

# AgroBuddy Traditional Remedies for Diseased Crops

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**Abstract - Agro Buddy is a mobile application that aims to support farmers in managing crop diseases and pests. It offers a comprehensive knowledge base that includes traditional remedies and sustainable pest control methods, providing farmers with innovative solutions to reduce their reliance on chemical pesticides. By incorporating traditional remedies and sustainable pest control methods, the app helps farmers adopt eco-friendlier and cost-effective practices. Additionally, the app is designed with a user-centered approach, incorporating feedback from farmers and ensuring that the interface is easy to use and understand. Agro Buddy is particularly beneficial for smallholder farmers, who often lack access to precision agriculture technologies and AI-powered crop management systems. By providing a cost-effective and accessible solution, the app helps bridge the gap between smallholder farmers and innovative farming practices. Moreover, Agro Buddy has the potential to increase the adoption of sustainable crop management practices, reducing the environmental impact of agriculture and contributing to a more sustainable future. Overall, Agro Buddy represents an innovative and sustainable solution to crop management. By incorporating traditional remedies, sustainable pest control methods, and cutting-edge AI-powered algorithms, the app empowers farmers to make informed decisions and adopt more eco-friendly and cost-effective practices. It has the potential to revolutionize the agriculture industry and contribute to a more sustainable future.**

**Keywords:** Machine Learning, Deep Learning, Image Processing, AI, NLP, Agro Buddy, mobile application, crop management, traditional remedies, sustainable pest control, AI-powered algorithms, eco-friendly, cost-effective, user centralized approach.

## I. INTRODUCTION

Agriculture is one of the most critical sectors of the global economy[1], providing food and livelihoods for millions of people worldwide. However, the agriculture industry is facing numerous challenges, including the impact of climate change, limited resources, and the prevalence of crop diseases [2],[3]. Crop diseases significantly affect food security, causing substantial crop losses and decreasing yields.

In response, farmers often turn to chemical solutions that can be expensive and harmful to the environment and human health. To address these challenges, we propose the development of a mobile app that utilizes machine learning (ML) and image processing (IP) techniques to identify and verify crop diseases and suggest traditional remedies for them. The app aims to provide a quick and accurate way for farmers and agricultural experts to diagnose crop diseases and promote sustainable traditional agricultural practices. The app's machine learning (ML) algorithm analyses images of crops submitted by users to detect potential diseases and provide an accurate severity prediction. The app then suggests traditional remedies for the infection, which are sourced from a centralized knowledge base of traditional remedies for various crop diseases. Additionally, the app includes a feature to allow users to add new traditional remedies to the system, which are analyzed using machine learning algorithms to ensure their authenticity and reliability. This proposed app has the potential to revolutionize the way farmers manage crop diseases, promote sustainable agricultural practices, and enhance the well-being of farming communities. By promoting non-chemical cures for crops, the app can benefit the environment and human health while enhancing farming communities' livelihoods.

## II. LITERATURE REVIEW

In this research mainly covers the agricultural practices in Sri Lanka. Our project scope mainly enfolds with cultivation and farming practices within SL. So,[4] a survey found in a July 2021 that three-quarters of SL farmers relied heavily on chemical fertilizers, while just about 10% cultivated without them. Almost all major crops grown in the country depend on chemical fertilizers. But SL had magnificent traditional farming and pest and disease control mechanism which are organic and less harmful for environment and people's health too. But nowadays Whole cultivation procedures are fully based on chemical pesticides and fertilizers are frequently and mostly used to control crop disease. Although excess usage of those in-organic crop management techniques will affect human's health and a negatively impact on environmental health hazards to farmers and other consumers too. Water pollution, Unnecessary Ionization on Soil, renal diseases, testicular diseases are some examples for them. Therefore, we

suggest an additional approach to overcome those challenges which are faced by farmers when managing crop related diseases. For implementation of this productive solution, we tent to use mobile application development strategies.

In recent years, several mobile applications have been developed to address the challenges faced by farmers in managing crop diseases. These applications help smallholder farmers to identify crop diseases and provide information on their management. However, most of these applications are limited in their scope, and they only focus on a few crop diseases. Furthermore, the information provided by these applications may not be up-to-date or reliable, which can lead to incorrect diagnosis and treatment[5]. According to the image recognition System to identify the crop diseases on paddy fields in Sri Lanka, the agriculture sector is a vital part of many rural areas and the most of the people take it as their employment[6]. However, crop diseases are done a significant threat to food safety, and farmers are often the ones who suffer the most from these diseases. Manual diagnosis of crop diseases can be challenging and time-consuming, but the with the improvement of the image processing techniques and methods have made it possible to create autonomous frameworks for disease field identification. Digital image processing is expanding quickly, and it is becoming an essential tool for detecting plant diseases quickly and accurately.

In recent years, machine learning-based techniques have gained popularity for identifying agricultural diseases using user-provided symptoms. The use of user-provided symptoms for disease identification in crops using machine learning-based algorithms is gaining traction. The accuracy and efficiency of disease identification can be greatly enhanced by including user observations alongside picture analysis. In addition, involving farmers and other non-experts in the disease identification process can help increase their awareness and knowledge of crop diseases and improve their ability to manage them. Crop diseases have massive impact on yields and also on the economy. So crop diseases identification and suggesting traditional remedies for those would be much more beneficial for small farm holders without using many complex or expensive systems. To our knowledge, this proposed system is the first one to detect multiple diseases and verify disease using user-provided observation data and suggest traditional remedies for the diseased crops. In this research[7], Plantix Mobile App, This mobile app is the most famous app among farmers. This mobile app can detect multiple crop diseases. This mobile app uses image recognition and machine learning algorithms to identify crop diseases but there is no severity detection, verify disease based on user observation and add new traditional remedies to the system. In this research[8], Agrio Mobile App, This also able

to identify multiple crop diseases using machine learning and image processing techniques but there needs to be more accuracy in identifying diseases in various parts of the crop like leaf stem fruit. And also there is no proper way to add remedies for the relevant disease. In this research[9], E-AGRO mobile app. In order to help farmers, make well-informed decisions in a timely manner, this research creates an online discussion forum and an automated chat service known as a "Chat-Bot." Focus group discussions and interviews with farmers, specialists, and other stakeholders helped create a standardized set of questions. Intentions that users may have, instances that users provide to elaborate on a particular intention, and entities that are distinct items referred to by an intention were all extracted from the inquiries. An AIML-trained model was used to make the prediction of intent from the provided example. But they did not provide any mechanism to detect diseases using user provide observations

Internationally, there is growing interest in traditional remedies for crop protection as an alternative to synthetic pesticides, which can have harmful effects on human health and the environment. In a study, traditional remedies were found to be effective in managing pests and diseases in maize crops[10]. The authors reported that the most commonly used remedies were neem (*Azadirachta indica*). which is effective in controlling pests such as fall armyworm and stem borer. In Sri Lanka, traditional remedies have been used for centuries in crop protection, and there is a wealth of knowledge on these remedies among farmers. However, there is a lack of organized and accessible information on these remedies, which makes it difficult for farmers to access and use them effectively. A study found that farmers in Sri Lanka had limited access to information on alternative methods of crop protection, and that there was a need for more organized and accessible information on traditional remedies[11]. There have been some efforts to document and promote traditional remedies for crop protection in Sri Lanka. For example, the Traditional Knowledge Digital Library of Sri Lanka (TKDL) was established 6 to document traditional knowledge in various fields, including agriculture. However, there is a need for more comprehensive and accessible databases that can be easily accessed by farmers.

Despite the availability of synthetic pesticides, traditional remedies for crop diseases have been used for centuries, and they are still used in many parts of the world, including Sri Lanka. For instance, in Sri Lanka, traditional remedies such as neem oil, turmeric, and ginger have been used to control pests and diseases in crops such as rice, tea, and fruits[12]. However, there is a lack of organized and accessible information on the traditional remedies, which makes it difficult for farmers to access and use them effectively. For example, a study conducted in Bangladesh found that smallholder farmers

lacked access to reliable information on crop management and relied on word-of-mouth information from fellow farmers and pesticide sellers[13]. Additionally, there is a lack of information on the effectiveness of these remedies in comparison to synthetic pesticides, which makes it challenging for farmers to decide which option to use. For example, a study conducted in India found that farmers who used traditional remedies had lower crop yields than those who used synthetic pesticides, but the traditional remedies were more cost-effective[14]. Furthermore, there is a lack of automated mechanisms to verify the authenticity of the remedies and filter out non-traditional and non-organic remedies based on keywords, which can make it difficult for farmers to trust the information provided. For example, a study conducted in Ghana found that farmers were wary of using traditional remedies due to concerns about their effectiveness and safety[15]. Additionally, farmers may not be able to distinguish between traditional remedies and other types of products that claim to be natural or organic but are not effective or safe.

### III. METHODOLOGY

As shown in Figure 1, Users upload images of diseased crops, which are then processed by a pre-trained Convolutional Neural Network (CNN) model to propose potential diseases. From the top three suggested diseases, users choose one for closer examination. A Chatbot engages users in symptom verification, posing targeted questions to refine the disease identification. Subsequently, a sequential model leverages user responses to further confirm the disease's accuracy. Users have the option to assess disease severity by submitting additional images, analyzed by a separate CNN model that returns a severity percentage. Upon accurate identification and severity assessment, the app recommends tailored traditional remedies, drawing on a machine learning model informed by regional and historical effectiveness data. The user interface presents confirmed diseases, severity information, and recommended remedies, fostering informed decision-making. Users can provide feedback for ongoing enhancement, while regular model updates refine disease identification and remedy suggestions based on real-world interactions and agricultural insights.

The Python programming language was used to develop the back-end server. And develop Machine Learning Models to accomplish this task. APIs used to end to end communication processes. Flutter framework used to develop mobile application.

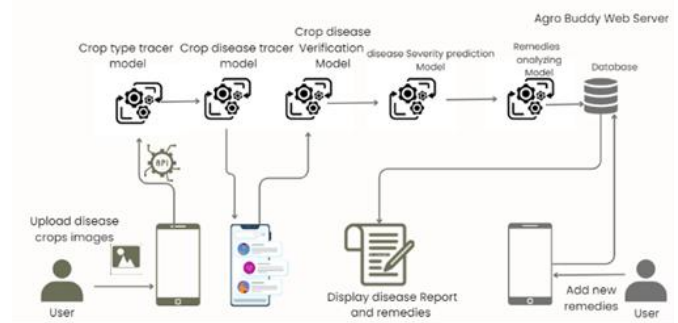


Figure 1: Overall System diagram

#### A) Crop Disease Detection using Images

A comprehensive methodology for automated plant disease identification using Convolutional Neural Networks (CNNs) are employed as the primary algorithm, with a single model trained for plant identification and separate models for disease detection in different plants. Specific datasets are curated for each plant category, consisting of labeled images and corresponding disease annotations. The images undergo preprocessing, including resizing to a standardized resolution of 150x150 pixels using the Python Imaging Library (PIL), ensuring uniformity in input dimensions. For plant identification, the model is loaded from the file in the directory using the Keras library. The loaded model predicts the plant species by passing the preprocessed image through the model, extracting class probabilities. The highest probability class index is mapped to the corresponding label, which is then outputted.

Disease identification models and class labels are loaded based on the respective plant category. Images are opened, resized, normalized, and processed using the loaded models. The 'predict' function generates a probability distribution over the disease classes, and one other function determines the index of the class with the highest probability. This index is utilized to retrieve the corresponding disease class label, which is subsequently outputted. The integration of plant identification and disease detection functionalities enables accurate plant classification and disease identification. This methodology holds substantial potential for effective plant monitoring and management, facilitating early disease detection and informing appropriate agricultural practices to mitigate the impact of plant diseases on crop yield and quality.

#### B) Disease Verification using ML

The primary dataset is sourced from a JSON file containing disease observation data, encompassing disease names and their corresponding sequences of observations. After data collection, a preprocessing stage is conducted, generating diverse permutations of observation sequences to capture various behavior combinations, guided by the option

to enable sequence learning. Model configuration entails defining critical parameters like vocabulary size, embedding dimensions, and maximum sequence length, along with factors such as an out-of-vocabulary token and the number of training epochs. The dataset is divided into training and testing subsets, with labels transformed into numerical representations using label encoders for consistent interpretation by the model. Textual data is transformed into a numeric format through tokenization, followed by the creation of padded sequences to ensure uniformity in length. The model architecture involves an embedding layer converting words into dense vectors, followed by global average pooling and dense layers with ReLU activation for pattern recognition. An output layer using softmax activation predicts disease categories. Training is executed on the training dataset, while evaluation occurs on a separate test dataset to measure loss and accuracy. The training process is visually represented through line plots illustrating training loss and accuracy, enhanced by moving averages. This structured methodology guides the systematic development of the disease tracing ML model, covering data processing, model configuration, training, evaluation, and visualization, ensuring the model's proficiency in predicting disease categories based on observation sequences.

### C) Severity Level detection of identified crop disease

In this study, methodology for classifying plant diseases into severity levels using Convolutional Neural Networks (CNNs). This methodology circumscribes with testing and training as main procedures of this research component. In the earlier steps after identifying plant and disease according to previous components, severity will categorize into three distinct level such as 10%, 50% and over 90% damage. CNNs are especially well-suited for tasks that involve extracting spatial patterns and features from images. CNN models exhibited a remarkable ability to accurately predict and differentiate the extent of crops deterioration. Image pre-processing, encompassing normalization and resizing techniques are comparatively used to made up the diverse dataset for predict severity level of diseased crops. Although our field-based survey and expertise advices and findings are also enormously valuable when processing the dataset. In the pre-processed dataset it comprises images for each plant type and severity level for enhance the effectiveness for model training and evaluation stages.



Figure 2: Severity of Tomato early blight at 10% 50% and 90%

The designed CNN architecture comprising with essential layers Conv2D, MaxPooling, Flatten and Dense enhanced with RELU activation function to perform consistent accuracy and performance across various severity categories. Not only that essential methodologies which are relevant for the initializing and training procedure such as image pre-processing, normalization and generalization. Before training and prediction, the dataset underwent image preprocessing steps. This entails resizing images to a standard size and normalizing pixel values to the [0, 1] range. Normalization of images can enhance the accurate feature extraction from uploaded images. Convolution layers are responsible for extraction features from uploaded images, we can gradually increase the filters for capture more complex patterns. Although pooling layers down sample spatial dimensions and mapping features which helps to minimize computational complexity. Thereafter, flatten layer used to map the 2D feature maps from Convolutional layers into 1-Dimensional vector array. This is served as input to fully connected layers, which process flattened feature vectors. At the last layer which is output layer consists neurons which are mapped according to the classes (in this part it should be three) and with the help of RELU activation function output probabilities can be mapped. The effectiveness of the suggested methodology is evaluated through extensive testing and validation, with a focus on precision and robustness across severity categories. The methodology achieves accurate severity classification, contributing to efficient plant disease management, by utilizing the strengths of different CNN architectures and tailored feature extraction.

### D) Traditional Remedies suggestion for diseased crops

This section outlines the systematic methodology employed to develop and validate the Traditional Remedies Suggestion System for Diseased Crops

The primary foundation of this research involved a comprehensive data collection process. In-depth consultations were conducted with seasoned agriculture experts and local farmers. Through these interactions, valuable insights were acquired regarding traditional remedies that have stood the test of time in addressing diverse crop diseases. We then organized the gathered information carefully. We put things into categories like where the farms are, what types of plants are grown, what diseases affect the crops, and how severe the problems are. This organization streamlined data storage and established a framework for subsequent analysis. To ensure the universal applicability of the chosen grading system, we checked them against information from various geographical regions. This was important to make sure our system would accommodate well for different types of farming landscapes.

Remedy Grade	Working District and severity
A	Galle 90%, Galle 75%, Galle 50%, Kandy 50%
B	Galle 50%
C	Galle 50%, Galle 75%, Kandy 50%, Kandy 75%, Colombo 50%
D	Kandy 90%, Kandy 75%, Kandy 50%

Table 1: Grading for a tomato plant disease XYZ

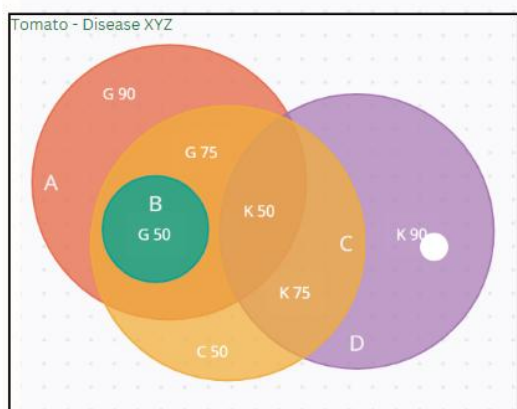


Figure 3: Grading Venn diagram

The heart of our research was the creation of a strong neural network model. By utilizing the Keras library, we meticulously designed the architecture of this model, using multiple layers, each with unique functions like ReLU and Softmax activation functions. This model was tailored to accurately predict the effectiveness of different remedies based on the input factors provided. The neural network model underwent intensive training, a critical phase of its development. This training process involved using a carefully prepared dataset and optimizing the model's performance through techniques like the Adam optimizer and sparse categorical cross-entropy loss function. The model was fine-tuned to achieve the best possible predictive performance.

We evaluated the model's effectiveness through rigorous testing using an independent dataset. Metrics such as accuracy and other relevant indicators were used to measure the model's ability to provide precise suggestions for traditional remedies across a wide range of diverse crop disease scenarios. The effectiveness of our Traditional Remedies Suggestion System was thoroughly assessed by analyzing its accuracy and other relevant evaluation metrics. This assessment offered a comprehensive understanding of the system's capability to

provide practical and relevant traditional remedy recommendations tailored to different crop disease situations.

In conclusion, our research methodology underscores the main goal of the Traditional Remedies Suggestion System: to equip farmers with effective and practical traditional remedy suggestions. Through this system, we aim to empower farmers to adapt their agricultural practices to effectively address the dynamic challenges posed by various crop diseases.

#### IV. RESULT AND DISCUSSION

To assess the strengths and weaknesses of different components, the study's functionality was evaluated across various scenarios.

##### A) Crop Disease Detection using Images

The proposed Convolutional Neural Network (CNN) model for automated plant disease identification was thoroughly evaluated using a diverse dataset of plant images. The model's performance was assessed based on its test loss and test accuracy, as well as its train loss and train accuracy. The obtained test loss of 0.072968 demonstrates the model's ability to make accurate predictions on previously unseen data. This low value indicates that the model's predictions closely align with the actual labels, highlighting its proficiency in identifying plants and detecting diseases. Furthermore, the achieved test accuracy of 0.97928 signifies that the model accurately classifies the plant images into the correct categories. This high test accuracy showcases the model's robustness in handling real-world scenarios. During the training process, the model displayed remarkable performance with a train loss of 0.0730, suggesting that it effectively learned the underlying patterns present in the training dataset. The corresponding train accuracy of 0.9793 further supports the model's success in fitting the training data. The observed consistency between the test and train metrics suggests that the model is neither overfitting nor under fitting. The marginal difference between train and test loss and accuracy implies that the model is generalizing well to unseen data. However, it is crucial to acknowledge that the evaluation was performed on a controlled dataset, and the model's performance in real-world settings with varying lighting conditions, image qualities, and plant variations may vary. The design of the separate modules for plant identification and disease classification contributes to the methodology's scalability. This modular approach enables the addition of new plant types and diseases without affecting the core architecture, thereby ensuring adaptability for future extensions. The robustness of the CNN architecture, utilization of data augmentation techniques, and the integration of ReLU activation functions collectively contribute to the model's exceptional performance.

### B) Disease Verification using ML Model

The performance and evaluation of the disease tracing machine learning (ML) model were meticulously conducted in accordance with the outlined methodology. This involved the development, training, and testing of the model using the dataset of disease observation sequences. Throughout the training process, the model exhibited commendable progress, attaining an approximate training accuracy of 91.2%, while the testing accuracy reached approximately 88.34%. These outcomes underscore the model's capacity to effectively learn and generalize patterns from the observation data, substantiating its adaptability. The methodology featured an insightful consideration: the incorporation of sequence learning through the generation of permutations of observation sequences. This strategic choice wielded a positive influence on the model's performance. By facilitating exposure to a diverse spectrum of input patterns, sequence learning propelled a marked enhancement in training accuracy.

### C) Severity Level detection of identified crop disease

The conducted study has successfully demonstrated the efficacy of the proposed methodology for assessing the severity of plant diseases using Convolutional Neural Networks (CNNs). By categorizing disease severity into three distinct levels—10%, 50%, and over 90% damage—the CNN models exhibited a remarkable ability to accurately predict and differentiate the extent of plant health deterioration. Through the application of image pre-processing, encompassing resizing and normalization, a diverse dataset of plant types and severity levels was effectively prepared for model training and evaluation.

The designed CNN architecture, comprising essential layers like Convolutional, MaxPooling, Flatten, and Dense, enhanced by ReLU activation functions, exhibited consistent performance across various severity categories. The integration of data augmentation techniques during training, coupled with the use of categorical cross-entropy loss and the Adam optimizer, facilitated optimal model learning and convergence. Metrics such as accuracy proved instrumental in evaluating the CNN models' precision in severity classification. The development of severity-specific classification modules, each utilizing pre-trained models, showcased the modular approach's effectiveness. The obtained accuracy values for each severity level underscored the methodology's ability to reliably determine the degree of plant health degradation. This modular design enhances the methodology's reusability and adaptability, thus laying the foundation for future extensions and applications.

### D) Traditional Remedies suggestion for diseased crops

The implementation and evaluation of the plant remedy suggestion system yield noteworthy results, showcasing the system's efficacy in providing accurate and relevant solutions for plant diseases. The system's predictive performance is notable across diverse scenarios involving regions, plant types, diseases, severity levels, and corresponding remedy grades.

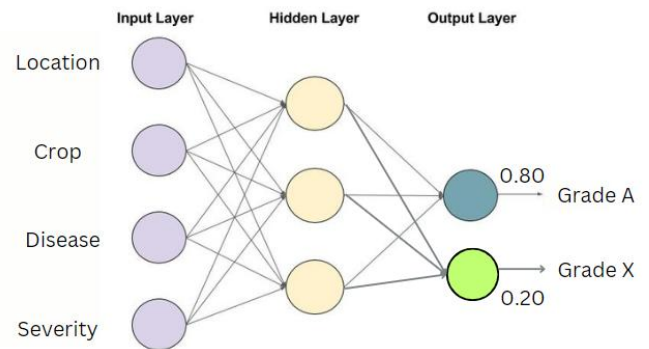


Figure 4: Feed forwarding neural network

Through meticulous visualization using scatter plots, the relationships between various factors become apparent. These visualizations underscore the significance of considering multiple factors in determining appropriate remedy grades. The trained neural network model demonstrates impressive predictive capabilities, accurately mapping input factors to suggested remedy grades. The evaluation metrics, particularly accuracy, reflect the system's proficiency in yielding suitable remedies. This robust performance underscores the system's potential in assisting plant owners, researchers, and agricultural practitioners in making informed decisions regarding plant disease management strategies. The modular nature of the methodology bolsters its reusability and adaptability. By considering a multitude of factors, the system can be applied across diverse plant types, regions, and disease severity levels. The successful execution of the methodology sets the stage for future advancements, including the refinement of model architecture, integration of real-time data, and expansion of the dataset for broader applicability.

## V. CONCLUSION AND FUTURE WORK

In conclusion, the development of the "Agro buddy Traditional Remedies for Diseased Crops" mobile app represents a significant step towards revolutionizing agricultural disease management. By combining cutting-edge technologies such as image processing, machine learning, and natural language processing, this app offers farmers a comprehensive and user-friendly tool for identifying, diagnosing, and treating crop diseases. The integration of a Chatbot-driven diagnosis system with an image-based disease identification model provides a powerful synergy, enabling

accurate disease assessment and tailored recommendations for farmers. This innovative app addresses the challenges of modern agriculture, where quick and accurate responses to crop diseases are essential for minimizing yield losses and ensuring food security. By leveraging the potential of deep learning and conversational interfaces, the app enhances the accessibility of expert agricultural advice, making it available to even the most remote farming communities.

In terms of this research's upcoming work, we Enhance disease recognition. For that continuously refining the image processing model's accuracy is crucial. Incorporating more diverse datasets, exploring new architectures, and considering multi-modal approaches that combine visual and textual information could improve disease recognition rates. Improving Chabot's intelligence. Developing the Chabot's natural language understanding and response generation capabilities is an ongoing endeavor. Incorporating advanced NLP models, such as transformer architectures, can lead to more intuitive and informative interactions with users. Enhancing the validation of traditional remedies is crucial. Conducting research to validate the efficacy of traditional remedies for crop diseases is essential. Collaborating with agronomists, ethnobotanists, and local communities can help integrate indigenous knowledge into the app's recommendations effectively. Improve this app to provide localized recommendations. That means customizing disease management advice and traditional remedies' effectiveness based on geographical and climatic factors can enhance the app's utility. Creating district or province-specific models and recommendations can account for varying agricultural practices and environmental conditions. The next important task is user engagement and education. To do that Incorporating educational components within the app to inform farmers about disease prevention, symptom recognition, and sustainable agricultural practices can empower them to make informed decisions. Integrating real-time weather and environmental data can enhance the accuracy of disease predictions and recommendations. This could involve partnering with meteorological agencies or leveraging IoT devices. Creating a platform for farmers to share their experiences, challenges, and success stories can foster a sense of community and encourage knowledge exchange. In future work, we hope to improve the accessibility of this app by ensuring the app's accessibility across different devices, network conditions, and languages is essential for reaching a wider audience. Because most of the farmers not familiar with foreign languages so we hope to improve this app using native languages like Sinhala and Tamil.

## ACKNOWLEDGMENT

The Sri Lanka Institute of Information Technology (SLIIT), local farmers and domain experts who provided assistance and guidance for complete this project successfully.

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**Citation of this Article:**

Adhikari A.M.I.Y., Ranathunga R.M.S.S., Wijayakumara N.W.D.H., Dasanayaka U.D.P.M., "AgroBuddy Traditional Remedies for Diseased Crops" Published in *International Research Journal of Innovations in Engineering and Technology - IRJIET*, Volume 7, Issue 10, pp 453-460, October 2023. Article DOI <https://doi.org/10.47001/IRJIET/2023.710060>

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