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Transfer Learning-based Areca Nut (*Areca catechu*) Disease Detection using CNN and SVM Approaches with ResNet-50 for Improved Deep Learning Performance

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ABSTRACT

Background: Fruit rot among Arecanut (*Areca catechu*) cultivation presents severe risks to agricultural yield together with product quality and agricultural profit margins. The timely detection of diseases along with accurate detection needs to be performed for minimizing economic losses and enabling sustainable agriculture systems.

Methods: The study implements deep learning through transfer learning of the pre-trained ResNet-50 model. A method flows from ICAR Hirehalli proprietary data processing through python software coding to Keras and TensorFlow implementation for model training. In addition to the assessment the study evaluated CNN along with SVM for traditional benchmarking purposes.

Result: The efficacy of ResNet-50 during training reached 98% accuracy while validation accuracy settled at 92.76% surpassing both CNN with 90.83% accuracy and SVM with 89.95% accuracy. After training the model reached a substantial loss level of 0.2 which proved learning efficiency as validation loss settled at 0.3 indicating robust generalization.

Key words: Agricultural automation disease classification, Convolutional neural networks (CNN), Crop disease detection, Deep learning, ICAR hirehalli dataset, Image classification, Machine learning, ResNet-50, Support vector machines (SVM), Transfer learning.

INTRODUCTION

The research designs an exact and efficient solution for crop disease identification within arecanut farming through detection and categorization of fruit rot conditions which diminish both harvest volumes and product quality. The employment of traditional manual disease detection methods requires a lot of time while proving untrustworthy which results in delayed actions and higher losses for crops. A real-time user-friendly detection tool forms part of the proposed system which facilitates improved crop management and lower economical risks for farmers. Various locations regard arecanut as their primary cash crop because it represents a major source of value for both rural communities and the agricultural economic sector. The main issue farmers face stems from disease outbreaks that primarily manifest as fruit rot. A machine learning system created to speed up disease recognition when integrated with disease recognition algorithms will assist in prompt disease detection and production enhancement for smart farming (Hemavathi *et al.,* 2023). Machine learning progress enables the system to utilize pre-trained CNN models for transfer learning when working with restricted datasets. The research methodology focuses on model reliability improvement which guarantees satisfactory performance throughout different conditions and disease types (Hegde *et al.,* 2023).

The study has three fundamental objectives to fulfil:

The application of transfer learning through optimized CNN (M.B.G. *et al.,* 2024) models enables precise detection of arecanut diseases while the model generalizes effectively due to training data diversity. A user-friendly system development produces a real-time analysis platform which incorporates optimized CNN models for providing instant image processing feedback during field decisions. The most optimal technique for arecanut disease detection requires assessing the performance between transfer learning algorithms against traditional CNNs and SVM classifiers (Mate *et al.,* 2022).

The structure of the paper is as follows: In section II we provided a related works on arecanut disease detection. Section III explains the proposed work on CNN, SVM and Transfer learning model and also details of datasets used

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in the model development. Section IV gives the methodology of the model development. Section V explains the detailed description of the results of each model. Section VI gives the comparison study of the model final section presents the conclusion.

Related work

The detection of accurate plant diseases serves as a fundamental requirement for maintaining healthy crops while achieving maximum yield production. The high-value crop arecanut experiences two major diseases which reduce both its productivity and quality throughout different growing areas. Deep learning technologies, particularly convolutional neural networks (CNNs) have accelerated disease detection systems during recent times. CNNs prove their effectiveness in disease diagnosis of arecanut through image processing based (Puneeth and Nethravathi, 2021) research. The research study from (Anilkumar *et al.,* 2021) managed to correctly sort healthy from diseased samples with 88.46% accuracy which proves CNNs have great value in agricultural diagnosis applications. Multiple stages of image analysis enable CNNs (Kavitha *et al.,* 2023) and (Karthik *et al.,* 2024) to identify faint disease characteristics. Deep learning adoption requires acceptance because of the successful results achieved within crop health research. Performance benefits (Hussain *et al.,* 2018) from transfer learning when training data remains at limitation levels. The modification of pre-trained models for specific duties presents transfer learning as an effective method for plant disease recognition. Research reveals that this technique raises both evaluation accuracy as well as generalization results above standard traditional methods.

Advancements in disease detection methods

Multiple disease detection on coconuts through transfer learning techniques has produced successful results based on research findings documented in (Kavitha *et al.,* 2023) and (Kumar *et al.,* 2021). Research evidence verifies how transfer learning serves as an effective tool to boost plant disease identification capabilities. The introduction of deep learning replaced previous image-based disease detection methods (Meghana *et al.,* 2022) that employed Support Vector Machines (SVM) (Balipa, 2022) as machine learning techniques. The extraction of crucial image features through SVMs resulted in effective health assessment of nuts as researchers demonstrated good performance (Dhanuja, 2020) and (Chandrashekhara *et al.,* 2019). Traditional diagnostic systems used in agriculture now trace their origins from these established methods.

Integration of AI in crop disease management

Crops yield better diagnoses when deep learning methods unite with standard machine learning practices for diagnosing arecanut (Dhanuja *et al.,* 2024) and coconut diseases. The correct identification of issues reduces agricultural flaws and ensures higher harvesting outcomes and farmers benefit from simple intervention solutions that trigger appropriate protective steps. Crop disease like yellow leaf disease (Nair *et al.,* 2014) management becomes stronger through the combined use of CNNs and transfer learning and machine learning systems. Deep learning models match expert-level skill in identifying coconut tree diseases as documented in (Kumar *et al.,* 2021) and (Smitha and Rajesh, 2024). Research findings that test artificial intelligence efficiency in farming make detection rates more effective. This paper refers to convolutional neural networks (CNNs) as the technique that will be used to categorize the soybean leaf diseases based on a Mendeley dataset that includes three classes, namely: Diabrotica Speciosa, Caterpillar and Healthy. Preprocessing of the images such as labelling, conversion to grayscale and scaling are given and the model is tested with 80-20 train-validation split to determine model accuracy (Bong-Hyun *et al.,* 2025). Another study used convolutional neural networks (CNNs) to identify diseases in soybean plants with a database sourced by Mendeley with pictures of healthy soybean leaves and ones infected with caterpillars and diabrotica speciosa. The CNN framework was used in the extraction of features and categorization of complex soybean leaf conditions with the help of convolutional, pooling and softmax networks (Abeer *et al.,* 2025). A number of researches have contrasted the mainstream classifiers such as SVM and Random Tree with contemporary deep learning algorithms such as CNN, Inception V3, VGG16 and ResNet50 on the problem of cotton leaf disease detection. They usually engage data augmentation and transfer learning to improve the performances of models (Ok-Hue, 2024). Combining these multiple methods improves the identification process to support green farming practices and sustainable food production systems. The development of innovative techniques will secure food safety because of their contribution to intelligent agricultural practices.

Proposed work

The proposed work establishes software which enhances fruit disease detection in arecanut fruits through the implementation of transfer learning elements. A better solution to diagnose areca nut fruit diseases through visible symptom and texture and color analysis can be developed.

Project modules

The work development involves multiple distinct modules which provide an organized process for detecting diseases in areca nut fruits. The system relies on all modules to function effectively and accurately for data collection at the beginning to model detection at the end.

Data collection

The dataset is collected from ICAR, Hirehalli and Kaggle. The disease detection dataset contains images of areca nut fruits affected by different diseases, as well as healthy areca nut fruits. The dataset comprises multiple images with labels

indicating the presence or absence of disease. The total number of images is 1115.

Anthracnose

Anthracnose in arecanut shown if Fig 1, caused by Colletotrichum gloeosporioides, shows as sunken, dark brown to black lesions that may spread across the fruit. In severe cases, fruits may drop prematurely. Detection involves identifying these visual symptoms and confirming with diagnostic methods.

Bacterial fruit blotch

The bacterial pathogen Acidovorax avenae subsp. citrulli inflicts BFB disease on fruits of the arecanut plant which produces dark waterlogged lesions that eventually break open and spoil plant tissue as shown in Fig 2.

Fruit rot

This fungal disease with the scientific name *Phytophthora palmivora* develops during rainy months as shown in Fig 3. The disease produces dark water-soaked spots on the afflicted area which enlarges and causes bad odors as the fruit falls prematurely. The disease has high transmissibility among dense plantations under humid environmental conditions.

Fruit split

The physiological disorder fruit split as shown in Fig 4. emerges because of environmental conditions together with nutritional disruptions and improper cultural techniques. The condition results in long cracks that develop on the nuts throughout the surface where they might cause decay or drying of vulnerable tissue areas affecting both premium value and production quantities.

Fungal infections

Different fungal pathogens attack all parts of the arecanut plant through leaves and fruits and stems which diminish its crop output together with product quality as shown in Fig 5. When fungi actively grow on the fruit it develops a white to grayish surface coating as a sign of colonization.

Pest damage

Nut Borers trigger substantial damage that affects the crop yield as shown in Fig 6. Larval feeding boreholes form on the nut surface which makes the affected nuts unfit for processing.

Healthy nuts

A healthy arecanut is as shown in Fig 7 is a sign of a well-maintained tree and favorable growing conditions.

Data preprocessing

Data preprocessing involves transforming raw data into an understandable format. Since real-world data is often incomplete, inconsistent, or lacking in certain behaviors or trends and likely to contain errors, data preprocessing is essential. It includes data cleaning, resizing images and augmenting the dataset to improve model performance.

The setup for a classification model in TensorFlow/Keras for identifying arecanut diseases. Below is the mathematical model of the key components and operations in the code:

Input data preprocessing

The dataset is loaded from a directory and images are resized to 256 × 256 pixels.



Fig 1: Anthracnose diseased nut.



Fig 2: Bacterial fruit blotch diseased nut.



Fig 3: Fruit rot diseased nut.



Fig 4: Fruit split diseased nut.

Dataset splitting

The dataset is divided 80-20% into training and validation sets. This operation ensures the model trains on one subset and is evaluated on another.

Image transformation and augmentation

The 'image_datasetfromdirectory' function resizes images and pre- pares them in batches:

$$Xresized[i] = Resize[Xi, (256, 256)]$$

Model implementation

The many machine learning models used to detect diseases in areca nut fruits are discussed in this section. Convolutional neural networks (CNN), support vector machines (SVM) and transfer learning with the ResNet-50 model are among the models that are researched. Each model is described in terms of its architecture, operational principles and suitability for the task at hand.

The paper has employed three notable techniques of machine learning in detecting disease on areca nut- Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs) and Transfer Learning. As the first DL architecture, CNNs, as represented in Fig 8 have the advantage of being able to identify textural and spatial features of an image via convolutional and pooling layers, and classify the data with fully connected layers. The figures shown in Fig 9 were SVMs which were conventional supervised models that process extracted features such as HOG or SIFT which promise high performance on smaller data sets. Fig 10 illustrates that we have used Transfer Learning, fine-tuning a pre-trained ResNet-50 (on ImageNet) to areca nut disease classification by freezing early layers (ResNets are trained to cater to a wide variety of tasks) and retraining the last classification head. This plan saved time of training and enhanced accuracy through prior knowledge using big data as a way of performing precise generalization on small areca nut data.



Fig 5: Fungal infections diseased nut.

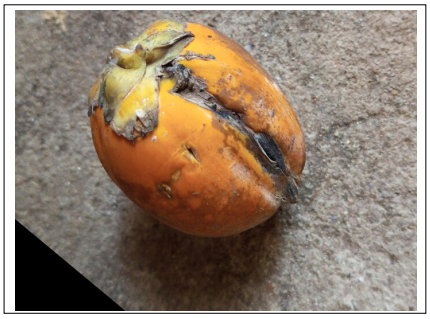


Fig 6: Pest damaged diseased nut.

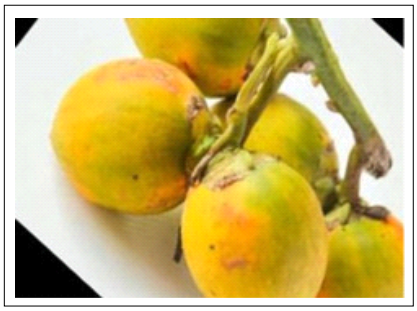


Fig 7: Healthy nuts.

MATERIALS AND METHODS

The implementation can be done in 5 steps:

- Selection of an appropriate dataset with effective features.
- Model implementation using deep learning algorithms.
- Comparison and selection of deep learning algorithms.
- Performance evaluation.

Selection of an appropriate dataset with effective features: For areca nut disease detection, the relevant features include various disease symptoms, images of healthy and diseased nuts and environmental factors if available and is shown in Fig 11.

a. **Data quality:** Ensuring the nuts quality and reliability of the collected arecanut data is crucial. Check for missing values, outliers, errors and inconsistencies that could affect the integrity of the dataset. Apply data cleaning and preprocessing techniques, such as normalization, imputation and outlier detection, to improve data quality.

b. **Feature selection:** Identify the most relevant variables (features) that contribute to disease detection while discarding irrelevant or redundant ones. This can be done using statistical methods (*e.g.*, correlation analysis, feature importance scores), domain knowledge, or automated feature selection algorithms (*e.g.*, recursive feature elimination, L1 regularization).

c. **Dataset splitting:** Once the dataset is prepared, divide it into training of data, validation data and test data sets. The training arecanut data set is used to train the machine learning model, the validation set is used to tune hyper-parameters and evaluate model performance during training and the test arecanut data set is used to evaluate the model's ability to generalize.

Model implementation using deep learning algorithms

a. **Model selection:** The choice for images should be a CNN model type using ResNet-50 as a suitable transfer learning approach supported by an SVM classification system. Factor in model complexity, data characteristics and available computational resources.

b. **Model design:** Developing the model structure requires defining each layer including activation functions and loss function and it requires regularizing through dropout and batch normalization. Together with multiple network design explorations you should modify model parameters to reach maximum operational output levels.

c. **Model training:** The prepared data undergoes training by implementing either SGD or Adam as the optimizer during model implementation. Model performance reaches its optimal levels during validation set monitoring while the adjustment of hyper parameters helps prevent over fitting from happening.

d. **Model testing:** The trained model undergoes assessment of previously unseen information that existed outside the training and validation intervals. Model performance should be assessed through the evaluation of accuracy together with precision and recall and F1-score metrics. Review misclassifications for potential improvements.

Comparison and selection of deep learning algorithms

By using both convolution and pooling methods, convolutional neural networks (CNNs) analyze image-based patterns as they learn to capture spatial relationships within visual data. SVMs have shown high efficacy in both classifying and regressing data with discernible boundaries, performing best when sufficient training samples and structured features are provided. With transfer learning, low data requirements allow pre-trained models from extensive base datasets to be adapted to new tasks, speeding up processing time while enhancing accuracy.

Performance evaluation

Evaluate the performance of convolutional neural networks (CNNs), transfer learning and support vector machines (SVMs) for areca nut disease detection based on key metrics such as accuracy, precision, recall and F1-score. Compare the efficiency of different models to determine which provides the best performance. Based on the results, select the most effective approach for areca nut disease detection.

RESULTS AND DISCUSSION

Convolutional neural network (CNN)

The convolutional neural network (CNN) model was implemented to detect diseases in areca nut fruits, providing a base- line for performance comparison with other models. Training and Validation Plots are as shown in Fig 12 displays the training and validation accuracy (left) and training and validation loss (right) across several epochs for a deep learning model.

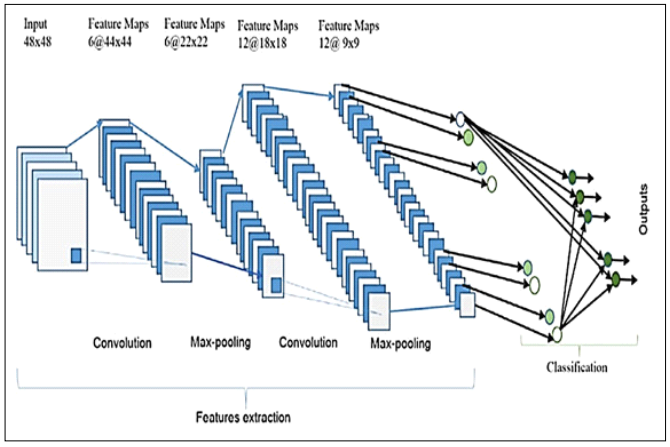


Fig 8: Block diagram of CNN model.

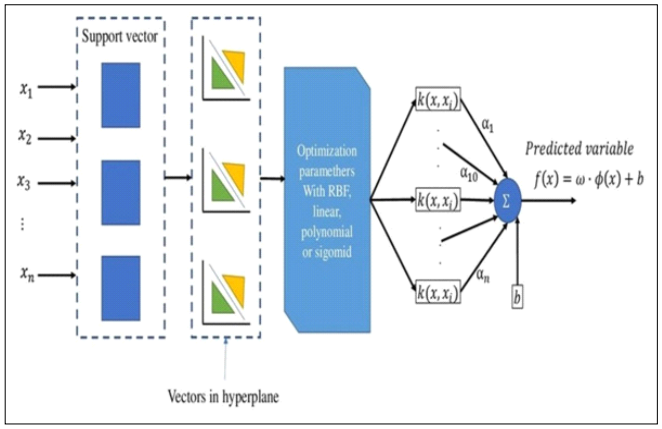


Fig 9: Block diagram of SVM model.

Training and validation accuracy (Left)

The training accuracy (blue line) shows how the model's accuracy improves on the training dataset over time (epochs). The Validation Accuracy (orange line) shows the model's performance on unseen validation data. A close alignment between these two curves indicates good generalization, while significant divergence might suggest overfitting.

Training and validation loss (Right)

The Training Loss (blue line) represents how the model's error on the training dataset reduces as it learns. The Validation Loss (orange line) shows how the error on the validation dataset changes. An increase in validation loss after a certain number of epochs may indicate overfitting.

The Accuracy of the model is calculated as:

$$\text{Accuracy} = \frac{\text{Prediction of number of correct datasets}}{\text{Predictions of total number of datasets}}$$

Accuracy is computed for both the training and validation datasets after each epoch Fig 12 depicts the observations made in the plots, the training accuracy improves steadily while the validation accuracy fluctuates slightly, suggesting possible overfitting after a certain point. The training loss decreases steadily, while the validation loss fluctuates and eventually increases, further supporting the hypothesis of overfitting and Fig 13 shows CNN model result representation.

The values of training and validation accuracy (Table 1) show that the model learns normally until approximately the 15th epoch and then the accuracy goes up to 95 and 90 respectively. When outside this range, the training accuracy increases whereas the validation accuracy stagnates, indicating that there is overfitting. Generalization may be optimal with the early stopping at the 6th-16th epoch.

Table 2 reflects the training and validation loss which indicates successful learning until 15th epoch when the training loss is 0.10 and validation loss is 0.20. It shows fine generalization in early training. But, at an epoch greater than 15, training loss remains to decline and validate loss oscillates and gets a small increment which is an indication of overfitting. Therefore, it can be assumed that the model is optimally performed at the 15th epoch.

Support vector machine (SVM)

Support vector machine or SVM is an algorithm for supervised learning that is applied in both classification

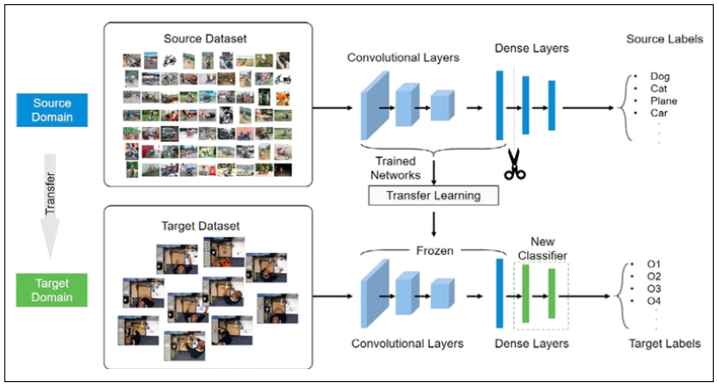


Fig 10: Block diagram of transfer learning with ResNet-50.

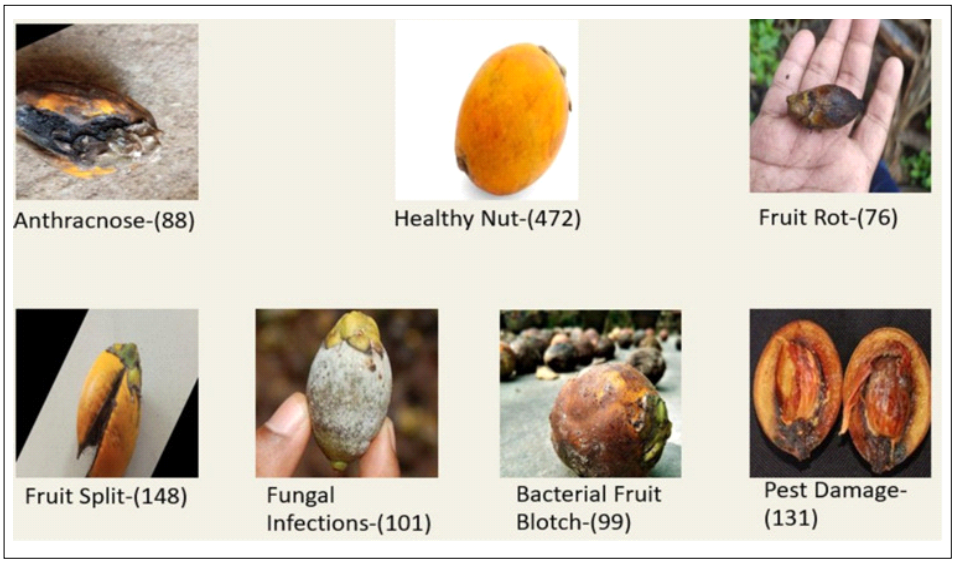


Fig 11: Datasets of different diseased nuts and healthy nuts.

and regression problems. It locates the ideal distinguishing hyperplane for different categories of data. In figure fifteen, the confusion matrix shows the actual values against the predicted values, where the labels on the y-axis are the actual values and those on the x-axis the estimated values, while the diagonal values indicate the level of correct results. In this case the validation accuracy achieved was 89.95% with 90% accuracy on different classifications of arecanut condition which included Pest Damage, Healthy Nut, Fungal Infection, Fruit split, Anthracnose, Bacterial Fruit Blotch and Fruit Rot. Diagonal cells (from top-left to bottom-right) show correct classifications of areca nut dataset is shown in Fig 14. A higher number here indicates more correct predictions for that particular class.

For example: Pest Damage has 17 correct predictions. Healthy Nut has 17 correct predictions. Bacterial Fruit Blotch has 93 correct predictions, which is the darkest cell, indicating the most confident predictions for this class.

The confusion matrix shows several predicted errors in the off-diagonal cells since Anthracnose was misidentified as Healthy Nut four times and Fruit Rot six times. The highest number of correct predictions occurred for Bacterial Fruit Blotch which exhibited a value of 93 and darker color cells in the confusion matrix indicate higher prediction accuracy. The model achieves strong performance in detecting Bacterial Fruit Blotch while facing difficulties to differentiate between Fruit Rot and Anthracnose and Healthy samples. The lack of sufficient training data and better features creates a need for improvement. Model performance becomes visible in the confusion matrix through its structure where actual labels correspond to rows and predicted labels form the columns. This tool enables accuracy assessment for nut condition classifications in different situations.

Transfer learning

Transfer learning gives leveraging pre-trained models to improve performance on a given specific task with fine-tuning and other techniques such as data augmentation, regularization and hyper param 000000eter tuning. Fig 15 represents the performance of a deep learning model during training and validation over 7 epochs.

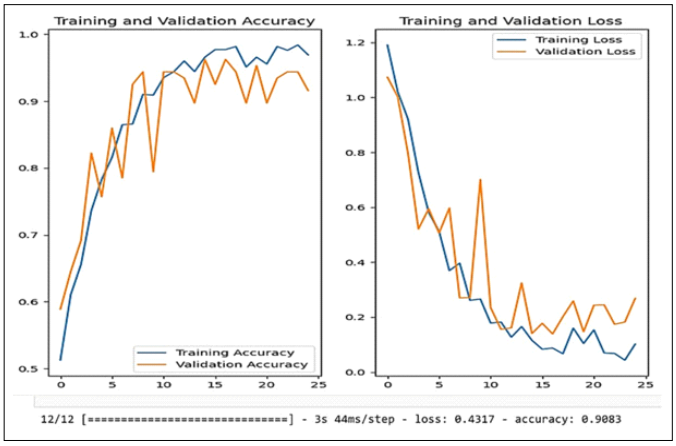


Fig 12: Training and validation accuracy (Left) and loss (Right) of CNN model.

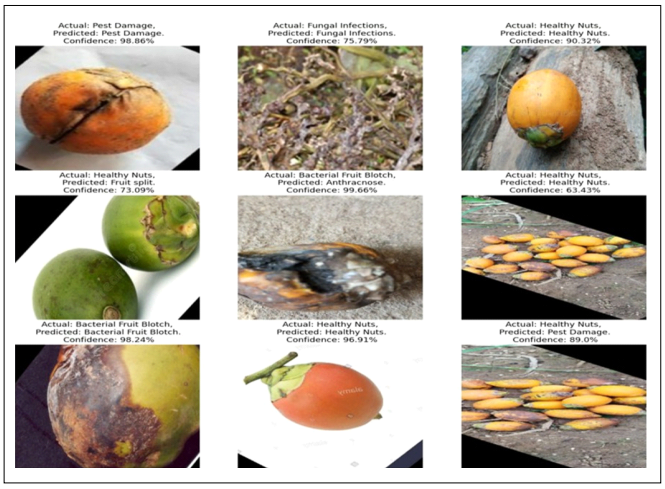


Fig 13: CNN model result representation.

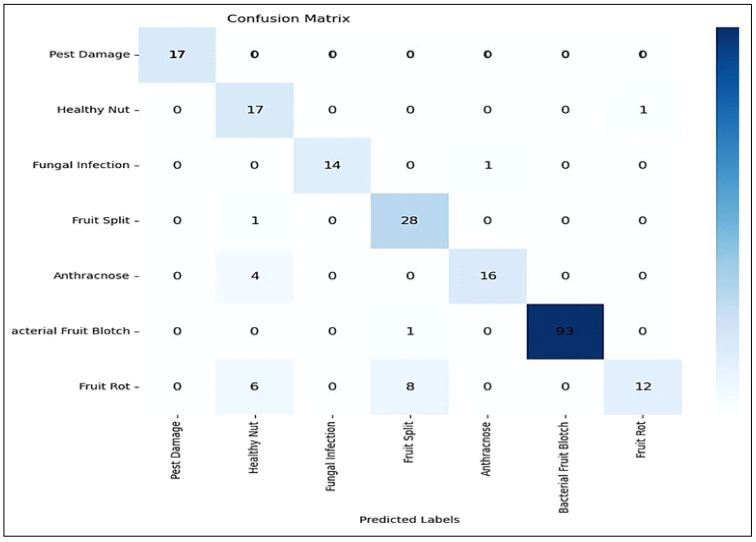


Fig 14: Graphical representation of SVM model result.

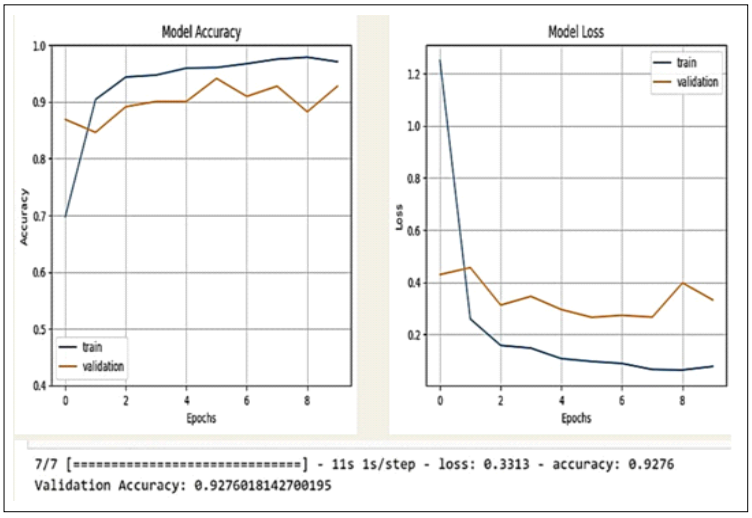


Fig 15: Graphical representation of transfer learning model result.

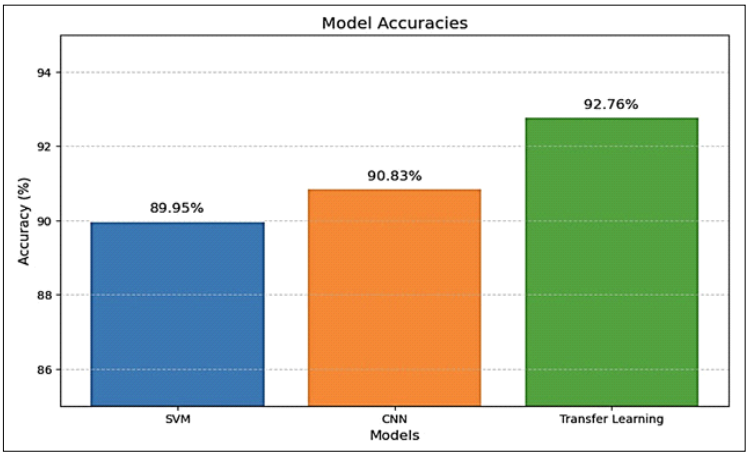


Fig 16: Graphical representation of comparison of SVM, CNN and transfer learning.

Table 1: Training and validation accuracy over epochs.

Epoch	Training accuracy	Validation accuracy
0	0.50	0.50
5	0.82	0.80
10	0.92	0.88
15	0.95	0.90
20	0.98	0.88
25	0.99	0.90

Table 2: Training and validation loss over epochs.

Epoch	Training loss	Validation loss
0	1.20	1.10
5	0.50	0.55
10	0.25	0.30
15	0.10	0.20
20	0.08	0.25
25	0.05	0.22

Model accuracy and model loss

The horizontal axis demonstrates epochs which represent the number of complete training cycles performed using the entire input information. To train accuracy blue line begins at under 0.9 then mounts above 0.98 before maintaining a stable position which demonstrates effective learning. The Validation Accuracy shows slight decrease to 0.9 which demonstrates effective model generalization. The accuracy curves demonstrate strengthening performance in training and validation while demonstrating limited model fitting problems between them. Model Loss is as shown in the Fig 16 effective learning process becomes apparent in the Blue Line because the loss value descends from approximately 1.2 to less than 0.2. During epoch 4 the validation loss took a drop, yet it showed slight variations afterward until it reached stability at 0.3 to 0.4. Minor over fitting occurs because to train and validation loss values remain slightly separated. Cross-entropy loss served as the choice of function to perform classification tasks.

Training and validation metrics

The model was trained for 7 epochs, achieving a validation accuracy of 92.76%, matching the training accuracy indicating strong generalization. The final validation loss was 33%, showing low prediction error. Training and validation metrics were calculated using the same formulas but on different datasets. While there's slight divergence between training and validation loss, it suggests only minor over fitting. The conclusion of the model is robust, achieving high accuracy with low loss. Performance was improved through fine-tuning, data augmentation, regularization and hyper parameter tuning.

Comparison of models

Model comparison

The performance of the different techniques (CNN, Transfer Learning and SVM) in predicting crop yield is measured by the R^2 score.

The bar graph compares the accuracy of three models:

- **SVM:** 89.95% (blue bar) - achieved the lowest accuracy, just under 90%.
- **CNN:** 90.83% (orange bar) - slightly outperformed SVM in accuracy.
- **Transfer learning:** 92.76% (green bar) - had the highest accuracy, making it the most effective model.

In summary, Transfer Learning performed best, followed by CNN, with SVM showing the lowest accuracy is represented in Fig 16.

CONCLUSION

An evaluation of the crop disease prediction capabilities for SVM, CNN and Transfer Learning models through their R^2 scoring system has been executed. The highest achieved accuracy of 92.76% belonged to Transfer learning because it surpassed both CNN at 90.83% and SVM at 89.95%. This research demonstrates that Transfer Learning performs best with pre-trained models because it works well for situations with restrained data as found in agricultural domains. The pattern recognition abilities of CNN were strong, yet it delivered slightly lower results compared to Transfer Learning. SVM works effectively for basic classification assignments and inadequately equipped systems while achieving marginally lower accuracy rates. Transfer learning achieves the best accuracy in addition to strong generalization capabilities which makes it a crucial instrumentation for agricultural precision. Further investigation should apply this method to detect diseases and pests in other fields.

Conflict of interest

All authors declared that there is no conflict of interest.

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