Development of an Intelligent System for Precision Banana Farming in Sri Lanka

Hewageeganage H.R.
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka

Munasinghe M.H.M.
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka

Lansakara L.M.C.S.
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka

Vidanagamage T.C.B.
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka

Thusithanjana Thilakarathna
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka

Thilini Jayalath
Department of Computer Science and Software Engineering
Sri Lanka Institute of Information Technology
Malabe, Sri Lanka

ABSTRACT
In Sri Lanka, banana is the most demanding fruit among consumers. Currently, Sri Lanka has about 60,000 hectares of territory under banana cultivation. Around 29 diverse types of bananas may be found. Most of them indigenous and unique to the country. This study focuses on developing an intelligent system (Mobile Application) designed for precise banana farming in Sri Lanka, taking into consideration the difficulties farmers face with dealing with diseases and pests, their lack of familiarity with best practices, the availability of agricultural officers, their capacity for problem-solving, and the potential for value-added banana products. The study uses a combination of methods to collect data from banana producers in several regions by combining surveys, interviews, and field observations. The findings focus on common diseases and insect infestations, insufficient farmer knowledge, shortage of agricultural officials who can effectively meet farmers' requirements and difficulty in handling cultivation activities efficiently and boosting banana plantation revenues. The study also evaluates the extent to which farmers may successfully address these issues and the chances to boost productivity through value-added banana products.

Keywords
Banana, Conversational AI, Convolutional Neural Network (CNN), Mobile Application, Intelligent System, BallTree, Geopy, AutoRegressive Integrated Moving Average (ARIMA), BARIMA

1. INTRODUCTION
Most of the people around the world's appeared to make their primary living from agriculture; if there are problems in this sector, it would harm the population's livelihood. In Asian countries, Banana is one of most significant and commercially important cultivation [1]. Banana cultivation takes up roughly Bananas are grown on 54% of all fruit growing lands. Data indicated in statistics for Sri Lankan agriculture sector [2], Sri Lanka's primary area for commercial banana cultivation is the Walawa region [1]. Approximately 60,000 hectares of territory are currently used for banana farming, and the nation produces about 780,000 metric tons of bananas each year. Kurunagala, Rathnapura, Hambanthota, Monaragala, Ampara and Jaffna are major districts of cultivating banana in Sri Lanka [1].

In Sri Lanka, banana is the one of the most fruit crop which is available throughout the year which is also consumed at a greater rate than any other fruit. [1] Apart from the banana fruit, banana leaves are used to serving food, wrapping food [3]and storing purposes. It is a dispensable plant for Sri

Lankans [4]. The most consumed and well-known varieties of banana are Pisang awak, Silk Banana, Pome Banana, Red Banana and Cavendish which is consumed as a cooking variety. Bananas can be varied according to different shapes, colors, sizes, textures, and flavors. Bananas are frequently used as a nutritious snack or as an ingredient in smoothies and other foods. They are an excellent source of vitamins and minerals, including vitamin C, vitamin B6, and potassium.

Nowadays, fruits can catch a variety of diseases, and early-stage manual disease detection can be challenging. In which, banana is a fruit that grows with an exceedingly high yield in several Asian countries. However, several factors cause the banana fruit to become infected with various diseases, which causes the complete fruit to perish and significantly lower product output [2]. There are several diseases and pest attacks that can be identified in bananas such as banana bunchy top virus, banana streak virus, anthracnose, black-sigatoka, and crown rot [1]. Most of the time, these diseases can be found by observing the plant and using the proper detection skills. Some of these illnesses are challenging to identify because they frequently exhibit similar signs. In that situation, the typical farmer needs professional assistance to identify the precise disease and apply the appropriate treatment [1]. That was one of the frequent issues that were identified during the survey.

Conversational AI systems have revolutionized various industries by providing interactive and personalized information to users. In the agricultural domain, such systems can play a crucial role in disseminating knowledge about crop cultivation and disease management. This research paper also focuses on the development of a conversational AI system that utilizes the RASA framework and integrates a knowledge base to provide users with information about banana plantation and diseases related to bananas [5].

Banana farming generates significant agricultural waste, including stems, leaves, inflorescences, and peels. These by-products contain bioactive compounds with various applications [6]. Farmers now have the opportunity to sell not only bananas but also these by-products. To facilitate transactions, factors like product type, nearest location, price, and quantity are considered. Wholesale buyers can purchase bananas and by-products and transform them into value-added products, such as plant-based meat alternatives, confectionery items, snacks, and health supplements. The proposed platform connects farmer-sellers and wholesale buyers, promoting the production and marketing of these value-added products. This approach aims to maximize the utilization of bananas and their by-products, fostering sustainability and profitability in the industry. Farmers and wholesale buyers can enhance their economic prospects while minimizing waste. By tapping into the potential of banana by-products, this initiative contributes to a more efficient and environmentally conscious banana farming sector.

2. LITERATURE REVIEW

The only fruit crop in Sri Lanka that is constantly available throughout the year and has a higher consumption rate than other fruits is the banana. Banana farming takes up about 54 percent of all fruit growing lands [1]. Both large-scale and smaller-scale banana farming are practiced in Sri Lanka. Smaller scale banana production is often used for domestic use. Kurunagala, Rathnapura, Hambantota, Monaragala, Ampara, and Jaffna are the principal banana-growing regions in the nation [1].

However, diseases and pest attacks could have been one of the major problems faced by Banana farmers in Sri Lanka due to lack of fertilizers and treatments. Disease was listed by 44% of farmers as the main obstacle to growing bananas [1]. According to the study of paddy and banana cultivation in Sooriya Wewa D.S. division [2], they have identified that bananas, unlike paddy, were more vulnerable to diseases. If the farmer can manage those diseases and provide the best solution to the identified disease, the crop can be cultivated easier. The major diseases observed by the study of [1] are, Sigatoka, Yellow sigatoka, Cordana, Anthracnose, Crown wilt, Panama wilt and Bunchy top virus. According to their analysis [1], the highest disease incidence was recorded by Banana Streak Virus (BSV) in Batticaloa district. In accordance with W.A.I.U. Bandara and the team's research [7], they have suggested a mobile application solution that makes it easier to diagnose pineapple-related disorders and employs a knowledgebase and conversational AI to act like a human counterpart. Additionally, the created mobile phone application generates a plan for product differentiation and a recommendation plan that enables farmers to make money by examining market trends.

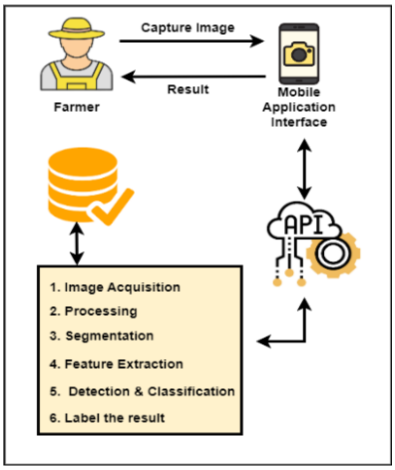

Figure 1: Disease Detection Process

They primarily used CNN (Convolutional Neural Networks) and image processing techniques for the disease diagnosis portion of the project since, as they said, image processing is suited for mobile phone implementation given that, according to their research, over 90% accuracy has been attained.

3. METHODOLOGY

3.1 Identification of banana diseases and pest attacks using CNN

To avoid needless yield losses, it is important to accurately identify banana diseases. For that, precise and accurate monitoring is required to stop the spread of illnesses and insect infestations. Farmers frequently omit this stage of cultivation due to the higher cost of monitoring. Farmers may easily increase their productivity and decrease harvest loss if the expense of monitoring is reduced [1]. The farmers might be given access to this mobile application to boost portability and accessibility. The suggested solution will specify the following in the banana domain:

• Yellow Sigatoka – Can be identified by yellow spots of chlorophyll appearing on the leaves.

• Cordana - Can be identified by light brown oval- shaped spots appearing on the surface of the leaf blade.

• Anthracnose - Can easily penetrate through the skin of the banana during ripening and spots on the banana skin are brown color and rounded shape.

• Banana Crown Rot - The cap and the necks of the banana may be thoroughly penetrated by a layer of yellowish mold, which will result in dry, black rot.

• Healthy Fruit

• Healthy leave

The following figure represents the component architecture,

The feature extraction and data labelling stages are the two key steps in the disease detection process. Based on the symptoms of the leaf or the fruit, feature extraction can be utilized to categorize each and every disease [1]. The categorization will then be used to process the image labelling. The mobile application's built-in camera is used for image acquisition, which is the first stage of image processing. Initially, the user must use a mobile application to upload or capture the infected plant in order to get the result. Then after Image pre-processing, segmentation, feature extraction, Image Detection, Classification and result labelling will be done.

3.1.1 Convolutional Neural Network (CNN) Architecture for disease detection.

Precision agriculture has advanced due to the suggested system's use of a Convolutional Neural Network (CNN) for the identification of diseases and pest attacks. The phases of feature extraction and classification make up the CNN architecture. Convolutional layers process input photos through filters to analyze them during feature extraction, collecting hierarchical and abstract patterns related to plant health. In the classification phase that follows, fully linked layers are used to analyze these features and make predictions regarding the presence of illness or pests. The CNN gains the ability to distinguish between healthy and diseased individuals by training on labelled datasets. This deep learning-based CNN-based method offers a comprehensive and automated method for identifying and dealing with plant diseases in the agricultural sector. [2]

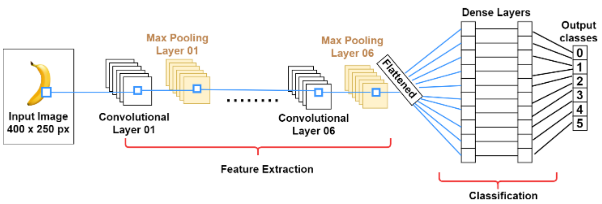

Figure 2: CNN Architecture

To add nonlinearity to the model, the system used a convolutional layer with a 3x3 filter size and the Rectified Linear Unit (ReLU) activation function. The input was converted into a feature map during this process, and then a pooling layer was used for dimension reduction to reduce overfitting by limiting the number of parameters [7]. Six convolutional layers, six max pooling layers, one flattens layer, and two dense layers compose the overall architecture, which has a total of 183,682 trainable parameters. This approach, which is distinguished by its application of convolutional and pooling layers, contributes to parameter management and effective feature extraction in addressing the issues of model complexity and overfitting.

3.1.2 Data Collection

Images were first divided into two categories, healthy and infected, on collecting them. CNN deep learning technique was used to analyze the data set that had been gathered. After obtaining all the images, they were divided into six classes and assigned the labels 0, 1, 2, 3, 4, and 5 to denote, respectively, healthy fruit, healthy leaves, yellow sigatoka, cordana, anthracnose, and banana crown rot.

3.1.3 Data Augmentation

The application of augmentation, which involves a number of techniques including rotation, width and height shifts, zoom, channel shift, and horizontal flip [7], is used to maintain more accuracy and recover data. Furthermore, all images are resized to 400 250 pixels in order to guarantee the consistency of the dataset's dimensions. By exposing the model to a variety of variances in the training data, this procedure tries to increase the model's robustness, ultimately enhancing its generalization performance.

3.1.4 Model Training and deploying

The process of training the model is done by using Keras and TensorFlow. Tensor flow is an open-source machine learning framework and Keras is a user-friendly neural network library that runs on top of the TensorFlow technology. In the model training process, when the dataset is loaded, it will classify into 6 predetermined classes as mentioned in the data collection stage. Then the trained model is deployed by using FastAPI, which offers advantages including speedy performance, automatic validation, and straightforward API development for delivering the model. When the farmer captured and uploaded the image from the mobile application, it will send to the classification process through the API and then predicted result will be displayed to the farmer.

3.2 A knowledge based chatbot to provide solutions for identified diseases and the user problems.

The methodology employed in this research entails a systematic approach to develop a conversational AI system integrated with a knowledge base, aimed at providing comprehensive information about banana plantation and diseases. To initiate the data collection process, a diverse dataset encompassing a wide range of user queries pertaining to banana cultivation and diseases is meticulously gathered. This dataset encompasses various topics such as cultivation practices, soil requirements, disease identification, and management strategies. Subsequently, the collected dataset undergoes pre-processing to eliminate any extraneous noise or irrelevant information that could impede the training process. The RASA framework is then configured, wherein the conversational AI system architecture is defined, comprising essential components such as the Natural Language Understanding (NLU), Core, and Action servers [3].

Through the utilization of supervised machine learning techniques, the intent recognition and entity extraction models are trained to accurately classify user intents and extract pertinent entities. Moreover, dialogue management is implemented to facilitate seamless handling of multi-turn conversations and generate appropriate responses based on the identified intents and entities. In parallel, a comprehensive knowledge base specifically tailored to banana plantation and diseases is developed, consolidating structured and unstructured data from reputable sources such as research papers, articles, and expert opinions. The knowledge base is meticulously organized and indexed to expedite efficient retrieval of pertinent information. The conversational AI model is subsequently trained utilizing the pre-processed dataset, and its performance is rigorously evaluated using relevant metrics. Furthermore, user feedback is solicited and analyzed to iteratively refine and enhance the system. By adhering to this methodology, a robust conversational AI system seamlessly integrated with a knowledge base is realized, offering accurate and invaluable information concerning banana plantation and associated diseases.

3.2.1 RASA as a framework for conversational AI

The knowledge base is constructed by gathering domain-specific framework has emerged as a prominent platform for the development of conversational AI systems, offering a comprehensive suite of tools and methodologies. Its modular architecture facilitates the seamless integration of essential components, including natural language understanding (NLU), dialogue management, and response generation. By harnessing machine learning techniques, RASA enables the creation of intelligent chatbots and virtual assistants capable of understanding user intents and providing relevant responses [2].

The framework's iterative learning approach allows the system to continually enhance its performance through user interactions and feedback. Moreover, RASA offers flexibility in data annotation, accommodating varied approaches for annotating intents and entities to suit specific application domains. With its open-source nature and a thriving community, RASA presents a compelling option for researchers and developers seeking to build conversational AI systems with sophisticated functionalities.

3.2.2 Data Collection

To train the conversational AI model effectively, a dataset comprising user queries, intents, and corresponding responses is collected. The dataset is specifically curated to include a wide range of questions related to banana plantation, cultivation practices, disease identification, and management.

3.2.3 Preprocessing and Annotation

The collected dataset undergoes preprocessing and annotation processes. Text cleaning techniques are employed to remove noise and irrelevant information. Annotations are added to identify intents, entities, and dialogue states, enabling the model to understand user queries accurately.

3.2.4 Knowledge base Integration

The knowledge base is constructed by gathering domain-specific information related to banana cultivation and diseases. It encompasses structured data, such as cultivation practices, soil requirements, and disease symptoms, as well as unstructured data, including research papers, articles, and expert opinions. The information is organized and indexed for efficient retrieval, after that the knowledge base is carefully aligned with the conversational AI system to ensure consistency. Regular updates are performed to maintain accuracy and relevance between the knowledge base and the system's responses.

3.3 Wholesale buyer and farmer interaction platform and a recommendation plan to get an additional income to the farmer.

The conducted research did not name the wholesale buyer-farmer interaction platform for the banana business as a development. By offering the answer for that strategy and enabling the matching of customers and sellers based on particular parameters like product type, price range, quantity, and location, the suggested platform closes the gap in the research that has already been done. It allows users to input their requirements and filters the data accordingly. The code then calculates distances between locations and identifies nearby stakeholders within a given radius. The goal is to assist users in finding and connecting with relevant stakeholders, streamlining the process of business transactions. Additionally, the code includes visualization techniques to provide insights into the distribution of wholesale buyers and sellers, as well as the locations of nearby stakeholders, aiding users in making informed decisions.

3.3.1 *Data Collection*

The data collection process will involve two stages. Firstly, qualitative data will be collected through in-depth interviews with a sample of wholesale buyers and banana farmers. A semi-structured interview guide will be used to conduct the interviews, allowing for flexibility in exploring relevant topics. The qualitative data will be analyzed thematically to identify patterns and themes within the data. Secondly, quantitative data will be collected using surveys and questionnaires distributed to a sample of wholesale buyers and banana farmers. Utilizing descriptive statistics like frequencies, percentages, means, and standard deviations, the quantitative data that was gathered will be reviewed.

3.3.2 *Data Acquisition and Preprocessing*

The buyer and seller datasets were imported using the pandas library to facilitate data handling and analysis. The datasets were obtained from CSV files, ensuring compatibility and ease of access for further processing. Data preprocessing techniques, such as filtering and selection, were applied to refine the datasets based on specific criteria.

3.3.3 *User Input and Filtering*

User input was collected to determine the user type (buyer or seller) and their product requirements, including product type, price range, and quantity. The appropriate dataset (buyer or seller) was selected based on the user type for subsequent analysis. Filtering techniques were employed to extract relevant data that matched the user's requirements from the selected dataset.

3.3.4 *Nearest Neighbor Search and Distance Calculation*

The BallTree algorithm from the scikit-learn library was utilized to perform a nearest neighbor search. The latitude and longitude coordinates of stakeholders were used to create a BallTree data structure, enabling efficient nearest neighbor queries. Geodesic distance calculations, implemented using the geopy library, were performed to determine the distances between the given location and the stakeholders' locations.

3.3.5 *Results Presentation and Visualization*

e names, IDs, and contact numbers of the matching stakeholders within a radius were displayed to the user. Scatter plots were generated using the matplotlib library to visualize the distribution of sellers for buyers or buyers for sellers. The locations of nearby stakeholders and the given location were plotted on a separate scatter plot, providing a visual representation of the stakeholders within the input radius.

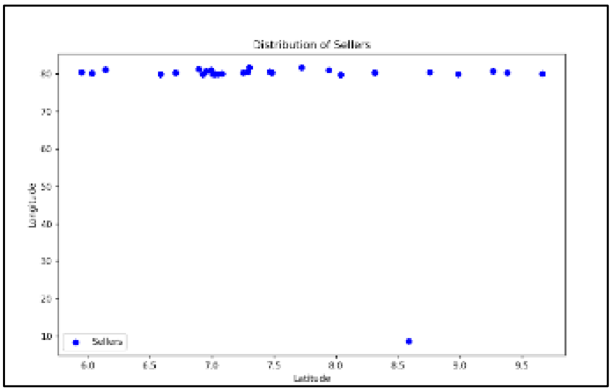

Figure 3: Graph view of seller distribution

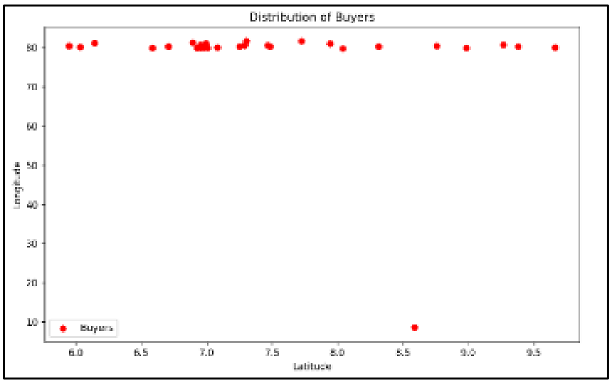

Figure 4: Graph view of buyer distribution

3.3.6 Buyer Recommendation Plan

To enhance the user experience and provide valuable guidance to buyers with specific product preferences, a comprehensive recommendation plan has been developed [4]. This recommendation plan is tailored to address the distinct needs and considerations of different types of buyers, focusing on the product types they are seeking. By leveraging the system's capabilities, buyers are equipped with insightful advice that aids them in making informed decisions. For buyers in search of products, such as "Banana," "Banana Blossom," "Banana Peel," "Leaves," or "Banana Stem," the recommendation plan provides targeted guidance on how to approach their purchases [5]. This approach is especially valuable in promoting sustainable practices, minimizing waste, and maximizing the utility of the purchased products.

3.4 Profit Optimization of Banana

Profit optimization in the banana industry involves maximizing revenue and minimizing costs to achieve the highest possible profitability. To achieve this, various factors need to be considered. Firstly, efficient cultivation practices should be employed, including selecting suitable banana varieties, optimizing planting techniques, and implementing effective pest and disease management strategies. By enhancing productivity and minimizing crop losses, farmers can increase their yield and revenue potential. Additionally, proper fertilization and irrigation techniques should be implemented to ensure optimal growth and quality of bananas. Efficient harvesting and post-harvest handling techniques, such as timely picking and careful handling to minimize damage, are essential to maintain the quality and extend the shelf life of bananas, reducing potential losses. Furthermore, optimizing transportation and logistics processes, including proper packaging and storage, can help reduce spoilage and ensure timely delivery to markets, maximizing the value of the crop. Market analysis and strategic pricing decisions are also crucial to identify demand patterns, target profitable markets, and set competitive prices to maximize sales and revenue. By integrating these practices and continually monitoring and adapting to market dynamics, stakeholders in the banana industry can optimize profits, foster sustainability, and drive long-term success.

3.4.1 Data Collection

Profit optimization in the banana industry involves leveraging datasets on prices, quantity, yield size, and harvest amount. Analyzing these factors allows for informed decision-making. By identifying price trends and market demand, farmers can strategically plan their production levels to meet consumer needs. Maximizing yield size through efficient cultivation practices and managing harvest amounts effectively minimizes losses and optimizes revenue. By studying the correlation between these variables, farmers can determine the most profitable combination of pricing, quantity, and yield size. This data-driven approach enables stakeholders to make informed decisions, reduce costs, maximize profitability, and drive sustainable growth in the banana industry.

3.4.2 Data Acquisition and Pre-processing

To optimize profits in the banana industry, a library called Pandas used to handle and analyze datasets. The datasets are gathered from CSV files, which make it easy to work with the data. Before analyzing the data, clean and refine it by removing unnecessary information and selecting only what needed. This helps us focus on specific criteria that are important for-profit optimization. By using these techniques, so that it can make better decisions based on the data and maximize profitability in the banana industry.

3.4.3 User Input and Filtering

To optimize profits in the banana industry, started by collecting user input to understand their specific product requirements. This includes information such as the type or variation of bananas they want to grow and the size of their land. Based on the banana variation specified by the user, select the appropriate dataset for further analysis. This dataset contains information about various banana variations, their prices, quantity, yield size, and harvest amounts. Using filtering techniques, extract the relevant data from the selected dataset that matches the user's requirements. For example, filter the dataset to include only the prices, quantity, yield size, and harvest amounts related to the specific banana variation chosen by the user. This allows us to focus on the data that is most relevant to their product requirements and enables us to make informed decisions for profit optimization in the banana industry.

3.4.4 ARIMA for Profit Prediction

The profit prediction process for banana cultivation using ARIMA involves gathering historical data for key variables like plant count, harvest amount, selling price, income, and profit. This data is collected at regular intervals, such as monthly or quarterly, to analyze past trends. The ARIMA model is then applied to each variable separately, considering autoregressive, integrated, and moving average components to forecast future values based on past observations. Once ARIMA predicts future values for these variables, income and profit are calculated. Income is projected by multiplying predicted harvest amount by selling price, and profit is computed by deducting production costs from income. While ARIMA aids in forecasting, it assumes linear relationships and might not capture all complexities in banana cultivation's profitability. This process assists farmers and stakeholders in decision-making for resource allocation, pricing, and overall profitability.

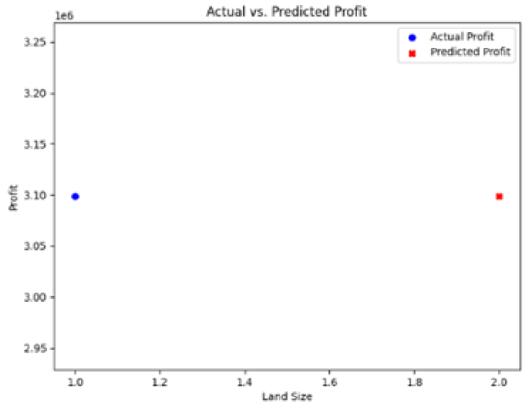

Figure 5: Actual vs predicted profit

4. RESULTS AND DISCUSSION

One of the key challenges highlighted in the research is the prevalence of diseases in banana farming. Notable diseases, such as anthracnose, yellow sigatoka, Cordana and crown rot often manifest with similar symptoms, making precise identification difficult for farmers. As a result, farmers often require professional assistance for accurate diagnosis and effective treatment, as these diseases can lead to substantial crop losses and economic hardships. To address this issue, the research introduces the concept of a conversational AI, leveraging the RASA framework and integrated with a knowledge base. This key feature has the potential to empower farmers with real-time guidance and information on best practices in banana farming, disease identification, and management. By bridging the knowledge gap, it can help farmers optimize their cultivation techniques and reduce the impact of diseases on their yields. The study also explores the untapped potential of banana by-products, including stems, leaves, inflorescences, and peels, which contain valuable bioactive compounds. Moreover, a profit optimization plan through yield management is an integral component of this approach. This plan not only maximizes resource utilization and minimizes waste but also ensures that crop yields are managed efficiently to enhance economic prospects for farmers and buyers. The proposed platform aims to connect farmer-sellers with wholesale buyers, facilitating the production and marketing of these innovative products. By aligning with sustainability principles and integrating yield management strategies, this initiative promises to boost profitability, reduce waste, and create a more environmentally conscious and economically viable banana farming sector. In summary, this research underscores the vital role of bananas in Sri Lanka's agricultural sector and the need for innovative solutions to address the challenges posed by diseases, knowledge gaps, and untapped by-product potential. The proposed conversational AI and by-product trading platform hold substantial promise for advancing the industry, improving efficiency, and promoting environmentally conscious practices. By empowering farmers and expanding the utilization of banana by-products, Sri Lanka's banana farming sector can enhance productivity and contribute positively to the livelihoods of those engaged in agriculture.

5. CONCLUSION AND FUTURE WORK

In conclusion, this study focused on the development of an intelligent system for precision banana farming in Sri Lanka by integrating remote sensing, data analytics, and machine learning algorithms. The results demonstrated the effectiveness and potential of the system in optimizing banana production and addressing the challenges faced by farmers in the banana industry. The remote sensing analysis provided valuable insights into the health and growth of banana plantations, aiding in targeted interventions and resource allocation. The disease detection and management module facilitated early identification and control of common banana diseases, reducing yield losses. The crop yield prediction models enabled farmers to make informed decisions regarding resource allocation and market planning. The decision support system integrated these modules, providing real-time recommendations for precise and sustainable farming practices. Overall, the developed intelligent system holds significant promise in improving banana farming practices and enhancing farm productivity in Sri Lanka.

Further research and improvement opportunities exist for the development of an intelligent system for precision banana farming in Sri Lanka. These include expanding the dataset and incorporating additional factors like soil characteristics and cultural practices to enhance system accuracy. Integrating real-time weather data and implementing predictive models for disease outbreaks can improve disease management capabilities. Additionally, incorporating advanced technologies such as IoT devices for real-time monitoring of environmental conditions and plant health can provide timely decision-making information. Field trials and on-farm validation are essential to assess practical applicability and impact. Scalability, adoption among farmers, economic feasibility, and cost-effectiveness should be explored. Continued research in these areas aims to provide farmers with effective tools for optimizing farming practices, increasing productivity, and supporting sustainable development in the banana industry.

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