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Fruit Quality Detection using Image Processing

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***Abstract*—The country's primary source of economic development on a global scale is the agriculture industry. The fruit's appearance plays a crucial role in describing its size, shape, and colour as well as its quality whether it is rotten or fresh. We can determine the fruit's shelf life that is, how many days it will last by utilising its quality. Farmers can use this information to determine when to harvest fruit to prevent it from becoming overripe. Additionally, this will support planning aimed at lowering crop losses and raising farmer incomes. This study presents the widely used methods of image processing, machine learning, and deep learning technologies for fruit quality recognition and maturity categorisation. In this paper we have used CNN as a primary model to identify fruits quality and compared it with Decision Tree Classifier.**

Keywords—Image processing, Machine Learning, Deep Learning, CNN, Decision Tree Classifier.

I. Introduction

Everything in agriculture is becoming mechanised these days, making human intervention in the system an expensive and time-consuming process that is not commercially viable. Fruit must be examined for quality before it is utilised to produce culinary products. Fruit quality in agriculture is influenced by a number of factors, including soil composition, water availability, and effective fertiliser application. When choosing high-quality fruits and vegetables for industrial production, more labour was needed in the past. Numerous automated technologies that are used to identify high-quality fruits have been developed in recent years.Using the supervised learning technique's classification algorithm, our suggested system can quickly and accurately determine the grade of fruit. These characteristics are used to divide the fruits into groups, such as rotten, middling, and good fruits. Utilising a traditional neural network approach, machine vision techniques can determine if fruit is fresh, 20% rotten, 50% rotten, or completely rotten.

In order to determine if an apple, orange, or banana is excellent or rotten, Convolutional Neural Networks (CNNs) are trained with photographs of these fruits in three different condition states. Many classification approaches are extended by artificial neural networks. In addition to the fruit's extracted features, it uses the form, colour, and size features that were provided during training to classify the fruits. The result is obtained by comparing these features. Ultimately, the fruits are divided into categories: fresh, 20% rotten, 50% rotten or completely rotten.

II. LITERATURE SURVEY

A. *Aim of Study*

This study aimed to classify fruits based on their shape and color using an image processing approach. A total of 7500 specimens with various regular and irregular shapes were chosen for this investigation. After acquiring and pre-processing the images, several features such as length, width, breadth, perimeter, elongation, compactness, roundness, area, asymmetry, centroid, centroid asymmetry, and width asymmetry were extracted. These features were then grouped using CNN and Decision Tree Classifier in which we used HOG to extract features. The characterization accuracy scores for CNN and DTC were 93.30% and 81.84%, respectively. These results suggest that CNN is a promising method for improving traditional fruit classification techniques.

B. *CNN*

Convolutional Neural Networks (CNNs) have become a powerful tool in the field of computer vision and image processing, achieving state-of-the-art results in various tasks such as image classification, object detection, and segmentation. This literature survey focuses on three main aspects of CNNs: training methods, architectures, and applications, with a special emphasis on image classification.

Training Methods

Transfer Learning

Transfer learning is a popular method for training CNNs, especially when the dataset is small. The idea is to use a pre-trained model on a large dataset like ImageNet and fine-tune it on the target dataset. This method has been shown to improve performance and reduce training time significantly [Yosinski et al., 2014].

Data Augmentation

Data augmentation is another common technique used to improve the performance of CNNs. It involves creating new training samples by applying transformations such as rotation, scaling, and flipping to the original images. This helps to increase the size of the training set and makes the model more robust to variations in the input [Krizhevsky et al., 2012].

Architectures

AlexNet

AlexNet, proposed by Krizhevsky et al. (2012), was one of the first CNN architectures to gain popularity. It consists of eight layers: five convolutional layers, some of them followed by max-pooling layers, and three fully-connected layers.

VGGNet

VGGNet, introduced by Simonyan and Zisserman (2014), is known for its simplicity and uniform architecture. It consists of 16 or 19 weight layers and uses small 3x3 convolutional filters in all layers.

ResNet

ResNet, proposed by He et al. (2015), introduced the concept of residual learning. It adds shortcut connections that skip one or more layers, which helps to alleviate the problem of vanishing gradients in deep networks.

Applications: Image Classification

Image classification is one of the most common applications of CNNs. The goal is to assign a label to an image based on its content. CNNs have achieved remarkable results in this task. For example, Krizhevsky et al. (2012) used AlexNet to win the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012. Since then, various CNN architectures have been proposed to improve the performance on this task

C. *Decision Tree Classifier*

The Decision Tree Classifier is a popular machine learning algorithm used for both classification and regression tasks. In the context of image classification, it can be combined with Histogram of Oriented Gradients (HOG) features for feature extraction. This approach allows for the classification of images based on their content by leveraging the structural information provided by HOG features.

Histogram of Oriented Gradients (HOG) Features

HOG features are a type of feature descriptor used in computer vision and image processing for the purpose of object detection. They are based on the appearance and shape of local objects in an image, which are represented by the distribution of intensity gradients or edge directions. The image is divided into small connected regions called cells, and a histogram of gradient directions is computed for each cell. These histograms are then concatenated to form a feature vector that represents the image (Dalal & Triggs, 2005).

Decision Tree Classifier

A Decision Tree Classifier is a tree-structured model where each internal node represents a feature, each branch represents a decision rule, and each leaf node represents an outcome. The tree is built in a top-down manner by recursively partitioning the data based on the feature that provides the best split, as measured by a criterion such as Gini impurity or entropy. The tree is then used to classify new instances by following the path from the root to a leaf node based on the values of the features (Quinlan, 1986).

Image Classification using Decision Tree Classifier and HOG Features

In the context of image classification, the Decision Tree Classifier can be used in combination with HOG features to classify images based on their content. The process involves the following steps:

Feature Extraction: HOG features are extracted from the training images to form a feature matrix.

Training the Decision Tree Classifier: The feature matrix is used to train the Decision Tree Classifier. The tree is built by recursively partitioning the data based on the HOG features that provide the best split[1].

Classification: The trained Decision Tree Classifier is used to classify new images. HOG features are extracted from the new images and used to navigate the tree from the root to a leaf node, which provides the predicted class.

The combination of Decision Tree Classifier and Histogram of Oriented Gradients (HOG) features is a powerful tool for image classification. The HOG features capture the structural information in the images by counting occurrences of gradient orientation in localized portions of an image.[2] This method is similar to edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization[3].

The Decision Tree Classifier uses the HOG features to make predictions. The classifier operates by recursively partitioning the feature space into regions based on the values of the input features, and then making a prediction for each region based on the majority class of the training samples in that region. Despite its simplicity, this approach has been shown to be effective in various applications, such as pedestrian detection and vehicle detection.

However, it should be noted that the performance of this approach depends on the quality of the HOG features and the complexity of the decision tree. The quality of the HOG features can be affected by factors such as the cell size, block size, and number of orientation bins used in the computation[2]. The complexity of the decision tree can be controlled by adjusting parameters such as the maximum depth of the tree and the minimum number of samples required to split an internal node.

Moreover, this approach may not be suitable for large-scale problems or complex images. In such cases, more sophisticated techniques such as deep learning may be required to achieve satisfactory performance[1].

In summary, the combination of Decision Tree Classifier and HOG features provides a powerful tool for image classification, but its performance depends on the quality of the HOG features and the complexity of the decision tree, and it may not be suitable for large-scale problems or complex images.

III. Methodology

A. *Dataset Collection and Preparation*

The first step in the methodology is to collect a dataset of fruit images. The dataset should contain a diverse set of images for each fruit class, including variations in lighting, angle, and background. For example, the DeepFruit dataset contains 7500 images of 3 different types of fruits captured under different light conditions, positions, and distances. The images should be preprocessed to ensure they are of the same size and format. Data augmentation techniques such as rotation, flipping, and zooming can be applied to increase the size of the dataset and improve the robustness of the model. In a study by Hossain et al. (2019), data augmentation improved the accuracy of a fruit recognition model significantly[8]. However, it is important to note that the quality of the dataset is crucial for the performance of the model, and insufficient light and non-inclusion of all fruit classes are limitations that should be addressed in future versions of the dataset[7].

B. *CNN Model Architecture*

The next step is to design a CNN model architecture for fruit identification. The architecture should consist of multiple convolutional and pooling layers, followed by one or more fully-connected layers. The convolutional layers are responsible for extracting features from the images, while the pooling layers are used to reduce the spatial dimensions of the feature maps. The fully-connected layers are used to classify the images based on the extracted features. The

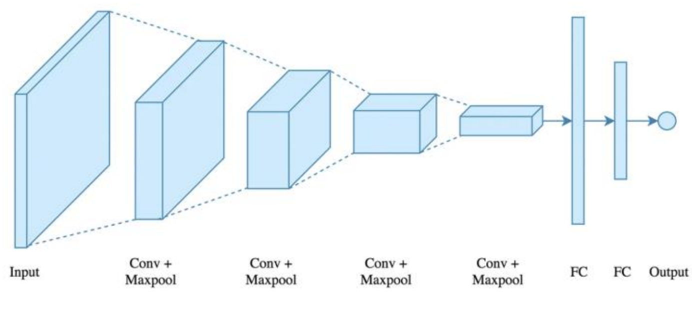

Fig 2: CNN Architecture

architecture should be designed to balance accuracy and computational efficiency.

As you can see in the above diagram, first after a image is uploaded it undergoes various transformations which comes under Image_Preprocessing attribute in which the image is adjusted to certain parameters of pixels, image_height, image_width, pixels and colours.Which are decided as per the models requirement, that is in what parameters of model is trained on a dataset of images.

CNN model is trained on 70% of dataset using Conv2D layer which extracts the features out of images, after that maxpooling is used to reduce the spatial data, after that again Conv2D is used with different parameters followed by max pooling then flatten function is used to transform 2D data into simpler 1D format which is necessary for feeding the data into next layer which is Dense, which is used to connect to all neuron's of previous layers and is used for making predictions based on extract features.At the end Dropout is used to randomly drop some neurons and features of certain data so that it can generalise in future and to prevent overfitting and again dense layer is used but this time sigmoid

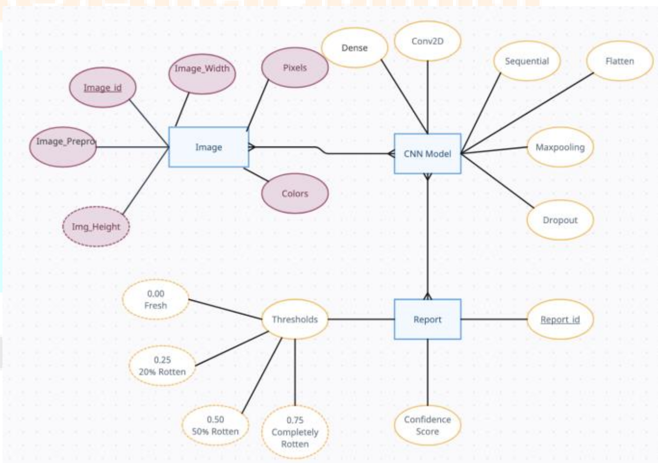

Fig 1: ER diagram of CNN

activation function is used which gives the predicted value in between 0 and 1 which is then used to find thresholds and classify the quality of fruits after training and testing of model

C. Model Training and Validation

Model	CNN	DTC
Parameters	7,978,277	643
Training Accuracy	93.56%	82.29%
Validation Accuracy	96.65%	82.34%
Training Time	2.761s	2.507s
Validation Loss	0.0925	0.1107

Fig 3: Result Comparison

The CNN model must be trained and validated in the third stage. It is necessary to divide the dataset into testing, validation, and training sets. The validation set is used to adjust the hyperparameters and track the training process, the testing set is used to assess the model's performance, and the training set is used to train the model. Gradient descent and backpropagation should be used to train the model, along with an appropriate loss function like binary cross-entropy for binary classification. It is recommended to assess the model's performance using measures like F1 score, recall, accuracy, and precision.

D. Model Deployment and Evaluation

The final step is to deploy the trained CNN model for fruit identification. The model is then integrated into a user-friendly application that allows users to upload images of fruits and receive predictions. The performance of the model is then evaluated in real-world conditions, and any issues or limitations should be addressed. The model should be regularly updated and retrained to improve its performance and adapt to new data.

In conclusion, the methodology for fruit identification using image analysis with CNN involves four main steps: dataset collection and preparation, CNN model architecture, model training and validation, and model deployment and evaluation. Each step is crucial for the success of the project and should be carried out with care and attention to detail.

III. Result

After creating a CNN model and Decision tree classifier model by training both the models on the same dataset of images, we concluded that CNN is far better image analysis model than decision tree.

The CNN method is employed to verify the quality. The neural network's training values and the retrieved fruit features are used to determine the quality. The suggested method reliably determines the fruit's quality. The outcome will be determined based on the thresholds it assigns the quality of fruits, and it will be returned to the System once more.This type of technology can be used in fruit and vegetable farms, juice factories, food safety businesses, fruit and vegetable packaging, etc.

Here are some of the comparison of key parameters:

As in the results, CNN performed way better and achieved validation accuracy of 96.65% as compared to 82.34% of Decision tree with much lower loss at 0.0925.

IV. Conclusion and Future Scope

Convolutional neural networks (CNN) and decision tree classifiers were used in the project "Fruit quality detection using image analysis" to effectively design and implement a fruit quality detection system. The accuracy of the CNN model was 96.65%, whereas the Decision Tree Classifier's accuracy was 82.34%. This illustrates how well CNN models perform in tasks involving the detection of fruit quality, especially when it comes to correctly categorising fruit photos according to their quality.

Future Scope:

1. **Improving the Decision Tree Classifier**: Investigate techniques to enhance the performance of the Decision Tree Classifier, such as optimizing hyperparameters, using ensemble methods, or incorporating additional features.
2. **Real-time Fruit Quality Detection**: Develop a real-time fruit quality detection system that can be implemented in agricultural settings, such as greenhouses or orchards, to provide farmers with immediate feedback on fruit quality.
3. **Integration with Robotic Harvesting Systems**: Integrate the fruit quality detection system with robotic harvesting systems to enable automated fruit picking based on quality criteria.
4. **Expanding the Dataset**: Incorporate a more diverse range of fruit types and quality conditions in the dataset to improve the model's generalizability and applicability.
5. **Transfer Learning and Domain Adaptation**: Explore the use of transfer learning and domain adaptation techniques to adapt the CNN model to new fruit types or quality conditions.
6. **Explainability and Interpretability**: Investigate methods to improve the explainability and interpretability of the CNN model, allowing farmers and agricultural experts to better understand the decision-making process of the model.
7. **Continuous Monitoring of Fruit Quality**: Develop a system for continuous monitoring of fruit quality throughout the ripening process, providing farmers with insights into the optimal time for harvest.
8. **Integration with IoT Devices**: Integrate the fruit quality detection system with IoT devices, such as sensors and cameras, to enable remote monitoring and management of fruit quality in agricultural settings.
9. **Comparative Analysis with Other Machine Learning Models**: Conduct a comparative analysis of the CNN model with other machine learning models, such as Support Vector Machines (SVM) or

Random Forests, to evaluate their performance in fruit quality detection tasks.

10. **Collaboration with Agricultural Research Institutes**: Collaborate with agricultural research institutes to validate the performance of the fruit quality detection system in real-world scenarios and gather feedback for further improvements.

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