Arecanut grading classification based on representational deep neural network with support vector machine

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Article Info

Article history:

Received Sep 18, 2024
Revised Mar 28, 2025
Accepted Jul 5, 2025

Keywords:

Convolutional neural network
Deep learning method
Machine learning
ResNet
Support vector machine

ABSTRACT

The grading of arecanuts before their sale is significant for enhancing profitability. The assessment of areca nut quality widely utilizes and respects both producer-level and wholesale dealer-level grading methods. This study proposes an advanced grading framework for white Chali-type arecanuts by developing a standardized image database and utilizing deep learning-based feature extraction. This research presents a novel approach by combining a representational deep neural network (ResNet) for automatic feature extraction with various spectral analysis methods, such as the Fourier transform and wavelet transform, to capture frequency-domain features. The support vector machine (SVM) model classifies these extracted features. The proposed system achieves an accuracy of 97.8%, which is significantly better than existing methods SVM with 72.5%, convolutional neural network (CNN) with 92.9%, AlexNet with 90.6%, and VGG19 with 90.2%. The results show that the proposed hybrid ResNet-SVM method improves accuracy, precision, recall, and F1-score, making it a more reliable and automated way to grade areca nuts. This method thus enhances efficiency, reduces manual effort, and ensures consistent quality assessment.

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1. INTRODUCTION

Traditional cultures have long used arecanuts, also known as betel nuts, and arecanuts are widely cultivated in South Asia, East Africa, and parts of the tropical Pacific. The tree's seeds yield its nuts [1]. X-ray radiography is a helpful, non-destructive method for examining the inside workings or quality characteristics of agricultural goods, such as arecanut. Combining visual assessment with destructive measures can accurately determine the genuine quality of an arecanut. Dissected arecanuts don't keep well, however. A non-destructive approach for grading arecanuts does not yet exist. To do interior investigations of arecanuts thoroughly and without inflicting harm, it uses X-ray imaging as a tool [2].

The manual segregation process takes a lot of time and might result in incorrect classification. Performance in multi-class problems has increased with recent developments in deep learning (DL). The current study uses an effective areca nut DL-customized convolutional neural network (CNN) to classify de-husked areca nuts into five groups, and compares the model's output with the conventional AlexNet architecture [3]. The goal is to categories areca nuts into excellent and poor-quality categories according to their color and texture characteristics. A conveyer unit, a lighting unit, and an image capture unit constitute the system. Image processing (IP) is handled by LabView on a PC as well as the sorting unit [4].

Technological breakthroughs may significantly impact the economic expansion of India's agriculture sector. One such area of agriculture is areca nut farming, where investments in automation and technology may increase agricultural profits by lowering production costs. Karnataka grows the areca nut, its primary crop, in fifteen distinct districts [5]. The suggested method uses IP to classify nuts into good and harmful categories. It takes as input images of raw (with husk) areca nuts. Background removal is a step in the classification process that eliminates shadow effects from the gathered images. Using the Otsu approach, the affected areas are identified. The raw areca nut set includes both healthful along with harmful areca nuts [6].

However, this used techniques from DL and machine learning (ML) to carry out automatic classifications. However, a thorough analysis of the arecanut's interior structure is necessary to determine its genuine quality. As a result, it used the X-ray imaging method to assess the interior worth of arecanuts. A new dataset of arecanut is created for X-ray images, as well as a DL architecture created on YOLOv5 for classification [7]. Areca nuts, also known as betel nuts, are a tropical crop. In terms of areca nut production and consumption globally, India comes in second. A multitude of diseases plague it, from root to fruit. There are few steps as crucial as cultivation classification when it comes to crop management. For varying grade levels, classification may be helpful [8].

Despite the addition of conventional as well as deep image techniques in hybrid networks, additional advancements in the deep image component are necessary to effectively utilize the image’s content. Thus, this article utilizes the strengths of both modules, relying solely on the deep network's robust feature extraction capabilities along with delegating the classification job to the SVM module. It uses the ResNet model for feature selection. All of these parts work together to make deep residual networks, and the SVM classifier does feature extraction and classification much more accurately. In the agricultural sector, grading the quality of arecanuts before they are sold is essential for ensuring fair market prices. Traditional grading methods, however, rely heavily on manual sorting, which is time-consuming and prone to human error. Additionally, these methods often fail to provide an accurate internal quality assessment, leaving a gap in ensuring the best quality for both producers and consumers. This proposed image classification technique integrates ResNet with SVM, and its key contributions are: i) initially with the input dataset an Fourier transform based spectral analysis method is employed to extract the features to understand the internal quality, ii) this research then additionally uses ResNet to extract image features and simultaneously enhance the network's generalizability by avoiding feature confusion during training, and iii) thus, this work uses a hybrid classification model using ResNet and SVM. By this hybrid model, the classification performance is improved, which is validated in terms of performance metrics such as precision, recall, accuracy, and F1-score.

The structure of this work is as follows: section 2 studies arecanut grading using DL in IP. Section 3 discusses the proposed technique. Section 4 provides the specifics of the study findings and their commentary. Section 5 concludes the text, followed by the references.

2. LITERATURE REVIEW

Recently, DL and ML techniques have gained significant attention in the agricultural sector, including in the classification and grading of arecanuts. Several studies have employed CNNs and other deep learning models to address different aspects of arecanut classification, disease detection, and quality assessment. Anitha *et al*. [9] introduced a segmentation-based approach termed U-Net, as well as mask region-based CNN (Mask R-CNN) for the arecanut bunches from tree image segmentation. The challenges of manually segmenting coconut bunches served as the motivation for this approach. Mask R-CNN was better than U-Net in segmentation tasks, but it didn't have a strong internal quality evaluation, which is important for accurate grading. When it comes to grading the interior quality of the arecanut, segmentation-based methods may not be adequate, particularly given that such evaluations are critical for differentiating between healthy and diseased nuts.

Anilkumar *et al*. [10] used CNNs to find diseases in arecanuts, leaves, and trunks as well as provide recommendations for treatment. With a dataset of 620 images, their algorithm was able to attain an accuracy of 88.46%, including both healthy and diseased images. But this method ignored the interior quality—an essential part of arecanut grading—in favor of more superficial features, such as visible diseases. The dataset's small size and lack of environmental component variety may also restrict the model's applicability.

Mallikarjuna *et al*. [11] explored the use of multi-gradient images with deep CNNs for multi-type arecanut image classification. The classification of damaged or diseased arecanuts was improved by their technique. It was good at fixing distortion on the surface, but it failed when it came to grading images with serious imperfections or poor quality. On top of that, their method relied heavily on hand-tuning the Sobel filters to extract features, which might be inefficient when used on a massive scale.

Patel and Patil [12] proposed an advanced CNN based approach that employs adaptive momentum backpropagation (BP), spatial pyramid pooling (SPP), as well as finite impulse response (FIR) filter for preprocessing. This approach improved the identification of fruit diseases while preserving the quality of the images. Unfortunately, it followed the trend of other CNN-based methods in not taking internal quality into consideration when evaluating arecanuts; this is especially important when it comes to grading.

Elaraby *et al*. [13] discussed the use of DL and IP to identify and categorize diseases in citrus trees. This method demonstrates the value of computer-aided diagnostics in farming with a strategy that focuses on diseases affecting citrus fruits. Unfortunately, it doesn't include arecanuts and doesn't assess internal aspects as thoroughly as your research aims to.

Billadi *et al*. [14] proposed a ML-based approach based on their color, texture, and density values. Despite the method's potential, it is limited to surface-level characteristics and fails to include interior structural defects—essential for complete grading—when classifying arecanuts into various quality groups. Krishna *et al*. [15] tackled arecanut disease prediction based on weather data and ML. The method relies on meteorological data, which restricts its use to external aspects rather than internal quality classification, and it ignores the grading component, although it is useful for disease prediction.

Lei *et al*. [16] investigated the correlation between the amount of live vegetation (LVV) as well as the arecanut yellow leaf disease severity using high-resolution UAV remote sensing images. Although this study adds knowledge of plant health, it doesn't solve the problem of evaluating the nuts' interior qualities or deal with quality grading from the inside.

Hegde *et al*. [17] utilized CNNs for disease in arecanuts, stems, and leaves, which were able to provide excellent suggestions for disease management. The technique has an important weakness when it comes to grading, however, as it is only good for identifying diseases and not for assessing the nuts' intrinsic quality. Jin *et al*. [18] applied remote sensing and ML algorithm for mapping arecanut planting distribution. Although the geographical distribution of arecanuts is better understood due to this study, the topic of quality-based arecanut classification or grading remains unclear. Table 1 tabulates the details of the existing work analysis.

Table 1. Literature works comparative analysis

Ref.	Method	Dataset	Advantages	Limitations
[9]	U-Net, Mask R-CNN for segmentation	Arecanut bunch images from images	Effective segmentation of arecanut bunches	Focuses only on segmentation and lacks internal quality assessment
[10]	CNN for disease detection	620 images of healthy and diseased	High accuracy in surface-level detection	Limited dataset does not consider internal quality
[11]	CNN and multi-gradients images	Arecanut images	Improved classification of damaged nuts	Do not address internal quality and rely on manual feature testing
[12]	CNN with adaptive momentum, SPP, and FIR	Fruit disease images	Preserves image quality for accurate disease detection	Focuses only on external features and lacks internal quality assessment
[13]	DL and IP for plant disease diagnosis	Citrus disease images	Effective for citrus disease diagnosis using computer-aided tools	Does not extend to arecanuts; lacks internal feature evaluation
[14]	ML-based sorting (color, texture and density)	Arecanut images	ML-based sorting of arecanuts by quality	Focuses on surface-level features; lacks internal quality analysis
[15]	ML for disease prediction	Weather data, farmer surveys	Predicts disease based on environmental factors	Focuses on disease prediction; does not address grading or internal quality
[16]	Remote sensing and ML for disease severity	UAV remote sensing data	Focuses on disease severity mapping using high-resolution imagery	Does not focus on grading or internal quality of arecanuts
[17]	CNN for disease detection	Arecanut, stem, and leaf images	Detects diseases with CNNs and provides preventive strategies	Lacks internal quality grading capabilities
[18]	Remote sensing and ML for spatial mapping	PlanetScope images	Provides high-resolution mapping of arecanut distribution	Does not address quality grading or internal characteristics of arecanuts

3. METHOD

Using ResNet and SVM and spectral analysis, this research proposes a model for white Chali arecanut image classification. Figure 1 provides a general outline of the proposed model. During the image preprocessing step, it all started with resizing the original image. Resnet performs an initial feature extraction on every image block while normalizing the data for appropriate features. This provides the feature maps in a one-dimensional format using fully connected layers, as the SVM classifier requires a specific data structure. The classifier then used the processed data to get the final result.

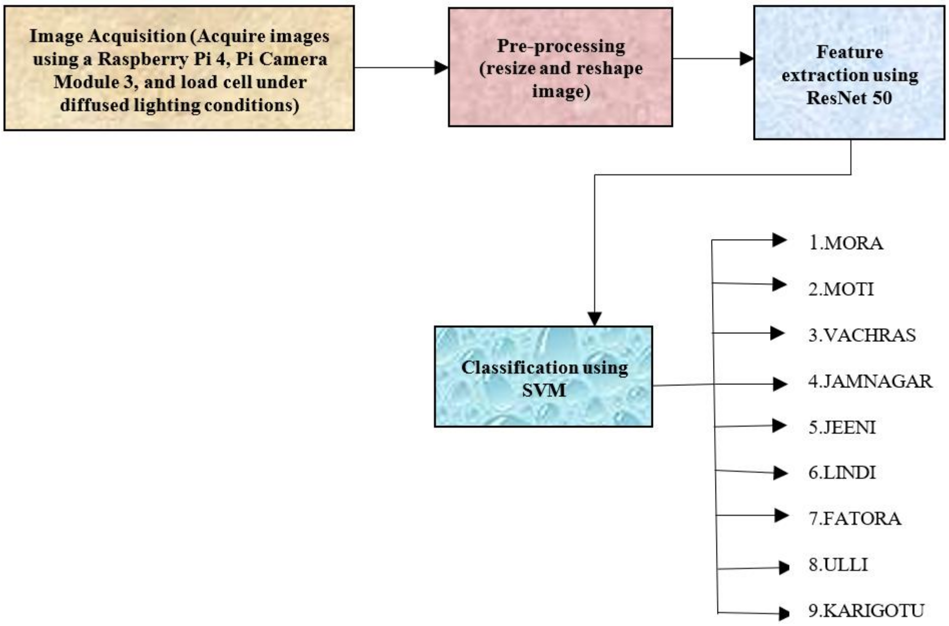


Figure 1. System architecture diagram

3.1. Image acquisition

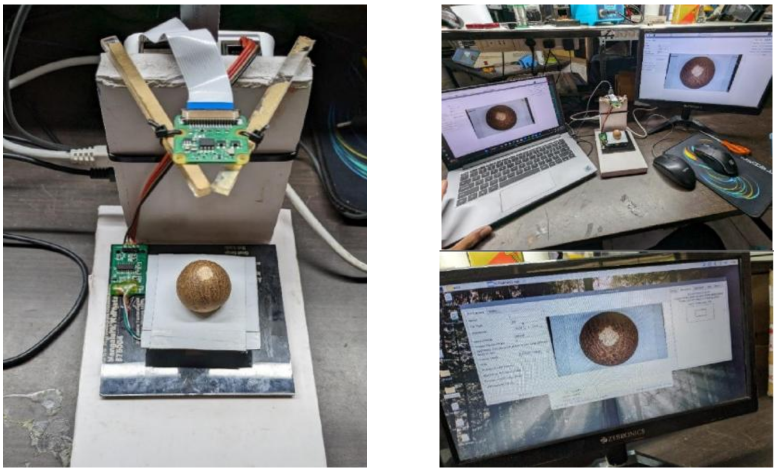
The arecanut's hemispheroidal form is most pronounced on the surface. It takes an image with a camera when the arecanut is resting steadily. To facilitate efficient capturing of arecanut image and weight, this work has developed an arecanut image acquisition unit by using the image acquisition unit such as the Raspberry Pi 4, Pi Camera module 3, and loadcell. The Raspberry Pi 4 uses an interface with the Pi Camera Module 3 for capturing images. The Pi Camera module 3 provides high-resolution image capture with optimal lighting control. Finally, the load cell measures the weight of the arecanuts alongside the image. The images are captured with diffused lighting to have almost uniform illumination. A total of 5675 arecanut images of 9 classes and their weight were captured for analysis purposes. Diffuse lighting achieves almost consistent illumination in the acquired images. The dataset for this study consists of nine classes: MORA, MOTI, VACHRAS, JAMNAGAR, JEENI, LINDI, FATORA, ULLI, and KARIGOTU. Additionally, an Excel file contains the weight of each of the nine classes. This study, used 30% for testing as well as 70% of the data for training. There are almost 600 white challi arecanut classes in this study. This has preprocessed this database by resizing, reshaping, and converting arrays of images. It also scales the images to 224×224×3 to feed them into ResNet [19]. This illustration is given in Figures 2(a) and (b).

3.2. Pre-processing

Initially this research applies spectral methods that is wavelet transform to preprocess the images before feeding them into the ResNet model. The Fourier transform and similar techniques work well for frequency analysis, but they can't pinpoint the exact location of features in an image. When it comes to textural feature extraction for image classification, the wavelet transform is superior since it can localize features in both time and frequency. The spectral features obtained capture texture-based distinctions between healthy and diseased arecanuts that might not be readily apparent in the raw image, improving the model's performance. Wavelet transform allows multi-resolution analysis of an image, as it can capture details at different scales. This is especially useful for detecting subtle textural patterns that differentiate healthy arecanuts from diseased ones, which might not be captured effectively by pixel-based deep learning alone. The multi-scale nature of wavelets helps the model to detect fine details and edges in the image that could be critical for accurate classification. These details might include micro-textural features like cracks, discoloration, or other subtle patterns that distinguish diseased from healthy nuts, improving classification performance.

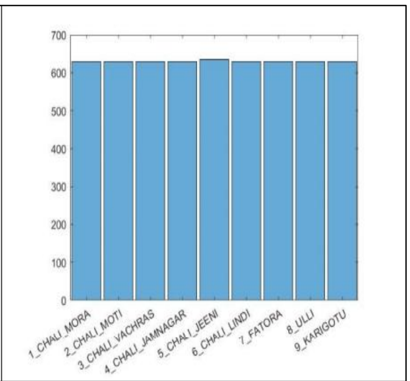
When looking for a method to capture both the low-and high-frequency components of an image—for example, fine textures or subtle patterns in arecanuts that differentiate healthy from diseased ones—wavelet transforms deconstruct the image into distinct frequency components at different scales. There are micro-textures and tiny surface irregularities in the arecanut images preserved by wavelets, which would otherwise go unnoticed by pixel-based features or even DL algorithms. Wavelet transforms are also an excellent choice to help in denoising images by focusing on relevant frequency components and suppressing irrelevant ones. This could be especially useful if the images have any noise (e.g., image artifacts, lighting variations, and background clutter). By extracting more relevant features (e.g., texture patterns or edges), the model is less likely to be confused by irrelevant details or noise, leading to improvements in precision and recall.

ResNet, being a deep convolutional network, extracts hierarchical features from raw images (e.g., edges, textures, and high-level patterns). However, it might miss certain frequency-domain features that could be key to classifying textures or surface anomalies. Wavelet-based features will provide a complementary view of the data by representing it in terms of frequencies and local textures. When combined with features learned by ResNet, the model gets a richer representation of the arecanuts, making it better at differentiating between subtle differences in textures that characterize healthy and diseased nuts.



(a)

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



(b)

Figure 2. Overall workflow of the image acquisition system and class distribution; (a) image acquisition unit and (b) arecanut diversity: counts across nine distinct classes

3.3. Representational deep neural network

There are many kinds of ResNet, but the most popular and cutting-edge for image classification are ResNet-18 and ResNet-50. This work makes use of the ResNet-50 model. An intermediate pool layer, 48 coiled layers, 1 MaxPool, and the ReLU activation algorithm make up the ResNet-50 model. Overfitting happens in a front-fed neural network when a hidden layer with a lot of parameters makes the network training depend on a small part of the data, even though that part only has the neurons needed to seal in the data using linear methods. ResNet is able to circumvent this problem. The overfitting issue hindered ResNet's ability to accurately categorize images [20], [21]. ResNet achieved to work with the vanishing gradient issue, which arises from iteratively multiplying the derivative value of the initial layers, thereby reducing the derivative value. Prior to the development of the residual network, researchers attempted to address these issues by introducing loss into the intermediate layer; however, the ResNet demonstrated incredible efficiency in dealing with these issues. The ResNet main principle is to decrease the number of layers by incorporating a shortcut connection. This relation eliminates or significantly decreases the need for one or more network structures, ultimately leading to fewer mistakes while training with data. Here are the original residual unit's in (1) and (2):

$$y_1 = h(X_1) + f(X_1, W_1) \tag{1}$$

$$X_{l+1} = f(y_1) \tag{2}$$

where f is the stack residual function of two 3×3 convolutional layers, x_l is the input feature, and w_l is a weights collection (along with biases). This is the operation that follows element-wise addition, as well as the function f is ReLU. In (3) configures the function h as an individuality mapping to calculate the features.

$$x_L = x_1 + \sum_{i=l}^{L-1} F(x_i, w_i) \tag{3}$$

L is the sum of the outputs of every residual function that preceded it, and the feature x_L is a series of matrix-vector products. The (4) functions as the loss equation, which is E, derived from the BP chain rule.

$$\frac{\delta E}{\delta x_l} = \frac{\delta E}{\delta x_L}\frac{\delta x_L}{\delta x_l} = \frac{\delta E}{\delta x_L}\left(1 + \frac{\delta}{\delta x_l}\sum_{i=l}^{L-1} F(x_i, w_i)\right) \tag{4}$$

In (4) shows the decomposition of the gradient $\frac{\delta E}{\delta x_l}$ into two additive components. One term $\frac{\delta E}{\delta x_L}$ conveys information directly, unaffected by any weight layers. The second term $\frac{\delta E}{\delta x_L}\left(\frac{\delta}{\delta x_l}\sum_{i=l}^{L-1} F(x_i, w_i)\right)$ propagates through the weight layers. The additive term $\frac{\delta}{\delta x_L}$ allows for the instantaneous transfer of any information to a shallower layer. In (4) suggests that canceling out the gradient $\frac{\delta E}{\delta x_l}$ for a mini-batch is unlikely. This is because, in general, the term $\frac{\delta}{\delta x_l}\sum_{i=l}^{L-1} F(x_i, w_i)$ cannot always be equal to -1 for each mini-batch sample. This means that even with arbitrary little weights, a layer's gradient will not disappear. Thus, by this ResNet algorithm, the most important features such as texture and color automatically [22].

3.4. Support vector machine

Binary learning classifier SVM is supervised. In this case, established labels help to show if SVM is classifying correctly. This can utilize it in learning to predict future data. SVMs are useful for both regression and classification as prediction tools. SVM automatically improves classification accuracy and avoids overfitting data by making predictions based on ML theory.

Figure 3 shows the support vector training. SVM also uses non-linear basis functions to conduct dimensionality mapping from low to high space. Using a learning approach derived from optimization theory, SVMs employ a hypothesis space of linear functions on a high-dimensional feature space. Sometimes, SVMs apply bias through statistical learning theory. To partition the data, SVM employs linear classifiers, often known as hyperplanes [23]. By this SVM the features extracted from Resnet is used to classify the arecanuts. The multiclass SVM is used in this work with linear kernel.

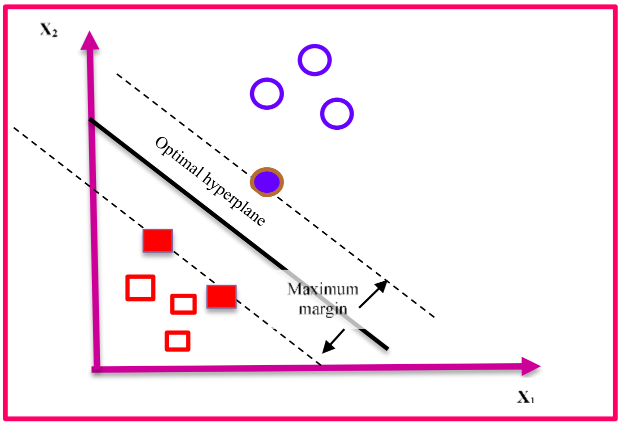


Figure 3. Support vector training

4. RESULTS

This work used a 64-GB Intel i5 processor PC for the testing. It created the algorithm model in Windows and then implemented it in MATLAB 2024a. In this study, 30% is used for testing, as well as 70% of the data for training from among 600 images for each white challi arecanut class. Hence, a total of 5400 images are in the dataset. This built a deep backbone network based on a ResNet model using the DL Toolbox. This study trained the SVM classification algorithm using the fitcecoc function. This section presents the experimental findings derived from the constructed dataset with nine classes. The proposed model uses other existing algorithms to get its classification findings. In terms of assessment metrics, the experimental findings show that the proposed ResNet-SVM model performs well.

4.1. Evaluation metrics

This constructs the confusion matrix using the following equations to evaluate the proposed ResNet-SVM model. One of the most important tools for assessing the classification models' performance is a confusion matrix. Here, it may find comprehensive data on the model's classification outcomes for every category and calculated using (5)-(9):

$$Sensitivity = TP/(TP + FN) \tag{5}$$

$$Specificity = TN/(TN + FP) \tag{6}$$

$$Precision = TP/(TP + FP) \tag{7}$$

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{8}$$

$$F1 - score = 2TP/(2TP + FP + FN) \tag{9}$$

where: TN is true negative, TP is true positive, FP is false positive, and FN is false negative.

Table 2 displays the outcomes of the proposed performance measure classification. All four metrics—precision, recall, accuracy, and F1-score—come out to 0.97%, and specificity is 99%. After incorporating wavelet transform features in the feature extraction pipeline, the model’s performance showed a slight but noticeable improvement. The precision is improved by 0.09%, recall by 0.09%, accuracy by 0.08%, specificity by 0.07% and F1-score by 0.09%. These results indicate that the addition of spectral analysis through wavelet transform improved the model's ability to accurately classify both healthy and diseased arecanuts, especially in terms of precision and specificity. The slight improvements in the metrics suggest that the model is now better able to distinguish subtle textural patterns indicative of disease, which were previously difficult to capture by the ResNet model alone. Figure 4 displays the proposed ResNet-SVM model's confusion matrix graph and Figure 5 shows the GUI output. In Figure 4, the numbers from 1 to 9 stands for the 9 different classes in this order MORA, MOTI, VACHRAS, JAMNAGAR, JEENI, LINDI, FATORA, ULLI, and KARIGOTU.

Table 2. Proposed classification results

Metrics	Proposed (without spectral analysis)	Proposed (with spectral analysis)
Precision	0.9787	0.9786
Recall	0.9784	0.9793
Accuracy	0.9784	0.9792
Specificity	0.9973	0.9980
F1-score	0.9784	0.9794

Table 3 displays the comparison results. The proposed model outperforms the other methods across all evaluation metrics, with an impressive 97.84% precision, 97.84% recall, 97.84% accuracy, 99.73% specificity, and 97.84% F1-score. SVM [18] method shows the lowest performance with 72.31% precision, 72.43% recall, 72.46% accuracy, 73.89% specificity, and 72.35% F1-score. CNN [17] provides a solid performance, with 92.78% precision, 92.89% recall, 93.05% accuracy, 94.03% specificity, and 92.82% F1-score. AlexNet [13] achieves 90.70% precision, 90.60% recall, 91.40% accuracy, 90.40% specificity, and 90.90% F1-score. VGG19 [13] performs slightly lower than AlexNet, with 90.10% precision, 90.30% recall, 91.10% accuracy, 90.20% specificity, and 90.70% F1-score.

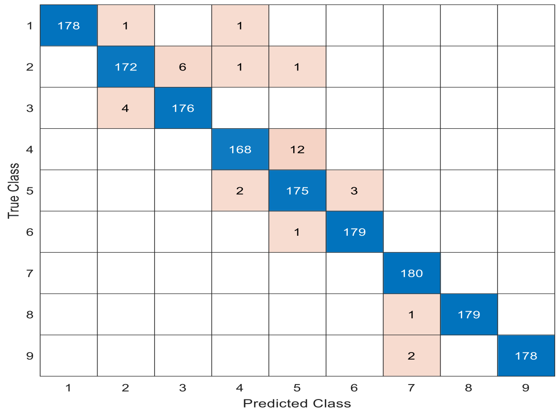


Figure 4. Proposed ResNet-SVM model confusion matrix graph

Figure 5. Method GUI output

Table 3. Comparison table

Method/metrics	Precision	Recall	Accuracy	Specificity	F1-score
Proposed	0.9787	0.9784	0.9784	0.9973	0.9784
SVM [18]	0.7231	0.7243	0.7246	0.7389	0.7235
CNN [17]	0.9278	0.9289	0.9305	0.9403	0.9282
AlexNet [13]	0.9070	0.9060	0.9140	0.9040	0.9090
VGG19 [13]	0.9010	0.9030	0.9110	0.9020	0.9070

The proposed hybrid approach (ResNet+SVM) shows superior results, consistently achieving 97-99% in all metrics, significantly outperforming the other methods. The baseline SVM classifier shows much lower performance, with results around 72% across all metrics. The CNN achieves 92-94% performance, indicating strong results but still falling short of the proposed model. Both pre-trained models, AlexNet and VGG19, show competitive performance but remain behind the proposed method, with results around 90-91%. In summary, the proposed model offers a substantial improvement over previous methods, delivering nearly perfect classification results (above 97%), while the SVM, CNN, AlexNet, and VGG19 models all perform notably lower, with accuracies ranging from 72% to 94%.

The proposed model performs excellently for most classes, with precision, recall, and F1-scores above 97%. However, some classes still show slightly lower performance metrics. Classes 2 and 7 have the highest false positive rates, indicating that the model has trouble distinguishing between these two classes. This may be due to similarities in their features, such as texture or shape. Upon inspecting misclassified images, it appears that some of the misclassifications occur due to noisy backgrounds or low-quality images. For example, Class 3 is often confused with Class 6, which might be due to their similar textural patterns.

Figure 6 illustrates the comparative performance of the proposed EfficientNet-SVM model against existing classifiers including SVM, CNN, AlexNet, and VGG19 across multiple metrics such as precision, recall, accuracy, specificity, and F1-score.

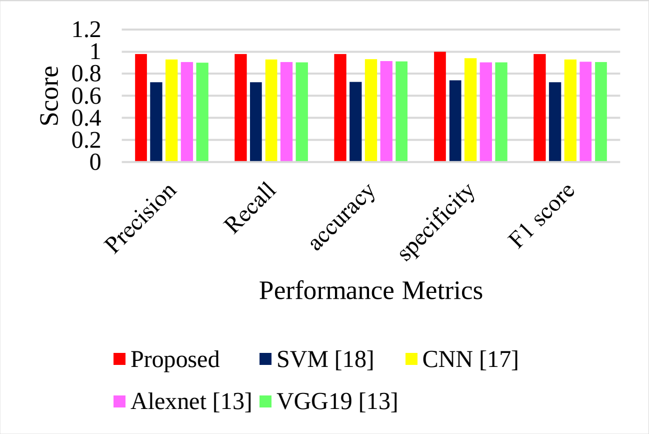


Figure 6. Comparison graph

The paired t-test compares two sets of related measurements. This work, compares the precision values for the proposed model with other models (SVM, CNN, AlexNet, and VGG19) across five different runs. Each run represents an independent trial where the model is evaluated under the same conditions, such as using different cross-validation folds, testing splits, or different random seeds. Furthermore a 5-fold cross-validation is done, and the model is trained on five folds and tested on the remaining folds. The following is the condition for the five different folds.

a. Run 1: model trained on fold 1, tested on fold 2.
b. Run 2: model trained on fold 2, tested on fold 3.
c. Run 3: model trained on fold 3, tested on fold 4.
d. Run 4: model trained on fold 4, tested on fold 5.
e. Run 5: model trained on fold 5, tested on fold 1.

After completing these five runs, the precision for each run is calculated to use those values to perform a paired t-test. The precision values for all the algorithms for five different folds are tabulated in Table 4.

Table 4. Paired p-test result for precision

Method/metrics	Fold 1	Fold 2	Fold 3	Fold 4	Fold 5
Proposed	0.9787	0.9800	0.9765	0.9792	0.9811
SVM [18]	0.7231	0.7255	0.7218	0.7259	0.7300
CNN [17]	0.9278	0.9301	0.9262	0.9290	0.9312
AlexNet [13]	0.9070	0.9100	0.9065	0.9054	0.9083
VGG19 [13]	0.9010	0.9032	0.9005	0.9028	0.9041

Also, the paired t-test results for precision are given below:

a. Proposed vs SVM: p-value=1, h=5.2648e-10.
b. Proposed vs CNN: p-value=1, h=1.0631e-09.
c. Proposed vs AlexNet: p-value=1, h=17 7.3767e-08.
d. Proposed vs VGG19: p-value=1, h=1.1721e-09.

For proposed vs SVM, the p-value for the paired t-test is 1, indicating that the proposed model significantly outperforms the SVM classifier in terms of precision. The corresponding h-value of 5.2648e-10 suggests a very strong rejection of the null hypothesis, confirming that the precision difference is substantial. Similarly, the paired t-test shows a p-value of 1 for the comparison between the proposed model and CNN. The h-value of 1.0631e-09 further supports that the precision difference between these models is highly significant. The comparison with AlexNet also yielded a p-value of 1, with a test statistic of 7.3767e-08, indicating that the proposed model's precision is statistically superior to AlexNet's performance. The paired t-test between the proposed model and VGG19 resulted in a p-value of 1, with an h-value of 1.1721e-09, confirming that the proposed model outperforms VGG19 with a statistically significant difference. These results suggest that the proposed ResNet-SVM model consistently outperforms the other methods in terms of precision, with highly significant differences across all comparisons. The precision improvement is consistent and statistically validated through multiple runs of the evaluation process.

4.2. Discussions

The white chali arecanut classification has shown encouraging results using the feature fusion approach provided in this study. Wavelet transform decomposes the image into multiple frequency components at different scales, capturing both low-frequency (global) and high-frequency (local) features. This is particularly useful for detecting micro-textural differences that are often indicative of disease. Wavelet-based features are less sensitive to noise and variations in lighting, making them effective for handling real-world image distortions and improving classification performance [24], [25].

The research shows that a ResNet-SVM hybrid model can classify white Chali arecanuts with good accuracy, recall, and precision. In order to identify arecanut diseases, the model integrates ResNet's DL capabilities with wavelet transform, which allows it to capture local and global textural information. Wavelet characteristics guarantee resistance to noise and illumination fluctuations, and the model's strong performance is a result of the integration of features from the frequency domain and the spatial domain. A more robust feature set is the result of the proposed method's capacity to merge ResNet with conventional ML (SVM). The model's ability to detect subtle disease signs is improved by using wavelet transform, which extracts multiscale information. Because the model can account for variations in both illumination and noise, it has a lot of practical uses, particularly in the agricultural sector, where both external variables often lead to distorted images. This model is able to identify healthy arecanuts with very few false positives, as shown by its high specificity and accuracy (around 97%).

Nevertheless, concerns about overfitting and generalizability pose constraints. Overfitting is a potential outcome of merging ResNet and SVM models because of their complexity. This is particularly true for datasets that are small or lack diversity. When the model is presented with data from diverse environmental variables, such as various kinds of lighting or plants, this problem might become much worse. Data augmentation, transfer learning, and regularization approaches may improve the model's generalizability to additional data, which can help with this problem. It may be computationally costly and tough for non-experts to rely on SVM's kernel function selection and hyperparameter optimization. For a more user-friendly approach, try looking at different classifiers or simpler models. Particularly in the field of precision agriculture, the ResNet-SVM model shows great promise for practical uses. Farmers may take prompt action to avoid crop loss, decrease pesticide usage, and increase yields by detecting diseases in arecanut crops early. Financial gains may follow from this in the form of reduced pesticide costs, higher yields, and more environmentally friendly agricultural methods. Furthermore, the approach might be implemented via the use of drones or smartphone applications, enabling farmers to affordably monitor diseases in real time.

To sum up, this model's approach to agricultural disease identification is promising since it combines DL with classical ML. The tool's potential to improve agricultural practices and economic results for farmers makes it important in precision farming, despite certain limitations related to model complexity and overfitting. This method has the potential to have an even greater effect on real-world applications if model generalization and hardware integration are further improved.

5. CONCLUSION

This study effectively categorizes white Chali arecanuts into nine groups using a ResNet with SVM hybrid model. This study, demonstrated the effectiveness of combining ResNet with SVM and further enhanced by incorporating wavelet transform for spectral feature extraction. The results show improvements in the model’s performance in precision, recall, f1-score, and accuracy. The wavelet transform integration enables to better capture both global and local textural features, addressing the challenges related to non-linear separability and overlapping categories. The use of ResNet's feature extraction capabilities and SVM's robust classification module provides a more precise and reliable classification framework for white Chali arecanuts, overcoming typical limitations such as noise sensitivity and outliers. Also, the study recognizes certain limitations and areas for further development. Firstly, the study does not explore various SVM kernel functions, so future work will delve into optimizing kernel parameters to assess how different kernels influence classification performance. Additionally, the current research relies on a single dataset, and while the results are promising, there is a need to validate the model's generalizability across a broader range of datasets. In terms of practical application, the model is currently implemented in a software environment, but there is considerable potential for transitioning this system to hardware for real-time deployment in agricultural fields. Future work will explore the feasibility of integrating the classification system into smart farming solutions, such as using drones or mobile devices, for automated disease detection and grading of arecanuts. Hardware implementation will help bridge the gap between lab-based research and on-ground agricultural practices, enabling farmers to access real-time, on-site assistance.

ACKNOWLEDGEMENTS

We gratefully acknowledge The Managing Director, CAMPCO Ltd, Mangalore, for granting permission to collect different grades of arecanut samples for this study. Our sincere thanks to Shri Santhosh Panjarike, Senior Manager, CAMPCO Ltd, Kavu, for his expert consultation during the sample collection process. We also extend our appreciation to The Research Director, Srinivas University, Mukka, for recommending and supporting this collaboration. The cooperation extended by CAMPCO Ltd has been instrumental in advancing this research.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [initials: AB], upon reasonable request.

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