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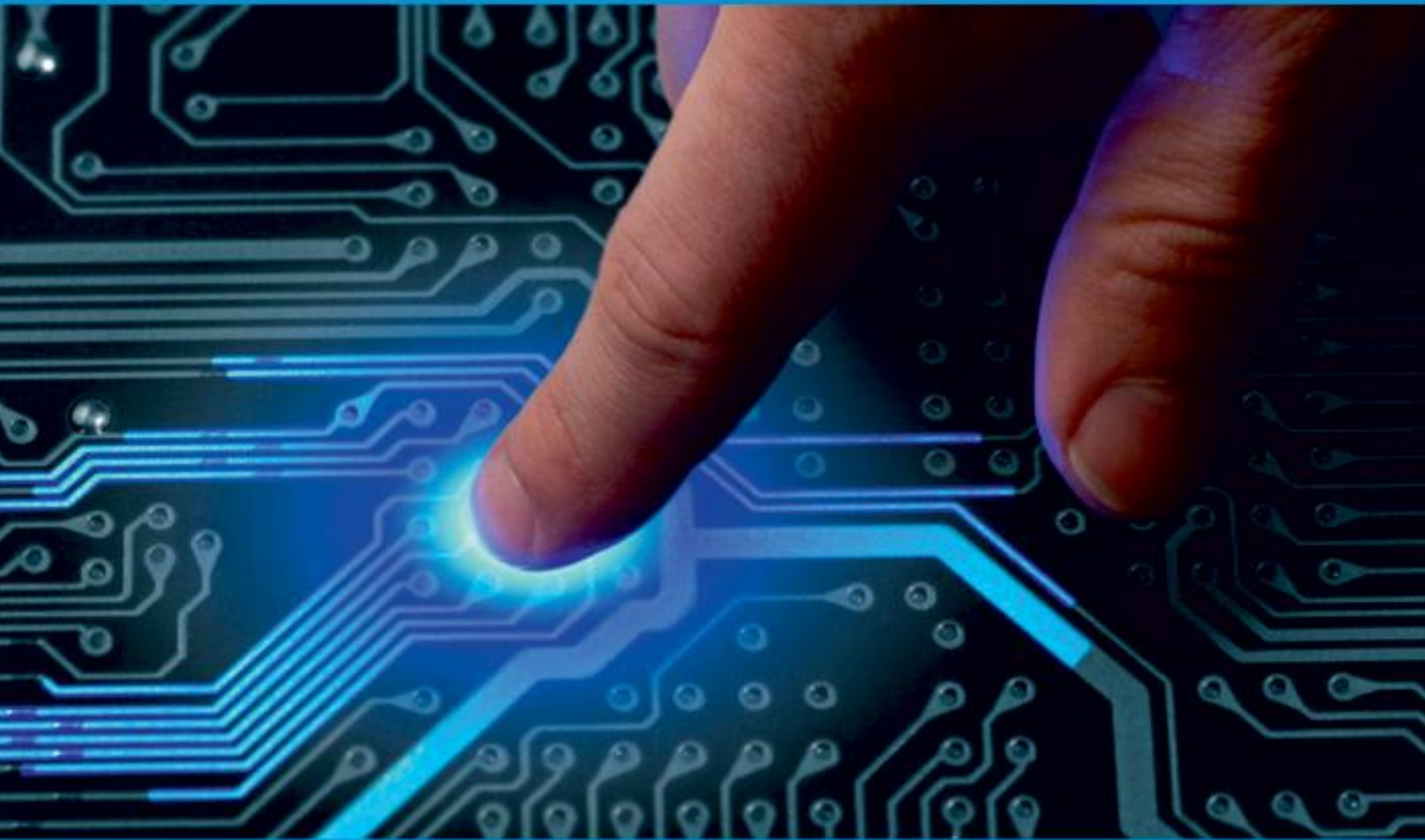

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Medicinal Leaf Detection Using Deep LearningApproaches

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ABSTRACT: Traditionally, farmers or experts rely on visual inspection of plants, devoid of any instruments, to detect and classify them. However, this method can be labor-intensive, costly, and prone to inaccuracies. Automated detection utilizing image processing techniques offers swift and precise results. This study delves into a novel approach for developing a model to identify plant leaves. The model employs deep convolutional networks to classify leaf images. Advancements in computer vision hold promise for enhancing and broadening the application of specialized plant protection, consequently increasing the demand for machine vision solutions in smart agriculture. The new training regimen streamlines the deployment process of the system. The article provides an extensive overview of the fundamental steps involved in constructing this detection model. These steps encompass gathering images to construct a database, which is subsequently evaluated by agricultural experts. Moreover, a deep learning framework is utilized for comprehensive CNN training. This methodological article introduces a pioneering technique for plant leaf detection. It employs a deep convolutional neural network trained and optimized to accurately analyze a database of plant leaves collected specifically for various plant ailments. The model's advancement and innovation lie in its simplicity. Leveraging deep CNN, the model can differentiatebetween healthy and diseased leaves, along with their surroundings, aided by background images consistent with other classes.

KEYWORDS: Medicinal plant leaf; deep learning; convolutional neural networks (CNN).

I. INTRODUCTION

Herbal medicine comprises plants scientifically proven to possess components beneficial to human health. Different plant parts are credited with various disease-fighting, disease-spreading, and disease-curing abilities. Indonesia boasts approximately 30,000 plant species, with 7,000 recognized as herbs with therapeutic properties. Due to their natural constituents and widespread availability, medicinal plants are viewed as a safer option compared to synthetic pharmaceuticals. Phytochemical screening techniques aid in determining the medicinal plant content, enabling the identification of potentially beneficial active compounds. Chemical medications contain inorganic and pure ingredients, whereas the human body is complex and organic. Consequently, chemical medications are deemed unsafe for human consumption and may pose long-term health risks if excessively used. Some chemical medications provide only symptomatic relief, necessitating indefinite usage for patients with certain conditions. Despite the availability of medicinalplants, public education about them remains insufficient, leading many to opt for chemical medications over natural alternatives. Therefore, there is a need for methods to assist the public in better recognizing medicinal plants, particularly focusing on the medicinal leaves introduced by these species. Various techniques, such as Neural Network, can differentiateleaves in photographs by analyzing their color, size, texture, and shape.

II. LITERATURE SURVEY

As per Muhammad, Nazeer, et al. [1], pre-trained models such as AlexNet and VGG19 CNNs are highly effective in feature extraction from given data with remarkable accuracy. After extracting these features, the convolutional neural network selectsthe optimal subset and feeds them into various classifiers, including KNN, SVM, PNN, Fuzzy Logic, and ANN.

As per Bhagat and Monu, et al. [2], A method that efficiently utilizes computational resources has been devised for distinguishing between healthy and diseased plant leaves through classification. If identified as unhealthy, the system further detects specific plant leaf diseases. The classification system is built on a Support Vector Machine (SVM), which is fine-tunedusing the Grid search algorithm. This approach employs SVM as the algorithm for disease identification and classification. The method offers a practical solution for farmers, enabling effective disease detection with minimal computational effort.

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As per Shruthi, U and V. Nagaveni et al. [3], the paper outlines the steps involved in a general model for classifying plant diseases and presents a comparative study of various machine learning classification algorithms. The study compares five distinct ML classification techniques for identifying plant diseases. Among these classifiers, the Support Vector Machine (SVM) is frequently employed by many researchers for disease classification due to its effectiveness.

As per Froldi, Guglielmina, et al. [4], Aloe latex and Frangulin B contribute only to a certain extent to the antiglycation and antiradical effects of methanolic and hydroalcoholic extracts from A. arborescens leaves. While the extracts themselves are completely non-cytotoxic, these two anthraquinones exhibit slight adverse effects on cell viability.

As per to Babu, Spoorthy N. et al. [5], The research team utilized a proteomic methodology to unveil the mechanisms through which aloe vera and its two constituents, namely carbohydrates and polypeptides, alleviate diabetes in streptozotocin-induced diabetic rats presents a complex physiological scenario marked by aberrant glucose metabolism and pancreatic dysfunction. Across a span of three weeks, distinct cohorts of rats were administered Aloe vera extract, carbohydrate component, and peptide/polypeptide fraction. The findings indicated that Aloe vera and its constituents restored normal glucose and insulin levels in the diabetic rats. Immunoglobulin G (IgG) and serum albumin were isolated from the rats' plasma, followed by a comprehensive proteomic analysis.

As per Gauri Deshpande and Pratiksha Shinde et al. [6], users will have access to image graphs of the gallery as well as historical information on plants, including common pests and diseases. Aloe vera, a naturally occurring substance, is extensively employed in the cosmetic industry at present. Despite numerous indications supporting its utility, rigorous studies are required to ascertain its actual efficacy. This article provides a concise outline of the aloe vera plant, its characteristics, mode of operation, and therapeutic uses. For thousands of years, aloe vera has been recognized and utilized for its health, cosmetic, and skin benefits. The name Aloe vera comes from the Arabic word "Alloeh," meaning "shining bitter substance," and the Latin word "vera," meaning "truth." Greek scientists 2000 years ago considered aloe vera a universal remedy, while the Egyptians referred to it as "the herb of immortality." Today, the aloe vera plant is used in dermatology for various treatments. As per Muhammad, Nazeer, et al. [7], the machine learning approach is recommended for the detection and categorization of healthy and diseased leaves. The study identified two healthy conditions (Aloe healthy and Apple healthy) and six types of diseases: Aloe blight, Aloe decay, Black fruit rot, Rust disease in apples, Decay in apples, Apple fungal disease. The primary purpose of this research was on detection and deep feature selection. The subsequent steps involved feature extraction, noise reduction from the captured images, and data augmentation. To address the critical issue of noise removal from any dataset, a nonlocal image filter algorithm was developed.

As per Sánchez, Marta, et al. [8], current pharmacological data indicates that most studies focus on the anti-cancer properties, protective effects on the skin and digestive system, and antibacterial attributes of Aloe vera. The latest research includes both in vitro and in vivo experiments, with clinical studies conducted exclusively on Aloe vera rather than its isolated compounds. Therefore, it would be valuable to investigate the therapeutic effects of key metabolites in various diseases and human conditions. The promising results from these foundational research studies encourage further clinical trials to explore the medicinal applications of Aloe vera and its main components, particularly for diabetes, cancer, and bone protection.

Researchers, including Uda, M. N. A.[9], have identified the fungus Pyricularia oryzae as the culprit behind rice blast disease—a significant and widespread threat to rice crops worldwide. Each year, this fungus wreaks havoc, destroying enough rice to feed approximately 60 million people. Even in mildly affected fields, productivity losses can reach up to 50%. As an alternative approach, scientists are exploring the use of herbal plants for managing plant diseases. Extracts derived from plants such as Acemannan, Kaffir lime, Elephant's trunk, and Ginger exhibit potential in managing rice blast disease. In a recent investigation, the antibacterial efficacy of these four botanical species against Pyricularia oryzae was assessed.

In this research, Aziz, Sumair, and colleagues et.al.[10] A computer vision framework was devised to detect and categorize plant diseases. The system suggested by the researchers extracts Local Tri-directional Patterns (LTriDP) from images of plantleaves across different categories. LTriDP features effectively gather pertinent data and depict each category with minimized dimensions. To classify the data, a multiclass support vector machine (SVM) approach was employed. The researchers carried out experiments using a dataset of Tomato leaves encompassing five unique categories. The outcomes showcased that their framework surpassed alternative methods reliant on commonly utilized feature descriptors, achieving an impressive overall accuracy rate of 94%.

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III. SYSTEM DESCRIPTION

The complete process of constructing a model for plant disease recognition using deep CNN is elaborated upon. The entire cycle is segmented into several fitting stages, commencing with the gathering of images for classificationemploying deep neural networks.

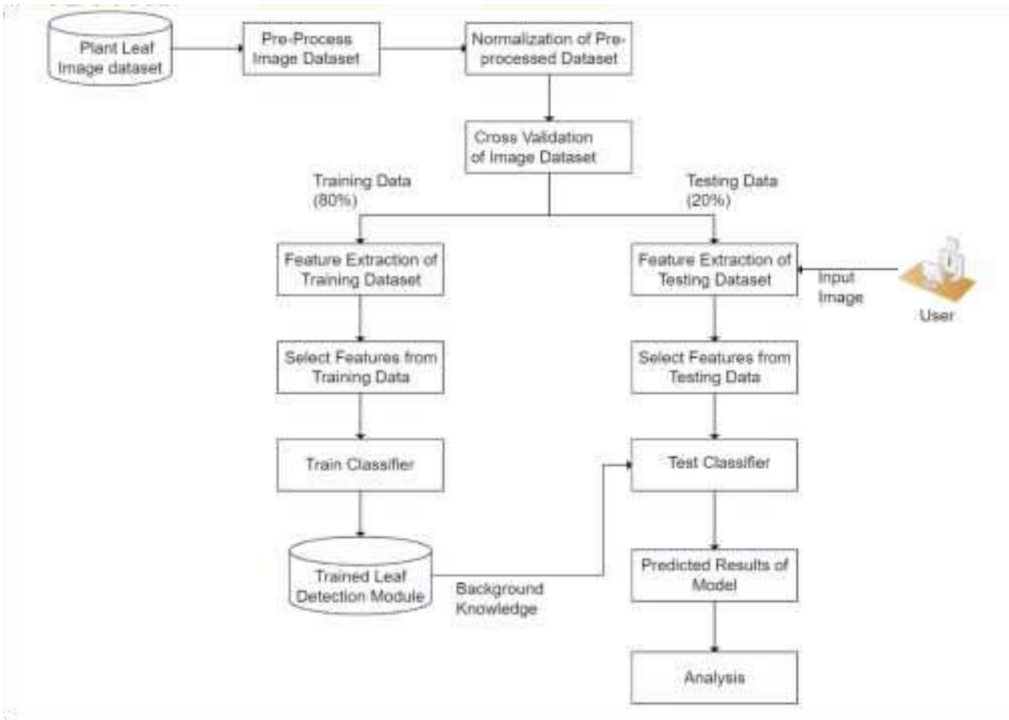

Figure 1: Architecture Diagram

Implement Process :

The architecture diagram depicts a procedure for classifying plant leaf images. Here's a breakdown of the process:
1. Compilation of Plant Leaf Image Dataset: Gathering a dataset comprising plant leaf images.
2. Pre-Processing Image Dataset: Enhancing the quality of raw images to prepare them for analysis.
3. Standardization of Pre-Processed Dataset: Ensuring uniformity across the pre-processed images.
4. Validation of Image Dataset: Split-ing the dataset into training (80%) and testing (20%) subsets for validation purposes.

Training Data (80%):
1. Extraction of Features from Training Dataset: Deriving features from the training dataset.
2. Selection of Relevant Features: Identifying and choosing pertinent features from the extracted ones. Training of Classifier: Educating a classifier using the selected features.
3. Establishment of Trained Leaf Detection Module: Storing the trained classifier in a module for leaf detection.

Testing Data (20%):
1. Extraction of Features from Testing Dataset: Deriving features from the testing dataset. Selection of Relevant Features: Identifying and selecting relevant features from the extracted set. Testing of Classifier: Evaluating the classifier using the selected features from the testing data. Obtaining Predicted Model Results: Gathering the results predicted by the model.

Analysis: Analyzing the predicted results.
1. User Input:
2. Users can input images for classification.
3. The input image undergoes feature extraction and selection.
4. The trained classifier is utilized to predict results for the input image. The predicted outcomes are subsequently analyzed.

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IV. ALGORITHM

Input: A Test Dataset containing assorted test cases, labeled as TestDB-Lits []; A Training dataset generatedduring the training stage, designated as TrainDB-Lits []; A Threshold value, referred to as Th.

Output: In the HashMap, entries representing class labels and similarity weights that surpass the threshold scoreare detected.

Step 1: For every test instance as depicted in the equation "test,"

$$Feature(k) = \sum_{m=1}^{n}(. featureSet[A[i] \ldots\ldots A[n] \Leftarrow \text{TestDBLits})$$

Step 2: Generate a feature vector from the "testFeature(m)" function.

$$\text{Extracted Feature Set x [t} \ldots \text{n]} = \sum_{x=1}^{n} (t) \Leftarrow testFeature\ (k)$$

Extracted_FeatureSetx[t] Contains the extracted characteristics of each instance within the testing dataset.

Step 3: For each training instance utilizing the function "trainFeature(l)"

$$= \sum_{m=1}^{n}(. featureSet[A[i] \ldots\ldots A[n] \Leftarrow \text{TrainDBList})$$

Step 4: Create a fresh feature vector using the function "trainFeature(m)."

$$\text{Extracted\_FeatureSet\_Y[t......n]} = \sum_{x=1}^{n} (t) \Leftarrow TrainFeature\ (l)$$

Extracted_FeatureSet_Y[t] contains the features extracted from each instance within the training dataset.

Step 5: Now assess each test instance using the entire training dataset.

$$weight = calcSim\ (\text{FeatureSetx} \parallel \sum_{i=1}^{n} \text{FeatureSety[y]})$$

Step 6: Return Weight

V. MATHEMATICAL MODEL

Define the system as S, enabling users to forecast plant leaf conditions:
$S=\{In,P,Op,A\}$ Identify the Input In as:
In={Q}
Where,
Q represents the dataset containing plant leaf information.Define the Process P as:
P={PR,No,FE,CL}
Where,
PR represents pre-processing performed on the input dataset of plant leaves.No indicates normalization conducted after preprocessing.
FE involves Feature Extraction and storing these features for future comparison.CL involves Classification utilizing CNN.
Characterize the Output Op as:Op={UB}
Where,
UB represents the updated result.
Lastly, denote Analysis Graph (Accuracy) as A.

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VI. RESULTS

The below Figure 2,3,4 describes an Medicinal leaf detection using feature extraction and deep learning methods. According to this figure we conclude the deep learning methods can achieves higher accuracy than traditional machine learning classifiers.

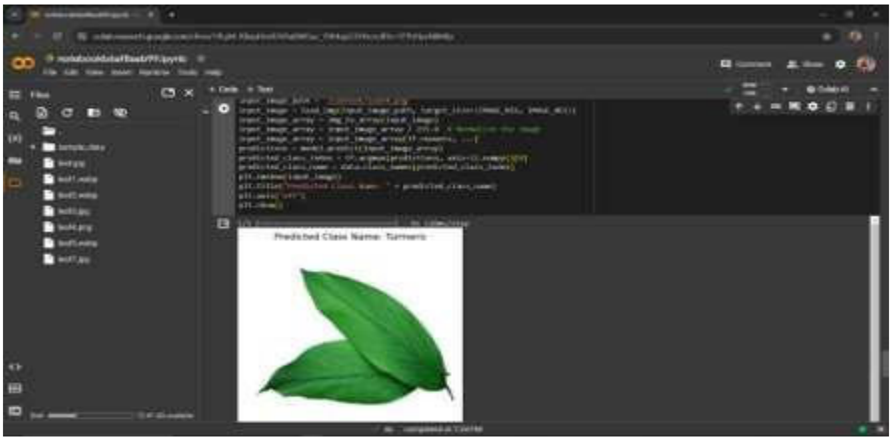

Figure 2:- Output 1

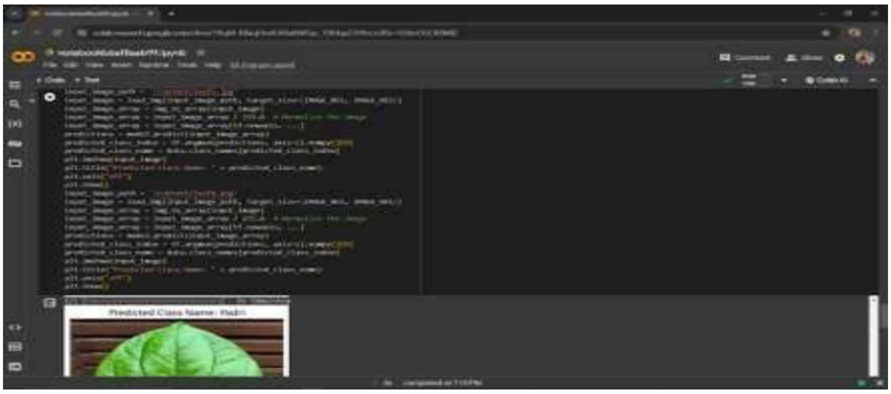

Figure 3:- Output 2

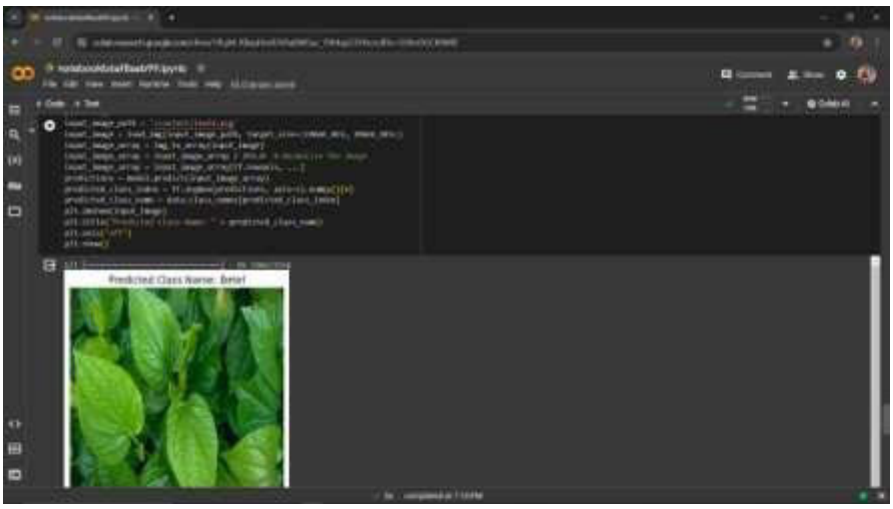

Figure 4:- Output 3

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VII. CONCLUSION

The proposed model describes a various feature extraction and selection techniques using CNN. In convolutional various heterogeneous features are extracted while in pooling non-essential features are eliminate before classification. Several experiments were conducted to determine the viability of the custom developed CNN model. A new plant leaf database image has been generated, including over 3495 unique images from the Kaggle.com. Theproposed custom CNN can able to achieve higher accuracy and lower error rate than conventional deep learning and machine learning classifiers.

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