Optimization of Disease Detection System for Improved Arecanut Cultivation by Machine Learning

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Abstract: Agricultural growth is crucial for ensuring a consistent food supply for ordinary people. To optimize disease detection methods and improve crop quality, data from various published research works is collected and analysed. These efforts aim to protect plants from diseases, enhancing both agricultural productivity and the country's economic contributions. This review compares machine learning and deep learning techniques for identifying and categorizing plant diseases. Images of arecanut leaves, trunk, stem and root were used as input for the research. The study focuses on disease detection systems implemented using various algorithms and compares their accuracy based on findings from published research. The results indicate that Convolutional Neural Networks (CNNs) consistently achieve better accuracy than traditional machine learning methods. Future research can explore advanced deep learning techniques to achieve even higher accuracy in plant disease detection.

1 INTRODUCTION

Agricultural land expansion has stabilized or even declined in many regions, despite increased production. Advancement in farming technology and efficiency gains also play a significant role, as higher crop yields now allow the same amount of land to produce more. Areca nut farming is a significant agricultural activity in India. Most concentrated in the southern and northeastern states. Karnataka gave 79% of India's total arecanut production. The total annual production of areca nuts in India is approximately 1.37 million tons, grown on around 0.52 million hectares of land.

Convolutional Neural Networks (CNNs), in particular, constitute deep learning models that have gained popularity due to their exceptional performance in image-based illness categorization. Research has used architectures including Res Net, VGG Net, and Mobile Net to accurately diagnose illnesses like bud rot, yellow leaf spot, and stem bleeding. The effectiveness of these models has been further improved by preprocessing methods such feature extraction, picture augmentation, and normalization.

Good agricultural practices, effective post-harvest management, and modern technology would help us to maintain the quality of areca nut. Fruit rot disease and other pests can be sustainably controlled using Integrated Pest Management (IPM). Plant health level is based on management of farmer practices; detection of disease has to be done before the spreading stage of the diseases from one plant to another. Tomatoes are among the most widely cultivated crops, with annual production exceeding 180 million metric tons. The export market is about $10 billion. Tomato cultivation per-hectare yields range between 50 to 100 tons, and protecting crops from diseases can ensure consistent productivity and profitability. Tomato disease detection plays a critical role in enhancing yield quality.

By gathering vegetation indicators and creating 3D models to measure disease severity, emerging technologies—such as UAV-based multispectral imaging—have shown promise for real-time disease monitoring. These advancements demonstrate how AI, IoT, and precision agriculture are revolutionizing the management of arecanut diseases. These tools give farmers actionable knowledge by facilitating early detection, categorization, and prediction insights, which encourage sustainable crop management and lower financial losses.

Over 125 million metric tons are produced in India each year, making up about 40% of the country's total food grain production. The high yield and export surplus play a crucial role in ensuring economic stability for millions of farmers while

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strengthening India's position in global agriculture. Effective detection not only preserves the quality of rice but also enhances productivity. To that end, we have come up with an automated system using machine learning techniques, a system that will contribute in country's agricultural development by automatically identifying and classifying diseases from the images of rice leaves. Where efficiency and accuracy are crucial. Accurately classifying weeds and crops is a major problem in modern agriculture since it's necessary for efficient resource allocation and management. Conventional techniques for identifying weeds and crops frequently rely on labor-intensive, time-consuming manual examination procedures that are prone to inaccuracy.

2 RESEARCH OBJECTIVES

Objectives will help us to sharpen the ideas of research work. The following objectives are utilized to study the disease detection on plants for healthy farming methods:

- To study the early detection of different diseases in Arecanuts.
- To analyse the methodologies of Machine learning and Deep learning to optimize the productivity

2.1 Motivation of study

Since agricultural practices play a major role in India's economic considerations, it needs to bring our country as one which performs well in agricultural production. Prevention and early detection of possible diseases will reduce crop death and further to improve the quality of crop as well as cultivation.

2.2 Role of Artificial Intelligence in Agriculture

The following are the major roles of Artificial Intelligence and deep learning technique:

- A form of deep learning technique called Convolutional Neural Networks (CNNs) has proven incredibly successful in automating agricultural activities including disease detection, crop classification and yield prediction.
- It has been found that popular designs like as Mask R-CNN, U-Net, Alex Net, VGG16, and InceptionV3 perform exceptionally well in agricultural applications, achieving exceptional accuracy and durability even under challenging field conditions.

2.3 Integration of IoT and Machine Learning

The following basic ideas about IoT and machine learning:

- By offering real-time insights, IoT-enabled data collecting using devices like Arduino and sensors for temperature, humidity, and soil conditions has improved precision farming.
- When combined with sensor data, Random Forest Classifiers (RFC) and LightGBM models have demonstrated efficacy in forecasting crop performance and illnesses, hence facilitating proactive decision-making.

2.4 Significance in Arecanut Cultivation

The following significance are:

- A major crop in many areas, Arecanuts confront difficulties such fruit rot and infections like Yellow Leaf Disease (YLD), which reduce productivity. Cutting-edge technologies such as CNN models, IoT-integrated systems, and UAV-based multispectral imaging offer encouraging options for early identification and management.
- High accuracy in arecanut detection and grading has been demonstrated using segmentation and classification models such as Mask R-CNN and hybrid CNN-SVM systems.

3 LITERATURE REVIEW

For the KR Sharathkumar. et al., (SharathKumar, and, Mohan, 2020) suggested a disease prediction detection system to track soil moisture (%), wind flow (m/s), rainfall (cm), temperature (°C), and humidity (%) in order to forecast the emergence of various illnesses. Environmental variables caused certain illnesses to manifest as expected. The illness impact was predicted using machine learning techniques such as Support Vector Machine Regression (SVMR) and Random Forest Classifier (RFC). Environmental data is gathered using a soil humidity sensor and a DHT-11. Certain illnesses (Mahali, fruit rot, Koleroga) can only be predicted by research that is restricted to certain places.

S. Anupama Kumar. et al. (Kumar, Anupama, et al., 2024) used Convolutional Neural Network techniques, concentrated on identifying the three main illnesses that harm areca trees: Yellow Leaf Spot, Stem Bleeding, and Mahali Disease (Koleroga). Various CNN algorithms, including MobiNet, ResNet, and VGG, are used to identify these disorders. Three separate metrics—the total parameters, trainable parameters, and nontrainable parameters—are used to compare the models based on three network architectures and the plant disease that is tracked. It was shown that accuracy rose as the number of non-trainable parameters decreased. The accuracy of the ResNet architecture is 79%, MobiNet is 86%, and VGGNet is 96% based on data gathered over 50 epochs. VGGNet outperformed the other two networks in terms of accuracy and overall performance.

Namra Mahveen. et al., (Mahveen, Namra, et al. , 2023) proposed a system which was based on Convolutional Neural Networks (CNN) for detecting diseases in arecanut crops, specifically targeting leaves, trunk, and fruit. CNN, a potent deep learning algorithm designed specifically for image analysis, analyzes input photos by giving different visual aspects learnable weights and biases. The CNN algorithm is able to differentiate between healthy and unhealthy arecanut plants by identifying patterns in these photos. Datasets from published literature that included a wide range of photos showing both healthy and ill plant samples were used in the CNN model's construction and assessment. In addition to accurately identifying diseases, the system sought to help farmers maintain healthy crops and increase output by offering helpful advice and recommendations. Pre-processing, feature extraction, model training, and classification were all phases of the system's operation. The accuracy percentage attained by the model was almost 88%.

Ms. Shwetha Kamath. et al., (Kamath, Shwetha, et al. , 2023)concentrated on machine learning methods to analyze different soil factors and apply the ID3 algorithm to identify illnesses early. The suggested technique detected the presence of the fungus that causes YLD in soil samples taken from arecanut crops. In order to predict crop health, this study used soil characteristics, such as micronutrients, in addition to pH, nitrogen (N), phosphorus (P), and potassium (K) levels. The ID3 technique was used to build a decision tree model based on user-provided inputs. The results were binary, meaning that the existence of a disease was either "Yes" or "No."

Tejaswi R. et al., (Tejaswi, Mysoremath, et al. , 2024) used the ResNet model to identify a number of illnesses that impact arecanut crops, including yellow leaf disease, fruit rot, and foot rot. RGB photos were processed using sophisticated methods such as global average pooling. Learnable weights are assigned by the model to differentiate between healthy and unhealthy plants. With a 97.5% accuracy rate on a self-gathered dataset, this system demonstrated its ability to help farmers detect diseases early and minimize crop losses. The study also demonstrates how well ResNet handles vanishing gradient problems, laying the groundwork for more extensive precision agricultural applications.

Dr.P.Sreenivasulu. et al., (Sreenivasulu, Lakshmi, et al. , 2024) applied a CNN-based techniques to approach arecanut diseases and achieved an accuracy of 94.8% across multiple conditions like fruit rot and yellow leaf disease. It involved robust preprocessing methods, such as normalization and augmentation, and employed advanced architectures like ResNet. The model demonstrated the feasibility of leveraging image-based deep learning techniques to assist farmers with accurate diagnosis and timely intervention, marking a significant step toward precision agriculture.

Rajashree Krishna. Et al., (Krishna, Rajashree, et al. , 2022) focused weather parameters such as rainfall, humidity, and temperature to predict fruit rot disease in areca nut. A unique dataset combining weather data and field surveys was created and validated using machine learning models like Random Forest Regression, achieving the best performance with a mean absolute error of 0.9. This approach emphasized proactive disease management and supports farmers in mitigating losses through early prediction.

Dhanuja K C. et al., (Dhanuja, and, Kumar, 2020) focused on the application of machine vision for detecting and classifying diseases in areca nuts, utilized advanced image processing techniques such as Gabor wavelets and GLCM. It has emphasized the role of precision agriculture in improving crop management and demonstrated the effectiveness of texture-based grading systems. By employed dataset of 700 images spanning various disease classes, the research achieved a classification accuracy exceeding 91%, showcasing the efficiency of convolutional models and neural network classifiers. The study further suggested that future work could focus on optimizing automated systems for real-time applications to improve scalability and usability in agricultural operations.

Kuo-Yi Huang. (Huang, Kuo-Yi, et al. , 2012) applied machine vision techniques to classify areca nuts. He used geometric and colour features along with a Detection Line (DL) algorithm for defect identification. It has employed a Back-Propagation Neural Network (BPNN) to sort areca nuts into quality categories with an accuracy of 90.9%. Combined image smoothing, feature extraction, and neural network classification, the study demonstrated an effective and automated solution to assess nut quality. This innovative method reduced manual effort and enhances consistency in quality evaluation, making it a significant contribution to agricultural technology.

Ajit Hegde. et al., (Hegde, Shetty, et al. , 2023) focused on convolutional neural network (CNN)-based system for detecting and classifying various diseases affecting areca palms. They classified diseases such as fruit rot, bud rot, and yellow leaf disease, achieved accuracy of 94.8%. It emphasized the practical benefits of deploying such models in agricultural settings in reduced manual inspections and improved crop management strategies. It also highlighted the potential of AI in advancing sustainable and data-driven crop management practices.

Anilkumar M G. et al., (Anilkumar, Karibasaveshwara, et al. , 2021) utilized convolutional neural networks (CNNs) for the early detection of diseases affecting arecanut, such as Mahali, stem bleeding, and yellow leaf spot. A dataset of 620 images, split into 80% for training and 20% for testing, formed the basis of the model and achieved an accuracy of 88.46%. Pre-processed steps like image resizing and augmentation, enhanced the feature extraction and improved classification reliability. The research highlights the practical utility of AI in agricultural disease management, offered both detection and remedy suggestions. This approach presented a significant step toward promoting smart farming and sustainable crop management. The findings emphasized the role of machine learning in minimized yield loss.

Shuhan Lei. et al., (Lei, Shuhan, et al. , 2021) applied UAV-based multispectral imaging and machine learning techniques to monitor yellow leaf disease in arecanut. Five vegetation indices (e.g., NDVI, LCI) were extracted from high-resolution UAV images, enabled the quantification of disease severity. Machine learning models, including BPNN and SVM, achieved the highest classification accuracies of 86.57% and 86.30%, respectively. The research further correlated the severity of the disease with the living vegetation volume (LVV) using UAV-constructed 3D models. This quantitative approach advances traditional qualitative disease assessments, offering precision in disease monitoring.

Shabari Shedthi Billadi. et al., (Billadi, Shedthi, et al. , 2023) applied machine learning techniques to find unique solution for good and defective arecanuts based on their color, texture and density value. Machine vision method is used to grade the arecanut. Various segmentation algorithms are available, and in this work, simple k-means clustering is applied to distinguish the arecanut from the background in the image. Classifiers like logistic regression, k-NN, naive Bayes classifiers, support vector machine (SVM), and ANN are used to identify the healthy arecanut from the spoiled one. The results indicate that among the classifiers tested, ANN demonstrates superior performance. Incorporating the newly derived density feature, the arecanut grading system achieves an overall accuracy of 98.8%. Experimental results demonstrated that the machine vision system, enhanced with density features, delivers a high success rate. Density features play a crucial role in arecanut classification.

Pallavi P. et al., proposed a new system using Convolutional Neural Networks and detected the diseases of arecanut in leaves and its trunk. The proposed method consists of three phases training phase, testing phase and GUI phase. Developed system recognized the features and anticipated crop diseases using data mining and data science techniques. Algorithm detected arecanut disease and provided solutions for the detected disease. The overall accuracy of the system is estimated to be 81.35%.

Suresha M. et al., (Suresha, Danti, et al. 2014) proposed work on diseased and unhealthy arecanut by implementing texture features of Local Binary Pattern (LBP), Haar Wavelets, GLCM and Gabor. Statistical method of correlation determined the query sample and histogram of training set. KNN classifier have been used for classification. The process was carried out in two stages, in first stage LBP is generated, hence it achieved 92% of success rate. Later in second stage Haar Wavelets, GLCM and Gabor resulted high success rate of 100% and high degree of discrimination has been found. This work can be extended to identify disease of fruits, flowers and seeds etc.

K. Rajashree. Et al., (Rajashree, Prema, et al. , 2022) applied Artificial intelligence method based on deep learning model to detect fruit rot disease. Sliding window concept were compared with Vanilla LSTM, stacked LSTM, and bidirectional LSTM models. Models are measured by validation loss and training loss with the help of Mean Square Error (MSE). There are 3,152 samples in the dataset, 80% of samples are used for training, and 20% are used for testing purposes. From 630 testing samples, only 100 are predicted. LSTM model predicted disease in crops such as rice and cotton. Based on RH, sunshine, temperature, and disease score data, with 67.4% accuracy. Vanilla GRU is the best model compared with all other models, with a low error rate of 1.3(MSV) and less processing time due to its fewer gates.

Jiawei Guo. Et al., (Guo, Jin, et al. , 2022)focused on remote sensing-based detection of Areca Yellow Leaf Disease (AYLD) using Planet Scope satellite imagery. Employed 13 spectral features that optimized through Correlation Analysis and independent t-tests to develop disease classification models. Random Forest algorithm achieved the highest accuracy 88.24%, Backpropagation Neural Network achieved 85.29% and AdaBoost achieved 67.65%. RF demonstrated superior error minimization and robustness for classifying healthy and diseased plants. It was emphasized the significance of feature optimization in improving model accuracy precise disease monitoring in agricultural and forestry applications.

Krishna A N, et al., (Anitha, Dhanesha, et al. , 2022)] investigated deep learning-based methods for segmenting arecanut bunches from field images, implementing Mask R-CNN and U-Net architectures. Both models eliminated pre-processing and handle challenges like illumination, occlusion, and complex backgrounds. A dataset of 1017 images (ripe and unripe) was used, split into training and testing sets. Mask R-CNN, pre-trained on COCO and fine-tuned, achieved superior accuracy with IoU of 67.88% and F1-score of 79.36%, outperforming U-Net accuracy with IoU 57.04%, F1 70.78%. These results demonstrated Mask R-CNN's is effective for precise segmentation, enabling automated yield estimation and harvesting, that offering a robust solution for agricultural automation.

Smita Nair, et al., (Anitha, Dhanesha, et al. , 2022) introduced a real-time PCR method for detecting the phytoplasma responsible for Arecanut Yellow Leaf Disease (YLD). The methodology involved designing primers targeting the 16S rRNA gene, followed by validation using spindle leaf tissue samples. Among four primer sets, QPF2/QPR2 exhibited consistent amplification, achieving accurate detection with a unique melting peak at 82.3 ± 0.5°C. This approach outperformed conventional PCR by reducing cross-contamination and enhancing sensitivity. The method's rapid and precise detection capabilities support early disease diagnosis, enabling better management of YLD in arecanut palms.

Niranjan Murthy Chandrashekarappa. et al., (Chandrashekarappa, Murthy, et al. , 2022) focused on designing and developing an efficient monitoring mechanism also called as efficient data sensing and monitoring (EDSM). Proposed model minimized the energy, reduced the false alarm rate, and enhanced the detection accuracy. It follows four steps, first step included the sensing device condition, second step will update the data strategy, third step follows data validation, and the fourth step include sensed data optimization. Proposed model outperformed the existing model with significant optimization and achieves 100% detection rate and failed to get even single false alarm rate. EDSM are proven to be efficient and solves various problem of existing model.

Vikram Kumar1. et al., (Kumar, Vikram, et al. , 2020) approached work uses two different data like one from researched data and another from real time collected from IoT (Internet of Things). Arduino Uno board and the sensors DHT-11 and soil humidity sensors are used to collect real time data. Work is based on machine learning algorithm to process the data. RFC (Random Forest Classifier) algorithm is used for classification of data. 300 data trees are used for prediction. Based on the MIN-SCORE output the disease is predicted. The predicated score from the RFC was most accurate. Compared to other algorithms RFC gave high performance.

Pushparani M.K. et al., (Pushparani, Kumar, et al., 2019) developed a system for efficient grading system based on computer vision technology. Arecanuts classified into different grades by using MATLAB Toolbox. Arecanuts differ from one another based on colour, size, and texture. colour feature use HSV Histogram colour transform, texture recognition uses Gabor filter and Gabor wavelet transforms. Support Vector Machine is used as a classifier. The application of main GUI was built using the MATLABs own UI building tool called GUIDE. processing based arecanut grading is a novel approach to sort arecanuts, implementation in real time give more accuracy in high performance for farmers.

Dr. Kalai Selvi T. et al., (Revathi, Arivuselvam, et al. , 2024) focused in comprehensive approach that combine recommendations of crop to detect diseases. System proposed based on leverages a hybridized technique utilizing the LightGBM (LGBM) model. The model focuses on developing robust LightGBM-based crop recommendation system and fine-tuning deep-learning models for accurate disease detection. Ensemble. Innovative developed system revolutionized agricultural technology by accessing a user-centric web application interface for farmers and stakeholders. Model's accuracy in validation phase shows 94.8% and test phase shows 94.2%. ResNet-50 based crop recommendation model predicts promising results.

Mr. Ajith Kumar Shetty. Et al., (Shetty, Pandu, et al. , 2024) developed a model to train the ResNet90 for improving automated weed and detecting the crop. Goal of this work is to improve automated classification systems' precision and to support more productive. Cutting-edge methods improved agricultural operations by differentiating images of weeds and crops used by both deep learning and conventional machine learning algorithms. 13 different input images fed to represent different species or crop. Logistic Regression showed relatively good accuracy, but not as high as the RF higher accuracy in image classification tasks.

Sandeepa Prabhu. et al. (Prabhu, Sandeepa, et al. , 2024) concentrated on drone technology by exchanging data and gathering data in real time. The fungus Phytophthora areeae causes koleroga, or fruit rot, which affects the majority of areca nuts. In this system, disease detection is done using drones. A camera placed on a drone takes pictures. To process the photos and distinguish between the healthy and afflicted ones, several techniques are employed, such as machine learning or computer vision algorithms. They identify patterns suggestive of illness and pinpoint areas of concern. An average detection rate of more than 90% was obtained. With the use of sophisticated imaging technologies and effective image processing algorithms, drones can now diagnose diseases with high accuracy.

Dong Xu. et al., (Xu, Dong, et al. , 2023) aimed to monitor the severity of Areca Yellow Leaf Disease (YLD) using UAV-based multispectral and thermal infrared imagery, addressing the urgent need for effective disease management in areca cultivation. The methodology involved collecting imagery from UAVs, utilizing the ReliefF algorithm for feature selection, and employing machine learning models like Random Forest to predict disease severity. With an R2 of 0.955 and a substantial correlation (0.753) between canopy temperature and disease severity, the results show great prediction accuracy. This study demonstrated the potential for wider applications and offered a scalable, accurate method for agricultural disease surveillance.

Balipa. et al., (Balipa, Mamatha, et al. , 2022) used CNN and SVM, two machine learning techniques, to create a system for identifying different arecanut disorders. To enhance training, the dataset—which included photos from farms in Shivamogga, Karnataka—was produced and enhanced. GLCM and GLDM matrices were used to transform the pictures into texture-based features. Comparing CNN and SVM classifier performance has been part of the technique. With an accuracy of 90% as opposed to 75% for SVM, CNN fared better than SVM, demonstrating its applicability for intricate image-based illness identification. This study showed how deep learning may be used to automate disease monitoring in arecanut farming, resulting in better crop management and early identification.

S.B. Mallikarjuna et al., (Mallikarjuna, Shivakumara, et al. , 2021) aimed to enhance the classification accuracy of arecanut images affected by various diseases, including rot, split, and rot-split. The authors propose a novel approach that combines multi-gradient images with deep convolutional neural networks (CNNs). By applying multiple Sobel masks to the input images, fine details are accentuated, providing vital clues for disease classification. These enhanced images are then processed using a CNN model, specifically AlexNet, to extract distinguishing features. The proposed method demonstrated superior performance on a four-class dataset, achieving higher classification rates, recall, precision, and F-measures compared to existing techniques. This research offered a promising direction for automated detection and classification of multiple arecanut diseases, potentially aiding in timely disease management and control.

Rashidul Hasan Hridoy. et al., (Hridoy, Hasan, et al. , 2022) focused on the detection of betel plant diseases using deep learning to support healthy production and mitigate economic losses. The authors utilized a dataset of 10,662 leaf images and applied transfer learning with various architectures, including AlexNet, VGG16, ResNet50, Inception V3, and EfficientNet B5. Efficient Net B5 achieved the highest test accuracy of 98.84% and the lowest misclassification rate, outperforming other models like AlexNet and VGG16. The results validated the approach as a reliable solution for precise disease diagnosis, enhancing agricultural management and productivity in the betel leaf industry.

R. Sujatha. et al., (Sujatha, Radhakrishnan, et al. , 2021) evaluated the efficiency of Deep Learning (DL) and Machine Learning (ML) models in identifying diseases in plant leaves. The study compared ML methods like Random Forest and SVM with DL architectures such as VGG-16, VGG-19, and Inception-V3. Results indicate DL models significantly outperform ML counterparts, achieving higher classification accuracy, with VGG-16 yielding the highest accuracy (89.5%). They have demonstrated the superior capability of DL for plant disease detection and classification.

Sharada Mohanty. et al., (Mohanty, Sharada, et al. , 2016) explored the application of deep learning for diagnosing plant diseases through leaf images. The study aimed to utilize advancements in computer vision for smartphone-assisted disease diagnosis, addressing global food security challenges. Using a dataset of 54,306 controlled images of healthy and diseased leaves, the authors trained a deep Convolutional Neural Network (CNN) to classify 14 crop species and 26 disease types, achieving a high accuracy of 99.35% on a test set. However, testing with diverse online images revealed lower accuracy (31.4%), highlighting the need for varied training data. The findings suggested a scalable method for global agricultural disease management through smartphone applications but emphasize the necessity of diverse datasets for better generalization.

Xin Yang and Tingwei Guo (Yang, Xin, et al. , 2017) examined how machine learning (ML) is utilized to detect, classify, and understand plant diseases, contributing to advancements in precision agriculture. It emphasizes the use of various ML algorithms, such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF), to diagnose diseases like Huanglongbing in citrus and powdery mildew in tomatoes. These methods have achieved classification accuracies as high as 92.8% in some cases. The research highlights challenges, such as the need for robust preprocessing and diverse datasets to improve accuracy, while also discussing potential applications in disease prediction and quantification. The study concludes that integrating ML with technologies like aerial imaging and sensors can significantly enhance agricultural practices and plant disease management.

Surampalli Ashok. et al., (Ashok. et al. 2020) aimed to develop an efficient system for identifying diseases in tomato plant leaves through image processing and deep learning methodologies. The authors employed image segmentation and clustering techniques to preprocess leaf images, followed by the application of Convolutional Neural Networks (CNNs) for disease classification. The proposed CNN model achieved a classification accuracy of 98.12%, outperforming other models such as Alex Net and Artificial Neural Networks (ANN), which attained accuracies of 95.75% and 92.94%, respectively. This research demonstrated the potential of deep learning approaches in accurately detecting and classifying tomato leaf diseases, thereby contributing to improved agricultural practices and crop management.

Arsenovic Marko. et al., (Arsenovic, Marko, et al. , 2019) aimed to make deep learning techniques for plant disease diagnosis more useful. Key issues in the subject are noted by the authors, including the need for improved generalization across a variety of scenarios, the scarcity of datasets, and limitations with real-world environmental circumstances (such as complicated backdrops and changing lighting). A unique two-stage CNN architecture that is intended for excellent accuracy in practical applications was put forth by the authors. Tests show that the model can manage situations involving many diseases and get an accuracy of 93.67% in difficult settings

Amrita S. Tulshan. et al., the work focused on the existing classification techniques like leaf disease detection to detect the diseased plant from images. Two classifiers of algorithms are used to compare the results, existing one is Linear SVM Classifier and proposed algorithm is KNN Classifier. Following steps carried out like image preprocessing, image segmentation, feature extraction. Existing one used 150 images for dataset, had accuracy of 97.6% and proposed algorithm used 75 images as dataset, had accuracy of 98.56%.

Halil Durmus. et al., applied Deep learning techniques to detect the disease on the tomato plant. Work is about to train a robot to detect the disease on real time based on different algorithm training data fed to robot. AlexNet and SqueezeNet are two different architectures used for the system. Tomato leaf input Data set was sent from the plant village. Training and testing are done using mobile supercomputer Nvidia Jetson Tx1 has 256 CUDA cores, quad core ARM processor,4GB RAM, 16 GB eMMC. PlantVillage data set contains 54.309 labelled images for 14 different crops, AlexNet performed with accuracy 0.9722. AlexNet performed slightly better than SqueezeNet. But SqueezeNet is good candidate for the mobile deep learning classification due to its lightweight and low computational needs.

Kawcher Ahmed. et al., the goal of the system is early detection of diseased plant by automated method instead of manual method that takes prolonged time for detecting the disease. Machine learning techniques were implemented for this research work. The most common rice plant diseases are leaf smut, bacterial leaf blight and brown spot diseases are detected in this work. Affected white leaf images are used as input. Supervised classification algorithms were applied to detect three diseases of rice. Logistic Regression, K-Nearest Neighbour, Decision Tree, Naive Bayes Classifier are classifiers used. Among them decision tree performed the best with 97.9167%accuracy on test data.

Murk Chohan. et al., developed plant disease detector based on deep learning. Using neural network plant disease detection model is developed. Initially augmentation is used for the dataset to maximize the sample size, then convolution and pooling layers are used. CNN architectures like simple CNN, VGG, and InceptionV3 are trained by Jupyter notebook and Keras API of Tensor flow. Images from 38 different classes and 20% of each class randomly chosen for testing. Model gave us more than 95% accuracy. Testing dataset gave more than 98% accuracy. It concludes that from accuracy CNN is highly suitable for automatic detection and diagnosis of plants. This system could be integrated into mini-drones to live detection of diseases from plants in cultivated areas.

Vishal Dineshkumar Soni. et al.,work investigated on the data mining to predict the disease. From collection of huge diseased data, the hidden patterns information found in medical field based on data mining. Reliable prediction models are built using the data mining techniques. In this method, classifier learning is carried out in one step before the genetic algorithm. Selection is based on genetic algorithms combined with the SVM classification. Method has been tested with Various other classifier of different types on the datasets for breast cancer, Lung cancer and Diabetes.

Zamani. et al., explored the combined use of machine learning algorithms and image processing techniques for the detection of plant leaf diseases. This study demonstrated the efficacy of a hybrid strategy in which machine learning models effectively manage the classification problem while image processing improves the feature extraction stage. This study's integration of machine learning models like Support Vector Machines (SVM) and Random Forest for illness classification with image processing techniques including feature extraction and picture enhancement is one of its important features. This method's benefit over simple image classification techniques is its capacity to increase illness detection accuracy by preprocessing pictures to emphasize significant characteristics prior to classification. The final findings demonstrate that integrating machine learning models with image processing produces high illness detection accuracy, with Random Forest and other machine learning models offering the greatest classification performance.

3.1 Observation from the Literature Review

Agriculture is the foundation of any nation, for past several years. Focusing precision farming helps us to maintain high yield quality. Machine learning, Iot and deep learning technologies are used to detect and predict the disease at early stage. Plant is susceptible to disease by comparing the data values, which we got using Iot sensors like DHT-11 [1]. The performance of VGG algorithm has high accuracy when compared with Resnet and Alexnet. But data storing space required is high for VGG. Even using soil samples detection of yellow leaf disease can be done at early stage. Machine learning techniques detect fruit rot by weather parameter data collected. In this method Random Forest regression (RFR) gave minimum error in prediction. Image processing detects the spot

Table 1: Pros and cons between two methods

Methods	Advantages	Disadvantages
Machine Learning	ID3 algorithm can handle both categorical and continuous data and its powerful tool for decision making [4].	Had low scalability, when training large set of data.
	Less computational power and Fast response for less data sets.	Predicted low accuracy for complex task.
Deep learning	Higher accuracy than machine learning Techniques.	When deeper networks are considered, there is a degradation problem where accuracy initially rises with increased depth but then reaches saturation decreases with further depth increases [5].
	Used in real time detection system.	Segmenting specific region of plant based on supervising learning required expertise in that domain.

and classify the quality of areca nut with CCD camera accurately and efficiently but is unable to inspect for covered blades [9]. CNN techniques evaluate probability score and provide solutions with responses to the end user that is displayed. Table 1 explains the advantages and disadvantages of both machines learning and deep learning methods.

4 METHODOLOGY

Deep learning and machine learning methods are used to classify, identify, and predict diseases in different types of plants. Data were collected from the published research papers to study and compare the multiple techniques used to detect the disease. Algorithms like ResNet, MobileNet, VGG, image resizing, Support Vector Disease (SVD), clustering, and Efficient Net B5 are based on deep learning methodology used in this paper to detect the diseases. Artificial Neural Network (ANN), LightGBM (LGBM), Support Vector Machine (SVM), Random Forest (RF), Decision Tree, Back Propagation Neural Network (BPNN), and AdaBoost are the various algorithms based on machine learning implemented here to detect the diseases. Table 2 shows the different methodologies used to detect the disease and visualized the infected plant.

5 PROPOSED METHOD

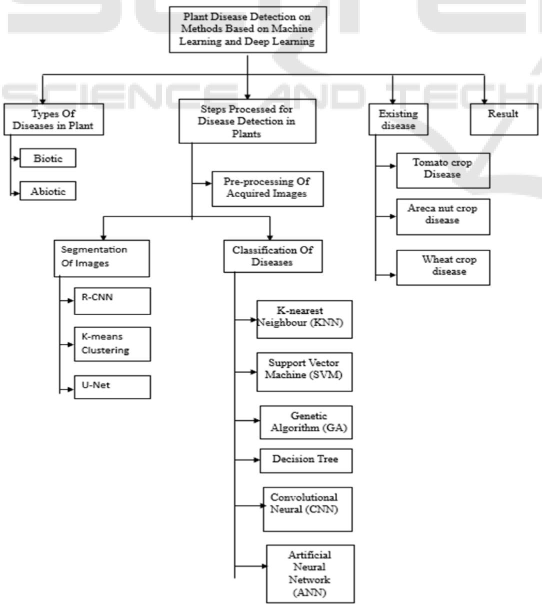

Figure 1: Flow chart for Disease detection process

Fig 1 shows the review work based on the data collected from various works, based on the study the work can be categorized and processed based on the proposed algorithm.

Table 3: Process for detection

Stage	Description	Techniques Involved
Types of Diseases in Plants	Identification of biotic (e.g., pests, fungi, bacteria) and abiotic factors (e.g., drought, nutrient deficiency).	Categorized as Biotic or Abiotic.
Steps for Disease Detection	Acquisition, Preprocessing, Segmentation, and Classification of Images to detect plant diseases.	Each step is detailed below.
Acquisition of Images	Collecting images of plants or leaves affected by disease using digital devices like cameras or drones.	Multispectral, Iot-Enabled cameras
Preprocessing of Images	Enhancing image quality by removing noise, resizing, and standardizing the dataset for better analysis.	Histogram Equalization, Filtering, Resizing, Normalization.
Segmentation of Images	Dividing images into regions to isolate diseased areas for further analysis.	Thresholding, Genetic Algorithm (GA), K-means Clustering.
Classification of Diseases	Using machine learning and deep learning models to classify plant diseases based on the processed images.	- Support Vector Machines (SVM) - Decision Trees - K-Nearest Neighbour (KNN) - Artificial Neural Networks (ANN) - Convolutional Neural Networks (CNN)
Disease Categories	Applying the above methods to specific crops and diseases, such as:	- Wheat Crop Disease Detection - Tomato Crop Disease Detection - Areca Nut Crop Disease Detection
Results	Evaluating the accuracy, efficiency, and applicability of models for identifying diseases.	Output results for specific crops based on the method used.

Stages of process, first one is to identify the types of diseases in plants, then processing them for disease detection in plants, then comparison with existing method for detection for better accuracy and finally the Results. Types of plants have two categories one is Biotic and another one is Abiotic. Disease detection has three stages like, segmentation of images, preprocessing of acquired images and classification of diseases. Segmentation process implements R-CNN, K-means clustering, U-Net. Disease can be classified based on K-nearest neighbour (KNN). Support vector machine (SVM), Genetic algorithm (GA), Decision Tree, Convolution neural network (CNN), Artificial neural network (ANN) are applied in this review paper for better results. Table 3 explains step by step for disease detection in plants with a small description.

6 RESULTS AND DISCUSSION

If From above the study, from various published research works based on machine learning and deep learning. The accuracy of disease detection system depends upon the data collected from the field; algorithms used for detection. For small set of data machine learning predictions are more accurate than deep learning. For complex applications, deep learning is more accurate.

Table 4 shows the accuracy of detected diseases based on the algorithms. By implementing higher accuracy methods avoids the error of detection that protects the farmer from early disease control. Disease control plays major role in farming to improve quality productivity. Future research work based on deep learning methods to disease detection in various plants gives better results. For an effective approach, extensive research needs to be studied and applied for disease detection.

Table 4: Accuracy of detected diseases

Type of diseases	Techniques	Algorithm	Accuracy
Koleroga	CNN	Res Net	97.5%
		MobiNet	86%
		VGG	96%
		Image resizing	88.46%
Yellow Leaf Disease	CNN	Res Net	97.5%
		SVD	86.30%
	Planet Scope Satellite imaginary	RF	88.24%
		BPNN	85.29%
		Ada Boost	67.65%
Based on Colour, Texture and Density	Machine learning	ANN	98.8%
Classification of Areca Diseases	Deep learning	Machine vision	90.9%
Crop Prediction	Machine learning	LGBM	94.20
Different Diseases of areca	Machine learning	Image Processing	90%
Betel leaf	Deep learning	Efficient Net B5	98.8%

7 CONCLUSION

Farmers need to be conscious in early detection of diseases that prevent them from spreading disease to other plants even these leads to production of low-quality yield. From above the study of research work paper published applied various algorithms to detect the diseases. Different diseases from various plants like areca nut, tomato, wheat plant, citrus gives variations in accuracy based on the method used.

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