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A Review: CNN Based Plant Disease Detection

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Abstract: Identifying plant diseases is the initial step toward mitigating losses in agricultural product yield and quantity. This work focuses on exploiting such technical breakthroughs, with an actual focus on plant disease detection. The system will analyze plant photos using cutting-edge image processing algorithms to precisely diagnose diseases, gauge the extent of damage, and make wise suggestions for necessary pesticides and nutrient supplements. The suggested remedy will identify particular nutrient deficits causing problems with crop health in addition to detecting the existence of illnesses. The system will aid farmers in making well-informed decisions about how to use nutrients and pesticides by integrating a thorough analysis. This will ultimately help to manage crop diseases in a timely and efficient manner, maximize agricultural yield, and reduce financial losses.

Keywords: Plant disease detection, Image processing algorithms, Agricultural monitoring.

I. INTRODUCTION

India primarily relies on agriculture, with approximately 70% of its population dependent on this sector. Crop loss is a major concern for the country and countries economy and productivity. Leaves are delicate part of the plant so the disease symptoms first shown on leaves [21]. Early disease identification is essential because of variety of crops and the requirement for appropriate insecticides. Farmers used to rely solely on labour intensive, human observation, which meant that professional monitoring was needed. Yet, effective substitutes have surfaced in the form of improved computerized and partially computerized determination of plant diseases in past several years.

It has been demonstrated that disease detection by symptom analysis on plant leaves is more precise, cost-effective, and quicker than manual observation [28]. This strategy is especially important because disease symptoms frequently show up on fruit, leaves, and stems. In order to give farmers a useful tool for early and accurate monitoring, especially in situations where they might not have a thorough understanding of crop diseases. For solving this scenario, numerous researchers from all over the globe have developed cutting-edge systems to facilitate autonomous identification of plant diseases using different kinds of machine learning (ML) [22, 26, 24, 25] and deep learning (DL) approaches [23, 27]. So, here we discussed the research on identifying plant diseases that has been proposed by several researchers.

This work focuses on exploiting such technical breakthroughs, with a actual focus on plant disease detection. This technology attempts to give farmers a comprehensive tool that not only recognizes diseases but also provides customized recommendations for required pesticides and nutrients by utilizing the power of sophisticated algorithms. This proactive approach aims to stipulate farmers with timely information, enabling them to make informed decisions and implement precision agricultural techniques, thus improving crop resilience and overall agricultural output.

II. BACKGROUND CONCEPT

A. Machine Learning (ML)

ML is an artificial intelligence (AI) advance in technology which offers systems the capacity to instinctively study from experience and get improve at it without needing to be obviously designed. The formation of software application which retrieve data further utilize to learn on their own is important target of ML. Learning begin with data or inspection, like examples, command to discover trends or modification in data and use the examples we provide to guide future decisions.

The central objective is to enable computers to study by itself , without lending a hand or without the participation of human being. Plant disease classification is aided by ML. Utilizing this technique is seen as an important first move toward eliminating plant diseases, and it has also raised crop production [29]. Experts are able to determine the source of plant illnesses and analyze them with the support of a variety of ML and DL techniques [4]. Among the machine learning (ML) techniques utilized in identifying illnesses decision-making are support vector machines (SVM) and K-means [31].

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1) SVM Classifier

SVM that is Support Vector Machine (SVM) is actually an supervised ML approach. It is can be applied for regression and classification. It can be used to solve the binary and multi-class classification problems depicted in Figs. (2) and (3) [32]. Two varieties of SVM are nonlinear and linear SVM. Different classes are created from the provided image by using linear or straight-line SVM. When linear lines cannot be used to classify the images, nonlinear SVM is used [33]. The main focus is actually to recognize hyperplane in the N-dimensional space which is used to split the data points into different feature space groups.

Thus, SVM generates a set of hyperplanes [35] or a single hyperplane [34]. These hyperplanes are utilize to categorize the data points into different group [36]. determining the best hyperplane to split the classes maximally and to perform well on data that has not been seen before [37].

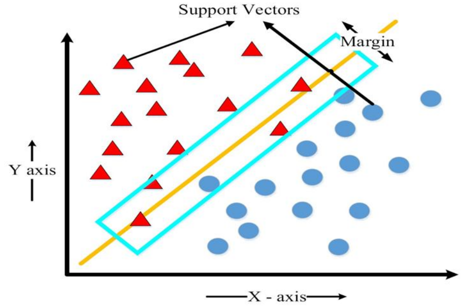

Fig 1 : Binary Classification using SVM [49]

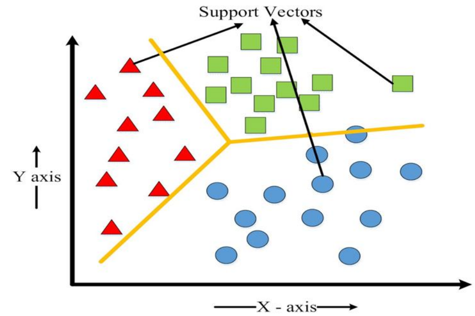

Fig 2 : Multiclass Classification using SVM[49]

2) KNN Classifier

The number of nearest neighbors that are taken into consideration while making predictions is represented by the letter "K" in KNN [38]. In machine learning, K-Nearest Neighbors has been employed in classification, statistical estimation, and pattern recognition [39]. The algorithm makes use of a distance metric, such as the Euclidean distance, in determining how similar two data points are [38] [40].

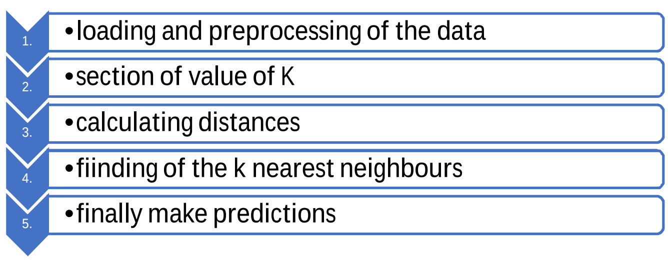

Fig 3: Process of KNN classifier

3) Deep Learning (DL)

DL is actually within area of ML [41], often used for the detection of objects [42, 43,51], picture classification, language processing [44, 45,52], and processing of natural languages [46, 47]. In the current the context, real-time applications and deep learning architectures for disease identification have become a focus [46]. Deep learning involves use of deep neural networks, which consist of multi-layered neural networks. It has capacity to figure out intricate links and patterns in data.

4) CNN

A specific category of ML known as CNN (Convolutional Neural Network) is a DL mechanism. To examine graphical information CNN extremely use. CNN constructed with the capability to automatically and appropriately identify features of the spatial hierarchy from the input data [48]. It consist of numerous layers. Out of every layer each layer conducts a specific role during the feature extraction and classifying process [47].

5) Convolution Layer

Most of computations originates in the convolutional layer of CNN, which is the principle structural component. For finding particular feature in this layer filter that is a relatively small weight matrix which is float across the receptive part of the input image.

6) Pooling Layer

Pooling layer is most important section right after the convolution layer. Like the convolution layer, it carried out task of cleaning of input images. But it additionally offers distinct role. Pooling layer lowering overall dimension of arriving data yet preserving the crucial data in order to enhance the whole accuracy of network.

7) Fully Connected Layer

This layer categorizes images depending upon feature acquired from prior layers. So that's why this layer is very important in latter phases of CNN. When a neuron in individual layer is said to be fully linked, it implies that every other neuron in the layer below it is connected as well. Various properties extracted from the former layers have been combined and entrusted to particular groups or outcomes from fully connected layer. In this layer all activation unit comprises an attachment for each input from prior layers, it enable the CNN to test whole features and then sorting the data.

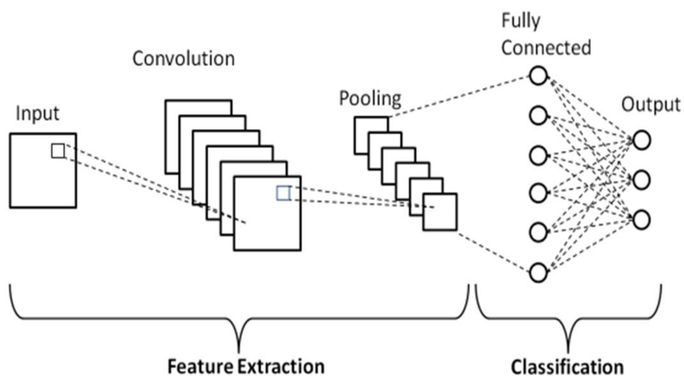

Fig 4 : Layers in CNN [50]

III. LITERATURE REVIEW

In this section, various methods for the identification of disease in plants are reviewed. Researchers have done a lot of studies on plant disease detection. Here are some works done by different authors.

1) DL-based methods have been proposed for realistic detection & identification of insect in soybean crops, as reported by Turkey D, Singh KK, et al. (2023). To evaluate the reliability of this method in insect detection accuracy, the performance of various transfer learning (TL) techniques was examined. The suggested approached achieved an efficacy of 98.75% with YoloV5, 97% with InceptionV3, & 97% with CNN. Among these, the YoloV5 algorithm proved to be efficient, operating at 53 frames per second in dynamic detection. Moreover, a data of agricultural diseases was compiled & annotated using a variety of imaging technologies. This approach simplified the study, reduced the workload for producers, & yielded superior results.
2) Ahmed I. & Yadav PK. (2023) have illustrated two viral, two mold diseases four bacterial infections & one mite-related illness using the "PlantVillage" dataset. Pictures of unaffected leaves from a twelve crop variety were also included. Machine learning approached like SVM, CNN, & GLCM were utilized for developing prediction models. The progression of AI in classification has paralleled the development of Artificial Neural Networks (ANNs) through back propagation. In extension of investigation Real-time leaf photos were used for illness identification, employing K-nearest neighbors (KNN) in addition to machine learning techniques. It observed that overall efficacy of 96%, 94%, 95%, & 97% for tomato plants, 99% & 98% for apple & rice plants, respectively. Precision, recall, & F-measure metrics assessed multi-layer classification, utilizing a dataset with one symptom pool per class.
3) Algani YMA, Caro OJM, et al.(2022) introduced an adaptive deep learning approach for disease identification & bifurcation termed Ant Colony Optimization with Convolutional Neural Network (ACO-CNN). ACO was utilized to evaluate disease diagnosis in plant leaves, while CNN classifiers were employed to eliminate texture, geometric plant location, color, texture from the provided photos. Various effectiveness metrics demonstrate that this approach outperforms previous methods in accuracy. These metrics are utilized for analysis & to propose a recommended approach. Concrete measures were taken to implement these strategies. Ultimately, in the form of accuracy, precision, recall, & F1-score, the ACO-CNN model outperformed C-GAN, CNN, & SGD models. The ACO-CNN model achieved 99.98% accuracy.

4) Dai G, Fan J, et al. (2023) introduced PPLCNet, a deep learning model incorporating GAP layers, a multi-level attention mechanism, & dilated convolution. Innovative meteorological data augmentation was utilized to exp& the sample size, enhancing feature extraction resilience & generalization. The model addresses insufficient data information extraction by extending the perceptual field of convolutional domains through saw-tooth dilated convolution with configurable expansion rates. A lightweight CBAM attention mechanism in the middle layer enhances information representation. Overfitting is mitigated by the GAP layer, reducing parameter quantity & complexity. During validation, the PPLC-Net model achieved a recognition accuracy of 99.702% & an F1-score of 98.442% on the retained test dataset. With 15.486 million parameters & 5.338 billion FLOPs, the model satisfies requirements for accurate & rapid recognition.
5) P. Nayar & S. Chhibber (2022) explored a novel method by employing leaf classification through deep convolutional networks (DCN) for creating disease detection model. The exp&ing field of computer presents facility to enhance & broaden the utilization of precision crop protection techniques, opening new avenues applications in precision agriculture. This methodology enables swift & direct implementation of the system. The study utilized a data containing 77,000 photos of both healthy & diseased plant leaves. By training a CNN to classify diseases in plant & discern their presence, another model was trained to detect diseases using YOLOv7. The advanced model achieved precision & recall rates of 65%, 59%, & 65%, while the trained classification model attained an efficacy of 99.5%.
6) A CNN solution based on DL was given by Kukadiya H. & Meva D. in 2022 for classification & differentiation of cotton leaf diseases. Various studies have been conducted on common leaf diseases in various crops; however, this researched provided a reliable & effective method to diagnosing leaf diseases in cotton. Three cotton leaf diseases if not discovered were successfully classified & identified by the suggested approach. CNN is the suggested model, with training & testing efficacy of 100% & 90%, respectively for identification & classification of cotton leaf diseases.
7) Adesh V. Panchal, Subhash Ch&ra Patel, et al. (2023) propose a process for identifying crop diseases by labeling affected leaves according to disease patterns, followed by pixel-based techniques to enhance information extraction from processed images. Feature extraction, image segmentation, & crop disease classification are then conducted based on identified patterns implementing a convolutional neural network (CNN). A public dataset comprising around 87,000 RGB-type photos, including healthy & diseased leaves, is utilized for demonstration.
8) Sami Ur, Fakhre Alam, Rahman, et al. (2023) introduce an image processing-based techniques for automated diagnosis & preventive measures of leaf diseases in tomato crops. Their approach utilizes the Gray Level Co-Occurrence Matrix (GLCM) approach of tomato leaves 13 statistical variables , which classified into various diseases using Support Vector Machines (SVM). Experimental results demonstrate high efficacy rates: 100% for healthy leaves, 95% for early blight, 90% for septoria leaf spots, & 85% for late blight. This method is operationalized as a mobile application.
9) Gangwar A, Rani G, & Dhaka VPS. (2023) propose an image segmentation-based, DL technique for tomato disease detection. Their approach utilizes the VIA tool for leaf masks, a adaptive U-Net model for image segmentation, & a convolution network for disease classification. With a 98.12% accuracy rate, this method shows promise for automatic tomato disease detection, potentially enhancing yield & reducing crop loss.
10) B. Paulos & M. M. Woldeyohannis (2022) give an innovative approach for identifying & categorized disease of coffee plant, stating that it is essential for increased output. Here, 1120 photos from the Wolaita Sodo Agricultural Research Center were utilized to train the DL model. To address data overfitting, an augmentation technique was employed. 3360 photos in all were utilized. To achieve the best results when classifying these diseases, they have contrasted training from scratch with TL techniques. This leads to a 98.5% accuracy rate for training from scratch & 97.01 & 99.89 efficacy rates for transfer-based learning using Mobilnet & Resnet50, respectively. When it came to classifying photos, the pre-trained Resnet50 model best than other alternative techniques.
11) Shoaib M. et al. (2022) propose a DL-based method for diseases identification of tomato plant, utilizing the InceptionNet model & a CNN architecture. With more than 18,000 segmented & non-segmented tomato leaf images, they trained the CNN using a supervised learning approach.by implementing U-Net & Modified U-Net segmentation algorithms; they achieved superior performance with the modified U-Net model, reached 98.66% IoU score & 98.73% on the dice.
12) Attallah O. (2023) presents a algorithm for autonomous diseases identification of tomato plant, by using three compact CNNs. By extracting deep features signals from the CNNs' last linked layer & incorporating components from all three architectures, they achieved high accuracy rates with KNN & SVM classifiers, reaching 99.92% & 99.90% accuracy, respectively.

13) Ksibi A. & Ayadi M. (2022) introduce a deep feature concatenation (DFC) technique, utilizing ResNet50 & MobileNet models to create the MobiResNet neural network. With a dataset of 5400 olive leaf photos captured by an agricultural UAV, MobiResNet outperformed ResNet50 & MobileNet, achieving an overall classification accuracy of 97.08%.
14) Albattah W., Nawaz M., et al. (2022) propose a robust method for classification of plant diseases using a Custom CenterNet architecture with DenseNet-77. By incorporating improved key point extraction & utilizing the Plant Village Kaggle database, their method proves more reliable & efficient than recent techniques for plant disease recognition.
15) Dharmendra Saraswat, Ahmad, Aanis, et al. (2023) conduct a comprehensive analysis of seventy research works on deep learning applications in agricultural disease diagnosis & control. Covering various aspects from dataset requirements to deep learning techniques, their review aims to guide future tool development & support farmers in managing plant diseases effectively.
16) Al-Gaashani MSAM, Shang F, et al. (year) propose a method for diseases identification of tomato plant using transfer learning (TL) & feature signals concatenation. Features are further extracted from pre-trained MobileNetV2 & NASNetMobile kernels & concatenated by implementing kernel principal component analysis. These concatenated features are then fed into a traditional learning system, where multinomial logistic regression (LR) achieves the highest accuracy of 97% among tested classifiers.
17) Amritha Haridasan, et al. (2023) introduces a computer vision-based methodology for identification of disease in rice plant, integrating DL, ML, & image processing tool techniques. This approach significantly reduces the reliance on traditional methods for safeguarding paddy crops against common diseases. By employing convolutional neural networks CNN & a support vector machine SVM classifier, the proposed approach achieves a validation accuracy of 0.9145, aiding in timely diagnosis & treatment recommendations.
18) Poornima Singh Thakur (2023) presents the "VGG-ICNN," a lightweight CNN for identification of crop diseases by plant-leaf images. Over using 6 million parameters, VGG-ICNN outperforms other high-performing deep learning models while covering a wide range of crop types across multiple datasets. Experimental results demonstrate high accuracy, particularly achieving 99.16% accuracy on the PlantVillage dataset & consistent performance across various crop datasets.
19) Shoaib et al. (2022) highlight the effectiveness of CNN models in obtaining improved detection accuracy using imaging data for classification of plant disease. CNNs excel in feature extraction & classification, outperforming other ML & DL techniques with accuracy rates ranging from 99% to 99.2%.
20) Upadhyay SK, Kumar A. (2022) propose an innovative method for analysing & classifying rice plant diseases depend on lesion size, shape, & color in leaf images. Utilizing a fully CNN trained of 4000 image samples, the proposed method achieves a high efficacy rate of 99.7%, surpassing existing methods for plant disease identification & categorization.

Sr. No.	Author	Year	Technique used	Author Claims	Our Finding
1.	Turkey D, Singh KK, Tripathi S.	2023	Deep Learning	1. Deep learning approached s for dynamic insect identification in soybean crops was presented. 2. To evaluate method's viability & dependability, various transfer learning (TL) models were tested for insect identification & detection accuracy.	This algorithm obtained an efficacy of 98.75%, 97%, & 97%, respt.by YoloV5, InceptionV3, & CNN.
2.	Ahmed I, Yadav PK,	2023	Machine Learnig - SVM, gray-level co-occurrence matrices & CNN	It investigates for 4 bacterial infections, 2 viral & mold diseases, one mite of illness using the "PlantVillage" dataset. images of unaffected leaves from twelve crop species were also presented.	Precision, recall, & F-measure metrics were used to evaluate multilayer classification issues, considering data with single symptom pools per class. The proposed method achieved high accuracy rates: 99% for rice plants, 98% for apples, & 96-97% for tomato trees.

3.	Algani YMA, Caro OJM, et al.	2022	Deep learning	this research article is based on Ant Colony Optimization using Convolution Neural Networks	An ACO-CNN algorithm performed well as compared to C-GAN, CNN, & SGD techniques . C-GAN, CNN, & SGD achieved accuracy ratings of 99.6%, 99.97%, & 85% respectively, whereas ACO-CNN model achieved 99.98%. efficacy
4.	Dai G., Fan J., Tian Z., & Wang C.	2023	DL model (PPLCNet) - dilated multilayer convolution	They presented a DL model name as PPLCNet, incorporating GAP layers, a multi-level attention algorithm, dilated convolution, & innovative meteorological data augmentation techniques.	The PPLC-Net model hits to accuracy of 99.702% & F1-score of 98.442% during validation using 15.486 million parameters & 5.338 billion FLOPs, it meets requirements for accurate & quick recognition.
5.	P. Nayar, S. Chhibber ., et al,	2022	Deep convolutional networks (DCN).	Used different strategy for utilizing deep convolutional networks (DCN) to support leaf classification in disease detection model.	This detection model achieved mean Average Precision (mAP) of 65%, precision of 59%, & recall of 65%, whereas the trained DCN classification model achieved an efficacy of 99.5%.
6.	Kukadiya H., Meva D.	2022	DL- CNN technique.	It provides solution based on DL has been introduced by them to identify & categorize cotton leaf diseases.	It classified & identified three significant cotton leaf diseases, crucial for early treatment. Utilizing a CNN model, the approach achieved 100% training accuracy & 90% testing accuracy for detection & classification of cotton leaf diseases.
7.	Panchal, Adesh V., et al	2023	DL-based technique.	They present a technique that involves labeling the leaves of contaminated crops according to the illness pattern.	CNNs (convolutional neural networks) are used to classify diseases. A public dataset of about 87 K RGB-type photos, containing both healthy & diseased leaves, is used for demonstration purposes.
8.	Rahman, Sami Ur, Fakhre Alam, et al	2023	Image processing tool	It provides identification & supervision of leaf diseases on tomato crops based on image processing algorithm uses Gray Level Co-Occurrence Matrix (GLCM) algorithm to calculate 13 distinct statistical variables from tomato leaves.	The suggested method boasts remarkable accuracy rates: 100% of healthy, 95% for early blight, 90% for septoria leaf spots, & 85% for late blight leaves. It is operationalized as a mobile application, providing practical implementation for users

9.	Gangwar A, Rani G, et al	2023	DL-based technique	They demonstrated an image segmentation technique based on DL that can be used to identify tomato disease. The VIA tool is used by the authors to make leaf masks.	The suggested technique uses a modified U-Net model to segment images, & a convolutional network is apply to classify images into ten categories. Its 98.12% accuracy rate demonstrated that it was a potentially useful method for automatically detecting tomato diseases, which can enhance tomato yield & lower crop loss.
10.	E. B. Paulos et al.	2022	DL technique.	They claims 1120 photos from the Wolaita Sodo Agricultural Research Center used to train the DL model, & to address data overflow, an augmentation technique was applied.	It used Mobilnet & Resnet50, trained with scratch yields an accuracy of 98.5%, whereas transfer-based learning yields rates of 97.01% & 99.89%. The pre-trained Resnet50 model is best classifying photos than other methods.
11.	Shoaib M, et al.	2022	DL-based technique.	The researchers proposed a DL-based system using image data from plant leaves to detect tomato plant diseases. They adapt InceptionNet model & CNN trained over 18,161 tomato leaf images using supervised learning for detection of various tomato diseases.	Detection of disease-affected regions utilized two cutting-edge semantic segmentation models: U-Net & Modified U-Net. The modified U-Net segmentation model demonstrated superior performance compared to the regular model model, achieving improvements of 98.66% accuracy
12.	Attallah O.	2023	KNN & SVM techniques.	The authors proposed a pipeline utilizing three compact CNNs for identification of tomato leaf diseases. They employed transfer learning (TL) to extract deep features from the last fully connected layer of the CNNs, aiming for a more concise & high-level representation.	The KNN & SVM algorithms hits remarkable accuracy rates of 99.92% & 99.90%, respectively, using only 22 & 24 features. A competitive potential of the proposed pipeline was demonstrated by comparing its experimental results for tomato leaf disease classification with those of previous research investigations.
13.	Ksibi A, Ayadi M, et al	2022	ResNet50 & MobileNet, using a deep feature concatenation (DFC) .	They presented (DFC) technique, for features extracted from input photos using 2 current pre-trained CNN models,	The MobiResNet model outperformed ResNet50 & MobileNet, achieving classification accuracies of 94.86% & 95.63%, with an overall performance of 97.08%.
14.	Albattah W, Nawaz M, et al	2022	Custom CenterNet framework- DenseNet-77	They provide robust solution for classifying plant diseases, based on DenseNet-77 as the basis network & a Custom CenterNet framework.	The researchers used the PlantVillage Kaggle dataset, known for its diverse characteristics, to evaluate their method. Their approach proved more reliable & efficient than recent methods for identifying & classifying plant diseases, as validated by qualitative & quantitative assessments.

15.	Ahmad, Aanis, et al	2023	Deep learning	They provide a comprehensive overview of seventy years of research on deep learning technologies & their current applications in agricultural disease detection & control.	Provide compressive literature on DL techniques & various signal processing tools for agricultural plant disease detection & control.
16.	Al-Gaashani MSAM, et al	2022	Machine Learning	They have suggested segmentation of tomato leaf diseases using TL & feature concatenation.	The literature confirmed that combining features improved classifier performance. logistic regression (LR) outperformed random forest (RF) & support vector machine (SVM), with highest accuracy of 97%.
17.	Haridasan, Amritha, et al	2023	Image processing tool, machine learning & DL.	They proposed a computer vision approach employing image processing, ML to detect diseases in rice plants.	A hybrid system of convolutional neural networks (CNN) & support vector machine (SVM) classifier was employed to classify various types of paddy plant diseases. The deep learning model, utilizing ReLU & Softmax algorithms, achieved the highest accuracy of 91.45%.
18.	Thakur, Poornima Singh, et al	2023	Deep learning	They introduced the "VGG-ICNN," a lightweight CNN designed specifically for detection of crop diseases from plant-leaf photographs.	The system attains 99.16% accuracy on the PlantVillage dataset, outperforming various current DL methods for detection of crop disease .Also when distinguished with recent CNN models, it consistently excels across all five datasets.
19.	Shoaib, M., Hussain, T., Shah, et al.	2022	DL technique	They emphasized that CNN models excel among deep learning methods for improving detection accuracy with image data. CNNs are characterized by multiple hidden layers, including convolutional & pooling layers, enabling effective processing & analysis of images.	Research findings indicate that convolutional neural networks (CNNs) can classify photos of diseased & pest-affected plant leaves with high accuracy rates (99–99.2%).
20.	Upadhyay SK, Kumar A.	2022	Convolutional Neural Networks (CNNs)	They devised effective approach for detecting rice plant diseases based on analyzing the size, shape, & texture of lesions present in leaf images.	they claims fully connected CNN method which is efficient, boasting an impressive efficacy of 99.7% on the available dataset. Which shows that this method surpassed other conventional method of detection of plant diseases.

IV. CONCLUSION

It is clear from the thorough literature assessment that by using Image processing adaptive techniques on plant disease detection, scientists have made great progress toward creating precise & dependable methods for recognizing & categorizing diseases impacting different crops. Of the various ways investigated, a few st& out for their creative strategies, solid findings, & useful applications. From the above reviews, Algani YMA, Caro OJM, et al. (2022) introduced a noteworthy methodology name as: Ant Colony Optimization - Convolutional Neural Network (ACO-CNN) for detecting & classifying plant leaf diseases. By leveraging the strengths of both convolutional neural networks & ant colony optimization, their method achieves impressive accuracy rates by extracting crucial information from images. The ACO-CNN model surpasses in terms of accuracy, precision, recall, & F1-score not only traditional methods but also modern DL models like C-GAN, CNN, & SGD. Their approach demonstrates outst&ing performance & reliability in disease identification & classification, achieving an impressive accuracy 99.98% with mentioned evaluation metrics. The outcomes attained by Algani YMA, Caro OJM, et al. (2022) highlight how well their suggested strategy works to provide solution for the problems related to detection of plant disease. They have developed a strong framework which precisely identify & categorize illnesses by utilizing the complimentary characteristics of CNN & ACO. This framework provides important insights for crop management & precision agriculture methods. Furthermore, the application of sophisticated DL methods such as ACO-CNN represents a viable avenue for further research projects aiming at improving the effectiveness & dependability of plant disease detection systems.

To sum up, the research conducted by Algani YMA, Caro OJM, et al. (2022) is noteworthy for its significant addition for detection of plant disease in agriculture sector. By combining conventional optimization methods with cutting-edge deep learning techniques to tackle intricate agricultural problems is demonstrated by their creative methodology & outst&ing performance metrics. Their work therefore forms the basis for future developments in the creation of dependable & effective methods for the detect ion & provide treatment of plant diseases in agriculture sector.

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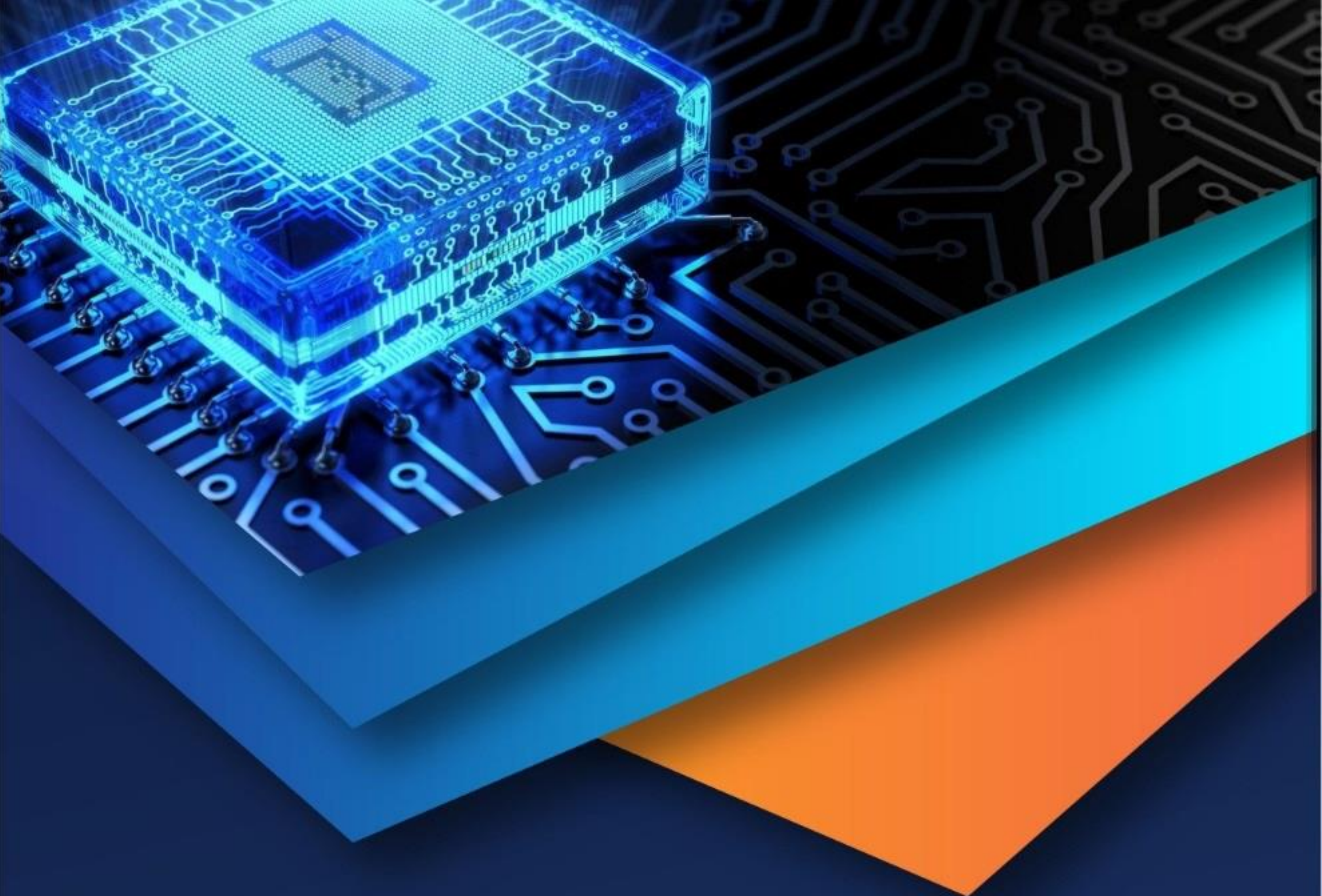

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