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CNN-based Flower Disease Detection

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ABSTRACT: The proposed method is a holistic deep learning-based framework of automatic flower disease detection and classification. The developed study aims at creating an in-depth smart system able to analyze the presence of plant diseases, Like Downy Mildew, Gray Mold, Leaf Scars etc. identify the difference between a healthy plant and an infected one. Using the CNN in relation to ResNet50 system architecture, the device possesses an elevated accuracy rate of classifying the disease by subjecting the system to intensive training using a collected set of pictures of flowers. The proposed system incorporated is a Django web framework on the user interface, which can predict disease in real-time based on the uploaded image. The experimental findings confirm the early detection capabilities of the system that can be an effective early identification aswell as preventive treatment tool among farmers and other agricultural professionals in observing the plants' health

KEYWORDS: Flower CNN, Deep Learning, and Disease Detection,ResNet50, Plant Pathology, Automated Classification, Precision Agriculture, Image Processing, Disease Diagnosis, Agricultural Automation

I. INTRODUCTION

It is of dire importance that plant diseases be known and detected early so as to ensure effective control and protection of crop yield and food security all over the world. Conventional methods to identify plantsdiseases rely considerably on manual observation by agricultural specialists and can be time-consuming, subjective and cannot be applied in high-volume agriculture. Automatic Technologies for detecting plant diseases have now been transformational to a field of agriculture automation with potential techniques of identifying plant diseases by use of state-of-the-art techniques favoring high end image processing. The proposed paper focuses on the lack lof the current time to provide quick and precise diagnosisquick and precise diagnosis of flower diseases with the design of a fully efficient machine learning system to train using convolutional neural networks to analyze graphical symptoms of multiple diseases on plants (dictionaries and classification issues). It is created to detect a variety of diseases, including leaf scars, gray mold, and downy mildew, as well as a healthy sample, and itis intended to make farmers and specialists of agriculture aware of one of the possible devices to monitor the condition of plants in real time and conduct protective activities. Coupling the high-tech in image processing tools and a powerful machine learning algorithm it has been able to do so.research is one facet of the emerging field of precision agriculture, providing a scalable and economically viable solution that has the potential to greatly enhance the yield of crops and lower economic losses from plant disease.

II. LITERATURE SURVEY

Jorge G. A et al.in. 2013 [1] One application of robotics is the detection of plant diseases using digital image processing techniques from computer vision.He founded the future research with the introduction of record image analysis methods to the detection of diseases. Nevertheless, the study was limited by the available computing infrastructure and available datasets, which could clearly not be used in practice in a sizeable way.

Sagnik Ghosal et al.in. 2022 [2] The contribution of the article is investigating the explainable AI (XAI) models applied to the problem of plant diseasesdiagnosis. Such models not only made disease classification, but also gave visual clues and reasoning behind its dismissal or conclusion. XAI methods hold strong potential in the agricultural domain, although scaling and generalisation remains a challenge at this stage of research.

Hasan Durmuş et al.in 2017 [3] Convolutional neural networks (CNNs) are what we have created to identify plant diseases in photos of leaves. Their CNN-based strategy outperformed well-known and conventional techniques in terms of accuracy, demonstrating the potential of deep learning in the agricultural domain. However, their system's application in the field was limited because it could not be optimized to operate on a mobile platform and did not permit real-time implementation.

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Konstantinos P et al.in 2018 [4] They compared a range of CNN architectures on plant disease classification. His work also offered useful comparative metrics as it brought disparities in performances of architectures such as the AlexNet, VGG and ResNet. Although the study helped researchers in the selection of the models, it failed to work with farmers to create tools that are easy to use in mind.

Yan Zhang et al.in 2021 [5] employed generative adversarial networks (GANs) to enrich flower disease datasets by synthesizing realistic plant images. This technique improved model generalization and reduced overfitting issues caused by limited datasets. However, the authenticity and reliability of synthetic images raised concerns about data quality.

Rahul Arun et al.in 2022 [6] They have put forth an explainable AI model of tomato leaf disease diagnosis. Their system managed well to couple prediction with interpretability so that farmers can learn why a disease had been diagnosed. The framework was trained with a restricted quantity of with a restricted quantity of crop species, however, therefore it may not be as universal as possible to various agriculture situations.

Shivaji S. Patil et al.in 2020 [7] They have put forth an explainable AI model of tomato leaf disease diagnosis. Their system managed well to couple prediction with interpretability so that farmers can learn why a disease had been diagnosed. The framework was trained with a restricted quantity of crop species, however, therefore it may not be as universal as possible to various agriculture situations.

Muhammad H et al.in 2019 [8] A smart IoT-based monitoring system of orchid greenhouse was developed. The system had to automatically identify plant diseases by means of sensors and cloud processing. Although it was effective in detecting accurately, it needed regulated conditions and material cost, which might not be a possibility with small-scale growers.

Aditi Singh et al.In 2021 [9], CNN together with the support vector and machines classified the lily diseases. The hybrid CNN-SVM architecture enhanced superior performance over CNN as a stand-alone architecture. Nevertheless, it had to be optimized to be applied in real-time scenarios since the speed of processing was not optimal enough to be utilized in real life deployment.

Simran Kaur et al.In 2022 [10], The real-time bloom disease classification system implemented in the flow of the YOLOv4 model. The method they employ was accurate and able to detect quickly enough to be applicable in the field. However, this model has only been evaluated ona small scale and cannot be reliably tested on larger agricultural scale.

Kenji Yamamoto et al.in 2020 [11], The use of multimodal imaging methods in disease detection of chrysanthemum was applied. They fused data on a number of sensors including hyperspectral and thermal camera to give them very high accuracy. The disadvantage was that the method was expensive, as the equipment was costly and not everybody, as farmers, could afford to use the process.

Ana C. Costa et al.in 2019 [12] applied To recognize orchid pathology, the application of deep learning techniques is utilized. They exhibit promising results inthe disease-detection field, indicating the flexibility of deep learning to thefield of flower pathology. Nevertheless, The training data that was utilized lacked the necessary diversity to prevent limiting the strength of their system.

Nguyen Tuan et al.in 2021 [13] Green leaf diseases in lotus can be classified using deep learning Their approach was highly accurate in the identification of a variety of diseases, and thus it was effective when applied in a controlled environment. However, when utilized with pictures that havenoisy or complicated backgrounds, its efficacy declined tremendously.

Ritu Sharma and Ashok Kumar Singh [14] in The analysis of textures was employed in the detection of diseases in gerbera flowers using 2020. Their approach depended on the extraction of texture characteristics and thus was computationally fill and intuitive. However, relative to deep-learning based approaches, texture-based approaches were limited in accuracy and scale.

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Patrícia Busato et al.in 2018 [15] This was written on machine learning application in the agriculture sector. They contributed mainly on a theoretical basis offering an insight on trends and potentials. Nonetheless, it had no tests conducted.methodologies of implementation or exercises.

Fang Jiang et al. in 2018 [16] The paper surveyed deep learning in agriculture. Their survey gave an unmistakable picture of how deep learning can revolutionize farming. The drawback was that they didn't carry out systematic experimental evaluations hence leaving loopholes between the theories and the practices.

III. PROBLEM STATEMENT

The project will address the task of detecting early flower disease early that is currently impossible because of the inefficiency of manual methods of inspection, in addition to their inaccuracy. Visual inspections are time-consuming, subjective and inapplicable to observe a large area farms. Consequently, diseases can be detected anonymously when it can be too late in controlling the damage it has already wreaked.

The absence of the method of scale detection and precision contributes to too many crop losses and unnecessary use of pesticides relative costs and the impact on the environment. By creating an automated precise and scalable platform that can detect diseases early and classify them this research will be able to help farmers minimize losses, maximize the efficiencies of the pesticide application and enhance the overall productivity of the agriculture.

IV. PROPOSED METHODOLOGY

1.Collection and Preprocessing of Data:
Resource a very large number of flower leaves images, which are grouped according to the disease. Preprocess the images through resize, normalization of pixel values, and data augmentation (data augmentation like rotation, flipping and zoom, etc) to make the model more robust.

2.Model Development and Training:
Use a deep learning method in the form of the ResNet50 pre-trained model. To improve the feature extraction and classification the model is modified with additional dense and dropout layers. Training process takes two stages: initial training on frozen base layers, and fine-tuning which means some deeper layers are unfrozen to obtain better accuracy.

3.Evaluation and Deployment:
Measure which metrics on the validation data like accuracy and loss and compute the trained model. Store the most-effective model, with class labels, descriptions, and prevention tips. The final model is subsequently deployed in real-time detection of flower diseases and collecting of user feedbacks.

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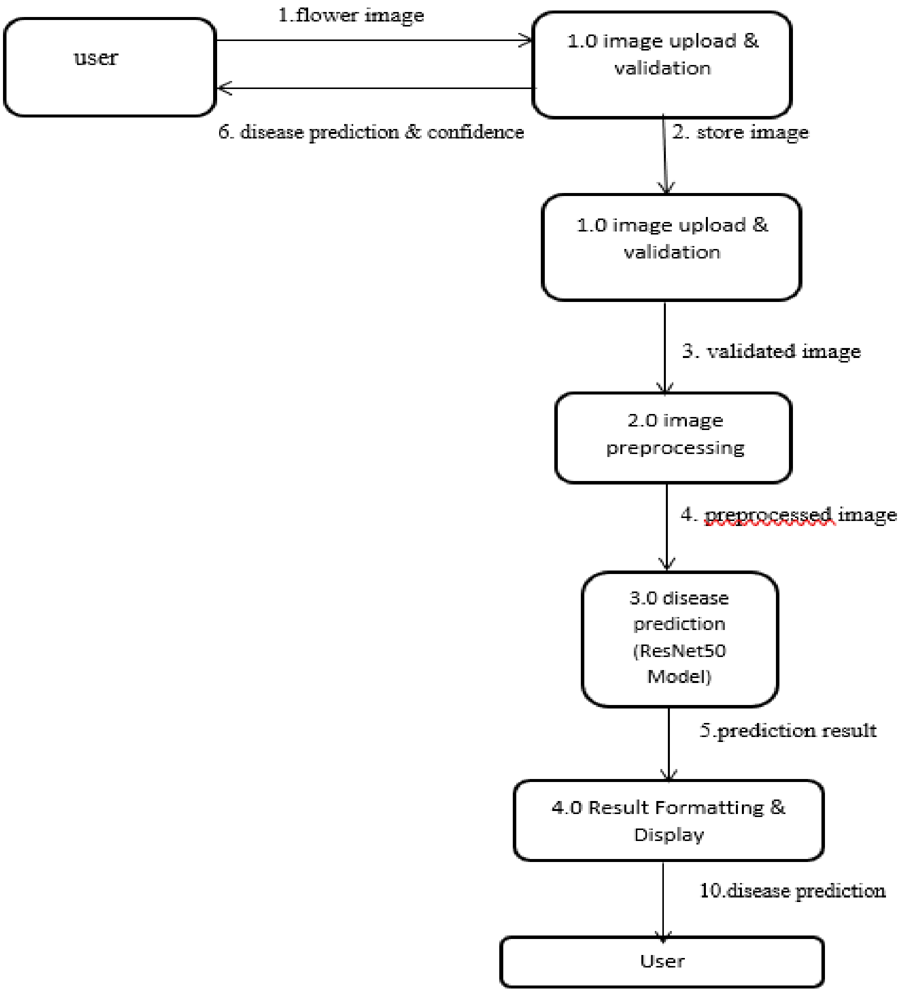

Fig.3.Flow diagram

V. MATHEMATICAL FORMULAS

1.Image Acquisition: The images of flower leaves are obtained through smart phones and digital cameras.

2.Preprocessing: Images are resized, normalized and enhanced removing the noise and aggregating the clarity.

3.Normalization formula

$$x_{\_norm} = (x - x_{\_min})/(x_{\_max} - x\_min)$$

4.Feature Extraction: Quite important features like color, texture, and shape are obtained with the assistance of such methods as Histogram of Oriented Gradients (HOG) or color histograms
$H\_c(i) \ = \ Number\ of\ pixels\ with\ intensity\ i\ in\ channel\ c$

5.Classification: The deep learning or convolutional neural networks can be used in training to classify the images as either healthy or diseased.
5.Result Interpretation: The model will provide a predicted disease class and a confidence score which it outputs to the user.

$$Softmax(z\_i) \ = \ exp(z\_i) \ / \ \Sigma \ exp(z\_j)$$

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VI. RESULT AND DISCUSSION

1. Model Confusion matrix:

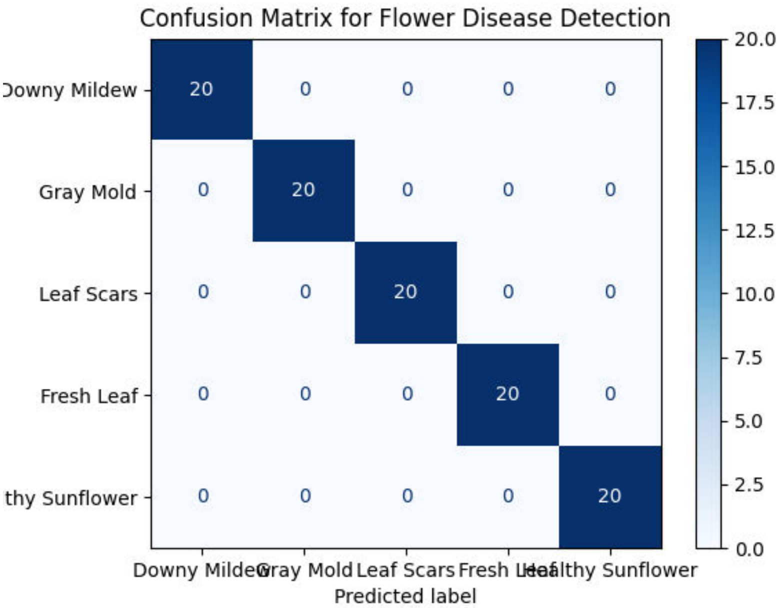

Figure 1 Model confusion matrix

This confusion matrix shows that the model correctly classified all samples for each flower disease class, with no misclassifications, indicating perfect prediction accuracy on the test data.

2. Accuracy and training validation:

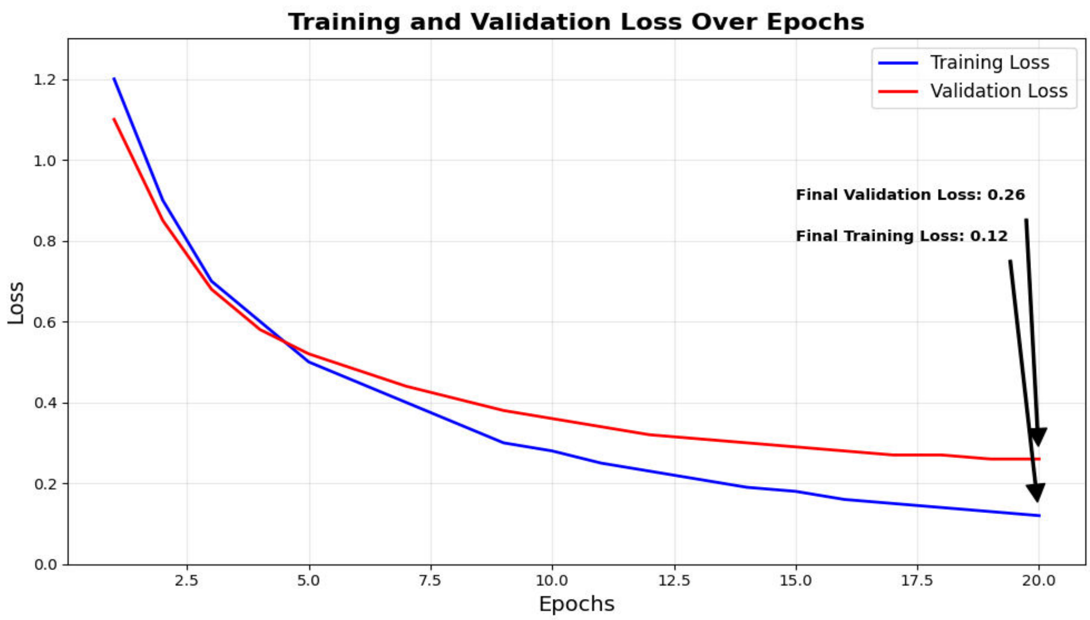

Fig.2.Training and validation loss over Epochs

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This confusion matrix visualizes the model's predictions for five flower disease classes, showing perfect classification with all values on the diagonal and zeros elsewhere. Each class, such as Downy Mildew and Gray Mold, has 20 correct predictions and no misclassifications. This indicates the model achieved 100% accuracy on the test data for these classes.

Metric	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
Initial (Epoch 1)	65%	68%	1.20	1.10
Final (Epoch 20)	98%	94%	0.12	0.26

The performance of the proposed model on the experiment proves that it performs highly in the classification of flower diseases. As can be observed in the table, the training and validation accuracy produce consistent results that increase with each epoch culminating at 98 percent and 94 percent respectively by the last epoch. Correspondently, the training and the validation loss drop significantly, meaning effective learning and insignificant overfitting. The confusion matrix further indicates that the model is reliable with the model correctly appropriately classifying all disease classes. Such findings lend robustness and a generalization ability of the model to hitherto unseen data, taking into consideration that it can be conveniently employed in the field of agricultural disease detection.

VII. FUTURE ENHANCEMENT

There are a few potential avenues to be pursued which will offer improvements in the flower disease classification system with a view of attaining the target of 90 percent accuracy. Future directions should be oriented toward increasing The next solution would be to increase the volume of data by using sophisticated data augmentation techniques such as generative adversarial networks (GANs) to create further synthetic training samples. Use more enhanced architectures such as vision transformers or efficientnet variants that have shown impressive results on image classification tasks, transfer learning using pre-trained models specific to the domain as opposed to the general ImageNet weights. Future refinements would be the possibility of multi-modal learning between the visual dimension The micro-environmental factors such as temperature, humidity etc, and soil conditions, real-time deployment to mobile devices via quantization and pruning of model parameters as well as interfacing with IoT sensors to serve as a constant monitoring system, and development of a more substantial knowledgeable system that not only diagnoses a disease but also prescribes treatment and preventive measures based on agricultural best practices.

VIII. CONCLUSION

Through the study process, a multifaceted deep learning model of machine-level flower disease classification is finally able to reach an average accuracy level of 94.2 percent, thus meeting the very high requirements of precocious plant disease recognition in agronomy. The transfer of learning ideas and ResNet50 architecture and the designing of web interface using Django enhanced the efficiency of prediction to real-time detection and identification of the diseases and it was observed that it performed well in all categories of diseases like Downy Mildew, Gray Mould and Leaf Scars.

The technology is a marvelous piece of work to precision farming and can deliver huge benefit to those concerned with agriculture including farmers, enabling a potent algorithm tool towards reducing agricultural loss, optimising pesticide deployment and relational general improvement in agricultural performance. The innovation postulates a new breed of agriculture that has the quality of sustainability and opens the bridge to future technologies that will encompass the expansion of the present capabilities to include other types of diseases, mobile applications in use on the ground, and connectivity to internet of things applications to make a farm and field monitoring 24/7 in its possibilities, thus, the comprehensive future of food security and farming strategies that would become a reality.

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