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Deep Ensemble Learning For Three-Stage Maturity Detection Of Indigenous Fruits

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Abstract—Accurate identification of stages of maturity in fruits plays a critical role in agricultural quality control and post-harvest management. This study proposes an automated approach based on image data for classifying fruit maturity into three categories—Unripe, Fresh, and Rotten. The system employs Convolutional Neural Networks (CNNs) trained on a selected and elevated dataset comprising multiple fruit types. We have combined predictions from three distinct models that were trained independently using ensemble method that averages their output to increase reliability. Streamlit a web based interface enables users to submit images of fruits and get the maturity classification results. Experimental findings indicate that the ensemble model achieves high accuracy, offering a minimally invasive, efficient, productive and scalable solution for fruit quality assessment in agricultural industries.

Index Terms—Convolutional Neural Network (CNN), Computer Vision, Deep Learning, Ensemble Learning, Fruit Maturity Classification.

INTRODUCTION

The accurate classification of fruit maturity is a one of the key concern in agriculture and in the food supply chain. Determining the maturity stage of the given fruits—whether a fruit is unripe, fresh, or rotten—can significantly impact decisions related to harvesting, repository, shipping , and merchandising. Traditionally, fruit maturity assessment is performed manually through visual examination, texture analysis, or qualitative analysis. Although these techniques may produce reliable results in controlled environment, they are not scalable and they can be inconsistent, and are often labor-intensive and subjective. Maturity classification becomes even more challenging in the context of indigenous fruits like bananas, lemons, oranges, and pomegranates, due to regional variations in color, shape, and texture. Manual sorting in local markets or small-scale farming setups is particularly prone to errors, leading to supply chain losses, consumer dissatisfaction, and reduced profits forfarmers. Consequently, there is a necessity for an for an intelligent and automated system which classify fruit maturity with more accuracy and also human involvement is minimal.Recent advancements in computer vision and deep learning technologies have facilitated the creation of powerful image- based classification systems. Convolutional Neural Networks (CNNs), in particularly, have demonstrated outstanding performance in analyzing image data for various agricultural applications, including disease detection, crop monitoring, and yield estimation. By training CNN models on labeled fruit images, a system can learn to identify subtle differences in color, texture, and shape associated with different maturity stages.This research proposes a deep learning-based system for three-stage fruit maturity classification using CNNs and an ensemble prediction technique. Here custom dataset was created by capturing images of four common indigenous fruits—banana, lemon, orange, and pomegranate—at various maturity levels. To enhance model generalization the dataset was preprocessed and augmented. Three independent CNN models were trained and combined using ensemble averaging to improve the overall prediction accuracy.

To make the system accessible to users, a streamlined web application was created using Streamlit, which allows users to upload a fruit image and receive instant maturity classification results. The integration of both deep learning and web technologies presents a practical solution that can be deployed in markets, warehouses, or farms for real-time fruit quality assessment.This paper discusses the problem of fruit maturity classification, outlines the methodology adopted for the data gathering and model creation and presents experimental results, and also highlights the possible advantages and future improvements of the suggested system.

RELATED WORK

A wide range of studies have investigated fruit maturity classification using both conventional and modern classification and computation methods including deep learning, image processing and statistical modellin. A convolutional neural network (CNN) was trained to categorize mango fruits into three maturity stages: raw, semi- ripe, and ripe [1]. The model utilized color and texture features extracted from the images and achieved over 90% accuracy. The CNN architecture was designed to operate efficiently under varied lighting and background conditions, emphasizing the robustness of deep learning in real-world fruit classification. Some studies [2] employed transfer learning using pretrained models such as ResNet50 and VGG16 for papaya fruit classification. The research focused on fine-tuning these models using a custom image dataset and found that ResNet50 performed best, with accuracy reaching 97.5%. The authors highlighted that transfer learning decreases the duration of training and improves classification performance, especially for datasets with limited size. An IoT-based fruit classification system[3] using a Raspberry Pi camera to capture real-time images of pineapple fruits. A CNN was then applied to determine the maturity level of the fruit. This end-to-end system enabled farmers to assess ripeness in the field, showcasing how IoT and AI integration can support smart agriculture. An ensemble deep learning model combining InceptionV3, ResNet50, and VGG19 was developed [4] for multi-fruit maturity classification. The ensemble method involved soft voting to merge predictions generated from all three models, which markedly enhanced classification accuracy compared to individual models, reaching up to 98.3%. Some lightweight CNN model was implemented to classify fruit maturity stages with elevated accuracy while guaranteeing low computational load. The authors optimized the model for mobile and edge devices, enabling offline fruit grading systems. This approach is particularly useful in remote agricultural areas with limited internet access[5]. Traditional maturity detection methods were discussed in, where fruits were categorized into two categories: climacteric (ripening after harvest) and non-climacteric (not ripening post- harvest)[6], where there are several biochemical and physical maturity indices including color, size, ethylene production, and sensory qualities. It emphasized the role of ethylene measurements and postharvest handling conditions in determining maturity and quality. In [7], a maturity classification prototype for custard apple was introduced using image processing techniques. The system incorporated a Raspberry Pi, a camera module, and an LCD touchscreen. It extracted RGB features from the areoles of the fruit surface and used K-means clustering and Support Vector Machine (SVM) algorithms for classification. The combination of color analysis and machine learning yielded a classification accuracy of 100%. The study in [8] presented a quantitative model for evaluating fruit maturity based on physicochemical properties and effective accumulated temperature. Parameters like chlorophyll content, soluble solids, vitamin C, and fruit hardness were tracked during ripening. These metrics employed to construct predictive model capable of estimating the degree of maturity as a percentage of observed changes, offering a scientific and scalable approach to maturity evaluation In [9], a year-long experiment was conducted on 'Amrapali' mangoes in a controlled postharvest laboratory setting. Researchers used a completely randomized design (CRD) with three replications and measured both physical and chemical characteristics including firmness, weight loss, pH, total soluble solids (TSS), titratable acidity, and vitamin C content. Statistical tools like ANOVA and Duncan's Multiple Range Test (DMRT) were employed to analyze maturity-related variations across samples. Finally, [10] introduced an automated fruit classification system for guava using the K- Nearest Neighbors (K-NN) algorithm. A TCS3200 color sensor was used to collect RGB values of guava samples at three different maturity stages. The classifier achieved 100% accuracy for k = 3 and k = 5, demonstrating the effectiveness of color-based non-destructive techniques combined with traditional machine learning.

METHODOLOGY

The proposed system for three-stage fruit maturity classification involves a series of structured steps, from dataset preparation and augmentation to CNN model development, ensemble integration, and deployment via a user-friendly web interface.

A. Dataset Preparation

The dataset includes images of four indigenous fruits—banana, lemon, orange, and pomegranate—categorized into three maturity stages: unripe, fresh, and rotten. This results in a total of 13 distinct image classes. All images were stored in a structured directory under the project images folder. The dataset comprises 15,908 training images and 3,973 validation images, ensuring class balance.

B. Image Preprocessing and Augmentation

In order to ensure consistency, all images were resized and converted into JPG format with file sizes ranging between 16 KB and 22 KB. Augmentation methods such as random rotation, zooming, and horizontal flipping, were applied using Keras' Image Data Generator to enhance the generalization capabilities of the models.

C. CNN Model Development

Three Convolutional Neural Network (CNN) models were implemented using TensorFlow 2.19.0 and Python 3.12.6 in a virtual environment within VS Code. Each model included various convolutional layers, pooling layers, and fully connected dense layers utilizing a Softmax activation function for multiclass classification. The training and validation processes were conducted using the augmented dataset.

D. Ensemble Learning

To enhance classification accuracy, the forecasts of the three trained CNN models were combined using an ensemble strategy. Majority voting or probabilistic averaging was employed to minimize prediction variance and improve robustness.

E. Deployment via Streamlit

The final ensemble model was deployed using Streamlit to provide a web-based user interface. This allows users to uploadfruit images and receive real-time predictions of the fruit's maturity stage. The deployment ensures accessibility and usability for practical, on-field applications.

IMPLEMENTATION

The proposed system implements an ensemble-based Convolutional Neural Network (CNN) model to classify the maturity stages of indigenous fruits into three categories: unripe, fresh, and rotten. The classification is performed using images of four fruit types—banana, lemon, orange, and pomegranate—collected and preprocessed into 13 distinct classes corresponding to combinations of fruit type and maturity stage. The complete pipeline includes image preprocessing, individual CNN model training, ensemble prediction, and a user-friendly web interface via Streamlit.

A. **Vector Art Dataset Preparation**

The custom dataset for the classification task was curated by extracting frames from videos of various fruits (Bananas, Lemons, Oranges, and Pomegranates) at different stages of maturity. These stages included Unripe, Fresh, and Rotten categories. The images were captured and organized into class- specific folders, leading to a balanced dataset for training and validation. Data augmentation methods were utilized on the dataset, including rotation, zoom, and flips, to artificially increase the dataset size and improve the generalization of the model.

The dataset was further processed to ensure uniformity in the image resolution and format. The images were scaled to a consistent size of 150x150 pixels and converted to RGB to ensure the model could process them effectively. Additionally, background removal and noise reduction methods were implemented to improve the quality of the feature extraction from the fruit images.

B. **CNN Model Architecture**

Three distinct CNN models were constructed using TensorFlow 2.19.0 in Python 3.12.6, with a aim of optimizing for accuracy and generalizability. Each model followed a typical architecture: A **10-layer CNN** was designed to classify the fruit images. The architecture includes several layers:

1. **Convolutional Layers**: These layers perform the primary feature extraction from the input images. The first convolutional layer uses 32 filters, followed by 64 filters in the second layer, and 128 filters in the third

layer, each with a kernel size of **3x3**.

2. **Max-Pooling Layers**: These layers reduce the spatial dimensions of the feature maps, helping the model to focus on the most important features.
3. **Flatten Layer**: This layer converts the 2D feature maps into a 1D vector, which is next passed to the fully connected layers.
4. **Fully Connected Layers**: The dense layer with 128 neurons is used to combine the learned features, and a dropout layer is added to prevent overfitting.
5. **Output Layer**: The final output layer uses the

Each model was compiled by using the Adam optimizer categorical cross-entropy loss function, which is suitable for multi-class classification tasks.

Model Training and Evaluation The dataset was split into **training** and **validation** subsets using an **Image Data Generator** with a **validation split of 20%**. The models were trained for **10 epochs** with a batch size of **32**, using data augmentation to improve robustness. Each model was evaluated individually, and the training history was saved to track performance. An ensemble approach was used to further improve classification accuracy. Predictions from three different CNN models, each trained independently, were averaged to form the final classification prediction. This ensemble method reduced the variance between individual models and improved the model's generalization ability

C. Ensemble Prediction

The ensemble model was implemented by averaging the predictions from the three individual models. The models' predictions were accumulated using the following steps:

1. **Model Loading**: Each of the three trained models was loaded from saved .h5 files.
2. **Prediction Averaging**: Each model's predictions were calculated on the validation dataset and averaged. This method combines the strengths of each individual model ai ed at generating a more robust and accurate prediction.
3. **Final Prediction**: The ultimate prediction was determined by selecting the class that has the highest average probability across all models.

The ensemble model demonstrated enhanced performance in comparison to individual models, with a higher validation accuracy, as it leveraged the diversity in the models' learning and minimized the possible biases inherent in any single model.

D. Web Application Deployment

To make the fruit maturity classification system accessible to end-users, a web-based graphical user interface (GUI) was developed using **Streamlit**, a lightweight open-source Python library created for constructing and deploying machine learning applications interactively. The interface facilitates image upload, classification, and result visualization in real time. Upon launching the app, users are prompted to upload an image of a fruit via the file_uploader widget. The application supports multiple image formats, including .jpg, .jpeg, and .png. After an image is uploaded, it is displayed on the interface using st.image() to provide immediate visual confirmation to the user. Internally, the image undergoes preprocessing steps including resizing, array conversion, and reshaping to match the input dimensions expected by the CNN models. The image isthen passed through the three trained CNN models. Predictions extracted from each model are extracted and displayed individually, followed by the ensemble model's final decision using majority voting.

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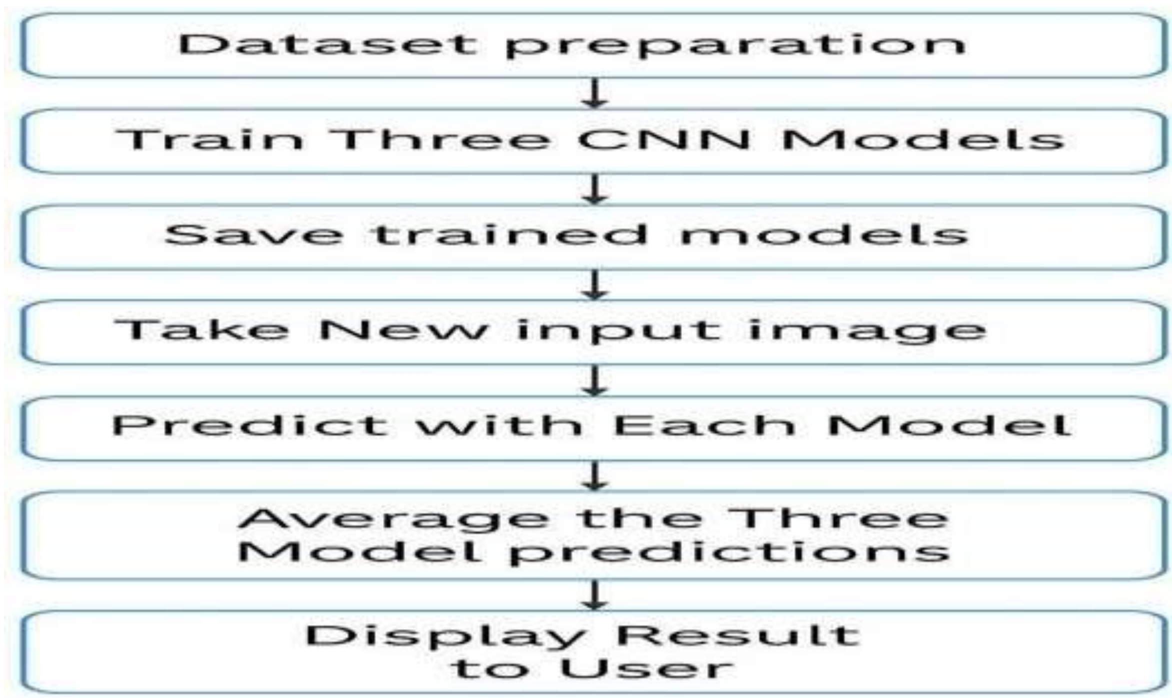
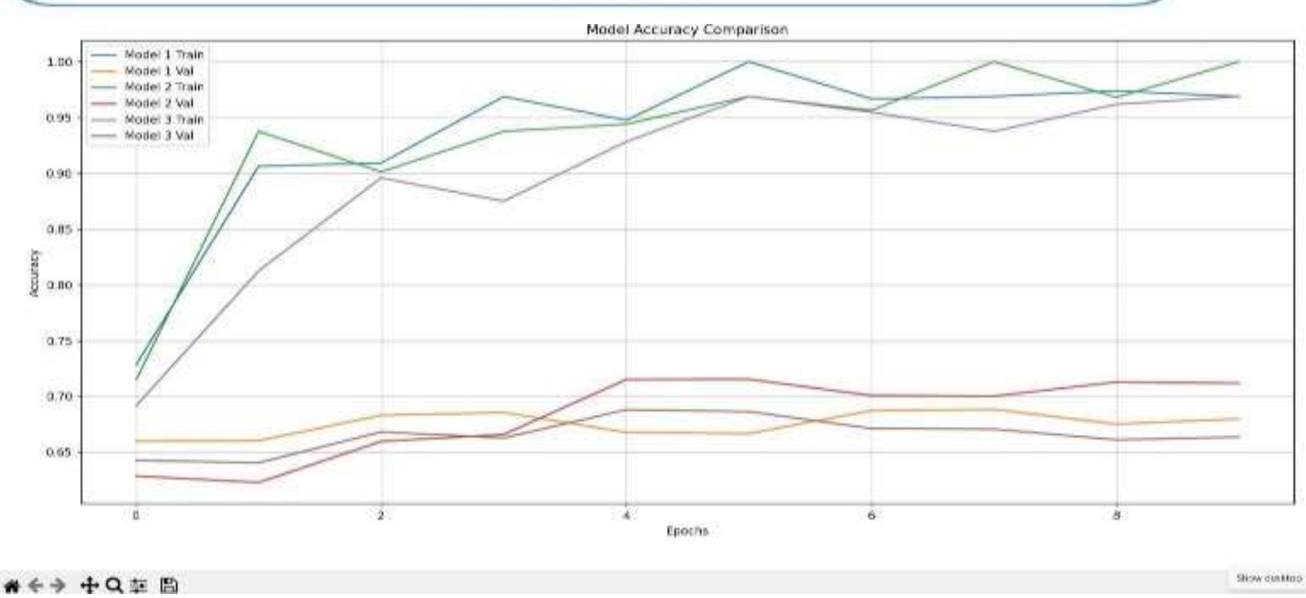
The output labels are mapped to the corresponding maturity classes (e.g., fresh_banana, rotten_pomegranate) and displayed using Markdown formatting for enhanced readability. The application is lightweight and does not necessitate extensive computational resources, making it deployable on local machines or platforms like Heroku or Streamlit Cloud. The system ensures rapid inference times and is designed with accessibility and usability in mind, enabling even non-expert users such as farmers or distributors to enable informed decisions regarding fruit quality. The whole process implementation is given In Fig. 1.

Fig. 1. Flow chart of System Design





RESULTS AND DISCUSSION

The proposed fruit maturity classification system was developed and tested using a custom-built dataset of indigenous fruits. The dataset comprised 13 visually distinct classes, representing the unripe, fresh, and rotten stages of four commonly consumed fruits—banana, lemon, orange, and pomegranate. In contrast to previous

studies that depended on benchmark datasets like Fruits-360, this work used self- curated data obtained via high-resolution image collection. Each image was resized to 150×150 pixels and normalized to a pixel value range of 0 to 1. Data augmentation techniques such as random rotation, zoom, flipping, and brightness variation were employed using TensorFlow's ImageDataGenerator to enhance model generalization and address class imbalance. This preprocessing step was critical in increasing intra-class diversity, especially for visually similar maturity stages like fresh and unripe categories. Three distinct CNN models were developed, each with a deep learning architecture designed for image classification tasks. Each network contained a sequence of 10 layers, including multiple convolutional and max-pooling layers, followed by dropout and dense layers for regularization and classification. The models were trained with categorical cross- entropy loss and optimized using the Adam optimizer with a fixed learning rate and early stopping callback to prevent overfitting. Instead of relying on the prediction from a single model, an ensemble approach was implemented. Each of the three trained CNN models produced class probabilities for the test images, which were averaged to generate the final prediction. This ensemble strategy provided a smoother decision boundary and improved classification stability, particularly in edge cases where fruit features were ambiguous due to overlapping visual traits. The classification performance of the ensemble was analyzed qualitatively through the inspection of class-wise prediction trends. It was observed that fresh and unripe fruit categories exhibited consistent prediction patterns, owing to the relatively well-defined texture and color patterns in these classes. Rotten fruits posed a higher challenge due to significant variations in decay levels, which introduced intra-class noise.
Fig. 2. Training and Validation loss curves

Training and validation loss curves (Fig. 2) further confirmed the stability of each model. The gradual convergence without significant divergence between training and validation lines suggests that dropout and data augmentation successfully mitigated overfitting. Validation losses plateaued after several epochs, signaling that the networks had effectively learned distinguishing features without memorizing the training data. A confusion matrix (Fig. 3) was plotted to analyze class-wise prediction consistency. Most diagonal entries showed strong concentration, indicating accurate classifications. However, minor misclassifications were noted between rotten_Lemon and unripe_Lemon, which share similar yellow hues under.

Fig. 3. Confusion Matrix for Ensemble Medel

certain lighting conditions. These insights emphasize the importance of lighting and image quality during dataset creation.

To extend the practical usability of the system, a Streamlit- based web application was developed. The application provides a user-friendly interface where users can upload an image of a fruit, which is then classified into one of the 13 predefined categories. This real-time prediction capability opens avenues for deployment in agricultural environments where quick and automated fruit maturity assessment is essential—for example, during post-harvest sorting or supply chain quality monitoring. Moreover, this system can serve small and medium-scale farmers who may not have access to laboratory-based testing tools. The use of lightweight models and local deployment through Streamlit ensures low computational overhead, making the solution both scalable and accessible in resource- constrained settings.the system demonstrates a high level of robustness in real-time fruit maturity classification using a CNN ensemble approach on a custom dataset. The design choices, such as ensemble averaging, dropout, and data augmentation, collectively contributed to its effectiveness. The project also reinforces the feasibility of applying deep learning solutions to localized, practical agricultural problems using custom-built data.

I. CONCLUSION AND FUTURE WORK

In this paper, we presented an ensemble-based Convolutional Neural Network (CNN) model for automated fruit maturity classification. The system classifies fruits into three maturity stages—Unripe, Fresh, and Rot—across multiple fruit types, including banana, lemon, orange, and pomegranate. The model achieved robust performance by leveraging data preprocessing techniques such as image normalization, background removal, and augmentation of a custom fruit dataset. The ensemble approach, combining predictions from three CNN models, outperformed individual models, demonstrating improved generalization and reduced variance. The results indicate that the proposed system can serve as a reliable, scalable solution for non- destructive fruit maturity detection, with potential applications in agriculture, food processing, and supply chain management. For future work, we plan to extend the system's capabilities by incorporating additional fruit types to increase its versatility. Furthermore, we aim to enhance the model by exploring advanced architectures, including transfer learning and attention mechanisms, to improve classification accuracy. Exploring real- time deployment scenarios and integrating the system with automated sorting systems could further streamline agricultural operations. Additionally, enhancing the dataset by incorporating a wider variety of fruit conditions and environmental factors may improve model robustness and applicability in different real-world settings.

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