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AI based approach for Fruit Grading to enhance the livelihood of Rural farmers

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Abstract: Fruit grading is essential for price fixing, especially for farmers whose livelihood is dependent on this produce. Due to the lack of standard quality assessment system, the manual grading in this micro-level environment has several inconsistencies and it is often influenced by local middleman. This study proposes a light-weight framework using deep learning which enables on-device inference for fruit grading under rural agricultural environments without the need of internet connectivity and cloud-based infrastructure. After the preprocessing of the raw data, it is input to a deep learning model, and fruit grade is computed. The framework is specifically designed to provide assessment and grading entirely on a mid-range android based mobile device, which is affordable to rural farmers.

***Index Terms* – Deep Learning, Fruit Grading System, Livelihood, Farmers, Minority class**

I. Introduction

Agriculture is one of the primary backbones of the Indian economy [1], and it contributes significantly in the national GDP. The majority of Indian population is dependent on local agricultural produce, and it is the primary source of income of the rural farmers, several of whom belong to the minority class as well. The agricultural output is diverse in India, and agricultural productivity is crucial for the economic growth and rural development. Among various agricultural produce, India is also one of the large producers of fruits globally. So, fruit grading is crucial to bridge the produce from harvest to make it available to customers in the market.

Traditionally, the fruit grading is manually performed by the farmers or local distribution channel in rural India. The quality is usually determined by factors such as size, color, ripeness, texture, and presence of any defects or disease [2]. Due to the lack of standard quality assessment system, the manual grading in this micro-level environment has several inconsistencies and it is often influenced by local middleman. This usually results in undervaluation of the produce, and the farmer community bares significant losses which significantly impacts the local rural and the adjoining semi-urban markets with disrupting fair trade and hindering the economic development in the region [3]. These challenges are also acknowledged by the Government of India, and several notable initiatives can be observed towards technology-enabled trading platforms such as Agri-Stack digital infrastructure and e-NAM (National Agriculture Market) to integrate farmers directly to the marketplace [4]. While large-scale industries employ advanced grading systems based on expensive technologies such as hyperspectral imaging, near-infrared (NIR) spectroscopy, the challenge of low-cost solution that can be adoptable by the farmers remains unsolved.

Several efforts have been carried out over the decade to develop an image-based grading system by incorporating computer vision and deep learning techniques [5]. The majority of such systems require dedicated large-scale computational hardware resources and high-bandwidth internet connectivity. Additionally, the computational cost of the state-of-the-art architectures based on Convolutional Neural Networks (CNN) such as ResNet-50, VGG-16 are expensive and require a remote server, which makes it unsuitable for the farmers to operate in rural areas with limited internet connectivity.

In this paper, we propose a light-weight framework using deep learning which enables on-device inference for fruit grading under rural agricultural environments without the need of internet connectivity and cloud-based infrastructure. The framework is specifically designed to provide assessment and grading entirely on a mid-range android based mobile device, which is affordable to rural farmers.

We first discuss the method for dataset creation, followed by data pre-processing techniques, and then the proposed framework is discussed in detail. The design of the framework emphasizes the practical usability for farmers in rural regions by maintaining privacy, computational efficiency, and practical deployment under resource constraint environment.

II. Related Works

In 2017, a prototype of an automated fruit grading system was designed by Ali and Thai [6] to detect surface defects from the images captured using camera in a rotating desk using MALAB. Chopra et.al. incorporated spectrophotometry and ensemble machine learning techniques to design an automated system to segregate fruit based on their predicted grade [7]. The system was trained using 1366 samples of apples, and the system achieved an accuracy of 72% on unseen test data. Another work on apple grading and sorting was performed by Zhang et. al. [8], an infield grading and sorting system was developed to meet the commercial needs for the fruit singulation, rotation, and transportation using pitch-variable screw conveyors. The grading was performed based on size and color using a low-cost imaging system, and the sorting performed with paddle sorters.

In 2020, Bhargava and Bansal [9] explored several techniques such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Sparse Representative Classifiers (SRC), and Artificial Neural Networks (ANN) for fruit identification and grading. The study was performed on four types of fruit with thirty features, out of which twelve geometrical features were used for fruit identification. The system was developed using four different dataset and achieved highest accuracy of 95.72% with the SVM system. In the same year, Mon and Aung proposed volume estimation method for mango grading using images [10]. The proposed algorithm based on image processing estimates the thickness of mango based on light intensity distribution in the image and reconstructs a 3D shape of mangoes. The experiment was conducted using 150 samples and achieved an accuracy of 91.5%. Another study was performed by Kumar et.al. for sorting and grading tomato incorporating vision approach along with SVM classifier [11]. The defects were identified and segmented using Gabor wavelet transformation and then classified into ripe or un-ripe categories using SVM and observed significant improvement in accuracy over other existing systems for grading tomatoes.

In recent years, due to the effectiveness of various deep learning techniques such as CNNs for feature extraction from images, a rise in studies and implementation are done for fruit grading systems. Patil et.al. studied several machine learning techniques such as SVM, ANN, and CNN for grading and sorting of dragon fruits [12]. Some of the notable works using deep learning techniques are provided in table 1.

Sl. No.	Authors	Year	Fruit Type	Techniques Used	Brief Results
1	Ghosh & Singh [13]	2026	multi-fruit (apple, banana, and orange)	Hybrid CNN (pretrained) + LSTM	The model achieved an accuracy of 98.9% for determining freshness of fruit.
2	Azadpour et al. [14]	2025	Oleaster	Mask R-CNN	Oleaster detection accuracy is 92%.
3	Albaaji et al. [15]	2025	Multi-fruits, (Mango, Apple, Orange and Guava)	YOLOv8 based custom model	Achieved an accuracy of 97.7% in species identification, 98.9% in origin determination.
4	Huang et al. [16]	2025	Multi-fruit (dataset of 27 types of fruit category with 5000 images)	Transformer	Achieved classification accuracy of 97.5%.
5	Kumar et al. [17]	2025	Mango	CNN + Probabilistic NN	Achieved accuracy of 98% in classification, and 97% in grading
6	Oyefeso et al. [18]	2025	Multi-fruit (oranges, tomatoes, and mangoes)	SVM	achieving classification accuracy of 100%, precision of 96%, recall of 92%, and F1 score of 89%
7	Khan et al. [19]	2025	Multi-fruit (apple, banana, lemon, peach, tomato)	CNNs, YOLO, MobileNetV2	Surveyed studies on various deep learning-based models' effectiveness with observed grading accuracy above 90%.
8	Moya et al. [20]	2025	Tomato (2145 image dataset)	YOLOv8	model achieves a classification accuracy of 99.6% and a size estimation accuracy of 97.1%
9	Cong et al. [21]	2025	Citrus fruits (sunburn detection)	Enhanced YOLOv8	the model achieves a mAP50 of 92.7%, a Precision of 86.6%, and a Recall of 87.2%
10	Hayat et al. [22]	2024	Multi-fruit (Apple, banana, guava, lime, orange, pomegranate, dates, and mango)	CNN (based on MobileNetV3)	The proposed system achieved minimum accuracy of 98.86%

III. Data Acquisition, Dataset Creation and Preprocessing

Most of the fruit image datasets which are openly available online were captured using high-grade camera sensors. However, the application of the grading system is under the rural environments using mid-range smartphone camera. So, dataset creation is the necessary first step for the development of the system. The dataset should include images of the fruits collected from forests, farms, local markets, and storage locations under different discussed environmental factors. During the image collection phase, various features of the captured fruit image such as ripeness stage, surface defects, visible disease symptoms, size, and grade have to be recorded in a metadata file for the later use in the training phase of the deep learning model. The grade is divided into four categories; Grade-A *(premium quality)*, with uniform color, desirable mature size, and no defects; Grade-B, with acceptable local market quality with minor defects; Grade-C: low quality with a lot of defects but consumable; and Grade-D *(defective)*: unfit to consume due to severe damage or disease and unfit for sale. The grading assessment has to be performed manually during data collection phase, and a suitable grade is assigned to the captured fruit image.

Subsequent to the dataset creation, the pre-processing is to be performed to amplify the relevant dominant features from the fruit images. In the first stage, implementation of a Gaussian function is an effective way to improve the contrast of the image. Then Gabor wavelet transform is applied to extract the texture-based features [23]. The output is then resized into a low dimensional space of 224 x 224 pixels to reduce the computation cost overheads while system training. The stages involved in the image data preprocessing are provided in figure 1.

Figure 1. Preprocessing stages of raw Fruit images.

IV. Proposed Framework

This section first presents the objectives, followed by the proposed framework for the development towards the fruit grading system using deep learning techniques. The system has to rely solely on the on-device computational resources without any dependency on remote server and internet connectivity or any cloud infrastructure. The end-to-end pipeline requires a lightweight deep learning model that enables real-time fruit quality assessment directly on commonly available android-based smartphones.

The primary objectives for the system design of the proposed framework are discussed as below:

i. **On-device computation:** All the computations are performed using on-device resources for the end-to-end pipeline such as image pre-processing, feature extraction, deep learning model inference for quality classification.

ii. **Light-weight model:** The classification task is performed by a lightweight deep learning model with low computational cost to efficiently operate on mid-range smartphones which are affordable and commonly accessible by the farmers in rural regions of India.

iii. **High reliability:** The system should be able to perform the classification task with a reliable accuracy despite the variation in the environmental factors such as lighting, orientation, background, and noise.

iv. **Scalable architecture:** The architecture of the framework should be scalable, that allows addition of new fruit species and types in future.

4.1. Proposed deep learning model architecture:

The proposed deep learning model is inspired from MobileNetV1 architecture introduced by Howard et al. in 2017 [24]. The proposed architecture is designed using three sequentially connected deep learning network blocks, Convolutional block, attention block, and ANN block. The overall deep learning pipeline is provided in figure 2. The convolutional block is configured using Depth-wise Separable Convolutions (DSC) network, where each DSC block with k x k convolutional kernel is applied into a depth-wise spatial convolution followed by 1 x 1 point-wise convolution. The Convolutional block performs the spatial feature extraction process and reduces the dimension of the feature-map and passes it to the attention block. This network setup ensures low computational cost when compared to full convolutional operation performed by standard Convolutional Neural Networks (CNNs), and the cost reduction is given in equation 1 below:

Figure 2: Proposed Deep Learning model pipeline

$$\frac{\boldsymbol{Cost_{DSC}}}{\boldsymbol{Cost_{std}}} = \frac{1}{N} + \frac{1}{k^2} \qquad \text{...(1)}$$

Where, N is the number of output channels and k is the kernel dimension. The DSC block is then followed by hard-swish activation. Subsequently, the extracted feature vectors are then passed through a compact attention block to capture the local spatial contextual patterns. The output is then passed though the ANN block with two layers of Feed Forward Networks (FFN) configured with 256 units in each layer with ReLU activation and a final layer with SoftMax to give the final output of the classified fruit grade. The layers in the ANN block are batch normalized and a dropout is set to 0.2 to randomly drop 20% of the network connections during training to reduce overfitting. While training the model, sparse categorical cross-entropy is used as the loss function, and the model is trained till convergence or early stopped when no noticeable change is observed during three consecutive epochs.

The proposed pipeline is a light-weight solution compared to large-scale deep learning models. The initial training can be carried out in a GPU enabled systems with large batch size to attain better generalization and later can be deployed into mobile devices (mid-range android smartphones) using TensorFlow-lite (TFLite). This enables on-device computation for inference generation without the need of any additional computational resources.

4.2. Evaluation Metrics

The curated fruit image dataset is split into three parts: 70%, 20%, and 10% for training, validation, and testing. The model performance of the model is then measured using the metrics such as accuracy, precision, recall, and F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad ...(2)$$

$$Precision = \frac{TP}{TP + FP} \quad ...(3)$$

$$Recall = \frac{TP}{TP + FN} \quad ...(4)$$

$$F1\ score = \frac{2 * Precision * Recall}{Precision + Recall} \quad ...(5)$$

4.3. Field Validation

Subsequent to the laboratory benchmarking and evaluation, the trained model's performance is required to be tested under real environment scenario. A field validation study has to be conducted in collaboration with rural farmers and local markets. The model is tested and validated using ten samples/grade for each fruit under consideration with random sampling with replacement technique. The model is then re-evaluated under this scenario and a new performance score calculated and compared with the laboratory experiment benchmark. When the accuracy of the model reaches a desired threshold then it is ready for deployment into smartphones. Otherwise, new fruit samples needed to be collected and added to the existing dataset and retrain the model. The process is continued till the desirable field validation score is achieved. The iterative process of the model re-training is provided in figure 3.

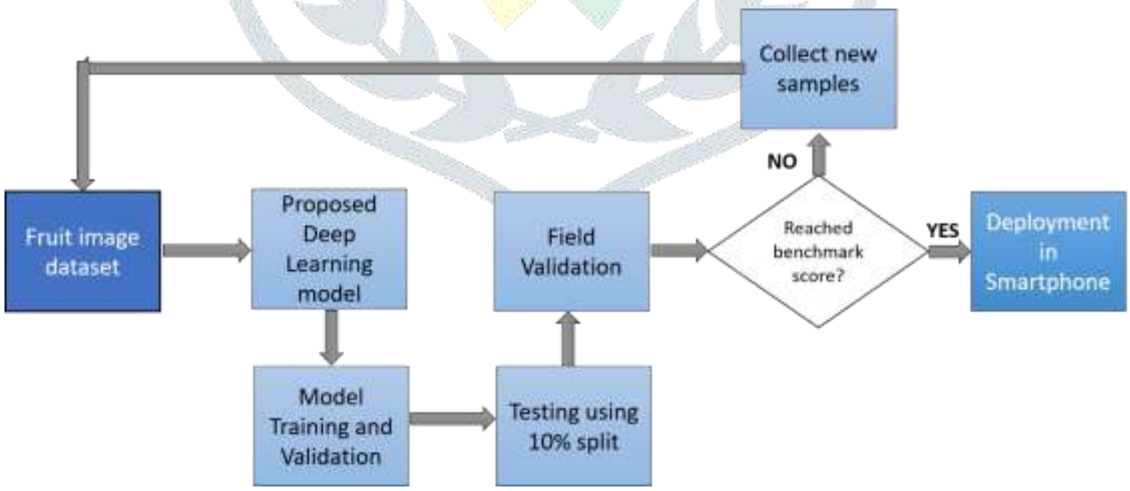

Figure 3: Iterative training and field validation of the proposed model.

V. CONCLUSION

This study proposes a framework for fruit grading so that the farmers get the fair price for their produce and are not left at the mercy of middlemen. To make it ready for deployment at the grass root level, the trained deep learning model has to be executed as application entirely in the android-based smartphone. So, the model is to be converted into a mobile-friendly format using quantization. The quantization process reduces the model size by incorporating quantization-aware training, which accelerates the inference by converting the trained weights into lower precision such as 8-bit integers instead of higher precision floating-point values. The model conversion is performed by exporting the trained model using TensorFlow Lite (TFLite). As part of ongoing work we propose to test the model on secondary as well as primary data and improve upon it for further improvement. Further, the training of farmers for readiness to handle the application is also to be initiated.

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