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Arecanut Classification Using MobileNetV2 and SVM: A Lightweight Deep Learning Approach for Precision Agriculture

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Abstract— To guarantee quality and productivity in agriculture, automated classification of Arecanuts is necessary. The time-consuming and error-prone manual examination is the backbone of traditional classification systems. Using MobileNetV2 for feature extraction as well as Support Vector Machine (SVM) for classification, this work proposes an effective deep learning model to discriminate between healthy and unhealthy Areca nuts. The model is assessed using important performance indicators after being trained on the user-defined dataset. The proposed model succeeds where more conventional CNNs have failed by striking a compromise between accuracy and computational efficiency. Outperforming traditional approaches, the experimental findings provide a 96.85% classification accuracy with 96.85% recall, 99.61% specificity, and 96.85% F1-score. The design of the model is lightweight, which allows it to be deployed in real-time on embedded and mobile devices. In order to improve agricultural decision-making, this study presents an efficient, scalable, and accurate method for automated Areca nut classification. We will be integrating with smart farming apps that use the Internet of Things (IoT) in the future.

Keywords: Areca nut classification, deep learning, MobileNetV2, Precision agriculture, Support Vector Machine (SVM)

1. INTRODUCTION

The Areca nut is a major cash crop in many tropical countries; however, there are a lot of different ways to categorise it according to its morphology, geography, and botany. Protein, fat polysaccharides, fibre, and polyphenols are the main components of the areca nut. Alkaloids such as arecoline (0.1-0.7%) as well as arecadine, guvacoline, along with guvacine are also present, but at lower amounts. One usage for tannins is as a colour in the textile industry; they are a byproduct of processing immature nuts [1]. Arecanut classification is automated by employing different deep learning (DL) and machine learning (ML) approaches. An adaptive genetic algorithm combined with DL to classify arecanut X-ray images effectively. This method improves quality assessment by improving classification accuracy for arecanut diverse grades [2].

Similarly, a comprehensive survey on various arecanut classification techniques is conducted, highlighting the role of Convolutional Neural Network (CNNs), Support Vector Machine (SVMs), and deep feature extraction. It is identified that the major challenge in the manual classification of arecanut is the time-consuming nature of existing segregation methods [3]. Segregation is a crucial step in the Areca nut manufacturing process. Most commercial shops handle quality segregation by trained staff, which significantly prolongs the process of determining product pricing. This research presents an approach that uses CNNs and Mobile Nets to distinguish between healthy and unhealthy Areca nuts. A dataset is produced that included images of both healthy and sick nuts. The augmentation approach is also employed to improve the dataset [4].

In another work an optimized DL model is introduced that reduces computational cost while maintaining classification efficiency. This work demonstrates how lightweight CNN models like MobileNet and ResNet can be used for effective classification [5]. "Fruit detection" describes a subfield of computer vision and image processing that employs sophisticated algorithms and approaches to automatically identify and categorise various fruits. When it comes to ceremonial offerings (Banten), fruits play a crucial role. They play a crucial role in making sure that ceremonial offerings are full. The primary objective of fruit detection in the agricultural industry is to identify fruits in image form, making it useful for a wide range of purposes, such as inventory control, automated categorisation in the agricultural image, and medical applications for dietary pattern monitoring [6].

DL-based feature extraction techniques are in trend in recent days due to their superior performance over existing approaches. A multi-gradient-direction-based DL model is developed for arecanut classification, significantly improving accuracy utilizing hybrid feature selection techniques [7]. In a similar study, [8] demonstrated the effectiveness of DL models for automated arecanut classification, emphasizing texture and shape-based feature selection to improve accuracy [8].

To improve classification efficiency, [9] explored various ML-based classification methods, proving that transfer learning techniques significantly improve recognition accuracy in large-scale datasets [9]. Biassed learning and poor generalisation result from the uneven proportion of Areca nuts in the datasets. Some Arecanuts often lead to misidentification due to their similar texture and colour patterns. It is costly and time-consuming to compile large-scale labelled datasets, which are necessary for traditional DL models. It is difficult to do real-time classification on mobile devices due to the resource-intensive nature of most DL models. The proposed technique circumvents these constraints by incorporating the following significant enhancements:

- Feature extraction is done using MobileNetV2 which is a lightweight CNN design, which improves the accuracy.
- Classification using SVM is done consequently that aids in the classification of classes, which lessens the misclassification.
- Data augmentation enhances generalisation capability and balances the dataset.
- Precision, recall, and specificity are improved over existing CNN models.

This is how the article is structured: Section 2 focusses on the existing works done on the classification of Areca nut images using mobilenet and SVM. Section 3 discusses the proposed technique. Section 4, analyse the study and its findings in depth, and also highlights some of the research's shortcomings. Section 5 concludes the article, followed by the references.

2. LITERATURE REVEIW

Li et al. [10] introduced a diffusion transformer combined with a knowledge graph to improve agricultural classification tasks. This method mixes graph-based reasoning with DL to advance accuracy in classifying agricultural products. The model mainly relies on a single-view training system, which limits its ability to capture multi-perspective data. The advantages consist of improved classification accuracy and better contextual understanding of data. However, limitations include dependency on structured knowledge sources and lack of multi-view adaptability.

Naik et al. [11] discussed to classify X-rays of areca nuts; comparing how well traditional CNN models work with quantum CNN (QCNN). The Shufflenet model, with a scale factor of 2.0, excelled in classification accuracy. The accuracy attained by the ShuffleNet model using QCNN is quite remarkable. Compared to conventional CNN models, QCNN-based models demonstrated much higher classification accuracy, demonstrating QCNN's superior performance efficiency. One of the constraints is that although QCNN models were quite accurate, their size (28.40 MB) was too big for certain contexts that don't have a lot of resources. Furthermore, the use of QCNN may limit the model's usefulness in all circumstances, depending on hardware and computing resources. A dataset of Areca nut X-ray images was employed to investigate classification algorithms.

Ghate et al. [12] explored about the hyperparameter optimization in YOLO-based models for arecanut classification and grading. This work proposed a modified YOLO model that includes GhostNet, Transformer blocks, and deep feature extraction to improve classification performance. The advantages of this work include enhanced model efficiency, improved accuracy in feature recognition, and real-time applicability. However, the approach faces computational challenges and requires high-quality input images for optimal performance.

Naik et al. [13] used X-ray imaging to grade areca nuts without damaging them. The study suggests a hybrid areca nut grading model based on the YOLOv5 (You Only Look Once) architecture. This model improves performance by combining the Stem, Ghost Net, and Transformer blocks. The hybrid model demonstrated great accuracy in this experiment. Because of its small size (9.5 MB), the model may be easily integrated into X-ray equipment for use in industrial applications. One potential drawback is that the method may not work as well in more complicated or severe situations. Particularly when dealing with specialised equipment, the model's deployment in rural or isolated areas might cause logistical issues. Specifically for the purpose of automatic grade interpretation, a dataset consisting of X-ray images of areca nuts.

Saranya et al. [14] implemented using the Cuckoo Search Algorithm (CSA), an optimisation strategy inspired by nature, a method for nut image segmentation is presented. The CSA can enhance the efficiency of segmentation algorithms, enabling automated sorting and yield estimates.

These algorithms assist in extracting crucial information linked to nuts, such as size and quality. Supporting automated sorting and quality control, this approach effectively improves segmentation accuracy. CSA is useful for enhancing the overall performance of segmentation algorithms by optimising their guidance parameters. The project focusses on agricultural applications, which will help the food industry with yield estimates and quality assessment. The main drawback is that segmentation via CSA might be resource intensive. The outcomes, which significantly depend on the quality and consistency of the input images, affect the algorithm's resilience. Although it is not stated in the research, the dataset used for segmentation tasks is centred on nut images.

Hegde et al. [15] defined a CNN-based method for disease detection in Areca nut plants. The CNN network was trained using a private dataset of 1,100 images of healthy and ill Areca plants. With accuracy serving as the principal measure of assessment, the model employs binary cross-entropy as a loss function. Additionally, it recommends efficient methods of disease prevention and control. Using the Areca plant's nuts, trunks, and leaves as examples, this study shows that the CNN model can detect diseases in these areas. It streamlines the detection process, making it easier to manage huge plantations without relying on physical labour or visual examinations. Adding safeguards improves the system's usefulness in the real world. Reliable disease detection requires a well-designed laboratory setting, which limits its field usefulness. With just 1,100 images to work with, the dataset's small size might affect the model's accuracy. Our unique dataset includes 1,100 images of Areca nuts, stems, and leaves in both healthy and sick states.

Naik et al. [16] highlighted a YOLOv5 architecture-based DL model for efficient and lightweight real-time Areca nut detection. The YOLOv5 neck structure uses a Feature Pyramid Network (FPN), and Darknet-53 convolutions use Ghost Net to boost speed. With a small footprint of only 1.9 MB, this type is ideal for use in industrial settings. The model allows real-time Areca nut detection and grading, which is valuable in commercial settings. Reduced deployment costs are a result of the model's small size, which makes it suitable for industrial applications and lightweight. One drawback is that a hybrid model, which incorporates several cutting-edge approaches, can be difficult to put into practice and would require a dedicated setting for processing data in real time. Its efficiency could change as a result of operational factors and deployment size. The research specifically uses an Areca nut image dataset for detection and grading tasks. But it doesn't say how many images are in the dataset. Table 1 shows the existing review work.

Table 1. Existing work

Papers and Authors	Methodology	Advantages	Limitations
Naik et al. [11]	Transfer learning with CNN and QCNN	Achieve a higher level of classification accuracy when using ShuffleNet.	The size of the model (28.40 MB) and transfer learning may require significant resources.
Naik et al. [13]	X-ray imaging and YOLOv5-based hybrid grading model (Stem, Ghost Net, Transformer blocks)	With a non-destructive grading process and a lightweight model (9.5 MB), and appropriate for inclusion in X-ray equipment.	They might have trouble being deployed in rural or distant areas, and they might not be able to handle very complicated situations or harsh weather.
Saranya et al. [14]	CSA applied to nut image segmentation	It improves the segmentation process for evaluating quality, estimating	Because of the computational difficulty of CSA on big datasets, this requires

Vol. 22, No. 1, (2025)
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		production, and sorting.	tweaking to account for different nut image quality.
Hegde et al. [15]	CNN-based system (includes trunks and leaves), with a proprietary dataset of 1,100 images	Recognise and classify diseases across nuts, trunks, and leaves, provides recommendations for preventive actions, and boasts a simple design.	For cross-validation in bigger plantations, visual examination is still necessary, since the dataset used was limited to 1,100 photographs
Naik et al. [16]	YOLOv5 architecture with Ghost Net and FPN for real-time areca nut detection and grading	Efficient and lightweight (1.9 MB model size), ideal for real-time industrial applications, accurate classification, and compact design	Lack of generality without more testing in varied environments, and the results may not be consistent across all scenarios.
Meshram et al. [17]	Developed a hyperspectral imaging model combined with transformer-based deep learning for crop classification.	Improved disease classification accuracy, efficient feature extraction.	May not generalize well to other crop types.
Ngugi et al. [18]	Introduced a feature selection technique for optimizing deep learning-based agricultural classification.	Reduces computational cost, enhances interpretability.	Sensitive to data imbalance and requires tuning.

3. Proposed Methodology

An Areca nut classification model that combines MobileNetV2 with SVM leads to outstanding efficiency and accuracy, is implemented in this work. The MobileNetV2 network extracts deep features, and then uses an SVM classifier for final classification. Then the dataset is pre-processed, which includes healthy and sick Areca nut images, by resizing, enhancing, and normalising them to improve the model's

Vol. 22, No. 1, (2025)
ISSN: 1005-0930

generalisation. The performance indicators such as recall, specificity, accuracy, and precision are employed to evaluate the model's effectiveness after training it on a stratified dataset. The proposed approach uses SVM for classification, in contrast to conventional CNN classifiers, which use fully linked layers. This hybrid model is well-suited for practical agricultural applications, according to the findings, as it increases classification accuracy while preserving computing economy. Figure 1 shows the proposed flow diagram.

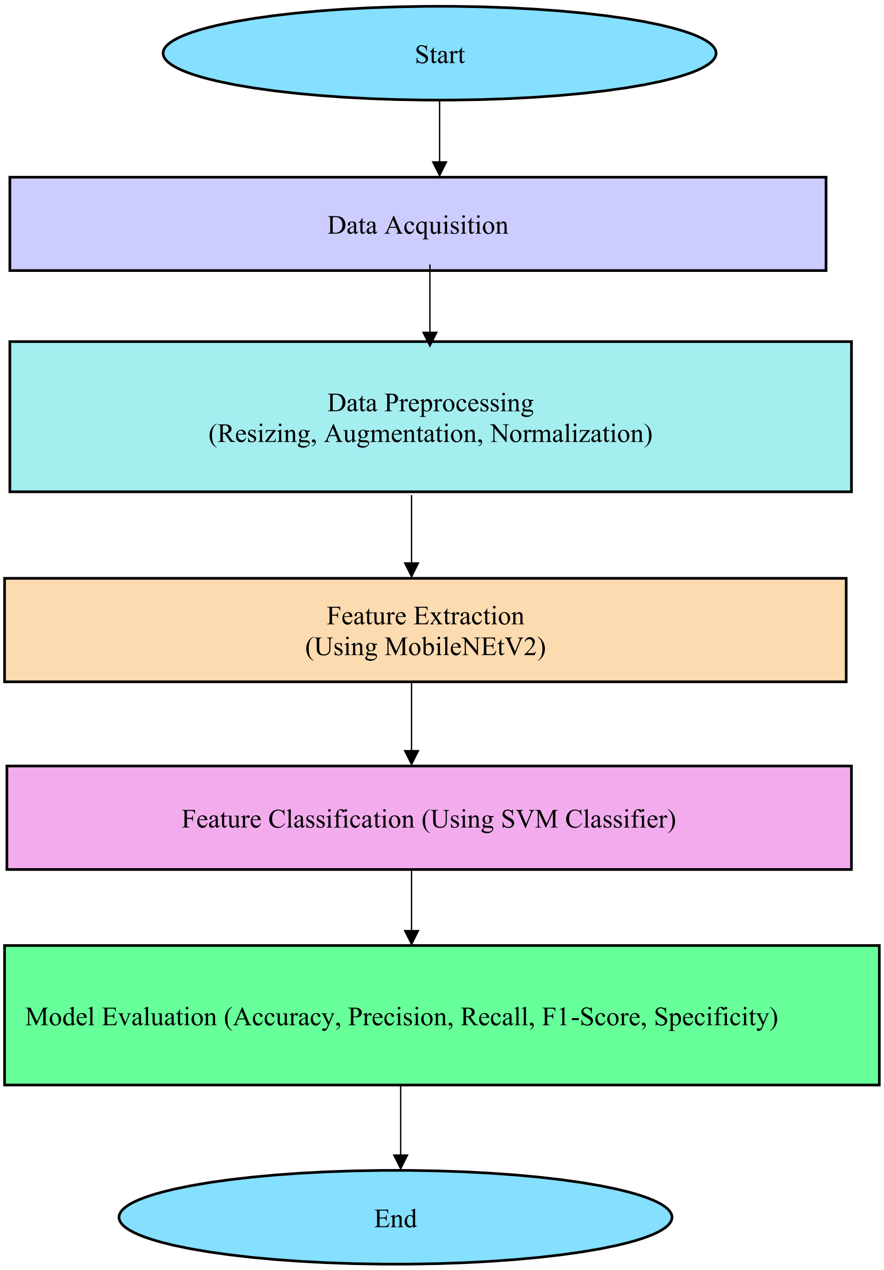
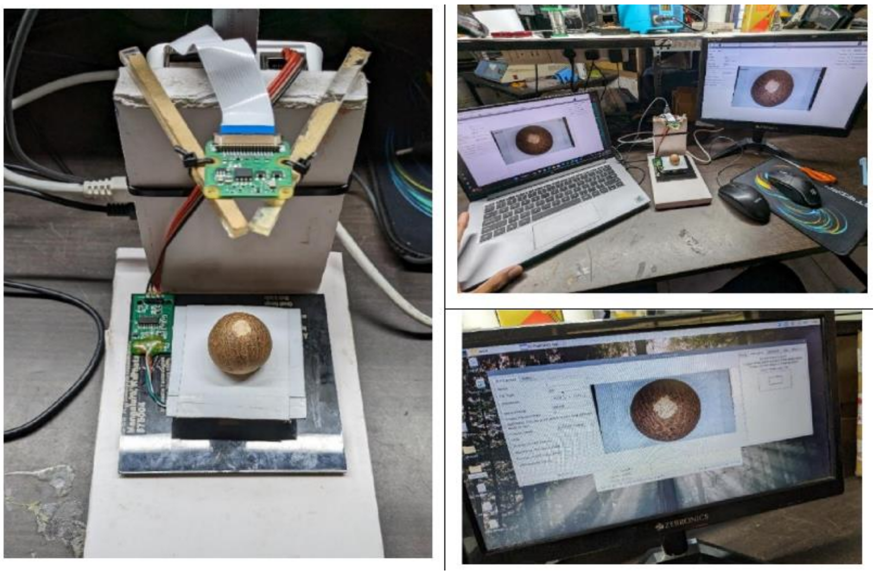


Fig. 1 Proposed Flow diagram

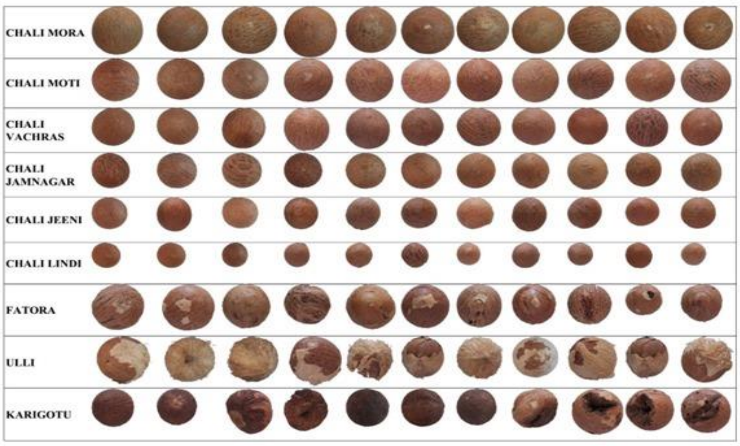
Vol. 22, No. 1, (2025)
ISSN: 1005-0930

3.1. Image Acquisition

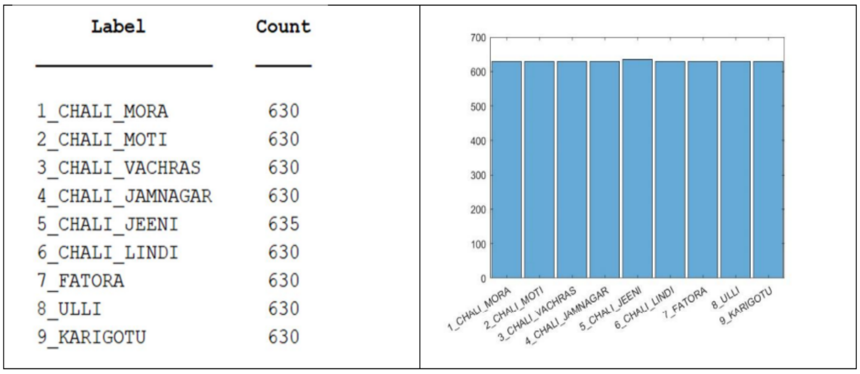
The surface of the arecanut displays its hemispheroidal shape to the greatest extent. When the arecanut is calm and relaxed, a camera can capture its image. Using a Raspberry Pi 4, Pi Camera Module 3, and a load cell, an Arecanut Image Acquisition Unit is created to help with the efficient capture of weight and images of these nuts. A diffused lighting system is employed to capture the images, which resulted in almost consistent illumination. Recordings of 5675 Arecanut images in 9 classes is given, along with their corresponding weights, for analysis. With diffuse lighting, the obtained images have almost uniform illumination. Morti, Vachras, Jamnagar, Jeeni, Lindi, Fatora, Ullibi, and Karigutu are the nine classes that make up the dataset used in this research. The weights of all nine classes are also included in an Excel file. This research used 30% of the data for testing, and 70% for training. This research incorporates nearly 600 images for each class. This dataset is pre-processed by downsizing, reconfiguring, and converting arrays of images. In order to send the images into MobileNet, it additionally scales them to 224 × 224 × 3. Figure 2 provides the necessary illustration.



(a)



(b)



Label	Count
1_CHALI_MORA	630
2_CHALI_MOTI	630
3_CHALI_VACHRAS	630
4_CHALI_JAMNAGAR	630
5_CHALI_JEENI	635
6_CHALI_LINDI	630
7_FATORA	630
8_ULLI	630
9_KARIGOTU	630

(c)

Fig. 2 (a) Image Acquisition unit (b) Different Classes (c) labels and counts with nine different arecanut classes

3.2. Preprocessing Steps

This study's preprocessing phase includes the following procedures. After retrieving the dataset directory, image loading automatically labels the images. Image resizing verifies that all images are the exact size needed for MobileNetV2 (224×224×3) input. Augmentation of data ensures that there is no imbalance in the classes by selecting images at random.

3.3. MobileNetV2 for Feature Extraction

Real-time deployments utilise MobileNetV2, which is an efficient and lightweight CNN. When compared to other CNNs like ResNet and VGG, it uses linear bottlenecks and depthwise separable convolutions to cut computation time by a huge amount. The main parts of MobileNetV2 are

- Depthwise Separable Convolutions: It uses two independent layers instead of the usual convolutions. The depthwise convolution applies a single filter per input channel. Then the pointwise convolution (1x1 Conv) combines features across channels.
- Linear Bottleneck Layers: While lowering the number of parameters, it helps keep high-dimensional feature maps.
- Inverted Residual Blocks: This use shortcut connections to preserve spatial information.

The standard convolution operation is denoted as in equation (1).

$$Y = W * X + B \qquad (1)$$

Where X is the input image, W represents convolutional filters, B is the bias term and $*$ denotes convolution. Depthwise Convolution is denoted as in equation (2).

$$Y_d = \sum_c X_c * W_d \qquad (2)$$

Where Y_d is the depthwise convolution output, X_c represents the input channel and W_d is the depthwise filter. Pointwise Convolution is denoted as in equation (3).

$$Y_p = \sum_i Y_d * W_p \qquad (3)$$

Where W_p is the pointwise filter.

3.4. SVM for Classification

When it comes to classification problems, one potent supervised learning technique is SVM. In a high-dimensional space, it operates by finding an optimal hyperplane that optimally divides several classes. MobileNetV2's logits layer pulls out deep features, which are then fed into an SVM classifier instead of a fully connected layer to help with classification. The hybrid approach is particularly useful for enhancing accuracy and class separability in borderline instances. Here the hyperplane equation used is equated in (4):

$$\omega^T x + b = 0 \qquad (4)$$

Where ω is the weight vector, x is the feature vector and b is the bias term. Optimization function is denoted as in equation (5) and (6).

$$min \frac{1}{2} \|\omega\|^2 \qquad (5)$$

Subject to

$$y_i(\omega^T x_i + b) \geq 1 \qquad (6)$$

Where y_i represents class labels and x_i represents feature vectors. Kernel Trick for Non-Linear Data is denoted as in equation (7).

$$K(x_i, x_j) = \emptyset(x_i).\emptyset(x_j) \qquad (7)$$

Where $\emptyset(\boldsymbol{x})$ is a transformation function.

4. RESULTS

For this study, the hardware requirements include a 16 GB of RAM and an Intel Core i5 processor. MATLAB 2023a, together with the Deep Learning Toolbox and the Image Processing Toolbox, is the software that was used.

4.1. Performance Measures

The different performance measures analyzed include the accuracy, precision, recall, specificity and f1 score. Accuracy measures the overall correctness of the model equated as in equation (8).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (8)$$

Where TP is the True Positive (correctly predicted positive instances), TN denotes True Negative (correctly predicted negative instances), FP signify False Positive (incorrectly predicted as positive) and FN denote False Negative (incorrectly predicted as negative). Precision measures how many of the predicted positive cases are actually positive and is formulated in equation (9).

$$Precision = \frac{TP}{TP+FP} \qquad (9)$$

Recall indicates how well the model identifies true positive cases and is mathematically stated in equation (10).

$$Recall = \frac{TP}{TP+FN} \qquad (10)$$

F1-Score is the Harmonic mean of precision as well as recall, balancing both metrics and is equated in equation (11).

$$F1 - score = 2.\frac{Precision.Recall}{Precision+Recall} \qquad (11)$$

Specificity measures the ability to correctly identify negative cases and is mathematically stated in equation (12).

$$Specificity = \frac{TN}{TN+FP} \qquad (12)$$

This table 2 shows how the proposed MobileNetV2 + SVM model stacks up against other top-level DL classifiers, like ResNet-50 (2023) [19], VGG-16 (2024) [20], and CNN + Softmax (2025) [21].

Table 2. Comparison Table

Model	Precision	Recall	Accuracy	Specificity	F1-score
Proposed (MobileNetV2 + SVM)	0.9688	0.9685	0.9685	0.9961	0.9685
ResNet-50 (2023)	0.9456	0.9443	0.9462	0.9923	0.9449
VGG-16 (2024)	0.9321	0.9302	0.9318	0.9897	0.9311
CNN + Softmax (2025)	0.9205	0.9187	0.9193	0.9865	0.9196

Because of its effective feature extraction and strong SVM classification, the proposed model higher accuracy (96.85%) outperforms ResNet-50 (94.62%), VGG-16 (93.18%), and CNN + Softmax (91.93%). Depthwise separable convolutions in MobileNetV2 provide more effective feature extraction, leading to fewer classification errors as compared to other models. By improving decision boundary learning, SVM outperforms ResNet-50 (94.43%), VGG-16 (93.12%), and CNN + Softmax (91.87%) in recall (96.85%). By properly identifying negative samples (healthy Areca nuts) while minimising false positives, the proposed model surpasses all existing appraches with a specificity of 99.61%. A high F1 score of 96.85% indicates that the model is strong when it comes to Areca nut classification, as it maintains an ideal trade-off between recall and accuracy. Figure 3 displays the performance metrics comparison graph.

Vol. 22, No. 1, (2025)
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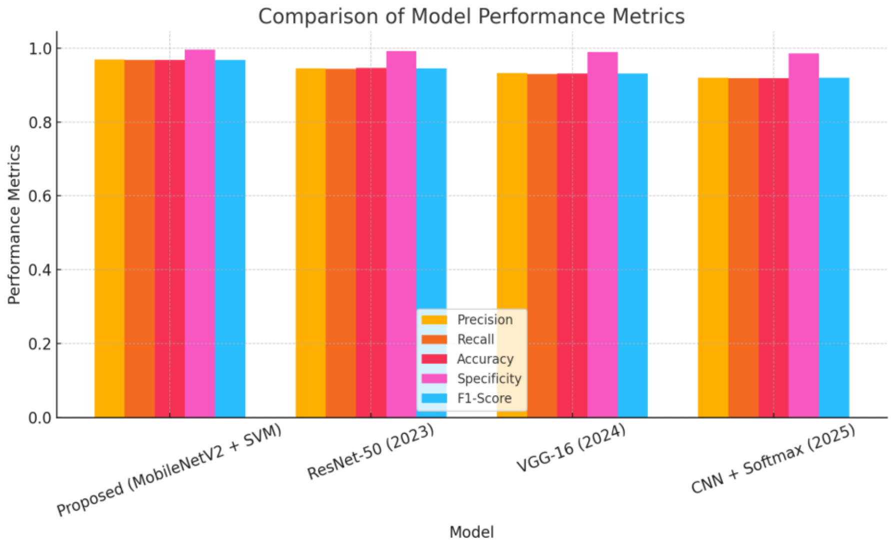

Fig. 3 Comparison graph

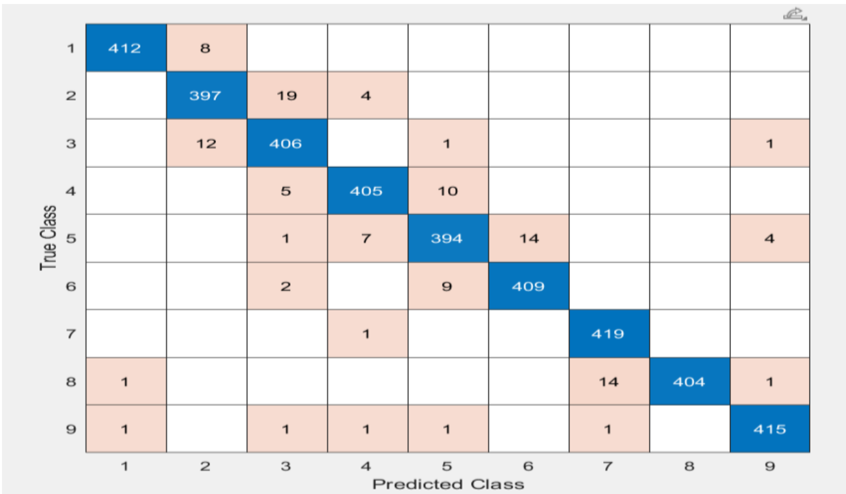

Fig.4 Proposed confusion Matrix

Figure 4 displays the proposed confusion matrix. The provided confusion matrix visualises the classification performance of the proposed MobileNetV2 image + SVM model. The number of occurrences of the predicted class (columns) being classed as the true class (rows) is shown in each cell. The diagonal cells (blue) represent examples that have been properly categorised, indicating the model's excellent performance across the majority of classes. Misclassifications are shown by cells that are peach in colour and are marked by an off-diagonal.

Since most of the data are located along the diagonal, the model shows outstanding accuracy. The general trend indicates that the classifier is dependable, while there are occasional misclassifications, especially in closely related classes. The stated performance parameters (Precision: 0.9688, Recall: 0.9685, Accuracy: 0.9685) are supported by this confusion matrix, which affirms the robustness of the MobileNetV2 + SVM technique in classification tasks.

4.2. Discussions

With its efficiency optimizations, MobileNetV2 uses a much smaller number of parameters compared to ResNet50 and VGG-16. While reducing computational cost, depthwise separable convolutions enhance feature extraction. Instead of fully coonected Softmax layers, the proposed model uses SVMs for classification. This makes decision boundaries clearer than with most DL classifiers. The model does a great job with borderline cases, owing to the MobileNetV2's high-dimensional feature extraction and SVM's great classification abilities. The proposed model is more suited for mobile applications and edge computing devices than ResNet-50 and VGG-16, which both need significant GPU computation.

5. Conclusion

The proposed MobileNetV2 + SVM model for Areca nut classification is an efficient, effective, and scalable approach. With the help of the light MobileNetV2 architecture for feature extraction and SVM for classification, the model is 96.85% more accurate than popular CNN classifiers such as ResNet-50 (94.62%), VGG-16 (93.18%), and CNN + Softmax (91.93%). While maintaining classification performance, MobileNetV2's inclusion of depthwise separable convolutions greatly decreases computing costs. Furthermore, the model accurately recognises areca nuts with a specificity of 99.61%, resulting in minimal false positives. With a recall of 96.85% and a precision of 96.48%, the model successfully detects infected areca nuts, even in difficult real-world situations. To make areca-nut classification easier in the field, the model will be optimised for embedded and mobile devices in the future. Further, the model will be applied to an IoT smart farming system to track the quality of Areca nuts in real-time. For better generalisation, it would be beneficial to gather a more varied dataset that accounts for various lighting situations, camera angles, and environmental variables. Continuing to investigate hybrid CNN-SVM models and deep learning architectures based on transformers as potential means of improving performance

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