Machine Learning based Efficient Fresh Fruit Quality Assessment

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ABSTRACT: In an increasingly technology-driven world, the ability to identify and assess fruit quality has important implications for agriculture, food production, and consumer welfare. Quality assessment of images plays a pivotal role in various fields including manufacturing, healthcare, agriculture, etc. Fruit quality assessment using image processing techniques are described in this work. Fruit quality can be assessed using factors such as shape, size, and color of the fruit. The goal of the model is to predict the quality of fruit based on its external characteristics. In this system, Machine learning Based Efficient fresh fruit quality assessment is proposed in this analysis. Image preprocessing removes noise and data augmentation is used to reduce overfitting. The background interference is minimized in this segmentation. This model extracts discriminative features such as color, texture, shape, and surface defects from fruit images by using pretrained weights its improves learning efficiency and classification performance by using Inceptionresnetv2. This model extracts deep features by fully connected and Softmax layers to classify fruits into quality categories such as fresh, defective, or rotten to enhance classification accuracy and reduces manual feature engineering for reliable solution.

KEYWORDS: Fruit Quality, Inceptionresnetv2, Quality Assessment, Agriculture, Machine Learning

I. INTRODUCTION

The horticulture industry plays a vital role in the economic growth of a nation [1]. LThe horticulture industry remains the backbone of nations economy to achieve inclusive development, with more than 60% of the population engaged in the sector providing approximately 24% of gross domestic product (GDP) [2]. However, pests have intensified over time, becoming a mounting stressor on farmers due to damages caused to plants grown [3].

The potential revenue from fruit production, processing, and export for farmers has been impacted by fruit loss caused by pests and diseases [4]. Fruit analysis for a variety of aspects is essential to increasing quality and reducing waste[5]. Automated computer vision and image processing techniques have been applied to pre- and post-harvesting procedures to enable prompt analysis of damage inflicted on fruits[6]. Fruits have great relevance for humans because of their nutritional value, such as being a source of vitamins A, C, B1, and B-9. This has greatly improved research in the analysis and processing of fruits, as it feeds into horticulture industries, thus improving the economic sectors of different nations[7]. Various studies have attempted to develop methods that automate fruit processes such as detection, classification, and estimation of quality yields, among others. Usually, the damage inflicted on fruits is due to pests and disease infections, affecting their quality for use in the production and marketing sectors. The fruit industry depends on early identification of fruit damages and the causing conditions to prevent them from spreading from one fruit to another, which results in extreme fruit yield declines and substantial economic losses [8].

Annually, a large proportion of export fruit is rejected due to signs of damage caused by pests and disease infections. This causes losses to farmers as quarantine restrictions are imposed by fruit-importing countries that, in turn, hamper horticulture trade, especially between African and developed nations is considered as an example [9]. These pests have become a significant constraint in production and marketing, with their management cited as a challenging issue worldwide [10]. For instance, an ICIPE-led African Fruit Fly Programme assessment revealed that out of 1.9 million tonnes of mangoes produced in Africa annually, about 40% are wasted due to fruit fly damage [11]. As a result of such damages to fruits, diseases and pests have imposed substantial danger to farming, causing deterioration of the quality of fruits and sometimes even endangering the orchards [12]. This has called for the need to alleviate challenges associated with manual methods of assessing and investigating fruit quality, which is based on the visual experiences of trained professionals. These methods are inconsistent, time-consuming, labour-intensive, tedious, cost-intensive, and subjective [13] yielding low efficiency and unstable accuracy, thus the need for timely and automated identification systems to quickly and accurately detect and diagnose fruit damage infections and reduce such losses and associated costs [14].

II. LITERATURE SURVEY

M. Deshpande, R. Kamathe, V. Hanchate, I. Pathan, S. Bhadre and S. Kangane, et al. [15] proposes a lightweight, real-time fruit quality assessment system that identifies fruit type and evaluates freshness using deep learning. MobileNetV2 with transfer learning is used as the core model, trained on around 3,200 annotated images of apples, bananas, mangoes and oranges collected from the FruitVision dataset. All samples were resized to 224×224 pixels and labelled for both fruit category and quality (fresh/rotten). The trained model was converted to TensorFlow Lite and deployed on a Raspberry Pi 4B paired with a USB camera for live prediction. The system achieves 98.95% accuracy for fruit classification and 97.27% accuracy for quality grading under controlled testing. The results highlight that a low-cost, portable embedded setup can perform fruit quality analysis reliably, making it suitable for markets, farms, retail shops and supply-chain monitoring.

J. Chen, G. Huang, L. Liu, Z. Xu and Q. Yang, et al. [16] introduce FruitMMBench, a comprehensive multi-modal benchmark designed to assess the ability of fruit quality assessment. A comprehensive metric is carefully designed by jointly considering many aspects. The resulting large-scale FruitMMBench contains 5,465 collected fruit images and dedicated quality labels including the following aspects: fruit classification, quantity recognition, maturity, surface condition, quality status, and edibility recommendation. By extensive evaluations on FruitMMBench, we find popular LVLMs struggle to provide reliable results in fruit quality assessment and their performances vary greatly. The test results reveal that the ability of current LVLMs to analyze fruit quality in real-world scenarios is still weak and needs to be paid attention to and enhanced in the future.

A. Mohite, R. Joshi, S. Kunjir and M. Kodmelwar, et al. [17] introduces a new web application that uses the deep convolutional neural networks to address this important task. This project focuses on three widely consumed fruits: apple, banana and orange. Using the Kaggle dataset (fresh and rotten fruits for classification), we initialize our approach by training a deep CNN model on a set of well-defined clean fruit images. This first training step provides the model with basic information about the shape, contours and features of the desired fruit. The innovation lies in retraining the model based on real fruit images. As our model copes with the complexity of real-world variations in light, orientation, and fruit quality, it becomes adept at distinguishing apples from oranges and bananas.

A. Thulaseedharan and A. Choudhary, et al. [18] propose a fruit detection system based on their qualities. Sorting fruits by humans is a time-consuming process, subject to inconsistencies and influenced by surrounding conditions. In this camera-based fruit quality assessment system, the fruits are detected and predicted under qualities like Fresh and Rotten. In the system, the Camera module captures the image of the fruit and then sends it to the Quality Assessment module. In this module, the information from that image is extracted and tested based on YOLOv5. After detecting the quality, the system indicates to the the user whether the fruit is fresh or rotten. This helps the user to easily get to know about the quality of the fruit and can segregate the fruits according to their freshness. This automatic fruit handling system helps every user in a smart home to save time and buy better quality fruits.

R. L. Devi *et al*., [19] presents a novel fruit picking and quality analysis system that leverages deep learning techniques to automate the harvesting process and assess fruit quality in real-time. Utilizing a combination of image processing and deep learning, the system analyzes visual attributes such as color, texture, and shape to evaluate fruit quality. The proposed solution not only reduces labor costs and minimizes waste but also ensures that only high-quality produce reaches consumers. Experimental results demonstrate high accuracy rates in fruit detection and quality assessment, showcasing the effectiveness of deep learning in agricultural applications.

A. Kumar, R. C. Joshi, M. K. Dutta, M. Jonak and R. Burget, et al. [20] novel deep learning-based architecture Fruit-CNN has been proposed to identify the type of fruit and their quality assessment of realworld images in multiple visual variations which achieves a test accuracy of 99.6%. The proposed architecture takes minimal time to train the large dataset and test fruit images in comparison with state-of-the-art deep learning models which proves its wide applicability in precision agriculture. More images belonging to various classes can also be trained with fewer parameters which result in fast training of models and less processing time.

I. A. Mazni, S. Setumin, A. A. Sunak Joseph, M. Khusairi Osman, M. S. Osman and M. Subri Tahir, et al. [21] automatic non-destructive quality assessment of fruits using a Convolutional Neural Network (CNN) regression model based on images will be developed. Ficus Carica L. (figs) was used as a sample validation for the quality predictor. Three different stages (stage 1, stage 2, and stage 3) of fig fruit images were captured using a Pi camera and implemented in raspberry Pi3 model B+. The developed model will be used to predict the internal quality of fig fruits. In this paper, the quality of fig fruit was assessed in terms of its chemical properties which is the Brix sugar value (%). The model has been trained and validated to have a Root Mean Square Error (RMSE) of 1.38. Hence, the quality predictor is based on this prediction model and the performance was tested to give an RMSE of 0.99.

S. T. Meti and G. S. Veena, et al. [22] Fruit Classification and Quality Assessment System is being developed as a solution to this problem. In addition to deep neural networks, it makes use of a two-stacked ensemble technique. Random Forest, K-Nearest Neighbors (KNN) and Decision Tree models are all included, and each model brings a special strength to the classification problem. Convolutional Neural Networks (CNNs) are used because they are good at extracting features from visual input, and they work well for classifying fruit images in particular. Effective model architectures are identified by the project through thorough comparison analysis. The accuracy and reliability of various models are improved by combining them through ensemble learning approaches. With the goal of greatly advancing fruit classification and quality assessment, the resultant system delivers high accuracy and resiliency in demanding agricultural situations, guaranteeing dependability and efficiency in practical applications.

L. A. S K and P. Vinothiyalakshmi, et al. [23] proposes a model for image-based techniques for quality assessment using deep learning methodologies. It discusses about various deep learning algorithms like Convolution Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Regional Convolution Neural Networks (RCNNs) and Generative Adversarial Networks (GANs) etc. The proposed model makes it easier to work these algorithms that are applied and the Dataset image size is minimized by Dimensionality Reduction, to get the higher accuracy.

H. Waghare, D. Rane, S. Kumbhar, R. Livingston and O. Narveer, et al. [24] proposes a Fruit Quality Monitoring System (FQMS) based on Machine Learning (ML), Internet of Things (IoT), and image processing to automatically analyze fruit quality. The system uses an ESP32-based IoT platform with a camera module to capture live fruit images, which are preprocessed by wavelet transforms and MobileNetV2-based cropping and classified by Convolutional Neural Network (CNN) to assess characteristics like ripeness, color, and defects. IoT sensors track environmental parameters, such as temperature, humidity, and ethylene gas, to enhance storage conditions. Tested on a dataset of 2160 apple images, the FQMS obtains 91% training accuracy, 89.9% testing accuracy, and 92% (defective) and 93% (good) F1 scores.

J. E. Rao, M. Devisri, B. J. Nayak and B. L. Sirisha, et al. [25] fruit quality assessment using image processing techniques are described in this work. Fruit quality can be assessed using factors such as shape, size, and colour of the fruit. The goal of the model is to predict the quality of fruit based on its external characteristics. The method begins with capturing a high-resolution picture of the fruit, followed by preprocessing, which involves improving the image's brightness and reducing noise. The image is then subjected to arithmetic operations in order to determine numerical attributes such as mean, variance, and standard deviation. Fruit quality assessment is done based on numerical values. Bananas are used as input samples for quality assessment in the suggested work.

III. FRAMEWORK OF MACHINE LEARNING BASED EFFICIENT FRESH FRUIT QUALITY ASSESSMENT

In this section, framework of Machine Learning Based Efficient Fresh Fruit Quality Assessment is observed in Figure 1. The fruit sample is collected and given as input. Then the data is pre-processed to remove unwanted data. Then, the images are re-sized and augmented data. The images are Resize all images to a fixed dimension suitable for normalize pixel values to perform data augmentation such as Rotation, Flipping, Zooming and brightness adjustment. Image acquisition obtains high-quality fruit images either from a camera or a publicly available dataset to capture clear fruit images to ensure sufficient resolution for accurate defect detection. After image acquisition, the image are segmented and extracts relevant features. Then, the data is splitted into training data and testing data. The InceptionResNetV2 is applied. This model automatically extracts meaningful features without manual intervention to learn both fine and coarse visual details through Inception modules by using residual connections to improve learning in very deep networks to achieve high classification accuracy with transfer learning.

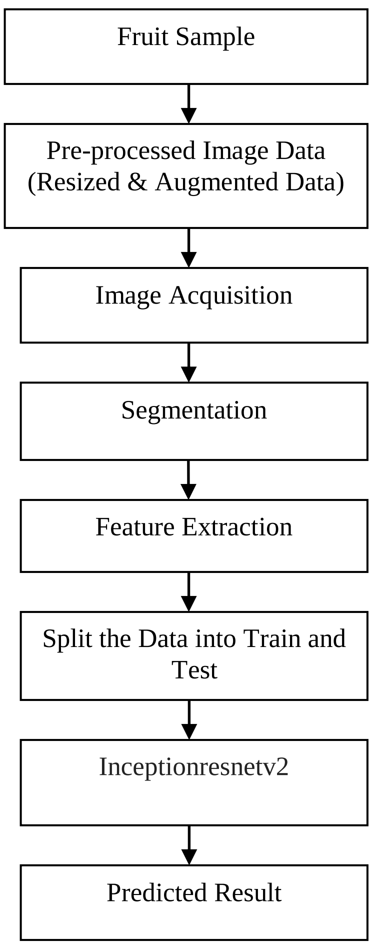

Figure 1. Framework of Machine Learning Based Efficient Fresh Fruit Quality Assessment

Data can be available in various forms: Structured tables, unstructured tables, Images, Audio files, Videos. Etc. A machine cannot directly understand the free text, video, or image as it is; it is necessary to convert the given data into 1s and 0s. So, raw data cannot be directly fed to the machine learning model and expects it to get trained. Data Pre-processing is the First step in Machine learning in which the data gets transformed/Encoded so that it can be brought in such a state that now the machine can quickly go through or parse that Data. In other words, it can also be interpreted as that the model algorithm can promptly analyze the features of data. Data pre-processing is the most important and influential for generalization performance of a Supervised Machine Learning Algorithm. The quantity of training data grows exponentially concerning the input space dimension. According to an estimate, time spent on pre-processing can take up to 50% to 80% of the entire classification process, proving the importance of pre-processing in building a model. It is also essential to improve the data quality for better performance. Data processing consists of steps to be followed before starting the analysis with the actual data for the model.

Image segmentation is the process of extracting the region of interest, and it plays a vital role in the process of plant disease detection. In this task the enhanced image is subdivided into several regions or areas. Image segmentation partitions an input image into nonoverlapping, homogeneous, and connected regions. This would simplify the representation and something which contains more information and would be easily analyzed. After image segmentation, the image of a plant leaf is divided into healthy and infected regions and this process is stopped when no further division is required. The major goal of segmentation is to analyze the images so that one can do feature extraction from the image data. The image segmentation process can be conducted based on similarities present in images or based on discontinuities.

Feature extraction is the process of extracting task specific information from the signal to meet users' intent. The features can be extracted in various forms, e.g., amplitude measurement, peak power, spectral density parameters etc. Feature extraction demands high computational efforts and mathematical analysis for univariate and multivariate environments. It encompasses three key domains: spectral, spatial, and temporal.

IV. RESULT ANALYSIS

In this section, result analysis for Machine learning Based Efficient fresh fruit quality assessment is observed.

The Figure 2, shows page for quality detection of fruit by its image in Machine learning Based Efficient fresh fruit quality assessment.

Figure 2. Fruit Quality Detection Page

The Figure 3, shows page for quality detection result in Machine learning Based Efficient fresh fruit quality assessment.

Figure 3. Fruit Quality Detection Result

The Figure 4, shows the accuracy graph for Machine learning Based Efficient fresh fruit quality assessment using InceptionResNetV2

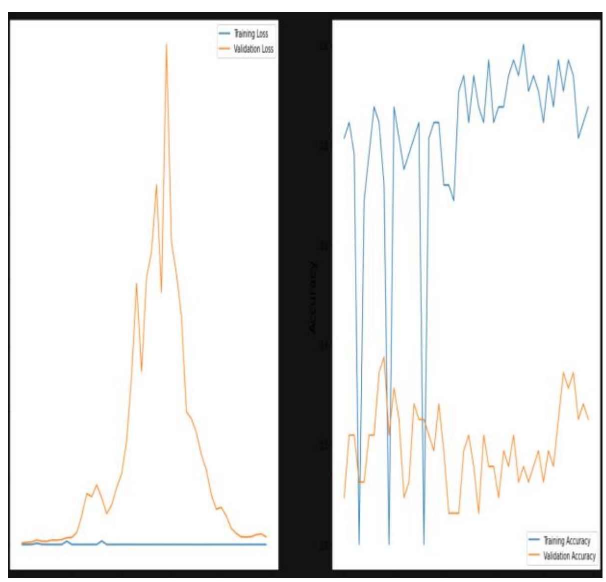

Figure 4. Accuracy Comparison Graph

V. CONCLUSION

Fruits play an important function in our diet by providing essential fibers, vitamins, and minerals. Accurate detection of fruit ripeness can enhance quality control and reduce food waste. Freshness plays a crucial role in determining the quality of fruits and vegetables, directly impacting consumer health and influencing nutritional value. Fresh produce used in food processing industries must go through multiple stages—harvesting, sorting, classification, grading, and more—before reaching the customer. This paper introduces an Machine learning Based Efficient fresh fruit quality assessment. Image preprocessing removes noise and data augmentation is used to reduce overfitting. The background interference is minimized in this segmentation. This model extracts discriminative features such as color, texture, shape, and surface defects from fruit images by using pretrained weights its improves learning efficiency and classification performance The InceptionResNetV2 is applied. This model automatically extracts meaningful features without manual intervention to learn both fine and coarse visual details through Inception modules by using residual connections to improve learning in very deep networks to achieve high classification accuracy with transfer learning.

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