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Leaf Analytica Through AI

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***Abstract-** The Proposed system aims to develop a robust and reliable system for automated plant disease detection using machine learning algorithms. The proposed system utilizes image processing techniques to extract relevant features from images of plant leaves exhibiting symptoms of diseases. These features are then fed into various machine learning models, including convolutional neural networks (CNNs), support vector machines (SVMs), and decision trees, to classify the presence and type of disease accurately. Key components of the Proposed system include dataset collection, preprocessing, feature extraction, model training, and performance evaluation. A diverse dataset comprising images of healthy and diseased plantleaves from multiple plant species will be curated and annotated. Preprocessing techniques such as normalization, augmentation, and noise reduction will be applied to enhance the quality of the input images. Feature extraction methods, including handcrafted features and deep learning-based feature representations, will be explored to capture discriminative information from the images effectively. Various machine learning algorithms will be trained and optimizedusing the extracted features to achieve high classification accuracy. The performance of the developed system will be evaluated using metrics such as accuracy, precision, recall, and F1- score through cross-validation and testing on unseen data. The Proposed system aims to provide farmers and agricultural stakeholders with an efficient tool for early detection and management of plant diseases, ultimately contributing to improved crop health and increased agricultural productivity.*

***Keywords-Convolutional Neural Networks, Support Vector Machines, Decision Trees, Precision, recall , F1-Score,Feature Extraction Methods**.*

I. INTRODUCTION

To meet the projected demand, global cropproduction must increase by at least 50% by 2050[1]. Currently, most production occursin Africa and Asia, where 83% of farmers are family operators with little horticultural skills [2, 3]. For this reason, the yield decreases by more than 50%; because thereare too many pests and diseases [4]. The development of computer vision models offers a fast, standard and accurate solutionto this problem. It can also be used as a practice once the course is completed [5]. Easy to use, all you need is an internet connection and a smartphone with a camera. Popular commercial applications "iNaturalist" [6] and "PlantSnap"[7] show how this happens. The experience is also dedicated to building relationships online. There are approximately 5 billion smartphone users worldwide in 2020 [8]. 1billion users are in India and 1 billion usersare in Africa. According to Statista, these numbers have been increasing every year for the last decade [9]. By following these guidelines, we believe that artificial intelligence applications will play an important role in the development ofagriculture in the future. . The various layers of collaborative care have been appreciated by researchers due to theconsistent emergence of good outcomes [11] . The CNN model has changed a lot since the introduction of LeNet (1988). Complex functions such as nonlinearity of ReLu and overlapping pooling [12] have become features of modern architecture. . Most importantly, architectural evolution 21. It is a requirement for large and complex documents in the century [13]. ResNet (2015) reported additional features[14]. This combines dynamic cross-linking with multibatch normalization. This allows training to reach a higher level of learning [15]. In 2019, Wu et al. He compared ResNet with VGGNet, GoogLeNet and DenseNet and found that ResNet was the most effective solution in classifying fruit diseases [16]. Architectures including AlexNet, LeNet and GoogleNet (2014) areoften combined into a dedicated framework [16, 17]. Wallelign proposed such a structure; The model has threeconvolutional layers, a maximum pooling layer, and fully connected MLP with Relu processing, achieving 99% accuracy [18]. It is very important for model performance. Bacterial, bacterial, and fungal infections can be difficult to distinguish and can oftenhave overlapping symptoms. br> is produced during the reaction. Due tocomplexity it is better to use RGB objects [10, 20]. This produces clear, noise-free images that take longer to train than grayscale data, but are all suitable for plant disease models [21]. Immutable data or data may affect the reliability of the model. This can be managed in a variety of ways, such as using strategies such as support or transfer of learning. This can be done by adding functions such as scaling, rotation, adding color changes or contrast changes. However, the image transformation must reflect valid data expectation [18]. When used incorrectly the accuracy of the product will continue to decrease even if additionalinformation is produced. This includes adjusting the model's weights before training. The ImageNet database is frequently used for this purpose and contains more than 14 million images [23]. In 2016, Mohanty et al. These results are presented in studies aimed at the distribution of crop diseases. Since ImageNet contains images that are not related to specific functions of plants, it is surprising that pretraining plants can improve performance. Current research suggests that pretraining ImageNet can improve performance, but pretraining specific tasks will reduce overtraining. .The subject has not been investigated due tothe lack of major botanical data [25]. Augmentation can also be used for pre-trained models. However, since such a model is already learned, the results will begreater when applied to an untrained CNN [26]. > Ability of the model. When examining images with simple background information, the accuracy of classification will depend on this combination [20]. Therefore, it may not be reliable when trying to use live video. The need for this information is clearly stated in studies [24, 20]. . This technique can also be used in situations where the classifier needs to be aware of the situation. For example, this may involve understanding the extent of bacterial damage around infected tissue rather than the infected tissue itself [28, 29]. The classification of diseases has been active since the 1990s. Positive results havebeen reported even at this early stage. Early research also helped identify the machine's limitations, showing that it was unable to overcome poor image quality. Therefore, the importance of careful and preliminary data collection is emphasized [30]. The impact of segmentation will continue in 2020. The combination with specific images has good research potential [31]. Special imaging should be used for early detection of the disease [32]. Chlorophyll fluorescence (CFI), infrared thermography (IRT), hyperspectral (HSI), and multispectral (MSI) imaging have the unique ability to identify symptoms not yetvisible to the naked eye. These can be used individually or together when necessary [32]. For example, IRT has the best ability to detect temperature. This was done days before symptoms appeared in testing for crop diseases, including rose downy mildew [33] and rice FHB [32]. Due to limited available resources, the subject of early exploration has not yet beeninvestigated. [22, 33] As academic interest in this field grows, so do the tools requiredto capture these unique images. However, at this stage it is not a practical tool for remote farmers. For this reason, it is not appropriate to include studies on these users[34].

II-MATERIAL & METHODOLOGY

2.1. Material

Dataset Used:

New Plant Diseases Dataset (Augmented)-This dataset is recreated using offline augmentation from the original dataset. This dataset consists of about 87K rgb images of healthy and diseased crop leaves which is categorized into 38 different classes. The total dataset is divided into 80/20 ratio of training and validation set preserving the directory structure. A new directory containing 33 test images is created later for prediction purpose.

2.2Methodology:

using Convolutional Neural Networks (CNNs) for plant sickness detection is an efficient technique because of CNNs' ability to automatically examine discriminative features from pics. here's a pointwise technique to put into effect plantsickness detection using CNN:

Data set:

accumulate a dataset along with photographs of healthy flowers and plant life laid low with numerous sicknesses. make sure the dataset covers a wide variety of plant kinds and illnesses.

Annotate each photograph with the corresponding disease label.

Data Preprocessing:

Resize all photos to a uniform size (e.g., 224x224 pixels) to make certain consistency.

Normalize the pixel values to a selection among zero and 1. augment the statistics to increase the rangeof the dataset. techniques like rotation, flipping, and zooming can be used.

Data Extraction:

break up the dataset into schooling, validation, and testing units. A not unusual cut up might be 70% training, 15% validation, and 15% trying out.

Model structure:

design the CNN architecture. A common preference is

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to use a pre-educated CNN model together with VGG, ResNet, or Inception, and satisfactory-tune it for the specific undertaking.
replace the previous couple of layers of thepre-skilled version with new layers suitablefor plant disorder class. those new layers commonly consist of absolutely related layers observed by using a softmax layer fortype.

Model Training:
Initialize the CNN with pre-trained weights if the usage of a pre-skilled version.Teach the model the use of the education set. Usestrategies like mini-batch gradient descent and backpropagation to update the model weights. Display the version's overall performance at the validation set and adjust hyperparameters as a result to save youoverfitting.

Data Testing:
Examine the skilled version on the checking out set to assess its performance. Metrics together with accuracy, precision, consider, and F1-score can be calculated. Analyze the confusion matrix toapprehend the version's overall performance on character classes.

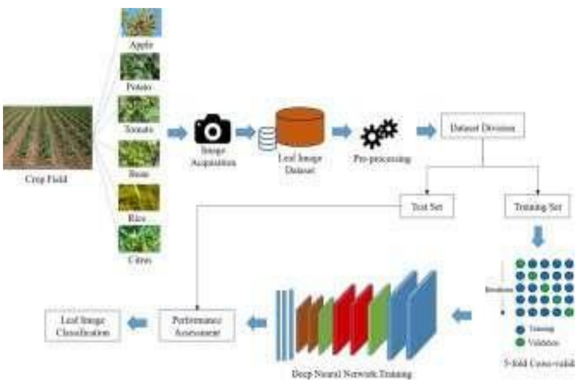

Fig - CNN Model for Plant Disease Detection

FINE TUNING
If the version overall performance isn'tgreat, don'tforget first-class-tuninghyper parameters or the version structure. test with one-of-a-kind augmentation strategies or regularization methods toenhance generalization.

Deployment:
once glad with the model's performance, deploy it for real-international use. this could involve integrating it into a web or mobile application or deploying it on facet devices for on-toolinference.

Monitoring and Maintenance:
constantly monitor the model's performance within the real-global environment.

Retrain the model periodically with newfacts to make certain it remains correct as the distribution of statistics adjustments overthe years.

By following this system, you can effectively make use of CNNs for plant disorder detection, providing a valuable device for farmers and agricultural researchers to diagnose and mitigate plant illnesses.

3. FINDINGS:

The importance of utilizing CNNs for plant disease detection due to their ability to extract discriminative features from images automatically. It also highlights the significance of building a diverse dataset with images of healthy and diseased plant leaves from various species for training machine learning models.

4 CONCLUSION:

Image transformation strategy Use featureslike scaling, rotation, and color changes to transfer learning.
Pretraining on ImageNet can improveperformance, but task-specific pretraining reduces overfitting.
Plant Disease Detection System It uses CNN, SVM and decision trees for feature extraction and classification.
It evaluates system performance using metrics such as accuracy, precision, recall, and F1-score.
It aims to help farmers detect and treatdiseases early to improve crop health and productivity. It includes data preprocessing, model training, testing, tuning, and deployment steps. It highlights the importance of different datasets and a systematic approach for effective use ofCNNs in plant disease detection.

REFERENCES

[1] *M. Hunter, R. Smith, M. Schipanski, L. Atwood and D. Mortensen, "Agriculture in 2050: Recalibrating Targets for Sustainable Intensification", BioScience, vol. 67, no. 4, pp.386-391, 2017. Available: 10.1093/biosci/bix010. Fig. 10. Confusion matrix – validation dataset Fig. 11. Top losses plotted – validation dataset Fig. 12. Confusion matrix – test dataset*

[2] *"PlantVillage", Plantvillage.psu.edu, 2020. [Online]. Available: https://plantvillage.psu.edu/. [Accessed: 31-Jan- 2020].*

[3] *D. Klauser, "Challenges in monitoring and managing plant diseases in developing countries", Journal of Plant Diseases andProtection, vol. 125, no. 3, pp. 235-237, 2018. Available: 10.1007/s41348-018-0145- 9.*

[4] *A.Muimba-Kankolongo, Food crop production by smallholder farmers in SouthernAfrica. Elsevier, 2018, pp. 23-27.*

[5] *J. Boulent, S. Foucher, J. Théau and P. St- Charles,*

"Convolutional Neural Networks for the Automatic Identification of Plant Diseases", Frontiers in Plant Science, vol. 10, 2019. Available: 10.3389/fpls.2019.00941.

[6] *"iNaturalist", iNaturalist, 2020. [Online]. Available: https://www.inaturalist.org/. [Accessed: 30- Jan- 2020].*

[7] *I. Ltd., "Success-stories - PlantSnap: Training the world's largest plant recognition classifier.Imagga Technologies Ltd.", Imagga.com, 2020. [Online]. Available:https://imagga.com/success-stories/plantsnapcase-study. [Accessed: 31-Jan- 2020].*

[8] *"Smartphone users worldwide 2020 |Statista", Statista, 2020. [Online]. Available: https://www.statista.com/statistics/330695/nu mber-ofsmartphone-users-worldwide/. [Accessed: 22- Apr-2020].*

[9] *K. Liakos, P. Busato, D. Moshou, S. Pearson and D. Bochtis, "Machine Learning inAgriculture: A Review", Sensors, vol. 18, no. 8, p. 2674, 2018. Available: 10.3390/s18082674.*

[10] *Y.Toda and F. Okura, "How Convolutional Neural Networks Diagnose Plant Disease", Plant Phenomics, vol. 2019, pp. 1-14, 2019. Available: 10.34133/2019/9237136.*

[11] *Atabay, H. A. 2016b. A convolutionalneural network with a new architecture appliedon leaf classification. IIOAB J 7(5):226–331*

[12] *A. Krizhevsky, I. Sutskever and G. Hinton,"ImageNet classification with deep convolutionalneuralnetworks",Communications of the ACM, vol. 60, no. 6, pp. 84-90, 2017. Available: 10.1145/3065386.*

[13] *S. Jadhav, "Convolutional Neural Networks for Leaf Image-Based Plant Disease Classification", IAES International Journal of Artificial Intelligence (IJ-AI), vol. 8, no. 4, p. 328, 2019.Available: 10.11591/ijai. v8.i4.pp328-341.*