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ANDROID AGROSCAN: CUTTING EDGE PLANT PATHOGEN DETECTION SYSTEM

Dr. S.K. Mydhili, Professor, Department of ECE, KGiSL Institute of Technology, Coimbatore.
T.A. Benazir, PG Scholar, Department of ECE, KGiSL Institute of Technology, Coimbatore.

ABSTRACT
Agriculture's significance lies in its role in securing food supplies and addressing the mounting needs of a burgeoning population. Crop diseases constitute a substantial threat to agricultural productivity and economic stability in India. With over INR 290 billion in annual crop losses attributed to pests and diseases, the agricultural sector faces substantial challenges. India records approximately 5,000 out of 30,000 plant diseases globally, leading to an estimated decline of 5 million tons of crop yield annually due to fungal infections. Farmers traditionally rely on expertise for detecting crop diseases. This is accomplished through visual inspection or by submitting images in internet to specialists for analysis. To address these challenges, an automatic crop disease detection and classing system capable of identifying and categorizing three major diseases: Black Horse Riding, Brown color Spot and Bacterial Leaf Streak leveraging digital image processing techniques and the Naive Bayes algorithm, is implemented through an Android application. The system involves a process of capturing images, preprocessing, segmenting, and classifying them based on the disease type, utilizing a Naive Bayes probabilistic linear classifier. Developed using Android Studio with Java as the primary language, the application identifies crop diseases by analyzing pixel intensities, predicts crop growth, and evaluates sunlight conditions for optimal development. Furthermore, it offers tailored recommendations for suitable fertilizers and pesticides corresponding to the detected disease. Achieving an average accuracy rate of around 90%, this implementation significantly reduces the dependence on manual labour and augments agricultural productivity.
Keywords - Naive Bayes classifier, Plant diseases, Android application, Image processing.

I. INTRODUCTION

The survival of the human race heavily hinges on the natural food supply, which is completely reliant on agricultural endeavors. As the population continues to grow, so does the need for sustenance, making agriculture an ongoing pursuit. Crop ailments result in reduced productivity, affecting the overall harvest. Detecting these ailments early can significantly enhance crop yields. Traditional disease detection methods, which rely on visual examination, tend to be expensive, time-consuming, and occasionally inaccurate. Hence, utilizing digital image processing methods alongside the Naive Bayes probabilistic neural network algorithm can enhance the precision of disease detection and categorization in an automated fashion. The principal objective is to create an Android application capable of capturing images, recognizing disease types, and recommending suitable fertilizers and pesticides. This strategy not only amplifies crop yields but also diminishes labor expenditures. In India, rice is the primary crop, experiencing a consistent surge in demand. The primary hurdle to meeting production target is bacterial infection. In severe instances, this infection can result in yield reductions of 50%. This study delves into three major infections: Brown Spot, Black Horse Riding and Bacterial Leaf Streak predominantly affecting rice and wheat, although they also affect other crops like maize, sugarcane, palm, ornamental plants, and others.

This study utilized a plant disease dataset that is freely accessible and commonly utilized in the agricultural field for image dispensation. The dataset contains images depicting plant leaves afflicted with different diseases alongside images of healthy leaves. The paper is structured as follows: Part II entails a review of the existing literature, while Part III outlines the planned methodology, including the utilization of a plant disease dataset and the implementation of the Naive Bayes classifier for disease detection. The algorithm of the study is presented in Part IV and the results are discussed further in Part V. The paper concludes in Part VI, offering insights into the expected outcomes.

II. EXISTING LITERATURE

The hasty evolution of machine learning in agricultural imaging has brought about a paradigm shift in the detection of plant leaf diseases, enabling accurate identification of symptoms like discoloration and lesions. Supervised algorithms such as SVMs, Naïve Bayes Classifier and random forests, along with unsupervised techniques like clustering, analyze large datasets to distinguish between healthy and diseased leaves. These automated systems reduce diagnosis time, improve accuracy, and empower farmers with timely interventions, ultimately enhancing crop yields and ensuring food security.

The rice plant is plagued by two diseases, Brown Spot in leaf and Leaf Blast, which are identified using map called Self Organizing Map (SOM), an unsupervised learning method boasting a correctness of nearly 92% in [1]. Researchers employed SVM and Gaussian kernel function in [2] to classify variety of diseases in paddy. And also, Fuzzy classifier is utilized to distinguish various diseases in wheat plants, achieving an 88% accuracy for disease detection and a 56% accuracy for disease type classification [3]. Employing Python, SVM classifiers and Artificial Neural Networks (ANN) are utilized in [4] for detecting and categorizing maize diseases, with ANN achieving accuracies ranging from 55% to 65% and SVM achieving accuracy about 75%. Fuzzy Classifier algorithm is designed to recognize nine different diseases affecting finger millets in [5]. This system analyzes symptoms to detect diseases and offers recommendations for their control.

An approach was introduced in [6] employing the VGGvgg16 Convolutional Neural Network model (CNN) for disease identification in pearl millet, resulting in an accuracy of 95%. Alexnet was utilized to identify 14 distinct diseases affecting olive plants, allocating 80% of the dataset for training and the remaining 20% for testing, yielding an accuracy of 99.11% [7]. A system for leaf disease detection is developed in [8] using a SVM classifier, achieving a 96% accuracy in detecting Anthracnose and Chimaera. In [9], a system proposed for the detection and classification of four different diseases in groundnut leaves, employing a Back propagation in MATLAB and achieving an accuracy of 97.41%. Utilizing algorithms such as Multiclass SVM, Naive Bayes, K-Nearest Neighbor, and Multinomial Logistic Regression, researchers classified three distinct diseases found in sunflowers with accuracies of 92.15%, 89.075%, 89.32%, and 92.57% respectively. Across all four classification algorithms, the accuracy of distinguishing healthy leaves remained at a perfect 100%, as noted in the study [10]. Healthy and damaged leaves were distinguished using the K-Nearest algorithm, achieving an accuracy rate of approximately 95%, according [11]. Researchers developed an automatic system to identify Mildew disease in healthy plants and assess its brutality, employing the KN algorithm for disease detection and a decision tree for severity estimation. This method proposed in [12], achieved an accuracy rate of 82.5%. Deep Convolutional Neural Network (DC NN) training and testing encompassed 18 disease classes across various plant parts, as indicated in the study.

Six models were devised, among which the ResNet50 and InceptionV2 models exhibited superior performance. The developed system has achieved accuracy of approximately 90% in [13]. Then an image processing technique was established utilizing SVM to discern two primary diseases of tea, namely Algal Leaf Spot and Brown Blight Disease, from the healthy tea leaves [14]. The proposed system attained a success rate of around 93% with the utilization of half black coffee beans and half healthy coffee beans. Grey scale images were employed for K-means clustering and color feature extraction was applied for the process of segmentation. The results, achieved using MATLAB software, were 100% accurate [15]. An application has been developed employing the Backpropagation algorithm, which categorizes two diseases are coffee leaf rust and coffee leaf miner are detected from normal coffee leaves. Additionally, the application provides an estimation of disease severity [16]. An experiment on Texture-Based Recognition of Disease was shown in [17], yielding a coefficient of kappa with 0.900 and 0.933 sensitivity. Likewise, employing Deep Learning Disease Recognition, the same parameters were calculated and resulting as 0.97 and 0.98.

The Artificial Neural Network developed in [18], effectively distinguishes between diseases of two cucumber crop, downy mildew and powdery mildew, achieving an 80.4% classification accuracy. Then Graphical User Interface (GUI) has been established in [19], to diagnose and treat the identified diseases. In a separate study [20], a Backpropagation neural network achieved a 90% accuracy in discerning healthy pomegranate leaves from diseased ones. Experiments were conducted on the leaves of three commonly afflicted grape diseases using MATLAB. Utilizing LAB color model with the feature extraction yielded an accuracy of 82.5%, while employing both LAB and HSI color models increased accuracy to 90%. Disease classification was performed in [21] using Multiclass SVM. An SVM classifier was employed to classify two grape diseases, downy and powdery mildew, achieving an accuracy of 88.89%. Image processing methods are utilized to identify citrus leaf disease [22]. Gray-Level Co-Occurrence matrix (GLCM) is employed for feature extraction, while disease classification is carried out using support vector machine (SVM) algorithms.

The developed method in [23] using machine learning (ML) to classify white scale disease (WSD) infestation stages in date palm trees from leaflet images. Extracting features from the dataset, including GLCM texture and HSV color moments, ML algorithms like SVM, KNN, RF, and Light GBM were tested. SVM with combined GLCM and HSV features achieved the highest accuracy of 98.29%. An AI-powered handheld device developed in [24] utilizing deep learning technology. It utilizes Edge Computing Service to categorize rice crop images into healthy and stressed states, identifying fungal and bacterial infections. It boasts a commendable test accuracy of 93.25% and remains user friendly on smartphones post deployment. Utilizing Machine Learning (ML) and Internet of Things (IoT) data from crop fields, this approach [25] predicts disease probability before onset by analyzing environmental conditions. The model, employing Multiple Linear Regression (MLR), accurately forecasts disease occurrences. Tested on blister blight in tea plants, it achieved a remarkable 91% accuracy in predicting disease.

III. PROPOSED WORKFLOW

The proposed Android application for plant disease detection utilizes the Naive Bayes algorithm to accurately identify diseases based on leaf symptoms, while also analyzing disease progression and impact on plant development. It calculates the percentage of affected leaf area and generates tailored recommendations for fertilizers and treatment methods. Focusing on diseases like Black horse riding, Bacterial leaf steak, and Brown spot, it provides specialized interventions.

Bacterial Leaf Streak

Bacterial leaf streak, which primarily affects wheat plants, which eventually turn into linear lesions of brown color between leaf veins. At first appearing dark green, this streak may shift to a brownish or yellowish-gray color in severe cases. In extreme instances, the entire leaves can become brown and perish. To control the disease, farmers often resort to applying copper-based fungicides or using the pesticide Epsom salt. The potential crop loss attributed to leaf streak disease due to bacteria ranges from 10% to 40%. Figure 1 illustrates the appearance of this disease.

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Fig.1 Bacterial leaf streak disease

Brown Spot

Brown spot means fungal disease, predominantly affects rice crop and soybean plants, causing brown lesions on infected seedlings and resulting in rusty brown leaves. Affected seedlings either die early or suffer from stunted growth. The application of fungicides such as triadimefon, which can aid in reducing the disease spread. Prolonged wetness in leaf can exacerbate the seriousness of the infection within 5 to 36 hours. Brown spot disease can lead to yield losses ranging from 8% to 15%, with premature defoliation of the canopy potentially increasing losses to between 25% and 50%. Figure 2 illustrates the appearance of brown spot disease.

Fig.2 Brown Spot disease

Black Horse Riding

The affliction known as black horse-riding disease predominantly targets monocotyledons. Patch formations triggered by this ailment are primarily attributable to pathogenic fungi. Once these fungi infiltrate the leaf, they persist, causing degradation of leaf tissue and resulting in varying sizes of spots. Dark discoloration characterizes, deceased parts on the leaves, while the periphery of affected regions may exhibit hues of red or purple. In advanced stages, the disease prompts complete leaf defoliation. Mitigation strategies include chemical fungicides or various organic alternatives like Neem Oil, Copper, Potassium, Lime Sulphur. Figure 3 and figure 4 illustrates the manifestation of black horse-riding disease and the proposed workflow.

Fig.3 Black Horse-Riding disease

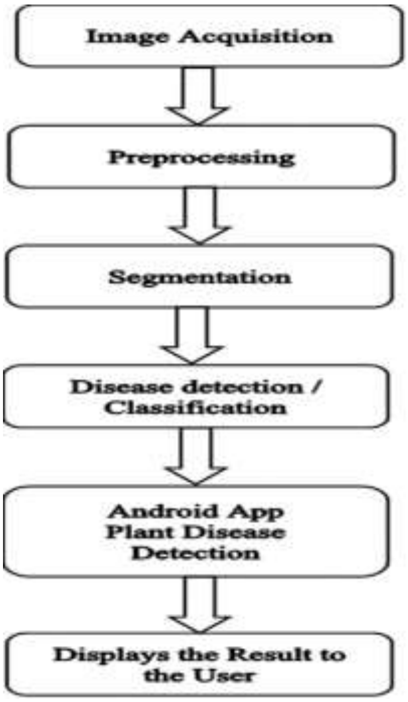

Fig.4 Proposed Workflow

A. Image Acquisition

For image acquisition, high-quality images of both diseased and healthy leaves are obtained using a high-resolution mobile phone camera or sourced from online repositories. Leaves of varying canopy sizes are deliberately chosen to facilitate easier classification. Within the Android application, users can select images from their device's gallery as shown in figure 5.

Fig.5 Image Acquisition

B. Image Pre Processing

In the preprocessing stage, unwanted noise from images is removed using specific techniques as follows:

RGB to Gray Color Conversion: Transformation of the input RGB image into a grayscale image, where each pixel represents a single intensity value, simplifying subsequent analysis.

Bitmap Extraction: Extraction of the bitmap representation of the grayscale image to isolate the relevant regions of interest from the background, facilitating more focused analysis.

Histogram Analysis: Examination of the pixel intensity distribution within the grayscale image to generate a histogram graph, enabling visualization of the image's tonal range and aiding in subsequent processing steps.

C. Image Segmentation

Image Segmentation is a fundamental aspect of image processing, involving the division of an image into distinct segments or regions. This process simplifies analysis by breaking down the image into more manageable parts.

Fig.6 Image Segmentation

Following histogram analysis, threshold-based segmentation is employed, where pixels are secret as background or foreground based on their predefined threshold compared to a intensity values. This process results in a binary image where pixels are assigned either a value of 0 or 1, indicating background or foreground, respectively. While simplistic, threshold-based segmentation remains effective for segregating objects of attention from the background. The segmented image in figure 6 facilitates subsequent analysis and feature extraction tasks, aiding in the accurate identification and characterization of objects within the image.

D. Disease Detection and Classification

In the classification segment and disease detection, the segmented leaf images are subjected to classification using a probabilistic classifier based on Bayes' theorem and Naive Bayes algorithm. Renowned for its efficiency and suitability for smaller datasets, Naive Bayes offers a robust framework for distinguishing between different diseases, leveraging distinct pixel values indicative of each condition.

Post-segmentation, the input leaf image undergoes a systematic comparison against all potential disease classes, wherein the algorithm computes the probabilities associated with each disease manifestation. Through probabilistic inference, the algorithm identifies the disease with the highest probability, thus providing a precise diagnosis. Furthermore, the application interface presents a visual representation detailing the percentage level of the part of leaf affected by the detected disease, facilitating comprehensive disease characterization and aiding in the formulation of targeted management strategies for optimal crop health.

E. Android Application Development

The mobile application was developed using Android Studio, starting from the ground up. Utilizing the Android SDK, the application was engineered to ensure full compatibility with all Android devices. The primary programming languages employed were JAVA and XML, with XML utilized for implementing the frontend components of the application, including the user interface layout and design. Conversely, JAVA served as the backbone for implementing the backend functionality, encompassing the logic and functionality of the mobile application. Through the seamless integration of these programming languages and technologies, the application was crafted to deliver a robust and user-friendly experience for Android users.

"Plant Analyzer" is an Android application designed for detecting three distinct leaf diseases. The app interface comprises multiple buttons for user interaction. Upon selecting the "Change" button, the user can upload a leaf photo from the device's gallery for disease detection. The application employs a pre-trained model utilizing a database of annotated leaf images for comparison.

Upon selection of the leaf image, the application conducts a comparative analysis against the existing dataset. Utilizing image processing techniques and pattern recognition algorithms, the app recognizes whether the leaf is affected or not. Subsequently, the application provides a detailed diagnosis by specifying the disease name along with the percentage of infection present on the leaf.

The functionality of the application is underpinned by machine learning algorithms, enabling efficient and accurate disease detection. Leveraging the capabilities of the Android platform, "Plant Analyzer" offers a user-friendly interface and seamless integration with device functionalities. Through its sophisticated image analysis capabilities, the application empowers users with timely and precise information for effective disease management in plant cultivation.

F. Growth Prediction

Additionally, the application assesses sunlight conditions, categorizing them as favorable or unfavorable based on disease severity. A disease presence exceeding 5% indicates suboptimal sunlight conditions. Leveraging disease type information, the application offers tailored fertilizer and pesticide recommendations to optimize plant health and mitigate disease impact. This predictive functionality enhances agricultural decision-making, enabling proactive management strategies for optimal crop growth and yield.

IV. PLANT LEAF DISEASE DETECTION – ALGORITHM

Step 1: Create a dataset.
Step 2: Choose an input image
Step 3: Check whether the quality of the image matches the level of the required quality.
Step 4: If the quality is not as good as required, the image quality is enhanced and the image is used afterward.
Step 5: RGB colored image of leaf is converted into greyscale image.
Step 6: The bitmap is extracted so that the required part of the leaf is separated from the background.
Step 7: Draw histogram graph with the pixel intensity of the image.
Step 8: Threshold-based segmentation is done to convert into binary image.
Step 9: Images are classified based on Naive Bayes algorithm.
Step 10: The result for each segment is given out which states whether the area is affected by any disease or not.
Step 11: The segment that is stated diseases is further processed.
Step 12: Every segment with the diseased image is fetched using artificial networks to examine whether there are high deviations between the pixels of its neighboring units.
Step 13: If the pixel has a high deviation, it is colored red, indicating a disease on the particular part of the leaf.
Step 14: Percentage of the diseased portion of the leaf is calculated based on pixel intensity and growth prediction is done.

V. RESULTS AND DISCUSSION

The Android application “Plant Analyzer” developed for plant disease detection offers a user-friendly interface for seamless interaction. Upon installation, users can select an image from the device's gallery for analysis as shown in figure 7. The application presents two options: "Change Image" and "Continue," facilitating easy navigation.

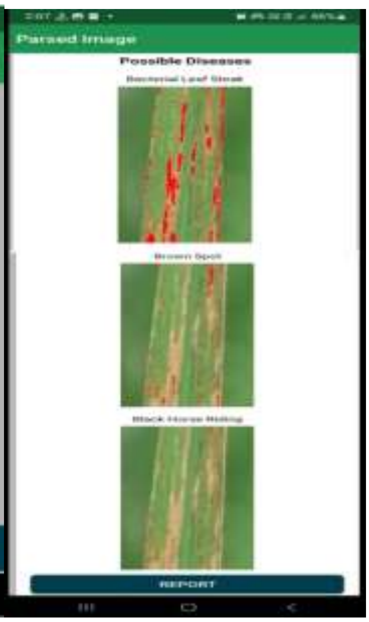

Fig.7 Plant Analyzer App Fig.8 Parsed Image

Upon selecting "Continue," the application progresses to the next page as shown in figure 8, where the input image undergoes analysis for potential diseases. The image is compared against known symptoms of diseases such as Brown spot disease, Bacterial leaf streak and Black horse riding. Regions of the leaf similar disease symptoms are highlighted in red, aiding in visual interpretation.

Upon selecting the "Report" option, the application displays the disease with the highest probability and also the infection percentage as shown in figure 9. This comprehensive analysis provides users with valuable insights into the severity of the detected disease.

Fig.9 Result with % of infection

Overall, the application's intuitive interface, comprehensive analysis capabilities, and integrated recommendations empower users with the tools and insights needed for efficient plant disease detection and management.

VI. CONCLUSION

The culmination of the research presents a robust Android application for plant disease detection, consolidating both advanced machine learning algorithms and best image processing techniques. Through meticulous RGB to grayscale conversion, bitmap extraction, and histogram analysis during image preprocessing, image quality enhanced, ensuring precise disease analysis. Leveraging thresholding-based segmentation and the Naïve Bayes classifier, our application achieves superior disease identification rates, particularly for Black horse riding, Bacterial leaf streak and Brown spot leaf, boasting an exceptional average accuracy exceeding 98%.

The proposed work underscores the pivotal significance of early disease detection in curbing crop losses and elevating agricultural productivity. Featuring an intuitive user interface and real-time disease identification capabilities, our application emerges as an indispensable tool for farmers, agricultural experts, and researchers alike. By empowering users with prompt disease recognition and efficient management strategies, our application catalyzes improvements in crop health, amplifies yields, and fosters the adoption of sustainable agricultural practices.

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