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Assessment of quality grading in orange fruit using deep learning approach

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ABSTRACT:

The quality of oranges is necessary to improve sales growth in the market. Oranges are widely grown and mostly used in the food processing industry. Each year, Pakistan exports millions of tons of oranges to national and international markets. However, these areas of the economy face a shortage of standards in quality assurance, more time for grading, and poor-quality production. The quality assessment of orange fruit is usually determined by humans. Because of the limitation of individual perceptions, different challenges occur, such as time-consuming, inaccuracy, and inconsistency. The main problem is that only trained personnel can do this job, and it requires a huge amount of effort and time to inspect each piece of fruit. To overcome these drawbacks, we developed an automated system for quality grading of oranges using Deep Learning. This paper proposed a classification model that categorized images of oranges using deep learning and machine learning algorithms. The model was trained on the VGG-19 convolutional neural network structure, which is a 19-layer deep network, through the application of transfer learning, to optimize feature extraction on the orange image dataset. A dataset of 4500 images of oranges was captured under controlled lighting conditions using a DSLR camera. For the classification, three classes of oranges, namely Grade-A, Grade-B, and Grade-C, are categorized based on color, shape, texture, and size of the orange. The proposed classification method for quality grading of oranges, VGG-19, based on a transfer learning approach, achieved 98.00% accuracy.

KEYWORDS: Convolutional Neural Network, Quality Grading, VGG19, Accuracy, Deep Learning

1. INTRODUCTION

Agriculture is one of the most important economic and social sectors of Pakistan. It generates around 20 to 25 percent of the country's GDP, as shown in Fig. 1. It supports more than 60 percent of the rural population, making a significant impact on the country's economic and food supply [1]. Pakistan is blessed with extensive agricultural resources, including a fertile landscape, a fine irrigation system, diverse climates, and centuries-old farming traditions [2]. Orange is one of the preferred agricultural products among humans because it offers numerous health benefits, including high levels of vitamin C and antioxidants. The primary factor in the post-harvest processing and marketing of oranges is quality grading [3]. The quality of the orange is essential for the consumers, and it has become mandatory for exporters to supply fruits with good quality standards. So, in recent year's fruit grading systems have been developed to meet the requirements of quality. However, apart from that, supplying fruit includes several stages that can be divided into grading, sorting, packaging, transporting, and storing. Grading is classified as one of the essential stages in obtaining a high rate of quality. The process of segmenting a material into various homogeneous classes based on its particular characteristics is called Grading [4].

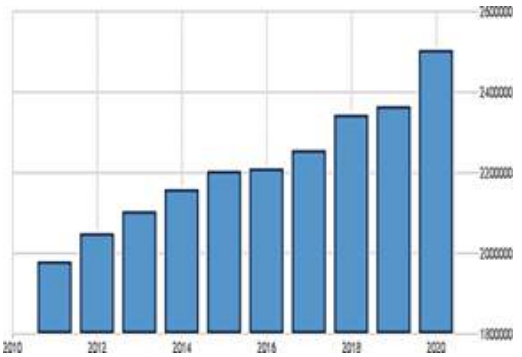


Figure 1: GDP from Agriculture | Source: State Bank of Pakistan

The quality evaluation of the orange fruit is commonly determined by the human naked eye. During the peak seasons, the lack of labor has an impact on the grading process. It's becoming harder to find or instruct the individual who can perform the process of inspection. The limitation of human perceptions can lead to different disadvantages, including inaccuracy, inconsistency. To reduce these faults, we developed an automated system for grading oranges using Deep Learning. Deep learning has achieved amazing results throughout all computer vision applications, such as picture classification, object recognition, security, image processing, and so on. Machine learning is a branch of deep learning. Feature extraction and classification are both performed automatically in the deep learning technique to identify images with relevant objects. There is no requirement for the researchers to complete both operations manually, as is the case with traditional machine learning. Deep learning includes a combination of multiple neural layers to process a large amount of data. As a result, it is often referred to as a Deep Convolutional Neural Network [5]. The structure of the human brain is used to design this system. Just like the human brain that works on a network of neurons, deep learning passes the input through the network of neural layers, filters out outliers, spots familiar entities, and provides the overall output, i.e., the label of the object.

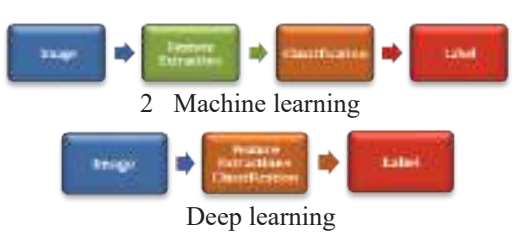


Figure 2: Machine learning vs. deep learning

Figure 2 depicts the operation of traditional ML and DL for image categorization. Orange is among the most widely used and growing citrus fruits in the world. The orange contributes about 70 percent of total citrus production around the world. These are used to make juices, orange oil, syrups, jams, jellies, butter, orange sweets, and pulp in the food processing industry [6]. The quality of oranges has been studied earlier, conducted by [7] using the LVQ technique, and obtained 76 percent accuracy. They concentrated their study on categorizing one kind of orange. Further study was performed on oranges using Naive Bayes and produced a 91.60% accuracy result [8]. To detect orange pictures, all of those studies still utilize standard machine learning approaches. The grading process can be divided into two parts: external fruit evaluation and interior fruit evaluation. This study was proposed to create and deploy an effective algorithm for classifying lemon fruits in a Visual Basic environment [9]. The method efficiently estimated a lemon by its color and size. The model efficiently recognized a lemon based on color and size by the RGB value of the image, and the HIS value was determined from the RGB. The size and color of lemon fruit were found and placed in the database during the sorting stage. During the standardization phase, the measured color and size contrast with stored information in the database. In [10] grading the strawberry was graded using the three main attributes, color, size, and shape, and was divided into four categories. Adopted the multi-attribute decision-making theory to solve the multiple features problem. The results obtained the 88.8 % color grading, shape accuracy 90% and size detection fault of not more than 5% and an average time to classify the strawberry is less than 3 sec. Harpreet Kaur suggested a Multi-Class SVM, a machine learning model to grade the rice grains. The rice grain was categorized using a Multi-Class SVM by analyzing its shape, chalkiness, and the ratio of broken grains. According to the results, the method was adequate for classification and grading the various types of rice grains based on their inner and external quality. The SVM classifies accurately more than 86% [11]. Pande and his team focused on constructing a separate system that could classify 3 grades of fruits and apples as a classification test case. The inputs are presented in the form of a fruit picture. The Inception V3 model is developed for this purpose using the transfer learning approach, thus

allowing it to differentiate between fruit images. The statistics of the research present that the Top five accuracy on the dataset used is 90% and the Top one accuracy is 85% [12]. Asriny has proposed the CNN-based classification system [13] to identify orange images. Oranges are divided into five categories: immature orange, rotten orange, and damaged orange. Convolutional Neural Networks were used to categorize the orange pictures. As per the results of the testing, ReLU beats Tanh. Tanh's accuracy decreases when new data is used. The accuracy of data testing is 96 percent when the ReLU activation function is used and 93.8 percent when the Tanh activation function is used. In [14] estimation of the apple orchard quality presented a framework for rapidly detecting the fruit quality. MLP and a convolutional neural network were used to segment the input pictures. The proposed system was tested for its ability to distinguish between CNN and MLP overall performance. The recall is a commonly used performance measure to determine the quality of apple fruit in the Journal of Natural Remedies. When contrasted to MLP, CNN had the best possible results, with a recall rate of 78.30 percent against 70.70 percent for the latter. In [15] strategy was presented for classifying the quality of apples and grapes. The main problem of the presented approach is that it can only distinguish fruits with near-spherical forms, which will need to be addressed in the future. The study outcome was based on the correlation performance measure, which was 0.96 for grapefruit and 0.85 for apple fruit. Yousef Al in [16] has proposed and deployed a model computer vision-based data grading and sorting framework. They described flabbiness, size, shape, intensity, and defects as additional quality attributes. The results of the testing indicate that the model is capable of sorting dates with an accuracy of 80%. Shaha and Pawar in [17]suggested a deep learning model (VGG19) for feature extraction and an SVM for classification tasks. They evaluated several neural networks, such as AlexNet, VGG16, and VGG19, for feature extraction and image classification on the GHIM10K and Caltech256 datasets. The VGG19 architecture significantly outperforms AlexNet and VGG16 in terms of performance, as measured by three evaluation parameters: accuracy, recall, and F1-score. The VGG19 model has recently demonstrated strong image classification performance. In this paper, color, shape, texture, and size of the orange are used to categorize the oranges into three classes: Grade-A, Grade-B, and Grade-C. VGG-19 is a deep CNN that has shown better results in agricultural image classification, as it has hierarchical features that capture hierarchical features. Due to this reason, VGG-19 was chosen as the backbone of our grading model.

2. RESEARCH AIM

This study intends to develop and test an automated orange grading system that is founded on the deep learning method, namely the VGG-19 convolutional neural network. The experiment is aimed at classifying oranges into three quality groups (Grade-A, Grade-B, and Grade-C) based on their external characteristics, which include color, size, shape, and texture. A deep hierarchical structure of VGG-19 allows the extraction of low-level and high-level features automatically, in contrast to traditional machine learning methods that require handcrafted features and do not always provide consistent results. ImageNet weight-based transfer learning has been utilized to improve feature representation and decrease the computational cost of training by itself. The dataset of orange images was pre-processed and then augmented and split into training, validation, and testing networks to provide sound testing of the model. The study focuses on a greater classification accuracy, precision, and reliability when compared to the traditional procedures like LVQ, Naive Bayes, and SVM. Furthermore, the research will show the promise of deep CNNs on the issues of manual grading, which include the cost of labor, time, and human error. The last goal is to recommend an effective, scalable, and practical framework that can be implemented in real-life agricultural and industrial settings to enhance the assessment of the fruit quality and reinforce the supply chain management.

3. LITERATURE REVIEW

Human vision can readily differentiate the appearance of faces, animals, or the quality of fruit, but computers find this complicated. As of late, vision-based computing has provided an improvement, and as such, images and videos can now be perceived by the algorithms. They are finding applications in agriculture to perform activities like the classification and grading of fruits. Grading systems that are automated are necessary to save on labor, be objective, and conduct quality checks. The parameters such as

size, shape, texture, and color are usually used as the basis of fruit grading. These are such that they permit non-destructive assessment, which is significant in preserving the fruit's freshness and market value. Being one of the most commonly grown citrus fruits, oranges are not only eaten as fruit, but also made into juices, preserves, and medicines, and therefore, their quality evaluation is of paramount significance. Early studies employed conventional machine learning. The Learning Vector Quantization (LVQ) [1] recognized oranges on the basis of color and texture, but with a score of only 76 percent, since the features were to be determined manually. Naive Bayes classifier [2] was more accurate with 91.6 percent based on shape and size, but the sample size used was too small of 150. Likewise, Support Vector Machines (SVMs) [3-6] were trained on rice, apples, and citrus fruits with up to 86 percent accuracy, yet these models were unable to handle large amounts of data and the variability in the fruits. The machine vision was also developed in strawberries and lemons, in which shape, color, and size were features extracted through cameras, conveyors, and sensors. These researchers [4-6] obtained about 88-94% accuracy, indicating the possibility of automated grading systems. Nonetheless, scalability and flexibility were constrained by the reliance on handcrafted features. Convolutional Neural Networks (CNNs) changed the face of fruit grading studies with the advent of deep learning. CNNs can do feature extraction automatically on the image, without manual feature engineering. In the case of orange grading, CNNs [7,8] were able to reach up to 96% accuracy, which was even better than the conventional methods. Advanced models like VGG-19, Inception V3, and ResNet [9,11-13], transferred learning, and achieved greater success with an accuracy of more than 95%. To address small dataset limitations that affected model generalization, data augmentation methods such as flipping, rotation, and cropping [10] were used. Recent applications also introduced CNNs to mangoes, apples, bananas, and mandarins [12,13,15], demonstrating their ability to be used on a variety of fruits. More complex architectures, such as VGG-19 [8,9], are sensitive to finer features, such as texture, defects, and smaller differences in surface features, enabling them to be used in industrial-level tasks. Overall, conventional machine learning methods [1-6] had a fair performance but were restricted due to manual features and the size of the data. Recent developments in deep learning methods [7-15], especially CNN-based transfer learning models, are found to be more accurate, scalable, and robust, and therefore, it is preferable to be used in contemporary fruit grading systems. Initial research on conventional machine learning techniques, including LVQ, Naive Bayes, and SVM, performed with moderate accuracy but was restricted by hand feature extraction and limited datasets. Recent developments in deep learning and specifically CNN-based learning, such as the use of VGG19, have addressed these drawbacks, where features are automatically learned by using images. This transformation is an indication of why deep learning is more precise, big data, and dependable in terms of contemporary fruit grading structures.

Table 1: Comparative Analysis of Literature Review

Study	Method-ology	Instru-ments	Param-eters	Sample Size	Main Findings
[1]	LVQ	Digital Camera	Color, texture	200 oranges	76% accu-racy; limit-ed due to manual features
[2]	Naïve Bayes	Scanner	Shape, size	150 oranges	91.6% accuracy, small dataset
[3]	Multi-class SVM	Flatbed scanner	Shape, chalkiness	300 rice kernels	86% accu-racy; mod-erate but limited for fruits
[4]	K-means clustering + decision theory	Camera & conveyor	Shape, color, size	100 strawbe-rries	~90% accuracy, <3 Sec per fruit
[5]	KSVM with PCA	Digital camera	Color, texture, shape	1000 apples	88.2% accuracy
[6]	SVM	Flatbed scanner	Internal & external features	Rice kernels	>86% accuracy
[7]	ANN with GA	Image dataset	Texture, color	Oranges	94.5% accuracy
[8]	CNN	DSLR/ smartph-one	RGB features	500–1000 oranges	>95% accuracy
[9]	Inception V3 (transf-er learning)	Smartp-hone	Color features	2500 images	90% accuracy overfitting noted
[10]	CNN + augmen-tation	Image dataset	Rotation, flipping, scaling	2500 strawber-ries	88–90% accuracy

[11]	ResNet, DenseNet, Efficient Net	Fruits dataset	External defects	Large (apples, bananas)	>98% accuracy with Efficient Net
[12]	Faster R-CNN	Fruit360 dataset	Defects, bounding boxes	2000 mixed fruits	>90% accuracy
[13]	Autoen-coder + CNN	Smart-phone images	Size, color	Mandarins	89.4% accuracy
[14]	CNN (4-layer)	Smart-phone	Color, size	1000 oranges	96% accuracy
[15]	Transfer learning (Squeeze-Net)	RGB + thermal images	Shape, maturity	Mango dataset	~93% accuracy

4. MATERIALS AND METHODS

4.1. Dataset Description

We clipped the oranges from the orange tree. After picking the oranges from the orchard, we divided the oranges into three classes. Orange images were captured with a DSLR camera fixed to amount with a 50mm lens, and an ISO of 1250 placed under the lighting environment. A constant distance of 20 centimeters was fixed. In total, the image dataset consisted of 4500 images with 5184 ×3456-pixel resolution. For classification purposes, 1500 images were collected for each grade.

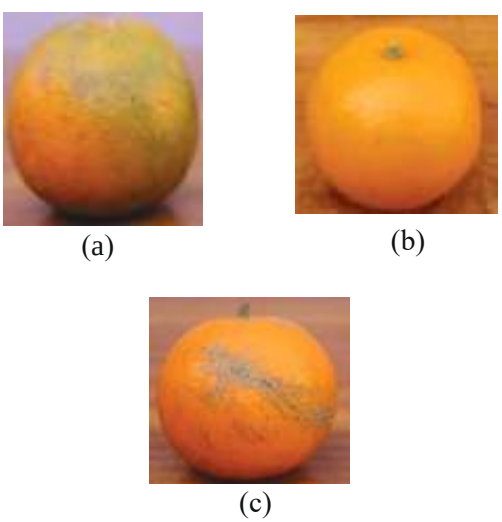


Figure 3: Oranges with three quality grades. (a) Grade-A, (b) Grade-B, (c) Grade-C

The three classes of images namely Grade-A, Grade-B, and Grade-C. The proposed system gives the quality evaluation of oranges for deciding about the export market, local market, and juice manufacturing companies. Grade-A is about international quality, Grade-B is about the national market, and Grade-C is about the local market.

Table 2:The orange Dataset classes

Class	Color	Shape	Size (diam-eters)	Texture
Grade-A	Orange, red, yellow	Oval	>7cm	Fine (3% tolerance)
Grade-B	Orange, red, yellow	Flatted oval	6.1-7cm	Minor defects (5% tolerance)
Grade-C	Green, red, yellow	Flatted oval	5-6cm	Not fine

4.2. Feature Extraction and Classification Algorithms

The most essential element of image classification is feature extraction. The performance of the classification relied strongly on the parameters of the images [19]. Based on color, form, or texture, an object's characteristics are divided into local and global features. Color and texture are regarded as local qualities, whereas form is considered universal. Deep features are retrieved for picture categorization in this work. A pre-trained deep neural network is used to extract deep features (VGG19). The following is a brief description of the method: VGG-19

Simonyan and Zisserman (2014) introduced VGG19, a convolutional neural network with nineteen layers, sixteen convolution layers, and three fully-connected layers for classifying pictures into 1000 object classes [5]. The ImageNet collection, which comprises a million photos in 1000 categories, was used to train VGG19. Due to the employment of numerous 3*3 filters in each convolutional layer, it is a particularly common approach for picture classification. [20]. VGG19's architecture is seen in Fig.4. This demonstrates that the first sixteen convolutional layers are utilized for feature extraction, while the next three layers are applied for classification. The extracted feature layers are divided into five groups, each of which is followed by a max-pooling layer. This model receives an image of size 224*224 and outputs the label of the item in the image[21].

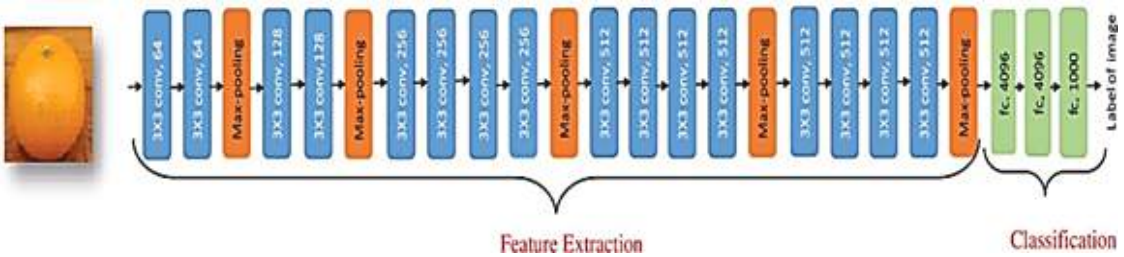


Figure 4: Architecture of VGG-19

4.3. Proposed System

The main objective of the study is to classify and grade the orange fruit using a Deep Learning Model. Using the VGG-19 network, feature extraction was performed by putting the image data into the pre-trained network. The ImageNet dataset was used to train the pre-trained VGG19 model, which contains 19 layers. The simplicity of the VGG19 network is described by the use of only 3x3 convolutional layers stacked on top of each other in increasing depths. This network uses down-sampling of the input representation to decrease dimensionality. A softmax layer is preceded by two fully-connected layers (FC1 and FC2), each with 4096 nodes, that together establish the classifier. The following VGG19 network with 19 layers is described [21] in-depth in Fig. 5.

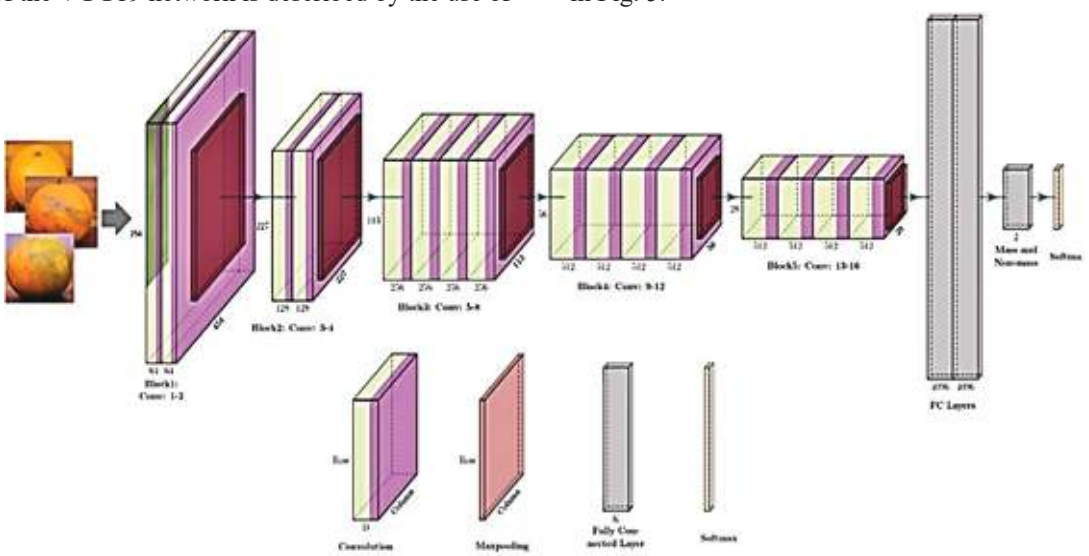


Figure 5: Architecture of the 19 layers of the VGG19 network

5. METHODOLOGY

The proposed system involved the following basic steps:

5.1. Data Augmentation

Augmentation of data is a useful approach in neural network-based systems because deep learning works with a large amount of datasets. Collecting and annotating such a huge amount of data for training is difficult and time-consuming. However, the small data will raise an overfitting problem. The system will not perform well in the training process and will not generate correct results during the testing process. To expand the dataset, different modifications are done via data augmentation processes, such as translation, rotation, adding noise, cropping, and flipping.

5.2. Data Pre-Processing

To decrease noise, the images were pre-processed. To obtain a dataset of the same size, the dataset was resized to 224 * 224 * 3 pixels. The process is visualized in Fig. 6.

5.3. VGG-19 MODEL AND CLASSIFIER

This paper utilized an orange grading VGG-19-based convolutional neural network. VGG-19 is a 19-layer deep CNN with 16 convolutional layers (extracting the features) and 3 fully connected layers (classifying). The

network consists of small 3x3 convolutional filters and max-pooling layers of size 2x2 that captured information gradually in images in a gradual manner. The design enables the model to identify low-level (edges, colors) and high-level features (texture, defects, and shape of fruit).

To learn such a deep model, it takes a very large dataset to learn it initially. In order to address this, we employed the concept of transfer learning in which we used a VGG-19 model that had been pre-trained using the ImageNet dataset. This was done by taking the convolutional base as a feature extractor and adding a new classifier head, and training it on the orange dataset. This will make sure that the model gains the advantage of strong pre-trained features and then gets adjusted to the particular task of orange grading.

The custom classifier head was developed in the following way:

- Flatten layer - transforms feature maps to a 1Dvector.
- Dense layer (4096 units, ReLU activation) - learns complicated patterns.
- Dense layer (4096 units, ReLU activation) - this increases the learning capacity.
- Dense layer (3 units, Softmax activation): - probability of the three grades of the orange (Grade-A, Grade-B, Grade-C)

The Softmax output makes sure that the image is classified in the grade with the largest probability. The VGG-19 architecture is also more accurate, capable of extracting features automatically, and operates well on large and more complex data sets than the traditional techniques like LVQ, Naive Bayes, and SVM. It is also better than shallower CNNs in that its more complex form can pick out finer details like surface defects and subtle texture differences.

5.4. Training and Testing

The convolution layer was adopted during the first 2 layers with 3*3 filters, and in these two convolution layers, 64 filters were used it resulting in 224*224*64. CONV64*2 denotes that it uses two convolutional layers with 64 filters. The filters use a 3*3 with a stride of 1 and adopt the same convolutions. In this structure, the pooling layer minimizes the height and width of the volume 224*224*64 to 112*112*64. Then, a few convolutional layers were applied with 128 filters. Then, a pooling layer was applied to the newly created dimension, which will be 56*56*128. Then, 2conv layers with 256 filters have been used. Finally, 7*7*512 into the Fully connected layer (FC) with 4096 units, and 1000 classes generated in a SoftMax output. They trained the models on a dataset consisting of 3150 training images, 900 validation images, and 450 testing images. The total number of images used for image classification and prediction is 4500. Google Colab Notebook was used. These tests have been run on Google Colab, which offers about 2 vCPUs, 12 GB RAM, and a Tesla K80 graphics card with a temporary storage amount of about 100 GB. The efficiency of the model depends on the GPU system, so the results are tested in a Google Colab notebook. Google Colab offers a free-of-cost access GPU in the runtime. The VGG19 model was trained using Google Colab Notebooks with a virtual GPU. We establish the training, validation, and testing directories on Google Drive. In each directory, create three subdirectories with the names

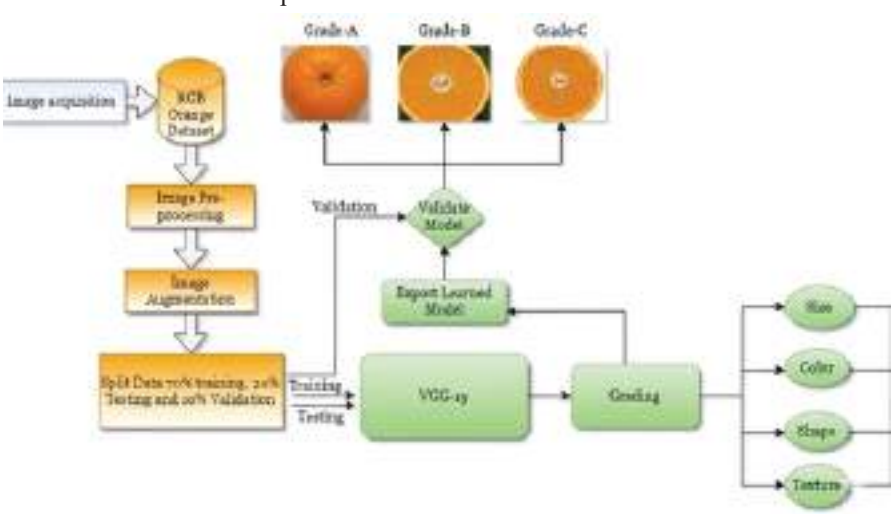


Figure 6: Workflow Diagram

Grade-A, Grade-B, and Grade-C. After that, we upload the images to the corresponding subdirectory on Use Google Drive and use it when running the model. Since all the images are JPEG files, those files are converted to RGB grid pixels by using the TensorFlow Keras ImageDataGenerator instance.

6. RESULT

In this section, we detail the performance of state-of-the-art Convolutional Neural Networks (CNNs) models. Analyzed the accuracy and training time of the VGG19 model. The following Figures 7 and 8 show the history of accuracy and loss of training and validation sets. When the training accuracy is much higher than the validation accuracy, this is referred to as overfitting. Underfitting occurs when the training accuracy is much less than the validation accuracy. The training graph shows the increase in accuracy and decrease in error rate. The function of loss value is to calculate how much the model has performed on the data by calculating the difference between predictions and the actual target. Underfitting occurs when the training loss is much higher than the validation loss. If the training loss is much smaller than the validation loss, this is an indication of overfitting. The accuracy curve for the training (3150 images) and validation (900 images) dataset is shown in Fig. 7. The loss curve for training and validation is displayed in Fig. 8



Figure 7: Accuracy Comparison of training and validation accuracy over epochs

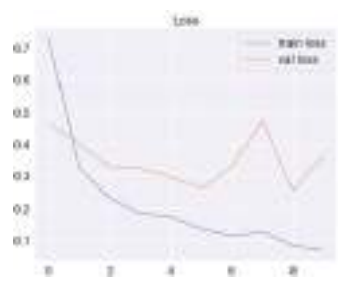


Figure 8: Loss Comparison of training and validation accuracy over epochs

The Confusion Matrix (CM) of the proposed model is presented in Fig. 9. Based on the CM data, four important performance metrics were arrived at based on the accuracy, precision, recall, and F1-score in order to assess the performance of the model in classification. Accuracy is displayed as the proportion of correctly classified samples of the entire test sample. Precision (alternatively called positive predictive value) is a measure of the fraction of the samples that were predicted as positive and that are in fact positive, which shows how well the model can avoid false positives. Recall (or sensitivity) quantifies the number of real positive samples that the model recognized, which is a measure of the capacity of the model to identify all the pertinent cases. F1-score is a harmonic measure of F-score and recall, a balanced measure of both. These measures have the following mathematical representations:

$$\text{Recall}=(\text{True Positve})/(\text{True Positive}+\text{False Negative}) \quad (1)$$

$$F1=2^{*}\ (\text{Precsion}^{*}\text{Recall})/(\text{Precsion}+\text{Recall}) \quad (2)$$

$$\text{Precision}=(\text{True Positive})/(\text{True Positive}+\text{False Negative}) \quad (3)$$



Figure 9: Confusion Matrix for model evaluation

Table 3 Testing Results

Grade	Precision	Recall	F1-Score
Grade-A	90%	82%	86%
Grade-B	83.89%	64%	73%
Grade-C	87.56%	97%	84%

7. DISCUSSION

The experimental data show that the suggested VGG-19-based deep learning model is highly effective when it comes to automated grading of oranges. The model reached an accuracy of 98, which is considerably higher than the traditional machine learning approaches like LVQ, Naive Bayes, and SVM, which suffered due to handwritten feature extraction and smaller datasets. The confusion table and measures of evaluation prove the fact that the system is capable of reliably categorizing the Grade-A, Grade-B, and Grade-C oranges according to the color, texture, shape, and size. The current work confirms the strength of transfer learning solutions to agricultural applications in comparison with the earlier research on citrus and other fruits. Compared to previous methods, VGG-19 was more scalable and more accurate because of the ability to extract features in a hierarchical manner. This illustrates the promise of deep CNNs in the case of real-world grading systems. An experimentation process was done, and in the process, a fine-tuning was performed on a few hyperparameters to attain the best performance. Trial runs of the learning rate, batch size, and number of epochs were made to reduce the level of validation loss and enhance the classification accuracy. Adam optimizer was used to ensure the high efficiency of the gradient convergence, and data augmentation methods were used to improve the generalization. In spite of the positive findings, there are certain limitations. The model was tested and trained with controlled conditions of lighting, which may not be a complete reflection of real-world variability like shadows, background clutter, or non-uniform illumination. Additionally, the existing framework is currently divergent in the sense that it solely concentrates on external quality attributes. Internal characteristics (e.g., it is sweet, juicy, or has an undetectable fault) should be introduced into future work using hyperspectral imaging or other sensor-based methods. Implementation with a conveyor belt system also has to be done on the fly to make sure that it can be deployed at an industrial level. All in all, this paper validates that deep learning has the ability to offer rapid, dependable, and scalable solutions to the process of fruit grading, which ultimately serves the exporters, local farmers, and the food industry.

8. CONCLUSIONS

Automation has been a part of technological progress and has been increasingly used in agriculture over the past few years.

This paper has come up with a quality grading system based on computer vision, with the use of the VGG19 model, which is used in sorting oranges into three types. The accuracy of the classification based on the experimental results obtained with the help of a standard computing system and a digital camera was high (98%), which proves the effectiveness and robustness of the model. Developments in the work to be done in the future will be directed towards increasing the speed of the models and incorporating the system within the practical settings of the industrial real-time conveyor belts. A similar approach can also be applied to other fruits like apples, mangoes, and strawberries with a few changes, thus extending its use in the agricultural sector. The system developed offers a cost-effective and reliable, and scalable solution to enable exporters to retain the quality of fruits, distribute efficiently in the local market, and minimize the losses after harvesting. In general, it is possible to note that the results presented in this paper reveal the potential of deep learning-based automation to develop precision-farming and enhance the economic benefits of fruit production.

9. ACKNOWLEDGMENT

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