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AI-Driven Banana Leaf Spot Disease Detection Using Advanced Machine Learning Models

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Abstract: *Banana plant life are crucial for meals protection in tropical regions, regardless of the reality that bananas are susceptible to diseases inclusive of leaf spot sickness (LSD), which can seriously affect crops. Traditional detection strategies are labor-intensive and errors-inclined, while present computerized systems often lack sufficient accuracy in unique environments, leaving a big hollow in illness manipulate. This look at develops a Convolutional Neural Network (CNN) model based totally on ResNet50 shape to categorise banana leaf illnesses into four lessons Cordana, Sigatoka, Healthy and Pestalotiopsis. The version makes use of statistical upgrades to simulate one of a kind field situation, enhancing its generalization abilties. Preliminary consequences display that the ResNet50-based definitely model achieves promising accuracy in the course of the disease vicinity, suggesting its capacity as a precious device for early detection. This automated reaction may be covered into mobile gadgets, facilitating proactive illness control and helping sustainable banana farming practices.*

Key Words: *Banana LSD, CNN, ResNet50, disease classification, data augmentation, sustainable agriculture.*

I. INTRODUCTION

Fitness of crops remains very important in guaranteeing food security and also sustaining agricultural activities especially when it comes to staple crops such as bananas, which is likely vital in the masses of tropical and subtropical regions. However, these plant life are clearly susceptible to a myriad of leaf sicknesses, including banana leaf spot sickness [1], that can reduce yields significantly unless it is curtailed immediately. When untreated, diseases such as propagate without warning everywhere in the banana farms, and they become threats not only to crop production but also to the lives of farmers who strongly depend on banana production to provide their livelihood [2]. Thus, the development of convenient and strong sickness-tracking technologies is necessary to advance the stability and stability of agriculture [3].

Conventionally, detection of sickness in banana flowers has been through manual examination, where the growers or experts examined the plants visually to determine signs and symptoms of contamination. This method of approach though realistic to a certain extent, is especially heavy labour-wise when it comes to large farms as every plant must be tended to by man or woman [4]. Besides, human errors are subject to the guide inspections, to be precise, because the signs and symptoms of the illness and the symptoms and symptoms are both subject to variations due to environmental factors, it is difficult to comprehend infections at low stages even when timely intervention is most convenient [5]. As a result, the traditional approaches often miss the precision and the ability to scale to the existing practices in the agricultural sector [6].

Technological solutions to the ones obstacles are offered by technological advances in machine studying, specifically, in laptop imaginative and prescient. Convolutional neural networks (CNNs) have verified strong in photograph-based definitely assessment, allowing them to identify subtle fashions and differentiations in leaf-textures and colorings, which point to disease [7]. This feature renders CNNs somewhat suitable to identify symptoms of sickness on banana leaves, which will reduce the necessity to inspect the guide and introduce the farmers to a gadget that can react unpredictably and successfully to infections [8]. In this test, we present a CNN-based entirely model that detects the banana leaf illnesses with a significant level of precision, professional on a labelled dataset that is hosted on Kaggle consisting of each healthy and sicken leaves. This version utilizes augmented photograph facts to enhance beautification of flexibility in different circumstances [9]. The approaches of data augmentation test various environments, along with variations in lighting fixtures and orientation, which strengthen the capacity of the version to generalize across the real-world wide occurrences [10]. The entire dataset of pix was scaled to 224x224 to simplify processing a choice that trades detail and computational overall performance [11].

To explore the dataset distribution further, we used Matplotlib visual library of Python to visualize sample pix, which provided us with the indispensable information on representation of categories of diseases. The visualization option provides a balanced dataset, which reduces biases within the model predictions [12]. The capabilities of this CNN-based completely sickness-detection device do not end at this task, as it can be used to scale to crop tracking. The model is able to provide proactive intervention by providing farmers with a reachable and accurate diagnostic tool that can help to prevent massive outbreaks in the fate of the destiny. Other fashions can be ported into mobile applications or agricultural machine, being more readily available even in a ways flung farming area [13].

Such equipment encourage sustainable operations, minimize the loss of crops, and contribute to better meal security by means of limiting the use of chemical remedies and also permitting precise, information-driven sickness management [14]. In cease vision of crop disease detection will be combined with deep studying as a super development in the agriculture industry. The application of CNN-based models in this mission shows the practical cost of CNN- based models in identifying and managing the banana leaf diseases, supporting the advanced agricultural activities and supporting the provision of more robust food [15].

II. RELATED WORK

Novel refinements in the profound getting to know, especially convolutional neural networks (CNNs) have propelled immense upgrades in the type and detection of plant sicknesses, which encompass those related to banana leaves. One fine piece of work through [16]. Optimizes the use of leverages switching learning using information augmentation methods to achieve an effective classification of banana leaf illnesses, attaining immoderate accuracy on the various resistance of over one and half disorder categories. It proves how the use of transfer learning can enhance the average overall performance during constrained-statistics settings.

To supplement this strategy, [17] was able to give a full analysis of image augmentation technique, whereby they enhance robustness of the strong versions by considering the variances in the appearance of the leaves with respect to environmental factors. This type of augmentation is of great importance to applications where perceived integrity in data is difficult to maintain. [18] were able to come up with a hybrid model, which is a combination of CNNs and Gabor features extraction to enhance the ability to choose a functional to maximize the detection of illness in complex data, including banana leaves. The technique enhances the accuracy of classes by conserving the important visible patterns, which are valuable in coding the differences between the textures in leaves and the appearances of disease. Also, research has focused on the effective CNN architecture that can be used in real-time and low-beneficial resource conditions.

Alwan et al [19] considered applying lightweight model, together with MobileNet, in banana plantation on-field tasks. This have a look at brought into the limelight the utility of implementing sickness detection algorithms within cellular or embedded framework, which helps agriculture with the handy resource of providing quick diagnostics wanton of the heavy beneficial useful resource of heavy computation. A ground-breaking contemporary have a peep through Bhuiyan et al[20] introduced "BananaSqueezeNet," a promptness, light-weight CNN model, specifically formulated to detect three excellent banana leaf diseases: Pestalotiopsis, Sigatoka and Cordana. The model it uses Bayesian optimization to maximize class overall performance and manages to achieve a super accuracy of 96.25 which is even better than current CNNs such as EfficientNet and ResNet. In addition to the ability to figure out not unusual diseases in leaf, BananaSqueezeNet also evaluated the accuracy of its software in the detection of additional ailments affecting bananas, and thus the software is considered an all-purpose diagnostic environment when working with banana growers. This approach explains why model efficiency and model accuracy are important in illness diagnostics to support sustainable agriculture.

This observe presents a light-weight CNN model specifically to the real-time detection of banana leaf diseases through photographs taken with the help of smartphones. The objectives of this method is to provide farmers with an efficient tool of well-timed disorder control. The light-weight form is no longer handiest useful in quick in picture processing and evaluation but also in allowing farmers to directly identify infections and respond in advance to minimize the losses of capabilities crops. Through using the cool development in deep mastering, our solution proposal attempts to market sustainable banana farming habit in the long run leading to increased food withstand and agricultural resiliency.

III. PROPOSED SYSTEM

A. Dataset Collection

Fig. 1. Sample Images of Banana Leaf Diseases

The dataset utilized on this task is derived from Kaggle, containing pix of banana leaves amassed from the experimental vicinity of Bangabandhu Sheikh Mujibur Rahman Agricultural University (BSMRAU) and various banana fields in Bangladesh. This dataset comprises 937 pictures spanning four training: wholesome leaves, Pestalotiopsis leaf blight, Sigatoka, and Cordana, as proven in Fig. 1. Each photograph become meticulously classified thru an professional plant pathologist[21]. The authentic dataset included preliminary augmentation strategies carried out by means of using the authors, along with Gaussian blur, horizontal flipping, cropping, linear contrast adjustments, shearing, translations, and rotational shearing. Building upon this, extra augmentation strategies were carried out in the direction of the pre-processing section of model education in this assignment to enhance version robustness and reduce the risk of over-becoming through introducing more variability to the education pictures.

The dataset come to be divided into training, validation, and trying out devices, with 70% of the photographs allocated for education, 15% for validation, and 15% for sorting out. The education set consists of four hundred images consistent with elegance inside the augmented dataset, making sure a diverse and balanced example of leaf conditions, it really is critical for effective disorder kind, resulting in a whole of 1,six hundred pictures [22]. The method of very thorough selection and supplementing of the banana leaf data, its systematic division into training, validation and testing units, contribute to the improved ability of the model to effectively identify sicknesses of the leaves.

B. Preprocessing of Dataset

The pre-processing of the dataset cognizance of creating geared up banana leaf images that would be useful in model schooling, whilst using the ResNet50 architecture, this would ensure that it is compatible. The images are then scaled down to the most recent size of 224x224224 pixels, it is necessary to maintain the consistency throughout the span of data. The dataset is further divided into training, validation, and take a look at gadgets mainly on the basis of distinctive percentages 70, 15, and 15, respectively [23]. This division enables ensuring that all the magnificence is represented sufficiently in all subsets so that learning and evaluation should be balanced. The elegance labels are then inverted to integers to catalyze the expertise of the facts by the model and then converted right right to one-heat coded form. This ciphering allows the version to group the photos in two classes in an effective way. The data is further enhanced with a variety of measures to add variation and beautify the strength of this model albeit the fact that the pixel values are yet to be normalized in this pre-processing step [24]. On balance, these preprocessing techniques are essential to the process of optimization of the education process and the accuracy of the version in identifying banana leaf sicknesses.

Its actualization caused alarm the careful gathering and preprocessing of a dataset of images of banana leaves with several diseases. The database ended up being sorted under individual folders according to each category, and it is easy to access and manipulate. To have rich and severa representation of the target lessons, images had been sourced based on an augmented dataset. After collection, some preprocessing measures included the resizing of the photos to have a constant size, 224x 224, to maintain some level of consistency at some point in the dataset, allowing the version to succumb to a way to the photos [25]. The data set was then configured to be divided into schooling, validation and attempting out subsets in a pre-empted ratio so that the information regarding the version performance could be evaluated unbiasedly. Also beauty labels have been coded directly into one-warm layout that is critical in case of multi-elegancy type requirements. This based approach to facts series and preprocessing ensured that the version changed into knowledgeable on a nicely organized and carefully representative dataset, thereby improving its capacity to because it ought to be classify banana leaf illnesses [26].

C. Augmentation of Data

The information augmentation strategies implemented on this study enhance the authentic dataset's variability, contributing to a higher version. In addition to the initial augmentation techniques included within the augmented dataset, consisting of Gaussian blur, horizontal flipping, and cropping, additional strategies were accomplished during the preprocessing section. These embody rotation range, permitting the images to be randomly rotated within a centered degree, which allows the model grow to be invariant to object orientation. Width and pinnacle shifts allow slight translations of the pix alongside the x and y axes, making sure that the model learns to understand functions irrespective of their proper positioning within the frame. The inclusion of zooming allows the model to be extra resilient to varying object sizes, while shear transformations provide each other layer of range with the useful resource of distorting the snap shots along one axis [27].

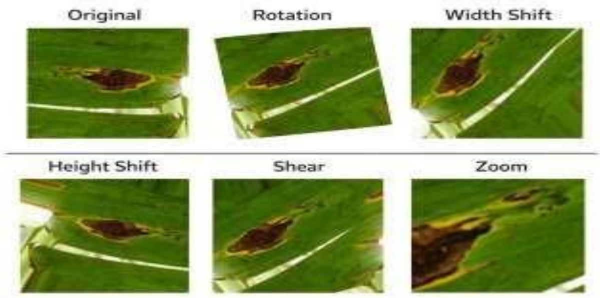

Fig. 2. Augmentation of Banana Leaf

Fig 2 is presentation of pix after augmentation. Lastly, the ones augmentation strategies collectively assist to simulate actual-world situations, stopping over-turning into thru developing diverse training samples that beautify the model's generalization functionality across unseen statistics. By integrating these extra augmentation techniques, the model is better prepared to deal with variations in banana leaf photos and in the end enhances its usual overall performance in sickness elegance obligations [28].

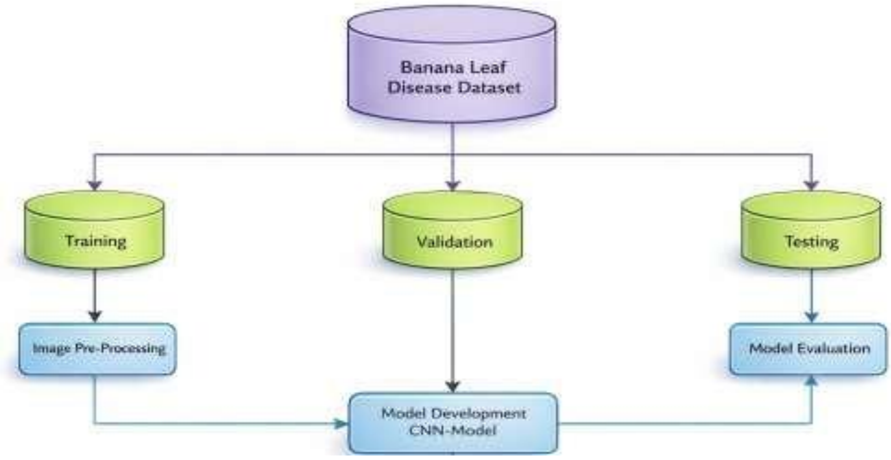

Fig. 3. Purposed Model

D.Model Training

The technique carried out on this have a look at makes use of a deep learning method for the class of banana leaf sicknesses, employing a first-rate-tuned version of the ResNet50 structure. This version, famed for its intensity and residual connections, helps effective learning thru alleviating the vanishing gradient hassle often encountered in deep networks. Targeting ResNet50 form is launched using pre-educated weights based on the ImageNet extraction, allowing the version to exploit discovered out dataset, which provides a strong foundation of representations of functions of a huge variety of pix in Fig. 3. The structure of the version comprises of the ResNet spine and a knocking down layer that converts the three-D output of the convolutional base directly into a 1D array to enable the information to be successfully systemized into the following dense layers. Complex functions are learned by a dense layer containing 32 devices and using ReLU activation, and the final output layer uses the softmax activation multi-class magnificence to produce opportunity distributions across the given instructions of leaf illnesses [29].

This method is particularly potent because it allows exploiting the switch studying, which facilitates the speeding up of the schooling strategy and the rise in the overall performance of the version in the context of the specific task of classifying an illness. With the help of a well-configured architecture such as ResNet50, the method not only provides prohibitively high accuracy, but also flexibility to new facts, which is why it is an effective tool in the field of agricultural diagnostics [30]. The combination with the latest technologies ensures that the version remains robust and inexperienced, ultimately helping farmers to control crops more efficiently and help to maintain healthy plantations.

The version education system implemented a convolutional neural network (CNN) based totally at the ResNet50 structure, that's in particular powerful for photograph class duties because of its deep mastering abilities and residual connections that mitigate the vanishing gradient difficulty. The ResNet50 model emerge as initialized with weights pre-educated on the ImageNet dataset, providing a strong basis for function extraction. To optimize universal performance, unique layers of the ResNet model have been frozen throughout initial education, allowing the model to focus on getting to know excessive-level skills at the same time as preserving the discovered representations from the pre-knowledgeable weights. This method concerned freezing all however the remaining 4 layers, which were high-quality-tuned to conform to the best trends of the banana leaf sickness dataset. This training was based on a batch time of 32 with 15 epochs, and the Adam optimizer was employed with a cosine decay that goes to know price schedule that has allowed advanced convergence by dynamically adjusting the studying price [31]. This painstaking training approach, in combination with the augmented banana leaf disease data set, led to high wonderful accuracy and normal normal performance of the magnificence model, which showed that the ResNet50 architecture is effective in agricultural packages.

E. GUI Design

The action-oriented consumer interface (GUI) of the picture kind program is claimed to be user-friendly and intuitive material, which introduces a soft format with the major buttons: "Upload Image and Predict" and "Exit." The Upload Image and Predict button allows customers to present a report dialogue through which they could select a picture report without problems through their tool. The type of files that can be chosen include jpg ,jpeg as well as png. After picking a photo, the software program scans it, and then uses an existing prediction model, which reveals the outcome in a message field and is easy to see. On the other hand, the Exit button provides a candid means to leave the utility devoid of a similar movement. It has a clean interface that makes the process of browsing the picture class device easy to customers so that even individuals with limited technical knowledge can utilize it. The normal design pays much attention to functionality simultaneously offering the use of the seamless interaction to the audience appealing with image type tasks.

F.Validation

The validation in this implementation is a critical process in terms of determining the overall performance of the version and the generalization of it to unseen data. It entails the use of another validation dataset, consisting of 15 percent of the total dataset, to evaluate the model at the end of every schooling epoch. This machine can be used to continuously monitor the concept of the model to observe based on the schooling figures with simultaneous experimentation of its predictive electricity upon new and untried data [32].

The main purpose of validation is to provide a separate evaluation of the version effectiveness with a differentiation between the under-becoming and over-becoming situation. Under-turning into is taking place when the version does not identify the underlying patterns within the facts of education, which is at the core of the awful typical achievement in the schooling and validation units. On the other hand, over-fitting occurs when the version acquires the noise and facts of the education facts to an extent that it adversely affects its operation on novel data. Validation will enable grow to know about those problems at an early stage of the schooling approach. In addition, the validation accuracy is monitored especially to identify the ability of the version to predict the things out of the training set, a key indicator of the capacity of the version to be applied in generalization [33]. To increase the reliability of the version, a checkpoint mechanism is also implemented, which compares the weights of the model every time the model is able to reach the optimal accuracy of validation in schooling. This method is such that the wonderful acting model structure is maintained, and hence the risk of selecting a version that works well at the training statistics but poorly at the unseen examples is reduced.

G. Performance Evaluation Method

A robust cluster of metrics is essential in the evaluation of a system learning version particularly in photo class duties in order to discern the proficiency and reliability of the model during adverse additives. In this exercise, specific to this study class of banana leaf ailment the use of CNN model with a spine of ResNet50 was utilized, metric jointly with the accuracy precision, maintain in thoughts, F1-rating, and specificity were used to capture the overall performance profile. All the metrics provide accurate clues, contributing to determining the strengths of the version, and any possible areas of the version improvement in determining diseased vs. Wholesome leaves.

Accuracy: It is the portion of general predictions that the model had been assigned right. This measure provides a familiar measure of performance throughout all intercession by considerating the sum of the correct forecasts (both exceptional and dreadful) to the total broad range of instances as Eq. (1). An example of this is that an accuracy of 98.60% is an indication of the model performing as per standard, in an efficient manner to determine the conditions of the leaves so as to obtain as many snap shots as possible.

$$\text{Accuracy} = (TP+TN) / (TP+TN+EP+FN) \quad \dots (1)$$

1) Precision: Calculates the percentage of genuine high quality predictions to the total amount of true positives and faux positives. In simpler words, it informs us that most of the pix which are supposed to be diseased (or to be of a given family of choice) are doubtless correct as Eq. (2). High precision shows a low fake powerful price, that is important in conditions in which incorrectly flagging a wholesome leaf as diseased should cause needless interventions. Here, a precision score of 0.97 indicates that the version has a immoderate price of accurate predictions the various positives.

$$\text{Precision} = (TP) / (TP+FP) \quad \dots (2)$$

2) Recall: High precision shows a low fake powerful price, that is important in conditions in which incorrectly flagging a wholesome leaf as diseased should cause needless interventions as Eq. (3). Here, a precision score of 0.96 indicates that the version has a immoderate price of accurate predictions the various positives.

$$\text{Recall} = (TP) / (TP+FN) \quad \dots (3)$$

3) F1-Score: F1-Score is the harmonic suggest of precision and recall, presenting a balanced metric while there's a want to account for each faux positives and faux negatives as Eq. (4). It is in particular useful whilst the dataset has beauty imbalance, because it balances the alternate-offs between precision and bear in mind. The F1-rating of 0.97 on this task means that the version continues a robust balance among figuring out actual positives and heading off fake positives.

$$\text{F1 Score} = (2*TP) / ([2*TP]+FP+FN) \quad \dots (4)$$

4) Specificity: It measures the version's capability to correctly understand wholesome leaves with the aid of calculating the ratio of proper negatives to the sum of authentic negatives and pretend positives. In disease detection, excessive specificity is important, as it guarantees that healthful leaves aren't misclassified as diseased. as Eq.

(5). The version achieved a specificity rating of 1.00 meaning that it should be found all healthy cases, a truly ideal result in ensuring that the simplest surely diseased leaves are detected.

$$\text{Specificity} = TN / TN + FP \quad \dots (5)$$

All in all, these measures combined portray the strength in the model that classifies banana leaf diseases showing a high level of predictive evaluation in different parts of the evaluation. The respective top scores in all measures justify the effectiveness and accuracy of the version in realistic global programs.

IV. RESULTS

The typical overall performance of the version was tested with the help of the test dataset, and the results were impressive. Upon the process of education and great-tuning, the version achieved an accuracy of 98.60%, which showed a stable ability to be used successfully in classifying banana leaf disorder sorts. The Precision was estimated at 0.97, which means that it possessed too much self-concept in the great prediction, whereas the endure in mind was 0.96, which showed whether or not the model was useful in finding its applicability. The F1-rating of 0.97 indicates the consistency between precision and don’t forget. Also, the model had a specificity of 1.00, which revealed the effectiveness of the model to identify non-diseased leaves. These ramifications justify the strength behind the version in that it should be identifying and categorizing the diseases in banana leaves. This was shown in Fig. 4.

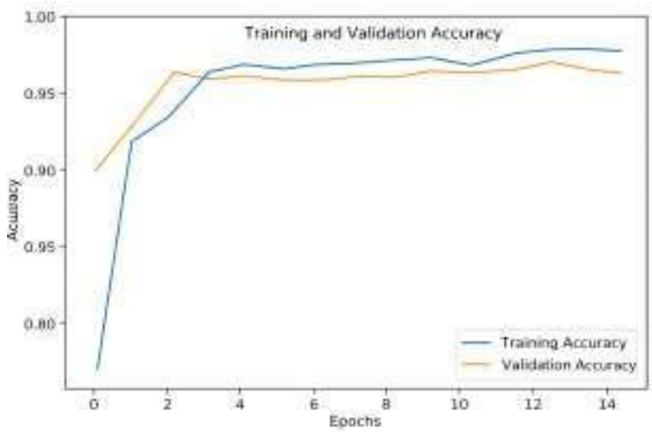

Fig. 4. Training and Validation Accuracy over Epochs

V. CONCLUSION

The banana leaf spot sickness detection business lucratively uses advanced deep learning of strategies to handle a significant farming dilemma, with a solid program of the ResNet50 form and the usage of transfer achievement to expand model normal overall performance. The addition of data augmentation methods supplements the ability of the model to generalize at one point in many datasets thus minimizing the possibility of over-turning into and more generally, becoming part of its accuracy and strength. Nevertheless, the ways to develop and expand are possible. The success of the model can be further more potent through diversifying the schooling information ensuring it covers an increased variety of ailments and environmental conditions. Also, the possibility of reasoning further feature extraction and classification overall performance can be realized by considering possibility architectures, or hybrid styles in particular. It can be possible to real-time information provided by the IoT devices to conduct dynamic monitoring and quicker identification of ailments in the field.

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