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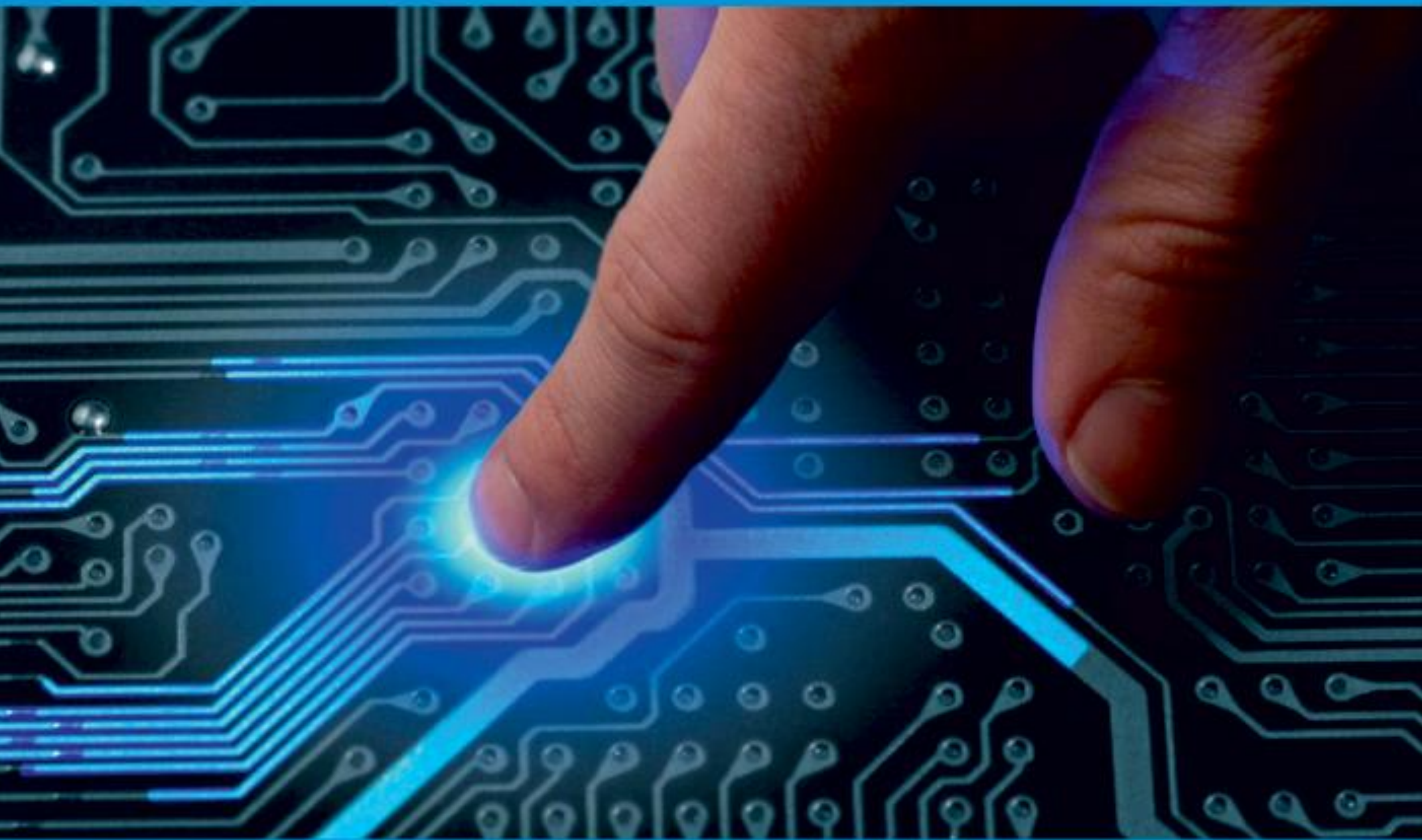

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Mango Fruit Classification based on Ripeness

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ABSTRACT: The classification of mango fruit based on its ripeness is crucial for the agricultural industry and fruit supply chains to ensure optimal quality control and efficient distribution. This study proposes a machine learning-based approach to classify mango fruits into different ripeness stages.The proposed methodology involves the collection of a large dataset of mango images at various ripeness stages, including unripe, semi-ripe, and fully ripe. Preprocessing techniques such as image enhancement and feature extraction are applied to extract relevant features from the mango fruit images. These features include color histograms, texture descriptors, and shape characteristics.A supervised machine learning algorithm, such as Support Vector Machines (SVM), Random Forest, or Convolutional Neural Networks (CNN), is employed for mango fruit classification. The extracted features are used as input to train the model, which learns to differentiate between different ripeness stages based on the provided ground truth labels.
The performance of the proposed classification model is evaluated using various metrics such as accuracy, precision, recall, and F1-score. Cross-validation techniques may also be employed to validate the model's generalizability and robustness.The experimental results demonstrate the effectiveness of the proposed approach in accurately classifying mango fruits based on their ripeness. The classification model can aid in automating mango fruit sorting processes, improving quality control, and optimizing fruit distribution in supply chains.The proposed methodology can be extended and applied to other fruit classification tasks, contributing to the advancement of agricultural practices and promoting efficiency in the fruit industry.

KEYWORDS:CNN – Convolutional Neural Network, AlexNET, ReLU, SVM

I. INTRODUCTION

Mango is one of the most popular and widely consumed tropical fruits known for its rich flavour and nutritional value. The ripeness stage of mangoes plays a crucial role in determining their taste, texture, and overall quality. Efficient and accurate classification of mango fruits based on ripeness is essential for the agricultural industry, supply chain management, and consumer satisfaction.Traditionally, mango ripeness assessment has relied on subjective methods such as visual inspection and manual palpation, which are time-consuming, labor-intensive, and prone to human bias. To overcome these limitations, machine learning (ML) techniques have emerged as a promising approach for automating the mango fruit classification process.

Machine learning algorithms can learn from large datasets of mango images and extract meaningful features that characterize the different ripeness stages. By leveraging these extracted features, ML models can classify mango fruits into categories such as unripe, semi-ripe, and fully ripe with a high degree of accuracy.The application of ML in mango fruit classification offers several benefits. It enables rapid and objective assessment of ripeness, facilitating efficient sorting, grading, and quality control processes. ML-based classification also minimizes the risk of human error, ensuring consistency and standardization in fruit evaluation.

This research aims to explore and develop a mango fruit classification system based on ML techniques. By training a model on a diverse dataset of mango images at different ripeness stages, the study seeks to create an accurate and reliable classification framework. The proposed system holds the potential to revolutionize mango fruit grading and enhance the efficiency and profitability of the mango supply chain.In this study, we will investigate various ML algorithms such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), or Random Forests to identify the most suitable approach for mango fruit classification based on ripeness. The performance of the models will be evaluated using appropriate metrics, and the results will be compared with traditional manual classification methods.The successful implementation of a ML-based mango fruit classification system will have significant

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implications for the agricultural industry, enabling farmers, suppliers, and retailers to make informed decisions, enhance product quality, and meet consumer demands more effectively.

II. RELATED WORK

According to Varsha Bhole et al. [1] in 2020, the factors like bruises, color, appearance etc. affect the quality of the fruits and also influence the consumers. This research focuses on non-destructive techniques that determine the maturity levels of the mango for evaluating the quality with increased accuracy. So, we have proposed an automatic mango fruit grading system using non-destructive techniques like thermal imaging and transfer learning with pre-trained SqueezeNet model which is a new era at present.

According to Mohammed A. Alkahlout et al. [2] in 2021, they proposed an approach that uses deep learning-based learning of images of 10 different fruit from Kaggle website. They use a pre trained CNN Model VGG16. In this paper, they trained and validated the proposed model and tested its performance with un-seen dataset for testing. The Accuracy rate we achieved was 100 %. This indicates that their proposed model can effectively predicate and classify different fruit without error and with full performance. As for future work, they can generalize the evaluation of the proposed framework for more classes (using extra fruit and vegetable). They will also investigate the effect of different parameters such as activation function, pooling function optimization method, and a loss function. The proposed framework can also be deployed into a cloud-based framework.

According to HAMDI ALTAHERI et al. [3] in 2019, a real-time machine vision framework for date fruit harvesting robots in an orchard environment was proposed based on deep learning. The framework consisted of three models used to classify date fruit bunches according to their type, maturity, and harvesting decision. Transfer learning with fine-tuning was used in the classification tasks. Two pre-trained CNN models were investigated, namely AlexNet and VGG-16. To build a robust machine vision system, we used a rich image dataset of five date types for all maturity stages. The dataset was designed with a large degree of variation that represents the challenges in natural environments and date fruit orchards. The proposed approach achieved excellent classification accuracies on this challenging dataset with a high classification rate. The results showed that a pre-trained CNN could achieve robust date fruit classification without the pre-processing of images to removebackground noise or enhance illumination. The best accuracies were obtained by the fine-tuned VGG-16 model, which achieved 99.01%, 97.25%, and 98.59% accuracies with classification times of 20.6, 20.7, and 35.9 msec for the date fruit type, maturity, and harvesting decision classification models, respectively. As for future work, we will improve the dataset by including testing images captured from different date orchards. We will also investigate more recent CNN models to minimize the usage of memory and lower computational complexity. One more area to investigate is the confusion in the maturity detection of date fruit, including labeling rules, and the interference among maturity stages.

According to Tej Bahadur Shahi et al. [4] in 2022, they presented a novel attention- convolution module based MobileNetV2 to classify the fruit images. There method has achieved the stable classification accuracy of 95.75%, 96.74%, and 96.23% on Dataset 1 (D1), Dataset 2 (D2), and Dataset 3 (D3), respectively. Given the lightweight nature of our model, they method has a great potential to be adopted by industries closely related to the fruit growing and retailing or processing chain for automatic fruit identification and classifications in the future. Their method has some limitations. First, our method relies on MobilenetV2 architecture. Hence, their model has not been tried with other user-defined lightweight backbone architectures. Second, their method uses online data augmentation only for their experiments. The performance of their model could be further improved by using or partly using other advanced offline data augmentation techniques, such as the Generative Adversarial Network (GAN).

According to Khalied Albarrak et al. [5] in 2022, in this study, a CNN-based model is proposed capable of classifying eight different popular date fruits in Saudi Arabia. The proposed model is trained on an in-house dataset which contains around 1750 images of eight different date fruits with a frequency between 204 and 240 for each class. Different preprocessing techniques have been incorporated into the proposed model to improve the accuracy rate such as decayed learning rate, model checkpointing, image augmentation, and dropout. An existing architecture (MobileNetV2) has been adopted for a proposed model for classification.

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III. PROPOSED ALGORITHM

CNN

Convolution: The purpose of convolution is to extract features from the input image. It preserves the spatial relationship between pixels by learning image features using small squares of input data. It is usually followed by ReLU.

ReLU: It is an element-wise operation that replaces all negative pixel values in the feature map by zero. Its purpose is to introduce non-linearity in a convolution network.

Pooling: Pooling (also called down sampling) reduces the dimensionality of each feature map but retains important data.

Fully-connected layer: It is a multi-layer perceptron that uses SoftMax function in the output layer. Its purpose is to use features from previous layers for classifying the input image into various classes based on training data.
The combination of these layers is used to create a CNN model. The last layer is a fully connected layer.
A convolutional neural network (CNN) consists of many neural network layers. Two different types of layers, convolutional and pooling, are typically alternated. The depth of each filterincreases from left to right in the network. The last stage is typically made of one or more fully connected layers.

Input: Test Dataset which contains various test instances TestDB-Lits [], Train dataset which is built by training phase TrainDB-Lits [] , Threshold Th**.**
Output: HashMap < class label, Similarity Weight > all instances which weight violates the threshold score.
Step 1: For each testing records as given below equation

$$testFeature(k) = \sum_{m=1}^{n} (.featureSet[A[i] \dots \dots .. A[n] \leftarrow \text{TestDBLits})$$

Step 2: Create feature vector from $testFeature(m)$ using below function.
Extracted_FeatureSetx [t..…n] = $\sum_{x=1}^{n}$(t)$\leftarrow testFeature$ (k)
Extracted_FeatureSetx[t] holds the extracted feature of each instance for testing dataset.
Step 3: For each train instances as using below function

$$trainFeature(l) = \sum_{m=1}^{n} (.featureSet[A[i] \dots \dots .. A[n] \leftarrow \text{TrainDBList})$$

Step 4: Generate new feature vector from $trainFeature(m)$ using below function
Extracted_FeatureSet_Y[t……n] = $\sum_{x=1}^{n}$(t)$\leftarrow TrainFeature$ (l)
Extracted_FeatureSet_Y[t] holds the extracted feature of each instance for training dataset.
Step 5: Now evaluate each test records with entire training dataset

$$weight = calcSim\ (\text{FeatureSetx} \mid\mid \sum_{i=1}^{n} \text{FeatureSety[y]})$$

Step 6: Return Weight

IV. PSEUDO CODE

Step 1: Generate all possible routes for mango classification.
Step 2: For each node of each route, calculate the Total Energy (TEnode) using equation (1).
Step 3: Repeat the following steps until no route is available to transmit the packet:

For each route, check the condition:
if (Ripeness Based Energy (RBE) <= TEnode):
Put the node into sleep mode.
else:
Select all routes that have active nodes.
end if

Step 4: Calculate the total transmission energy for all the selected routes using equation (2).
Step 5: Select the energy-efficient route based on the minimum total transmission energy.

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Step 6: For each node in the selected route, calculate the Ripeness Based Energy (RBE) using equation (3).
Step 7: Go back to Step 3.
Step 8: End.

V. SIMULATION RESULTS

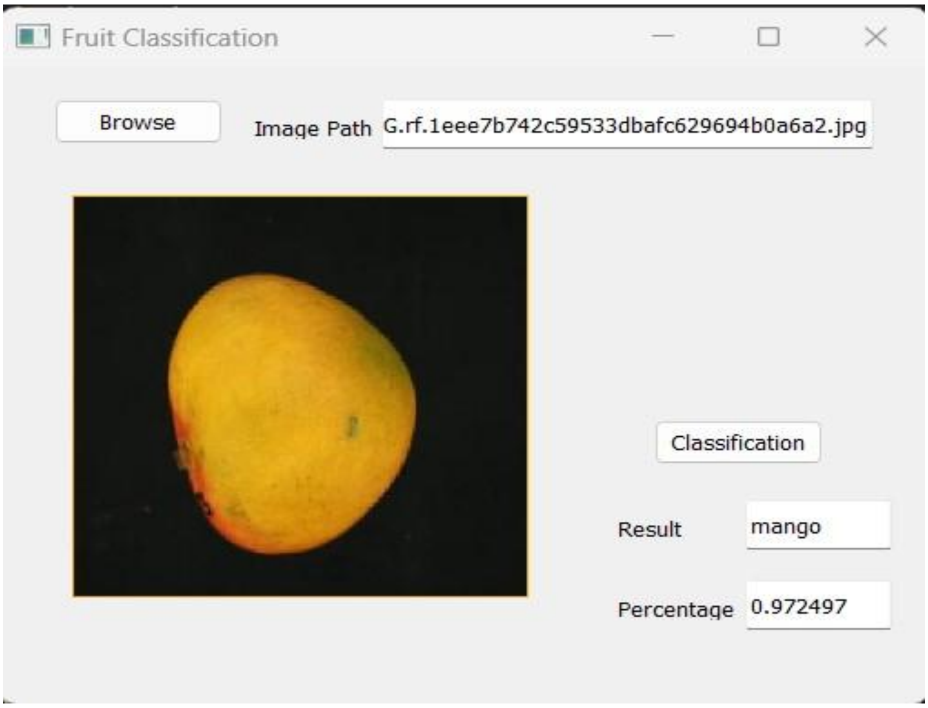

Fig 5.1 Identification of Mango fruit

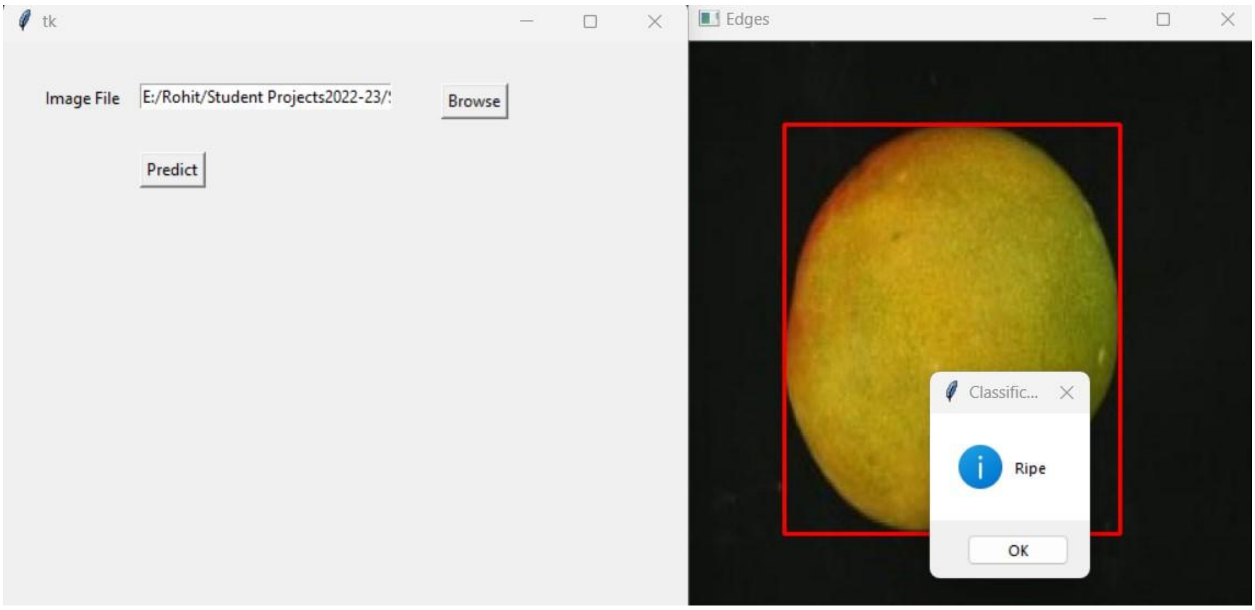

Fig 5.2 Classification of Mango Fruit (Ripe)

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VI. CONCLUSION AND FUTURE WORK

In conclusion, the application of machine learning for mango fruit classification based on ripeness shows promising results. The proposed methodology leverages image analysis techniques, feature extraction, and supervised machine learning algorithms to accurately classify mango fruits into different ripeness stages. The experimental results demonstrate the effectiveness of the approach in achieving high classification accuracy, contributing to quality control and efficient distribution in the agricultural industry. The use of machine learning allows for automation and scalability in mango fruit sorting processes, reducing human error and improving overall productivity. By accurately identifying the ripeness stage of mango fruits, farmers, suppliers, and retailers can optimize their operations, ensuring that the right fruits reach consumers at the right time.

There are several potential avenues for further research and improvement in mango fruit classification based on ripeness using machine learning. Expanding the dataset by including a wider variety of mango cultivars and ripeness stages can enhance the model's ability to generalize across different mango types. Integrating non-invasive sensors or IoT (Internet of Things) devices that measure parameters like firmness, sugar content, or aroma can complement image-based classification and improve accuracy. Designing user-friendly mobile applications that leverage the trained models for mango ripeness classification can empower farmers, suppliers, and consumers to assess fruit quality easily and make informed decisions.

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