International Research Journal of Innovations in Engineering and Technology (IRJIET)

ISSN (online): 2581-3048
Volume 7, Issue 10, pp 170-176, October-2023
https://doi.org/10.47001/IRJIET/2023.710022

MangoWise: Intelligent Farming Assistance for Budding, Planting, and Disease Prevention

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***Abstract* - This study introduces MangoWise, an intelligent farming application that integrates technology and agriculture to support mango cultivation. MangoWise provides disease diagnosis, fertilization advice, mango variety identification and market analysis. The methodology includes CNN-based disease detection, CNN architecture for budding, market analysis using various models and a soil analysis system for optimal fertilizer recommendations. The results show high accuracy in disease detection, budding time detection and market analysis. MangoWise provides a comprehensive solution for mango farmers, addressing various aspects of cultivation, thereby contributing to the advancement of agriculture and technological integration.**

Keywords: Mango disease, CNN, budding, machine learning, image processing, IOT, market analysis.

I. INTRODUCTION

Amid rapid technological progress, advanced nations are fusing agriculture and technology to automate practices. The creation of an intelligent app tailored for mango cultivation signifies a significant agricultural breakthrough. MangoWise, born of agricultural expertise, addresses challenges by connecting farmers with specialists. This mobile app, leveraging diverse domains, swiftly detects diseases, offers informed fertilization advice, identifies mango varieties, and analyzes markets. MangoWise extends beyond the farm, aiding in variety identification, market analysis, and budding techniques. The paper outlines its structure: a literature review (Section II), methodology (Section III), and outcomes (Section IV), MangoWise stands as a comprehensive assistant, meeting varied demands in mango cultivation.

II. LITERATURE SURVEY

The landscape of plant disease detection has evolved towards leveraging smartphone image processing methods, resulting in enhanced user accessibility [1]. CNN-based algorithms have been proposed to streamline plant disease diagnosis, with an emphasis on time and computational efficiency [2]. More advanced approaches involving K-means clustering and CNNs have surfaced, facilitating accurate disease identification based on color, shape, and texture [3]. In the context of mango cultivation, optimal budding timing has been identified as a critical factor for success, particularly in monsoon conditions [4].

Research efforts have explored various techniques, from conventional neural networks (CNN) to pattern analysis, to effectively identify plant trunk characteristics [5][6]. Diving into the mango industry, studies by Rathnayake and De Silva [7] and Sriram et al. [8] shed light on the complexities of production, distribution, and classification using CNNs. Object detection methodologies, exemplified by Shi et al. [9], have further enhanced the accuracy of mango variety identification through real-time detection using the YOLO network. Notably, nutrient composition (NPK values) plays a pivotal role in fertilization, as highlighted in [10]. The consequences of improper fertilization are discussed by K. H. S. Peiris [11], while optimization strategies considering NPK levels and crop age are proposed in [12]. Innovative techniques such as pH-based NPK estimation and associated fertilizer recommendations are introduced by F. Siva [13], underscoring the multidimensional nature of mango cultivation practices.

III. METHODOLOGY

The MangoWise was developed to respond to farmers' queries regarding diseases in mango cultivation, and the system mainly comprises 4 subcomponents as follows.

a) Mango disease detection & and suggest remedies.
b) Mango plant budding timing identification.
c) Market analysis based on mango variety identification.
d) Fertilizer and quantity suggestion.

A new Android application has been created to streamline the incorporation of various features, and the system's high-level architecture is illustrated in Figure 1.

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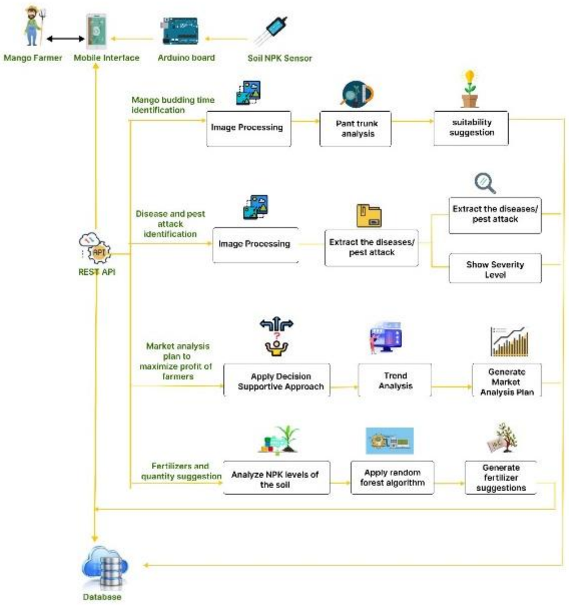

Figure 1: System diagram

a) Mango Disease Detection and Suggest Remedies

The accurate identification of mango diseases is crucial to minimize yield losses. Extensive research has been conducted to identify key diseases affecting mango cultivation. The proposed solution will identify the following in the mango domain:

- Healthy Mango.
- Anthracnose - Characterized by dark, sunken lesions on fruit and leaves.
- Powdery Mildew - Visible as white powdery patches on leaves and shoots.
- Sooty Mold - Black or dark brown powdery growth on leaves, stems, and fruits caused by honeydew secretions from sap-sucking insects.

1) Dataset Collection

The collected dataset was analyzed using the CNN techniques. Images of healthy mango leaves, Anthracnose, Powdery Mildew, and Sooty Mold were captured during field visits to various locations across the country. These images were then classified into four classes: Healthy, Anthracnose, Powdery Mildew, and Sooty Mold.

2) Data Augmentation

To ensure higher accuracy and extract usable data, augmentation techniques were applied. This involved utilizing rotation and horizontal flip techniques. Additionally, all images were downscaled to a uniform size of 240 x 240 pixels to maintain consistency in the dataset's dimensions.

3) Convolution Neural Network (CNN) Architecture

The utilized architecture involves a Convolutional Neural Network (CNN) with the Xception model. Pre-trained layers of the Xception model are frozen during training to prevent overfitting. Additional layers, such as a convolutional layer, a max pooling layer, a flatten layer, a dense layer, and a softmax layer, are subsequently added. The convolutional layer extracts feature from the input image, followed by the max pooling layer, which reduces the dimensionality of the feature maps. The flatten layer plays a crucial role in converting the output of the convolutional layers into a one-dimensional vector, enabling the dense layers to learn complex relationships in the data. Finally, the softmax layer generates class probabilities.[14]

4) Convolution Neural Network (CNN) Model Training and Testing

Color is a crucial aspect of image processing; hence, RGB channels were utilized for all photos in this study [15]. The mango leaves dataset was partitioned into three subsets: 80% for training, 10% for testing, and 10% for validation, using a batch size of 64. The training procedure employed well-established deep learning frameworks, TensorFlow and Keras [16]. To identify four classes in this research, class names were automatically assigned based on the folder names in the user-supplied dataset. The model was optimized using the Adam optimizer.

After completing training and validation, the fully trained and validated model was deployed using Fast API. To classify images acquired by mobile devices, a REST service was utilized to transmit the images to the model, providing the user's predicted results.

The model has been effectively deployed within the Google Cloud Platform (GCP) environment. In this configuration, images captured by mobile devices are sent to the model via a REST service hosted on GCP. The model analyses the received images and returns the user's predictive results. This integration facilitates utilizing the model's capabilities and GCP's infrastructure and services.

b) Mango Plant Budding Timing Identification

Timing is vital for successful mango grafting, influencing process outcomes. Grafting combines scion and rootstock for better mango varieties. Ideal timing is the active growth season, with abundant sap flow and cellular activity, aiding graft union healing and integration.

The proposed system will identify the following stages in the mango grafting domain.

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- Plants do not mature enough for grafting.
- Suitable plants for grafting.
- Plants with too thick (too much matured) trunks for grafting.

1) Dataset Collection

A novel dataset was curated, featuring mango plant images at different growth stages. It's divided into three categories: immature plants, ideal for grafting; suitable plants; and those too advanced for grafting. Captured from diverse locations, the dataset is labeled "early," "suitable," and "late" to denote plant conditions.

2) Data Augmentation

To enhance dataset accuracy, various augmentation techniques were applied, including rescaling, flipping, rotation, zoom, contrast adjustments, and random Gaussian modifications. This enriched dataset diversity, aiding the model's learning process. Additionally, images were downscaled to a consistent 256 x 256 pixels, maintaining uniformity for streamlined analysis while retaining essential mango plant features.

3) Convolution Neural Network (CNN) Architecture

The architecture employs a CNN built upon the VGG16 model, known for strong image classification. It includes a flattened layer, a dense ReLU layer with 256 units, a dropout at 0.5 rate for regularization, and a dense softmax layer for predictions.

The VGG16's feature map is flattened for processing. A dense ReLU layer captures complex patterns. Dropout prevents overfitting. A softmax layer generates class probabilities. This architecture combines VGG16's feature extraction with added layers for robust classification. Flattening, dense, and dropout layers enhance generalization, aiming for accurate results.

c) Market Analysis Based on Mango Variety Identification

Identifying mango varieties is a crucial aspect of this research, which aims to utilize advanced image processing and deep learning techniques for accurate recognition of diverse mango types. The goal of this study's market analysis is to gain insights into the mango industry, including market size, trends, the competitive landscape, and consumer behavior. The analysis is conducted using a combination of primary and secondary data sources, followed by techniques for extracting meaningful information from the data. The market analysis findings are essential for comprehending the current status of the market and making educated decisions regarding mango variety identification and market strategy.

1) Data Collection

The market study relied on surveys of mango consumers and industry stakeholders. The study asked about customer preferences, purchase behavior, brand impression, and purchasing decision factors. To evaluate market trends, pricing tactics, and distribution routes, mango industry leaders were interviewed.

Secondary data sources included industry reports, market research, and government publications. Data on market size, growth, historical prices, and competitor analysis was beneficial from these sources.

2) Price Analysis

The price analysis section explores the historical price data of different mango varieties. It examines price trends over time, taking into consideration seasonality, supply and demand dynamics, and market competition, among other factors. The purpose of this analysis is to identify pricing patterns, identify price influencers, and assess the price elasticity of mangoes.

3) Model Training & Testing

We utilized various supervised machine learning algorithms/models and divided the dataset into training and testing sets in order to predict prices. We specifically employed the ARIMA, SARIMA, SES, GBM, and LSTM time series forecasting algorithms to the data and evaluated their performance to determine which algorithm was most appropriate to our goal.

d) Suggest Best Fertilizer and it's Quantity

The system assesses soil nutrition, recommends suitable fertilizers and quantities to curb deficiencies and enhance productivity. It mainly focuses on:

1) Soil analysis.
2) Optimal fertilizer suggestion.
3) Appropriate fertilizer amount suggestion.

1) Soil Analysis

Soil data is analyzed using an NPK RS-485 sensor and Arduino UNO. Data is converted from NPK sensor to TTL using RS-485 to TTL converter for Arduino communication. An Arduino code displays readable sensor data. Data is sent to mobile via HC-05 Bluetooth. The system operates on a 9V battery. After the sensor is inserted into the soil for nutrient levels (N, P, K in ppm), results are displayed on the mobile app.

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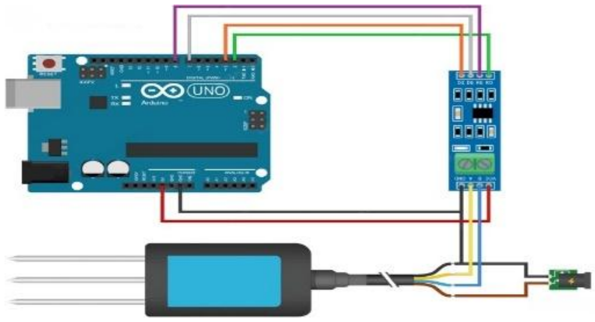

Figure 2: Circuit diagram of the IOT device

2) Optimal Fertilizer Suggestion

Analyzed soil samples using an IoT device to gather data for model creation, focusing on optimal mango growth regions in Sri Lanka's dry and intermediate zones. Gathered relevant soil and fertilizer data from local agricultural research institutes (Horana and Bataatha). Conducted feature selection, data cleaning, and preprocessing for model development. Split dataset into training and testing subsets. Used three supervised classification algorithms to build and test models, determining the most accurate one for predictions.

3) Appropriate Fertilizer Amount Suggestion

The data preprocessing part has done as the above step. Used three regression algorithms: random forest, gradient boosting, and decision tree, to assess accuracy. The output of the fertilizer suggestion model (the suggested fertilizer) is considered as an input for this model and also, this model gets the suitable NPK levels for mango trees according to the growth stage and age of the tree, from the database as inputs. Used random forest regression algorithm to propose the optimal fertilizer quantity for reaching recommended NPK levels as it shows the highest accuracy.

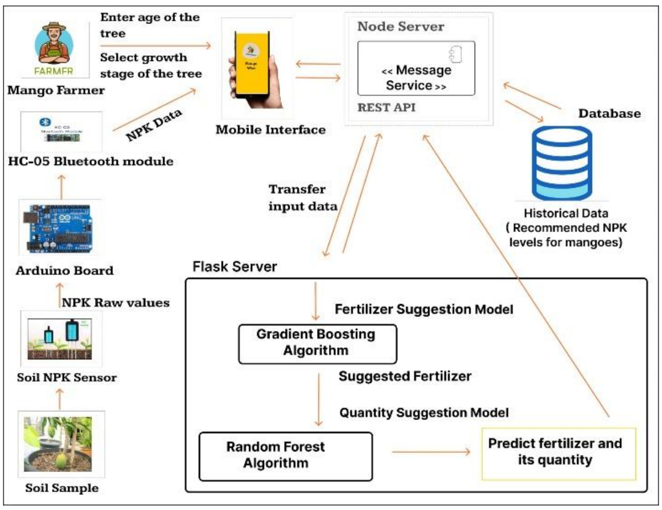

Figure 3: Overview of the fertilizer suggestion system

IV. RESULTS AND DISCUSSION

a) Mango Disease Detection and Suggest Remedies

Convolutional Neural Network (CNN) architecture was used to train the proposed disease detection model for mango. The training was conducted over 50 epochs with 64 samples per set. The following is a summary of the progress and performance metrics for training:

- Epochs: The model has trained over 50 epochs, with each epoch consisting of iterations through the training dataset.
- Batch Size: During each epoch, the training data was processed in batches of 64 samples, optimizing computational efficiency.

The model's performance was evaluated using two important metrics: loss and accuracy (Figure 4).

- Loss: The loss metric measures the deviation between predicted and actual values. The model exhibited a decreasing loss trend from an initial loss value of 0.6609 to a final loss value of 0.0227. This indicates the successful acquisition of pertinent patterns from the training data.
- Accuracy: The accuracy metric represents the percentage of correctly predicted instances relative to the total number of instances. The model's accuracy trended upward, starting at 0.7138 and culminating at 0.9932. This demonstrates the model's accuracy in classifying mango leaves as healthy or diseased.

Figure 4: Training and validation accuracy-Disease detection

The model's performance was evaluated further using a validation dataset that it had not seen during training. The validation dataset contained samples not previously encountered by the model, thereby providing a reliable estimation of its generalization ability.

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- Validation Loss: The model achieved a validation loss of 0.0178, indicating its ability to generalize well on unseen data.
- Validation Accuracy: The validation accuracy reached a high value of 0.9950, affirming the model's capacity to classify mango leaves accurately.

The convergence of loss and increased accuracy over epochs suggests effective learning and the model's ability to capture disease-specific patterns.

b) Mango Plant Budding Timing Identification

To determine the optimal architecture, the model was trained using the default CNN architecture, as well as RenMax50 and VGG16 architectures.

Table 1: Accuracy Comparison

Architecture	Accuracy
Default CNN	46.66%
RenMax 50	83.75%
VGG 16	96.25%

The default CNN achieved 46.66% accuracy, while RenMax50 improved to 83.75%. Remarkably, VGG 16 outperformed all, reaching 96.25%. VGG 16's complex design adeptly captured intricate patterns, ensuring highly accurate predictions. Architectural choices significantly affected performance, with VGG 16 leading, followed by RenMax50 and the default CNN.

Training spanned 30 iterations, producing results tabulated by accuracy and loss probabilities.

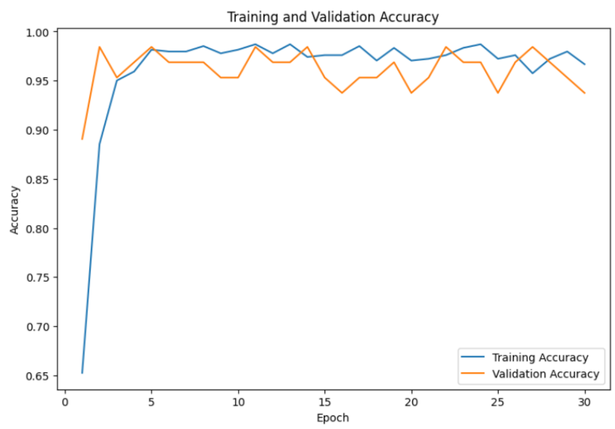

Figure 5: Training and validation accuracy-planting and budding

The heatmap below illustrates the confusion matrix, with color intensity indicating sample count alignment between true and predicted classes.

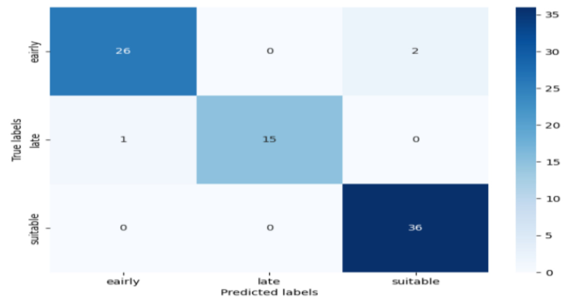

Figure 6: Confusion matrix

c) Market Analysis

The market analysis phase utilized a range of time series forecasting models including ARIMA, LSTM, and SES to examine historical mango price data. This research study analyses machine learning accuracy using Root Mean Squared Error (RMSE), a typical method. The optimal model for prediction is one with a low RMSE value. As indicated in table 2, the ARIMA model was chosen as the most accurate model for price prediction.

Table 2: Results of Mango Market

Model	RMSE Value
ARIMA	121.6213
LSTM	122.3651
SES	130.0853

d) Suggest Best Fertilizer and it's Quantity

For the fertilizer suggestion model, the Decision tree classifier, Random Forest classifier and Gradient boosting algorithms got 72.77%, 85.34% and 92.14% accuracy respectively. As gradient boosting got the highest accuracy it selected to build the final model for fertilizer prediction. Below diagram shows the accuracy for each algorithm.

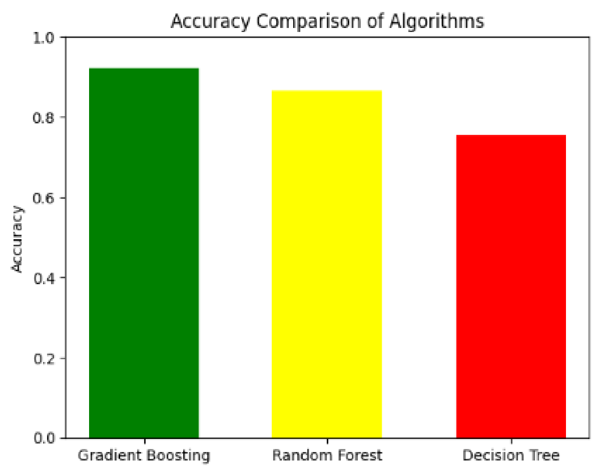

Figure 7: Model accuracy comparison

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When considering the fertilizer quantity suggestion model, the random forest regressor algorithm got the highest accuracy of 89.35% when the number of decision trees equals to 100 and the initial random state equals 43. The below image shows the accuracy evaluation for a model that is built from the random forest regressor algorithm.

```
Random Forest Regressor:
Mean Squared Error: 1094.3185294117648
Mean Absolute Error: 18.251680672268908
R-squared: 0.8935494539278452
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Figure 8: Random forest regressor accuracy

By the combination of the above two models, the system predicts the most suitable fertilizer and its quantity according to the available NPK level of the soil to maximize the health and quality of the mango trees and fruits by minimizing nutrition disorders.

V. CONCLUSION

Finally, MangoWise uses technology to address the challenges of mango growers. This smart farming program covers everything from disease prevention in mangoes to market analysis and fertilizer recommendations. The potential of modern image processing is demonstrated for disease detection. MangoWise detects diseases accurately and allows farmers to correct them a harvest loss. For transplantation, budding time detection using deep learning technologies improves the viability of mango cultivation.

The market analysis illuminates mango agriculture by revealing market trends, pricing tactics and consumer behavior. MangoWise uses time series forecasting models to help farmers make output decisions. The app analyzes soil and recommends fertilizers for healthy tree growth and high-quality fruit with the use of IoT and machine learning.

As an intelligent farmer assistant, MangoWise helps farmers to increase productivity, sustainability, and profitability with data-driven insights. MangoWise's approach demonstrates the potential of agricultural innovation and offers a bright future for technology and farming.

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Citation of this Article:

Yasantha Mihiran P.P, Sanjula Dulshan I.G, Lakshan H.A.D, Dilsha Thathsarani W.H, Aruna Ishara Gamage, Thilini Jayalath, "MangoWise: Intelligent Farming Assistance for Budding, Planting, and Disease Prevention" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 170-176, October 2023. Article DOI https://doi.org/10.47001/IRJIET/2023.710022

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