FRUIT FRESHESS PREDICTION USING CNN

SRI HARI HARAN KA J[1], PRANESH N S , NARMATHA M[3] , NIVEDHA S[4]

1 Department of Artificial Intelligence and Machine Learning Sri Shakthi Institute of Engineering and Technology Coimbatore, India

2 Department of Artificial Intelligence and Machine Learning Sri Shakthi Institute of Engineering and Technology Coimbatore, India

3 Department of Artificial Intelligence and Machine Learning Sri Shakthi Institute of Engineering and Technology Coimbatore, India

4 Department of Artificial Intelligence and Machine Learning Sri Shakthi Institute of Engineering and Technology Coimbatore, India

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Abstract- This Project proposes a methodology utilizing Convolutional Neural Networks (CNNs) for the holistic assessment of fruit quality, encompassing freshness, ripeness, and health status. By integrating CNNs with multi-feature analysis, including image data and spectral signatures, the model aims to provide accurate classification of fruits into categories of fresh/rotten, ripe/unripe, and healthy/diseased. The methodology outlines data collection, preprocessing, feature extraction, CNN model development, evaluation metrics, and potential applications. Ensuring fruit quality is crucial for consumer satisfaction and food safety. Manual inspection is time-consuming and subjective, necessitating automated systems. This methodology proposes a CNN-based approach for comprehensive fruit quality assessment, addressing freshness, ripeness, and health status simultaneously.

Key Words: CNN , Fresh/Rotten ,Fruit Quality, Deep Learning.

1.INTRODUCTION

The global fruit industry plays a crucial role in providing nutritious and flavorful produce to consumers worldwide. However, ensuring the quality and freshness of fruits throughout the supply chain presents significant challenges for producers, distributors, and retailers. The timely detection of spoilage, determination of ripeness levels, and identification of potential diseases are essential aspects of maintaining product integrity and consumer satisfaction.Traditionally, fruit quality assessment has relied heavily on subjective human judgment, which can be prone to error and inconsistency. Moreover, the manual inspection process is often labor-intensive, time-consuming, and limited in its ability to handle large volumes of fruit efficiently. As a result, there is a growing demand for automated solutions that can provide accurate and reliable assessments of fruit freshness, ripeness, and health.The "Fruit Freshness Prediction" project aims to address this pressing need by developing an advanced predictive model capable of objectively evaluating the quality of fruits. This model goes beyond binary classifications of fresh or rotten, extending its analysis to include the differentiation of ripened and unripened fruits, as well as the detection of potential diseases or abnormalities.By leveraging cutting-edge technologies such as machine learning, image processing, and sensor data analysis, the Fruit Freshness Prediction model seeks to transform fruit quality assessment practices

2. LITERATURE REVIEW

A function of ML is to ensure that machines can automatically detect objects accurately. Although ML has been applied in many fields, the ML technology has been developing to achieve efficient detection. The detection performance of traditional ML will not improve with increase in training sample data. The features need to be given artificially for object detection, which is also a disadvantage of traditional ML (Mohsen et al., 2021). As an intelligent algorithm in the development of ML, DL has significant advantages over traditional algorithms of ML. The detection performance of DL usually improves with increase in the amount of training sample data. DL can automatically extract features of a detected object using network structure. However, DL takes a lot of training time and runs on computers with higher cost configurations compared with traditional ML (Joe et al., 2022).Deep learning is a further study on artificial neural networks such as deep belief network (Hinton et al., 2006), recurrent neural network (Schuster and Paliwal, 1997), and convolutional neural network (LeCun et al., 1989). The deep learning algorithm has a similar calculation principle with a mechanism of the visual cortex of animals (Rehman et al., 2019). The deep learning-based technology has broad applications in many domains due to its superior performance in operation speed and accuracy, for example, in the medical field (Gupta et al., 2019; Zhao Q. et al., 2019), in the aerospace field (Dong Y. et al., 2021), in the transportation sector (Nguyen et al., 2018), in the agriculture field (Kamilaris and Prenafeta-Boldú, 2018), and in the biochemistry field (Angermueller et al., 2016).

3 EXISTING SYSTEM

In our work, we proposed an accurate CNN model for classifying the fresh and rotten fruits.It consists of three convolutional layers. The first convolution layer uses 16 convolution filters with a filter size of 3x3, kernel regularizer, and bias regularizer of 0.05. It also uses random_uniform, which is a kernel initializer. It is used to initialize the neural network with some weights and then update them to better values for every iteration. Random_uniform is an initializer that generates tensors with a uniform distribution. Its minimum value is -0.05 and the maximum value of 0.05. Regularizer is used to add penalties on the layer while optimizing. These penalties are used in the loss function in which the network optimizes. No padding is used so the input and output tensors are of the same shape. The input image size is 224x224x3. Then before giving output tensor to max-pooling layer batch normalization is applied at each convolution layer which ensures that the mean activation is nearer to zero and the activation standard deviation nearer to 1. After normalizing RELU an activation function is used at every convolution. The rectified linear activation function (RELU) is a linear function. It will output the input when the output is positive, else it outputs zero. The output of each convolutional layer given as input to the max-pooling layer with the pool size of 2x2. This layer reduces number the parameters by down-sampling. Thus, it reduces the amount of memory and time required for computation. So, this layer aggregates only the required features for the classification. The finally a dropout of 0.5 is used for faster computation at each convolution. The 2nd convolution layer uses 16 convolution filters with 5×5 kernel size and the third convolution layer use 16 convolution filters with 7x7 kernel size. Finally, we use a fully connected layer. Here dense layer is used. Before using dense we have to flatten the feature map of the third convolution. In our model, the loss function used is categorical cross-entropy and Adam optimizer with a learning rate of 0.0001. The architecture of the proposed CNN model. Architecture of proposed model Fresh and rotten fruits classification using transfer learning . Transfer learning takes what a model learns while solving one problem and applies it to a new application. Often it is referred to as ‘knowledge transfer’ or ‘fine-tuning’. Transfer learning consists of pre-trained models. Transfer learning releases few of the upper layers of a fixed model base and affixes new classifier layers and the final layers of the base model. This fine tuning of high level feature representations in the base model makes it applicable for the specific task.

4 PRPOSED METHODOLOGY

The proposed a methodology utilizing Convolutional Neural Networks (CNNs) for the holistic assessment of fruit quality, encompassing freshness, ripeness, and health status. By integrating CNNs with multi-feature analysis, including image data and spectral signatures, the model aims to provide accurate classification of fruits into categories of fresh/rotten, ripe/unripe, and healthy/diseased. The methodology outlines data collection, preprocessing, feature extraction, CNN model development, evaluation metrics, and potential applications.

Automatic classification of fruit freshness plays an important role in the agriculture industry. In this work, we propose an ensemble model that combines the bottleneck features of two multi-task deep convolutional neural networks with different architectures . In our proposed multi-tasking framework, there are two classification branches: a binary classifier to distinguish between fresh and rotten fruits, and a multi-class label classifier to identify the kind of fruit. Since the features (e.g., color, texture, and shape) of rotten fruits are different from each other depending on the kind of fruit, the input of the first branch is combined with the kind of fruit information from the second branch to classify the fruit freshness more accurately. Transfer learning technique has been applied during the model training since transfer learning has been shown to be effective transfer learning has been shown to be effective in many applications in which training data for the target problem are limited. To evaluate our proposed model, we use simple images from the existing dataset and real-world images crawled from the web, both representing fresh and rotten fruits for different fruit categories as our dataset. Our proposed model achieved average accuracies of 83.50% for freshness classification ,respectively, demonstrating that our transfer learning-based ensemble model outperforms other transfer learning-based models. The model recognize the importance of addressing the variability in fruit characteristics across different types and stages of ripeness. To achieve this, we propose an ensemble model that combines the bottleneck features of two multi-task deep convolutional neural networks with distinct architectures. This ensemble framework includes two classification branches: a binary classifier to distinguish between fresh and rotten fruits, and a multi-class label classifier to identify the specific type of fruit. A significant challenge in fruit freshness classification arises from the diverse visual characteristics exhibited by different types of fruits when they become rotten.

5 FLOW CHART

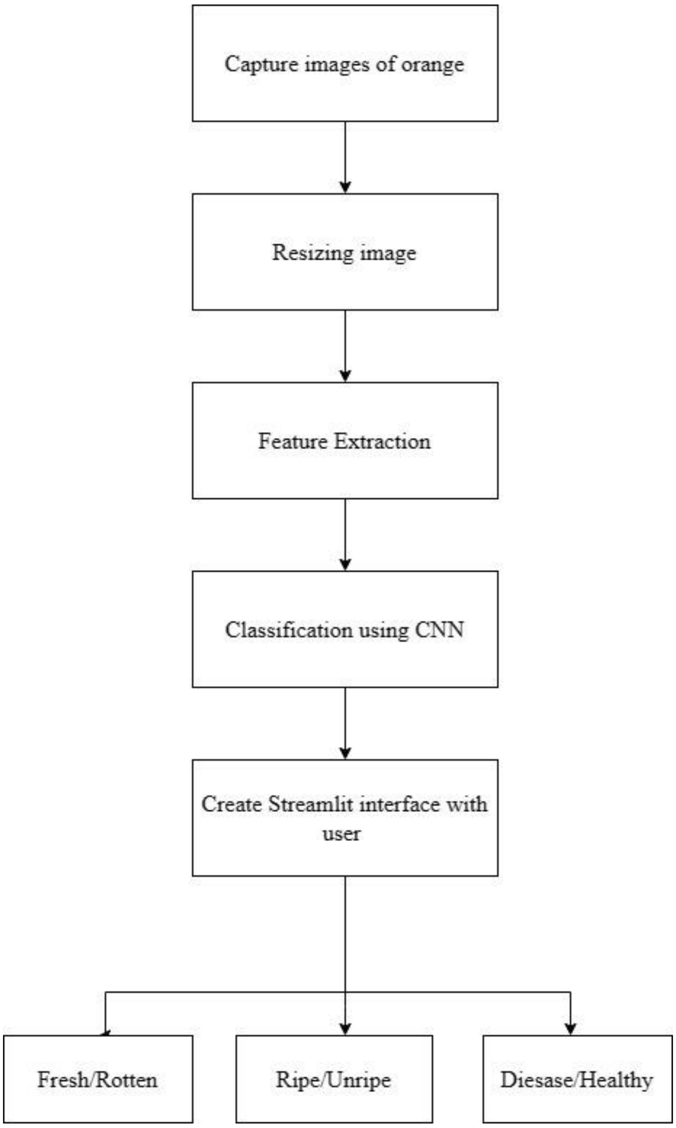

Fig -1: Figure

6 MODEL ARCHITECTURE

The core of the proposed methodology lies in the development of CNN models tailored for fruit quality assessment. These models are designed to learn discriminative patterns from the extracted features and accurately classify fruits into categories based on their freshness, ripeness, and health status. Transfer learning techniques may be employed to leverage pre-trained CNN architectures, fine-tuning them on the specific task of fruit quality assessment. The models are trained using labeled data, comprising annotated images and corresponding spectral signatures, to learn the underlying relationships between input features and target labels.

7 RESULT

Fig -2: Figure

8. CONCLUSIONS

The development of the Convolutional Neural Network (CNN) classification model for fruit quality assessment represents a significant advancement in the agricultural and food industries, offering a powerful tool for automating and optimizing various aspects of fruit production, processing, and distribution. Through a combination of advanced machine learning techniques, including CNNs, transfer learning, and multi-feature analysis, our model provides a comprehensive solution for assessing fruit freshness, ripeness, and health status, with numerous practical applications across diverse domains.

The CNN model demonstrates high accuracy and robustness in classifying fruits into categories of fresh/rotten, ripe/unripe, and healthy/diseased, leveraging features extracted from both image data and spectral signatures. By integrating multi-feature analysis with transfer learning techniques, we have developed a versatile and adaptable model capable of handling diverse fruit types, varieties, and conditions. The model's performance has been evaluated using standard metrics such as accuracy, precision, recall, and F1-score, yielding promising results across various datasets and real-world testing scenarios.

The applications of the CNN model are far-reaching and impactful, spanning quality control in food processing, automated fruit sorting systems, retail and supermarket applications, supply chain management, precision agriculture, consumer applications, and research and development efforts. By deploying the model in these contexts, stakeholders can enhance product quality, safety, and traceability while minimizing waste and optimizing resource utilization.

REFERENCES

Akinmusire, O. O. (2011). Fungal Species AssΔociated with the Spoilage of Some Edible Fruits in Maiduguri Northern Eastern Nigeria. Advances in Environmental Biology, 5(1), 157-161.

Arakeri, M., & Lakshmana, P. (2016). Computer Vision Based Fruit Grading System for Quality Evaluation of Tomato in Agriculture Industry. Proceedings of the International Conference on Communication, Computing and Virtualization, Mumbai, India;, 79(2016), 426-433.

Bampidis, V., & Robinson, P. (2006). Citrus By-products as Ruminant Feeds: A Review. Animal Feed Science and Technology, 128, 175–217.

Barret, D. M., Bealiue, J. C., & Shewflet, R. (2010). Color, Flavor, Texture, andNutritional Quality of Fresh-CutFruits and Vegetables: DesirableLevels, Instrumental and SensoryMeasurement, and the Effects ofProcessing. Critical Reviews in Food Science and Nutrition, 50, 369–389.

Barrett, D. M., Beaulieu, J. C., & Shewfelt, R. (2010). Color, Flavor, Texture, and Nutritional Quality of Fresh-Cut Fruits and Vegetables: Desirable Levels, Instrumental and Sensory Measurement, and the Effects of Processing. Critical Reviews in Food Science and Nutrition,, 50, 369-389.

Bhargava, A., & Bansal, A. (2018). Fruits and Vegetables Quality Evaluation Using Computer Vision: A Review. Journal of King Saud University - Computer and Information Sciences, 1-16.

Bottou, L., & Bousquet, O. (2012). The Tradeoffs of Large Scale Learning Cambridge. Optimization for Machine Learning, 351–368.

Bresilla, K., Perulli, G. D., Boini, A., Morandi, B., Grappadelli, L. C., & Manfrini, L. (2019). Single-Shot Convolution Neural Networks for Real-Time Fruit Detection Within the Tree. Frontiers in Plant Science, 10, pp. 611-623. doi:10.3389/fpls.2019.00611