Journal of
Agriculture and Biology
ISSN: 3007-1755 (Print), 3007-1763 (Online)

Check for updates

ROOTS PRESS

Research Article

Automated Identification of Citrus Fruits Nutrients Through Non-destructive Analysis

Shahid Iqbal[1], Aamir Hussain[1,2], Salman Qadri[1], Abdul Razzaq[1], Muhammad Talha Jahangir[3]

[1] Institute of Computing, Muhammad Nawaz Shareef University of Agriculture, Multan, Pakistan.

[2] Department of Informatics, Modeling, Electronics, and Systems Engineering (DIMES), University of Calabria, Rende, Italy.

[3] Department of Computer Science, Muhammad Nawaz Shareef University of Engineering & Technology, Multan, Pakistan.

ABSTRACT

The development of digital technology has played a significant role in digitizing this world. This technology has enabled the storage, processing, and analysis of data using a cloud-based platform that benefits farmers. Image processing is a technique that involves performing specific tasks on an image to extract useful information. Citrus fruits such as mandarins, lemons, grapefruits, and oranges are the most widely grown fruits in the world. Citrus is a large plant cultivated primarily in the world's tropical regions due to its abundance of vitamin C, Total Soluble Solids (TSS), Titratable Acidity (TA), and pH. To find out these nutrients, we need to consult with a horticulturist. The traditional approach is costly, complex, and time-consuming for a common farmer. The study aims to provide an efficient and cost-effective solution to achieve the same goal. This work trains an efficient deep learning-based system to process data more efficiently and precisely. A framework is developed to automate the system for classifying and detecting nutritional values from images of different citrus fruits. The system is trained using the Transform Learning Approach (TLA) and Single Shot Detection (SSD) V2 to process the custom dataset. Results obtained from the experiments show that the accuracy achieved with our proposed methodology approaches 97%. This non-destructive predictive analysis of citrus fruit will pave the path for prescriptive analytics to enhance the qualitative productivity of the fruit.

Keywords: Citrus fruits, Vitamin C, Total Soluble Solids (TSS), Titratable Acidity (TA), Single-Shot Detection (SSD) V2, Deep Learning.

OPEN ACCESS

Correspondence
Aamir Hussain
aamir.hussain@mnsuam.edu.pk

Article History
Received: August 14, 2024
Accepted: October 20, 2024
Published: November 06, 2024

INTRODUCTION

Fruit exports are essential for earning revenue for any Country and indispensable for a Country with an agrarian economy. In Pakistan, citrus fruits are the most important fruit crops grown in 160,000 hectares, with a production of 1.5 MMT annually (Ali et al., 2023). While human sorting and grading can be performed, it is unreliable, time-consuming, unpredictable, costly, and easily influenced by environmental factors.

Citrus fruits are known as 'hesperidium,' a type of berry that develops from a single ovary with 8-16 carpels clustered around and joined at the floral axis and covered by a tough, leathery rind (Schneider, 1968). The fruit's endocarp, which is an edible portion, is composed of segments (carpels) that contain juice vesicles and seeds. The peel is divided into two parts: the exocarp, also known as flavedo, and the endocarp. The epicarp, protected by a cuticle, the hypodermis, the external mesocarp, and the oil gland, comprise the flavedo (Ning et al., 2025).

https://doi.org/10.55627/agribiol.002.02.1164

Citrus is a primarily grown and consumable fruit crop worldwide (Ali et al., 2024). Due to the presence of abundant phytochemicals, including vitamins A, E, B, and C, minerals, antioxidant compounds, and dietary fiber, citrus fruits possess numerous health-beneficial properties. In Pakistan, citrus is grown in an area of 0.19 million ha, from which a yield of 2.27 million tons is obtained. Approximately 95% of the citrus production originates from Punjab province, primarily for the Kinnow mandarin (Usman et al., 2020).

Apart from Kinnow, a small number of oranges, lemons, grapefruits, limes, other mandarins, kumquats, and tangelos are also produced. From a market perspective, citrus consumption is increasing, necessitating the introduction and commercialization of new citrus varieties. Fruit Physico-chemical attributes are essential quality standards for selecting and commercializing promising citrus varieties (Bermejo et al., 2011). These quality standards are influenced by the type of rootstock, scion, environmental factors, and cultural practices.

Peel color is one of the most significant fruit quality traits, as it affects consumers' visual perception and influences their decision to purchase the fruit. Billions of people worldwide consume citrus fruits, particularly mandarins, for their distinctive, delicate, and appealing flavor, a combination of sweet, sour, fruity, and fresh notes (Şengül et al., 2025). Citrus has been shown to minimize the risk of cancer, heart disease, and diabetes due to various bioactive compounds, including vitamins, phenols, flavonoids, carotenoids, dietary fiber, and minerals.

Various factors, including climate conditions and agricultural practices, influence the production and quality of citrus fruits. Citrus production has always depended on rootstocks. A suitable rootstock is crucial for citrus as it significantly influences the orchard's lifespan and productivity. Rootstock's ability to induce disease tolerance or resistance is the primary explanation for their widespread use in citrus production. Tree age is also a factor that influences fruit quality characteristics. A young tree gives better quality than an old tree; TSS and sugars were high in young trees. Canopy position also has a significant impact on fruit quality. Fruits from the top of the canopy have a higher TSS and TSS: TA ratio than the inner side of the canopy.

Nutrition is also a factor in fruit quality. NPK is essential for cell division, growth, photosynthesis, and respiration. Fruit quality parameters, both externally and internally, appear to be influenced by macro- and micronutrients (Shaaban and Abdel-Ati, 2025). Citrus trees in Pakistan have a relatively short lifespan, typically lasting only 25 years on average. Tree decline begins at ten, the prime age of development, in more than 40% of cases. Compared to fruit from middle-aged and old trees, fruit from younger apple trees had the lowest storage capacity, with firmer fruit that quickly lost flavor and consistency during shelf life and storage.

Literature Review

In the past, various methods were employed for detecting the varieties of different fruits and vegetables. However, these methods require information related to preprocessing, baseline correction, and wavelength selection. Previously, we required expertise and chemicals to inspect the fruit, which caused damage to the fruit (Prasad et al., 2024). The enhancement of deep learning models and methods enabled the determination of the composition of nutrients in citrus fruit (Cai et al., 2025). Old methods for determining the composition of nutrients in citrus fruit involved destructive sampling, which was challenging to implement and design for large-scale applications. Today, much research has been conducted on non-destructive techniques, such as Raman Spectroscopy and hyperspectral imaging, to classify fruit quality [6]. Non-destructive testing (NDT) (Ali and Hashim, 2022; Liu et al., 2024) has been utilized as a quality testing method (Vijayakumaran, 2023) in agriculture. To analyze the vitamin C content in oranges. Similarly, Shah et al. (2020) employed near-infrared (NIR) spectroscopy to predict TSS in mandarins, achieving an R^2 value of 0.89. These applications demonstrate the change from destructive examination to laboratory measurement of the computerized image.

Deep learning has revolutionized the field of computer vision, enabling more accurate fruit quality assessment. Convolutional Neural Networks (CNNs) have been used to detect and label various features of the fruits. Emerging a machine-based model with deep learning algorithms or a comprehensive experimental model for the classification and detection of products with incredibly high accuracy rates. Additionally, a study that combined non-destructive surface thermal inductive analysis with deep learning found it to be useful for quantifying the ripening of guava (Low et al., 2024; Mimma et al., 2022; Zhou et al., 2025).

The research paper states that the ResNet-50 model was used for detecting citrus diseases and nutrient deficiencies with an accuracy of 94%. Another study is (Roy et al., 2021), which also involves Shen et al., 2024) SSD (Single Shot Detector) for citrus fruit detection in real-time, showing better performance compared to the conventional methods (Gan et al., 2020). Transfer Learning (TL) reduces computational costs without compromising accuracy. Trained a VGG-16 model to estimate the degree of maturity for citrus and achieved 96% accuracy. Similarly, MobileNetV2 was used to estimate TSS in lemons with a Mean Absolute Error (MAE) of 0.3%.

Image-based nutrient analysis relies on the analysis of color, texture, and spectral properties. Support Vector Machines (SVM) were used in one study to predict the relationship between citrus peel color and vitamin C concentration, achieving an R^2 value of 0.85. Additionally, a multispectral imaging system was developed to predict Titratable Acidity (TA) with an accuracy of 91% (Younis et al., 2019). Despite progress, challenges remain, including dataset variation and limitations in real-time deployment (Lamsal et al., 2024). The future direction should be toward edge computing for on-field processing and multimodal sensor fusion (Marzougui et al., 2023), such as RGB and thermal image fusion, for improved accuracy (Górriz et al., 2023).

The literature reviewed highlights the potential of deep learning and image processing for non-destructive analysis of citrus nutrients. SSD V2 and transfer learning-based models have been demonstrated to be highly accurate (>95%) in predicting vitamin C, TSS, and TA (Hadipour-Rokni et al., 2023). The incorporation of machine vision technologies into the agricultural sector has enabled the instantaneous and non-destructive determination of food quality and authenticity. Such systems, in conjunction with deep learning methods, have found applications in numerous areas of food processing. A review of the subject provided an extensive overview of the significance of machine vision and deep learning in food authentication, highlighting their roles in detecting adulteration and evaluating quality attributes (Kumar et al., 2015). These models should be optimized for real-world agricultural applications in future studies.

MATERIALS AND METHODS

The objective of this research was to develop a robust model of citrus fruit varieties that can identify the nutrients present in citrus fruits. Figure 1 shows the proposed system methodology.

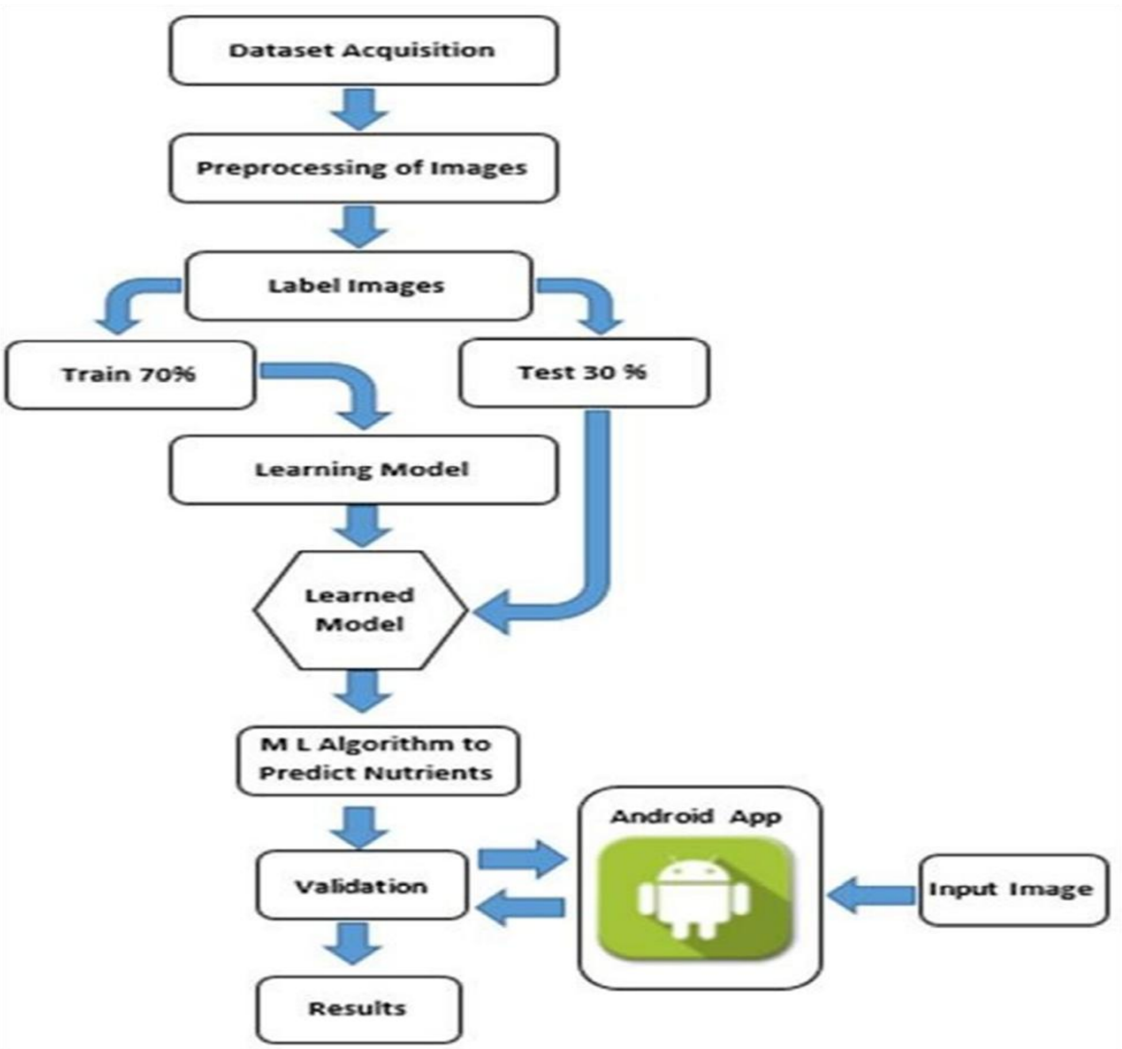

Figure 1. Proposed Methodology.

The proposed system accurately recognized the citrus fruit variety and nutrients. The model designed in the research has the following steps:
Dataset Collection
Citrus fruits Identification
Finding nutrients

Dataset Collection

The citrus fruit images dataset will be collected from the Citrus Jorum Plasm unit Muhammad Nagar Form Arif Wala, Pakistan. More than 700 high-resolution images of citrus fruits were taken with a Canon D3D camera. Some examples of dataset images are shown in Figure 2. To classify the above-mentioned citrus fruits, the variety dataset was split into a training dataset and a validation dataset with a ratio of 75% and 25%, respectively. The CNN classifier (Inception v3) was then trained on the training dataset.

Figure 2. Example images of collected dataset.

Citrus Fruits identification

For easy identification, the Deep Convolutional Neural Network (SSD MobileNet-V2) presents a transfer learning approach for the development of a model. SSD MobileNet v2 detects several compounds in the image. Its strategy is based on a feed-forward Convolutional network that generates a fixed-size array of bounding boxes and scores for the objects in the boxes (Howard et al. 2017). SSD architecture is illustrated in Figure 3. T

here are two parts in the model: first, feature map extraction, and second, convolutional filter application to detected objects. Manual labeling of citrus verity in images is the initial step for training the model. Two subfolders (train and test) formed from labeling. These subfolders summarize the appearance features of target objects into feature vectors relating to the training and testing labels. The ratio of data in these subfolders is set at 70:30, respectively. In the next stage, the feature vector relating to the training label is used as input for the learning model. Finally, the model created for the recognition task of citrus fruits is given by the classified model obtained from the feature vector corresponding to the testing label.

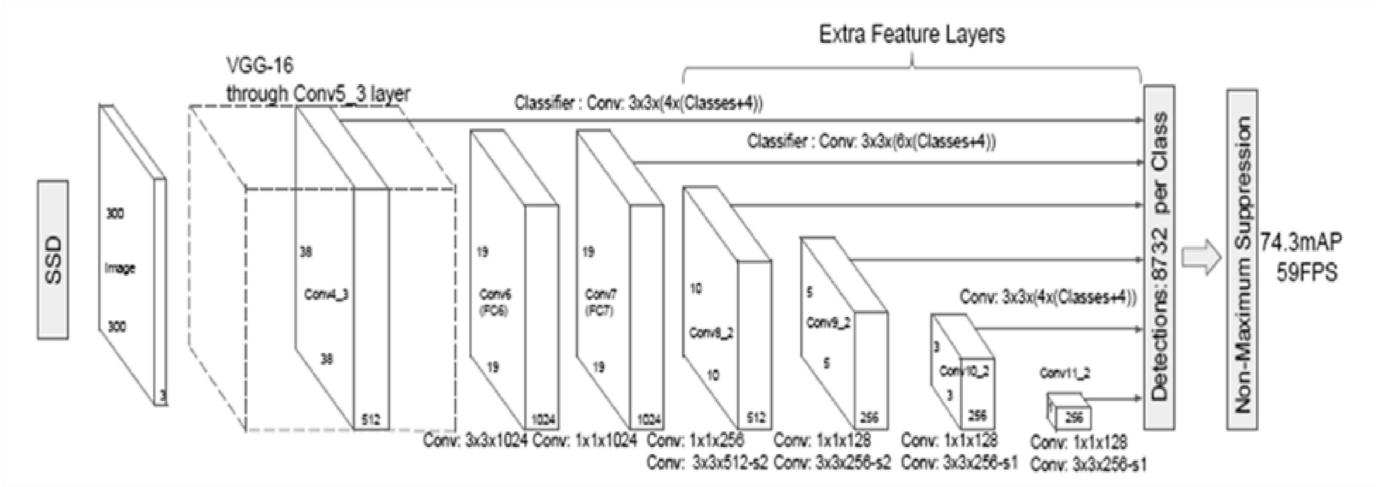

Figure 3. The architecture of SSD MobileNet V2 (Howard et al. 2017).

RESULTS

Results of Citrus Fruits Classification

Hyperparameter tuning achieved results at 70 % and 30% of the training dataset and the testing dataset at 50 Epochs with 16 batch sizes, respectively.

Variety	Per class accuracy	Test Loss %	Learning Rate	Training Time /min
Amber Sweet	93%	0.2	0.01	2:40
Succri	91%	0.19	0.01	2:40
Cara Cara Navel	89%	0.18	0.01	2:40
Sulstiana	92%	0.2	0.01	2:40

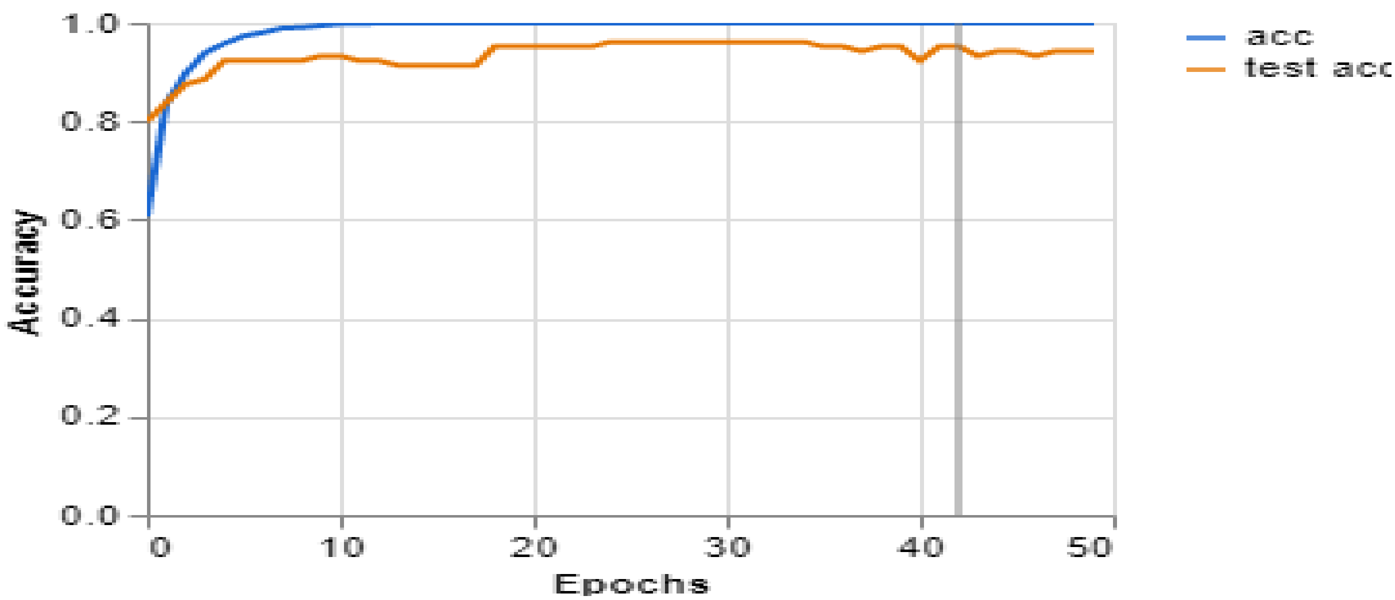

Figure 4. Test accuracy of Citrus classification achieved at 50 Epoch with 16 Batch size.

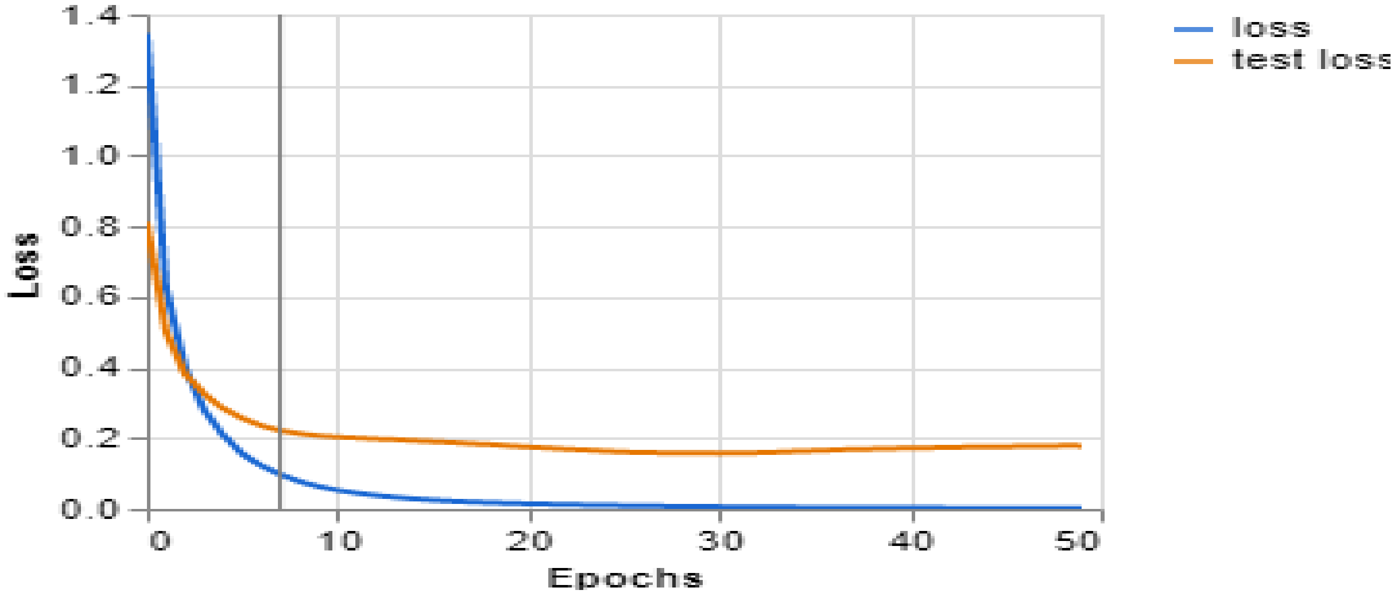

Figure 5. Test loss of citrus fruits classification at 50 epochs with 16 Batch sizes.

Figure 4 shows that at 50 epochs, the 16-batch size model achieved a test accuracy of 91.25% in citrus fruit variety classification. The graph of Figure 5 shows that at 50 epochs, the 16-batch size model had a 0.2 test loss in citrus fruit variety classification.

Confusion Matrix for Classification Results

The confusion matrix evaluates the accuracy of the model's prediction. It can be used to determine the model's confusion about the class when it makes the wrong prediction. In the matrix below, the Y-axis shows the actual class, whereas the X-axis shows the model's prediction against the respective classification.

In Figure 6, predictions of ResNet152 architecture can be figured out; it made two false positives such as it predicting wrong (Cara Cara Navel) and (Sulstiana) instead of actual citrus fruit, which was Amber Sweet and Succri in actual fruits.

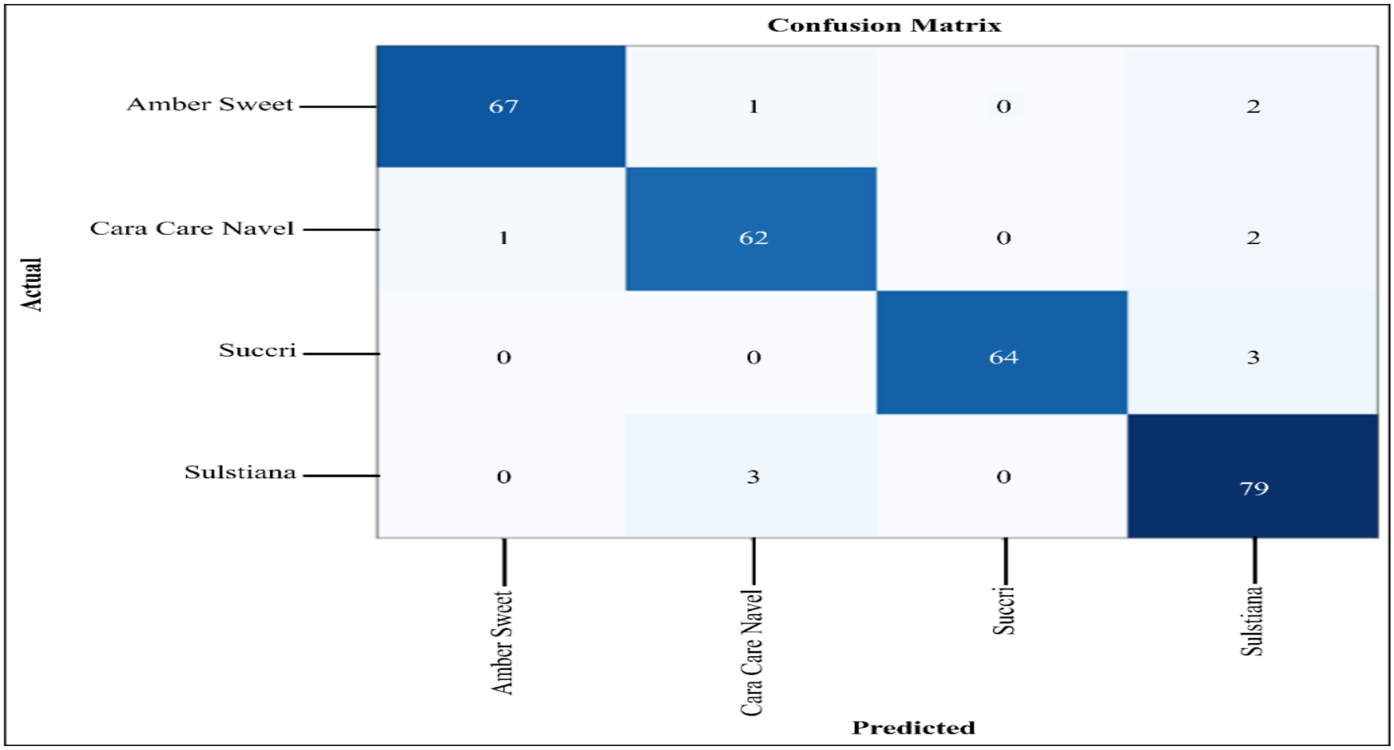

Figure 6. Confusion Matrix (ResNet152 architecture) of citrus fruits classification.

Similarly, the ResNet152 model outputs four false negatives, predicting the wrong citrus fruits, namely Amber Sweet, Cara Cara Navel, Succri, and Sulstiana, instead of the actual fruits, which were Cara Cara Navel and Sulstiana, respectively. In the above confusion matrix model, two incorrect predictions occur due to similarities among various varieties, and the model achieves 97% accuracy in classification.

Recall (TP/FN+TP**)**

Precision (TP/FP+TP**)**

F-1Score (2 * Recall * Precision / Recall + Precision**)**

Identification and finding of nutrients to predict citrus fruit variety

The experimental values found by the horticulturist in a horticulture research lab at MNS – University of Agriculture, Multan through destructive analysis of each citrus fruit verities (For example, Amber Sweet, which is a citrus fruit variety has nutrients (TSS, TA, pH, and Vitamin C)) are allocated to the detected respective variety identified by this model in figure 7.

Figure 7. Citrus fruit detection and nutrient prediction.

CONCLUSIONS

The paper proposes a deep learning model that utilizes Convolutional Neural Networks (CNNs) for the non-destructive examination of nutrient content in citrus fruits, enabling automatic classification and nutrient measurement without resorting to destructive methods. The model automatically identifies vital features in images, including color, texture, and shape, which are indicators of nutritional content, thereby improving accuracy and efficiency. Experimental findings demonstrate high classification accuracy, rendering this approach a reliable alternative to conventional analytical methods, with significant savings in processing time and operational expenses. The deep learning model accommodates changes in the appearance of fruits, enhancing robustness among various citrus fruits and enabling quick decision-making for farmers and food professionals. This study further indicates the potential of CNN-based models in promoting smart agriculture, post-harvest technology, and AI-based quality evaluation.

Future Work

Future improvements, such as the incorporation of hyperspectral imaging, transfer learning methods, and real-time implementation, are expected to further enhance the system's accuracy and scalability. By eliminating the need for destructive test procedures, this research promotes green farming practices and advanced nutrient analysis, resulting in improved fruit quality, reduced loss, and increased agricultural yield.

ACKNOWLEDGEMENTS
Not applicable.

AUTHOR CONTRIBUTIONS
All authors contributed equally to this research.

COMPETING OF INTEREST
No conflicts of interest have been disclosed by the authors.

REFERENCES
Ali, M.M., Hashim, N. 2022. Non-destructive methods for detection of food quality. In *Future foods* (pp. 645–667). Elsevier.

Ali, S., Hameed, A., Binyamin, R., Alam, M.W., et al 2024. Morphogenetic characterization of Xanthomonas citri pv. citri and its management. *J. King Saud Univ. Sci.*, *36*(8), 103339.

Ali, S., Hameed, A., Muhae-Ud-Din, G., et al 2023. Citrus canker: a persistent threat to the worldwide citrus industry—An analysis. *Agronomy*, *13*(4), 1112.

Cai, L., Li, J., Zhang, H., et al 2025. Determination of the SSC in oranges using Vis-NIR full transmittance hyperspectral imaging and spectral visual coding: A practical solution to the scattering problem of inhomogeneous mixtures. *Food Chem.*, 143239.

Gan, H., Lee, W. S., Alchanatis, V., et al 2020. Active thermal imaging for immature citrus fruit detection. *Biosyst. Eng.*, *198*, 291–303.

Górriz, J. M., Álvarez-Illán, I., Álvarez-Marquina, A., et al 2023. Computational approaches to explainable artificial intelligence: advances in theory, applications and trends. *Information Fusion*, *100*, 101945.

Hadipour-Rokni, R., Asli-Ardeh, E. A., Jahanbakhshi, A., et al 2023. Intelligent detection of citrus fruit pests using machine vision system and convolutional neural network through transfer learning technique. *Comput. Biol. Med.155*, 106611.

Kumar, S., Ahlawat, W., Kumar, R., et al 2015. Graphene, carbon nanotubes, zinc oxide and gold as elite nanomaterials for fabrication of biosensors for healthcare. *Biosens Bioelectron.*, *70*, 498–503.

Lamsal, R. R., Acharya, U. K., Karthikeyan, P., et al 2024. Implementing Internet of Things for Real-Time Monitoring and Regulation of Off-Season Grafting and Post-Harvest Storage in Citrus Cultivation: A Case Study from the Hilly Regions of Nepal. *AgriEngineering*, *6*(3), 2082–2100.

Liu, R., Li, Y., Li, T., et al 2024. A rapid, non-destructive, and accurate method for identifying citrus granulation using Raman spectroscopy and machine learning. *J. Food Sci.*, *89*(12), 9354–9368.

Low, E. S., Ong, P., Sim, J. Q., et al 2024. Integrating deep learning with non-destructive thermal imaging for precision guava ripeness determination. *J. Sci. Food Agric.*, *104*(13), 7843–7853.

Marzougui, A., McGee, R. J., Van Vleet, S., et al 2023. Remote sensing for field pea yield estimation: A study of multi-scale data fusion approaches in phenomics. *Front. Plant Sci.*, *14*, 1111575.

Mimma, N.-E.-A., Ahmed, S., Rahman, T., et al 2022. Fruits classification and detection application using deep learning. *Sci. Program*, *2022*(1), 4194874.

Ning, X., Weng, C., Chen, S., et al 2025. Lipid and polyphenol removal on the structural, physico-chemical and technological properties of passion fruit epicarp flour. *Food Chem: X*, 102345.

Prasad, C., Kumar, S., Rathod, S. D. 2024. Hybrid Ensemble Model for Accurate Orange Quality Prediction Using CNN, Random Forest, and Gradient with Multispectral Data Integration. *2024 ICAIQSA*, 1–4.

Roy, K., Chaudhuri, S.S., Bhattacharjee, S., et al 2021. Classification of Citrus Fruits and Prediction of Their Largest Producer Based on Deep Learning Architectures. *Advances in Smart Communication Technology and Information Processing: OPTRONIX 2020*, 147–155.

Şengül, M., Gökçe, S., Karakütük, İ.A. 2025. Vitamin C, Sugar Content, Color Intensity and Some Physicochemical Properties of Watermelon and Orange Peels. *Pharmata*, *5*(1), 1–6.

Shaaban, M.M., Abdel-Ati, L. 2025. Enhancing Yield and Fruit Quality of Sweet Orange (Citrus Sinensis) in Response to Foliar Application of Amino Acids and Micronutrients. *Assiut J. Agric. Sci.*, *56*(1), 199–212.

Shah, S. S. A., Zeb, A., Qureshi, W. S., et al 2020. Towards fruit maturity estimation using NIR spectroscopy. *Infrared Phys. Technol. 111*, 103479.

Shen, C., Wang, R., Nawazish, H., et al 2024. Machine vision combined with deep learning–based approaches for food authentication: An integrative review and new insights. *Compr Rev Food Sci Food Saf., 23*(6), e70054.

Usman, M., Rehman, W., Fatima, B., et al 2020. Fruit quality assessment in pigmented grapefruit (Citrus paradisi Macf.) for varietal diversification. *Pak. J. Agri. Sci*, *57*(4), 1029–1034.

Vijayakumaran, C. 2023. A Comprehensive Analysis of the Developments and Applications of Deep Learning in Citrus Plant Disease Detection. *2023 ICAISS*, 699–703.

Younis, K., Ahmad, S., Osama, K., et al 2019. Optimization of de-bittering process of mosambi (Citrus limetta) peel: Artificial neural network, Gaussian process regression and support vector machine modeling approach. *J. Food Process Eng.*, *42*(6), e13185.

Zhou, X., Hu, X., Sun, J. 2025. A review of fruit ripeness recognition methods based on deep learning. *Cyber-Physical Systems*, 1–35.