[1]Sneha Ramdas Shegar

[2]Dr. Pawan Bhambu

Fruit Quality Analysis and Disease Detection using Deep Learning Techniques

Abstract: - Defective fruits are the main reason for worldwide financial catastrophes in agricultural production. It affects both the dependability and quality of the fruits. Post-harvest, quality checking requires a significant amount of time and labor-intensive skill. Automatically identifying fruit quality enables saving time and labor during harvest. Various algorithms have been created using machine learning and image processing methods to detect and categorize fruit quality. A system using Convolutional Neural Networks (CNN) and transfer learning techniques has been developed to enhance the fruit classification process. Two methods are suggested for predicting fruit freshness. One tailored CNN architecture is proposed by modifying the network's parameters to suit the dataset. The second technique utilizes the pre-trained VGG model with transfer learning to assess the freshness of the fruit. The proposed models are capable of differentiating between fresh and spoiled fruit by analyzing the input photos. This research used 70 diverse types of fruit, such as apples, bananas, oranges, and others. The first CNN obtains 98.55% accuracy for heterogeneous fruit dataset while second VGG16 achieves 99.05% accuracy on similar dataset. The plant village global dataset is utilized with various fruit categories. As a result, The VGG16 provides higher accuracy than conventional CNN and other deep learning algorithms.

Keywords: Yolov3 model, VGG16, U-Net, Fruit Detection, Segmentation, image processing, deep learning, fruit detection

I. INTRODUCTION

Due of the lack of agricultural jobs and the rapid advancement of artificial intelligence (AI), robots have garnered significant attention in the agricultural sector. Agricultural robots carry out labor-intensive agricultural duties, enabling farmers to focus on farm management. One of the most renowned agricultural robots is the harvesting robot. Agricultural robots for harvesting have significantly improved in speed and efficiency, leading to increased interest in their use for gathering fruits and vegetables. Recent studies have been carried out on fruit identification. Automated harvesting may be best achieved using vision technology, with accurate identification serving as the basis for subsequent tasks such as picking in fruit or vegetable harvesting. Developing a precise and reliable fruit identification approach is a significant challenge because to the similarity or blockage of fruits, branches, and other environmental obstacles, as well as the unpredictability of the orchard environment. Efficient and prompt collection of crop development data is essential for the success of smart agriculture. Robot harvesting systems in orchards need to accurately identify fruits and determine their position. Fruit identification may also quickly assess the quantity of fruits in a certain region. Orchard management may use computerized fruit scanning to monitor fruit drop, forecast production, and plan market strategies appropriately. Machine vision-based fruit detection approach may recognize fruit development data, detect sickness and insect outbreaks, predict yield, determine harvesting time, and do other tasks. Robotics is becoming more common in orchards for tasks like as yield estimate, yield modeling, and automated picking. Machine vision acts as the eyes of an intelligent robot, enabling it to see its environment, acquire information, and improve its job accuracy and efficiency. Fruit is often considered the most prevalent kind of produce on Earth and a crucial source of nourishment. Due of the varying color and texture of fruits, the main issue for a fruit harvesting robot in natural environments is achieving consistent detection. Environmental variables significantly influence fruit setting %, causing variations in fruit amount according on climate and surroundings. One of the first methods for systematically detecting fruits was physically gathering information on their color, structure, shape, and other characteristics. The paper discusses a deep learning approach for identifying fruits in a field. We captured images of fruit at the farm with a standard RGB color camera and identified the fruits in different lighting and obstruction conditions. The main study material is comparing the results in the paper with fruit identification using the U-Net algorithm

[1] PhD Scholar: Department of computer engineering

shegarsneha1@gmail.com

[2]Associate Professor Department of Computer Science Engineering, VGU University Jaipur

pawan.bhambu@vgu.ac.in

with MobileNetv2 backbone to verify the applicability and efficacy of the proposed approach in fruit detection. YOLOv3 enables rapid and accurate recognition of many types of fruits in different environmental settings. The rest of this article is structured as follows. The second segment reviews previous work. The last part details the functionality of the fruit identification technology and its use in the plantation. The test data and comparison analysis are presented in sections four and five. The sixth part contains the summary and plan of action for the future.

II. LITERATURE SURVEY

According to D. Kundu et al. [1] When it comes to agricultural uses, ML approaches are quite important. These strategies include qualitative approaches for automated rating as well as quality evaluation of fruits. The agricultural standard, efficiency, and financial prosperity of a nation are all improved by the implementation of automated processes. When it comes to the export industry, one of the most important indicators is the assessment of the fruit's condition, namely the recognition of superficial flaws in every fruit. Mangoes, which have become highly popular in Bangladesh, are a good example of this, as these fruits are especially in demand there. On the contrary, the physical rating of mangoes is a process that requires a lot of manual labour, is susceptible to errors, and is highly contingent on personal opinion. A YOLOv7 incorporated Discrete wave transformation machine vision technique has been developed as a result of this investigation. The categorization of mangoes of excellent quality is accomplished through the use of a DT and a SVM in the proposed model. The findings of the experiments indicate that the proposed approach achieved an accuracy rate of 96.25% when the method underwent training and evaluation with a publicly available mango database.

The objective of Basri et al. [2] is to evaluate and contrast the outcomes of four different feature extraction algorithms in the context of the early detection of disease outbreaks on cocoa fruits. Local Binary Pattern (LBP), Gray-level Co-occurrence Histograms (GLCH), Grey Level Co-occurrence Matrix (GLCM) and Hue Saturation Value (HSV) are the image extractor techniques which were utilised in the present study. Furthermore, the SVM model was utilised for the classification in order to assess the outcomes of the extraction process derived from the cocoa picture dataset. The findings of the classification obtained through the usage of SVM demonstrated the best efficiency on feature extraction HSV across the various kinds of Kernel SVM utilised, with the RBF Kernel exhibiting an accuracy level of 80%. Additionally, the effectiveness of HSV in recognising infections on cocoa was evaluated according to performance metrics scores. The results demonstrated that, on average, HSV had a higher value compared to other techniques for extracting features.

According to T. Mahendran et al. [3] Within the majority of developing nations, the banana is especially widely consumed and widely used as a medicinal food. Over the course of banana farming, pesticides have been responsible for a significant increase in the incidence of disease. The ML methods in this farming field bring about improvements in productivity in farming industries, especially due to the current development of NN, which appear to have a higher degree of accuracy. After conducting this investigation, a new extraction and categorization approach has been suggested for the purpose of identifying diseases that affect banana. The picture had initially been pre-processed depending on the pixel, and then it was resized utilising ROI selections. After that, the picture was divided using homogeneous optimal cut border division, which was performed depending on the border of the training picture. Finally, the picture was resized utilising ROI selection. The collection of information is accomplished via the utilisation of GLCM and the categorization is performed out through the utilisation of convoluted deep neural networks (CDNN). Both the mathematical modelling of banana and the classification process of DL have been completed successfully. Both of these techniques have the potential to be utilised in the detection of diseases that affect agricultural products.

According to A. Hessane et al. [4] One of the most important aspects of oasis farming is the production of date trees. As a result, the latter aspect is an important factor in the socioeconomic status of a great number of nations, particularly Morocco. Yet this precious tree has been weakened by a number of illnesses, which can cause devastation to both the economy and the ecology. In addition to lowering the output of date fruits, white scaling constitutes one of the most damaging insects that can have a severe impact on the nutritional value of date fruits. Consequently, the prompt identification of diseased plants is fundamental to the implementation of any kind of pest control Programme. The purpose of this research is to offer an approach which is intended to autonomously categorise the level of infection caused by Date Palm White Scale Disorder. This structure is built on approaches that involve feature extraction and ML. The GLCM features and the HSV Colour Moment were taken out and

concatenated, after which they were applied to a K-Nearest Neighbours (KNN) classification algorithm, which achieved better than the mean accuracy of 96.90% during the training process. Furthermore, more performance metrics are computed in order to acquire further information regarding the stage-wise classification efficacy of the proposed method. In the final phase, a comparison study is carried out among the proposed framework and a few methodologies which are based on the most recent State of the Art (SoA). Due to this, the proposed strategy is superior than the SoA dependent models in regards to a variety of performance criteria.

According to Aurangzeb Magsi, et al. [5] The diagnosis of diseases and surveillance of the development of plants are two examples of the complicated agricultural issues that are addressed by a multitude of biotechnology software programmes which are being created for offering analytical treatments. Dates are a nutritious fruit that contributes around 4% to the overall economic output of Pakistan. District Khairpur is responsible for contributing about 81% of the country's total date output. There are around 22 different varieties of dates which can be grown in various regions of Pakistan. One thing that has been discovered is that both national and international emptor are not capable of appropriately recognise different kinds of dates. The purpose of this research is to propose an approach for identifying dates through the application of DL techniques. These techniques rely on the extraction of colour, form, and dimension features. In terms of methodology, a dataset containing 500 photos of fruit is developed for the intent of evaluation, comparable to the 360-dataset. In order to conduct the investigations, the three different kinds of dates: Aseel, Karbalain, and Kupro were used. There were a total of 500 date fruit specimens obtained, out of which 350 and 150 have been utilised for the training and testing purposes respectively. The best performance outcome, of 97.2% during the fourth epoch, is achieved by using an amalgam of many hidden layers and one hundred epochs. For the purpose of analysing and measuring the correctness of the data, a confusion matrix is utilised, and the value of 89.2% is obtained as a True Positive.

Priya P et al. [6] provides a comprehensive description of feature collection approaches for crop and fruit illnesses which are made possible by computerised imagery processing. Infectious illnesses that affect crops and fruits are the most significant agricultural goods. To be able to acquire a greater quantity of items with added value, it is vital to have an effective quality control system. There are a number of programmes which claim to be able to retrieve the correct data from the database of coloured images. This investigation is being conducted with the primary objective of developing a user-friendly interface which will enable users who are not proficient in digital literacy, particularly farmers, to get data from the internet in a simple and effective way. Furthermore, in order to provide ranchers with the ability to detect the infection affecting their crop, as well as its root causes and signs, through the utilisation of image processing, with no resorting to traditional methods, and to detect the illness. Within the scope of this work, a review of the utilisation of texture assessment in the detection of crop and fruit illnesses has been provided. In order to validate the suggested algorithm, it was applied on the photos of apple fruit. Through the utilisation of the coloured picture segmentation technique, it is feasible to evaluate the n number of diseases in a manner that is both successful and cost-effective. This is accomplished by assigning specific intensity patterns to those disorders. In the first step of the colour transformation process, the RGB space is transformed into the HSV space. This is carried out since HSV is an effective colour descriptor. The process of concealing and eliminating green pixels using a predefined level of threshold. Following that, the k-means clustering method is utilised, which is the segmentation process. As part of the colour co-occurrence matrix, these areas are utilised for the purpose of texture assessment. The last step is to contrast the texture attributes of the typical fruit picture to the texture properties of the picture. There are four distinct kinds of feature acquisition strategies that are being explored for the purpose of efficient analysis. It is anticipated that these methods will have an effective detection and categorization of diseases affecting fruits and vegetables.

According to Rashiduzzaman Shakil et al. [7] Dragon fruit is a significant component in agricultural production all over the world. Notwithstanding this, it continues to gain prominence and is a potential alternative in regions which are resource-poor and ecologically deteriorated due to the many health advantages it offers. Despite this, a significant number of dragon fruit farms are being affected by the illness, which has resulted in a decrease in their production, and the mechanism for diagnosis is still traditional. The lack of experience in disease detection and treatment among farmers led to a decrease in the standard of their crops and goods. A limited amount of study was conducted as a consequence of this in order to provide assistance to those particular farmers who require proper agricultural aid. As a result of this investigation, a self-governing agro-based approach which can identify dragon illnesses has been developed. This system makes use of a comprehensive review of feature selection methodologies. The photos are cleaned up using a variety of image-processing algorithms after the collecting of

real-time pictures of the dragon has been completed. Once the segmentation method is complete, the two significant features are extracted. Feature selection approaches such as the analysis of variance (ANOVA) and the least absolute shrinkage and selection operator (LASSO) are utilised in order to evaluate the feature rank on the basis of the mutual rating. In order to evaluate the efficacy of the ML methods, six different ML classifiers were used to apply to the feature sets which were deemed to be highest, and the effectiveness of these classifiers was evaluated utilising various performance evaluation criteria. An analysis of classifiers depending on the ANOVA and LASSO feature set revealed that the AdaBoost and RF classifiers for the LASSO feature ranking method achieved the highest accuracy of 96%.

H. Kaur et al. [8] provides a detailed analysis of a number of research efforts that have been conducted in the subject of disease identification and categorization in papaya crops. Comparisons have been made between various studies in terms of the issue areas, methods, illnesses, and sections of the papaya tree being implemented, as well as the datasets utilised that corresponded to existing research. The datasets which were utilised for this work are the primary focus of attention. For the purpose of comparison, the most important elements to take into consideration are the accessibility of the dataset, the dimension of the dataset in regard to the amount of photos utilised (if any), and the original source of the dataset. There has been a significant amount of research conducted on either leaf or fruits as this has been discovered. The most significant obstacle is the lack of a sufficient dataset encompassing diseases which can be found in many areas of the papaya plant, such as the leafy part, fruit, stems, and so on. The dataset, with respect of the quantity of photos, is perhaps not readily accessible in the public domain for use later on or it is inadequate in regards of its size.

According to Tayyab Rauf [9] Infections can affect plants just as much as they can affect mammals. Citrus is a significant plant that is primarily cultivated in tropical regions of the globe owing to the fact that it contains a high concentration of vitamin C and other essential elements. A significant number of diseases associated with citrus have had a negative impact on the growing of citrus fruit, which eventually results in a decline in the nutritional value of the fruit and a depletion of financial resources for the farmers. Over the course of the last ten years, computational imaging and machine vision methods have gained widespread acceptance for the purpose of identifying and categorising conditions that affect plants. The diagnosis of infections in citrus plants at early stages serves avoid the diseases from spreading throughout the fruit trees, which in turn reduces the amount of economic damage that producers experience. There is a presentation of an image dataset containing citrus fruits, branches, and stems in this research. The collection contains photographs of citrus fruits and departs, both of plants in good health and those that have been affected with illnesses including black spot, canker, scab, greening, and melanose. The majority of the photographs were taken in December month from orchards located in Pakistan. This was the time of year when the fruit were on the verge of ripening and the highest number of infections were discovered on citrus plants. The Citrus Research Centre, which is part of the state of Punjab in Pakistan, and the Faculty of Computer Science (CS) and Engineering at the Institute of Gujrat worked together to collect the dataset. The dataset can be accessed by the Faculty of CS at the Institution from which it was acquired. The dataset could be useful to investigators who are developing computer apps to assist producers in the early diagnosis of plant illnesses. These investigators utilise ML and machine vision techniques to construct these applications. Mendeley enables users to access the dataset without charge.

A dataset of guava pictures, which includes both diseased and unaffected fruit and foliage, is presented by Aditya Rajbongshi et al. [10]. The dataset is divided into six different groups: for guava fruits, there are Phytophthora, Scab, Styler end Rot, and Unaffected fruit; for guava leaves, there are Red Rust and unaffected leave pictures. Each and every photograph was primarily taken from the guava field which is situated at the Bangladesh Agricultural University during the month of July. This is the time of year when the guava are about ready to be harvested, and the illnesses are discovered in the guava plants. This dataset is primarily intended for investigators working with machine vision, ML and DL in order to design a system which can identify the guava disease in order to provide aid to guava growers in their production.

III.   PROPOSED SYSTEM ARCHITECTURE

The proposed system has developer with two different dataset such as Kaggle fruit disease dataset and real time on field dataset using CNN. The images provide essential physiological data on the health of fruits using machine learning, enabling precise predictions. Deep learning has been extensively used in classification systems. This

instructional technique relies on the training inputs and anticipated results. The efficacy of this technology is growing and is gaining popularity in areas like image processing and classification.

Dataset Collection: The research used the Fruits 360 dataset. The collection contains 90,380 photos depicting 131 distinct types of fruits and vegetables. RGB pictures having a resolution of 100 by 100 pixels, where each pixel has 3 values. The training dataset consists of 67,692 photos, while the testing dataset has 22,688 images. This study utilizes a limited subset of the fruit 360 dataset, including just 10 distinct species of fruit: strawberries, apples, corn, bananas, tomatoes, potatoes, oranges, pineapples, and peaches. We selected 70 fruit types, resulting in a smaller dataset that allows for faster training of the neural network. The training set has 35133 photos, whereas the test set comprises 11804 images. The predictive model was created by adjusting the CNN architecture using Google's Colab. The technologies use Tensor Flow, a powerful deep neural network design. Google's open-source machine learning framework is widely used. The framework includes cutting-edge predictive modeling and advanced deep neural networks.

Training: During the inference step, the acquired model examines new data and generates forecasts. Feature vectors serve as a representation of the data throughout both the training and inference stages. Model testing assesses the ultimate predicting ability of the model by assessing its performance on new data. The model is used to draw conclusions from unexamined data during the process of inference. The same process is followed while using the model for testing. Once the network is trained, it may make predictions by processing fresh data in real-time, as seen in Figure 3. The file's history will be used for prediction purposes, and users will get warnings about the fruit's freshness.

Testing: Convolutional networks differ from standard single-layer neural networks by having several hidden layers, as seen in Fig. 4. CNNs use convolutional layers and pooling layers in their structure. Convolutional layers identify and extract characteristics from pictures, whereas pooling layers decrease their size. The characteristics are sent to the fully linked layers after the photos have been reduced to a manageable size. The ultimate softmax activation mechanism categorizes the labels based on their freshness as either fresh fruit or rotting fruit. The feed-forward network is recognized for its capability to identify topological characteristics in an image. Images may be taught to recognize patterns using the back-propagation approach. All neurons inside a feature have identical weights during feature extraction. The steepness of this activation curve is due to mass. The bias parameter enhances the steepness of the activation function and determines the speed at which the function is triggered, hence improving the model's ability to fit the data well. While neurons receive various input pictures, they identify the same image characteristic.

The convolutional layer is a fundamental component of a Convolutional Neural Network (CNN) responsible for extracting features from data. The layer consists of programmable filters (kernels) that may be taught to recognize certain forms of visual material. The dot product between the local areas of the input picture and the filter is determined as the filter moves across the image during convolution. The pooling layer utilizes certain functions to summarize sub-regions in each grid, resulting in a reduction in the size of the feature maps and creating value. This layer prevents overfitting by intersecting the input and output of a sliding window. The pooling layer minimizes the network parameters and enhances the robustness of learnt features by reducing their sensitivity to size and orientation variations. The output of the layer before the fully connected layer is directly linked to the input of the Fully Connected layer. It does this by establishing connections between each of its neurons and every neuron in the layer directly underneath it. Non-linear combinations of these properties may be learned by including a fully linked layer. The training aims to reduce the loss. Consequently, the image classifier shows satisfactory performance after thorough training, achieving an acceptable level of accuracy. Minimize the cross-entropy loss at the conclusion of training. Subsequently, we evaluated the model using fresh input data, and it demonstrated excellent performance. Once the training phase is completed, the model's predictions on the status of the fruit have been shown to be correct.

IV. RESULTS AND DISCUSSION

The proposed approach consists of two distinct architectures. The first design involves creating personalized CNN. A neural network may efficiently learn spatial and related data using a CNN. Prior to the introduction of CNNs, training a neural network to identify spatial correlations was difficult due to the conventional tabular structure of input data. Neural networks may establish connections between various components of an image by

using Convolutional Neural Networks (CNNs). As one delves farther into a neural network, the traits learnt get more intricate. The first technique included using 2 by 2 filters, increasing the number of layers with depth, and concluding with a 2 by 2 MaxPooling layer that selects the maximum value in a specified area. To learn complex characteristics and remove linearity, we shall use the RELU activation function. To prevent overfitting, we will use dropout regularization, which randomly chooses nodes based on a predefined probability. The loss function will be computed using a softmax unit for classification.

Table 1 details the input and output forms and the parameter count in the customized architecture for fruit quality prediction. The output shape is a tuple that does not include the first member, which is "None". Table 3 displays the convolutional blocks together with the quantity of filters used in each. Every block utilizes consistent padding (=2), kernel size (=2), and Relu activation mechanism. The completely linked layers consist of 150 and 120 dense layers, followed by a softmax layer, and use dropouts of 30% and 40%.
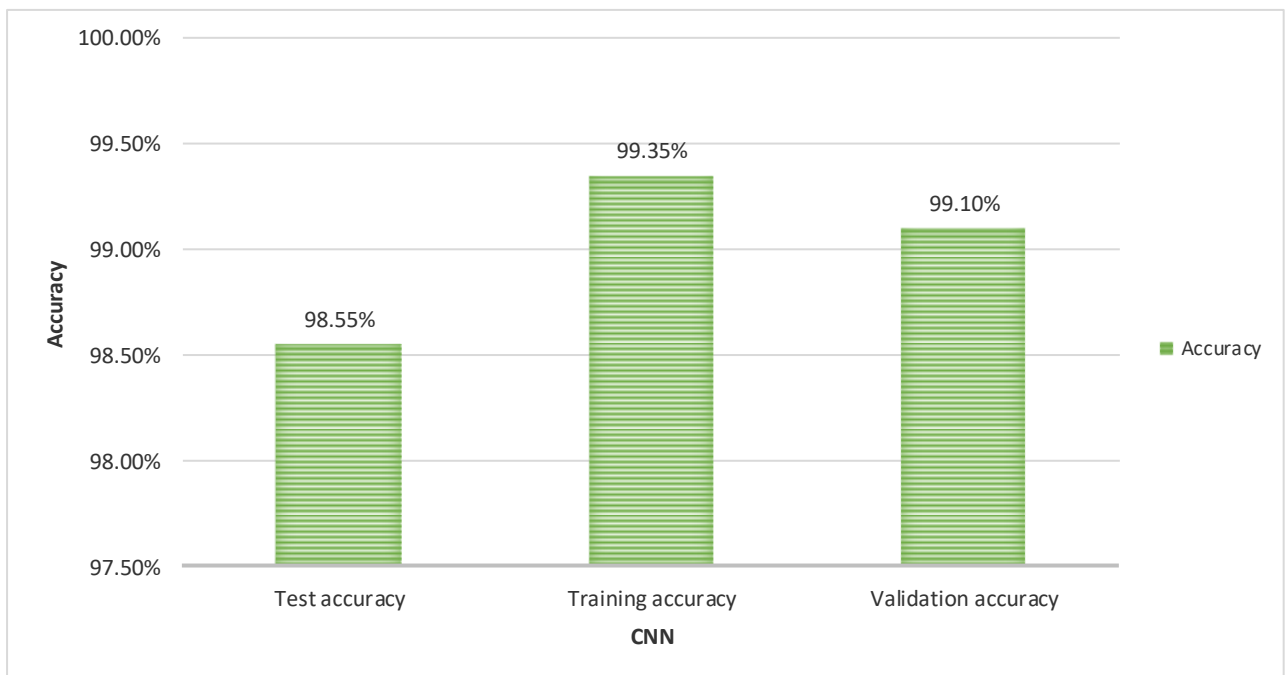

Figure 2: detection and classification accuracy of fruit disease using CNN model

Figure 2 above illustrates a comparative analysis of fruit disease detection and classification using CNN based deep learning models.
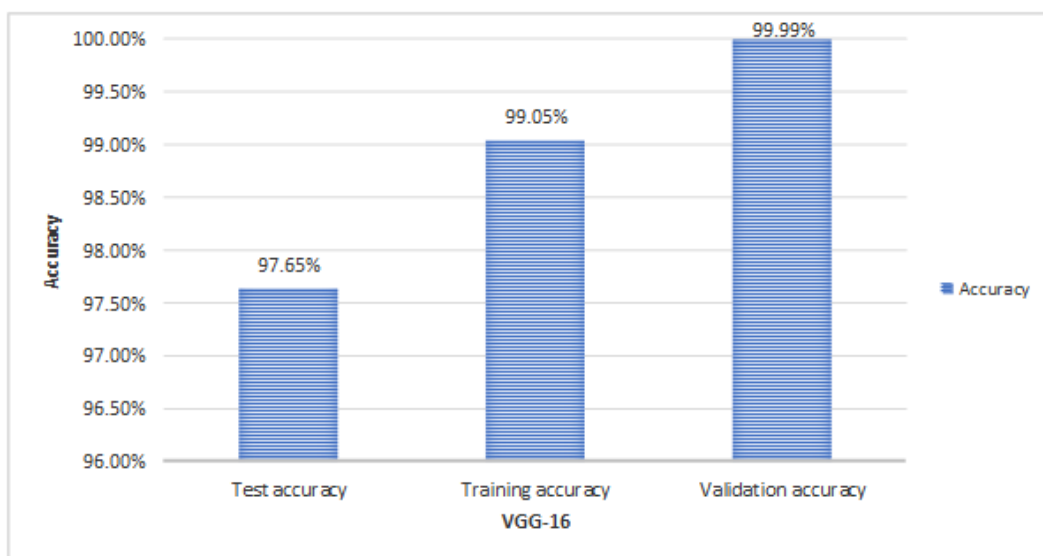

Figure 3: detection and classification using VGG-16 model

Figure 3 above illustrates a comparative analysis of fruit disease detection and classification using different deep learning models, including a hybrid model. The proposed models can yield superior outcomes by capitalizing on the advantages of various methodologies, particularly when handling intricate and varied data sources such as student comments. The VGG-19 model proposed shows approximately 0.02-0.03% greater accuracy compared to previous deep learning methods.

V.CONCLUSION

Individuals prioritize their health and choose for organic, fresh food. Prior to selling the fruits, it is crucial to sort them and remove any bruised ones. Both pre-harvest and post-harvest treatments are necessary for fruits. Fruit quality detection involves sorting and classifying harvested fruits into categories of edible and inedible. New automated methods have led to the development of digital agriculture. We want to provide a highly accurate model for fruit identification to streamline the agriculture sector. This research focuses on addressing several challenges related to fruit identification and introduces two frameworks for predicting fruit quality. The investigational study demonstrates that the findings surpass those of prior studies and have practical implications for contemporary agriculture. Despite the development of suitable, precise, and effective algorithms, real-time systems are still not available to the general public. Researchers in this subject may find the development of such a system extremely intriguing. We want to combine this method with the IoT to enable computers to automatically detect spoiled fruits. Reducing environmental impact by automatically detecting fruit quality. Advancements in technology have enhanced the agricultural industry by increasing safety, promoting environmental sustainability, and facilitating the prediction of crop yields. Studies have shown that the suggested system analysis can evaluate crop health and yield, as well as the influence of external elements such toxic chemicals or pesticides. Various plants have leaves that share similar forms and colours. Computer software can now accurately distinguish many types of plants and crops. Advanced AI methods like federated learning have the potential to improve the quality of products. Post-harvest activities performed by the farmer may impact the sustainability, risk, and income of a crop. DL-based farming utilizes sensors and data-driven insights to assist with decision-making. Machines can predict production, revenues, sicknesses, and quality autonomously without human involvement.

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