Coffee Leaf Rust Disease Detection with Deep Learning Algorithm and Wireless Sensor Network Integration

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Abstract— **The agriculture industry faces significant challenges from pests and diseases, which pose threats to crop production and the livelihoods of farmers. One such menacing problem is Coffee Leaf Rust (CLR), a fungal disease that wreaks havoc on coffee trees, causing defoliation and reducing yields. Timely disease detection is essential to mitigate the impact and protect crop value. This study proposes a diagnostic model for Coffea liberica, a coffee species, leveraging both Wireless Sensor Network and Deep Learning Algorithm. The system deploys wireless sensors strategically across the plantation to gather real-time data on plant health and environmental conditions. This data is then fed into sophisticated Deep Learning algorithms, which effectively analyze patterns and accurately identify CLR and other diseases. By detecting diseases early on, farmers can implement proactive measures like targeted treatments and cultural practices to mitigate CLR's effects and enhance overall plant health. This not only safeguards farmers' livelihoods but also ensures sustainable production of premium-quality coffee. The fusion of Wireless Sensor Network and Deep Learning equips farmers with timely information, empowering them to make informed decisions and implement efficient disease management strategies. The proposed diagnostic model serves as a valuable tool for monitoring and preserving the health of coffee plants, enhancing crop productivity, and bolstering the resilience of the coffee industry. Through this integrated system's implementation, our goal is to support farmers in combating pests and diseases, minimizing crop losses, and securing the long-term sustainability of coffee production.**

Keywords— Deep Learning Algorithm, Wireless Sensor Network, Coffee Leaf Rust (CLR), Coffea Liberica

I. INTRODUCTION

Coffee is produced from the ripe seeds of Coffea arabica Linn [1]. The beverage created from such coffee seeds is also known as coffee. Coffee is a top-of-line after-drink and a highly valued commodity [2]. According to Philippine Coffee Board Inc, only three of the seventy species of coffee are farmed. Coffea Arabica supplies 60% of the world's coffee, followed by Coffea Canephora (Robusta) at 25% and Coffea Liberica (Kapeng Barako) and other species at less than 1%.

In the Philippines, Cavite produced 25% of the Luzon coffee production, as reported by PSA, and is considered one of the country's top coffee-producing regions because of its quality and taste [3]. Cavite coffee farmers produced robusta, excelsa, arabica, and liberica coffee beans.

Climate unpredictability, nutritional inadequacies, and insect and disease risks are critical concerns for coffee farmers worldwide [2]. The most widespread and destructive coffee disease is coffee leaf rust. Coffee Leaf Rust (CLR), a fungus regarded as the most significant phytosanitary threat to coffee crops, is a disease that hinders coffee output. In the 1880s, the exportation of coffee beans by the Philippines placed the country in fourth place among all countries worldwide, but when coffee rust struck the country in 1889, coffee production decreased [4]. Now, the Philippines ranked 32nd in coffee production around the globe.

Once extreme degrees of severity are attained, little corrective measures may be taken. Inappropriate disease treatment can severely harm coffee plants. Although it is a disease with a rapid spread and devastating effects on the economy of coffee growers, visual examination, such as that performed while wandering through the fields, is adequate for identifying and diagnosing the disease.

Visual inspections, progression scales, and standard severity diagrams are among the tools used in this method to diagnose plant diseases. Personnel in charge of the crops will go through them when inspecting and handling the plants to identify and quantify symptoms of the sickness that causes them [5].

The researchers of this study aim to detect coffee leaf rust at its early stage and prevent its spread. Utilizing wireless sensors and mobilevnet to create a convolutional neural network with over 294 dataset is used in this model, achieving 88.14% of accuracy rate [6]. Thus, proposing this technology-based aid to the local agricultural department will alleviate the rampant spread of the leaf rust.

II. METHODOLOGY

Figure 1 illustrates the visual representation of how this study was executed. It provides a comprehensive and well-structured overview of the methods employed to accomplish the objectives of the study. The study comprises two main sections. The first part focuses on the microcontroller system, which incorporates the ESP8266 as its core component. The ESP8266 serves as the central control unit, facilitating seamless communication and coordination between the field devices and the application system. To enable effective monitoring, a network of wireless sensors is strategically deployed in the desired monitoring area. These sensors are specifically designed to capture and transmit data related to various environmental parameters such as temperature, humidity, nitrogen levels, potassium levels, phosphorous levels, and wind direction [7].

The wireless sensors continually collect data from their respective environments and transmit it to the microcontroller. Upon receiving the data, the microcontroller processes it using specific algorithms that analyze the readings and compare them against predefined threshold values [8]. Based on this processed data, decision-making algorithms within the microcontroller come into action. These algorithms evaluate the sensor readings against specific criteria to identify abnormal or critical conditions. If any readings exceed the predefined thresholds, the system triggers appropriate actions.

In cases where the sensor readings surpass the threshold values, the microcontroller initiates a notification process using GSM (Global System for Mobile Communications) technology [9]. The system sends a notification to a designated recipient, alerting them about the detected anomaly or critical condition. Furthermore, when the temperature and humidity levels exceed their respective threshold values, the system activates a water pump to address the situation.

Alternatively, when the sensor readings fall within the normal range, the microcontroller maintains its continuous monitoring of the data. It displays the values through an application system, allowing for easy visualization and tracking of the environmental parameters. Simultaneously, the microcontroller persists in its analysis, utilizing decision-making algorithms to ensure proactive surveillance. This approach ensures that the system remains alert and prepared to respond promptly to any deviations that may arise in the future.

In the latter part of the study, the Raspberry Pi (RPI) is employed for image processing tasks. Specifically, a convolutional neural network (CNN) is utilized on the RPI for this purpose [10]. The dataset is divided into two subsets using an 80-20 split. 80% of the dataset is allocated for testing the CNN model, while the remaining 20% is dedicated to its validation. This division allows for robust evaluation and assessment of the CNN's performance. After completing the testing phase, the CNN model will provide an accurate assessment to determine the health condition of the coffee leaf. It will analyze the input image and classify whether the coffee leaf is healthy or not based on the patterns and features it has learned during the training process. This classification will serve as a valuable indicator of the health status of the coffee leaf.

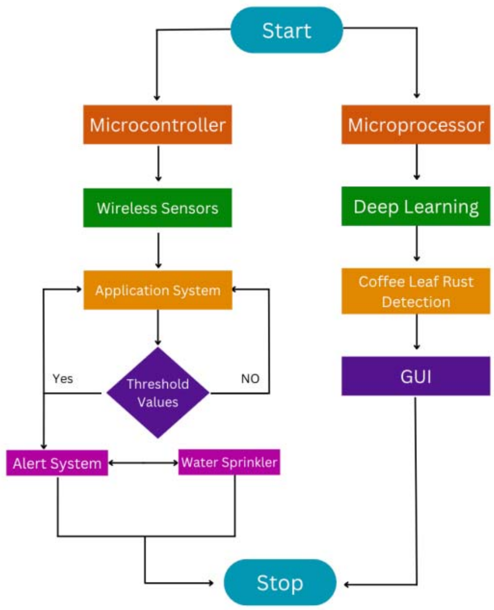

Fig. 1. Conceptual framework of Methodology

III. IMAGE PROCESSING

The first step in the process involved collecting data. This data consisted of images of coffee leaves, categorized into two classes: 'with_clr' (indicating leaves infected with Coffee Leaf Rust) and 'healthy' (indicating disease-free leaves). Each image was labeled accordingly to indicate its class.

After the data collection, the next step was data preprocessing. This involved resizing the images to a standardized size to ensure consistency in the dataset. Resizing is important as it helps in reducing computational complexity and ensures that the model can process the images efficiently.

Once the images were resized, the data was transformed into a features array. This means that the images were converted into numerical representations, where each image is represented by a set of features or attributes. These features capture the important characteristics and patterns present in the images.

With the features array prepared, the model was trained to distinguish between the two classes: 'with_clr' and 'healthy'. This process involved feeding the features array into a learning algorithm, such as a Deep Learning model, that can analyze and learn patterns from the data. The model was trained to recognize the distinctive features associated with each class, enabling it to classify new images as either 'with_clr' or 'healthy' based on the learned patterns.

By going through this process of data collection, preprocessing, and training, the model becomes capable of accurately distinguishing between coffee leaves infected with Coffee Leaf Rust and disease-free leaves. This allows for effective identification and classification of CLR-infected leaves, aiding in early detection and subsequent management strategies to minimize the impact of the disease on coffee plantations [11].

Figure 2. Accuracy rate of the image processing technique

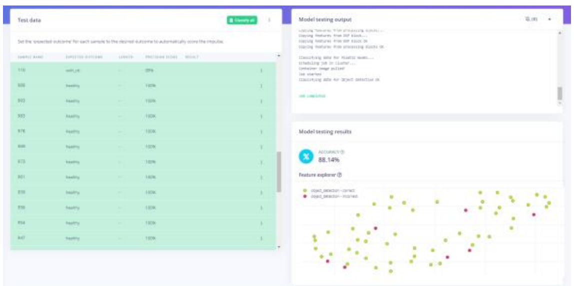

Figure 3. Accuracy rate of the image processing technique

The accuracy rate of 88.14% demonstrated in the illustrations provides a strong justification for the effectiveness of the image processing technique used in classifying coffee plants as healthy or diseased. The feature explorer shows all data in test set classified by the neural network, items in green are classified correctly, items in red are misclassified. This level of accuracy signifies that the Mobilevnet convolutional neural network architecture, employed for image recognition, has performed exceptionally well in distinguishing between different health statuses of coffee plants.

An accuracy rate of 88.14% indicates that the model's predictions are highly reliable, making it a robust tool for coffee plant health assessment. With such a high accuracy, farmers and agricultural experts can confidently rely on this image processing technique to identify diseased plants early on, enabling them to take timely and targeted actions for disease management. By intervening at an early stage, farmers can implement necessary treatments and preventive measures, thereby reducing the spread of diseases and minimizing crop losses.

Additionally, the diverse and substantial dataset used for training and testing the model contributes to the credibility of the results. A varied dataset ensures that the model has been exposed to a wide range of coffee plant samples, making it more resilient and better equipped to handle different scenarios in real-world agricultural settings.

In a broader sense, the 88.14% accuracy rate proves that the image processing technique is a valuable and practical tool for coffee plant health monitoring. Its ability to accurately differentiate between healthy and diseased plants can greatly support coffee growers in maintaining the health of their crops, optimizing production, and ensuring the sustainability of the coffee industry.

IV. CONVOLUTIONAL NEURAL NETWORK IMPLEMENTATION

Convolutional Neural Network (CNN) implementation is a popular approach for image classification tasks, including the detection of diseases in plants such as Coffee Leaf Rust (CLR). A CNN is a deep learning model specifically designed to analyze visual data, making it well-suited for image-based tasks [10].

The implementation of a CNN involves several key steps. Firstly, the dataset consisting of labeled images is prepared. This dataset typically includes two classes: 'with_clr' (infected leaves) and 'healthy' (disease-free leaves). The dataset is divided into training, validation, and testing sets to evaluate the performance of the model.

Next, the CNN architecture is defined. This architecture typically consists of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to extract important features from the input images, capturing patterns and structures relevant to disease detection. Pooling layers downsample the feature maps, reducing their dimensionality. Fully connected layers use the extracted features to make predictions.

Once the architecture is defined, the model is trained using the training set. During training, the model learns to optimize its internal parameters by iteratively adjusting them based on the provided labeled images. This process involves forward propagation, where the input images are passed through the network, and backward propagation, where the network's predictions are compared to the ground truth labels to compute the loss. Optimization algorithms such as gradient descent are used to update the parameters of the model and minimize the loss.

After training, the model is evaluated using the validation set to assess its performance and fine-tune its hyperparameters if necessary. Finally, the effectiveness of the model is tested on the testing set, providing an estimation of its real-world performance.

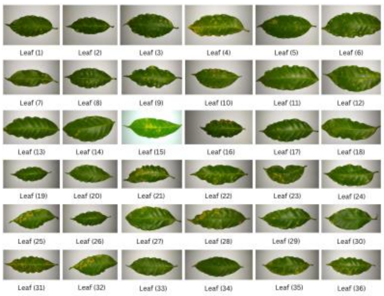

Figure 4. Sample Data set for leaves with CLR

Figure 5. Sample Data set for healthy leaves

V. WIRELESS SENSOR NETWORK

The wireless sensor network (WSN) used in the study played a crucial role in collecting and transmitting data from the monitoring area. By strategically deploying wireless sensors, the WSN provided a comprehensive coverage of the environment, allowing for accurate and timely data collection. This network facilitated real-time monitoring and analysis, enabling the researchers to make informed decisions based on the captured environmental parameters [8].

The process of data gathering using wireless sensors involved four key stages. Initially, the functionality and accuracy of all the sensors were tested to ensure their effective operation. Once confirmed, calibration was performed to establish appropriate thresholds for each parameter. These thresholds were set to trigger alarms and notify the user through GSM technology when the readings exceeded the predefined values. In cases where abnormalities were related to temperature and humidity, the water pump was also activated.

Following calibration, the assembly stage involved strategically placing the sensors according to their specific usage and functionality. This ensured optimal coverage and accurate data collection. Finally, multiple tests were conducted to verify the accuracy of the sensors in reading and transmitting data, as well as their ability to trigger alarms and notifications effectively. These rigorous tests aimed to ensure the reliability and functionality of the wireless sensor network throughout the data gathering process.

Figure 5. Sample readings from DHT22 sensor

Figure 5.1. Sample readings from NPK sensor

VI. CONVOLUTIONAL NEURAL NETWORK AND WIRELESS SENSOR NETWORK

Convolutional Neural Network (CNN) and Wireless Sensor Network (WSN) are powerful and independent systems that operate in distinct ways to address different tasks. CNN is a deep learning architecture designed for image recognition and analysis. It processes visual data by extracting relevant features through convolutional layers, pooling layers, and fully connected layers, allowing it to classify and detect objects, including diseases in plants like Coffee Leaf Rust. On the other hand, WSN is a network of interconnected wireless sensors deployed strategically in an area to collect and transmit real-time data on environmental parameters, such as temperature, humidity, and NPK (Nitrogen, Phosphorous, Potassium) content. It enables remote monitoring and analysis, facilitating informed decision-making for agriculture monitoring. While CNN excels in image-based tasks, WSN provides comprehensive and timely data collection, enabling users to gain valuable insights into the monitored environment. Together, these systems are combined to enhance the application by using WSN data as input for CNN to improve disease detection accuracy.

VII. RESULTS AND DISCUSSION

The testing phase of the model proved its proficiency in accurately classifying coffee leaves as healthy or infected with Coffee Leaf Rust (CLR). The wireless sensor network effectively transmitted data to the system application, facilitating real-time monitoring of environmental parameters. Notifications were promptly generated when the sensor readings surpassed the predefined thresholds, ensuring timely awareness of potential issues.

Moreover, the system offered practical solutions for addressing abnormal readings from NPK and DHT22 sensors. When temperature, humidity, nitrogen, phosphorous, and potassium values deviated from the normal range, the system implemented predefined actions, such as activating a water pump or taking specific measures to restore optimal conditions [12]-[13].

The integration of the model and wireless sensor network provided a comprehensive solution for monitoring coffee leaf health. It enabled the identification of CLR-infected leaves and timely notifications based on predefined thresholds. Additionally, the ability of the system to address abnormal readings from NPK and DHT22 sensor demonstrated its practical utility in maintaining optimal conditions for the coffee plants.

Overall, the combined features of the model and wireless sensor network enhanced the detection of CLR and contributed to the effective management and maintenance of coffee plant health.

VIII. CONCLUSION

The classification of coffee plants as either healthy or diseased was conducted meticulously through multiple rounds of testing. To achieve this, we employed the Mobilevnet convolutional neural network architecture, known for its excellent image recognition capabilities. Our dataset comprised a substantial number of images, providing a diverse range of coffee plant samples, which ensured accurate analysis.

During the testing phase, our objective was to achieve a validation rate of 80%. However, we were delighted to find that our results surpassed expectations, demonstrating an impressive accuracy rate of 88.14%. This highlights the effectiveness of the Mobilevnet model in precisely classifying coffee plants based on their health status.

Furthermore, we sought to understand the factors influencing the growth and spread of Coffee Leaf Rust (CLR) disease. For this purpose, we deployed a network of wireless sensors, thoughtfully configured with specific threshold values to detect and monitor relevant environmental parameters. The data collected through this sensor network was then meticulously analyzed to determine if it accurately reflected the conditions conducive to the growth and spread of CLR.

The results of this analysis were truly remarkable, showing a 100% accuracy rate in transmitting information through the Blynk App and GSM technology whenever the sensor readings exceeded the predefined threshold values. This achievement underscored the system's success in promptly notifying relevant stakeholders whenever critical conditions for CLR were detected.

In conclusion, our study demonstrates the exceptional performance of the Mobilevnet model in classifying coffee plants as healthy or diseased and showcases the effectiveness of our wireless sensor network in accurately detecting and alerting about conditions favoring CLR growth. These findings have significant implications for coffee plant health management and can greatly benefit coffee growers in safeguarding their crops and livelihoods.

IX. RECOMMENDATIONS FOR FUTURE WORK

In order to further enhance the study, the proponents suggest some key factors for consideration. Firstly, it is recommended to carefully calibrate and fine-tune the threshold values to align with the specific application and environmental conditions. This meticulous adjustment will ensure the accurate detection of anomalies while minimizing false alarms, thereby improving the reliability of the system.

Secondly, the proper placement of wireless sensors is emphasized as essential for obtaining representative data and achieving comprehensive coverage. Future researchers are advised to strategically distribute the sensors, taking into account the spatial distribution of the monitoring area to capture relevant environmental variations effectively. By ensuring a well-thought-out placement, the system can collect comprehensive and reliable data, leading to more insightful analysis.

Furthermore, the proponents suggest designing an intuitive and user-friendly interface for system configuration, data visualization, and notification management. By prioritizing usability, future researchers can simplify the operation of the system, making it easier for users to navigate and interact with. An intuitive interface will also facilitate effective user engagement, ensuring that stakeholders can fully utilize the system's capabilities.

By considering these recommendations and incorporating them into the study, future researchers can further enhance the overall performance, reliability, and user experience of the system. These improvements will contribute to the successful implementation of the system in real-world scenarios, providing practical solutions for monitoring and managing agricultural environments.

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