ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun487

# Implementation and Analysis of Citrus Lemon Fruit Image Classification Model Using Convolution Neural Network Architecture

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Publication Date: 2026/06/18

**Abstract: Automated fruit grading using deep learning offers an efficient alternative to manual inspection in precision agriculture. This study presents the implementation and comparative evaluation of convolutional neural network (CNN) architectures for Citrus lemon fruit image classification. Transfer learning models, including popular pre trained CNN models, together with a custom sequential CNN, were trained and assessed using accuracy, categorical cross entropy loss, ROC analysis, and precision/recall metrics. Experimental results indicate that EfficientNet achieved the highest testing accuracy of 98.46% with the lowest loss (0.038), followed by DenseNet (97.88%) and the sequential CNN (97.07%). The model demonstrated strong discrimination capability with a true positive rate of 0.968, false positive rate of 0.0073, and an AUC of 0.9806. Class wise evaluation produced balanced precision, recall, and F1 scores of 0.98. The findings confirm that efficient deep CNN architectures provide reliable and scalable solutions for automated lemon quality classification.**

***Keywords:*** *Citrus Lemon Classification, Convolutional Neural Networks, Deep Learning, Fruit Quality Assessment, Transfer Learning.*

**How to Cite:** D. R. Solanke; Mahendra Makesar; Rajesh Bhoyar; Suhas Pachpande (2026) Implementation and Analysis of Citrus Lemon Fruit Image Classification Model Using Convolution Neural Network Architecture. *International Journal of Innovative Science and Research Technology*, 11(6), 567-574. https://doi.org/10.38124/ijisrt/26jun487

## I. INTRODUCTION

Agricultural automation and precision farming have increasingly adopted computer vision and deep learning techniques to improve the accuracy, consistency, and efficiency of fruit grading and quality assessment. Traditional manual inspection of citrus fruits is labour intensive, time consuming, and prone to subjective variability, often resulting in inconsistent classification outcomes. In particular, Citrus lemon (lemon) fruit grading requires reliable identification of visual characteristics such as size, colour, texture, and surface defects to ensure market quality and reduce post-harvest losses. Automated image based classification systems therefore offer a scalable and cost effective alternative for real time agricultural decision making. Recent advances in convolutional neural networks (CNNs) have significantly improved image recognition performance across diverse domains, including medical imaging, industrial inspection, and agricultural phenotyping. CNNs automatically learn hierarchical spatial features from raw images, eliminating the need for handcrafted descriptors used in conventional machine learning methods. Moreover, transfer learning with pre trained deep architectures enables faster convergence and higher accuracy, even with limited agricultural datasets. Architectures such as ResNet, EfficientNet, XceptionNet, DenseNet, and MobileNet have demonstrated strong generalization capability due to their depth, optimized parameterization, and efficient feature reuse. Motivated by these developments, this work implements and comparatively analyses multiple state of the art CNN models along with a custom sequential CNN for Citrus lemon fruit image classification. The objective is to identify the most effective architecture that balances classification accuracy, computational efficiency, and loss minimization. Each model is trained and evaluated using standard performance metrics including testing accuracy, categorical cross entropy loss, and receiver operating characteristic (ROC) analysis, precision, recall, and F1 score.

Experimental results demonstrate that deep transfer learning models outperform conventional CNN designs. Among all architectures, EfficientNet achieved the highest average testing accuracy of 98.46% with the lowest categorical cross entropy loss of 0.038. DenseNet and the custom sequential CNN followed closely with accuracies of 97.88% and 97.07%, respectively, while ResNet and

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun487

MobileNet showed comparatively lower performance. The proposed system further exhibited strong discriminative capability with a true positive rate of 0.968, a very low false positive rate of 0.0073, and an area under the ROC curve of 0.9806. Class wise evaluation confirmed balanced learning behaviour, producing weighted precision, recall, and F1 scores of 0.98.

The findings establish that parameter efficient deep CNN architectures provide robust and reliable solutions for automated lemon fruit classification. The proposed framework contributes toward intelligent agricultural inspection systems and can be readily extended to other fruit grading and crop monitoring applications.

## II. REVIEW OF LITERATURE

Recent advances in computer vision and deep learning have significantly improved automated fruit recognition and grading systems, replacing manual inspection with reliable image based analysis. Early research focused on customized CNN frameworks for lemon and citrus classification, including fuzzy pooling–based ThinNet models [1], residual CNN approaches for lemon quality detection [2], and deep learning systems for automated citrus sorting and grading [3]. Optimized deep architectures such as Google Net further demonstrated robust feature extraction for circular fruit and vegetable classification [4], while CNN based citrus type recognition studies confirmed the feasibility of deep learning for agricultural automation [5].Subsequent works emphasized disease detection and quality assessment using specialized or optimized CNN designs. Coati optimized CNNs improved infected citrus fruit identification [6], and hybrid convolutional long term or recurrent structures addressed citrus canker disease classification [7]. Broader fruit recognition frameworks employing deep CNNs and multilayer architectures showed effective detection across diverse fruit categories [8], [9]. Transfer learning approaches using pre trained networks for citrus disease identification and fruit grading further enhanced classification accuracy and convergence speed [10]. Ensemble and stacked CNN strategies, including dual stack or multi model frameworks, achieved greater robustness and generalization [11], [12]. Similarly, ResNet based and generic CNN fruit classification systems reported high accuracy for fresh versus defective fruits [13], [14], while fast and efficient CNNs were proposed to reduce computational complexity [15].

To improve discriminative capability, multi optimization CNNs and deeper convolutional structures were introduced for enhanced feature reuse and stability [16], [17]. Transfer learning combined with CNN backbones demonstrated effective freshness classification under real world variations [18]. Several studies validated CNN based fruit recognition through comparative performance analyses across datasets [19]–[23]. More recently, transformer based vision models such as Vision Transformer and Swin Transformer have emerged as competitive alternatives for lemon quality assessment, achieving promising results in industrial environments [24]. Additionally, DenseNet, Xception, and other pre trained deep models have been applied to fruit recognition tasks with improved accuracy and reduced loss [25]. Contemporary research trends include deep learning–based quality assessment systems [26], multi class fruit classification frameworks [27], lightweight CNN implementations [28], and further validation of convolutional approaches across agricultural datasets [29], [30]. Hybrid deep learning strategies combining CNNs with traditional classifiers such as SVM have also been explored for citrus recognition [31], while optimized lightweight networks improve deployment feasibility on resource constrained devices [32]. Extensions toward citrus pest identification and defect detection highlight the adaptability of CNN based methods to broader agricultural challenges [33]. These studies collectively establish that deep convolutional and transfer learning architectures provide reliable, scalable, and high performance solutions for fruit image classification [34]. However, most existing works evaluate limited architectures or focus primarily on disease detection rather than comprehensive comparative benchmarking. This motivates the present study to systematically analyse multiple state of the art CNN models for accurate and efficient Citrus lemon fruit classification.

## III. DATASET

The dataset is designed for a binary image classification task aimed at assessing lemon fruit quality. Figu.1, showned two labeled categories: Good Quality and Bad Quality lemons. The class distribution indicates a slightly imbalanced yet nearly uniform dataset, with approximately 1,120 good-quality images and 950 bad-quality images, resulting in a total of about 2,070 samples. This near-balanced distribution is beneficial for training deep learning models, as it reduces bias toward a dominant class while still preserving realistic variability. The dataset size is adequate for training convolutional neural networks and supports effective generalization when combined with standard augmentation techniques.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun487

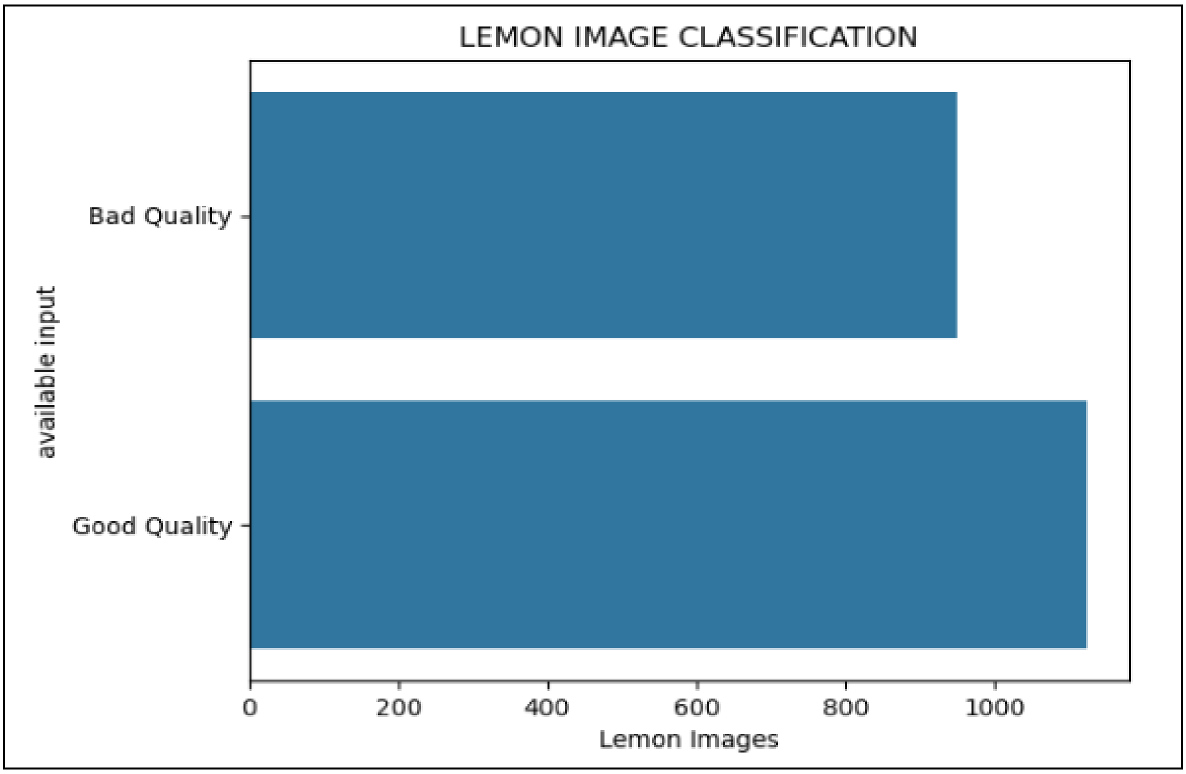


Fig 1 Iris Image Dataset Distribution for Implementation of CNN


Fig 2 Random Iris Images for Training and Testing

Randomly selected samples highlighted in Fig.2, distinct visual features that differentiate the two categories. Good-quality lemons typically exhibit a bright yellow or greenish-yellow color, smooth and uniform peel texture, intact shape, and minimal blemishes. In contrast, bad-quality lemons show visible defects such as dark spots, fungal growth, bruises, surface decay, discoloration, or irregular texture. These observable differences provide discriminative cues for automated feature extraction by CNN-based architectures, enabling the models to learn quality-related patterns effectively.

## IV. METHODOLOGY

The proposed methodology in Fig. 3, employs a deep convolutional neural network (CNN) architecture to automatically classify lemon fruit images into two quality categories, namely good and bad. Initially, all input images are resized to a fixed spatial resolution of 100 × 100 × 3 pixels to ensure dimensional uniformity and computational efficiency. A preprocessing stage is applied prior to feature extraction, which includes normalization of pixel intensities and optional augmentation operations to enhance model generalization and mitigate overfitting. This step standardizes the input distribution and improves the robustness of the learning process.

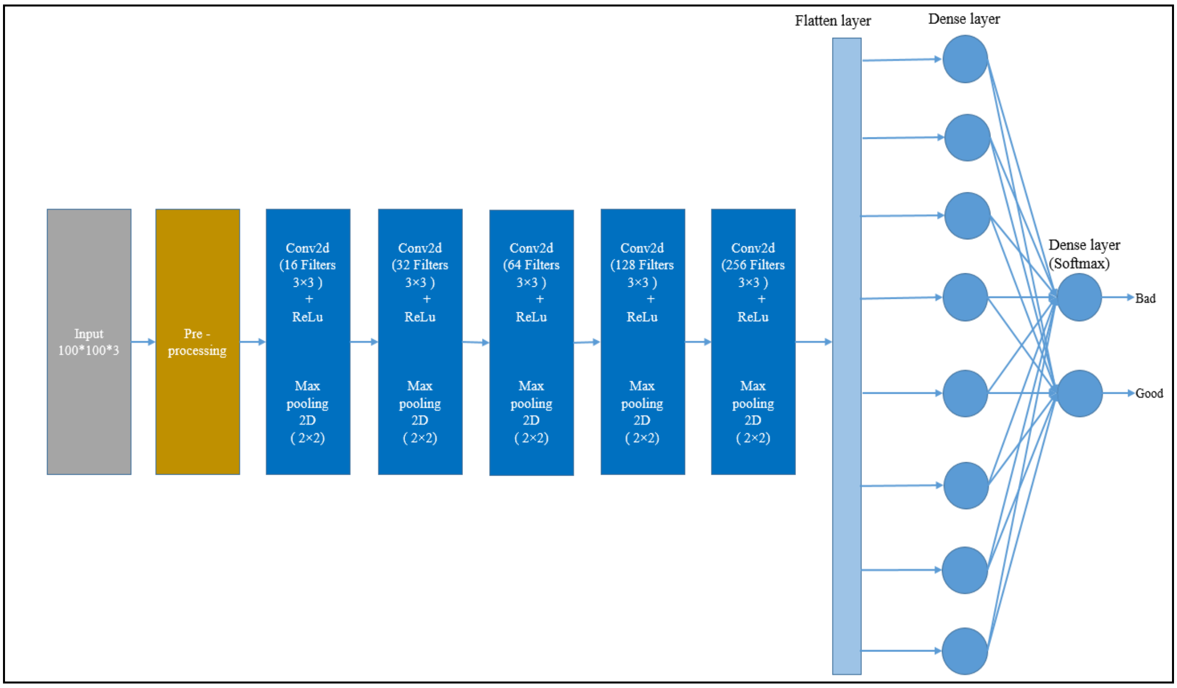


Fig 3 Proposed Convolution Neural Network

Following preprocessing, hierarchical feature extraction is performed using a sequence of convolutional blocks. Each block consists of a two-dimensional convolution layer with a kernel size of 3 × 3, followed by a Rectified Linear Unit (ReLU) activation function and a 2 × 2 max-pooling operation. The number of filters progressively increases from 16 to 32, 64, 128, and finally 256 across successive layers. This gradual expansion enables the network to learn low-level features such as edges and textures in the initial stages, mid-level features such as shapes and color variations in intermediate layers, and high-level semantic attributes such as surface defects, discoloration, or decay patterns in deeper layers. The max-pooling layers reduce the spatial dimensions of the feature maps, decrease computational complexity, and provide translation invariance while preserving the most discriminative information.After the final convolutional stage, the resulting multidimensional feature maps are flattened into a one-dimensional vector to facilitate integration with fully connected layers. The flattened representation serves as a compact descriptor of the extracted visual characteristics. This vector is then passed through one or more dense layers, where nonlinear combinations of features are learned to perform higher-level reasoning and decision making. These dense layers enhance the discriminative capability of the network by modeling complex relationships among the extracted features.The final classification is achieved using a Softmax output layer with two neurons corresponding to the binary classes. The Softmax function converts the raw logits into normalized probability scores, allowing the model to assign the most probable label to each input image. During training, categorical cross-entropy is employed as the loss function to quantify the discrepancy between predicted probabilities and ground-truth labels. The network parameters are optimized using backpropagation with a gradient-based optimizer, enabling iterative weight updates to minimize the loss.

- *Model Evaluation:*

Let the dataset be

$$\boldsymbol{D} = \{(\boldsymbol{x_1},\boldsymbol{y_1}),(\boldsymbol{x_2},\boldsymbol{y_2}),(\boldsymbol{x_3},\boldsymbol{y_3}),\ldots\ldots\ldots\ldots(\boldsymbol{x_i},\boldsymbol{y_i})\} \quad (1)$$

In k-fold cross validation, *D* is split into disjoint subset folds (*k*)

$$\boldsymbol{D} = \boldsymbol{D_1} \cup \boldsymbol{D_2} \cup \boldsymbol{D_3} \cup \ldots\ldots\ldots \cup \boldsymbol{D_k}, \boldsymbol{D_i} \cap \boldsymbol{D_j} = \boldsymbol{0} \ \boldsymbol{for}\ \boldsymbol{i} \neq \boldsymbol{j} \quad (2)$$

*For* $i^{th}$ *fold*

$$\boldsymbol{D^{(i)}_{Train}} = \boldsymbol{D}\backslash\boldsymbol{D_i}, \quad \boldsymbol{D_{val}} = \boldsymbol{D_i} \quad (3)$$

Let the model trained in the i-th fold produce a performance metric is the average (accuracy and loss etc.) $M^{(i)}$. Then, after training and evaluating across all k folds, the overall i-fold performance is computed as the average:

$$\bar{\boldsymbol{M}} = \frac{\boldsymbol{1}}{\boldsymbol{k}}\sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \boldsymbol{M^{(i)}} \quad (4)$$

This equation formalizes that the final performance metric is the average of the metric from all k folds, providing a robust estimate of the models generalization:

Let $\hat{y}_j^{(i)}$ denotes the predicted label for sample $x_j$ in fold i, and $y_i$ the true label. Then accuracy for fold i is:

$$\boldsymbol{Accuracy^{(i)}} = \frac{\boldsymbol{1}}{\boldsymbol{k}}\sum_{(\boldsymbol{x},\boldsymbol{y})\in \boldsymbol{D^{(i)}_{val}}} \boldsymbol{1}\left(\hat{\boldsymbol{y}}_{\boldsymbol{j}}^{(\boldsymbol{i})} = \boldsymbol{y_j}\right) \quad (5)$$

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jun487

Where 1 is an indicator function that equals 1 of the condition is true, and 0 otherwise.

The overall k-fold accuracy is the average of the accuracy across folds:

$$Accuracy_{CV} = \frac{1}{k}\sum_{i=1}^{k} Accuracy^{(i)} \tag{6}$$

If $\hat{P}_j^{(i)} = \left[\hat{p}_{j,1}^{(i)}, \hat{p}_{j,2}^{(i)}, \dots\dots, \hat{p}_{j,C}^{(i)}\right]$ is the predicted probability distribution over $C$ classes for sample in $x_j$ fold $i$, and $y_j$ is the true class label (one-hot encoded as $y_j$ ), the cross-entropy loss for fold $i$ is:

$$CE^{(i)} = -\frac{1}{\left|D_{val}^{(i)}\right|}\sum_{(x_j,y_j)\in D_{val}^{(i)}} \sum_{c=1}^{C} y_{j,c} \log \hat{P}_{j,C}^{(i)} \tag{7}$$

The overall k-fold cross-entropy (Log loss) is the average over folds:

$$CE_{CV} = \frac{1}{k}\sum_{i=1}^{k} CE^{(i)} \tag{8}$$

## V. RESULT AND DISCUSSION

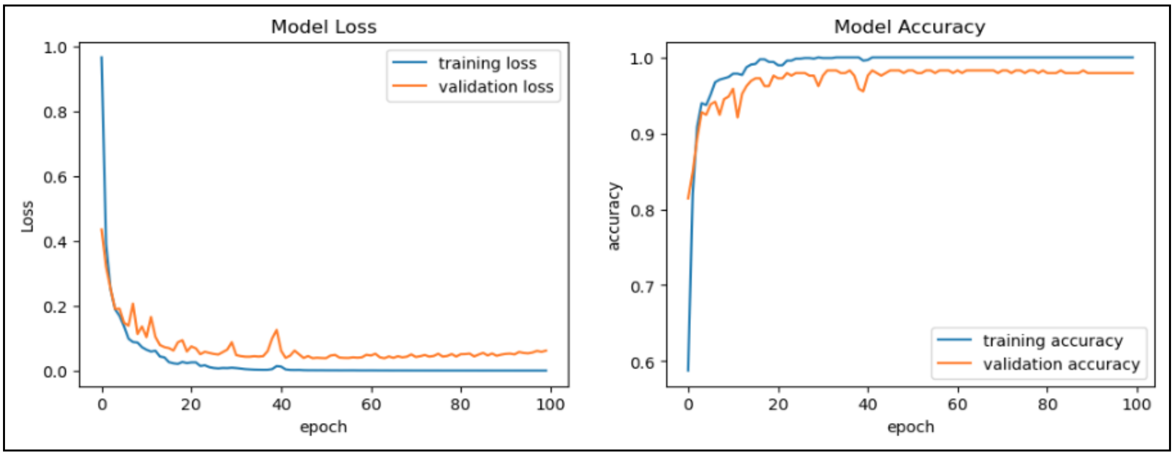

Fig 4 Training and Validation Curves for Loss (Left) and Accuracy (Right) Over 100 Epochs.

Table 1 Final Training and Testing Metrics Showing Average Accuracy and Loss Values.

| | |
|---|---|
| avg_training_accuracy: | 0.9886833041906357 |
| avg_testing_accuracy: | 0.9707560181617737 |
| avg_training_loss: | 0.03057140117598465 |
| avg_testing_loss: | 0.07058347262442112 |

Table 2 Classification Report Displaying Precision, Recall, and F1-Scores.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.96 | 0.99 | 0.98 | 273 |
| 1 | 0.99 | 0.97 | 0.98 | 350 |
| accuracy | | | 0.98 | 623 |
| macro avg | 0.98 | 0.98 | 0.98 | 623 |
| weighted avg | 0.98 | 0.98 | 0.98 | 623 |

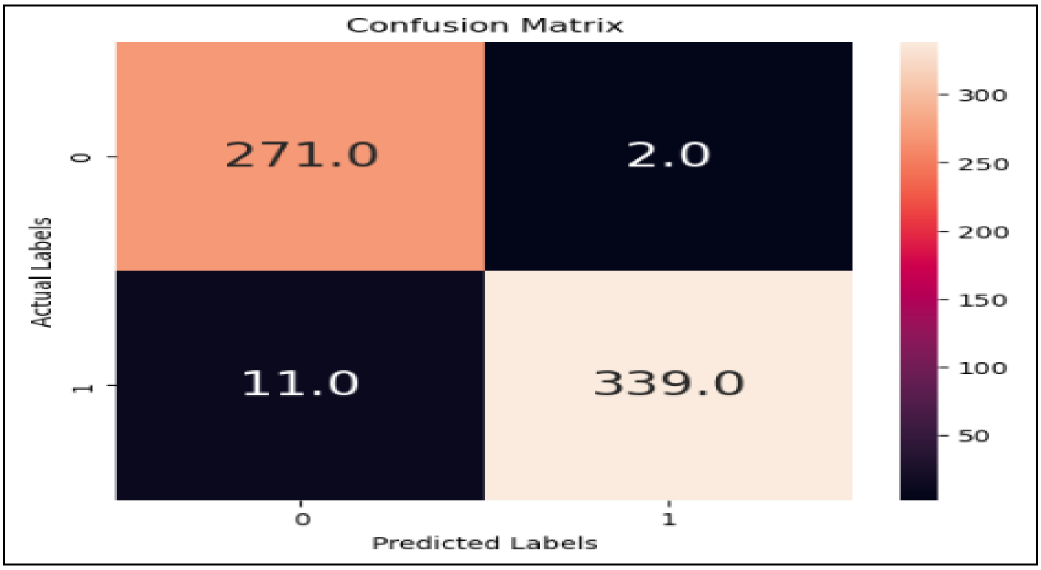

Fig 5 Confusion Matrix Illustrating Actual vs. Predicted Class Distributions.

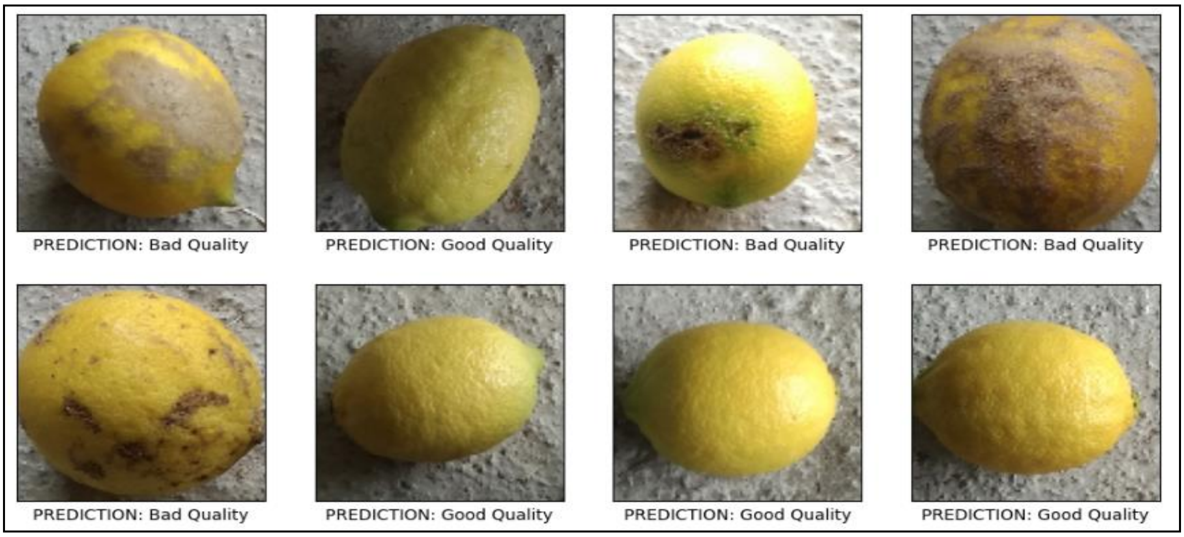


Fig 6 The Images Actually Predicted

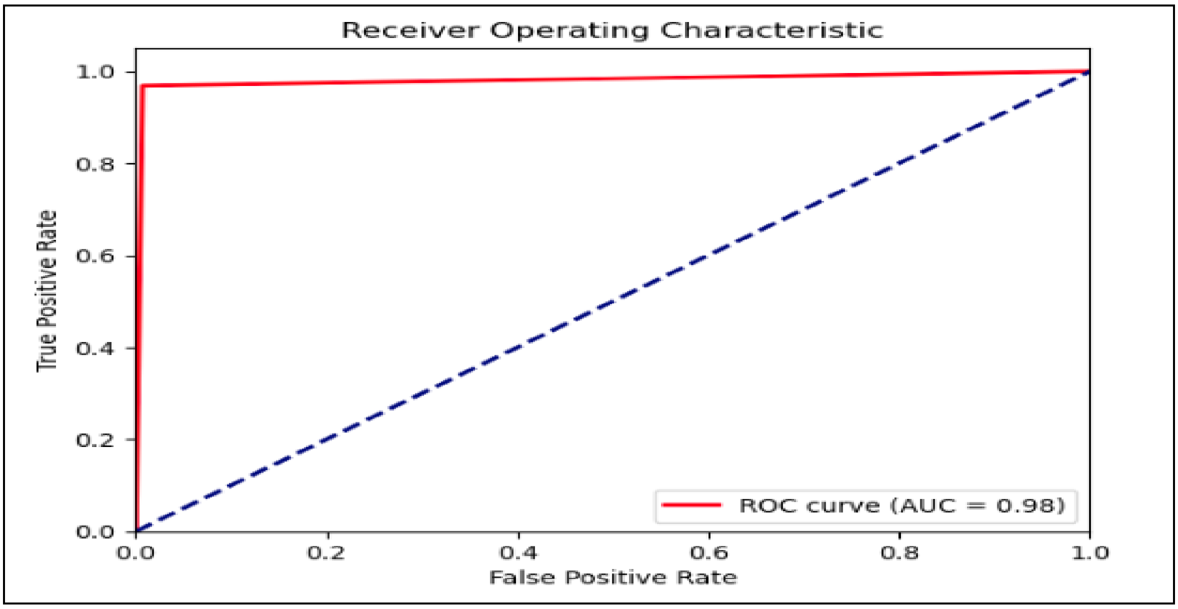


Fig 7 Receiver Operating Characteristics. Curve.

Table 3 Receiver Operating Characteristics

| | |
|---|---|
| False Positive Rate: | 0.007326007326007326 |
| True Positive Rate: | 0.9685714285714285 |
| Area Under Curve: | 0.9806227106227106 |

Table 4 Comparative Performance Evaluation of Different CNN Architectures

| CNN Model | Average Testing Accuracy | Categorical Cross Entropy |
|---|---|---|
| ResNet | 0.83978364 | 0.43407397 |
| EfficientNet | 0.98460674 | 0.03805296 |
| XceptionNet | 0.96382529 | 0.13303986 |
| DenseNet | 0.97879807 | 0.08203994 |
| MobileNet | 0.87627409 | 0.70468768 |
| Sequential CNN | 0.97075601 | 0.07058347 |

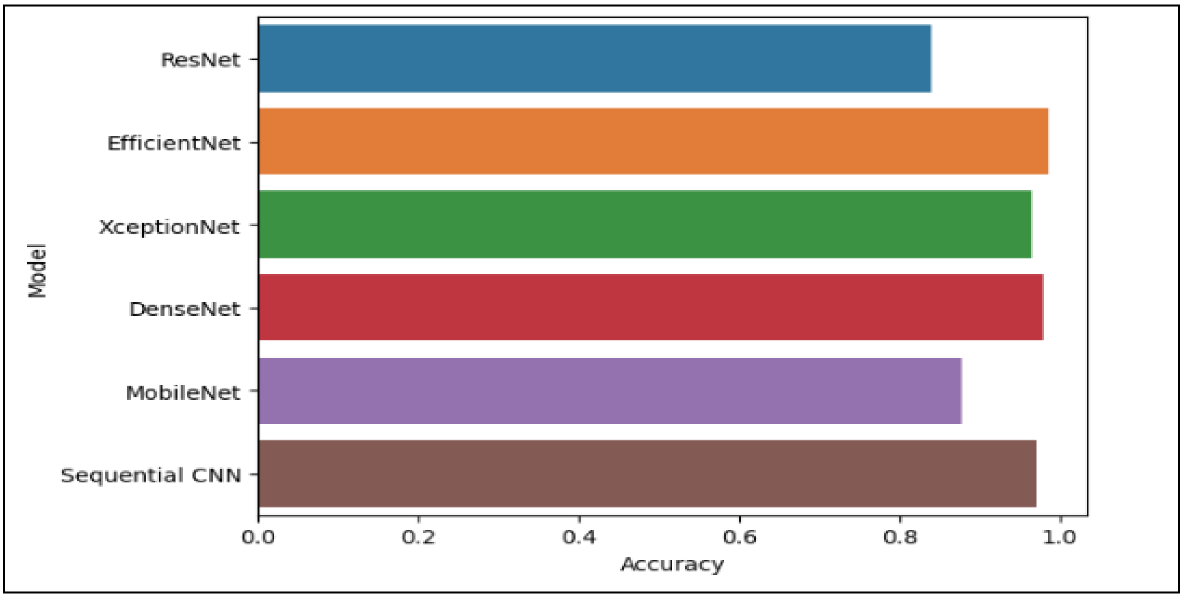


Fig 8 Comparative Analysis of Classification Accuracy

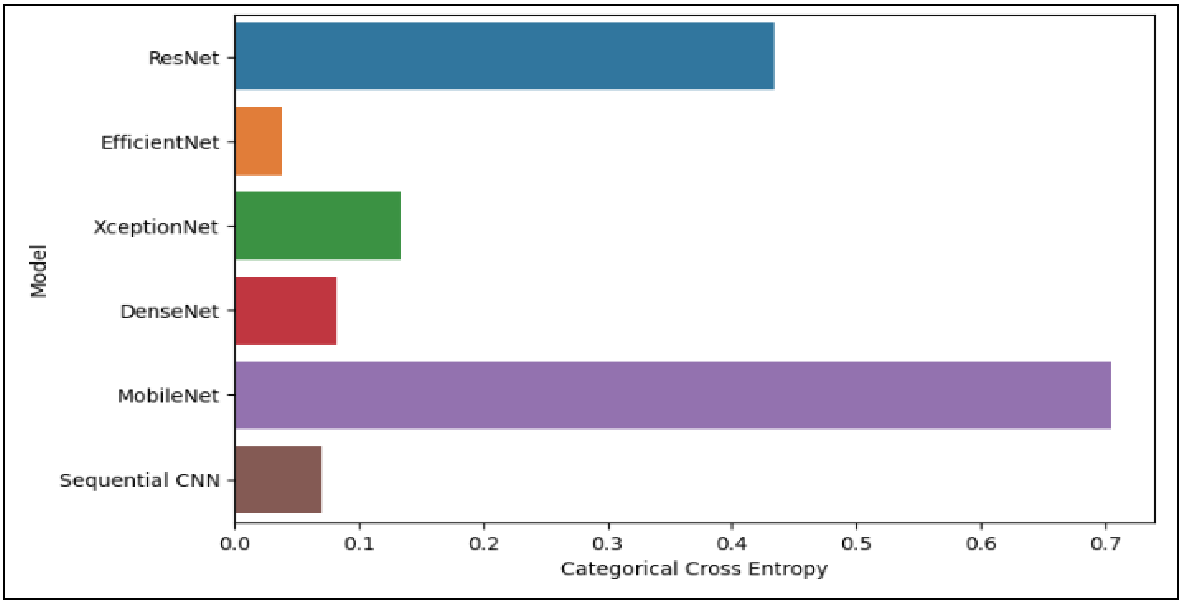


Fig 9 Comparative Analysis of Classification Log Loss (Categorical Cross Entropy)

## VI. CONCLUSION

This study presented the implementation and comparative analysis of deep convolutional neural network architectures for automated Citrus lemon fruit image classification, aiming to develop a reliable and efficient alternative to manual quality inspection. Experimental findings confirmed that deep CNN based approaches effectively capture discriminative visual features, resulting in high classification performance and stable convergence. Among the evaluated models, EfficientNet demonstrated superior performance with the highest testing accuracy (98.46%) and the lowest categorical cross entropy loss (0.038), followed by DenseNet (97.88%) and the proposed sequential CNN (97.07%). The sequential CNN further achieved an average training accuracy of 98.87% with a low testing loss of 0.0706, indicating good generalization. Receiver operating characteristic analysis yielded a true positive rate of 0.968, a very low false positive rate of 0.0073, and an area under the curve of 0.9806, confirming strong discriminative capability. The confusion matrix showed only a small number of misclassifications (271 true negatives, 339 true positives, 2 false positives, and 11 false negatives), while precision, recall, and F1 scores of 0.98 across classes validated balanced predictive performance.

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