RESEARCH PAPER

# DEEP LEARNING APPROACH FOR FRUIT QUALITY ANALYSIS

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***ABSTRACT***

In order to maintain market standards and customer satisfaction, grading the quality of a fruit is a crucial procedure in the Agro-processing sector. Grading has historically been done by hand using visual inspection, which is laborious, subjective, and vulnerable to human errors. The proposed work suggests an autonomous fruit quality evaluation system based on a Convolutional Neural Network (CNN) and deep learning approaches to get around these restrictions. Fruit photos are divided into three quality categories by the suggested system: Fresh, Mild, and Rotten. Training and validation are done using the FruQ-DB dataset. The dataset images are loaded into the unique CNN which automatically extract discriminative features from images after doing the necessary preprocessing steps. The suggested deep learning model outperforms conventional image processing and machine learning methods in terms of classification accuracy, according to experimental results. The system is effective, scalable, and appropriate for fruit grading applications in the real world.

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## I. INTRODUCTION

Fruit quality is important in the agricultural economy since it directly affects consumer happiness, market value, and export possibilities. Fruit grading is often done by experts who examine every fruit individualy, which is labor-intensive, inefficient, and heavily reliant on human judgment. Due to human weariness and subjective evaluation, such manual grading techniques frequently have low efficiency, irregularity, and mistakes, which eventually result in decreased quality assurance and financial losses.

An autonomous fruit grading system based on machine learning (ML) techniques is suggested as a solution to these problems. This system's goal is to grade fruits quickly, accurately, and consistently without the need for human intervention. In this study, a structured three-stage method is used to automatically classify four different fruit types—apples, pomegranates, oranges, and loquats—into three quality grades.

Food processing sector in India has perceived a growth of 7.93% FPI in manufacturing area and it ranks second largest producer of vegetables and fruit. Ministry of Food Processing Industries has recognized this area's growth and provide support and funding for creating innovative methodologies with potential distribution management, creating job opportunities, decreasing harvest crop loss, enhancing processing capacity and boosting processed food export. In the year 2024-25, around 161.4 million US Dolars worth of fruits and vegetables were exported by India. The major exported fruits includes mangoes, pomegranates, bananas, grapes, and oranges while major exported vegetables include potatoes, onions, tomatoes, and green chilies, etc. [1]

Then, we need to know about how the grading systems work flows with image capture then pre-processing in which the images are standardized followed by Deep learning classification where a trained CNN or object detector is used to assign grades and finally the automated sorting is done based on AI decisions. With deep learning-based grading systems across multiple fruit types including apples, bananas, oranges, guavas and mangoes often >97% very high accuracy rate can be achieved.[2]

An image is represented as a 3-dimensional array of pixel values. These values form the matrix of numbers which becomes the raw visual data the AI techniques use to learn features. Then we work on the Deep learning technique using Convolutional Neural Network (CNN) with ReLu which is robust and a standard method by which we can achieve high accuracy. The feature extraction process is highly valued because they automatically extract multi-level image features of color, texture, shape, size and its maturity without manual intervention, which is considered as a substantial advantage over the traditional machine learning methods. Color, gradients and edge features were detected by the early filters and the high-level features like objects; shapes were extracted when the design go deeper. This process is crucial in understanding the image features at different scales. The ReLU function itself enhances learning speed and performance compared to older activated functions. ReLU (Rectified Linear Unit has non-linearity property to the neural network system which is a must for learning complex and realistic patterns in data. Without this non-linearity, the network would behave like a linear system which fails to distinguish precise differences thus ReLU with efficient training leads to more stable learning. [3], [4]

Pooling in deep learning is down sampling technique that reduces features by summarizing to nearby values in order to overfitting, computation by extracting dominant features and discarding the noise. It is also the result of stacked convolution and ReLU layers. The fully connected layers created by the output allows the network to combine all the extracted features and learn which combinations are most predictive of each class as of Fresh, mild and Rotten.[5]

The last stage of the deep learning is the Softmax function which is a mathematical activation function which is specifically deployed in multi class classification where it converts logits into probabilities.

In summary, the need for effective and trustworthy grading methods is highlighted by the rising demand for premium fruits and the growth of the Indian food processing industry. Fruit grading by hand is inconsistent and not very scalable. By directly learning discriminative features from fruit photos, image-based deep learning approaches get over these restrictions. Accurate extraction of color, texture, form, and defect features is made possible by CNN. Robust multi-class grading is ensured by combining preprocessing, feature learning, and classification. For contemporary agri-food applications, deep learning-based fruit quality evaluation thus offers a scalable and precise option.

## II. LITERATURE SURVEY

### A. *Peixian Zhang, Xiuhong Li*

**Zhang and Li** [6] suggested an autonomous fruit grading system with high adaptability, emphasizing multi-fruit classification over single-fruit evaluation using traditional machine learning approaches. Their method uses a Random Forest (RF) classifier to grade fruit photos after extracting several manually created attributes, including texture, color, size, shape, and surface flaws. A dataset of 666 photos of apples, oranges, pomegranates, and loquats was used for the experiments. The findings showed that Random Forest achieved classification accuracies above 95% across all fruit kinds, outperforming SVM, KNN, and LDA in stability and accuracy. The proposed work states that, ensemble learning in conjunction with efficient feature extraction can produce results that are on par with deep learning while requiring less hardware and computing complexity. The dependence on manual feature design, however, suggests room for improvement using end-to-end deep learning models.

Using a variety of analytical approaches, including appearance analysis, nutritional profile, flavor assessment, electronic nose sensing, and multivariate statistical methods, **Chang et al.** [7] carried out a thorough fruit quality evaluation study on cherry tomatoes of various hues. Fruit color is closely associated with quality aspects such as lycopene content, soluble sugars, amino acids, mineral composition, and overall flavor characteristics, according to the study, which examined various colored tomatoes. Yellow tomatoes were shown to have better flavor quality when Principal Component Analysis (PCA) were used to successfully separate tomato varietals based on combined quality characteristics. The work offers a strong multi-dimensional framework for evaluating quality, however it mostly uses statistical analysis and laboratory-based measurements rather than automated image-based learning. In order to provide scalable and real-time fruit quality classification, deep learning-driven visual grading systems that can non-destructively infer quality features directly from fruit photos are required.

**Jiao et al.** [8] examined morphological traits, juice quality metrics, and mineral content to give a thorough framework for evaluating fruit quality for nine citrus varieties. To measure fruit quality variations between cultivars, the study used Nemoro Quality Index (NQI), Principal Component Analysis (PCA), cluster analysis, and the Integrated Quality Index (IQI) methodologies. Citrus varieties and fruit components varied significantly in qualitative features, according to experimental data, with pulp making up the majority of the fruit's total quality. The suggested method depends on laboratory-based measurements and statistical modeling even though it offers a reliable quantitative assessment of fruit quality using physicochemical indicators. Deep learning-based visual fruit grading systems can successfully fill a research vacuum caused by the lack of automated, image-based, and real-time assessment methods.

A thorough analysis and methodology for autonomous fruit categorization and grading based on size and ripeness utilizing machine vision and artificial intelligence approaches were described by **Lalam et al** [9]**.** The study draws attention to the shortcomings of manual grading techniques and underlines the efficiency of image-based methods that examine visual characteristics like color, texture, size, form, and surface flaws. For the classification of fruit quality across a variety of fruit kinds, including apples, bananas, oranges, mangoes, and dragon fruit, several machine learning and deep learning models are reviewed. According to the article, because deep learning can automatically learn hierarchical image features, they routinely obtain high grading accuracy over 90%. This is especially true for CNNs and transfer learning approaches. However, the research also highlights issues with real-time flexibility, cost-effective deployment, and dataset diversity, highlighting the need for strong deep learning models that can classify fruit quality into multiple classes with little manual feature engineering.

## III. PROPOSED SYSTEM

The proposed system loads fruit images from the FruQ-DB dataset. The images are preprocessed and its features are extracted using CNN. The system classifies the fruit into Fresh, Mild, and Rotten using a softmax classifier. The process flow of the proposed system is given below in Fig.1.

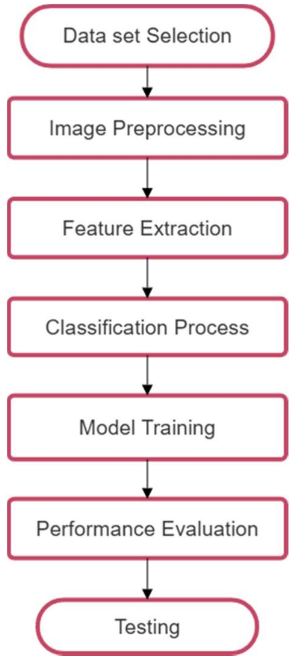


Fig. 1. Work flow of the proposed system

### A. Data Selection

The FruQ-DB [10] labeled dataset contains fruit images based on quality levels. The samples have variations in color, texture and surface blemishes which is suitable for training. The dataset was loaded in the proposed system using imageDatastore and the labels are assigned based on the folder names. 80% of the dataset is used for training and 20% is used for validation.

### B. Image Preprocessing

Image preprocessing is a mandatory step in image-based analysis. This is done by using augmentedImageDatastore. It prepares the image for deep learning efficiently by performing automatic resizing and data augmentation. This step is mandatory because the real time images may have different resolution, size and orientation. The convolutional neural network required the input images to be in a particular dimension; the proposed system resize the image into $128 \times 128 \times 3$. The step can also perform translation, reflection and rotation transformations if needed. This step reduces the manual resizing of images which consumes time and memory and provides efficient, scalable and uniform images for training and validation.

### C. Feature Extraction

In traditional image processing methods, the required features have to be selected manually and it is a knowledge driven process. But in the proposed method the custom convolutional neural network, automatically extracts discriminative features such as hue, textural information and defect patterns of the given dataset. The low-level details like color, contour and edges were extracted by filters on the convolutional layers. The following convolutional layer extract more complex features related to fruit quality like defect regions, texture, structural irregularities and discoloration patterns. To accelerate the convergence, after all convolution batch normalization layers are included. To model the complex visual relationships, ReLU [11] activation function enables the network by including nonlinearity.

Spatial dimensions of feature maps were minimized, so that max-pooling layers preserve the most noticeable features while lowering computational cost and enhancing robustness to minute spatial fluctuations. The CNN's learned hierarchical feature representations successfully differentiate between rotting, somewhat faulty, and fresh fruits. Following flattening, these extracted characteristics are sent to fully connected layers, which use the acquired knowledge and enable precise quality classification using the softmax classifier. High accuracy, flexibility, and resilience in fruit quality assessment are guaranteed by this deep learning-based feature extraction method.

### D. Classification Process

Classification is carried out in the suggested fruit quality grading system following the CNN's feature extraction phase [13]. The convolutional and pooling layers extract hierarchical features, which are then flattened and forwarded to the fully connected layers, which act as the decision-making component of the network. The learnt feature representations are combined and mapped to the target quality classes by these layers. During training, a regularization layer is used to improve generalization performance by randomly deactivating neurons in order to avoid overfitting. The softmax classifier is used for final classification. This classifier transforms the network outputs into normalized probability scores corresponding to each category. The anticipated quality grade is assigned to the class with the maximum possibility. The network parameters are tuned using the Adam optimization technique during training, and the classification layer measures the difference between predicted and real labels using categorical cross-entropy loss. Fruit quality may be accurately, consistently, and reliably graded using learnt visual characteristics thanks to this integrated classification process.

### E. Model Training

In the suggested technique, model training entails figuring out the ideal network parameters for precise fruit quality categorization. To achieve objective performance evaluation, the FruQ-DB training and validation ratio of the dataset is 80:20. Mini-batches of scaled fruit photos are fed into the proprietary Convolutional Neural Network during training to enable effective gradient computation and memory consumption. The Adam optimization algorithm, which adaptively modifies the learning rate to promote faster convergence and stable learning, is used to improve the network parameters, including convolutional filter weights and biases. The discrepancy between true classes and predicted class probabilities gives the loss function. The network iteratively modifies its parameters to reduce classification error over the course of several training epochs. Overfitting is avoided by monitoring the validation data and model's capacity on generalization. The CNN successfully captures discriminative information and delivers dependable fruit quality grading performance through this iterative learning procedure.

### F. Performance Evaluation

Standard classification parameters are used to evaluate the efficacy and dependability of the suggested CNN-based fruit quality grading system. The validation dataset, which is kept apart from the training data to guarantee objective assessment, is used to evaluate the model following training. The main performance statistic is classification accuracy, which shows the percentage of fruit photos that are properly categorized out of all samples. Furthermore, a confusion matrix is created to inspect the class-wise performance and reveal how effectively the system differentiates between the Fresh, Mild, and Rotten categories. The robustness of the learnt features is demonstrated by the confusion matrix, which emphasizes true positives, misclassifications, and inter-class confusion. The suggested CNN achieves high accuracy with low misclassification and the experimental findings validate the efficacy of automatic classification. Overall, the performance evaluation demonstrates that the suggested approach is dependable, effective, and appropriate for real-world fruit quality grading applications.

### G. Testing

The trained CNN model's capacity to correctly classify unseen fruit photos is assessed during the testing phase of the suggested fruit quality rating system. During testing, the trained network receives individual fruit photos that are not included in the training dataset. The CNN uses trained convolutional filters to extract pertinent visual information from these test photos after they have been scaled to the predetermined input dimensions. These features are then processed by the fully connected layers and the softmax classifier, which provide probability scores to each quality class. The class with the highest likelihood among Fresh, Mild, and Rotten is represented by the final output. The model gives reliable prediction in addition to the projected class label. The testing findings verify the practical usability of the suggested method by showing that the trained model evaluates fruit quality under various settings and generalizes well to fresh data. [14],[15]

## IV. RESULTS

Initially the FruQ database is fed to the proposed system. The dataset consists of 5,647 images, among which 2182 are Fresh, 1364 are Mild and 2101 are Rotten. Eighty percent of the dataset is allocated for training while the remaining is considered for validation. The images are resized to 128 × 128 × 3 and accepted through the custom convolutional neural network. Based on the extracted hierarchical features through multiple convolution, activation, normalization and pooling layers. A softmax classifier is used after fully connected layers to classify the retrieved features.

**TEST 1:**

The trained modes are tested with new and real time fruit images. Below Fig.2 shows the confusion matrix.

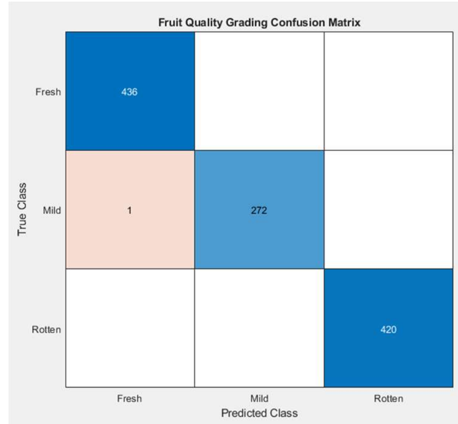


Fig. 2. Confusion Matrix of the sytems for test 1

The confusion matrix parameter was calculated by the following equations.

True Positive $(TP) = CM(i,i)$

False Positive $(FP) = \sum column_i - TP$

False Negative $(FN) = \sum row_i - TP$

True Negative $(TN) = N - (TP + FP + FN)$

From the confusion matrix we can derive,

TABLE I. VALUES OF TEST 1

| Class Type | TP | FP | FN | TN |
|---|---|---|---|---|
| **Fresh** | 436 | 1 | 0 | 692 |
| **Mild** | 272 | 0 | 1 | 856 |
| **Rotten** | 420 | 0 | 0 | 709 |

Class-wise Performance Metrics for given sample can be derived from table I.

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{436}{436+1} = 0.99771$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{436}{436+1} = 0.99771$$

$$\text{F1\_Score} = 2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision + Recall}} = 2\times\frac{0.99771\times 0.99771}{0.99771+0.99771} = 0.99771$$

Similarly, the performance metrics were calculated for other classes also. The results were given in table II.

TABLE II. CLASSWISE PERFORMANCE METRICS OF TEST 1

| Class | Precision | Recall | F1 Score |
|---|---|---|---|
| ***Fresh*** | *0.99771* | *1.00000* | *0.99885* |
| **Mild** | 1.00000 | 0.99634 | 0.99817 |
| **Rotten** | 1.00000 | 1.00000 | 1.00000 |

Every sample that is predicted to be fresh is accurate (no false positives) when the precision is 1.0. With a very low miss rate, a recall of 0.99771 indicates that nearly all real fresh samples are identified. Strong and balanced performance is shown by the high F1-score (0.99885). As a result, the decision is quite dependable when the model predicts Fresh.

Even though the Rotten class has a better F1-score, the CNN's softmax probability output is used to classify each individual sample. Decisions based on a single sample are unaffected by the F1-score, which represents the overall performance of the model's whole dataset. In this instance, the algorithm accurately identified the sample as Fresh since the extracted features of the input image produced a greater softmax probability for the Fresh class than Rotten.


Fig. 3. Confidence value for test 1

After feature extraction and the final fully connected layer, the CNN outputs raw scores as $Z_{fresh}$, $Z_{mild}$ and $Z_{rotten}$. The softmax function converts these scores into probabilities using,

$$P(i) = \frac{e^{Z_i}}{e^{Z_{fresh}} + e^{Z_{mild}} + e^{Z_{rotten}}}$$

$$\text{Predicted Class} = \arg\left(\max\left(P(i)\right)\right)$$

The class has been selected based on the highest probability.

$$\text{Confidence} = \max\{P(fresh), P(mild), P(rotten)\}$$

$$\text{Confidence}(\%) = \max(P) \times 100$$

Based on the above formula, Fig.3 shows that the confidence of the proposed system to predict the fresh fruit correctly is 99.94% and the accuracy of the system is 99.82%.

**TEST 2:**

The trained model is tested with another real time sample. The confusion matrix is given in Fig.4.

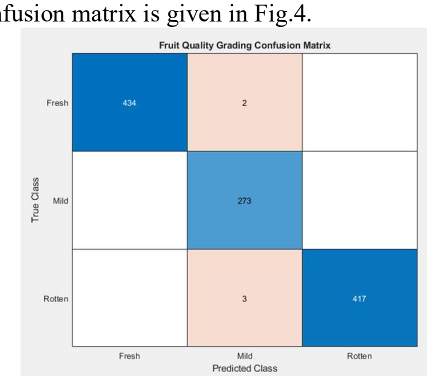


Fig. 4. Confusion Matrix of the sytems for test 2

From the confusion matrix values are calculated as follows: From the confusion matrix we can derive [12],

TABLE III. VALUES OF TEST 2

| Class Type | TP | FP | FN | TN |
|---|---|---|---|---|
| **Fresh** | 434 | 0 | 2 | 693 |
| **Mild** | 273 | 5 | 0 | 851 |
| **Rotten** | 417 | 0 | 3 | 709 |

Class-wise Performance Metrics for given sample can be derived from table III. For 'Mild' class,

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{273}{273+5} = 0.98201$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{273}{273+0} = 1$$

$$\text{F1\_Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0.98201 \times 1}{0.98201+1} = 0.99093$$

Similarly, the performance metrics were calculated for other classes also. The results were given in table IV.

TABLE IV. CLASSWISE PERFORMANCE METRICS OF TEST 2

| Class | Precision | Recall | F1_Score |
|---|---|---|---|
| **Fresh** | 1.00000 | 0.99541 | 0.99770 |
| ***Mild*** | *0.98201* | *1.00000* | *0.99093* |
| **Rotten** | 1.00000 | 0.99286 | 0.99642 |


Fig. 5. Confidence value for test 2

Based on the formula, the Fig.5 shows that the confidence of the proposed system to predict the fresh fruit correctly is 69.34% and the accuracy of the system is 99.56%.

**TEST 3:**

The trained model is tested with another real time sample. The confusion matrix is given in Fig.6.

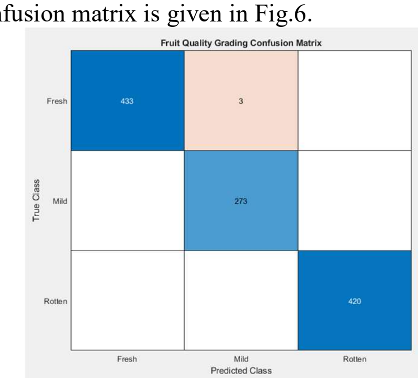


Fig. 6. Confusion Matrix of the sytems for test 3

From the confusion matrix values are calculated as follows: From the confusion matrix we can derive,

TABLE V. VALUES OF TEST 3

| Class Type | TP | FP | FN | TN |
|---|---|---|---|---|
| **Fresh** | 433 | 0 | 3 | 693 |
| **Mild** | 273 | 3 | 0 | 853 |
| **Rotten** | 420 | 0 | 0 | 709 |

Class-wise Performance Metrics for given sample can be derived from table V. For 'Rotten' class,

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{420}{420+0} = 1$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{420}{420+0} = 1$$

$$\text{F1\_Score} = 2\times\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} = 2\times\frac{1\times1}{1+1} = 1$$

Similarly, the performance metrics were calculated for other classes also. The results were given in table VI.

TABLE VI. CLASSWISE PERFORMANCE METRICS OF TEST 3

| Class | Precision | Recall | F1_Score |
|---|---|---|---|
| **Fresh** | 1.00000 | 0.99312 | 0.99655 |
| **Mild** | 0.98913 | 1.00000 | 0.99454 |
| **Rotten** | 1.00000 | 1.00000 | 1.00000 |


Fig. 7. Confidence value for test 3

Based on the formula, Fig.7 shows that the confidence of the proposed system to predict the fresh fruit correctly is 99.73% and the accuracy of the system is 80.20%.

The overall performance metric is given in Fig.8 and the accuracy and loss curves after the training and validation for 20 epochs and 50 iterations are given in figure 8.


Fig. 8. Performance Metrics

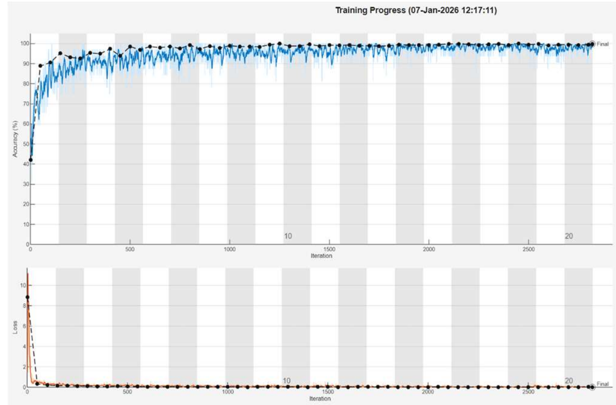


Fig. 9. Accuracy and Loss curve of the proposed system

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