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ENHANCING DISEASE DETECTION IN MANGO LEAF USING LOGISTIC REGRESSION AND NEURAL NETWORK

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ABSTRACT

In this research we increase the precision of the diagnosis of mango leaf disease, we employed sophisticated machine learning techniques in this project. We created a model using the "Orange" program to categorise mango leaf disease into eight groups: healthy, sooty mould, powdery mildew, gall midge, die back, cutting weevil, bacterial canker, and anthracnose. The main goal of this study was to use analytics and historical data to improve the accuracy and speed of disease identification. We used logistic regression and neural networks to evaluate different machine learning approaches. Logistic regression gave an accuracy of over 99.2%. But the neural network gave accuracy of 99.3%. The overall framework performed well on all the evaluation metrics: F1 score, recall, Matthews correlation coefficient (MCC). The results of the neural network demonstrate its ability to identify intricate patterns in the data, which is crucial for the diagnosis of illness. This study demonstrates how machine learning can increase mango leaf disease identification accuracy and dependability. Our data driven approach using the “Orange” software can handle large datasets efficiently and make crop health monitoring more accurate and reliable. Among the methods tested the neural network was the best and most precise method, it gives significant improvement in crop health supervision and disease management.

Keywords— Mango leaf diseases, Disease detection, Image classification, Machine learning, Logistic regression, Neural Networks, Image dataset, Automated detection, Orange, Sustainable agriculture, Crop health.

I. INTRODUCTION

Mango leaf disease detection and classification crucial for agricultural sustainability and food security, Identifying and categorising diseases of mango leaves is essential. The traditional method of identifying illnesses relies on the manual visual inspection of specialists, which is laborious, time-consuming, and prone to human error. Due to their rapid development, machine learning and computer vision systems are increasingly being used to diagnose plant diseases. Machine learning technologies, especially logistic regression and neural networks, enable the rapid and precise detection of mango leaf disease.which have demonstrated remarkable effectiveness in picture classification tasks.

In the past researchers have tried many ways to automate plant disease detection. In order to train machine learning models, early work concentrated on handmade feature extraction, which involved manually extracting texture, colour, and form descriptors from leaf photos for disease classification. While these worked moderately well they required domain expertise for feature selection and have been restrained in their capability to generalize across one-of-a-kind datasets and sickness types.

With the arrival of advanced machine learning techniques, computer vision has been revolutionized by allowing models to learn features straight from unprocessed data, eliminating the requirement for feature engineering by hand. Neural networks and logistic regression are two of these methods that have demonstrated significant promise in picture categorisation and have proven effective in agriculture. Researchers have created extremely accurate models for identifying and classifying mango leaf diseases, leading to improved disease control in orchards, by training these models on enormous datasets of annotated leaf photos.

We used a multi-phase approach in this investigation to determine diseases using traditional machine learning in Orange software. Our method involved development and training of logistic regression and neural networks. We began with preprocessing of mango leaf images dataset which included resizing, normalization and augmentation. Next, in order to extract features from unprocessed image data, we constructed a neural network architecture. Using the user friendly interface and robust features of Orange, we did feature selection, model training and evaluation and tried different configurations to find the best approach for disease classification. By using these methods we tried to achieve accurate and fast disease detection for mango leaf diseases and hence better management practices in orchards.

Our Model is effective in correctly diagnosing mango leaf diseases, as seen by its impressive 99.112% accuracy on the testing data.

Advantages of Machine Learning for Mango Leaf Disease Detection:

- High Precision
- Reduced Human Error
- Adaptability and Expandability
- Precision Agriculture

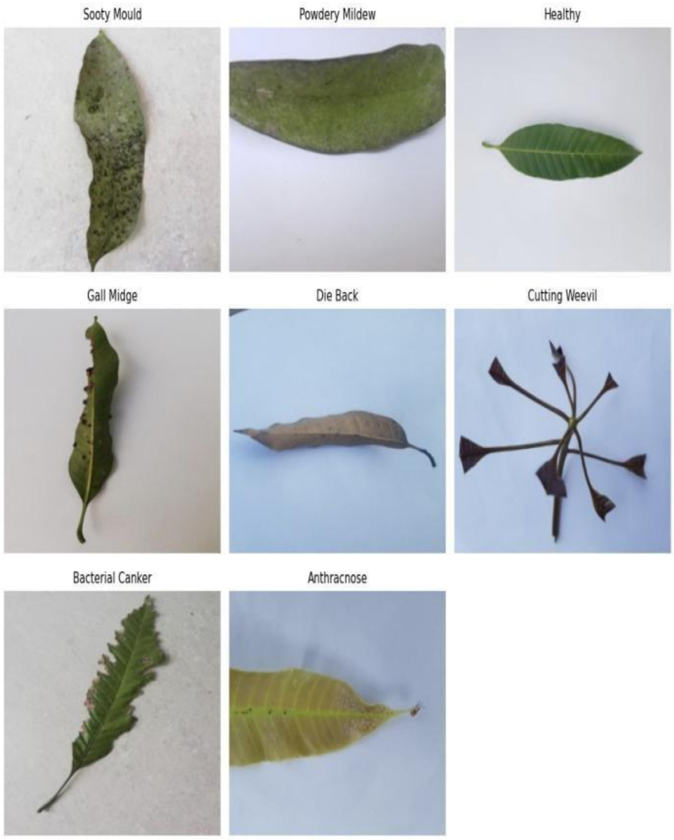

Fig. 1: Different types of Mango plant/leaf illness along with healthy leaf

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This paper is further classified into different sections. Section 2 is all about related work area regarding mango plant/leaf illness. Section 3 presents the dataset description on which we have trained the models. Section 4 is all about methodology which is done by us for required outcome. Section 5 consists of results. Further, this study is concluded in Section 6 with conclusion and its future aspects. Finally, ending up with the references in Section 7.

II. RELATED WORK AREA

A talented convolutional neural community for detecting seven distinguished mango leaf sicknesses created via Redwan Ahmed Rizvee et al. [1] presents LeafNet, a CNN model for detecting 7 mango diseases using leaf images from Bangladesh. Trained on a new region specific dataset, LeafNet outperforms AlexNet and VGG16 with 98.55% accuracy and better precision, recall, F-score and specificity. It helps in early disease detection and can boost mango production and national economy.

Mango Leaf Disease Detection Using Deep Learning by Sarder Iftekhar Ahmed et al. [2] Agriculture has not received much attention from the device studying network specially due to the lack of standard datasets. To address this, we created a ready to use dataset of mango leaves, consisting of 4000 images from 4 orchards in Bangladesh, a leading mango producer. The dataset contains 7 common diseases and while collected from Bangladesh, is applicable to other countries as the diseases are global. This dataset is designed to attract machine learning researchers and help in improving automated agricultural practices and boost mango production worldwide.

Mango Leaf Disease Detection Using Deep Learning by Nimisha Manoharan et al.[3] implemented using Google Colab to detect plant diseases as agriculture needs to support Asia's growing population. Diseases identification helps in preventing production loss and improving crop quality. The process involves inputting leaf images for preprocessing, segmentation, feature extraction and classification to help farmers monitor crop health. Disease detection is key to successful farming and image processing can be applied directly in the field to improve crop management.

Mango disease classification using (CNN) was developed by Yohannes Agegnehu Bezabh et al. [4] to address the significant impact of diseases and pests on mango yields, a major fruit crop. Pictures of both healthy and ill mango leaf were gathered from the Amhara Region's main production location, and then a variety of preprocessing methods were used, including picture scaling, noise reduction, and augmentation. To enhance classification performance, segmentation techniques such as Mask R-CNN and k-means were applied. CNNs were used to extract features, while fully connected layers were employed to build the classification model. The effectiveness of this method for high-precision image classification was demonstrated by the impressive results achieved by the ensemble model combining GoogleNet and VGG16: 99.87% training accuracy, 99.72% validation accuracy, and 99.21% testing accuracy.

Amisha Sharma et al. [5] used deep learning techniques to identify mango leaf diseases. Mango diseases and pests cause significant financial losses each year, and due to the similarity in their symptoms, farmers often struggle with accurate identification. To enable prompt and precise detection, this study aims to employ Convolutional Neural Networks (CNNs), which can autonomously extract features from raw images. We developed a CNN-based model for early detection and classification of mango leaf diseases by applying data augmentation techniques such as rotation, translation, reflection, and scaling to the collected dataset. The effectiveness of this approach was demonstrated by the trained model, which achieved an impressive 90.36% accuracy during testing.

Mango leaf disease diagnosis is tough because of crop variety, multiple disease symptoms and environmental factors. Current solutions are based on local data and are rarely used for early detection which results to big loss for farmers. This paper presents a (CNN)-based image processing method for mango leave disease detection. Through series tests, the model successfully classified healthy and damaged leaves with an accuracy of 97.92%.

This is a rapid and reliable approach for early disease detection, with the potential to be applied to other agricultural fields.

III. DATASET DESCRIPTION

URL = https://www.kaggle.com/datasets/aryashah2k/mango- leaf-disease-dataset/code

The data set used as analysis was sourced from the renowned data science platform, Kaggle. It encompasses a diverse range of mango leaf diseases, including infections caused by bacterial canker, sooty mould, powdery mildew, Gall Midge, die back, cuttingweevil, and anthracnose. Additionally, the collection feature images of healthy mango leaves, presenting a comprehensive overview for the studies performed.

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Table 1: Description of dataset

Diseases	Number of image samples used in processing.
Sooty Mould	500
Powdery Mildew	500
Gall Midge	500
Die Back	500
Cutting Weevil	500
Bacterial Canker	500
Anthracnose	500
Healthy	500

The accuracy and breadth of research on the application of deep learning techniques for the diagnosis of illnesses affecting mango plants and leaves are improved by utilising this openly accessible resource. This can help researchers to devise and test methods, compare different approaches, and improve the effectiveness of disease diagnosis in mangoes through leaf imperfections.

IV. METHODOLOGY

When identifying mango plant and leaf disease requires extensive data interpretation to ease the decision-making process. The approach taken involves systematic gathering and evaluating enormous volumes of data instead of relying on instinct and individual experiences. The vision this approach aims to achieve includes increasing agricultural output, controlling the spread of diseases, improving the identification of diseases, and evolving the treatment strategies. Initially, data is sourced to field research, IoT monitoring devices for temperature, humidity and soil conditions, remote sensing and laboratory testing, all of which focus on key environmental parameters. All of these factors combine to provide a holistic view of the mango leaf health. It is very important to mention however, that complex analysis cannot be performed without first cleaning and prepossessing the raw data. In turn, the great and reliability of the data meets a pressing need for data cleansing and preprocessing. Valid data ensures the integrity and validity of any analysis that is carried out.

Following the cleaning and organized of raw statistics, techniques for evaluating the data, including statistical analysis, machine learning models, and pattern recognition, include employed to extract trends and identify causal relationships. These methods assist in understanding the factors that lead to diseases of mango leaves, such as pest infestation, fungal infections and environmental stress. For these reasons, researchers and agricultural experts can develop strategies to proactively deal with these diseases better. A particularly important element of the data driven approach is the capacity to monitor and evaluate performance constantly. Continuous field data collection and analysis enables real-time evaluation of strategies for disease management. This immediate feedback loop makes certain that the actions taken are achieving the required results, be it containment, reduction or even elimination of a disease. As more data is collected and analyzed over time adjustments can be made to fine tune the existing strategies and ensure they continue to work. By using a data driven approach agricultural professionals get objective decision making, deeper understanding of pathogen dynamics, faster problem solving and ability to continuously improve disease prevention and treatment.

A. **Tool used**

We used the "Orange" software to identify illnesses of the mango crop and its leaves. An open-source program called "Mango" is well-liked for data processing and display. Its Orange Canvas enables users to create interactive data displays with extraordinary ease. Through monitoring channels, each module is independently able to transmit information to the rest, and every module has a GUI designed to be intuitive. Users can create pipelines using different modules that enable data analysis and modification as they see fit. The system also facilitates regression classification, grouping, and other forms of machine learning for varying tasks. These features are combined with tools for data evaluations and the system's cleanliness.

B. ***Proposed Model***

First, we used the "Orange" software to upload all our snaps to be able to import their files. This step is crucial for enabling the analysis of visual information. The files uploaded were subsequently attached to the Eye Viewer panel. One of the tools that allows us to confirm that the pictures have been loaded and processed is the so-called Eye Viewer, which is used to inspect and manipulate the photographs. The Eye Viewer was then linked to the Image Embedding module. Image Embedding transforms the images into numerical forms that ML methods can understand. This process, known as image embedding, prepares the images for further analysis by assigning them numerical values. This visualization is afterward connected to the Data Table unit,

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which processes information and displays it in table format. Now we can view the information and confirm that it has been formatted properly for evaluation. This technique changes the approach toward crop health management from one that is reactive to proactive interventions based on real time data information.

We then connected the Testing and Scores module with the Image Embedding module. In these segmentation components, the Test and Score module integrates various ML models to determine the accuracy of the results produced and how effective the models perform. These two forms were anchored on the Test and Score panel using the logistic regression and neural networks. These computations are integrated in the data analysis phase to predict the likelihood of diseases present in images of mango plants. We connected the matrix of confusion module to the Testing and Score module in order to examine the results. The classification results are visually represented by the Confusion Matrix. This also represents the model's overall performance. The words true positives, true negatives, false positives, and false negatives are used. Ultimately, the Image Viewer and Confusion Matrix were integrated. This helps us assess the test more easily and provides us with a comprehensive view of the model's effectiveness. outcomes by enabling us to show each distinct value next to the associated picture. By using a methodical approach, we can be confident that our framework was developed and assessed to diagnose problems in mango plants and leaves.

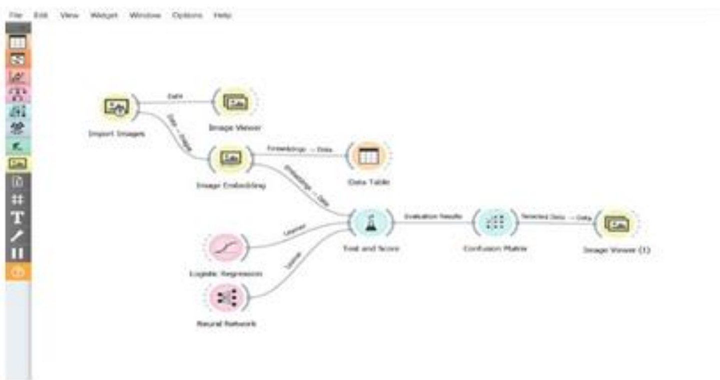
Data handled and modified via applying activation procedures to the scaled summed of the inputs through a sequence of secret layers. The ultimate forecasts are produced by the resultant layer. These are very effective for jobs requiring detailed patterns and enormous volumes of data, such picture and voice recognition. They can simulate complex, irregular interactions. Because of their adaptability and ability to gain insight from info, they are utilized in a variety of scenarios.

D. Model Evaluation and Equations

The suggested model's performance was assessed using AUC, CA, F1, Precision, Recall and MCC.

- ***AUC:*** It stands for Area under the ROC curve. It's a well-liked assessment metric for judging how well a binary classification model performs, especially in machine learning and diagnostic testing. The mass that the body expels is determined by clearance (volume/time) * AUC (mass*time/volume).
- ***CA:*** Classification accuracy is represented as a percentage, calculated by dividing the sum of true positives and true negatives by the total number of all possible outcomes (true positives, true negatives, false positives, and false negatives).

$$CA = \frac{TP+TN}{TP+TN+FP+FN}$$



(1)

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Fig. 2: Proposed model design to diagnosis Mango Plant/leaf diseases using orange tool

*C. **Algorithms used***

- ***Logistic Regression:*** Logistic Regression utilizes a statistical framework tailored for binary classification tasks, determining the probability that an input corresponds to a particular category. The sigmoid function, another name for the logistic equation, is applied by the framework to the linear mixture of the input characteristics, mapping the result to a result between 0 and 1. The input may then be divided into one of two groups using this likelihood. Because of its simplicity, it is a useful tool in situations when the input
- ***F1 score:*** Another well-liked assessment metric for binary classification problems is the F1 score. The performance of the classifier is summed up by a single number that combines precision and recall.
- Precision: It is the measurement tool used in binary classification problems to judge how well a classifier predicts the future. Out of all cases that the classifier classified as positive, it calculates the percentage of real beneficial predictions. It equals to true positives divided by sum of true positives and false positives.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

- ***Recall:*** It also known as true positive rate or sensitivity, measurement use in binary classification tasks to gauge how well a classifier can locate all occurrences that are positive in the dataset. Out of all real positive instances, it calculates the percentage of genuine positive forecast. It equals to true positive divided through sum of true positives and false negatives and goal variables have a linear connection.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

- ***Neural Networks:*** The structure and operations of the human brain are modelled by this family of machine learning frameworks. They are made up of layers of neurones, or interconnected nodes, with a certain weight given to each connection. After entering the input layer,the
- ***MCC:*** It stands for Matthews Correlation Coefficient. It is a statistic for assessing how well binary classification techniques work. It is especially helpful when handling unbalanced datasets since it offers a gauge of the accuracy of binary diagnoses.

V. Results

This section will look at the several models we drilled, how we adjusted the variables, and the models' output. The following are the models that we have taught and associated outcomes:

TABLE 2: Evaluation Results: Average over all classes

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.992	0.992	0.992	0.992	0.991
Neural Network	1.000	0.990	0.990	0.990	0.990	0.989

TABLE 3: Evaluation Results: Sooty Mould

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.997	0.987	0.988	0.986	0.985
Neural Network	1.000	0.997	0.986	0.990	0.982	0.984

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TABLE 4: Evaluation Results: Powdery Mildew

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.999	0.994	0.990	0.998	0.993
Neural Network	1.000	0.998	0.990	0.988	0.992	0.989

TABLE 5: Evaluation Results: Gall Midge

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.995	0.981	0.984	0.978	0.978
Neural Network	1.000	0.994	0.975	0.976	0.974	0.971

TABLE 6: Evaluation Results: Die Back

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.999	0.996	0.998	0.994	0.995
Neural Network	1.000	0.999	0.996	0.966	0.996	0.995

TABLE 7: Evaluation Results: Cutting Weevil

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	1.000	1.000	1.000	1.000	1.000
Neural Network	1.000	1.000	1.000	1.000	1.000	1.000

TABLE 8: Evaluation Results: Bacterial Canker

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.999	0.997	0.998	0.996	0.997
Neural Network	1.000	0.999	0.997	0.998	0.996	0.997

TABLE 9: Evaluation Results: Anthracnose

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.997	0.986	0.984	0.988	0.984
Neural Network	1.000	0.996	0.984	0.980	0.988	0.982

TABLE 10: Evaluation Results: Healthy

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	1.000	0.998	0.993	0.992	0.994	0.992
Neural Network	1.000	0.999	0.994	0.994	0.994	0.993

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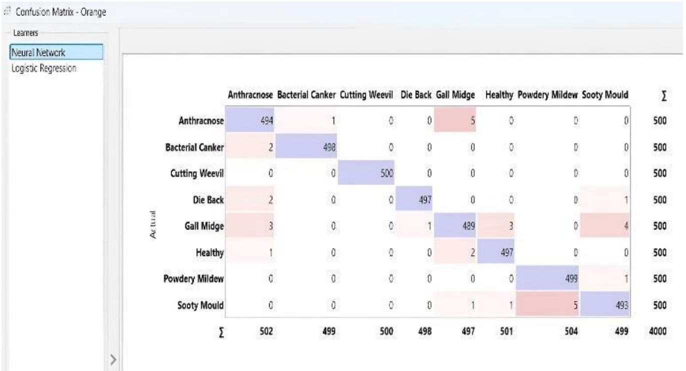
	Anthracnose	Bacterial Canker	Cutting Weevil	Die Back	Gall Midge	Healthy	Powdery Mildew	Sooty Mould	Σ
Anthracnose	494	0	0	0	6	0	0	0	500
Bacterial Canker	2	498	0	0	0	0	0	0	500
Cutting Weevil	0	0	500	0	0	0	0	0	500
Die Back	2	0	0	498	0	0	0	0	500
Gall Midge	6	1	0	1	487	3	0	2	500
Healthy	0	0	0	0	3	497	0	0	500
Powdery Mildew	0	0	0	1	0	0	496	3	500
Sooty Mould	0	0	0	0	3	0	6	491	500
Σ	504	499	500	500	499	500	502	496	4000

Fig. 3: Confusion Matrix of Logistic Regression



	Anthracnose	Bacterial Canker	Cutting Weevil	Die Back	Gall Midge	Healthy	Powdery Mildew	Sooty Mould	Σ
Anthracnose	494	1	0	0	5	0	0	0	500
Bacterial Canker	2	498	0	0	0	0	0	0	500
Cutting Weevil	0	0	500	0	0	0	0	0	500
Die Back	2	0	0	497	0	0	0	1	500
Gall Midge	3	0	0	1	489	3	0	4	500
Healthy	1	0	0	0	2	497	0	0	500
Powdery Mildew	0	0	0	0	0	0	499	1	500
Sooty Mould	0	0	0	0	1	1	5	493	500
Σ	502	499	500	498	497	501	504	499	4000

Fig. 4: Confusion Matrix of Neural Network

We discovered two significant issues with the Logistic Regression and Neural network models based at the confusion matrix results. Specifically, Bacterial Canker was often misclassified as Sooty Mould, and Sooty Mould was occasionally misidentified as Bacterial Canker. These misclassifications indicating a substantial difficulty in differentiating between these two categories.

When compared to Logistic Regression, the Neural Network approach demonstrates superior precision and reliability across the board. Based at the information provided, the Neural network(NN) is the optimal choice for this task, as it's performance, although not dramatically higher, remains consistently stable across all evaluation metrics. The Logistic

Regression technique achieved average accuracy of over 99.24% overall. In contrast, the Neural Network technique proved to be the most accurate solution, achieving average accuracy of over 99.39% overall.

VI. CONCLUSION AND FUTURE WORK

Using machine learning techniques, we successfully diagnosed eight distinct forms of mango leaf illnesses in this study: healthy, Sooty mould, Powdery mildew, Gall Midge, Die back, cutting weevil, Bacterial canker, and anthracnose were examined. The ability of two ML methods, Logistic Regression and Neural Network, to categorize these diseases was assessed. The Neural Network approach fared better than the Logistic Regression approach, achieving a classification average accuracy of over 99.39%, compared to the Logistic Regression method's results achieved average accuracy of over 99.24%. As a result, the Neural Network was determined to be the most precise and effective model for this purpose.

Finally a potential application of this study could be to integrate these models with mobile or IoT sensors to make real time disease diagnosis in the field. We can deploy this model and integrate this with an website or an application so that farmers can use this to detect disease in real time and apply necessary cure so that they suffer minimum or no crop loss and maximize their productivity.

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