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ORANGE FRUIT IMAGE QUALITY ASSESSMENT USING HYBRID MODEL

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ABSTRACT

Since ripeness is regarded by consumers as the most important quality indication in the crops industry, maintaining and monitoring its ripeness has become a major issue in the business of growing crops. Additionally, as it significantly affects the product's quality and consumer preferences, the product's appearance is one of the makers' most pressing worries. However, the forecasting of storage life and the selection of the best harvest dates are still largely based on individual interpretation and practical experience. Threshold segmentation and certain morphological techniques are used in the early stage of the extraction of an area of interest. The segmented orange images are then divided into training and testing data sets, and the second stage entails extracting color-based traits from them. Choosing the classifier training settings is the focus of the third phase. The final phase, which makes use of the previously trained ANN, categorizes the data. One of the most crucial conclusions of this study is that creating a neural network is an empirical process that requires a lot of trials in order to identify the ideal variables that will give the neural classification algorithm the best performance. initialization of weights, the quantity of hidden neurons. Based on the proposed model the accuracy and efficiency is 1.3% which is more accurate result.

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1.INTRODUCTION

Regardless of size, agriculture is one of the most significant industries in every country in the world. Farmers and fishermen in some developing countries have less access to technological improvements in their fields than people in other industrialised countries do. Consequences of restricted technology are numerous. The low quality of the vegetables, citrus fruits, and other crops produced is one of this method's most important side effects. The sole explanation for this effect is that it is determined using variables like shape, colour, and texture, among others, and this can definitely be a result of human error. The main need needed to assess the quality and ripeness of orange fruit is consistency. However, it turns into a a difficult task when it becomes repetitive effort [1]. According to [2],syste ms may automatically learn from and improve on their pre-programmed experiences by applying artificial intelligence (AI) machine learning. This is the main focus of machine learning software development, which allows users to access and use data to educate themselves. Finding patterns and improving judgements based on the examples we provide is the first step in the learning process, whether it begins with examples, hands-on experience, or teaching. The main objectives of this project are action adaptation and automated learning. No human involvement is necessary. Machine learning can be used to analyse large volumes of data. If you want to rapidly and precisely identify potentially lucrative opportunities or dangerous risks, it may also require [3].

2.RELATED WORK

The benefits of using technology in agriculture, according to the paper [4], cannot be overstated due to the impact it has on the sector, which includes, among other things, an increase in the quality and quantity of crops produced, a decrease in farming costs, and the provision of recommendations for immediate action. Traditionally, farmers have used observation to assess the health of their soy bean crops, keeping an eye out for any changes in the colour of the leaves and taking the appropriate precautions to safeguard the crop [5].This method is not entirely reliable since colour is sensitive to human perception, and failing to react when there are changes in the status of the soya beans, especially when they are illness-related effects may cause the predicted yield to be lower. To enable prompt action, soya bean leaves will be divided into a number of categories, including healthy, unhealthy/disease, ripe but not yet ready for harvest, and completely ripe but not yet ready for harvest. The study has used an artificial neural network for classification, which was accomplished through the use of Matlab, as well as the colour and textural characteristics of leaves, which were gathered by image processing techniques in the pre-processing phase. The classification of the various varieties of soya bean leaves was finished with a 95.7% accuracy rate.The research [6], revealed that one of the most significant indicators of orange fruit quality is the ripeness of the fruit. As a In order to promote high-quality output, controlling orange fruit maturity phases may be a crucial mechanical and agricultural issue. Since natural products are one of the most significant crops in the world, ripeness assessment of natural products is a crucial area for research because it has the potential to benefit from ensuring the timely delivery of high-quality products, which will boost participants' salaries [7].Many food processing industri es, including those that make orange fruit juice, jam, natural orange fruit flavours, and other related enterprises, depend on accurate orange fruit ripening stage detection. Farmers would benefit from knowing the stage of orange fruit ripening in order to harvest orange fruit at the best moment, which would boost productivity and lower the risk of crop failure. Although there are numerous techniques for determining the stage of ripening in orange fruit, including the internet of things (IoT), spectrometry, chromatography, image processing, and machine learning, the bulk of them are time-consuming and therefore useless. In addition, some procedures call for the employment of destructive detection techniques, which make oranges unfit for human consumption [8]. Machine learning can identify the ripening stage of orange fruit with minimal human effort and time commitment. Since this method solely uses photographs of orange fruit, the technique is also non-destructive. This study demonstrates that a Convolutional Neural Network classifier may be used to determine the ripening stage of orange fruit in a non-destructive manner Identifying Orange Fruit Ripening Stage Utilizing

CNN. The research [9], is about Mangoes and oranges that have been classified and a recognition approach, which has been established in this article, is used to forecast. In this study, decision tree algorithms (DTAs) and support vector machines were used to classify photos of orange fruit that were collected locally and online. For local datasets, orange fruit photos were categorised as faulty, ripe, and unripe, and ripe and unripe for public datasets. The suggested system uses a number of procedures, such as feature extraction, pre processing, and classificatio n. Scaling images, eliminating background distortion, and extracting colour and texture components from each image were done to bring the system into action [10]. The histogram and Haralick texture features were extracted as feature vectors and used as inputs for the transformation in order to convert each pre-processed image. Additionally, the retrieved local characteristics were used to calculate the locality-preserving projection (LoPP), which was then used as a feature for classification. In order to classify data, a fine tree DTA classifier and a one-against-one multi-class SVM classifier with a 30% holdout were used [11]. 328 locally taken example photos of mangos and oranges, along with 149 images collected from publicly accessible data, were used to assess the effectiveness of the suggested approach. Based on the studies conducted, different success rates at different levels were noted, although an excellent categorization accuracy of 100% and 92.9% stood out. was found on the public dataset, 91.3% on the local dataset, 90.2% and 91.1% on the local dataset using LOPP, and 91.3% and 92.2% on the local dataset using LOPP for mango and orange predictions, respectively. In the classification of mangoes and oranges, the results were 88.6%, 80.4%, and 85.6% for public, local, and LOPP datasets, respectively [12]. According to the study [13], the banana, an orange fruit belonging to the family Musaceae and genus Musa, is one of the most important orange fruit crops in the world, producing around one-fourth of all orange fruit worldwide. The banana is farmed in the tropics, and while it is primarily consumed there, it has acquired popularity all around the world. common way to have Cavendish, or dessert, bananas is fresh, but they can also be fried, mashed, and chilled before being baked or used as a topping for puddings or pies. Additionally, they can be used to flavor baked items like breads, cakes, and muffins. Plantains, a starchy food commonly known as "plantain," are grown and consumed in many tropical regions with varying cooking methods. At the moment of cooking, they are either mature or immature depending on the kind. Many orange fruits are rich in dietary fiber, potassium, manganese, and vitamin B6 as well as other minerals like magnesium, calcium, and calcium. phosphorous and iron. Additionally, fruit contains antioxidants. Machine learning will aid scientists in this investigation by helping them distinguish between various sorts of data. The dataset contains 8,554 photos altogether, of which 4,488 were utilized for training, 1,928 for validation, and 2,138 for testing. Orange is trained using 4,488 photos, 1,928 photos for validation, and 2,138 photos for testing. This was made possible by utilizing deep learning technology that has been widely applied. 30% of the image is used for testing and verification, while 70% of the image is used for learning. On a lengthy test set, we were able to show the reliability of our method and the usefulness of our trained model [14–16]. Mangoes and oranges have been classified and forecasted using a recognition approach, according to research [17], which has been established in this article. Support vector machines and decision tree algorithms (DTAs) were used in this study to classify photos of orange fruit acquired both locally and publicly. For local datasets and public datasets, the images of orange fruit were classified as defective, ripe, and unripe. The suggested system uses a number of procedures, such as feature extraction, pre-processing, and classification. Photos were scaled, backgro und distortion was eliminated, and colour and texture components were extracted from each image before the system was put into operation. The histogram and Haralick were used to convert each pre-processed image. The transformation's inputs were collected as feature vectors from the tex-ture's characteristics. Additionally, the retrieved local characteristics were used to calculate the locality-preserving projection (LoPP), which was then used as a feature for classification. In order to classify data, a fine tree DTA classifier and a one-against-one multi-class SVM classifier with a 30% holdout were used. 328 locally taken sample photos of mangoes and oranges, along with 149 images collected from publicly accessible data, were used to assess the recommended approach's efficacy. Various success rates were estimated based on the trials conducted, however an outstanding classification accuracy of 100% and 92.9% was attained on the public dataset, 91.3% and 90.2% and 91.1% on the private dataset, respectively [18-19].

3. PROPOSED MODEL

On local datasets, the classification rates to increase the amount of data accessible for ANN training, the orange fruit condition and data increase methods were used. In order to maximise the amount of data available for ANN on the local dataset, these photographs were collected from gardens in Sargodha, Pakistan. Using LOPP, the predictions for mango and orang-utan were respectively 91.3% and 92.2% on the local dataset. The classification rates for local datasets are for mangoes and oranges were 88.6%, 80.4%, and 85.6%, respectively, for public, local, and LOPP datasets [20-21].The ba-nana, an orange fruit belonging to the genus Musa and family musaceae, is one of the most important orange fruit crops in the world, making up nearly a quarter of all orange fruit output, according to the study [22]. The banana is grown in the tropics, and despite being mostly consumed there, it has acquired international acclaim for its flavour, nutritional benefits, and accessibility throughout the world. during the entire year. Bananas are typically eaten fresh as a caven-dish or dessert, but they can also be fried, mashed, and chilled before being baked or used as a topping for puddings or pies. Additionally, they can be used to flavour baked items like breads, cakes, and muffins. There are several tropical regions where plantains, a starchy food that is commonly referred to as "plantain," are grown and consumed. At the moment of cooking, they are either mature or immature depending on the kind. Many orange fruits are rich in dietary fibre, potassium, manganese, vitamin B6, and other minerals including magnesium, calcium, iron, and phosphorus when they approach their peak of ripeness. Also present are antioxidants. the fruit [23]. The machine learning approach used in this work will help scientists distinguish between various sorts of data. The dataset contains 8,554 photos altogether, of which 4,488 were utilised for training, 1,928 for validation, and 2,138 for testing. Orange is trained using 4,488 photos, 1,928 photos for validation, and 2,138 photos for testing. This was made possible by utilising deep learning technology that has been widely applied. 30% of the image is used for testing and verification, while 70% of the image is used for learning. On a lengthy test set, we were able to show the efficacy of our method and the practicability of our trained model [24]. Techniques employed are depicted in the figure. By applying the following arbitrary changes to the images that were displayed and created using the image data generator class from the keras library, the amount of data was increased by 600% [25]. We chose those six transformations since they have already been seen on artworks in our cutting-edge collection. Only the shear and zoom transformations among them have the capability of causing images to become so distorted that they are no longer recognisable. We therefore limited their range to a maximum of 0.2 points per variable. It is possible to alter the image in ways including resizing, rotating, and flipping it vertically or horizontally without significantly affecting it. It can no longer be identified. The proposed framework for this investigation is shown in detail in figure 1 below [26].

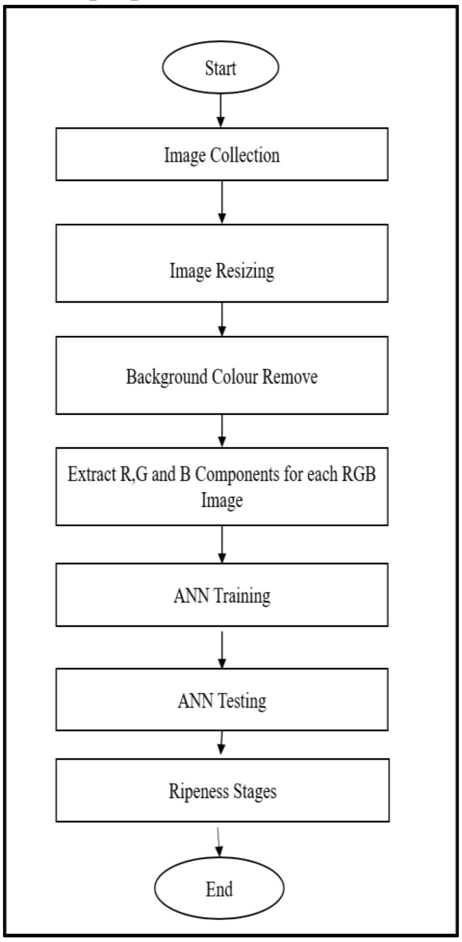

Fig.1 Proposed Framework

3.1 Data Collection

Pakistan is frequently thought of being an agricultural country. One of the major agricultural producers in the world, Pakistan, produces orange in significant amounts. Pakistan produces a variety of agricultural products, including orange fruits and vegetables. If the orange fruit being offered is of great quality and can be kept fresh for a long time, increasing the value of orange fruit sales price is more likely to be accomplished. The level of maturity present in the orange fruit itself significantly affects the fruit's overall quality [27]. The orange fruit's freshness, however, significantly affects how likely it is to deteriorate. Given that oranges are generally available and produced in big quantities, The accuracy with which orange fruit ripeness is assessed is highly significant because the evaluation of orange fruit maturity takes only a brief amount of time. The author's dataset on orange ripeness, which was employed in this study, includes data on oranges. Unripe oranges are distinguished from ripe oranges, who themselves are distinguished from each other. Each orange fruit category comprises 200 photos of ripeness and 200 photos of unripens, with the ripeness photos acting as the training data for the machine learning system. To gather test data on the fruits, each category of orange fruit has 200 images of mature orange fruit and 200 images of immature orange fruit. Each and every image of an orange fruit that has been captured are jpg-format photos with dimensions ranging from 2043 x 1772 to 2621 x 2166 [28-29].

3.2 Data Preprocessing

These six modifications were chosen because they had previously included artworks from our state-of-the-art collection. They are the only ones among them that have the ability to blur pictures so much that they lose their identity. The other two are the shear and zoom transformations. As a result, we restricted the allowable scoring range for each contender to no more than 0.2 points. The image can be changed without being so distorted that it is impossible to recognise it, for example, by scaling, rotating, and flipping it vertically or horizontally. This is being done through the creation of a system that can mimic human vision and assess an orange's level of maturity after taking a picture of the fruit [30]. A 9-layer convolutional neural network, as shown in figure 2, would be used for the job after a review of the pertinent literature. The design of this neural network structure was inspired by a model (Bhargava & Bansal, 2020) based on the VGG-16 architecture. This neural network has a similar architecture to the VGG-16 design, consisting of three convolutional layers coupled by three max pooling layers. Similar to the VGG-16 design, this neural network is made up of three convolutional layers coupled by three max pooling layers. For each convolutional layer in the final image, a 3x3-pixel mask was used [31]. Features extraction of orange fruit:The maturity index must be established by identifying consistent physicochemical

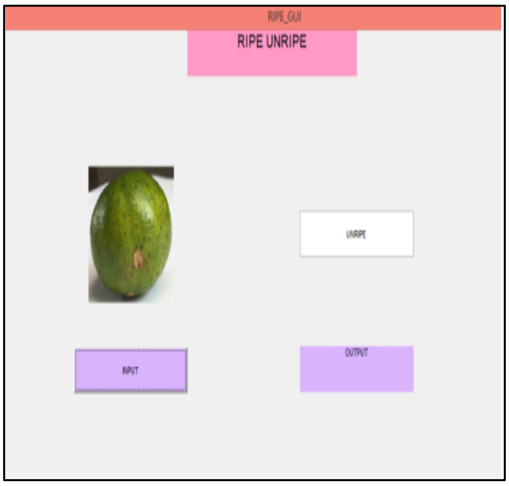

Fig.2 Fruit selection approch

When the product was rigorously watched throughout its .Development, measurement s were found. These measurements show a strong correlation between postharvest production and maturity.Size and ShapE: The fact that the orange fruit has achieved a given size.

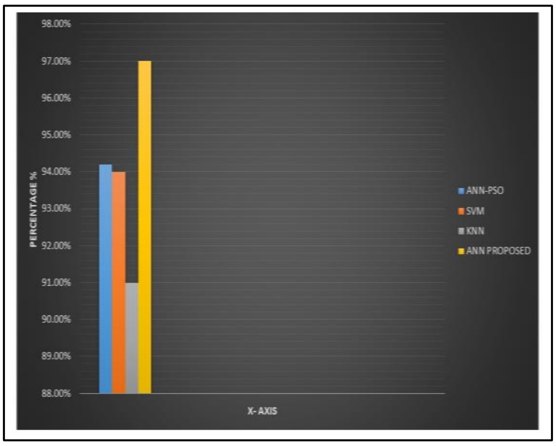

Fig.3. Accuracy Comparison

The size of any orange fruit type may be impacted by the quantity of orange fruits laden on the tree, meteorological circumstances, and management practises, making it impossible to rely solely on this as an indication of maturity [31]. Orange fruit that is fully mature and ripe, whether it is still on the tree or has been removed from it, will become less firm as it ripens. Although flesh firmness is a helpful minimum maturity criterion, it is insufficient on its own because it differs between types of orange fruits and is influenced by things including orange fruit size, weather patterns, and growth methods. 400 various images of trees were captured in the fields of Sargodha [32].These pictures shot on three separate occasions, with an interval of about one month between each set. In the next portion of this .Each of these three datasets will be referred to as SAR1 and SAR2 in this work. There are a total of 23 tree photos in the collection, compared to 16 and 44 in the separate datasets. Dusk, blazing sunlight, and shadows are a few examples of the lighting conditions that can be seen in the photographs. We established a baseline by meticulously counting and recognising every instance of an orange fruit that appeared in any of the input pictures [33-34].

4.RESULT

In our experiments, we carried out an automated ripeness count using the indicated technique, and we compared the results to the actual count. The experiment's results show that appropriate detection occurs 98.01% of the time. We also employed linear regression to characterise the relationship between the discoveries produced by the automation and the actual data in addition to figuring out the detection rate.The outcomes of plotting both human and automatic orange counts are shown in the figures. It is done in the second phase to separate a digital image into its component parts. The image that produces the outcome of image partitioning is subjected to the fundamental threshold holding procedures, and the consequent of image partitioning is created. By bringing down the complexity of the image, it makes the representation simpler. The citrus orange fruit is processed efficiently using the watershed approach, which makes use of picture intensity, threshold holding, region processing, and discontinuity detection.The below figure 4 shows the unripe orange fruit and its properties and resize the image.

Fig. 4. Unripe Orange Masking

An important consideration when deciding whether or not a situation is orange is the colour of the surface. It'll be able to spot imperfections, freshness, and the area of the citrus that is about to ripen. The average values for the three components—red (r), blue (h), and green (g)—are displayed below. BIC and CBIR have completed their work on content-based image retrieval in Fig. 4. Unripe Orange masking.order to separate the picture components, compute the logarith mic distance (dLog), and determine the mean grey value of the orange fruit.

5.Conclusion

Estimating the maturity of orange fruit is a crucial technique that directly affects the fruit's quality and marketing. The idea of using a computer vision system to automatically assess the maturity of fruits and vegetables has attracted the attention of many researchers. This method offers an effective solution to both of these issues while also reducing the sluggishness, time commitment, and high cost of human ripeness examination. The results of this study, which were published in Science, show that a classification technique based on artificial neural networks was utilised to estimate the freshness of orange fruit based on their hue. All aspects of the colour feature vectors, learning method, and ANN classifier structure were taken into account for this study.

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