FRUIT QUALITY CLASSIFICATION USING IMAGE PROCESSING TECHNIQUES

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ABSTRACT

Digital image processing is widely used in the classification and evaluation of fruit quality. This essay explores the process of determining whether a bunch of fruits is good or flawed. This helps the customer avoid purchasing faulty fruits and also helps the consumer prevent any unintended health problems that can result from consuming faulty fruits. Nowadays, it is imperative to check fruit products for flaws before releasing them onto the market. This addendum helps the business understand the client's contribution to determining the fruits' quality. Given the most recent developments in digital image processing technology, using these techniques to evaluate the quality of food products, especially fruits have become very significant. These techniques allow one to categorize fruits and identify which ones are rotten and which are good. Regarding the current disposition, it is critical to accurately identify food items and evaluate their quality. These automated technologies can reduce a great deal of manual labor and accelerate the food processing industry. Regarding this, the latest developments in Deep Learning-based architectures have brought forth a multitude of options that provide exceptional results in various categorization problems. Accurate recognition of food items along with quality assessment is of paramount importance in the agricultural industry. Such automated systems can speed up the wheel of the food processing sector and save tons of manual labor. In this connection, the recent advancement of Deep learning-based architectures has introduced a wide variety of solutions offering remarkable performance in several classification tasks. In this work, we have exploited the concept of CNN, DenseNet121 and NasNetLarge for fruit quality assessment. These have been applied on the images chosen from Fruitnet Database. The feature propagation towards the deeper layers has enabled the network to tackle the vanishing gradient problems and ensured the reuse of features to learn meaningful insights. Evaluating on a dataset of 19,526 images containing six fruits having three quality grades for each, the proposed pipeline achieved an accuracy of 86%. The robustness of the model was further tested for fruit classification and quality assessment tasks where the model produced a similar performance, which makes it suitable for real-life applications. The DenseNet121 outperforms NasNetLarge in terms of the performance metrics used such as F1 score, accuracy, etc. Hence, DenseNet121 is our preferred architecture for classification of fruits into good and bad ones.

Keyword: - *classification, image, quality, accuracy*

1. INTRODUCTION

More important to the satisfaction of the consumer than quantity of the same kind is quality [1]. A key element in assessing the quality of a product is the customer. Another way to conceptualize quality is as the culmination of all the characteristics involved in producing goods that meet customer needs [2]. The external features of fruits, such as color, texture, size, and form, mostly convey their direct sensory quality [3]. Businesses that deal with fruits consider the social environment, product significance, etc. [4]. Finding defects in items before they are sold or exported is one of the most crucial parts of quality assurance [5]. Conventional techniques for evaluating the quality are laborious, time-consuming, and unreliable [6]. These find application in agricultural research [7, 8].

Digital image processing techniques have been used more and more recently to enhance the quality of fruits. This is due to the techniques' persistence in producing significant advances in areas insensitive to the human eye [9]. Even though fruits were picked from the same tree on the same day, they may differ in terms of color, size, and form [10]. Food products naturally change color or texture after harvest for a variety of reasons, including temperature and humidity, fungal infections, the presence of volatile compounds, length of storage, and so forth. These changes depend on the maturity of the food and how it is stored. Furthermore, in a particular area of the fruit, the skin color of a healthy fruit may coincide with the color of another fruit of the same sort. Furthermore, it is critical to identify any foreign material on quality control lines, such as stems, leaves, dirt, or blemishes on the skin, and not mistake them for the real thing [11, 12].

These characteristics are dictated by the fruit's level of ripeness at harvest and the conditions in which it was stored. These include temperature and humidity, fungus infections, volatile material presence, length of storage, etc. It is also feasible to match the hue of one fruit's skin to that of another fruit that belongs to the same species. Moreover, it is imperative to distinguish any extraneous material on quality control lines, such as dirt, leaves, stems, or skin imperfections, and not confuse them with the actual thing [13, 14].

2. LITERATURE SURVEY

V. Hemamalini et al. [15] classified whether fruits were rotten or good using SVM and K-means clustering method for segmentation.

H. Yousef et al. [16] classified fruits as good or damaged using GA and a modified K-means clustering technique for fruit segmentation.

A. Hardy et al. [17] have used CNN to determine whether fruits are rotten or excellent.

Using a convolutional neural network pretrained on ImageNet, Nandila Bhattacharjee [18] was able to refine a classifier that distinguishes between rotten and good fruits.

Fruits are classified according to Elia Henrichs et al. into good and bad classes by using Fuzzy C method clustering [19].

3. METHODOLOGY

In this study, we employed the 'FruitNet' dataset comprising 19,526 images distributed across 18 classes, representing six different fruits categorized into various quality levels (good, bad, and mixed). Each image is of dimension 256 × 256. The dataset presents challenges including lighting variations, diverse backgrounds, and quality disparities, alongside inherent similarities in color, shape, and texture among fruits, further complicated by breed diversity. To effectively address these challenges, we employed a comprehensive methodology integrating two distinct Convolutional Neural Network (CNN) architectures: DenseNet121 and NasNetLarge, alongside a custom CNN. DenseNet121, renowned for its efficacy in image classification, addresses challenges such as vanishing gradients by incorporating residual connections and concatenating output from each layer to subsequent layers, ensuring the preservation of critical information throughout the network. NasNetLarge, known for its unique strengths, also contributes to the architecture. Additionally, a custom CNN architecture tailored to the dataset's specific characteristics is employed to further enhance classification performance. To manage the extensive parameter space resulting from concatenation and the integration of multiple architectures, the networks are structured into dense blocks separated by transition blocks, with down-sampling mechanisms to prevent parameter explosion. Transition layers incorporate batch normalization, 1 × 1 convolution, and 2 × 2 average pooling to optimize network performance. Given the dataset's class imbalance, runtime augmentation is adopted over traditional techniques like under-sampling or over-sampling. This approach introduces random augmentation with varying strengths in each epoch, diversifying challenges encountered during training to reflect real-world scenarios. Augmentation techniques include random rotation, horizontal and vertical flipping, height and width shifting, and shearing, ensuring the model encounters a diverse range of instances during training. In summary, our methodology integrates DenseNet121 and NasNetLarge, alongside a custom CNN architecture with runtime augmentation, to effectively address the complexities of the FruitNet dataset. This comprehensive approach facilitates robust training for tasks such as fruit classification, quality assessment, and classification with quality levels, leveraging the strengths of each architecture to achieve superior performance. Furthermore, we utilize an ESP32 camera for image capture to facilitate real-time prediction of fruits. Fig-1 shows the block diagram of the work. Fig-2 depicts the architectural diagram of the project.Fig-3 depicts the level 0 data flow diagram of the project whist Fig-4 depicts the level 1 data flow diagram of the project. The use case diagram is shown in Fig-5.

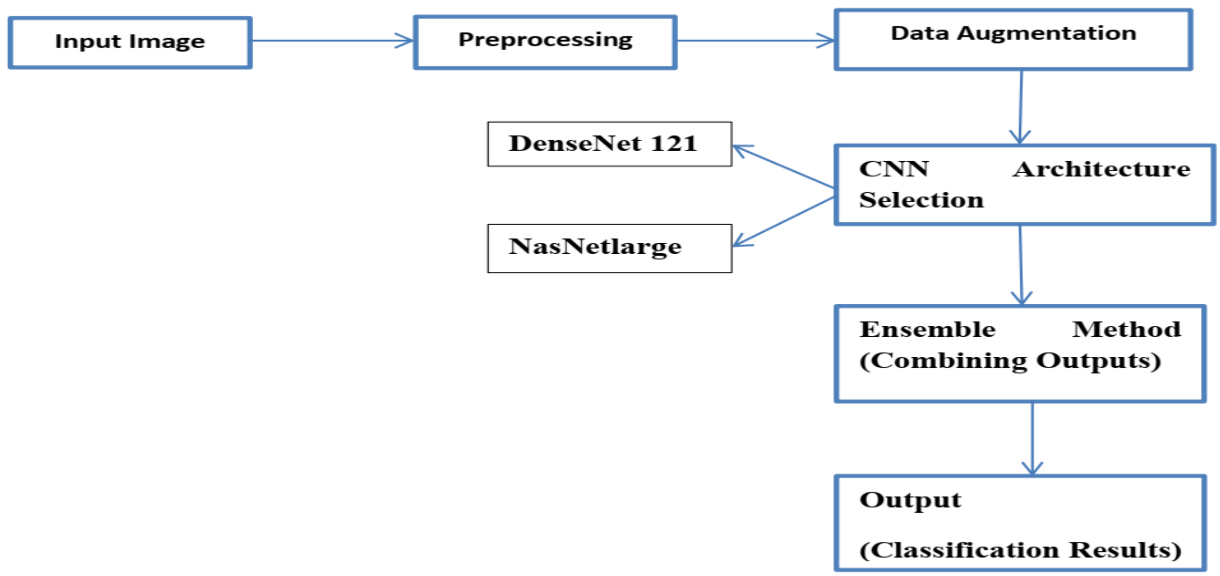


Fig -1: Block Diagram of the project.

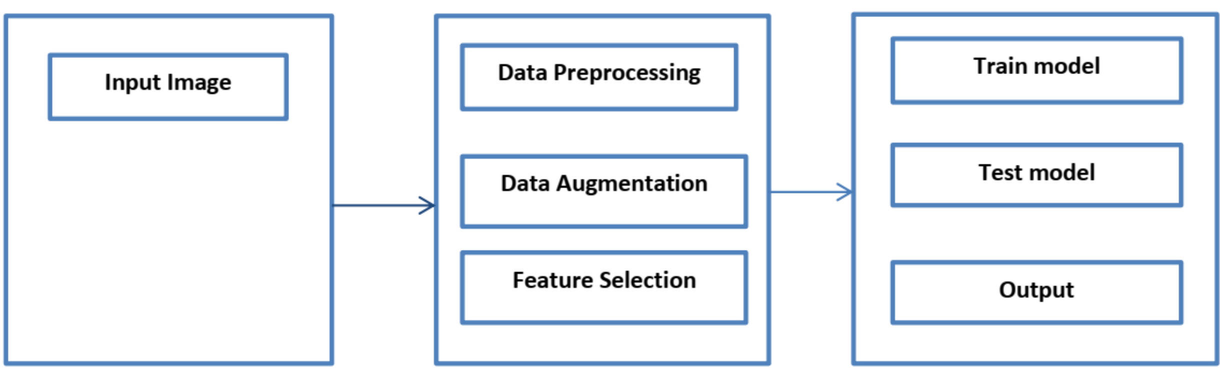


Fig -2: Architectural Diagram of the project.

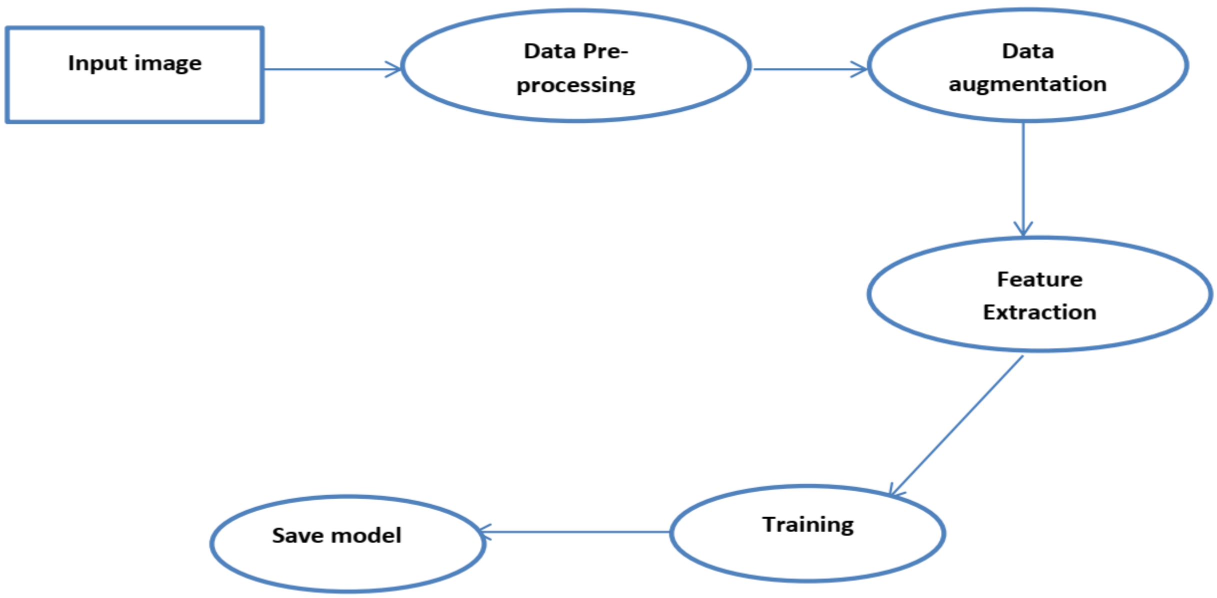


Fig -3: Level 0 data flow diagram of the project.

Fig -4: Level 0 data flow diagram of the project.

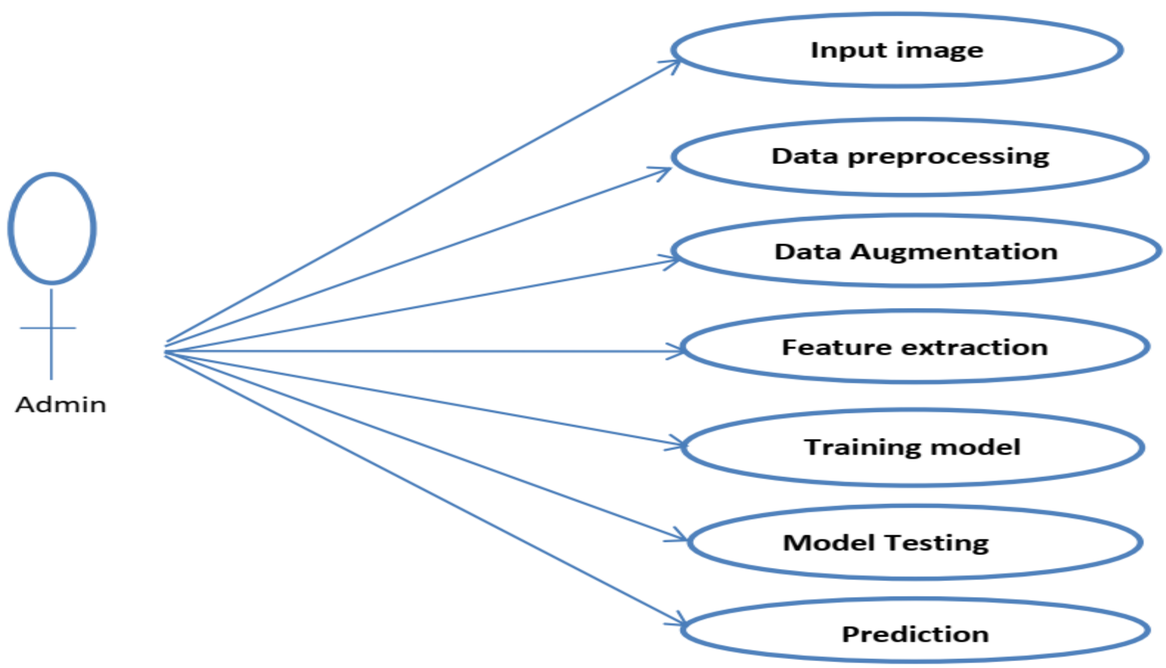


Fig -5: Use Case diagram of the project.

The hardware requirements include Processor (Intel Family), Version (Core i5 and Higher), Hard Disk (500 GB and more), RAM (16GB), and ESP32 Camera. The software requirements include Operating System (Windows 10), Programming Language (Python 3.8.x), and IDE (Jupyter Notebook).

4. ALGORITHMS USED

Two algorithms are used in the work, viz., DenseNet121 Algorithm and NasNetLarge Algorithm.

4.1 DenseNet121 Algorithm

DenseNet121 consists of several dense blocks, each containing multiple convolutional layers. Within each dense block, the output feature maps of all preceding layers are concatenated and fed as input to subsequent layers. This dense connectivity pattern allows feature reuse and facilitates information flow throughout the network. Transition layers, consisting of batch normalization, 1x1 convolution, and 2x2 average pooling operations, are inserted between dense blocks to down-sample feature maps and control the number of parameters. The final layers include global average pooling and a fully connected layer followed by softmax activation for classification.

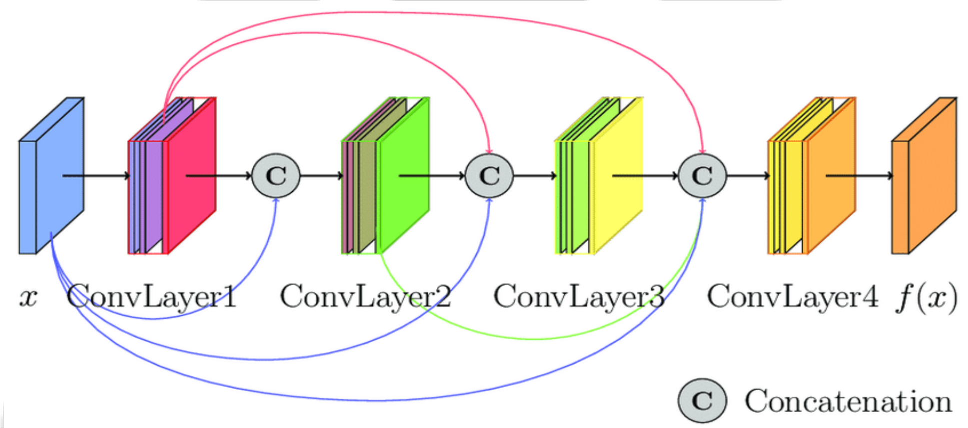


Fig -6: Use Case diagram of the project.

4.2 NasNetLarge Algorithm

NasNetLarge employs a cell-based architecture, where each cell consists of a set of predefined operations, such as convolution, pooling, and activation functions. The architecture is characterized by its ability to dynamically select operations for each cell during the training process. This is achieved through reinforcement learning-based search algorithms, where the network learns to adaptively design architectures that maximize performance on a validation set while minimizing computational costs. NasNetLarge represents a larger variant of the NasNet architecture, featuring deeper and wider networks with increased computational complexity. The exact architecture of NasNetLarge comprises multiple repeating cell structures, with each cell containing a set of operations selected based on learned policies.

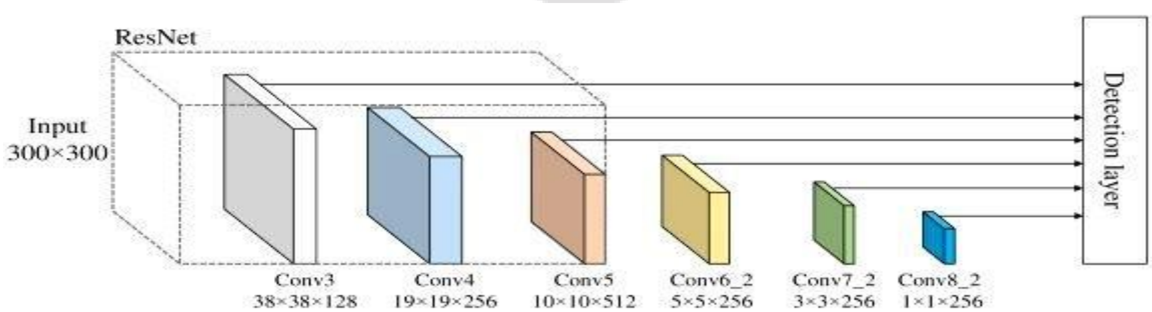


Fig -7: Use Case diagram of the project.

5. RESULT ANALYSIS

The classification reports offer insights into the performance of two distinct models: one employing DenseNet and the other utilizing NasNetLarge architectures. For the DenseNet model, the analysis reveals a concerning overall accuracy of merely 12%, indicating significant struggles in distinguishing between different classes. Most precision, recall, and F1-score values across classes are notably low, reflecting the model's challenges in effectively categorizing fruits. Additionally, both the macro-average and weighted-average F1-scores are dismal, suggesting poor overall performance. In contrast, the NasNetLarge model demonstrates significantly higher performance, with an overall accuracy of approximately 86%. While precision, recall, and F1-score values vary across classes, the model generally exhibits superior classification capabilities compared to DenseNet. The higher accuracy and improved performance metrics, including macro-average and weighted-average F1-scores, underscore NasNetLarge's efficacy in fruit classification tasks, positioning it as a more suitable choice for the dataset at hand.

The epoch versus loss graph is plotted for DenseNet121 is shown in Fig-8. This will visualizes the training and validation loss history, providng insights into the model's learning progress and convergence using a custom utility function.

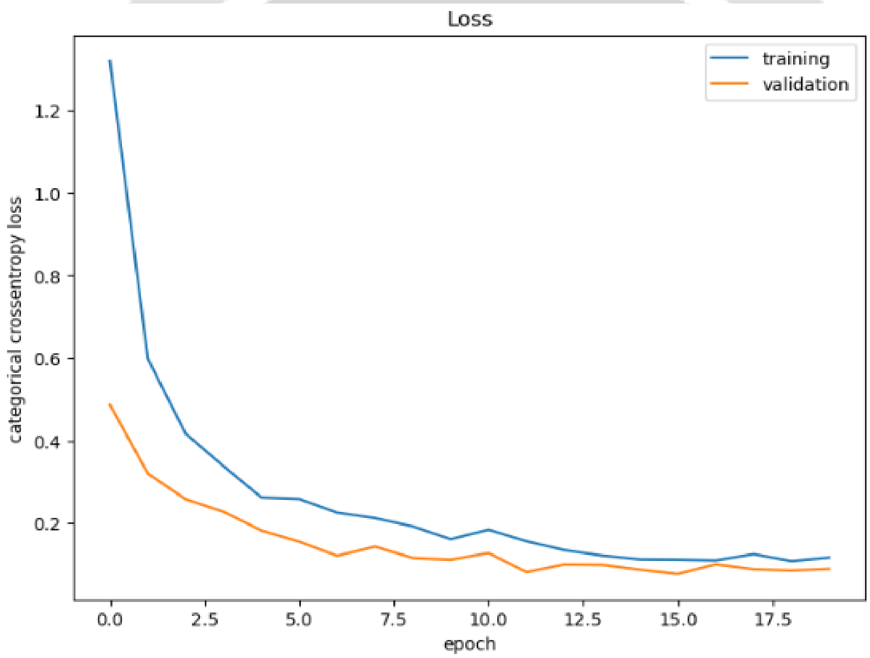


Fig -8: Epoch versus loss graph for DenseNet121.

The training and validation accuracy history over epochs using a custom utility function, offering insights into the model's performance improvement during training is shown in Fig-9 for Densenet121.

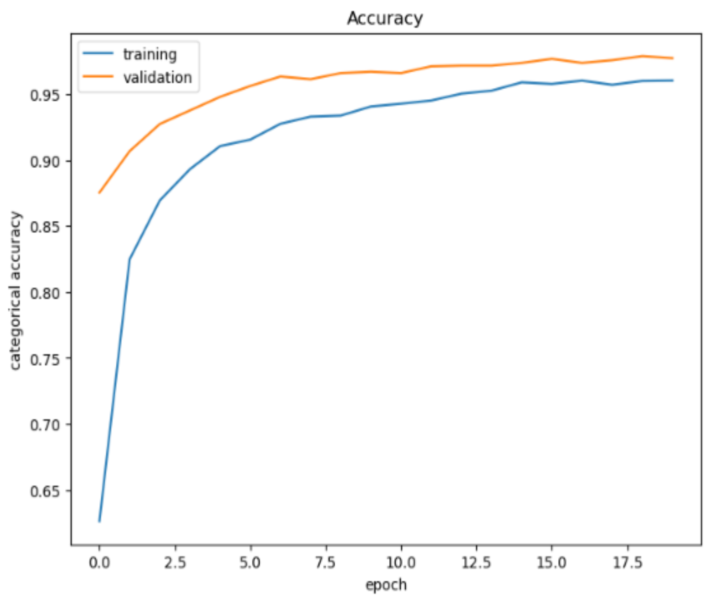


Fig -9: Epoch versus Accuracy plot for DenseNet121.

The text report displaying the main classification metrics, such as precision, recall, and F1-score, based on the true and predicted labels of a classification model. It provides a detailed evaluation of the model's performance on the test dataset for DenseNet121 and NasNet is shown in Table-1.

The confusion matrix based on the true and predicted labels of a classification model. It utilizes Matplotlib and scikit-learn's Confusion Matrix Display to create a visual representation of the model's performance, showing the distribution of predictions across different classes. For DenseNet121, the confusion matrix is shown in Fig-10.

Table -1: Precision, Recall, F1score values for NasNet and DenseNet121.

NASNET PERFORMANCE METRICS				DENSENET PERFORMANCE METRICS		
EPOCH	PRECISION	RECALL	F1 SCORE	PRECISION	RECALL	F1SCORE
0	0.71	0.87	.78	.38	.96	.54
1	.93	.97	.95	.94	.97	.96
2	.83	.86	.84	.82	.86	.84
3	.75	1	.86	.76	1	.87
4	.99	.96	.97	.98	.96	.97
5	.98	.96	.97	.99	.95	.97
6	.58	.81	.68	0.00	0	0
7	.92	.98	.95	0.00	0	0
8	.88	.91	.90	0.00	0	0
9	.74	1	.85	.78	1	.88
10	.93	.98	.95	.96	,95	.96
11	.90	.95	.92	.95	.96	.95
12	.53	1	.69	.56	.96	.70
13	.93	,90	.91	.90	.90	.90
14	.90	,85	.88	.91	.87	.89
15	.43	.88	.58	.48	.77	.59
16	.95	.94	.94	.94	.94	.94
17	1	.88	.94	1	.88	.94

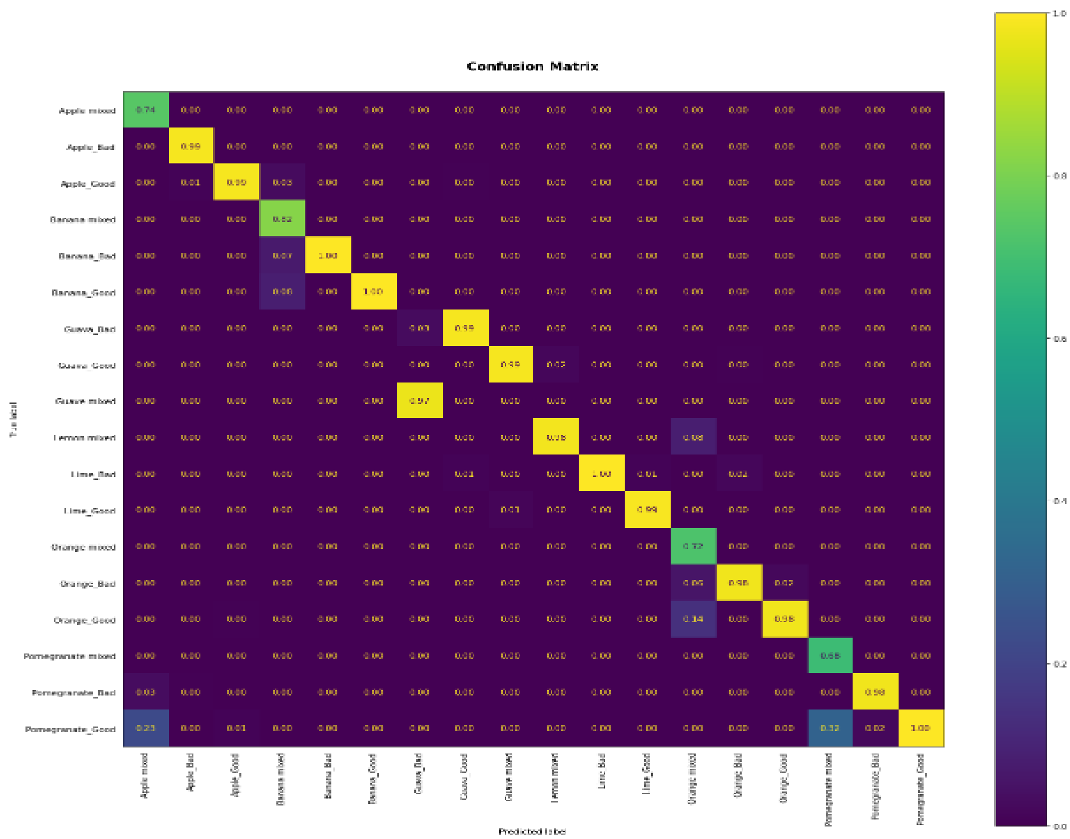


Fig -11: Confusion Matrix for DenseNet121.

The epoch versus loss graph is plotted for NasNetLarge is shown in Fig-12. This will visualizes the training and validation loss history, providing insights into the model's learning progress and convergence using a custom utility function. Epoch Versus Accuracy plot for NasNetLarge is shown in Fig-13.

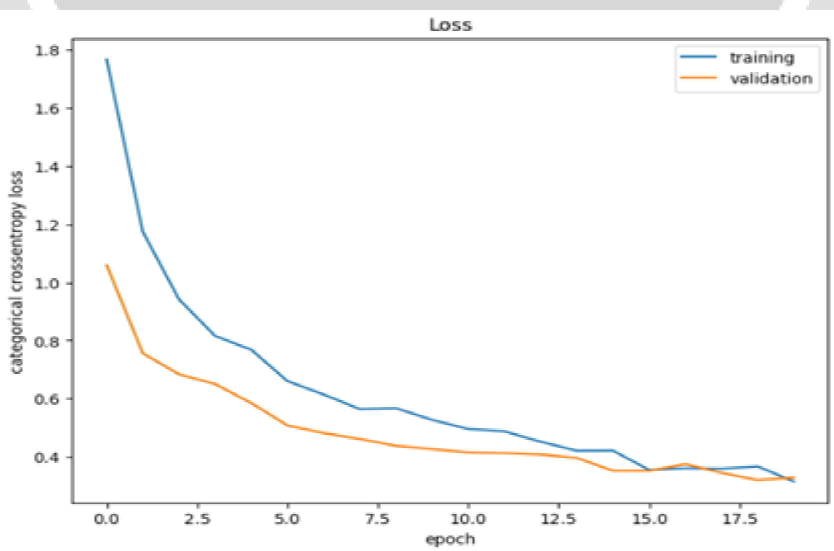


Fig -12: Epoch Versus Loss for NasNetLarge.

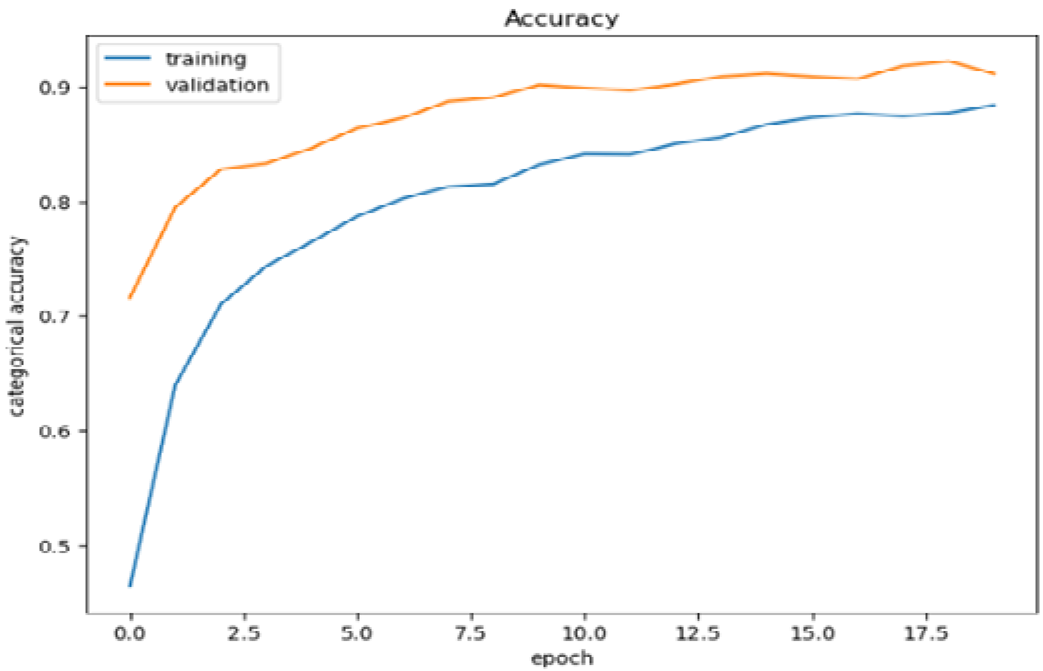


Fig -13: Epoch Versus Accuracy for NasNetLarge.

The confusion matrix for NasNetLarge is shown in Fig-14. Each input and output images are of dimensions 256 × 256.

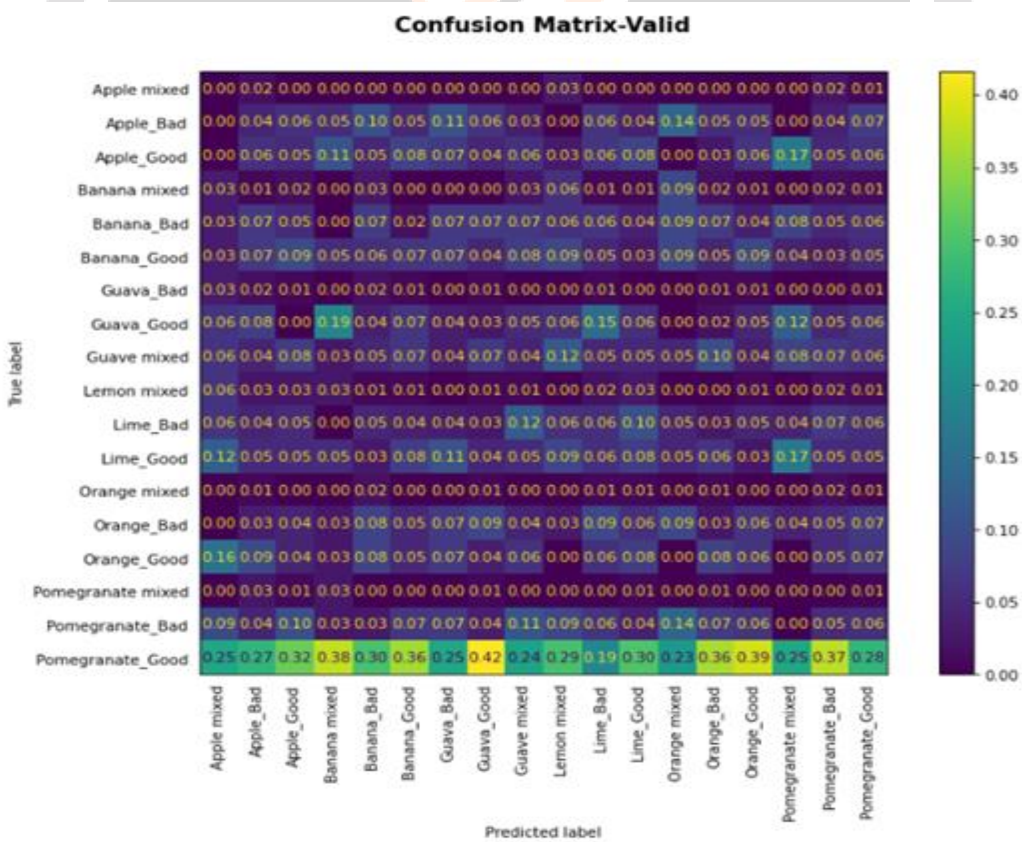
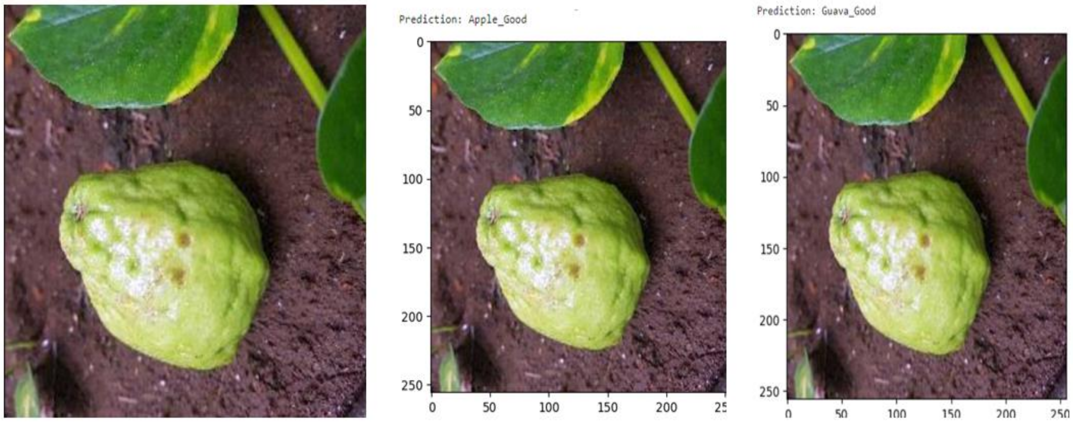


Fig -14: Confusion Matrix for NasNetLarge.

Although the authors have taken a big dataset, due to space-constraint in the paper, they have displayed the input and output for only guava fruit. This is depicted in Fig-15. Fig-15(a) shows the input guava fruit, whereas Fig-15(b) and Fig-15(c) show the classified result (as good) from applying NasNetLarge and DenseNet121 techniques respectively. One should note that apart from visual perception, the analysis obtained by performance metrics also are important to adjudicate the performance of the algorithms applied. Here, DenseNet121 takes high values of accuracy, precision, and recall and hence, it is our choice for fruit classification.



(a) (b) (c)

Fig –15 (a) Input guava image. (b) Classified result obtained using NasNetLarge method. (c) Classified result obtained using DenseNet121 method.

6. CONCLUSIONS

In this work, we proposed a pipeline utilizing densely connected convolutional neural networks (CNNs) for assessing fruit quality from images. Leveraging the internal dense connections of DenseNet121 and NasNetLarge architectures alleviated vanishing-gradient problems, strengthened feature propagation, and facilitated feature reuse in deeper layers. The capability of the model was further enhanced by employing run-time augmentation techniques. The robustness of the pipeline was thoroughly investigated across three different tasks: fruit classification, quality assessment, and fine-grained fruit-quality assessment, yielding an accuracy of around 86% for all tasks when using DenseNetLarge and 80% when using NasNetLarge. Furthermore, we conducted a detailed class-wise analysis and provided insights into the parts of the weights that influenced the decisions made by the model. Looking ahead, future extensions of this work could involve applying image segmentation and object detection models to accurately detect regions of bad-quality fruits. Additionally, assessing the degree of decomposition could be another intriguing task to explore further. Also, the recall, accuracy, and precision values of DenseNet121 are higher than those of NasNetLarge. Since the confusion matrix for DenseNet121 consists of higher values than NasNetLarge, the former one is our choice for classification of fruits into good and defective ones.

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