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A Survey on the State of Art Approaches for Disease Detection in Plants

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Abstract— Agriculture is the main factor for economy and contributes to GDP. The growth of the economy of many countries is based on agriculture. As a result, the yield factor, quality and volume of agricultural products, play a critical role in economic development. Plant diseases and pests have become a major determinant of crop yields throughout the years, as such illnesses in plants offer a serious threat and impediment to higher yields or production in the agriculture industry. As a result, From the outset, it becomes the major duty to correctly monitor the plants, to detect diseases thoroughly, and to determine methods of controlling or monitoring these plant diseases pests in order to achieve a higher rate of production growth and minimal crop damage. Using machine vision, deep learning methods and tools for extracting and classifying features, It could be possible to build a reliable disease detection system. Numerous researchers have created and deployed various ways for detecting plant diseases and pests. The potential of these methods has been examined in this work.

Keywords- Artificial neural network(ANN); deep learning; plant disease

I. INTRODUCTION

Machine learning's subset of deep learning, which employs specialized artificial neural networks. It's also a form of brain simulator. In the scientific world, this technique is quite popular. We used to have a lot of data but not enough processing capacity, but now we have a technology called Deep Neural Network that can analyse a lot of data [1]. Approximately 100 billion neurons in the human brain are linked by thousands of their neighbors. However, how these neurons are replicated in a computer remains a mystery. As a result, It creates a node-based or neuron-based artificial neural network [2]. It has input and output neurons, as well as many neurons coupled in the hidden layer.

In India, plant disease is mostly used in research. The diagnosis, or the recognition of symptoms, indications, and other indicators, necessitates both intuitive judgments and scientific approaches. Agriculture employs 70% of India's population, either directly or indirectly. As a result, the Indian economy is built on agriculture. Plant disease, of course, plays a main role in destroying plants and so diminishing agricultural goods both in terms of number and quality. Bacteria, viruses, and fungus are all responsible for plant illnesses that not only limit plant growth but can cause crop destruction [3, 4]. As per the study of grape plant [26] ,Black rot, Blight, Black measles, and Healthy are the various classes as per figure 1.

Figure 1. (a) Black rot affected (b) Blight affected (c)Black Measles affected (d) Healthy grape leaves

Study of plant illnesses involves the fields of examining visually detectable characteristics of plants, disease monitoring, and treatment options. In the beginning, most of the tasks of monitoring, diagnosing, and evaluating manual treatment of leaf and plant diseases was required by experts in these fields [5]. As a result, they necessitated a great amount of effort, a lengthy processing time, and a significant financial expenditure. In reality, precise diagnosis and Leaf disease classification can aid in prevention and reduction of agricultural drawbacks. Because different diseases affect different plant leaves, different methodologies must be utilized to identify various plant leaf diseases. Plant leaf diseases, for example, could be detected using image processing techniques.

Different approaches for detecting leaf diseases have been discussed in this study paper. Section 2 (Literature Review) shows study of different research papers, Section 3 is for comparative analysis of state of art methods using CNN, Section 4 (Methodology) tells about general way of flow by many researchers, Section 5 (Challenges) accumulates many problems faced by different researchers and in the last Section 6 (Conclusion) concludes the study.

II. LITERATURE REVIEW

The study of models applying deep learning to find various diseases in plant was released by Saleem et al. [1]. The following are some research holes: Early diagnosis of plant diseases is feasible using hyperspectral/multispectral images with effective DL architectures. For detecting and categorizing diseases, DL models must be improved. To identify plant diseases, a full empirical investigation is required, including data classes and sizes, learning rate, and illumination, among other things

X. Guan [2] integrated four CNN models. These are Densenet , Inception, Resnet and Inception Resnet to develop a method for detecting plant diseases. In total 31718 & 4540 pictures were used for training and validation respectively. Using this method 87% accuracy was achieved.

Kawasaki et al. [4] introduced a unique CNN-based plant disease detection model. Total 800 images were utilized in the training. This model correctly categorized disease and non-disease classes with 94.9 percent accuracy using a four-fold cross validation technique.

Existing plant disease detection systems have limitations and problems which were reported by Arsenovic et al. [5]. They released a fresh dataset with 79265 photos of leaves in natural settings. With 93.67 percent accuracy, researchers presented a unique plant disease categorization using a 2 different neural network design.

With accuracy of 98.29 percent and 98.029 percent for testing and training of all datasets, Jasim and Tuwaijari [6] employed CNN to identify and diagnose diseases in plant leafs. There are 20636 plant images in the Plant Village dataset, as well as 15 distinct leaf diseases , was used to focus on specific plant species such as tomatoes, peppers, and potatoes.

Nagaraju and Chawla [7] used deep learning models to automatically identify illnesses in hyperspectral pictures. For automatic disease identification, implementing new computer vision technology is insufficient, according to the researchers. The environment in which the input data is collected can have an impact on the illness classification analysis. Because disease symptoms aren't well defined, it's difficult to determine what constitutes healthy and sick sections. Because of the visual similarities in disease signs, present approaches must rely on variances to differentiate.

Amara et al. [8] used the LeNet architecture of the Convolutional Neural Network to present sigatoka and speckle type of banana leaf diseases, are classified using a deep learning approach. In terms of lighting, diverse backgrounds, and various resolutions, sizes, and orientations of real photographs, the outcome was successful.

Guo et al. [9] suggested a deep learning-based approach for plant disease diagnosis that increases precision, flexibility, and cost of training. This approach focused on recognizing and localizing damaged leaves using the network called RPN (region proposal network), followed by CV algorithm (Chan – Vese) to extract features. The final disease diagnosis accuracy with the transfer learning model was 83.57%..

Approaches for hyperspectral image processing in agricultural applications using machine learning classification were given by Hruska et al. [10]. Unmanned aerial vehicles now have access to hyperspectral sensors , allowing for the generation of large amounts of data while also proving to be useful in delivering correct results.

The Fuzzy C means approach for detecting leaf spots of cucumber was proposed and improved by Bai et al. [11] in complicated environments. This technique uses grey scale information from neighbors to improve noise filtering and overcome FCM's underuse of image pixel spatial information.

Barbedo [12] identified many significant problems, including the presence of complex backdrops that are difficult to separate, the lack of well-defined symptom boundaries, and uncontrolled recording circumstances that may exhibit picture analysis qualities that make it more difficult. Also the author offered potential remedies to few problems.

Brahimi et al. [13] used a huge dataset of 14828 photos of diseased tomato leaves. The learning algorithm features were extracted from CNN using raw photos automatically and with 99.18 percent accuracy. Here deep learning models (GoogleNet and AlexNet) were compared with shallow models.

Cruz et al. [14] proposed an approach for detecting OQDS on Xylella fastidiosa-infected leaves of Oleaeuropaea L with accuracy 98.6%. The new approach was using Transfer learning, a deep learning application that cope with a lack of appropriate training instances using the dataset, but their earlier work relied on well before GoogLeNet and AlexNet and GoogLeNet networks.

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DeChant et al. [15] established a 96.7 percent accurate technique on maize plants for identifying northern leaf blight lesions using pictures. The computational pipeline of Convolutional neural networks was utilized in this technique.

Durmus et al. [16] detected illness on the leaves of tomato plants using deep learning. The task was carried out in real time by algorithm-coded robots or by built sensors in a green house using close-up images of leaves. SqueezeNet and AlexNet designs were tested with accuracy of 94.3% and 95.65 percent respectively, in this study. The size of the SqueezeNet model was also discovered to be 80 times smaller than the AlexNet model.

Ferentinos [17] used simple leaf photos of healthy and ill plants to construct models of convolutional neural networks disease detection in plants. The model was trained using 87,848 photos from a dataset, combination of 58 classes and 25 plants of [plant, illness] pairs. A 99.53 percent success rate was achieved after training multiple model designs.

Using images collected from a camera with varying resolutions, a deep learning identification for pests and disease in tomatoes was given by Fuentes et al. [18]. Three families of detectors were employed to identify nine classes: Faster Region-based SSD i.e. Single Shot Multibox Detector, CNN and Convolutional Network based on region. They combined deep features using Residual Network (ResNet) extractors and VGG net. They demonstrated an approach for reducing the number of errors and improving accuracy during training by using class annotation and data augmentation.

Mindhe et al. [19] stated a deep learning tool for quickly detecting plant illnesses that anyone may use. This NN model was created to detect 14 different crop varieties as well as 26 different illnesses. The neural network ResNet 34 was employed, and the accuracy was 96.21 percent.

Lu et al. [20] suggested a method using deep CNN- for disease detection in rice plant leaves. CNN got training to identify ten rice diseases mainly using 500 images of healthy and injured rice plants. This model obtained 95.48 percent accuracy using 10-fold cross-validation, which is more precise and effective than the Convnet trained model.

Using CNN Ferreira et al. [21] detected weeds in soybean fields. Weeds are unwelcome plants that prevent soybean plants from growing, so they must be removed. Initially for the image dataset, a professional drone was used to take 15000 images of soil, broad leafs, grass and soybean weeds. The neural network was trained using the CaffeNet architecture. Using shape, colour, and texture feature extraction approaches, the outcomes of support vector machines , ConvNets, Random Forest and AdaBoost were compared. Using ConvNets the highest accuracy of 98% was achieved in identification of broadleaf and grass weeds.

Oppenheim and Shani [22] presented a deep CNN algorithm for potato illness classification. The system divides the tubers into five categories after training, including four damaged categories. The precision varies depending upto the ratio of training and testing. The maximum precision was 96.85%.with the 90 percent train – 10% test model, while the lowest was 83.21 percent with the 10 percent train – 90% test model.

Arshad et al. [23] demonstrated plant disease identification using ResNet50 with Transfer Learning for tomato, corn and potato. Total 16 classes can be identified of different plant diseases. Here 98.7% performance was achieved using ResNet50.

For 38 types of damaged plant leaves, Chellapandi et al. [24] compared deep learning and transfer learning models. VGG19, InceptionV3, ResNet50, Vgg16, InceptionResnetV2, DenseNet and MobileNet were the models used. Out of these models 99% accuracy was achieved with DenseNet.

Srinidhi et al. [25] used EfficientNet and DenseNet models to find out disease in Apple plant leaf. They classified into four categories the images of apple plant leaves: i.e. scab, rust, healthy and multiple disease. The apple leaf dataset is upgraded using Flipping , Canny Edge Detection and Blurring(data augmentation and picture annotation techniques).. The achieved accuracy was 99.8% and 99.75% using EfficientNetB7 and DenseNet respectively.

Akshai et al. [26] used CNN models like DenseNet, ResNet and VGG to classify the different plant diseases. They used CNN image based classification due to high success rate i.e. 98.27% using DenseNet.

Ashok et al.[27] proposed CNN based algorithm to identify disease in leaf of infected plant using hierarchical feature extraction (image processing approach) that map input image pixel intensities.The achieved accuracy was 98% .

Militante et al.[28] proposed model for early recognition and detection of 32 plant diseases using CNN. This system can recognize and detect various plant disease especially for apple, grapes , potato, corn, tomato and sugarcane. The achieved accuracy was 96.5%.

The comparative study of these papers over Dataset, Approaches used and Results obtained by the Researchers is shown in table 1.

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Table 1: List of research achievements using different deep learning approaches to identify disease in plants

S. No.	Researchers	Dataset	Approach	Result
1.	Xulang Guan [2]	Total 36258 leave images divided into 10 plant categories and 61classes of plant leaves.	Resnet, Inception Resnet, Densenet and Inception were combined of CNN type	87% accuracy.
2.	Kawasaki et. al [4]	Cucumber leaf images in total 800.	Used Caffe framework of CNN model	Average accuracy of 94.9%.
3.	Arsenovic et. al [5]	PlantVillage dataset of 79265 images.	Used traditional augmentation methods and generative adversarial networks.	93.67% accuracy.
4.	M. A. Jasim and J. M. Al-Tuwaijari[1]	20636 images of tomato, pepper and potatoes from PlantVillage dataset.	ConvNets variation of CNN model.	Accuracy of 98.29% and 98.029% for train set and test set respectively..
5.	Amara et. al [8]	3700 images from PlantVillage of banana categorized into healthy, black sigatoka and black speckle.	LeNet variation of CNN model.	Found accuracies for different combination of training and testing.
6.	Geo et al [9]	Dataset of 1000 leaves using Plant Photo Bank of China.	Using transfer learning model of deep learning.	83.57% accuracy.
7.	Bai et. al [11]	129 images of cucumber disease in diseased database of vegetable.	Updated Fuzzy C-means algorithm.	88% accuracy of segmentation.
8.	Brahimi et. al [12]	14,828 tomato leaves images of nine diseases.	Shallow models built on handcrafted features, like as AlexNet, GoogleNet, and others.	99.18% accuracy.
9.	Cruz et. al [14]	The PlantVillage database comprises 100 healthy olive tree leaves, 99 X. fastidiosa-positive leaves, and 100 X. fastidiosa-negative leaves.	CNN trained with stochastic gradient descent approach.	Olive Quick Decline Syndrome (OQDS) detection accuracy is 98.60 ± 1.47% in testing
10.	DeChant et. al [15]	Self-shot 1796 leaf photos of maize plants	Convolutional neural network computing pipeline.	96.75 accuracy for identifying NLB lesions.
11.	Durmus et. al [16]	Tomato leaves images from PlantVillage dataset.	AlexNet and SqueezeNet versions of CNN.	Accuracy of 95.65% and 94.3% with though testing for AlexNet andSqueeze Netrespectively.
12.	K. P. Ferentinos[17]	87,848 images of open database which contains 25 plant varieties of 58 distinct classes.	VGG and AlexNetOWTBn architecture of CNN model.	Classification accuracy is 99.53% using VGG model.
13.	Fuentes et. al [18]	5000 images of tomato from PlantVillage dataset under different environment conditions.	Region-based Fully Convolutional Network, Single Shot Multibox Detector, and Faster Region-based Convolutional Neural Network.	NA
14.	Mindhe et. al [19]	54,444 images from PlantVillage dataset	ResNet 34 version of CNN.	96.21%
15.	Lu et. al [20]	500 healthy and diseased images of rice	Multistage CNN model.	95.48% accuracy for 10 rice disease identification.
16.	Ferreira et. al [21]	15000 photographs of dirt, soybeans, broadleaf, and grass weeds	For training CaffeNet and for detection ConvNets architectures are used here.	98%.
17.	Oppenheim &Shani [22]	There are 2465 photos of potatoes.	VGG version of CNN model.	Categorization accuracy ranges from 83% to 96%.
18.	Arshad et. al [23]	PlantVillage dataset of tomato, potato and corn.	ResNet50 with transfer learning.	98.7% accuracy was achieved using ResNet50.
19.	Chellapandi et. al [24]	54,306 images of 14 types of plants from Git-Hub database of SP Mohanty.	Compared eight pre trained models with one self made model.	With DenseNet 99% accuracy was achieved.
20.	Srinidhi et al. [25]	3600 image dataset of apple leaf disease.	EfficientNetB7 and DenseNet models of CNN.	EfficientNet B7 and DenseNet achieved accuracy are 99.8% and 99.75% respectively.

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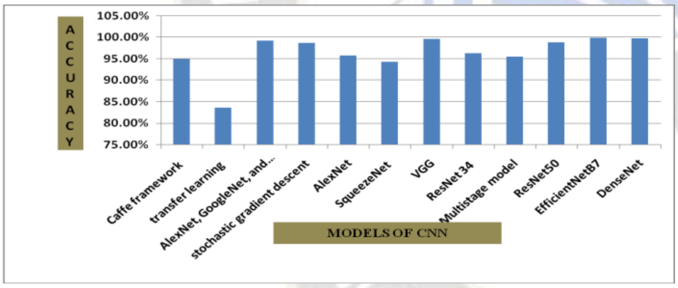
21.	Akshai et. al [26]	55,000 images of 14 species of plants from PlantVillage dataset.	Compared VGG, ResNet and DenseNet.	Accuracy of 98.27% using DenseNet
22.	Ashok et. al [27]	Tomato leaf dataset.	Hierarchical feature extraction based CNN algorithm.	98% accuracy.
23.	Militante et. al [28]	35,000 images of tomato, grape, corn, apple and sugarcane.	CNN based model.	96.5% accuracy.

III. COMPARATIVE ANALYSIS OF THE STATE OF ART METHODS

After reviewing the literature, we may compare the accuracy rates employed with different CNN models. The accuracy of diagnosis in plants using various methods may be observed in the bar graph. EfficientNetB7 has the highest accuracy of these algorithms, at 99.80% [25]. With 99.75 percent and 99.70 percent accuracy, DenseNet [25] and ResNet50 [23] came in second and third, respectively. Using CNN's transfer learning[9], SqueezeNet [16], and Caffe frameworks[4], we can examine 83.57 percent, 94.30 percent, and 94.90 percent of the lowest, second-lowest, and third-lowest accuracy, respectively. Figure 2 illustrates this. Figure 2. Accuracy Vs state of art methods analysis



IV. METHODOLOGY

A block diagram represented in Fig. 3 [6] shows Leaf Image Dataset, Image pre-processing, CNN model, Training , Testing and Disease detection of plant leaf.

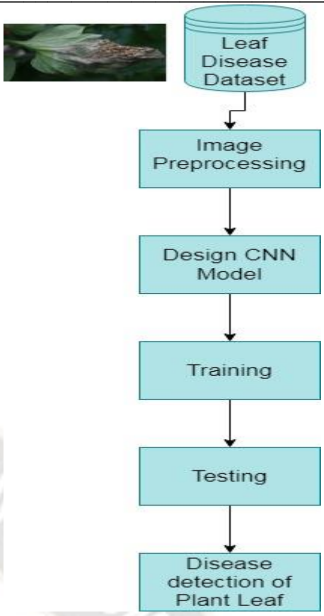


Figure.3. Methodology for Plant Leaf Disease Detection

A. Image pre-processing: The aim of pre-processing is to improve the quality of image so that we can analyse it more effectively. Pre-processing allows us to eliminate unwanted distortions and improve specific qualities that are essential for the application we are working on. Those characteristics could change depending on the application.

B. Design CNN model: In this paper CNN model is used to identify disease in plant due to its impressive accuracy and results.

C. Training: Training is the way by which learning of the system is performed. It is done using a part of dataset. It is an important part of the system over which the accuracy of the model depends.

D. Testing; Testing of model is performed with rest of images of dataset. If the accuracy is achieved with minimum threshold then this model will be used for unknown images.

Disease detection of plant leaf: After the completion of above mentioned steps i.e. image pre-processing, designing CNN model, training and testing , the final CNN model then can be used for real time data.

V. CHALLENGES AND FUTURE DIRECTION

Many researchers have expressed differing perspectives on this particular topic. These are given as:

- Detection of disease through large no of plants, using various techniques [6].
- In training model more classes of plant diseases can be added [24].
- Detecting different phases of disease in plant leaves [29].

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- Using a KNN classifier, detect plant leaf disease early [30].
- Analysis and diagnosis of plant leaf diseases through AI based classification and co-occurrence matrix [31].
- Using Random forest classifier and K-means approaches, locate cluster information and categorization of various infections. [32].
- Pre-processing and detection of plant leaf diseases (in Pomegranate , wheat &Brinjal) using neural network, image processing and K-means clustering methods [33, 34, 35].
- Early detection of potato plant leaves by SVM and machine learning [36].

Identification of plant disease and its classification using K-means and KNN through feature extraction like colour, texture, edges and morphology [37] etc.

VI. CONCLUSION

Plant disease detection is broken down into three steps: feature extraction, classification and segmentation. In general, a variety of deep learning and machine learning techniques have been extensively employed for precise disease, segmentation, and prediction. They've been used to extract features and classify them. Though these techniques outperformed older methods such as image processing in diagnosing plant illnesses, they also had drawbacks such as computer complexity, longer execution times, and greater prices. However, It is critical to develop a better efficient and effective technique for detecting plant diseases early on that takes less time and money to implement. As a result, more effort will be needed in the future to overcome existing challenges. Additionally, while creating efficient and reliable methods for early automatic identification of plant diseases, upgrading current work, which might be extended to identify all conceivable diseases connected to plants and plant leaves. In this particular topic of interest, there is clearly enough room to expand future studies and develop future work.

REFERENCES

[1]. Saleem, M.H. ,Potgieter, J., and Arif, K. M. (2021) " Plant disease detection and classification by deep learning," Plants, p.468.

[2]. Guan, X. (2021) "A Novel Method of Plant Leaf Disease Detection Based on Deep Learning and Convolutional Neural Network," 6th International Conference on Intelligent Computing and Signal Processing (ICSP), pp. 816-819, doi: 10.1109/ICSP51882.2021.9408806.

[3]. Barbedo, J.G.A (2019) " Plant disease identification from individual lesions and spots using deep learning," Biosystems Engineering, pp.96-107.

[4]. Kawasaki, Y., Uga, H., Kagiwada, S., and Iyatomi, H. (2015)" December. Basic study of automated diagnosis of viral plant diseases using convolutional neural networks," International symposium on visual computing, pp. 638-645.

[5]. Brahimi, M. , Arsenovic, M., Laraba, S. , Sladojevic, S., Boukhalfa, K., and Moussaoui, A.(2017) "Deep learning for plant diseases: detection and saliency map visualization," In Human and machine learning, pp. 93-117

[6]. Jasim, M.A., and Al-Tuwaijari, J.M.(2020) " Plant leaf diseases detection and classification using image processing and deep learning techniques," International Conference on Computer Science and Software Engineering (CSASE), pp. 259-265.

[7]. Nagaraju, M. , and Chawla, P. (2020)" Systematic review of deep learning techniques in plant disease detection," International Journal of System Assurance Engineering and Management, pp.547-560.

[8]. Amara, J. ,Bouaziz, B., and Algergawy, A. (2017)"A deep learning-based approach for banana leaf diseases classification," Datenbanksystemefür Business, Technologie und Web.

[9]. Guo, Y. , Zhang, J., Yin, C., Hu, X., Zou, Y., Xue, Z., and Wang, W. (2020)" Plant disease identification based on deep learning algorithm in smart farming," Discrete Dynamics in Nature and Society.

[10]. Hruška, J., Adão, T., Pádua, L., Marques, P., Cunha, A., Peres, E., Sousa., A., Morais, R., and Sousa, J.J.(2018)"Machine learning classification methods in hyperspectral data processing for agricultural applications, "International Conference on Geoinformatics and Data Analysis pp. 137-141.

[11]. Bai, X., Li, X., Fu, Z. ,Lv, X., and Zhang, L. (2017)" A fuzzy clustering segmentation method based on neighborhood grayscale information for defining cucumber leaf spot disease images," Computers and Electronics in Agriculture, pp.157-165,doi: 10.1016/j.compag.2017.03.004.

[12]. Barbedo, J.G.A.(2016)"A review on the main challenges in automatic plant disease identification based on visible range images," Biosystems engineering, pp.52-60.

[13]. Brahimi, M., Boukhalfa, K., and Moussaoui, A.(2017) "Deep learning for tomato diseases: classification and symptoms visualization," Applied Artificial Intelligence , pp.299-315, doi: 10.1080/08839514.2017.1315516.

[14]. Cruz, A.C., Luvisi, A., De Bellis, L., and Ampatzidis, Y. (2017) " X-FIDO: An effective application for detecting olive quick decline syndrome with deep learning and data fusion," Frontiers in plant science, pp.1741, doi:10.3389/fpls.2017.01741.

[15]. DeChant, C. ,Wiesner-Hanks, T. , Chen, S., Stewart, E.L., Yosinski, J. , Gore, M.A., Nelson, R.J., and Lipson, H.(2017)" Automated identification of northern leaf

blight-infected maize plants from field imagery using deep learning," Phytopathology, pp.1426-1432.

[16]. Durmuş, H. ,Güneş, E.O., and Kırcı, M.(2017)" August. Disease detection on the leaves of the tomato plants by using deep learning," 6th International Conference on Agro-Geoinformatics, pp. 1-5.

[17]. Ferentinos, K.P. (2018)" Deep learning models for plant disease detection and diagnosis," Computers and electronics in agriculture, pp.311-318.

[18]. Fuentes, A.., Yoon, S., Kim, S.C, and Park, D.S. (2017) "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition," Sensors, pp.2022.

[19]. Mindhe, O. ,Kurkute, O. , Naxikar, S. , and Raje, N. (2020) " Plant disease detection using deep learning," International Research Journal of Engineering and Technology, pp. 2497-2503.

[20]. Lu, Y. , Yi, S., Zeng, N., Liu, Y. , and Zhang, Y.(2017)" Identification of rice diseases using deep convolutional neural networks," Neurocomputing, pp.378-384.

[21]. Ferreira, A. dos Santos, Freitas, D.M., Silva, G.G. da, Pistori, H. , and Folhes, M.T.(2017) " Weed detection in soybean crops using ConvNets," Computers and Electronics in Agriculture, pp.314-324.

[22]. Oppenheim, D., and Shani, G.(2017)" Potato disease classification using convolution neural network," Advances in Animal Biosciences, pp.244-249.

[23]. Arshad, M. S., Rehman, U. A., and Fraz, M. M. (2021) "Plant Disease Identification Using Transfer Learning," 2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2), pp. 1-5, doi: 10.1109/ICoDT252288.2021.9441512.

[24]. Chellapandi, B. ,Vijayalakshmi, M. , and Chopra, S. (2021) "Comparison of Pre-Trained Models Using Transfer Learning for Detecting Plant Disease," 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS), pp. 383-387, doi: 10.1109/ICCCIS51004.2021.9397098.

[25]. Srinidhi, V. V. ,Sahay, A., and Deeba, K.(2021) "Plant Pathology Disease Detection in Apple Leaves Using Deep Convolutional Neural Networks : Apple Leaves Disease Detection using EfficientNet and DenseNet," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), pp. 1119-1127, doi: 10.1109/ICCMC51019.2021.9418268.

[26]. KP.,A., and Anitha, J.(2021) "Plant disease classification using deep learning," 2021 3rd International Conference on Signal Processing and Communication (ICPSC), pp. 407-411, doi: 10.1109/ICSPC51351.2021.9451696.

[27]. Ashok, S., Kishore, G., Rajesh, V. ,Suchitra, S., Sophia, S. G. G., and Pavithra, B.(2020) "Tomato Leaf Disease Detection Using Deep Learning Techniques," 2020 5th International Conference on Communication and Electronics Systems (ICCES), pp. 979-983, doi: 10.1109/ICCES48766.2020.9137986.

[28]. Militante, S. V. , Gerardo, B. D., and Medina, R. P.(2019) "Sugarcane Disease Recognition using Deep Learning," 2019 IEEE Eurasia Conference on IOT, Communication and Engineering (ECICE)" , pp. 575-578, doi: 10.1109/ECICE47484.2019.8942690.

[29]. Sladojevic, S. ,Arsenovic, M. ,Anderla, A., Culibrk, D., and Stefanovic, D.(2016)" Deep neural networks based recognition of plant diseases by leaf image classification," Computational intelligence and neuroscience.

[30]. Vaishnnave, M.P. , Devi, K.S., Srinivasan, P., and Jothi, G.A.P.(2019)" Detection and classification of groundnut leaf diseases using KNN classifier," IEEE International Conference on System, Computation, Automation and Networking (ICSCAN), pp. 1-5.

[31]. Khitthuk, C., Srikaew, A. ,Attakitmongcol, K. , and Kumsawat, P.(2018)" Plant leaf disease diagnosis from color imagery using co-occurrence matrix and artificial intelligence system," International Electrical Engineering Congress (iEECON),pp. 1-4.

[32]. Jhuria, M. , Kumar, A., and Borse, R. ,Anand, R. ,Veni, S. , and Aravinth, J.(2013)" An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method," International conference on recent trends in information technology (ICRTIT) , pp. 1-6.

[33]. SK Hasane Ahammad, , D. K. J.Saini, Phishing URL detection using machine learning methods, Advances in Engineering Software,Volume 173, 2022,103288, ISSN 0965-9978, https://doi.org/10.1016/j.advengsoft.2022.103288

[34]. Yadav, P, S. Kumar, and D. K. J.Saini. "A Novel Method of Butterfly Optimization Algorithm for Load Balancing in Cloud Computing". International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 8, Aug. 2022, pp. 110-5, doi:10.17762/ijritcc.v10i8.5683.

[35]. Jang Bahadur, D. K. , and L.Lakshmanan. "Enhancement of Quality of Service Based on Cross-Layer Approaches in Wireless Sensor Networks". Journal of Theoretical and Applied Information Technology ISSN: 1992-8645, 15th October 2022. Vol.100. No 19 ,

[36]. Jang Bahadur, D. K. , and L.Lakshmanan. "Virtual Infrastructure Based Routing Algorithm for IoT Enabled Wireless Sensor Networks With Mobile Gateway". International Journal on Recent and Innovation Trends in Computing and Communication, vol. 10, no. 8, Aug. 2022, pp. 96-103, doi:10.17762/ijritcc.v10i8.5681.

[37]. Shailesh Kamble, Dilip Kumar J. Saini, Vinay Kumar, Arun Kumar Gautam, Shikha Verma, Ashish Tiwari & Dinesh Goyal (2022) Detection and tracking of moving cloud services from video using saliency map model, Journal of Discrete Mathematical Sciences and

Cryptography, 25:4, 1083-1092, DOI: 10.1080/09720529.2022.2072436

[38]. Jang Bahadur, D. K. , and L.Lakshmanan “Improve Quality of Service in Optimization of Job Scheduling using a Hybrid Approach” Xi'an Shiyou Daxue Xuebao (Ziran Kexue Ban)/ Journal of Xi'an Shiyou University, Natural Sciences Edition ISSN:1673-064X Vol: 65 Issue 01 | 2022 DOI 10.17605/OSF.IO/DW57E

[39]. Jang Bahadur, D. K. , and L.Lakshmanan “Wireless Sensor Network Optimization for Multi-Sensor Analytics in Smart Healthcare System” Specialusis Ugdymas, ISSN NO: 1392-5369 Vol. 1 No. 43 (2022)

[40]. Saini D., An IoT and fog computing enabled intelligent health care monitoring system to the cloud storage, Turkish Journal of Computer and Mathematics Education (TURCOMAT) Vol12 No10(2021), 2085-2091(ISSN: 1309-4653)

[41]. Saini D, Novel Approach of Data Transformation for Privacy Assurance using Optimization of Genetic Algorithm, Design Engineering (Toronto) ISSN No:0011-9342 Scopus Indexed

[42]. D. K. Jang Bahadur Saini, P. Patil, K. Dev Gupta, S. Kumar, P. Singh and M. Diwakar, "Optimized Web Searching Using Inverted Indexing Technique," 2022 IEEE 11th International Conference on Communication Systems and Network Technologies (CSNT), 2022, pp. 351-356, doi: 10.1109/CSNT54456.2022.9787680.

[43]. D. Siddharth, D. K. J Saini, P. Singh, An Efficient Approach for Edge Detection Technique using Kalman Filter with Artificial Neural Network, International Journal of Engineering, Transactions C: Aspects Vol. 34, No. 12, (2021) 2604-2610

[44]. Anand, R. ,Veni, S. , and Aravinth, J.(2016)” An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method,” International conference on recent trends in information technology (ICRTIT) , pp. 1-6.

[45]. Elhassouny, A. , and Smarandache, F.(2019)” Smart mobile application to recognize tomato leaf diseases using Convolutional Neural Networks,” International Conference of Computer Science and Renewable Energies (ICCSRE),pp. 1-4.

[46]. Gaikwad, V.P. , and Musande, V.(2017)” Wheat disease detection using image processing,” 1st international conference on intelligent systems and information management (ICISIM) pp. 110-112.

[47]. Islam, M. ,Dinh, A., Wahid, K., and Bhowmik, P.(2017)” Detection of potato diseases using image segmentation and multiclass support vector machine,” IEEE 30th canadian conference on electrical and computer engineering (CCECE), pp. 1-4.

[48]. Pawar, R. , and Jadhav,A. (2017) ” Pomogranite disease detection and classification,” IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI), pp. 2475-2479.