Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606

Volume 08 Issue 02
2025

Research Article
https://doi.org/10.56979/802/2025

Citrus Fruit Postharvest Losses Analysis using Hybrid Features

Minhal Arshad[1], Muhammad Shehzad[1], Ramsha Ahmad[1], Manal Ahmad[1], Muhammad Yasir Khan[1] and Salman Qadri[1*]

[1]Institute of Computing, MNS University of Agriculture, Multan, Pakistan
[*]Corresponding Author: Prof. Dr. Salman Qadri . Email: salman.qadri@mnsuam.edu.pk

Received: February 03, 2025 **Accepted:** March 01, 2025

Abstract: The citrus fruit is an essential food source for humans, as it contains several vitamins and minerals, which makes it one of the most significant fruit crops globally. A wide variety of fascinating citrus fruits can be found in Pakistan. Most postharvest losses, 30-50% of the total production, are due to improper handling of fruits throughout the packing, shipping, and storing processes. Manual sorting of horticulture items increases postharvest losses however innovative algorithms and technology offer solutions to mitigate these losses. The focus of this research is to enhance current methods of fruit grading, decrease post-harvest losses and preserve fruit quality. Artificial intelligence (AI) models are used to grade citrus fruits for real-world applications. With the use of AI classifiers, we can categories citrus fruits into four distinct stages based on their ripeness: initial-ripe, semi-ripe, fully ripe, and defective or damaged. Each stage is distinguished by its own unique hybrid feature, color attributes (RGB), texture and size. Three Convolutional neural network (CNN) models namely, MobileNet, VGG16, and Inception V3 used to achieve accuracy of 97%, 98%, 95.6% on citrus fruit dataset. The VGG16 gives the best results on grading.

Keywords: Fruit grading; Hybrid features; Postharvest losses

1. Introduction

Pakistan is one of the world's top growers of citrus fruits, coming in at number 13th overall. Due to its advantages in nutrition and the economy, citrus is very essential. The most common fruit in Pakistan in terms of both production and area is the kinnow, which is a useful fruit [1]. Pakistan's citrus fruit production is 30% of total fruits. In Punjab province, about 90% of citrus fruits are produced and sold through various value chains both domestically and internationally. However, 10-12% of the total production is exported after being added to Pakistan, as most of the citrus fruit is consumed locally with little to no additional value [2].

Human life is incredibly busy today. Everyone wants to complete their work quickly, accurately, and cheaply. Therefore, only cutting-edge technology can satisfy this kind of desire. Fresh fruit must be graded for quality because consumers are becoming more concerned with it. After harvest, grading the fruits is a crucial part of post-harvest management. Fruits are graded according to their physical qualities, such as size, color, and texture, based on agro-climatic conditions. However, such grading requires a lot of skilled labor. To get around this, a mechanism for automatically classifying different fruit grades is required. Because of a poor procedure, it is now challenging to identify fruit by texture, size, and color, but by employing artificial intelligence, it is now simple to identify the right fruit [3].

Post-harvest losses in horticulture become worse by manual classification, but innovative technologies and algorithms provide ways to mitigate these losses [5]. This review's objective is to highlight the typical post-harvest illnesses of citrus fruits and the different pre-packaging remedies that can be applied to treat them and improve fruit quality. Maintaining citrus quality and lowering the incidence of postharvest decay has been made easier with the help of hot water, surface coatings, ultraviolet radiation, chlorine (hypochlorous), salt treatments, and microbial antagonists. To effectively manage infections before and after harvest, pre-packaging treatments should combine (1) disinfection; (2) curative; and (3) preventive measures [6].

Citrus spp., which is primarily found in the Mediterranean basin, is the most common fruit consumed by people. Postharvest losses can result in severe wastage, accounting for 30 to 50% of the overall crop, and are primarily brought on by infections and metabolic disorders of fruits. Harvested products must be managed, treated, stored, and transported properly to maintain quality and extend shelf life. Implementing modern technologies to improve treatments and keep track of the prevalence of fungal infections will define the post-harvesting of citrus fruits in the future. This will help to manage quality and minimize food losses [7].

Observing the potential for classifying eight citrus cultivars by utilizing fused characteristics and employing a machine vision (MV) technique. The categorization of eight citrus plant kinds using a unique fused multi-featured leaf dataset is the main goal of this study. Four machine vision classifiers MLP, RF, NB, and J48 were successfully deployed using the suggested fused dataset for assessment purposes. When classifying the citrus leaves, a distinct set of parameters is applied to the evaluation of the data set. All the classifiers produced effective results, but MLP stands out by reaching 98.14% accuracy on the eight different citrus plant kinds [8]. Machine vision-based automation system for inspection from the citrus field to post-harvest - a review [9].

Applied machine learning techniques to citrus fruits and leaves image datasets to detect and classify citrus diseases. Fruit plants are crucial to the development of every state's economy. Citrus is a well-known species of fruit plant that is abundant in vitamin C and is widely consumed throughout the Middle East and Africa [11]. The author developed a computer vision-based automated method for classifying and scoring lemons. It takes human mistakes out of the sorting process. Three classifications of lemons are used: ripe, semi-ripe, and a combined category for faulty and unripe lemons [12]. The authors leverage a fine-tuned CNN model, specifically the VGG16 architecture, which has been pre-trained on a large-scale image dataset, to learn from images featuring six different fruits obtained from the Kaggle platform. To ensure the effectiveness of their proposed approach, the authors put it to the test using a previously unseen dataset. Remarkably, the model achieves an accuracy rate of 100%, signifying its outstanding performance [13].

The objective of this study is to develop an automated system which enables the early detection and mitigation of postharvest losses, thereby reducing food waste, increasing economic effectiveness, maintaining fruit quality, and boosting the overall sustainability of the citrus fruit trade. And, to develop the best feature selection techniques for citrus fruit grading. Furthermore, to develop a robust model for grading citrus fruit to minimize post-harvest losses.

2. Materials and Methods

2.1. Study Domain

Since we have been working on image processing and computer vision, data acquisition is the first and most fundamental phase in our study. It is the act of using a camera to take pictures. It is not necessary to use a digital or DSLR camera, smart phone camera can also be used, but only if the images are of high quality. The use of a white and black background speeds up segmentation, and pre-processing of the acquired citrus images was completed as needed. Take the pictures at the same time to get better results from the output. One of the elements affecting how well a neural network performs is the dataset it is given to train on. The accuracy of the neural network is lower when there are fewer datasets assigned than when there are many datasets used in training it. Data augmentation is required to increase the variety of the current dataset to solve this issue. Any technique that artificially expands the initial training set with label-preserving modifications is known as data augmentation. Preprocessing and feature extraction are fundamental and widely employed steps in the identification of maturity, defect detection, classification, and grading of distinct types of fruits. Preprocessing techniques play a crucial role in enhancing the quality of images. During this stage, undesired atmospheric noise is eliminated, and the dataset is refined to prepare it for subsequent stages. The objective is to enhance image quality specifically for detecting the regions of interest in citrus fruit images.

2.2. Dataset

The oranges samples have been accrued from Multan agriculture lookup laboratory, Multan district of Punjab, Pakistan Citrus fruits are all members of the Rutaceae family and are the subject of this study. For database purposes, citrus fruit was gathered at Bypass Road, Block E Shah Rukn E Alam, (Multan) Pakistan. The testing variety we decided on for our study was known by the names Orange and Lemon. Citrus fruit photos are all 4160 * 3120 pixels, and there are no missing data in the dataset. The dataset was collected using the camera on a cell phone. Orange and Lemon were divided into four categories for practical purposes: "initial ripe," "semi-ripe," "fully ripe," and "damaged/defective".

Figure 1. Ripeness level of Oranges

In this study, a dataset for grading citrus fruit has been developed using images taken with a cell phone camera. First, we collected two varieties of citrus: orange and lemon. Each variety consists of 4 classes: initial ripe, semi-ripe, fully ripe, and damaged or defective. Every photograph that was taken was saved with the jpg extension and ranged in size from 4160 x 3120 pixels. The oranges are divided into four classes initial ripe, semi-ripe, fully ripe, and damaged or defective. Figure 1 shows the ripeness levels of oranges that is the variety of citrus fruit. The lemons are divided into four classes initial ripe, semi-ripe, fully ripe, and damaged or defective. Figure 2 shows the ripeness levels of lemons, which is the second variety of citrus fruit used in this study.

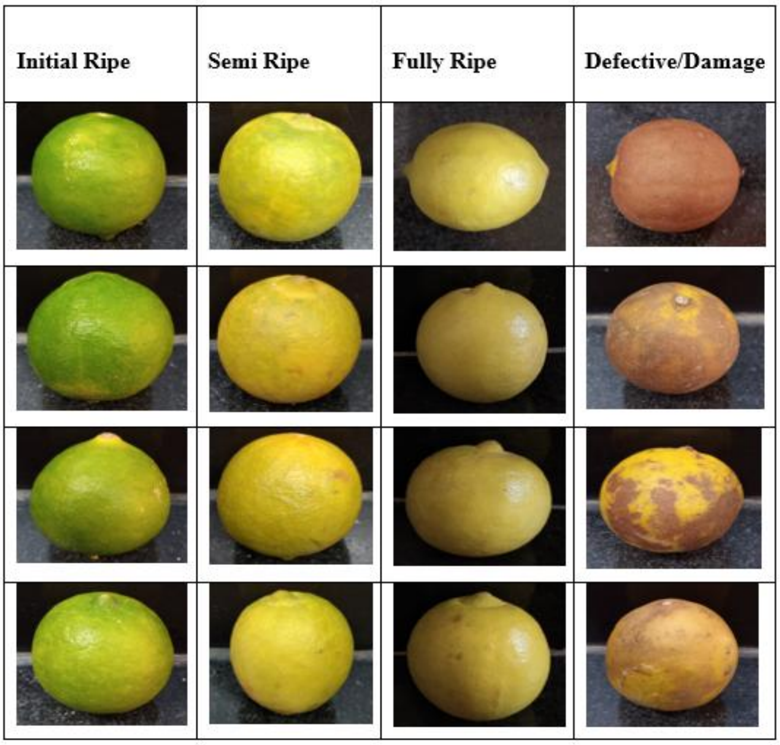

Figure 2. Lemon Ripeness Level

2.3. Method

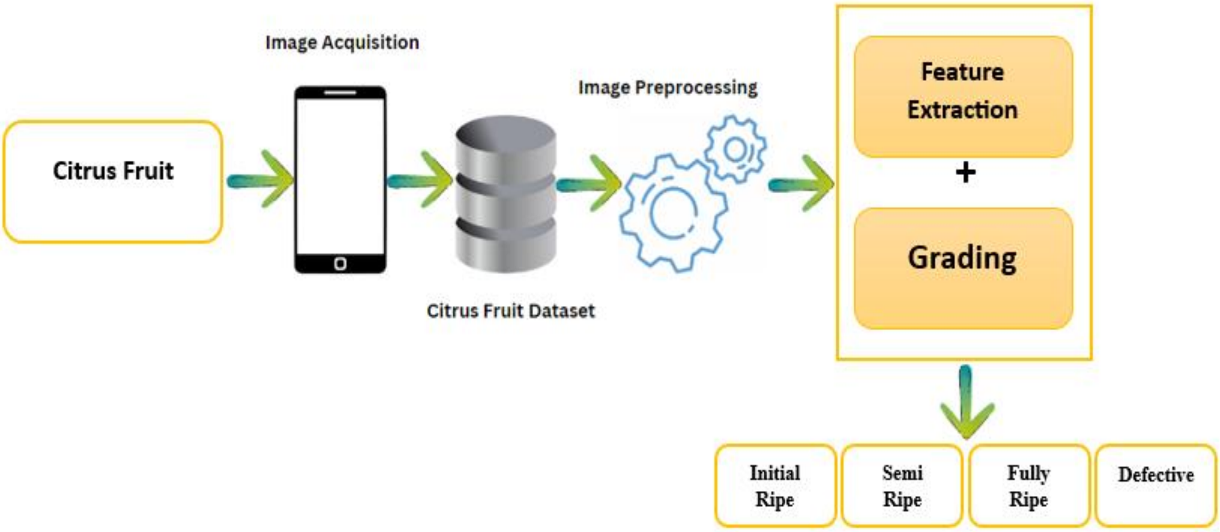

Figure 3. Proposed Methodology

Feature extraction is a method utilized to reduce the spatial dimensionality of the original dataset. Its purpose is to minimize computational requirements and memory usage within a network. Features are typically regarded as significant characteristics or points of interest. They are also referred to as descriptors or parameters utilized in the classification or grading process. Figure 3 shows the structural design of the Citrus

Fruit Grading System. When extracting features from an image, examples may include color values (such as RGB), texture, and the sizes of citrus fruits.

2.3.1. Feature Extraction Techniques

- **Color Value (RGB) Feature**

  The colors of citrus fruit were extracted using RGB color value, the most used image processing technique. The ripeness of citrus fruit is indicated by its colors. The result of the color feature is shown in Figure 4.

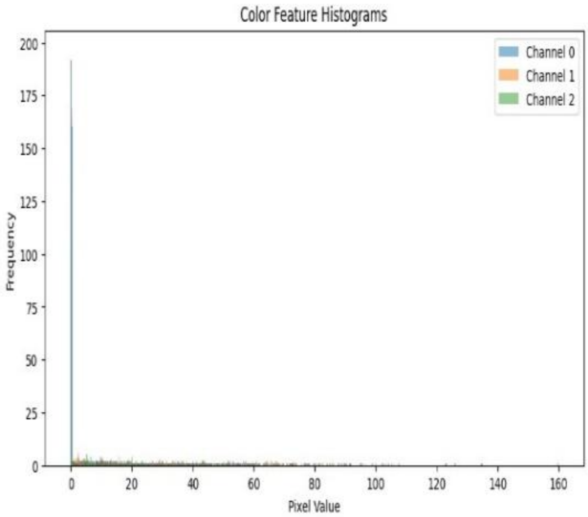

Figure 4. Color Feature Results

- **Texture Feature**

  Texture features are also known as a second-order measure. The distribution and appearance of elements on a surface are represented by texture. It is a crucial characteristic that predicts surface properties including contrast, roughness, orientation, entropy, etc. The result of the texture feature is shown in Figure 5.

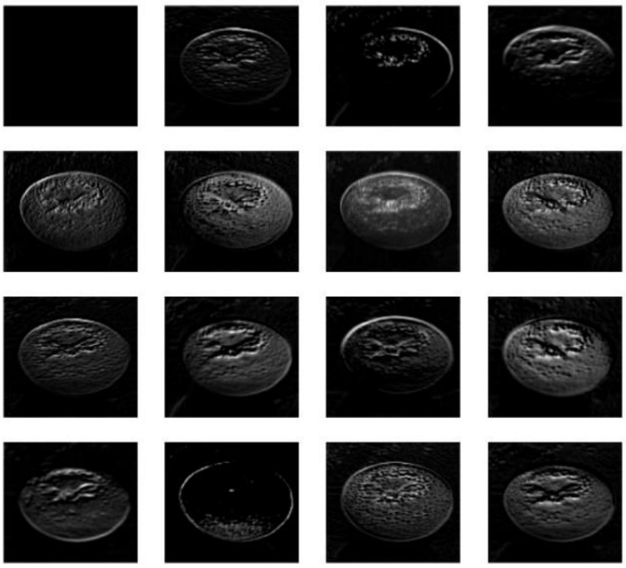

Figure 5. Texture Feature Results

- **Size Feature**

  The third most significant feature is citrus fruit size, which is calculated by counting the number of pixels under the fruit's area.

```
Size Features:
[[[ 0.          0.          0.          ...  0.          12.222926
    0.        ]
  [ 0.          0.          0.          ...  0.           1.3955228
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  ...
  [ 0.          0.          0.          ...  0.           4.4680653
    0.        ]
  [ 0.          0.          0.          ...  0.           4.2424173
    0.        ]
  [ 0.          0.          0.          ...  0.          11.430076
    0.        ]]

 [[ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  ...
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.58515537
    0.        ]]

 [[ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  ...
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]
  [ 0.          0.          0.          ...  0.           0.
    0.        ]]

 ...
```

Figure 6. Size Feature Results

2.3.2. To Minimize Postharvest Losses in Citrus Using Artificial Intelligence

For the model training of citrus fruit grading on Google Colab, we used three different algorithms VGG 16, MobileNet, and Inception v3. The convolutional neural network (CNN) architecture known as VGG16, or Visual Geometry Group 16, has generated a lot of interest in the field of computer vision. The VGG16 algorithm is well known for its ease of use and effective performance in image recognition applications. Simonyan and Zisserman created VGG16 for the ILSVRC 2014 competition. There are only 3x3 kernels used in its 16 convolutional layers. The authors' chosen design is comparable to Alexnet in that it increases the number of feature maps or convolutions as the network's depth increases. There are 138 million parameters in the network. Classification, detection, and other typical convolutional neural network tasks are performed with MobileNet. With a capacity of about 17MB, they can be used in mobile devices because of their small size. These are created using streamlined architecture.

To create both light and deep neural networks, this architecture utilizes depth-wise separable convolutions. Convolutional neural networks are effective tools for computer vision applications, and MobileNet is one such one [14]. Convolutional neural network (CNN) architecture Inception v3 was created to overcome the difficulties of deep learning models in terms of interpretability and computational efficiency. It is made up of convolutional, pooling, and inception modules, as well as several stacked layers. The core elements of the design are the inception modules, which combine parallel convolutions with variable kernel sizes to capture characteristics at various scales.

Inception v3 has demonstrated its efficiency in the realm of computer vision by achieving remarkable performance in image classification and transfer learning tasks. In developing nations such as Pakistan, postharvest losses pose a serious threat to food security, drawing significant attention from researchers and policymakers. These losses primarily stem from inadequate handling practices, limited technical expertise, outdated technology, and inefficient time management. This study specifically targets postharvest losses in citrus fruits, a critical issue affecting the agricultural sector. Leveraging advanced artificial intelligence models—including VGG16, MobileNet, and Inception v3—along with hybrid feature extraction (such as RGB color analysis, texture evaluation, and size measurements), we propose an optimized approach to reduce waste and enhance fruit quality preservation.

3. Results and Discussion

This study employed three advanced convolutional neural network architectures - VGG16, MobileNet, and Inception v3 - for automated citrus fruit classification. These models were selected based on their established performance in computer vision applications, particularly in image recognition tasks. Our experimental findings demonstrated classification accuracy of 98%, 97%, and 95.6% for VGG16, MobileNet, and Inception v3 respectively, confirming their effectiveness in assessing fruit quality and ripeness levels.

The high precision achieved by these deep learning models highlights the significant potential of artificial intelligence in revolutionizing postharvest fruit management. Implementing such AI-powered grading systems offers multiple advantages: (1) enhanced accuracy in quality assessment compared to manual methods, (2) improved efficiency in sorting operations, and (3) better-informed decisions regarding storage and distribution. These technological advancements can substantially reduce postharvest losses while optimizing the entire supply chain process in the citrus industry.

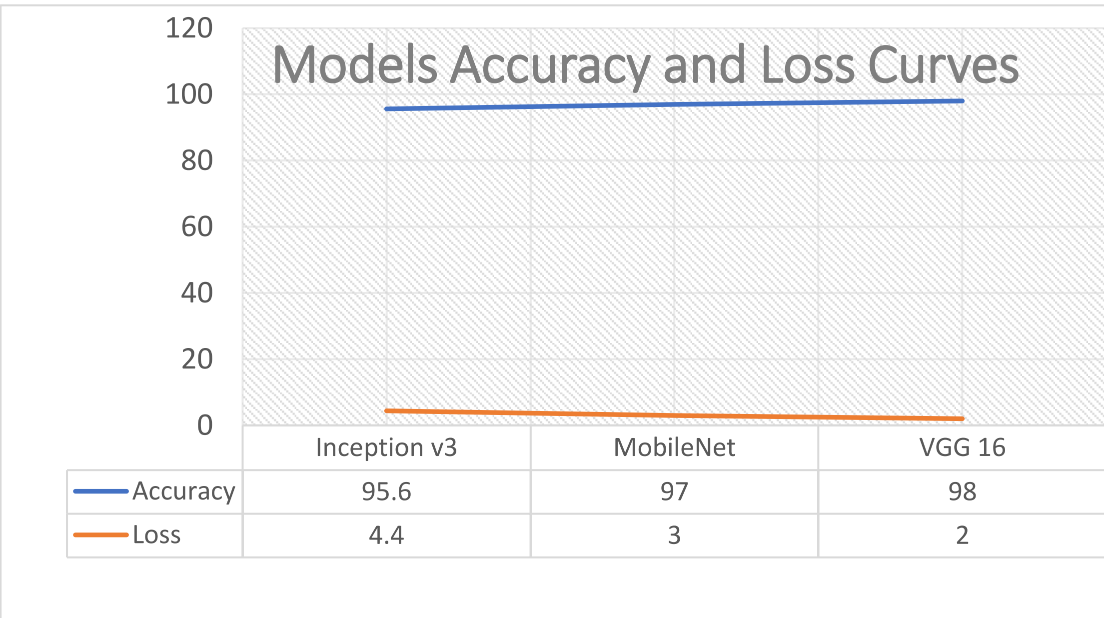

Figure 7. Accuracy Comparison of Models

This study implemented three deep learning architectures for automated citrus fruit quality assessment. Performance evaluation revealed that MobileNet achieved 97% classification accuracy, followed by VGG16 (98%) and Inception v3 (95.6%). Among these models, VGG16 demonstrated superior performance, establishing itself as the optimal choice for citrus grading applications. The exceptional accuracy of VGG16 can be attributed to its deeper network architecture and greater parameter capacity, which enables more effective extraction of complex visual features from fruit images.

This architectural advantage allows VGG16 to identify subtle quality indicators that might be overlooked by shallower networks. Additionally, VGG16's proven reliability across numerous image classification benchmarks further validates its selection for this application. The comparative analysis of model performance (presented in Figure 7) confirms VGG16's robustness and precision in fruit quality classification. These characteristics make it particularly suitable for industrial implementation, where both accuracy and consistency are paramount for effective postharvest management.

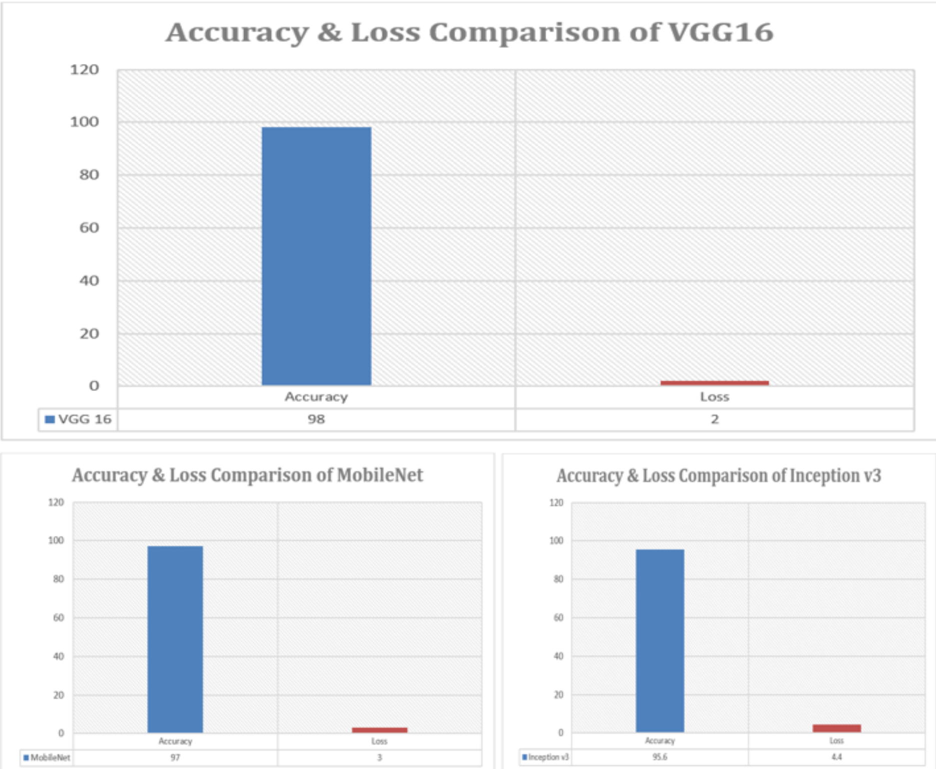

Figure 8. Accuracy and loss comparison of models

4. Conclusion

Our study contributes to the existing body of knowledge by demonstrating the practical application of hybrid features and CNN models for postharvest loss analysis and fruit grading. By incorporating color values, texture, and sizes as hybrid features, we captured a more comprehensive understanding of the fruit characteristics and achieved improved accuracy in the grading process. This approach can potentially be extended to other fruit crops, contributing to the overall efficiency and sustainability of the horticultural industry. In conclusion, the integration of hybrid features and CNN models, specifically VGG16, MobileNet, and Inception v3 holds promise in reducing postharvest losses and enhancing fruit grading in the citrus industry. The achieved high accuracy provides a strong foundation for the practical implementation of AI-based grading systems. This research opens avenues for further exploration and implementation of advanced technologies to optimize postharvest management practices and ensure the quality and market value of citrus fruit.

References

1. Mushtaq, S., M. Shafiq, T. Ashraf, M.S. Haider, S. Atta, K.S. Almaary and M.S. Elshikh. 2022. Enumeration of citrus endophytic bacterial communities based on illumine metagenomics technique. *PLoS One* 17.
2. Siddique, M.I. and E. Garnevska. 2018. Citrus Value Chain(s): A Survey of Pakistan Citrus Industry. *Agricultural Value Chain*. InTech. pp.1–21.
3. Sethy, P.K., S. Panda, S.K. Behera and A.K. Rath. 2017. On Tree Detection, Counting & Post- Harvest grading of fruits Based on Image Processing and Machine Learning Approach-A Review. *International Journal of Engineering and Technology* 9:649–663.
4. Ireri, D., E. Belal, C. Okinda, N. Makange and C. Ji. 2019. A computer vision system for defect discrimination and grading in tomatoes using machine learning and image processing. *Artificial Intelligence in Agriculture* 2:28–37.
5. Piedad, E., J.I. Larada, G.J. Pojas and L.V. V. Ferrer. 2018. Postharvest classification of banana (Musa acuminata) using tier-based machine learning. *Postharvest Biol Technol* 145:93–100.
6. Kassim, A., T.S. Workneh and M.D. Laing. 2020. A review of the postharvest characteristics and pre-packaging treatments of citrus fruit. *AIMS Agriculture and Food* 5:337–364.
7. Strano, M.C., G. Altieri, M. Allegra, G.C. Di Renzo, G. Paterna, A. Matera and F. Genovese. 2022. Postharvest Technologies of Fresh Citrus Fruit: Advances and Recent Developments for the Loss Reduction during Handling and Storage. *Horticulturae* 8:1–612.
8. Qadri, S., S. Furqan Qadri, M. Husnain, M.M. Saad Missen, D.M. Khan, Muzammil-Ul-Rehman, A. Razzaq and S. Ullah. 2019. Machine vision approach for classification of citrus leaves using fused features. *Int J Food Prop* 22:2071–2088.
9. Cubero, S., W.S. Lee, N. Aleixos, F. Albert and J. Blasco. 2016. Automated Systems Based on Machine Vision for Inspecting Citrus Fruits from the Field to Postharvest—a Review. *Food Bioproc Tech* 9:1623–1639.
10. Singh, A., G. Vaidya, V. Jagota, D.A. Darko, R.K. Agarwal, S. Debnath and E. Potrich. 2022. Recent Advancement in Postharvest Loss Mitigation and Quality Management of Fruits and Vegetables Using Machine Learning Frameworks. *J Food Qual* 2022:1–9.
11. Rauf, H.T., B.A. Saleem, M.I.U. Lali, M.A. Khan, M. Sharif and S.A.C. Bukhari. 2019. A citrus fruits and leaves dataset for detection and classification of citrus diseases through machine learning. *Data Brief* 26:1–7.
12. Mukhtar, T., S. Jamil, U. Arif, W. Razzaq and M. Wasif. 2021. Lemon Grading and Sorting Using Computer Vision †. *Engineering Proceedings* 12:1–55.
13. Abu-Jamie, T.N., S.S. Abu-Naser, M.A. Alkahlout and M.A. Aish. 2022. *Six Fruits Classification Using Deep Learning*.
14. Palakodati, S.S.S., V.R.R. Chirra, Y. Dasari and S. Bulla. 2020. Fresh and rotten fruits classification using CNN and transfer learning. *Revue d'Intelligence Artificielle* 34:617–622.