for these 15 classes automatically.

Table 3.1 Different classes and their corresponding number of images

Classes	Number of images
Apple	500
Avocado	500
Cauliflower	500
Cherry	500
Guava	500
Kiwi	500
Mango	500
Onion	500
Papaya	500
Peach	500
Pineapple	500
Pomegranate	500
Rice	500
Sugarcane	500
Tomato	500
Watermelon	500

Few samples of collected CVF dataset for each class, is provided in Fig. 3.1.

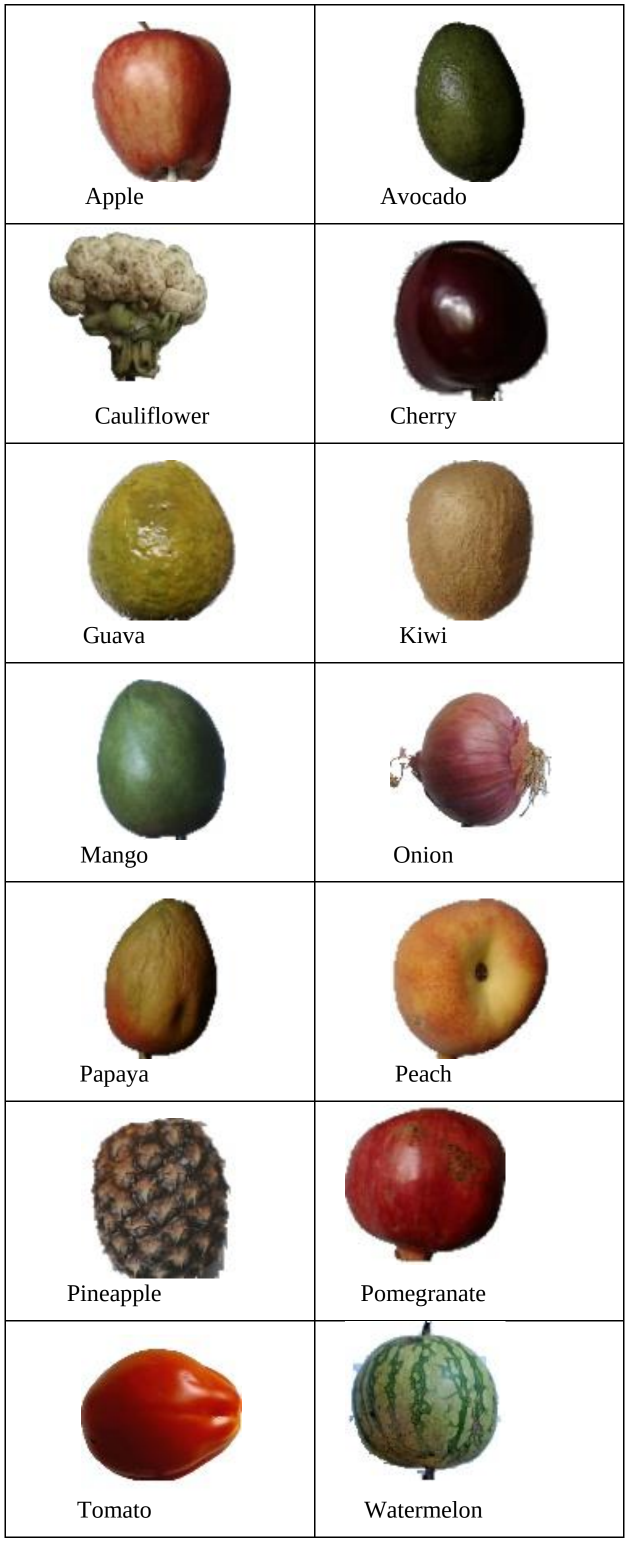


Figure 3.1 Sample of dataset for each class

3.2 Proposed Framework

In this section, the proposed transfer learning based automated crop analysis is discussed in detail. Where, the used pre-trained feature extraction models ResNet50 and MobileNet are explained. It is observed that though ResNet50 based crop analysis has better performance than MobileNet model, as reported in Result section. However, the size of ResNet50 architecture is heavier than MobileNet. This helps to decide that for limited computation resources on drone like platform i.e. Jetson Nano board, MobileNet based crop analysis with marginal performance variations is a better solution.

i) ResNet50

ResNet is an abbreviation for Residual Network. Residual Learning is the core principle of ResNet. ResNet50 is a 50-layer deep convolutional neural network. We can use the ImageNet database to load a pre-trained version of the network that has been trained on over a million photos. The network can classify photos into 1000 different object categories including keyboards, fruits, vegetables, pencils and a variety of animals [7]. As a result, the network has learned a variety of rich feature representations for a variety of images. The network's picture input size is 224x224 pixels.

The block diagram of the proposed ResNet50 architecture is shown in Figure 3.2, where the input is fed to the deep learning pre-trained model which is used under transfer learning concept and the deep features have been classified into three categories of crops, fruits and vegetables. For this purpose we have incorporated the dense layers and in the last, a softmax layer is connected to generate the predictions.

ii) MobileNet

MobileNet is a convolutional neural network built for mobility and embedded vision. It is based on simplified architecture that builds lightweight deep neural networks with low latency for mobile and embedded devices using depth-wise separable convolutions. MobileNet is made up of layers of depth-wise separable convolutions. A depth-wise convolution and a point-wise convolution make up each depth-wise separable convolution layer [7]. A MobileNet contains 28 layers if depth-wise and point-wise convolutions are counted separately. The width multiplier hyperparameter can be adjusted to reduce the number of parameters in a conventional MobileNet to 4.2 million [8]. The required input image is 224x224x3 in size.

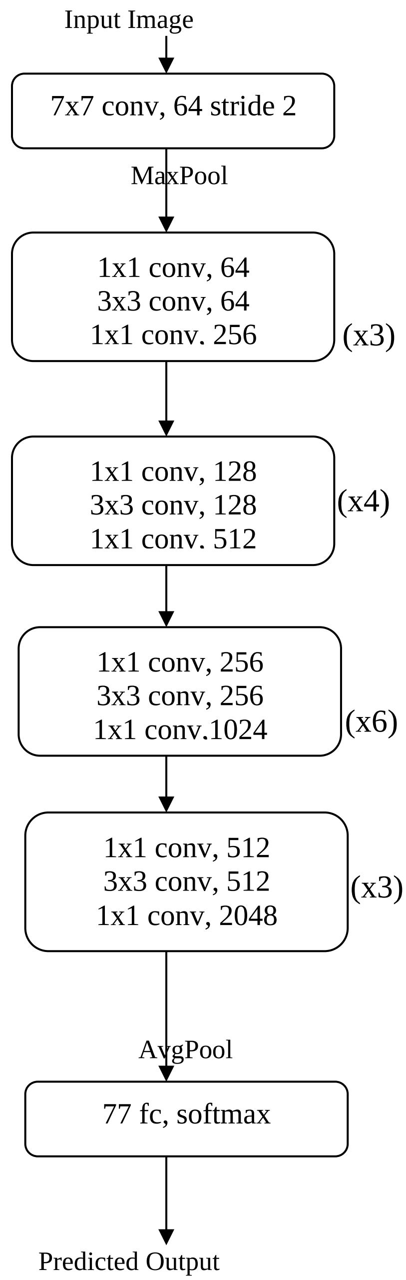


Figure 3.2 Layered Architecture of ResNet50 (Residual Concept)

3.3 Deployment of the model on Jetson Nano Developer Kit

The field of artificial intelligence(AI) computers is quickly developing where developers are continuously imagining innovative ways of applying neural networks that produce better accuracy and performance. A wide range of AI models and frameworks are being developed these days. The Jetson nano developer kit works with all of the most common AI frameworks and systems and have a powerful processing [9]. The NVIDIA Jetson nano is an embedded system-on module and developer kit from NVIDIA that has a 128-core Maxwell GPU, quad-core ARM A57 64-bit CPU and 4GB LPDDR4 memory. The Jetson nano developer kit is ideal for learning and developing AI and Robotics [10]. The Jetson carrier board includes USB 3.0 and 2.0 ports for connecting peripherals such as USB cameras, one MIPI CSI-2 camera connector, a 40-pin header that is compatible with many peripherals and add-ons, an HDMI display interface, and a Gigabit Ethernet port, all of which is often used in creation of edge and embedded projects. An 802.11 ac wireless networking USB adapter is also included in the developer kit.

NVIDIA's Jetson is a new unified accelerator device that is frequently employed with self-learning techniques. Such characteristics enable some applications, also including unsupervised multi-sensor machines, adaptive IoT devices, and advanced machine learning systems. As a compact and efficient processor, the equipment supports the execution of multiple neural network algorithms simultaneously [11]. It aids in the development of auditory detection, classification techniques, object recognition, fragmentation, and sound or speech processing applications. Transfer learning can also be implemented with pre-training systems that use Jetson nano and Computer Vision.

Jetson nano developer kit behaves like a compact processor used for application of AI and Machine Learning. For setting up our Jetson nano, we connect a desktop monitor with HDMI that acts as the head of our system. Then, a keyboard and mouse are connected. For internet connectivity, we connect a modem with Gigabit Ethernet cable to our processor. The developer kit uses a microSD card as boot device and for main storage. The libraries, model weights and our model can be uploaded onto the microSD card. Finally, a micro-USB cable is connected to the Jetson board for power supply and our system is ready to use.

Now, to obtain a relevant user interface on our system, we flash our microSD card with UBUNTU image file. The NVIDIA Jetson nano device can run a wide variety of advanced neural networks, including popular Machine Learning frameworks such as TensorFlow, PyTorch, Caffe, Keras, and others. For proper working of our model we upload an open-source library called TensorFlow. More than 6 GB of RAM is required to build the complete TensorFlow 2.4.0 package. To gain the extra space on our SD card, the best solution is to install dphys-swapfile. We can delete dphys-swapfile once the installation is complete.

Now that we have created a suitable environment on the Jetson nano Developer kit, we upload our ‘Transfer Learning based Image Classification’ model onto it. We have uploaded our model created with the MobileNet as the base model because of its small size, low-latency and low power consumption. The size of our model weights is 49.8 Mb and the total number of parameters that our model consists of is 4.2 million. For testing our model in real time, we connect a C270 Logitech webcam to calculate the frames per second (fps). The device's main characteristics are its light weight and low power usage. The specifications of Jetson nano Developer kit are listed in Table 3.3.

Table 3.3 Jetson Nano Developer kit specification

Processing	
GPU	128-core NVIDIA Maxwell
CPU	64-bit Quad-core ARM A57 (1.43 GHz)
Memory	4 GB 64-bit LPDDR4 (25.6 GB/s bandwidth)
Video Encoder	4Kp30 | (4x) 1080p30 | (2x) 1080p60
Video Decoder	4Kp60 | (2x) 4Kp30 | (8x) 1080p30 | (4x) 1080p60
Interfaces	
Networking	10/100/1000 Base-T Ethernet
Connectivity	Gigabit Ethernet, M.2 Key E
USB	4x USB 3.0, 1x USB 2.0 Micro-B
Display	HDMI and Display port
40-Pin Header	GPIOs, I2C, I^2S, SPI, UART
Camera	2x MIPI CSI-2 DPHY lanes
Storage	microSD
Power	Micro USB 5V~ 2.5A
Dimensions	100 mm x 80 mm x 29mm

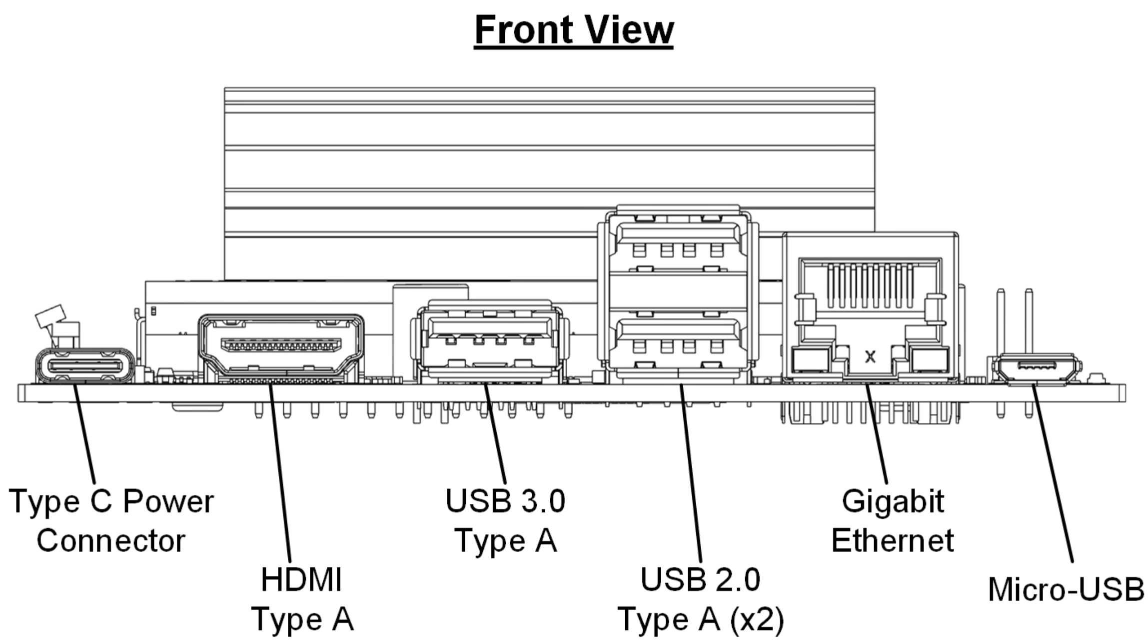


Figure 3.3 Jetson nano board (Front view)

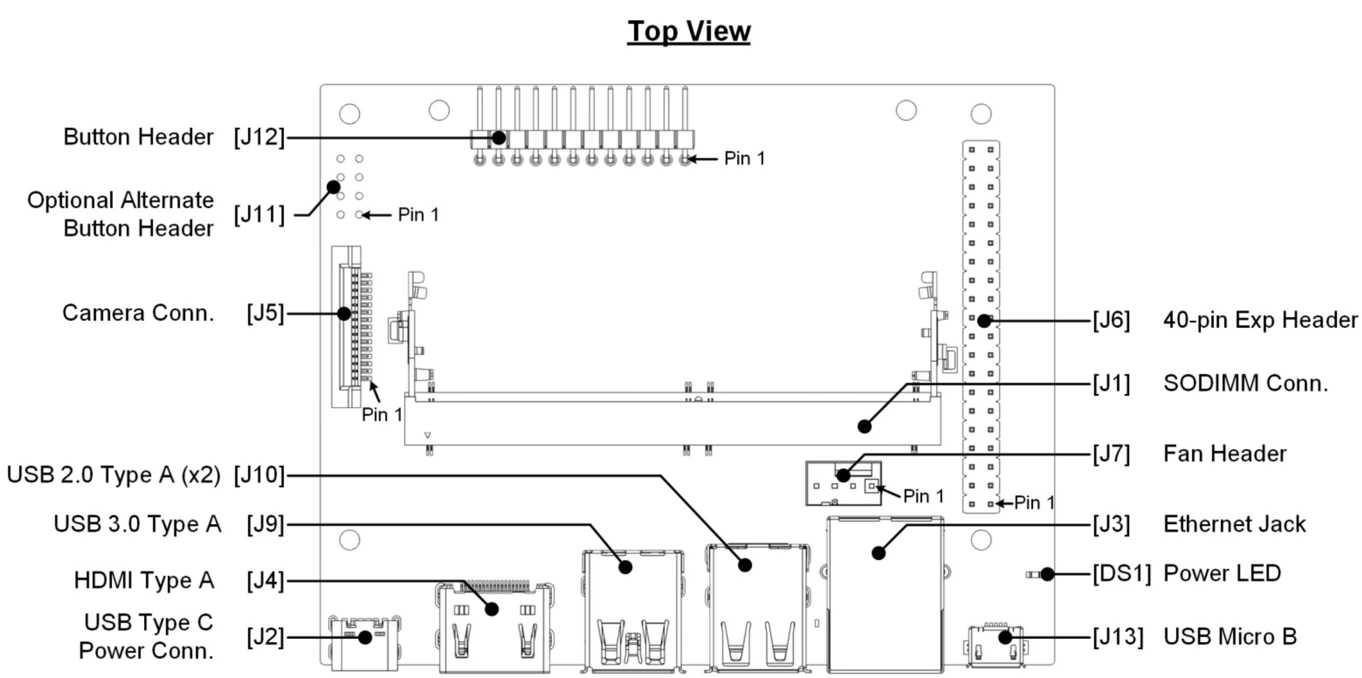


Figure 3.4 Jetson nano board (Top view)

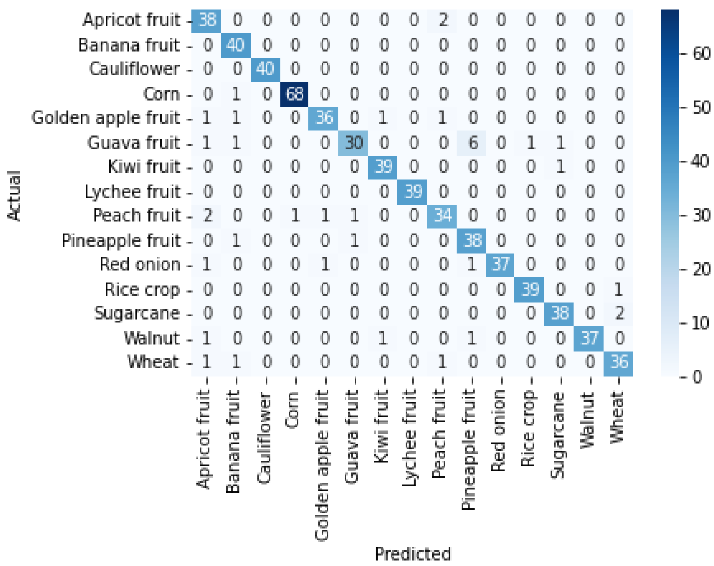
CHAPTER 4

EXPERIMENTAL RESULTS

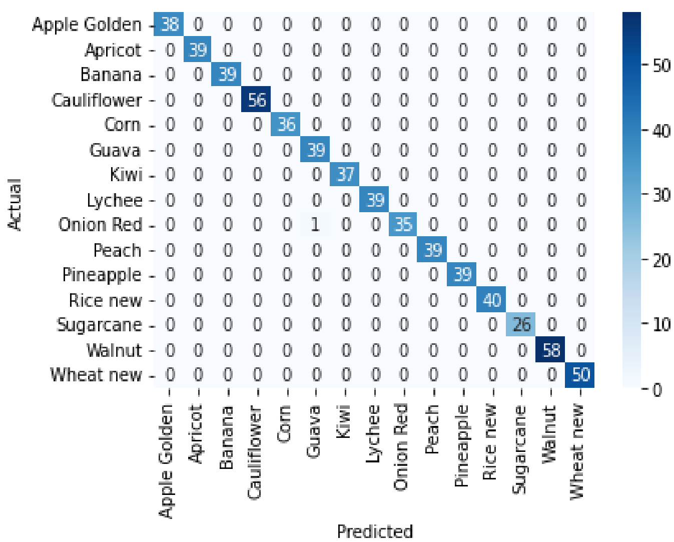
In this chapter, various training, testing and validation results for ResNet50 and MobileNet have been shown. A confusion matrix has been generated in order to understand the training outcome of each class more clearly [12]. To validate the performance of the proposed model, one publicly available dataset Fruit 360 Kaggle dataset is used. Fruit 360 dataset provides a wide range of fruits, crops and vegetables that includes the images at every possible angle of each class. The 360 degree image of the classes helps our framework to analyse the classes more accurately. Also, in order to help our classifier model, learn about the characteristics of specific crops and fruits, we have collected a dataset of 15 different classes, named as Multi CVF (Crop-Vegetable-Fruits) dataset. In total, there are 7500 images of all the classes collectively. The dataset also covers the samples of rotten crops, vegetables and fruits to provide generalisability to the model. Moreover, a comparison between the models have been done and it turns out to be that the model trained with ResNet50 as the base model with manually collected dataset gives out the best test results. Therefore the ResNet50 model is uploaded on the Jetson Nano Developers kit for further testing.

4.1 MobileNet

The response of MobileNet framework for automatic dataset is shown in Figure 4.1(a) and the response for manual dataset is shown in Figure 4.1(b). The validation accuracy and loss for automatically collected dataset and manually collected dataset is mentioned in Table 4.2. The maximum validation accuracy of this model is attained by using the manual datasets with a validation accuracy of 99.87% when the model was trained on 20 epochs. The test accuracy of the model is 97.68% whereas the testing loss is 7.52%.



(a)

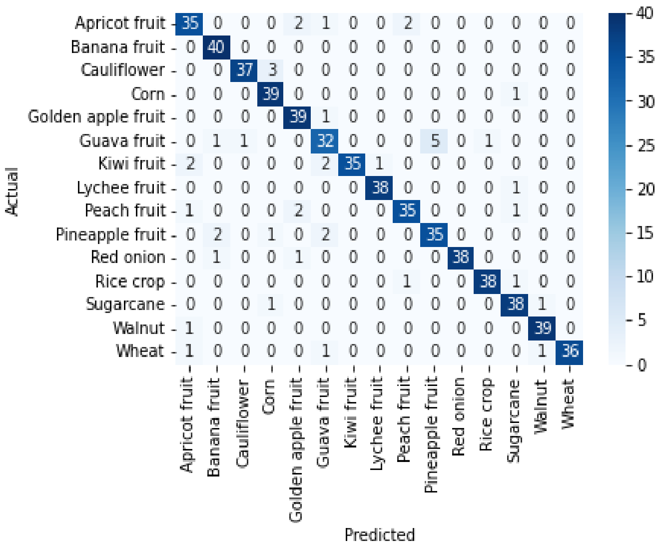


(b)

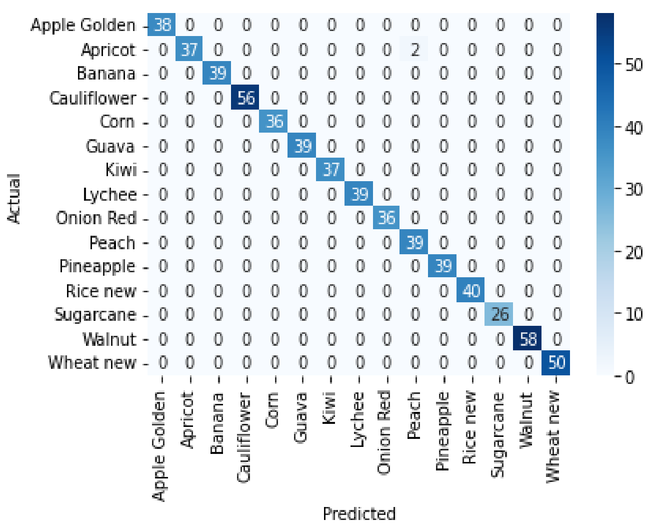
Figure 4.1 Confusion Matrix of (a) Automatically Collected CVF Dataset, and (b) Manually collected CVF Dataset samples using pre-trained MobileNet architecture

4.2 ResNet50

The response of ResNet50 framework for automatically collected CVF dataset is shown in Figure 4.2(a) and the response for manually collected CVF dataset is shown in Figure 4.2(b). The validation accuracy and loss for automatically and manually collected dataset is mentioned in Table 4.2. The maximum validation accuracy of this model is attained by using manual datasets with 100% accuracy when the model was trained on 20 epochs. The test accuracy of this model turned out to be 99.35% whereas the test loss is 3.92%.



(a)



(b)

Figure 4.2 Confusion Matrix of (a) Automatically Collected CVF Dataset, and (b) Manually collected CVF Dataset samples using pre-trained ResNet50 architecture

Table 4.2 Test Accuracy and Loss

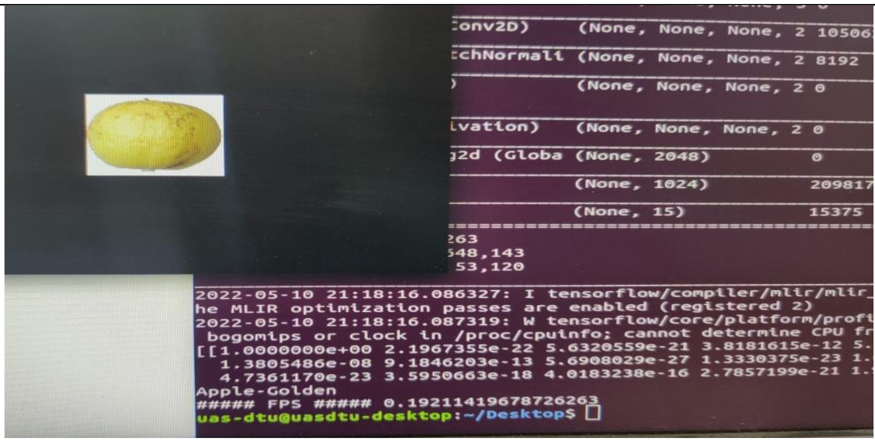
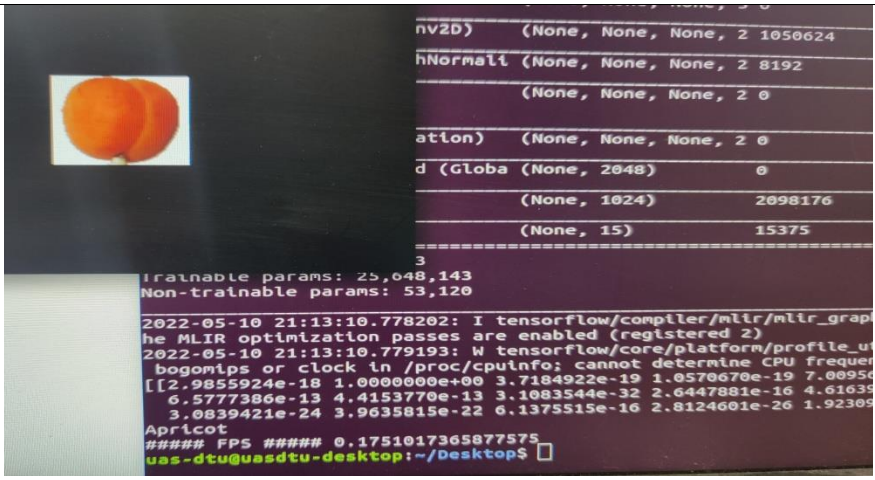
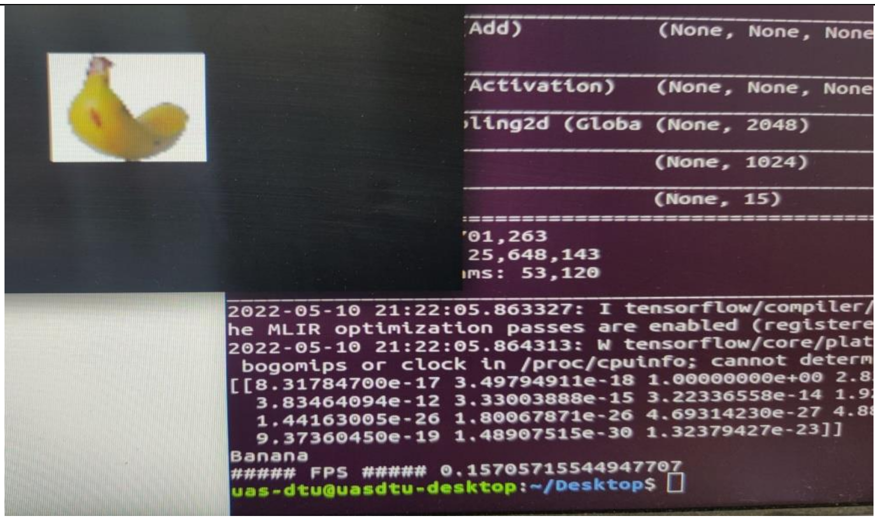
METHOD	TEST ACCURACY	LOSS
Fruit Recognition from images using deep learning [12]	98.66	0.0439
Image classification in galaxy with Fruit 360 dataset [13]	97.24	0.0816
Multi CVF image recognition	99.35	0.0033

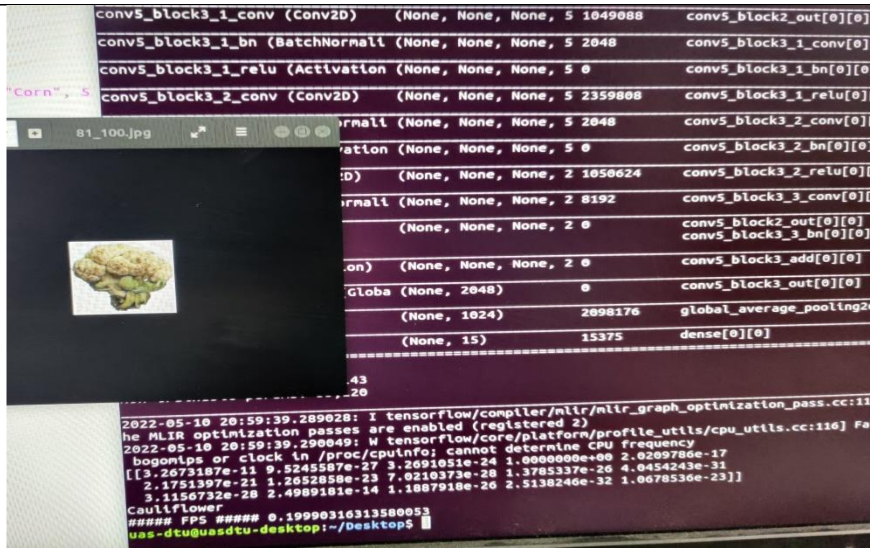
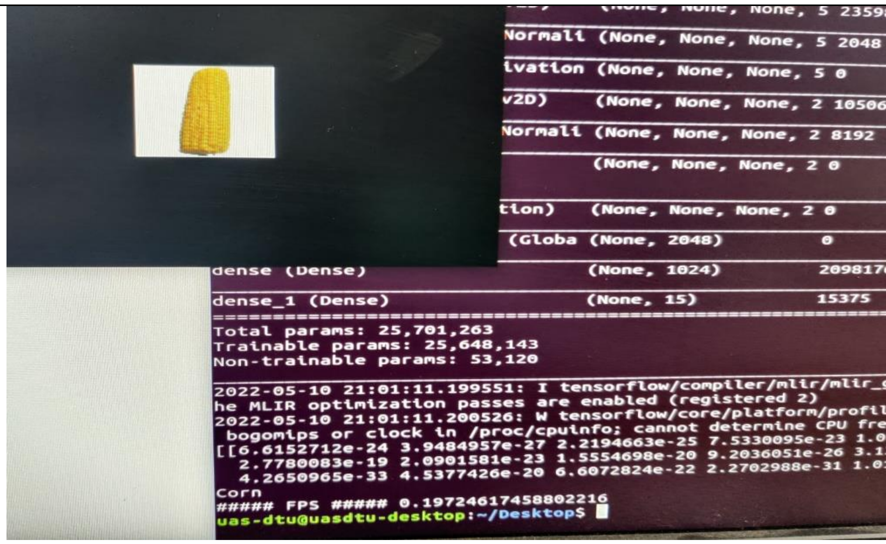
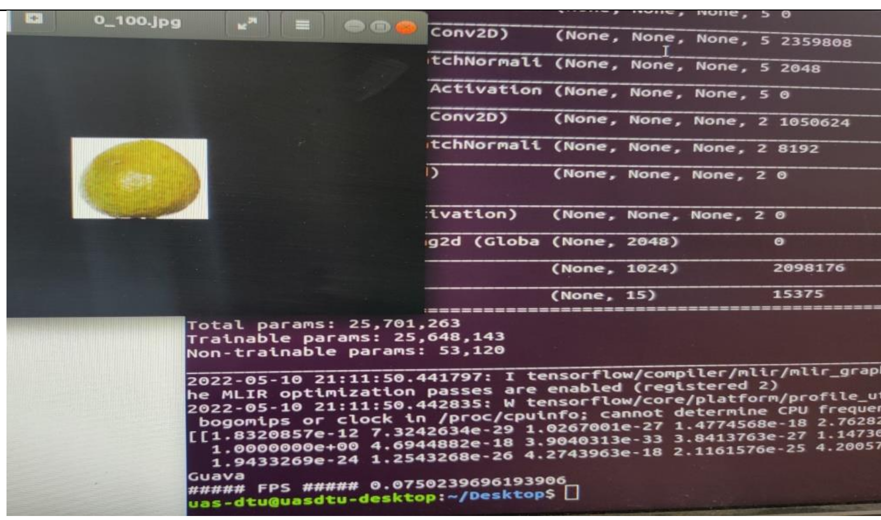
A comparison is shown in Table 4.2, where the models being compared are trained and tested with the same Fruit 360 dataset. As we can see that the results obtained for multi-CVF dataset are better than. The images that we used include the different sizes of the fruits and crops that give a better understanding of the respective class to the model and more generalizability.

4.3 Results on Jetson Nano Developers Kit

After successfully setting up the Jetson Nano Developers Kit, we tested our ResNet50 model trained with manually collected dataset that had the maximum test accuracy. We tested the predictions made by our model by showing the images of different classes to the camera connected to the Jetson Nano Kit. In all the cases, the predictions made by the model were correct. We also calculated the time it takes for our model to process one frame. The results derived after testing the ResNet50 model on the Jetson Nano Developers Kit are as below:

Table 4.3 Test result for each class on Jetson Nano Developer kit

Name of the Class	**Result Image**	**Time Taken to Process a Frame (milliseconds)**
Golden Apple		192.11 ms
Apricot		175.10 ms
Banana		157.05 ms

Cauliflo wer		199.90 ms
Corn		197.24 ms
Guava		75.02 ms

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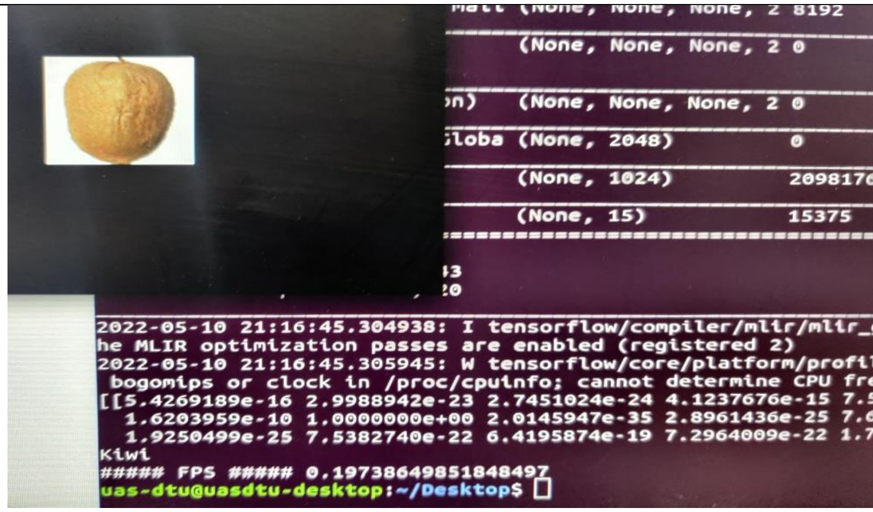
<tr><td>Kiwi</td><td>
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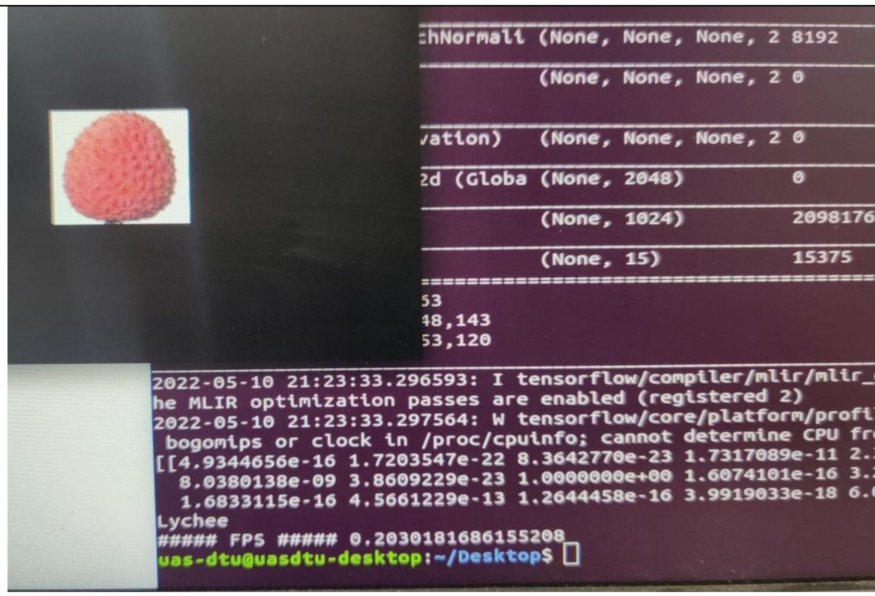
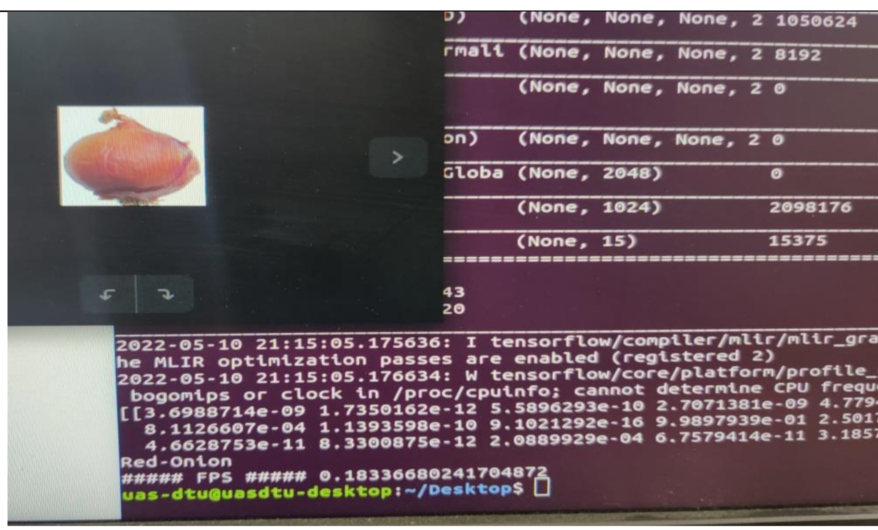
<tr><td>Lychee</td><td>
</td><td>203.01 ms</td></tr>
<tr><td>Onion</td><td>
</td><td>183.36 ms</td></tr>
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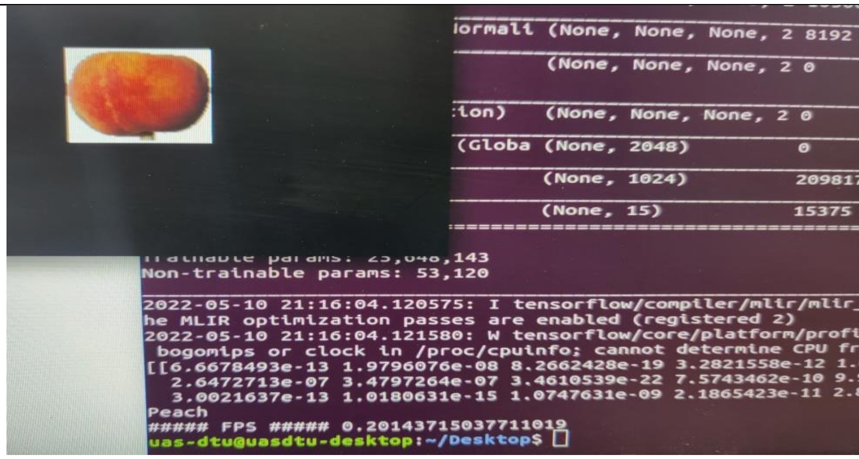
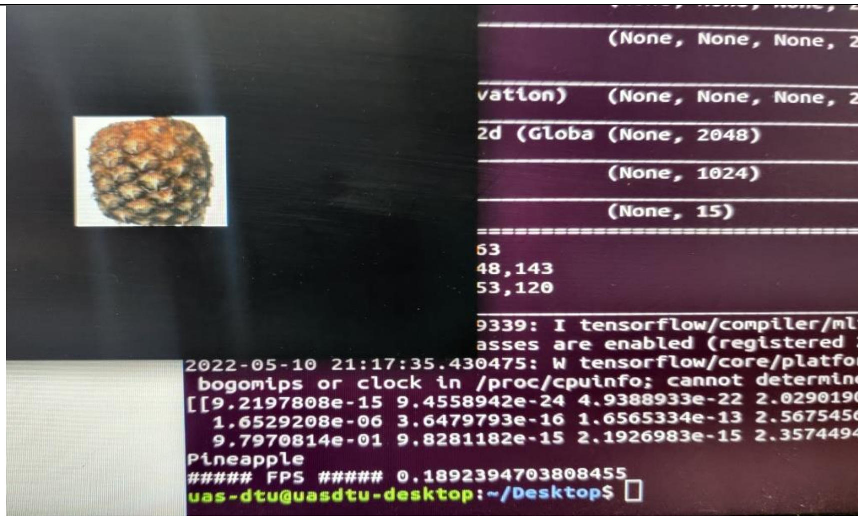
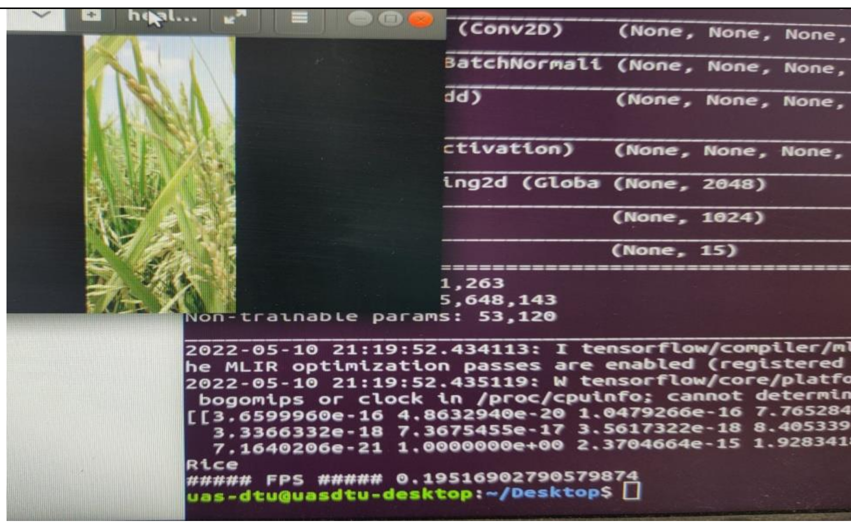
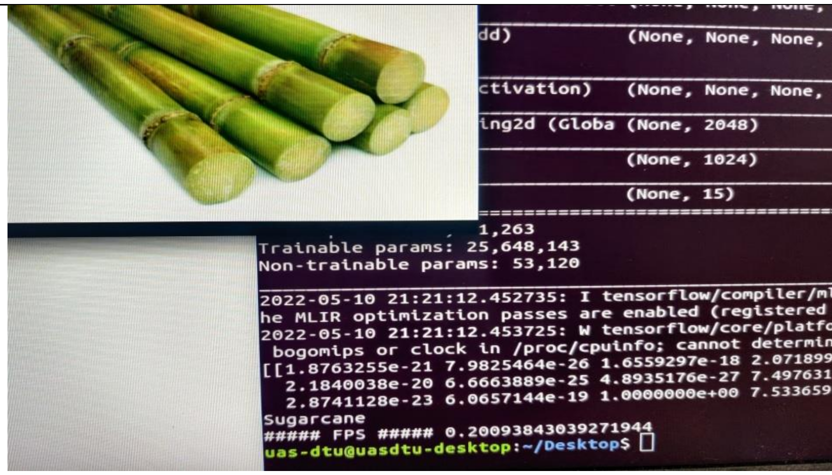
Peach		201.43 ms
Pineapple		189.23 ms
Rice		195.16 ms

<table>
<tr><td>Sugarcane</td><td>
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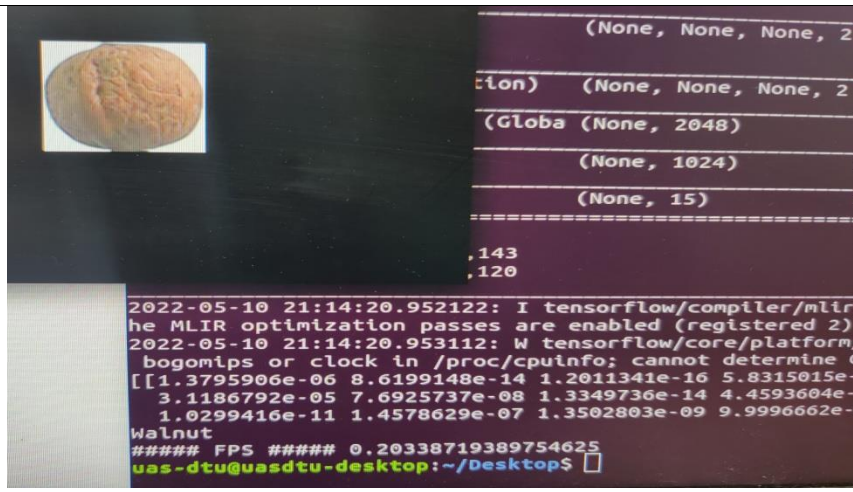
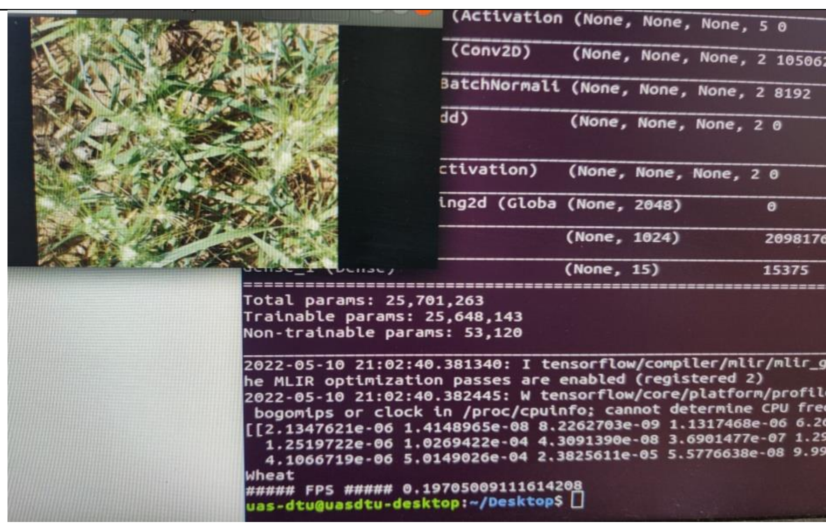
<tr><td>Walnut</td><td>
</td><td>203.38</td></tr>
<tr><td>Wheat</td><td>
</td><td>197.05 ms</td></tr>
</table>

Average time taken by the Jetson Nano kit to process the frames can be calculated as:

Average Time:

$$\frac{192.11+175.10+157.05+199.90+197.24+75.02+197.38+203.01+183.36+201.43+189.23+195.16+200.19+203.38+197.05}{15}$$

Therefore, average time it takes for our setup to process one frame = <u>184.49 ms</u>

Chapter 5

Conclusion and Future Scope

In this major project work, we used the notion of transfer learning to solve the challenge of assessing the quality of fruits and crops in this experiment. To test the two pretrained models, a dataset comprising 15 distinct items (crops, fruits and vegetables) was gathered. The validation accuracy as well as the validation loss is used to evaluate these models. Both the models were trained on 20 epochs and also both the models were fed with the same datasets. The ResNet50 model achieves the best validation accuracy predicated with data, which turns out to be 100 percent. The ResNet50 framework also achieves the maximum test accuracy based on data, which is 99.34 percent.

After deploying our model on the Jetson Nano Developer's Kit, we tested out model in real time and checked the predictions made by the system. All the predictions done by the system were accurate. Moreover, we calculated the amount of time it takes for the system to process one frame while testing in real time.

The average time it takes for the system to process one frame is 184.49 ms.

The future prospect of this work includes exploring and training with more pretrained models. Moreover, real-time images can be tested in order to obtain clearer information about a field of crops or vegetables.

A camera with high resolution capturing quality can be optimized with Jetson Nano Developer's kit to detect the classes in real time. This setup can be further connected to an unmanned aerial vehicle. A sprinkler system can further be attached to the unmanned aerial vehicle for watering or sprinkling plant medicines. This project can be a helping hand for the farmers in our agricultural sector.

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