Object Sorting in Automated Fruit Grading System Utilizing Machine Vision And Neural Network Classification

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Abstract- Automation in agriculture enhances productivity, sustainability, and the national economy. The main emphasis of this study was on fruit sorting. The fruits selected for the project included lemon, peach, mango, banana, apple, and orange. The initiative aimed to implement automation in the sorting and categorising process to minimise post-harvest human errors. The assembled mechanical system comprised a conveyor belt, actuator, and image-capturing chamber. A camera was utilised to capture the digital photos. Image blur could be eliminated by developing a system capable of capturing the image before the multi-class fruits are inserted into the conveyor belt. The study employed image processing techniques to gather valuable attributes for the purpose of fruit classification. ResNet and transfer learning algorithms were applied to acquired images. The RGB colour model was employed to choose the colours. The noise was diminished after eliminating the foreground. The following data was obtained: the area of the fruit, the average skin colour, the global standard deviation of the individual colour channels (Red, Green, and Blue), differences in contrast enhancement, and the local standard deviation of the three colour channels. A Back-Propagation Neural Network (BPNN) was provided with nine inputs. To train the neural network, a total of 250 samples were collected from 10 distinct categories, including ripe, healthy, as well as faulty and unripe samples. The approach achieved a classification accuracy of approximately 97%.

Index Terms- About four key words or phrases in alphabetical order, separated by commas. Keywords are used to retrieve documents in an information system such as an online journal or a search engine. (Mention 4-5 keywords)

I. Introduction

For a long time, images have been the main way to represent the complexities of the human mind in terms of food and agriculture. Nevertheless, the process of visually quantifying fruits and vegetables has been hindered by labor-intensive methods, subjectivity, and vulnerability to external factors. The reliance on human inspectors and "best-if-used-before dates" in determining market prices highlights the necessity for a more resilient and uniform methodology. This research explores the capacity of machine vision systems to bring about significant changes in the field of fruit sorting and categorization.

The traditional dependence on skilled human inspectors for quality assessments has been found to be susceptible to errors, unpredictability, and a lack of consistency among evaluators. The discipline of computer vision and image processing is increasingly being recognized as a possible solution for traditional analysis and quality monitoring in agriculture. This is especially apparent in the ongoing evaluation of fruits and vegetables based on different standards, ranging from the period before harvesting to the period after harvesting. Figure 1 demonstrates the rising importance of computer vision applications in agriculture, as evidenced by the growing number of research articles.

Digital imaging technologies offer a more efficient method for analysing photographic data in agriculture. Image processing in agriculture encompasses a wide range of applications, such as land identification, nitrogen recognition, detection of pest-infected areas, automatic categorization, and disease detection based on shape, texture, and colour. Computer vision-based pattern recognition and image processing are widely used in agriculture for safety and quality assessments. Computer vision technology in the evaluation of fruits and vegetables replicates the visual capabilities of the human eye to perceive, understand, and identify visual attributes. Subsequently, this data is inputted into machines that assess and categorize the quality.

Studies in the field of quality analysis, particularly in relation to fruits, have made great progress by focusing on individual fruits or adopting technique-centric methods. In the last twenty years, machine vision has been applied in agriculture for tasks such as assessing the quality and quantity of crops, as well as categorizing them. The incorporation of artificial intelligence (AI) algorithms for categorization and assessment has advanced, granting farmers enhanced accuracy and authority over their products.

The significance of fruit sorting and grading in the post-harvesting process cannot be exaggerated. Manual sorting, known for its high level of human labour involvement, requires a significant amount of time and resources. The utilisation of computer vision techniques in the proper classification of fruits and vegetables holds great potential for transformational applications when implemented wisely by farmers. Methods such as product enumeration, employing digital photographs, and automated sorting based on quasi-visual characteristics offer accurate categorization without causing damage to the goods.

This study analyses and tackles the difficulties linked to the sorting of fruits after they have been harvested, with a particular focus on the necessity of automated technologies. The lack of dependability in manual grading, which can result in financial consequences and possible wastage of food, highlights the pressing need to create native techniques for fruit classification. The subsequent parts will explore the precise problem statement, the significance of fruits in agriculture, and the overall goals and objectives of this study.

II. Literature Review

Computer vision experts have made extensive efforts to construct systems for visually classifying and categorising fruits. Qualities like as colour, size, and surface defects can be utilised to categorise fruits. Advanced techniques such as spectroscopy and laser imaging are used to identify weaknesses in intricate systems. This section explores several techniques and documents for classifying and evaluating citrus fruits, including lemons and oranges.

This technique can be employed to gather data pertaining to attributes such as colour and mass [3]. In order to facilitate the categorization and dissemination of the product, the author developed a rudimentary prototype. A very advanced fruit sorter has the ability to categorise fruits at a speed exceeding 10 fruits per second, employing several criteria such as colour, shape, and imperfections.
The classification of tomatoes was achieved using computer vision, as demonstrated by [4]. It was determined that the sorting of tomatoes could only be accomplished through the use of pictures and computer vision technology. The overall error rate amounted to 2.06 percent. It is feasible to categorise mangoes based on their colour and shape. A reference shape can be utilised to make comparisons between geometric attributes, such as form. Shape analysis is advantageous for certain types of mangoes. Another valuable attribute is the pixel value for the purpose of grading. If the pixel value exceeds 100, the skin is considered to be in a healthy and clean state. According to research, this method has an accuracy rate of 83.3% [5].
Mangoes can be classified based on their ripeness. The mango is captured through the lens of a digital camera. The pseudo median filter is employed in the second stage to eliminate the noise. Prior to conducting edge detection on the image, it undergoes a conversion process to a binary format. The technique, as stated in reference [6], has an overall precision rate of 90%. The HIS colour model was devised as a novel method for assessing fruit quality. A digital image of fruit was obtained using a Charge-coupled device (CCD) and subsequently transformed from the RGB colour space to the HIS colour space. In order to acquire the colour intensity histogram, we exclusively utilised the hue H channel. The recursive neural network received the histogram as an input. The output of the network was an evaluation of the quality of the fruit [7].

A method for grading and classifying date fruits was proposed. The system comprised both hardware and software components. A camera was installed into the hardware sector's conveyor belt system. The computer was equipped with software to assess and determine the contents of the acquired file, specifically focusing on the dates. The overall accuracy factor was determined to be 80%. It was found that assessing the unevenness of fruit was challenging [8]. A robot capable of apple recognition and picking was developed using machine vision technology. A physical system was created to be mounted on a tractor. The images were taken with a camera. The image underwent additional processing to detect any defective apples. The apples were collected using a suction-based device. The user's text is "[9]".
A study was conducted to investigate the measurement of food colour in computer vision applications. The study examined the benefits and drawbacks of colour measurement in the context of food. It also highlighted the potential for future advancements and growth in this subject. The user's text is "[10]". The techniques for identifying flaws in apples were provided in a comprehensible manner. The automatic light adjustment was seamlessly integrated into the process using this technology. The approach was established by enumerating and differentiating between the actual defect and the terminal end. The data was classified using a support vector machine [11].
By employing pattern recognition approaches such as nearest prototype, edited multi-seed nearest neighbour, and linear regression, [12] proposed a lemon sorting system. Features extracted from the image include the mean values of the Red, Green, and Blue channels, the image's size, standard deviation, and the minimum and maximum values of the grey level image. In India, samples were collected from five diverse breeds of goats in different regions throughout the country. The focus of their investigation was solely on ripeness. Our methodology closely aligns with research on maturity ratings, but we surpass it by using advanced techniques for detecting damaged fruit. They achieved a 100% accuracy rate by employing linear regression.

The development of a fruit recognition system [13] enables the sorting of mixed fruits based on their respective types. The distinguishing features of fruits in fruit recognition were their shape, size, and colour. The accuracy rate of 100 percent was obtained from 120 samples. In 2010, [14] suggested a method of grading lemons based solely on their colour and volume. Defect-based categorization was absent. The lemons that were big and yellowish were classified as grade B, whereas the lemons that were small and greenish were classified as grade C. By utilising two cameras, they were able to obtain a comprehensive perspective of the lemons.

In 2013, a fairly sophisticated technique for identifying imperfections in lemons was introduced by [15]. This work was based on the technology of fluorescence imaging, which was used to extract the fluorescent component of citrus fruits. The fluorescent components were discovered using spectroscopy. Luminous components and spectroscopy are employed to analyse the chemical composition of lemon peel, enabling the identification of defects and imperfections. The approach had an accuracy rate of approximately 85%.
The facilitation of pattern recognition was enhanced with the utilisation of Curvelet transformations, as stated by [16]. Pattern recognition algorithms were employed to assess the fruit's quality. The curvelet transform, a multi-resolution technique, can be employed to extract both local and global information associated with the surface of the fruit. The process was tested with lemons and guavas. The mathematical properties were obtained by applying a Curvelet transform to the texture of each pixel. Both Support Vector Machine (SVM) and Probabilistic Neural Network (PNN) models were constructed utilising these characteristics. Subsequently, their effectiveness was evaluated by comparing

their performance on two distinct categories: those with no health issues and individuals with faults. The Support Vector Machine (SVM) outperformed the other algorithms with a success rate of 96 percent.

A study conducted by Swapnil Pawar [17] devised a system that utilises the roundness value and colour of a fruit to accurately identify it. By employing the K-Nearest Neighbours algorithm, it is possible to classify an object as a fruit and subsequently analyse it for flaws. We employed a rudimentary thresholding technique to pinpoint the problematic region. In order to be classified as pure skin, a pixel must surpass a specific threshold value; otherwise, it is deemed a defect. There is a specific quantity of defective pixels. The process [18] involved the use of citrus fruits such as lemons, oranges, and sweet limes. The utilisation of colour features was found to be adequate for the classification of objects inside a single image. The classification was based exclusively on the hue component of the HSV colour system. Several techniques were employed to assess the accuracy of categorization. The process of categorising colours resulted in a 90% accuracy rate. Furthermore, the examination of fruit maturity took advantage of the fluctuation in colour. The hue mean and median were utilised to assess the extent of colour variance.

The variable sunlight distribution around the spherical form hinders the detection of imperfections in spherical fruits. The study studied the occurrence of scar tissue and copper burn, which are common in oranges. The Butterworth filter was applied to transform a non-uniform spherical orange image into a uniform illumination distribution. The approach was shown to possess a deficiency in its ability to detect the stem end. The stem end was identified using colour image ratios of red and green, along with procedures for deleting large and extended portions. The technique has a success rate of 98.9 percent in identifying problems. However, the technique proved incapable of discerning various types of defects [19]. [20] invented automated citrus fruit picking. The authors acknowledged the significant variability in field circumstances between different studies. An appropriately constructed and effective artificial illumination was necessary to maintain system uniformity. In addition, there was a need for energy-efficient processing units, together with a camera capable of capturing photos.

A. Fruit categorization and Evaluation

The market has a restricted availability of fruit with exceptional quality. The preservation of fruit quality is achieved by the process of sorting and grading [6]. Various machine vision systems have suggested the use of automation for fruit sorting, fruit grading, and other agricultural applications. Machine vision has been utilised to study several applications such as mango inspection and grading system, mango maturity prediction, and vegetable automated sorting [7]. Citrus, apple, and strawberry are among the often utilised fruits.

Distributed computer image processing technology was utilised to demonstrate the automated assessment and classification of fruits. An automation system has been developed for food companies to meet international quality standards. Experts are usually expected to provide a rationale for fruit maturity. Due to the inherent challenges in human discernment throughout fruit maturation, the process of manual sorting is both labor-intensive and arduous. A maturity prediction technique [9] is employed to ascertain the ripeness of the mango. The technique is specifically developed to assist with manual sorting. Acquiring a costly sorting apparatus to uphold and enhance product quality can pose challenges for specific small agro-industrial enterprises. A sorting and grading machine, based on computer vision, was designed to tackle the problem of a complex and bulky system [9].

The utilisation of machine vision in a classification and grading system ensures the attainment of accuracy, precision, and efficiency, while simultaneously minimising waste. Fruit and vegetable processing systems that are automated are specifically intended to meet the demands of the market. These demands are influenced by various aspects, including the level of ripeness, the size, the density, and any defects on the skin of the produce [10]. Analysing the image necessitates the development of algorithms. The image processing technique can be employed to modify a diverse range of fruits. Image processing has demonstrated extensive use in several agricultural goods [11]. Moreover, the application and evaluation of computer vision methods in agricultural inspection encompass a diverse array of concerns. To ensure precise outcomes, it is essential to take into account factors like the level of ambient light.

Computer vision (CV) refers to a collection of methods and strategies used to acquire digital visual input from the external environment and subsequently analyse it. The method of MV analysis can be advantageous for industrial inspections, medical visualisations, legal enforcement, and aesthetic impacts. Due to its speed, consistency, and rest times, MV is widely favoured across several industries. Machine Vision can rapidly assess tens of thousands of data points within seconds. However, the human operating system is constrained in its capacity to process information as rapidly as a machine vision-based system. Furthermore, the productivity of a human being is significantly less reliable compared to that of a machine vision system. Machine vision systems, in contrast, have the ability to operate continuously without interruption, until maintenance is required. In contrast, people are restricted to working for a maximum of 8 hours each day.

Machine Vision is a method used to examine and interpret digital images. Digitising an image involves converting an input picture into the desired output picture using digital methods. Image processing, image analysis, and computer vision are the main subdivisions of digital image processing. It is employed in the implementation of a camera for the purpose of image processing. The camera captures a picture, which is subsequently processed by its internal processor. The image will undergo noise reduction, sharpening, brightness changes, and other similar enhancements. Now is the appropriate moment to produce a hard copy of the photo, since the resulting image has been stored in the memory. Once caught or recorded, a photograph will undergo image analysis. Analyses are conducted by considering the object's features, form, and texture. Image analysis can be utilised for tasks such as object detection and segmentation. Computer vision mostly encompasses the advanced image processing conducted on computers and digital image processing devices. The computation picture category requires the creation of a set of algorithms that may be used for independent navigation and analysis of scenes. The primary applications of this technology include facial recognition, fingerprint recognition, and object tracking.

III. METHODOLOGY

Fig.1 depicts our proposed approach for assessing the quality of multi-class fruits. This method was developed to overcome the constraints of hand fruit sorting. The majority of it consists of these two components: I Fruit handling An image processing module. The fruit handling system is utilised not only for transporting the fruits on the conveyer belt, but also for capturing images. The images of the fruits are analysed using image processing techniques to determine if the tomato is faulty or not, as well as its level of ripeness.

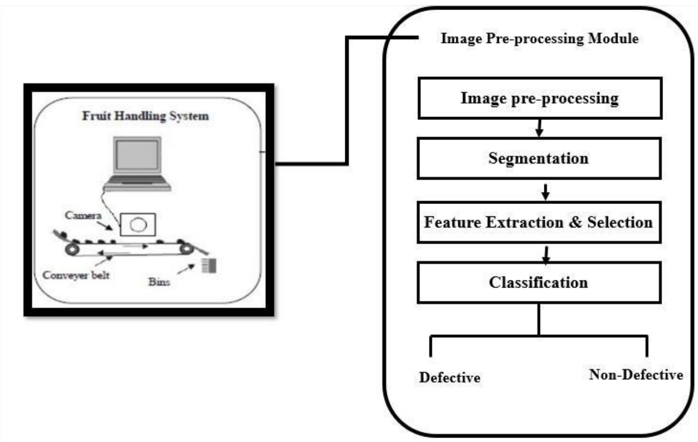

Figure1. Methodology Block diagram

A total of 251 distinct fruit images were generated in this study by the utilization of various picture editing procedures, such as flipping, rotating, translating, applying mean or median filters, altering the colour, and implementing a Gaussian filter. Subsequently, the photos underwent preprocessing. In the initial stage of the procedure, all pictures were resized to dimensions of 227 by 227 pixels. Various techniques such as intensity modulation, edge sharpening, de-noising, filtering, and histogram equalization were utilized to improve the quality of the photos. The return on investment (ROI) for fruit segmentation was determined following the enhancement of the images. The extraction of features from each image is crucial due to their distinctiveness. The identification of fruit photos necessitates the extraction of crucial features. To minimize the presence of repetitive data, it was necessary to extract distinctive characteristics from the dataset. However, upon closer scrutiny of the fruit images, it becomes apparent that there is minimal variation in terms of shape, edge, and texture. Consequently, the subsequent protocols would be put into effect. The first optimization of the application was focused on utilizing factors such as quantization level, direction, magnitude, and features for texture analysis of fruit pictures. The image is partitioned into 3x3 pixel cells in order to retrieve specific features. Subsequently, the two cells are compared. Once the central pixel has a value of 1, the neighboring cells will be immediately assigned a value of 0, and this process will continue. The histogram of each cell is generated using a cell-specific formula (1).

$$LBP_{R,T}(T,q) - \sum_{t=0}^{T-1} s(g_t - g_c)2^t, S(t) - \{1\ t > 0\ 0\ otherwise\} \quad (1)$$

The equation was employed to differentiate adjacent pixels into T-bit binary integers (1). Binary patterns have distinct values as a consequence. This equation calculates the grey level of the central pixel in the nearby neighborhood. Additionally, it exhibits pixels that are evenly spaced, with R representing Radius and S representing Sample Images. HOG features are employed to obtain a precise quantity of histogram bins. The proposed study utilizes a higher quantity of histogram bins in specific segments of the images. The initial photographs were resized to dimensions of 64x128 and subsequently converted to grayscale. The gradient for each pixel was calculated using Equation (2).

$$\{dx = P(x+1, y) - p(x, y) \qquad dy = p(x, y+1) - p(x, y) \quad (2)$$

The pixel value at the coordinates (x, y) is denoted by P, whereas the gradient axis (x, y) is represented by dx and dy. The gradient orientation was determined using an equation (3).

$$\Theta(x, y) = tan^{-1}\frac{dy}{dx} \quad (3)$$

A. Data Acquisition

Image processing begins with digital capture. Controllable light is essential for a clearer image. Controlling the background and camera-object distance improves photos and consistency. Parameters greatly affect picture segmentation. Continuous backgrounds don't need pre-processing. A digital camera captured RGB-based image. To ensure photo consistency, the camera's brightness and AWB increases were manually adjusted. We disabled automated metering and stored video frames from the stream.

Table 1. Number of images in dataset and its various dataset division

Image sets	Lemon images	Peach Images	Apple Images	Mango Images	Orange Images
Training set	2162	2129	2162	2154	2175
Testing set	926	913	928	924	933
Both sets	3088	3042	3090	3078	3108

B. Data Normalizing

Numbers represented retrieved features. The five fruit sample characteristics were pooled in a matrix. Each group contributed 50 training examples till 1205. Machine learning algorithms need normalised data as suspended numbers from 0 to 1. The matrix was converted to 32-bit floating-point data and divided by each row's biggest integer. Standardized floating-point data from 0.0 to 1.0 was used.

C. Labelling & Training

Supervised learning techniques for training and classification require sample labels. Labels created floating-point matrices. We utilized two machine learning methods for training. The OpenCV machine learning library had both methods-built in. multilayer backpropagation perceptron network. The storage facility kept the learnt weights. Results will be discussed in later sections.

D. Image pre-processing

The collection of data precedes its processing. After converting the RGB photos to grayscale, the resulting resolution is 512 by 512 pixels. The data is subsequently purified using the de-noising technique. Subsequently, the techniques of Imad simple and Histogram equalization are employed to enhance the quality of brain MR pictures. The diagram below illustrates the methodology employed in pre-processing.

E. Feature Extraction

After image preprocessing, ROI extracts patch features. Image feature extraction aims to extract data for classification. These diseases have many symptoms. Based on attribute form, the suggested model may diagnose diseases. Form, axis, area, and angle affect their qualities. The classification of brain tumour illnesses began with these traits. Many image properties can be used to classify it. The greatest results depend on extracting the right features and knowing which ones to extract. One photograph can reveal colour, shape, and other geometric elements. Fruits are classified by texture and statistical metrics like GLCM, LBP, and HOG.

F. Classification

The experiment ended with image categorization after feature extraction. Start with fruit graphics. With the recovered attributes, ML classifiers classify many multi-class fruits. Based on pixel intensity, digital images can be classified using supervised learning. Pairing classifiers improves prediction performance. Ensemble categorization [48]. An additional classifier improves the model's accuracy.This research will involve many machine learning models.

IV. EXPERIMENTATION

The experimentation phase of the study employed a diverse dataset comprising images of various fruits, sourced from a publicly available database and a fictitious fruit collection. Lemon, peach, apple, banana, and orange were among the fruits analyzed. The study presented innovative methodologies for image analysis and evaluation, with a particular focus on the final step of categorization and classification. Multiple classifiers were employed to predict unique classifications for each pixel in a digital image, enhancing forecast accuracy through the majority voting approach.

Table 2. Images Distribution

Image Type	Total Images
Lemon	3041
Apple	3087
Mango	3087
Peach	3077
Orange	3107
Total images	15,445

Deep learning ResNet methods, coupled with feature selection and transfer learning, formed the backbone of the classification process. The 'k'-nearest neighbor approach played a crucial role in finding an unknown data points nearest neighbor, with the value of 'k' significantly influencing algorithm performance. The study included lemon, peach, apple, banana, and orange categories, employing various input values and a model featuring numerous decision trees.

A critical phase involved training a multi-class Classifier model using ResNet and transfer learning on a dataset consisting of 3061 fruit photos. A fivefold cross-validation method was adopted for comprehensive model assessment. The images' distribution across lemon, apple, mango, peach, and orange categories was meticulously outlined, totaling 15,445 images.

Data augmentation emerged as a pivotal step, contributing to enhanced deep learning (DL) training accuracy by augmenting the dataset. The process involved changes such as random erasure and kernel filters. Image resizing was deemed essential, with all images standardized to 512 x 512 pixels for consistent algorithm input.

The dataset underwent a test-train split, allocating 80% for training (10,777 images) and 20% for testing (4,618 images). The training performance was closely monitored, with neural network performance reaching its peak after 21 iterations. Recognition performance was achieved through six additional iterations, addressing overfitting concerns.

Error analysis featured prominently in the evaluation, with cross entropy plots illustrating optimal solutions after 21 iterations, showcasing a decrease in both training and testing errors.

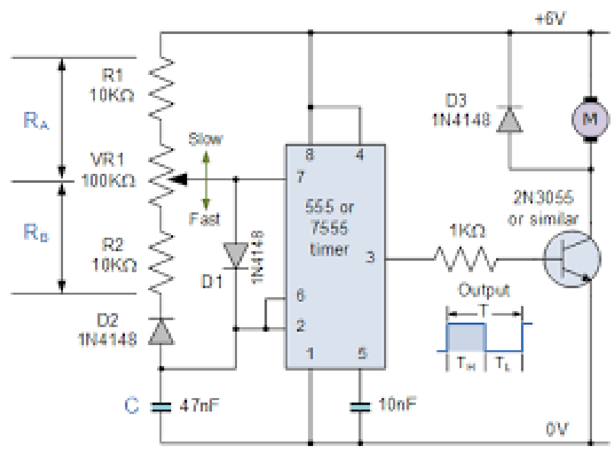

Figure 2. PWM for motor speed control

The confusion matrix provided insights into classification accuracy, revealing an impressive 94% overall accuracy rate. Simulation results encompassed the construction of a dual H-Bridge for motor control, with the associated table detailing input-output relationships for motor direction. Pulse width modulation (PWM) for motor speed control was implemented, utilizing a raspberry pi and a power MOSFET. The experimentation phase concluded with the presentation of oscilloscope findings, illustrating the modulation of motor speed through a virtual oscilloscope on Proteus.

V. Results & Discussion

The study utilized four performance metrics, namely precision, recall, F1 score, and accuracy, to evaluate the results of the Machine Learning algorithms. The proposed methodology diverges from prior methodologies that concentrated on identifying between healthy & Effected fruits. Instead, it effectively discovered and categorised between healthy and effected multiclass fruits. Table 3 demonstrates that the suggested model outperforms existing approaches in a comparison analysis.

Table 3. Performance Statistical Analysis

Classes	*Precision*	*Recall*	*F1 score*	*Accuracy*
Lemon	0.9377	0.9538	0.9538	0.956
Apple	0.9459	0.9451	0.9451	0.955
Peach	0.9239	0.9180	0.9180	0.957
Mango	0.9888	0.9768	0.9768	0.954
Orange	0.9901	0.9919	0.9919	0.955

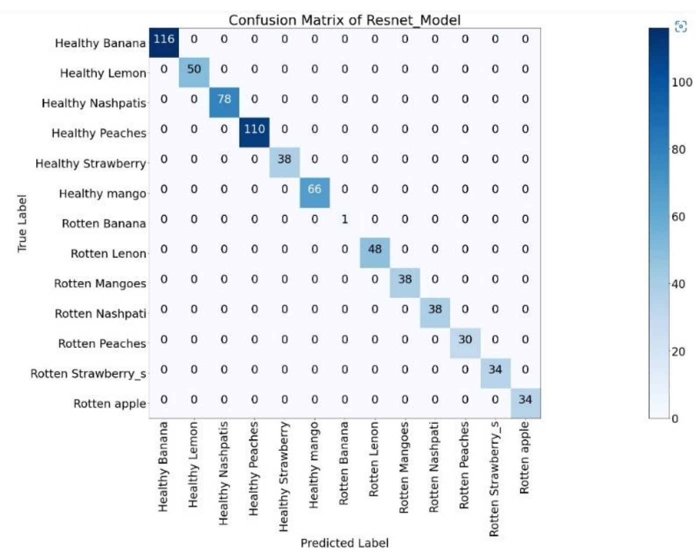

Figure 3. Confusion Matrix

The study examined multiple performance parameters, including as accuracy, recall, precision, specificity, and F1 score, each providing distinct insights into the model's capabilities. Equations were employed to quantify these measures, guaranteeing a thorough assessment of the suggested approach.

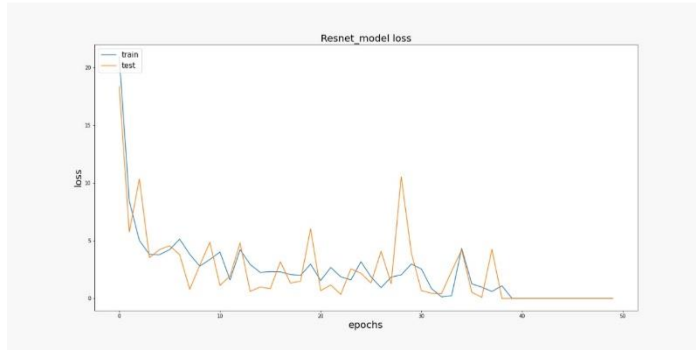

Figure 4. ResNet Model loss and Accuracy

Cross validation is a statistical technique used to assess the performance and generalizability of a predictive model. It involves dividing the available data into many subsets, or folds, and then training. The recommended strategy was compared against expert evaluations using cross-validation. The dataset, consisting of photos of lemons, mangoes, peaches, and apples, was subjected to evaluation by certified experts using the recently devised methodology. The proposed approach demonstrated a remarkable level of effectiveness, with an overall accuracy of 95.547%.

Table 4. Cross Validation for Experts

S. No	Classes	Dataset for Expert test	Predicted True	Expert opinion	Error Percentage	95.547% Over all accuracy
1	Lemon	20	19	1	5%	
2	Apple	20	20	0	0%	
3	Mango	20	18	2	10%	
4	Peach	20	19	1	5%	
5	Orange	20	19	1	5%	

A comprehensive statistical analysis was conducted using an independent t-test to assess the effectiveness of the technique and to compare the incorrect rate differences between the test and cross-validation data. The data presented in Table 5.5 demonstrated a normal distribution in each group. The t-test results revealed a statistically significant distinction between the test and validation outcomes, with a considerable effect size (d=1.704), confirming the practical usefulness of the study in real-life scenarios.

The results collectively indicate that the proposed model is highly effective in detecting and classifying tumours. It outperforms existing approaches and demonstrates excellent levels of precision, recall, and accuracy across several tumour categories.

Table 5 Variation in cross validation and in test data

		Levene test for equality of Variances							T-test for equality Means			
		Mean	SD	F	Sig	t	df	Sig(2-tailed)	Mean Diff	Std.Error diff	95% Conf. Interval	
											Lower	Upper
Performance of Developed methods	Test	5.1	1.67									
	Valid	15	7.9	5.88	0.041	-2.734	8	0.026	-9.88	3.614	-18.214	-1.545

The model's performance across classes was evaluated using critical criteria such as precision, recall, F1 score, and accuracy. Table 3 displays the statistical analysis of performance for the lemon, apple, peach, mango, and orange categories, demonstrating remarkable precision, recall, F1 score, and accuracy scores for each class.
The confusion matrix, a crucial statistical tool in machine learning classification, was utilised to evaluate the performance of the algorithm. An in-depth analysis was conducted on the true positives, true negatives, false negatives, and false positives of each class, which yielded valuable insights into the accuracy of the model and its propensity to misclassify.

VI. CONCLUSION

The research demonstrates the effective use of computer vision and image processing techniques to tackle the complex issues related to sorting and grading fruits after they have been harvested. Our main goal was to automate these operations in order to reduce human errors, improve operational efficiency, and minimise wasteful practices. The physical system that was created consisted of a conveyor belt, an image capturing chamber, an actuator, and sorting bins. This system was used for the purpose of automating the sorting process. By utilising a camera to capture images and implementing subsequent procedures such as pre-processing, feature extraction, and machine learning, the system demonstrated strong and reliable capabilities.

The pre-processing stage involved essential procedures, such as isolating the topic by cropping the image and reducing high-frequency elements with Gaussian filtering. The process of feature extraction involved calculating the average values and overall standard deviations for the RGB colour channels. These metrics were used to evaluate the ripeness of the object and any defects on its surface. The inclusion of additional parameters such as fruit area and local standard deviation enhanced the overall categorization of fruits. The subsequent machine learning stage employed a multilayer perceptron for classification, with training incorporating feedforward and backpropagation methods. The resulting classifications provided the system with instructions to direct the actuator in order to achieve the most efficient distribution of fruit into sorting bins.

As we contemplate the achievements of this research, natural opportunities for future endeavours arise. Integrating a multicamera system, consisting of a minimum of two cameras, could improve scanning capabilities, allowing for a more thorough evaluation of fruits inside the chamber. In addition, the incorporation of processors such as x86 or AMD64 in hardware improvements could enable the real-time execution of region-based segmentation algorithms, hence enhancing the speed and efficiency of processing. Augmenting the dataset with other contextual information, such as weather and location data, presents a significant opportunity to acquire more profound insights, especially in relation to various fruit varieties in Pakistan. Moreover, doing a thorough comparative examination of outcomes derived from different machine learning algorithms holds the potential to reveal the best appropriate methodology for the intricate operation of fruit sorting and grading. By embracing these future directions, the automated fruit sorting systems will continue to evolve and improve, making them suitable for various circumstances and obstacles.

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