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Ml Based Farming System – Casava Leaf Disease Detection

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Abstract- The ML-based farming system for cassava leaf dis- ease detection proposes a solution to automate the identification and diagnosis of diseases affecting cassava plants. This system leverages machine learning (ML) techniques to analyse images of cassava leaves and accurately classify them into healthy or diseased categories. The proposed system employs convolutional neural networks (CNNs), a type of deep learning architecture, for robust and efficient leaf disease detection. A dataset of la- belled cassava leaf images, comprising both healthy and diseased samples, is collected and used for model training. The CNN model is trained on this dataset to learn the visual patterns and features associated with different cassava leaf diseases. During the inference phase, new images of cassava leaves are fed into the trained CNN model, which predicts the presence or absence of diseases. The ML-based system provides a quick and reliable assessment of the leaf health status, allowing farmers to take proactive measures such as targeted treatments or removal of diseased plants to prevent further spread. The proposed system offers several advantages over traditional manual diagnosis methods. It eliminates the need for human experts, reducing the time and expertise required for disease identification. Additionally, the ML model can handle large volumes of data, making it scalable for real-time monitoring of large- scale cassava farms. The ML-based farming system for cassava leaf disease detection has the potential to significantly improve the efficiency and productivity of cassava farming. By enabling early disease detection and intervention, farmers can implement appropriate disease management strategies, minimize yield losses, and optimize crop health. Overall, the ML-based farming system offers a reliable and cost-effective solution for cassava leaf disease detection, empowering farmers with timely and accurate information to make informed decisions and safeguard their crop health.

Keywords- ML-based farming system, cassava leaf disease detection, machine learning, image analysis, healthy leaves, diseased leaves, convolutional neural networks, deep learning, labelled dataset, model training, visual patterns, feature extrac- tion, inference phase, prediction, disease classification, leaf health assessment, proactive measures, targeted treatments

I. INTRODUCTION

Disease identification in plant is most important in successful farming system. In general, a farmer rec- ognizes the symptoms of disease in plants by using naked eye observations and this requires continuous monitoring. However, this process is more expensive in large plantations and sometimes this may be less accurate. In some countries like India, farmers may have to show the specimen to experts, this makes time consuming and more expensive. Also, a single infected plant can spread the disease. Here, proposes a deep learning-based plant disease detection system to identify and classify the diseases. It analyses the plant leaf images collected from different plants. In this proposed work, dataset used is cassava dataset. It includes 4 categories of cassava leaf images- Cassava Bacterial Blight (CBB), Cassava Brown Streak Dis- ease (CBSD), Cassava Green Mottle (CGM), Cassava Mosaic Disease (CMD), Healthy. The deep learning algorithm used for detection of cassava leaf disease is EfficientNet algorithm. It is a type of CNN that scales all dimensions in the input data uniformly. The proposed system helps to identify plant diseases quickly and hence improve the crop yield.

Problem Statement • Automatic detection of plant dis- eases is an essential research topic as it may prove benefits in monitoring large fields of crops, and thus automatically detect the symptoms of diseases as soon as they appear on plant leaves.

The symptoms of plant diseases are conspicuous in dif- ferent parts of a plant such as leaves, etc. • Manual detection of plant disease using leaf images is a tedious job. • Hence, it is required to develop computational methods[1] which will make the process of disease detection and classification using leaf images automatic.

Methodology • Uses deep learning technique for clas- sification and it make use of neural network[2] to process input data. • Neural network is a set of algorithms that mimic the human brain. • In this project, EfficientNet algorithm is used to implement cassava plant disease detection. • Efficient- Net is a type of Convolutional Neural Network (CNN) in which scaling method that uniformly scales all dimensions of depth/width/resolution. • In CNN, mathematical operation used is Convolution operation. • The main building block of this network consists of MBConv to which squeeze-and-excitation optimization is added. • MBConv is similar to the inverted residual blocks used in MobileNet v2. • These form a shortcut connection between the beginning and end of a convo- lutional block. • The input activation maps are first expanded using 1x1 convolutions to increase the depth of the feature maps. • This is followed by 3x3 Depth-wise convolutions and Point-wise convolutions that reduce the number of channels in the output feature map. • The shortcut connections connect the narrow layers whilst the wider layers are present between the skip connections. This structure helps in decreasing the overall number of operations required as well as the model size.

II. LITERATURE REVIEW

1. Detection of Plant Leaf Diseases Using Image Seg- mentation and Soft Computing Techniques

Vijai Singh A and A.K. Misra (2017)[1] proposed an algo- rithm that employs image segmentation techniques for the automatic detection and classification of plant leaf diseases. The method involves using digital images of different plant leaves to identify affected areas. After preprocessing, where green-colored pixels are masked using a computed threshold, useful segments are extracted. Genetic algorithms are then used for segmentation. For feature extraction, the color co- occurrence method is applied, considering both texture and color. These extracted features are classified using a Support Vector Machine (SVM) classifier. The process includes steps such as image acquisition, preprocessing (including smoothing and contrast enhancement), masking green pixels, removing masked cells, segmenting infected clusters, computing fea- tures, and finally classifying the disease.

2. Leaf Disease Detection Using Image Processing

Sujatha R, Y. Sravan Kumar, and Garine Uma Akhil (2017) presented a leaf disease detection technique using k-means clustering and SVM classifiers. The process follows five stages: image acquisition, preprocessing, segmentation, feature extraction, and classification. The original image is enhanced and converted to HSI format before k-means clustering is applied using the Euclidean distance metric. The SVM classifier is then used to identify the disease, and the affected leaf area can be quantified as a percentage. Segmentation is used to partition images into super-pixels, followed by contrast enhancement to prepare for classification. Figure 2 represents the plant image in various segments.

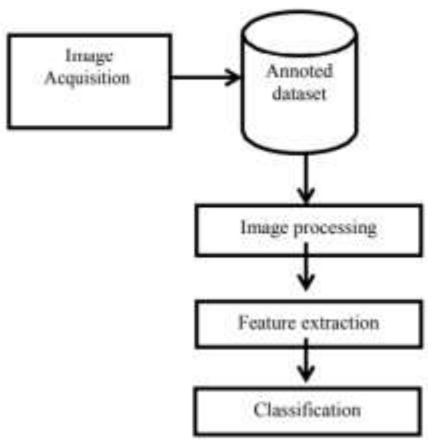

Fig.2 . plant image in various segemnts

3. An Identification of Crop Disease Using Image Segmentation

K. Vinoth Kumar and T. Jayasankar (2019) introduced a method utilizing deformable models for detecting crop diseases through image segmentation. The RGB images are transformed into perceptually uniform color spaces to en- hance color differentiation. The methodology comprises an Image Processing Segment (enhancing and segmenting the leaf from background) and a Pattern Recognition Segment (feature extraction and matching with known diseases). The process involves transforming images, constructing color-spatial repre- sentations, clustering patches using k-means, and quantifying variances through GLCM energy.

4. Plant Disease Detection Using Machine Learning

Shima Ramesh, Mr. Ramachandra Hebbar, Niveditha M, Pooja R, Prasad Bhat N, and Shashank N (2018) used the Random Forest algorithm to classify healthy and diseased papaya leaves. RGB images are converted to grayscale for feature extraction using Hu moments and Haralick features. The paper outlines phases such as dataset creation, feature extraction (using HOG, Hu moments, Haralick texture, and color histograms), training, and classification. RGB images are also converted to HSV for histogram calculation. The system effectively detects whether a leaf is diseased or healthy.

5. A Review on Machine Learning Classification Techniques for Plant Disease Detection

Shruthi U, Dr. Nagaveni V, and Dr. Raghavendra B.K. (2019) provided a comprehensive review of plant disease detection systems and compared various ML classifiers. The process involves image acquisition, annotated dataset creation, image preprocessing, segmentation, feature extraction (using GLCM and other methods), and classification. The classifiers compared include SVM, ANN, KNN, Fuzzy Logic, and Deep Learning. Results indicate CNNs outperform other classifiers in detecting multiple plant diseases with higher accuracy.

6. Classification of Plant Leaf Diseases Using Machine Learning and Image Preprocessing Techniques

Pushkara Sharma, Pankaj Hans, and Subhash Chand Gupta (2020) proposed an AI-based system for automatic plant leaf disease detection. The model is divided into image collection, preprocessing (noise removal and HSV conversion), segmen- tation (using k-means clustering), and classification using logistic regression, KNN, SVM, and CNN. CNN achieved the highest accuracy among the models tested.

7. Rice Leaf Disease Detection Using Machine Learning Techniques

Kawcher Ahmed, Tasmia Rahman Shahidi, Syed Md. Ir- fanul Alam, and Sifat Momen (2019) proposed a system to detect rice leaf diseases such as leaf smut, bacterial blight, and brown spot. Clear images of affected leaves are preprocessed and fed into a feature selection module. Correlation-based feature selection is used, and classifiers like KNN, J48, Naive Bayes, and Logistic Regression are applied. The Decision Tree classifier achieved over 97% accuracy using 10-fold cross- validation.

8. Diagnosis of Tomato Plant Diseases Using Random Forest

Meghana Govardhan and Veena M.B. (2019) developed an automated system for identifying tomato plant diseases using ML and image processing. Diseases such as Early Blight, Late Blight, and Mosaic Virus are considered. Features including shape, color, and texture are extracted using Haralick Texture, Color Histogram, and Hu Moments. Random Forest is used for classification, achieving an overall accuracy of 95%.

9. Plant Diseases Detection and Classification Using Machine Learning Models

Poojan Panchal, Vignesh Charan Raman, and Shamla Mantri (2019) investigated various techniques for image segmentation and classification of diseases in plants like tomato, pepper, and potato. Segmentation is done via k-means clustering or HSV value alteration, followed by GLCM-based feature extraction. Multiple classifiers such as Random Forest, KNN, Decision Tree, and SVM are compared. Random Forest yielded a detection accuracy of 98%.

10. Deep Learning for Image-Based Plant Detection

Prasanna Mohanty et al. proposed a CNN-based system to identify healthy and diseased plants across 14 species, achieving 99.35% accuracy on test data. However, perfor- mance dropped to 31.4% with real-world images from online sources, indicating the need for more diverse training data and model variations.

11. Detection and Classification of Leaf Disease Using Artificial Neural Network

Malvika Ranjan et al. proposed an approach using ANN to detect plant diseases from leaf images. By selecting key feature values, the ANN model distinguishes between healthy and diseased leaves with an accuracy of 80%.

12. Detection of Unhealthy Region of Plant Leaves and Classification Using Texture Features

S. Arivazhagan outlined a four-step disease identification method: RGB image color transformation, green pixel detec- tion and removal, segmentation, and texture statistics compu- tation. These features are used by classifiers to determine the disease type.

13. Applying Image Processing Technique to Detect Plant Diseases

Kulkarni et al. proposed using ANN with Gabor filters for early plant disease detection. The method delivers a recognition rate of up to 91% through feature extraction and classification.

14. Plant Disease Detection Using CNN and GAN

Emaneul Cortes introduced the use of GANs for disease detection. While GANs showed potential in classification, background-based segmentation didn’t improve model accu- racy significantly.

15. CNN-Based Inception v3 Model for Animal Classification

Jyotsna Bankar et al. demonstrated how the Inception v3 model, typically used for object classification, could also be applied to plant disease classification due to its ability to categorize and distinguish images effectively.

III. EXISTING SYSTEM

Leaf shape description is a crucial challenge in the process of plant identification, as the shape of a leaf holds significant information necessary for accurate classification. Over the years, various shape-based features have been extracted and analyzed to describe leaf morphology in an effort to improve the identification process. Despite the progress in research and the availability of numerous image processing techniques, there still remains a lack of a fully accurate and universally applicable system that can capture a leaf’s image and immediately classify it based on its unique attributes. This gap highlights the need for a more refined and comprehensive approach to automatic plant leaf classification.

In plant leaf classification, leaves are primarily categorized based on their distinct morphological characteristics such as shape, size, edge pattern, vein structure, and texture. These physical traits serve as key identifiers in differentiating be- tween species. To enhance the accuracy and efficiency of classification, several computational and machine learning techniques have been employed. Among them, Fuzzy Logic is widely used due to its ability to handle uncertainties and imprecision associated with real-world data, such as variations in leaf shapes caused by environmental conditions. It provides a flexible reasoning framework, making it suitable for dealing with vague or ambiguous inputs, which are common in leaf datasets.

Another popular method is Principal Component Analysis (PCA), which is used for dimensionality reduction. In the context of leaf classification, PCA helps in simplifying the complex data by transforming it into a set of uncorrelated principal components. These components retain the most significant variations present in the original dataset, thereby reducing computational complexity and enhancing the performance of classification models. By focusing on the most relevant features, PCA allows more efficient training and testing of classifiers.

The k-Nearest Neighbours (k-NN) classifier is also extensively applied in leaf classification due to its simplicity and effectiveness. It works on the principle of instance-based learning, where a leaf image is classified based on the majority class among its 'k' nearest neighbors in the feature space. The effectiveness of k-NN depends largely on the quality of feature extraction and the selection of an appropriate distance metric. This technique proves particularly useful when the dataset contains well-defined and labeled instances, allowing new samples to be accurately matched with similar existing examples.

IV. PROPOSED SYSTEM

The proposed system focuses on the automatic detection of plant leaf diseases by utilizing advanced image processing[2] and machine learning techniques, particularly Convolutional Neural Networks (CNNs). The core idea is to extract critical features such as shape, color, and texture from leaf images, enabling effective classification[3] of whether a plant is healthy or diseased. If the plant leaf is found to be diseased, the system not only identifies the disease but also suggests appropriate remedies. These suggestions aim to promote healthier plant growth and ultimately enhance agricultural productivity[4]. High-resolution images of plant leaves are captured to ensure accurate analysis, and these images undergo pre-processing[5], such as resizing and grayscale conversion, to standardize the inputs for further analysis. Figure 1.1. represents the overall process.

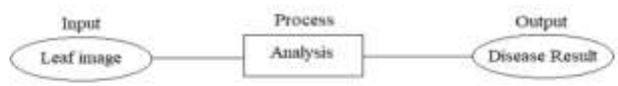

Fig.1 Overall Process

Once pre-processed, the images are passed through a CNN- based feature extraction module which applies several convo- lutional layers and max-pooling to capture essential patterns and reduce spatial dimensions[6]. This feature data is then used to predict the presence and type of disease. To make the system accessible, a web platform has also been developed that integrates the trained machine learning[7] models, allowing users—regardless of their technical expertise—to interact with the system through a simple graphical interface. Users can upload leaf images, and the tool processes[8] the inputs in real- time to generate predictions and display results through a user- friendly interface.

The system architecture includes several components: data loading, pre-processing, feature extraction via CNN[9], disease prediction, and visualization of data insights using tools like Matplotlib and Seaborn. The CNN model is trained using Keras and incorporates dropout layers to prevent overfitting. EfficientNet, a family of CNN

models known for balancing[10] performance and computational cost, is used to enhance classification efficiency. Training is performed with binary cross-entropy loss for classification tasks and mean absolute error (MAE) for regression tasks like age prediction in some extended applications.
To further analyze the workflow, system diagrams such as Data Flow Diagrams[11] (DFDs), Use Case Diagrams, and Sequence Diagrams are incorporated. The context diagram illustrates the entire data journey from input (image capture) through pre-processing, feature extraction, and disease pre- diction. Separate Level 1 DFDs show the roles of various users like Admin, Agriculture Officers, and Farmers, each interacting with the system for data input, analysis, and result visualization. Use Case Diagrams define the functional expectations of the system, highlighting its offered capabilities and user interactions. Sequence Diagrams[12] provide a time- sequenced view of system operations, showing how objects interact during a scenario.

A detailed feasibility study was also conducted to assess the system's viability, particularly in detecting diseases in cassava plants. This study covered market demand, techni- cal feasibility, data availability, algorithm design, hardware requirements, and stakeholder engagement[13]. It concluded that deploying such a system is both technically feasible and agriculturally beneficial. The use of estimators for initializing cluster centers enhances automation and accuracy compared to existing systems that require manual input. Overall, the system not only automates plant disease detection but also offers practical, environmentally friendly recovery sugges- tions—positioning it as an innovative, accessible[14], and efficient solution in the domain of smart agriculture.

V. SYSTEM IMPLEMENTATION

The system runs on an 11th Gen Intel(R) Core(TM) i3- 1115G4 processor with 2 cores, supported by 8 GB SODIMM DDR4 SDRAM. It includes a 1TB hard drive for storage and a 15.6″ Full HD LED display with a brightness[15] of 250 nits. The screen resolution is 800 x 600 pixels and supports a 24-bit True Color palette. Input devices include a PC/AT enhanced keyboard and a Logitech PS/2 port mouse. Additional drive options are available if required.

Processors in a system typically comprise two essential units: the Control Unit (CU) and the Execution Unit (EU). The CU includes a fetch unit responsible for fetching instructions from memory, while the EU implements[16] instructions related to data transfer, data conversion, arithmetic, logic operations, and program control tasks such as interrupts and jumps. The processor follows a cycle of fetching and executing instructions in the order they are retrieved from memory.

Processors can be categorized into several types: General Purpose Processors (GPPs), microprocessors or microcontrollers, embedded processors, digital signal processors, media processors, Application-Specific System Processors[17] (AS- SPs), and Application-Specific Instruction Processors (ASIPs). These processors can exist as cores within an Application- Specific Integrated Circuit (ASIC) or a Very-Large-Scale Integration (VLSI) circuit.

Compilers and Related Tools

A compiler is a software tool that converts source code written in high-level programming languages into machine code or assembly language, primarily for the purpose of creating executable programs. A cross-compiler[18] can generate executable code for a platform different from the one on which the compiler itself is running. Conversely, a decompiler translates low-level machine code back into a high-level programming language. A language converter or translator converts source code between different high-level languages. The compilation process generally involves several steps: pre-processing, parsing, semantic analysis[19], code generation, and code optimization. Assemblers, on the other hand, convert assembly language instructions into machine code. They resolve symbolic names into memory addresses and translate mnemonics into actual operation codes (opcodes).

Software Requirements
The system operates on Windows 10 Pro and is developed using Python for both the frontend and backend[20]. The development environment used is Visual Studio Code (VS Code), a widely adopted IDE offering various tools and extensions for efficient coding and debugging.

Technical Description
Artificial Intelligence (AI) refers to the simulation of human intelligence in machines programmed to think, learn, and act like humans. AI systems aim to mimic human cognitive functions such as learning, reasoning, perception, and problem- solving. A key characteristic of AI is its ability to make rational decisions in order to achieve specific goals.

AI is a broad interdisciplinary field that integrates machine learning, deep learning, natural language processing, robotics, and computer vision. Machine learning, a subset of AI, focuses on enabling systems to learn and adapt from data without explicit programming. Deep learning, a further specialization of machine learning, uses artificial neural networks with multiple layers to analyze complex patterns in large datasets. This enables high performance in tasks such as speech recognition, image analysis, and language understanding.

The practical applications of AI are vast and span numerous industries including healthcare, finance, transportation, manufacturing, and entertainment[21,22,23]. AI systems are used in medical diagnostics, fraud detection, autonomous vehicles, voice assistants like Siri and Alexa, recommendation engines, and more.

Despite significant advancements, AI still faces several challenges, such as ethical concerns regarding algorithmic bias and job displacement. Moreover, current AI systems often lack common sense and contextual understanding[24], which can lead to errors or misinterpretations. Nevertheless, AI continues to evolve rapidly and has the potential[25] to revolutionize a wide range of industries through intelligent automation and data-driven decision-making.

IV. CONCLUSION

There are various methods available for detecting plant diseases and recommending remedies. Each method comes with its own set of advantages and limitations. Visual analysis, while being the least expensive and simplest method, lacks efficiency and reliability. On the other hand, image processing techniques offer significant advantages such as high accuracy and reduced processing time. In this context, the use of K-means clustering and Neural Networks (NNs) has been explored for the effective clustering and classification of plant leaf diseases. The primary objective of the proposed approach is to accurately and efficiently recognize plant diseases. Experimental results suggest that the approach is effective and capable of accurately detecting leaf diseases with minimal computational effort. In addition to the availability of cultivation tools, farmers require accurate and timely information to manage crops efficiently. Providing such information through a software-based service can greatly assist farmers in their agricultural practices.

Future Enhancement
To further improve the accuracy of the classification process, hybrid algorithms such as Artificial Neural Networks, Bayes Classifiers, and Fuzzy Logic can be employed. Developing a mobile application is also a potential enhancement, offering users a convenient and user-friendly platform for disease detection. Another extension of this work will focus on estimating the severity level of detected diseases automatically. Additionally, the project aims to integrate multimedia support by automatically generating audio and video content related to plant diseases and their solutions once a disease is detected. Furthermore, as part of future enhancements, an IoT-based system has been developed to provide real-time information about weather conditions and the environmental status of farming areas, thereby supporting better decision-making in agriculture.

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