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A Hybrid Approach of Deep Learning and Optimization for Medical Plant Recognition and Classification

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Abstract— *Immense popularity has been gained by Medicinal herbs in the pharmaceutical industry due to their having least amount of side effects and their cost becoming less compared to the present-day pharmaceuticals. Consequent to these inferences, many individuals have shown a potential fascination towards the subject of automated medicinal plant identification. There are multiple aspects for advancement in the design of a powerful classification having the reliable capability of identifying medicinal herbs in real - time. The efficiency and robustness of several deep learning and optimization approaches for plant recognition and classification that use leaf images being in prevalence in the last few of years are studied in this survey. In addition, the analysis of their benefits and setbacks are discussed. For specific deep learning and optimization techniques, the survey discusses about the image processing approaches, which are used for the leaf identification and retrieval of important leaf features. Based on common plant traits including shape, vein, texture, and a combination of various parameters, the efficacy of these deep learning and optimization techniques during the identification of leaf photos is categorized. Several researches highlight on plant leaf based recognition, as it can be easily accessed in comparison with other plant parts. In this study, an analysis on the techniques and classifications helpful in identifying the different plants lately has been explained. In addition, this survey consists of a comparative analysis of those techniques based on the accuracy that the classifiers achieve. To comprehend and analyze the methodologies in the form of a roadmap, this survey will be helpful to those who are new to the field of research.*

Keywords— *Medicinal Plants, Robust Classifier, deep learning and optimization techniques, Multiple Features and Leaf Images*.

I. Introduction

There are numerous plant species existing in this huge world, which constitutes a remarkable plethora of many useful properties [33]; others are slowly on the verge of dying, and still,feware dangerous to mankind. Even with the style that plants have been the elementary resource for mankind, still they are rudimentary for all the lifestyles that have emerged [1]. It is crucial to evaluate and collect as many plants as you can in order to make the most of them and protect the plant species. Perception of dark plants relies hugely on the general learning that a master botanist endows. The optimal process for successful and possible perception of plants involves a manual-set up together approach considering the morphological characteristics [2]. In this way, an elaborate section of the technique was developed in comprehensively understanding these plant species based on data gathering and skills of humans. Irrespective of this, this technique of manual confirmation is also difficult and feared much [3]. Hence, many experts have focused on helping the transformed course of action of plants with respect to their physical properties. Structures have evolved to the point where they employ an increasing number of challenges to automate the process of amended request; nonetheless, the methodologies are extremely near. The basic components of these techniques include gathering the leaves, doing some preliminary preparation to identify their unique characteristics, planning the leaves, filling the database, preparing for affirmation, and, in the end, reviewing the results. The stem, flowers, petals, seeds, and even the whole plant may be utilized in an electronic approach, despite the fact that leaves are commonly used for plant conspicuous verification. on-homegrown professionals may employ a mechanized plant recognizing evidence structure to swiftly and accurately identify plant species [4]. Plant classification is essential to the science behind organized features research and has a broad variety of applications anticipated in agriculture and health[5]- [7]. As compared to methodologies like cell science or molecule biology, the leaf image classification strategy is the most preferred option for leaf plant order. Previous experts attempted to distinguish the plant based on its image shade histogram, edge highlights, and surface data. Using neural networks, research has been done so far to classify plants as trees, shrubs, and herbs [8]. Only by paying attention to the tiniest details, a woman's effort has improved. An essential component of plant arrangement is the leaf-recognizable evidence (9). Plants may reliably be harvested using different plant parts. There are items that expand multidimensional nature in three dimensions. A fundamental and easier method to understand the plant order is to see each leaf as an individual. Every leaf image is categorized using multiple related techniques. Using test images of a variety of leaves, a knowledge base is created. Each illustration of a leaf is linked to the corresponding plant details [10].

In the last few decades, many approaches have been introduced. In this survey, the deep learning and optimization techniques are employed for plant disease identification, inspired by the progress of deep learning and optimization techniques and their application practically. Elaborate search of the benchmark literature has provided no proof that researchers

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have delved deep into deep learning topic for plant diseases identification using the leaf images.

II. Related Works

Deep learning and optimization-based methods are already widely used in benchmark approaches for recognizing plant species. Convolutional neural network (CNN), for example, are employed in deep learning-based approaches to extract information from and classify photographs of leaves.

A. Deep learning based techniques for plant species identification and classification

Riaz et al., [11] proposed a plant identification approach that uses multipath multi deep convolutional network. For the purpose of identifying different types of plant images, a multi-path multi-deep convolutional network is given in this research, and therefore the resulting model represents the image in a much remarkable manner compared to conventional CNN. Elaborate experimental analysis on standard plant datasets have observed that with no pre-trained models used, the proposed shallow network demonstrates highly power-packed performance with respect to recognition of plant species. Experiment findings indicate that multi-path multi CNN are more efficient at learning unique characteristics. This research makes use of two datasets such as Leaf Snap and Malaya Kew and accuracy of 99.38% and 99.22% is achieved correspondingly.

Manasa et al, [12] the usage of the watershed method and a convolutional neural network for plant identification. Several pre-processing stages are applied to the input image, in the scenario where the leaf has several leaves surrounding it, and watershed algorithm is applied for distinguishing every leaf. The pre-processing of the images takes place during the training phase, and the characteristics that are extracted are classified. During the testing stage, the images, which are not considered training goes through processing and validated by sending them to the neural network. To solve the classification issue in this model, a pre-trained convolutional neural network is used. The network is successfully trained, resulting in a validation accuracy of 100% thanks to the Stochastic Gradient Descent method with momentum. Network performance assessment confusion matrices. Plant sizes vary. Due to different growing circumstances, the same flora has different sizes.

Based on this Hu et al., [13] for plant leaf recognition at various sizes, a multi-scale fusion convolutional neural network (MSF-CNN) was suggested. Initially, the input image is down-sampled into many low-resolution images. The MSF-CNN framework then learns features at different depths from these images. With the help of a concatenation function, which combines the feature maps learnt on multiple scale images from a channel viewpoint, the feature combination between two different scales is achieved at this stage. The ultimate feature that may be used to estimate the plant species shown in an input image is obtained through the final layer of the MSF- CNN, which combines all of the information from the several different sources. The approach that has been suggested is evaluated using two different datasets, namely Malaya Kew and LeafSnap.

Amara et al. [14] performed tests using a subset of the Plant Village dataset that included 3700 images of banana leaves. The lighting, size, backdrop, attitude, and orientation of the scene that was chosen for the image capture did not match the requirements established by Mohanty et al. and Amara et al. They used the LeNet architecture and demonstrated the greatest classification accuracy, which was 96%.

Yadav et al. [15] recommended an automated segmentation system, a deep learning model for illness detection, and bacteria from peach leaves. An overall classification accuracy of 98.75% is shown by experimental analysis performed on both lab data sets and actual farming. In [16], using transfer learning and InceptionResNetV2 as its foundation, authors propose disease prediction from rice leaves.

Chen et al. [17] further demonstrated the use of transfer learning to identify illnesses in rice plants. Using an attention technique to learn inter-channel correlations, MobileNet-V2 was chosen as the backend. An overall accuracy of 99.67% was achieved when compared to other widely used, freely available data sets. In order to recognize the plant leaf disease, deep transfer learning is rapidly getting popular.

In [18], Three CNN models Verdict, VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 are used in the automated disease diagnosis method that the authors suggested for the Vigna Mungo plant. When VirLeafNet-3 was utilized in an experimental study on a manually created data set, the accuracy was 97.40%.

HulyaYalcin (2016) [19] presented a CNN model for identifying the kind of plants based on the image sets acquired from smart agro-stations. The design is taken in the form of a preprocessing phase to eliminate the image features. The vital aspects to be focused are configuration of the CNN design and breadth since they have an influence over the identification potential of neural network model. 16 types of plants were used and their comparison is done with other techniques; it is found from the initial observations that the classification performance of the CNN based approach was outstanding compared to other schemes.

AmalaSabu (2017) [20] shows how difficult it is to solve the computer vision challenge of universal leaf identification. Studies in botany and other fields of study in various parts of society, such as medicine, might benefit from an efficient leaf recovery strategy for Ayurveda plants. It is possible to distinguish the leaf pictures. The various techniques are studied and the classifications for leaf recognition are carried out.

Lee, S.H., (2017) [21] The use of leaf attributes as an input and convolution has also been explored in relation to one of the images of plant leaves that was obtained. A neural network is used to recognize patterns in plant depth information. CNN was primarily used only for the enhanceddepiction of the features and to effectively study the Leaf organisms DN (Deconvolutional Network) is brought into use. It facilitates much better identification of plant leaves and their populations.

Ghazi, M.M., (2017) [22] to define the identification of the diverse plants, three transfer learning models were employed. LIFECLEF 2015 was used to examine the Network. These three models conducted their study using Google Net, VGGnet, and Alex Net.

Barbedo, J.G. (2018) [23] analyzed the main variables influencing the model and effectiveness of plant pathology-related deep neural networks, as well as the in-depth examination of the topic, showing the advantages and drawbacks, contributing towards strong inferences on plant pathology [8].

Zhu, X., (2018) [24] utilizes CNN (Complex Background) for identifying the small objected plant leaves. The proposed technique suggested the implementation of sample-normalization based on V2, due to which the accuracy of Region CNN is improved. The final generation of images is produced by retrieving the residual images from the quality image sub-samples, which are separated into hundred. It is found by the application of this technique that it is much quicker compared to traditional region convolutional neural network.

Garcia-Garcia (2018) [25] proposed a deep learning approach to pay attention towards high occupancy classification. The subjects of deep learning are reviewed. This provides the necessary relevant information on deep learning for the future goals.

Kaya, A., Keceli. (2019) [26] recommended transfer Learning for Plant Classification for Deep Learning. On the basis of DNN for four current datasets, this study examines the influence of four distinct transference training models on plant categorization. Finally, Transfer Learning underpins plant categorization self-prediction and analysis, according to their theoretical studies. RNN-CNN uses End-to-End, Fine modulation, Cross Dataset Fine modulation, Deep Integrated Fine tuning, and Classification formats.

Wei Tan, et al [2018] [27] presented D-Leaf, which is an innovative CNN-based mechanism. Pre-trained AlexNet, fine-tuned AlexNet, and D-Leaf were three separate CNN algorithms that were used to pre-process the leaf images and extract the features. Support Vector Machine (SVM), Artificial Neural Network (ANN), k-Nearest-Neighbor (k-NN), Nave-Bayes (NB), and CNN were the five machine learning techniques that were taken into consideration for the categorization of these characteristics. To calculate the morphological characteristics according to the standard, a traditional morphometric method based on Sobel segmented veins was used. The testing accuracy of the D-Leaf model is 94.88%, which is higher than both the standard AlexNet (93.26%) and refined AlexNet (95.54%) models. Moreover, CNN models outperform state-of-the-art morphometric assessments (66.55%) in terms of performance. It is noted that the ANN classification model adopts appropriately to the characteristics that CNN gives.

Grinblat et al [2016] [28] deep CNN were used to identify plants by leaf vein patterns. White beans, red beans, and soybeans were emphasized by the writers. CNN applications, popular in advanced systems, eliminate the need for custom feature extractors. Also, the efficacy of the stated model is hugely enhanced when this deep learning model is used. It is found this model yields the reasonable accuracy. Finally, intriguing vein patterns can be found through the testing of produced models applying a basic visualization tool.

Zhang et al. [29] have developed two modified versions of the widely used convolutional neural network model for the recognition of nine different varieties of maize leaves. By using Google Net and Cifar10, the accuracy of the identification evidence is improved, coming in at 98.9% and 98.8%, respectively. The combined ensemble of pooling activities, a suitable expansion of a Relu limit and dropout efforts, and various model parameter modifications may boost acknowledgement accuracy. The course of action figuring is employed to produce a variety of test situations with solid power if the train test set is 80-20 exactly.

B. Optimization based methods for plant species identification and classification

Ghasab et al [2015] [30] presented a smart approach providing ant colony optimization (ACO) in the form ofa leaf image-based attribute decision-making method for plant species identification. The ACO technique is helpful in expediting into the attribute search space so that the highly distinguishing features for the detection of different species is obtained. From the leaf images, a collection of potential characteristics is extracted to create a feature search space, including form, morphology, texture, and color. For the purpose of classifying species, SVM uses the chosen characteristics. To demonstrate the effectiveness of the system, about 2050 leaf images were acquired from two separate plant datasets, such as FCA and Flavia. After an examination of the report, it was discovered that the ACO-based technique achieves an average accuracy of 95.53%, indicating that the suggested algorithm has the potential to be used in the categorization of a variety of plant species.

Zhao et al [2015] [31] introduced an innovative means to identify the plants because of the geometry that their leaves portray. In contrary to earlier researches whose focus has been on simple leaves, the proposed approach is capable of rightly identifying both simple and compound leaves. A novel attribute capable of recording the global and local shape data individually, which lets them to be evaluated one by one during classification is proposed. Also, it is claimed that when differentiating between two leaves, it is desirable to "count" the amount of various shape patterns rather than matching the obtained shape attributes points sequentially. The counting-based shape descriptor discriminative is superior for classification and efficient in computation and storage. The system outperforms benchmark approaches in recognition accuracy, throughput, and storage requirements on five leaf image datasets.

Sabu et al [2017] [32] proposed a computer vision method for identifying the species of Ayurveda medicinal plants found in India's Western Ghats. The suggested methods combine a k-NN classifier for classification with a collection of SURF and HOG properties extracted from leaf images. Experiments have shown that the inferences are found to be sufficient to develop apps for practical application.

Siravenha and Carvalho [2015] [33] examined the contour-centroid distance's discriminative power in the Fourier frequency domain while ensuring specific invariance as a method for the identification and classification of plants based on their leaf shapes. In addition to this, the influence that different feature selection methods have on the classification accuracy is investigated. Accuracy of 97.45% was achieved by the combination of a collection of feature vectors in the principal components space and a feed forward neural network.

Lehoucq and Rowe (2016) [34] have presented an approach for the identification of compound leaves making using concentric circles to study the leaf's exterior to include shading patterns in double images, and in this case, dividing the patterns to distinguish complex leaves. For locality generating approach using seed focuses and grouping them with similar qualities that aid highlight extraction procedure, the Radial Basis Function neural system is more efficient. Around 96% of Flavia informative index leaves are estimated by the method. At that point, it's done with a few Internet leaf images with 100% accuracy.

Chouhan et al. [35] discussed that the natural leaves illness is decided by the classification of plants applying Bacterial Foraging Optimization Based Radial Basis Function (BRBFNN). Radial basis function neural network (RBFNN) is used to analyze the structure of leaves based on their disease, and bacterial foraging optimization (BFO) is then used to analyze the speed and precision of the regions. By seeking for and collecting seed focuses with essential characteristics for the highlight extraction method, the district developing calculation increases the system's output.

Heba F. Eid, (2016) [36] recommended an innovative mechanism for differentiating every kind of plant leaf. The PSO technique was used in order to extract the relevant information from the leaf images. After then, a technique called information acquisition and discretization was used in order to choose the most important characteristics from the data that had been gathered in an earlier stage. The model was verified using the publicly accessible Flavia dataset and compared to many excellent classification methods, showing an improvement in detection accuracy.

Vijai Singh et al., (2016) [37] proposed an image division method for mechanical exams and plant leaf disease labeling. This research presents a literature review on labeling techniques, particularly in the chosen research area. Genetic Algorithm (GA) is utilized for segmenting the images. The given algorithm was experimented on few fruit species and is found to be an effective algorithm for the identification and labeling of the fruits under particular disease group.

Sethy et al., (2019) [38] have put forward an innovative scheme that highlights on diseases, and it makes the most use of the advantages of the K-means, multi class SVM, and PSO algorithms. which are often observed in rice leaves. Features are extracted through GLCM. The SVM classifier was useful in correctly identifying the illness, and the use of the PSO method led to an increase in the identification accuracy achieved. It was determined that 97.91% accuracy was achieved.

Kaur et al., (2017) [39] PSO algorithm and SVM algorithm were used to provide a combinational improvement for identifying and classifying the unhealthy plant. The suggested method made use of the information that was created for four diseases, including Alternaria alternative, bacterial blight, cercospora leaf spot, and bacterial blight. The ratio of the disease spread in the plant leaf is decided during the labeling process.

Chandaet al., (2019) [40] developed a classification of plant leaves where the weight value is evaluated using a back-propagation methods initialized to the neural network connections and later these weights are optimized applying PSO to get over the common drawback of slipping into local optima and misclassification, commonly seen in neural networks. The images pertaining to the leaves infected because of diseases resulting due to fungi and bacteria were considered in the experimental study and it yields an accuracy of 96.2%.

C. Hybrid Optimization Techniques for Plants Classification

Optimization implies selecting the 'best' mechanism among the different choices. Based on the scenario, the optimal path is selected. During optimization, the primary aim could be just the reduction in the production expenditure in addition to the maximization of the production efficiency. The procedure of optimization algorithm executes in a repeated manner and its compares different solutions until an optimum or a reasonable solution is attained. Deterministic and stochastic algorithms are the two key types of optimization algorithms that are now widely used. As the name suggests, deterministic applies a set of rules to the stochastic algorithm's randomization to transfer one answer to another. Few hybrid artificial neural networks with optimization techniques like Genetic Algorithm (GA), Ant Bee Colony (ABC), Differential Evolution (DE), Group Search Particle Swarm Optimization (GSPSO), Firefly method, and others are used for standard data sets and real-time plant classification experiments. A revolutionary Swarm-based hybrid algorithm AC-ABC Hybrid optimizes feature selection by fusing Ant Colony and Artificial Bee Colony (ABC) algorithms. The time-consuming global search creates the key answers, and the hybridization of bee algorithms prevents ants from stagnating. In the suggested algorithm, ants weigh exploitation carried out by bees, which change the feature subsets that the ants create in the form of their food sources, while deciding on the best ant and best feature subset. Thirteen standard data sets from the University of California, Irvine (UCI) are used by the algorithm for the evaluation. The effectiveness of the suggested approach in increasing classification accuracy and feature selection is fairly high, as shown by the results of the studies [41].

C. S. Sumathi put forward the application of Genetic Algorithm for the network weight optimization while training, Optimization of digital analysis is made possible. Differential Evolution (DE) uses NPD-dimensional parameter vectors for concurrent direct search. Selection, mutation, and crossover. Genetic Algorithms, which are iterative, maintain a population of structures that are potential solutions for domain-specific issues. Reproduction, crossover, and mutation provide new potential solutions. MATLAB extracts features. The extracted characteristics trained classification algorithms. Experimental results show that the hybrid DE-GA method improves neural network classification accuracy. Optimized Differential Evolution and GA optimization techniques determine classification accuracy [42]. Genetic weight optimization-based neural network algorithms are used to classify damaged plant leaves more accurately. Contrast, correlation, energy, homogeneity, and leaf area are considered characteristics.

Preprocessing and leaf feature extraction are done on the segmented image. During a given number of iterations, genetic algorithm revises neural network weight. Lastly, the classification accuracy of sick plant leaves in classes 2, 3, and 6 is analyzed. Genetic weight optimization-based neural network systems of sick plant leaf undergo categorization to increase classification accuracy [43].

Stephen Gang Wu et al. developed a unique hybrid mechanism of PSO and IWD (intelligent water drop) fused to be the hybrid IWD-PSO strategy for optimizing ANN for Iris classification. IWD/PSO [44]. It is validated in terms of accuracy and SSE when compared with IWD and PSO separately taking into consideration the number of hidden layers and also the hidden nodes, as shown by the results of the model, which confirm the superior performance of the hybrid IWD-PSO technique. The results of the model also confirm the superiority of this technique. While using this hybrid algorithm, it is possible to acquire enhanced search results. Techniques such as the IWD, PSO, and IWD-PSO are used in the process of optimization for Ann. According to the findings of the comparison, IWD-PSO-ANN performs much better in terms of SSE and accuracy rate than its predecessors, IWD-ANN and PSO-ANN. It has been shown that the hybrid IWD-PSO technique that was presented is one that, if implemented in the form of an optimization scheme for ANNs, can provide desired results. The research also shows that comparing optimization strategies improves neural network performance. In the future, this hybrid IWD-PSO approach can solve additional optimization issues.

Yeni Herdiyeni et al. recommended a hybrid method called GSPSO that relies on PSO and uses a PSO model and GSO model [45]. PSO is part of GSO. The fuzzy classifier is derived from fuzzy set theory using many-valued logics. In addition, for the classification step, a Multilayer Perceptron Neural Network (MLPNN) paradigm is utilized. These kinds of approaches are chosen with the intent of providing a quicker training to find solutions to the problems involving pattern identification applying the numerical optimization approach. As a result, the hybrid GSO technique has been used in this research to select an ideal and deterministic feature subset. This algorithm was developed in response to the social search behavior of animals in the world, which has since been shown to be quite violent. Any PSO model may help locate a decent search space with a high likelihood of containing a point of global optimization using GSPSO method. This method involves the GSO searching its local search space with rangers' assistance.

Jixiang Du et al. recommended a hybrid technique, made up of artificial neural networks and PSO focused at categorization. According to the results of the research, image capture was implemented in four farms that had Agria potato combination under regulated illumination conditions provided by white LED lamps[46]. In order to choose the six characteristics that are absolutely necessary for distinguishing potato plants from weeds, a decision tree is used to analyze the differences between the two.For the purpose of testing the proposed model, the database was divided into two groups: (1) training data, which were useful in training the hybrid ANN PSO, and (2) test and validation data, which were used for the assessment of the network. Finally, ANN-PSO classifies inputs as potato plants or weeds. Bayesian classifiers compare as well.

In [47] an innovative fruit-classification tool is presented. The technique proposed comprises of multiple processes: Firstly, a four-step pre-processing was carried out, prior to combining the color, shape, texture features. Next, to achieve feature reduction, principal component analysis was used. In addition, the technique which is the ensemble of “Hybridization of PSO and ABC (HPA)” and “single-hidden layer feed forward neural-network (SLFN)”, referred as HPA-SLFN is introduced in the form of an innovative classification. It is proven from the results of research that in comparison with the contemporary approaches, proposed HPA-SLFN yields an accuracy of 89.5%.

III. Inferences From Recent Works

Our planet boasts of the existence of thousands of plants species, many of them having therapeutic value, and few others would be on the verge of extinction, and still others, might be harmful to mankind. Not only are plants a vital resource for people, but they also serve as the fundamental building blocks of many food chains. It is important to carry out thorough research and classification of plants so that they can be used and conserved. A botanist with expertise has inherent knowledge that is essential for identifying unfamiliar plants. Consequently, a much researches has been carried out to help in the prior detection of plants based on physical characteristics. Even though there is some similarity between the techniques, the algorithms developed till now utilize multitude of actions for automating the process of classification. Preparing the gathered leaves, identifying their unique traits, classifying them, creating a dataset, teaching recognition algorithms, and lastly analyzing the results are the steps in the process. Despite the fact that leaves are the most common way to identify plants, an automated approach might also employ stems, flowers, petals, seeds, and the whole plant. For the improvement in data quality, data having unwanted content requires to be removed from source data. Also, the data might include additional number of features and therefore the time taken for identification might increase.

IV. Solution

Plants contribute significantly to human lives and have an important role in the welfare of the world population. These constitute a key resource for food, raw materials, pharmaceuticals, and other needs. Time unknown, few plants have gained popularity for used in specialized treatments for a specific sickness or ailments. Many people are aware of their value and have shown interest in knowing more about the means of using special plants for treating particular conditions. Until now, different plants, in specific, herbal medicine plants, have hugely influenced the human health worldwide. At the beginning, just a few preprocessing models may be utilized for the classification of those plants. These models include noise reduction, edge detection, and enhancement. In the future, optimization-based feature selection will be considered for the selection of key features in order to decrease the amount of time spent. Finally, deep learning and optimization or hybrid form of learning models are used for classification.

V. Conclusion

Based on the survey, in conclusion, it can be said that the performance of soft computing models in the categorization of plant leaves has been exceptional. With the presence of several strong technologies, non-destructive assessment of plants is possible. Computer vision and scalable computer models classify. ANN, CNN, PNN, Heuristic, and Meta heuristic optimization methods are examined for plant categorization. Hybrid optimization requires selecting and combining algorithms, to have an optimal balance. To derive hybrid mechanisms, the algorithm is selected, which has to be fall under the class of one asset having an exploration rate and another with a reasonable exploitation rate. As a result, few hybrid classifiers designed through the combination of deep learning approaches, with various Meta heuristic optimization techniques (MHOA) in the literature are elucidated. Still several experiments with deep learning optimized in various domains for decision are ongoing.

References

1. Nazarenko, D.V., Kharyuk, P.V., Oseledets, I.V., Rodin, I.A. and Shpigun, O.A., 2016. Machine learning for LC–MS medicinal plants identification. Chemometrics and Intelligent Laboratory Systems, 156, pp.174-180.
2. Tapák, P. and Huba, M., 2016. Laboratory model of thermal plant identification and control. IFAC-PapersOnLine, 49(6), pp.28-33.
3. Kiani, E., Al Shahadat, M. and Sadikoglu, F., 2017. Child perceptionbased plant species identification. Procedia computer science, 120, pp.357-364.
4. Noon, S.K., Amjad, M., Qureshi, M.A., Mannan, A., “Use of deep learning techniques for identification of plant leaf stresses: A review”, Sustainable Computing: Informatics and Systems, Vol.28, Dec,2020.
5. Saidi, M.N., Ladouce, N., Hadhri, R., Grima-Pettenati, J., Drira, N. and Gargouri-Bouzid, R., 2010. Identification and characterization of differentially expressed ESTs in date palm leaves affected by brittle leaf disease. Plant science, 179(4), pp.325-332.
6. Rumpf, T., Mahlein, A.K., Steiner, U., Oerke, E.C., Dehne, H.W. and Plümer, L., 2010. Early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance. Computers and Electronics in Agriculture, 74(1), pp.91-99.
7. Rizos, D., Feltrin, G. and Motavalli, M., 2011. Structural identification of a prototype pre-stressable leaf-spring based adaptive tuned mass damper: Nonlinear characterization and classification. Mechanical Systems and Signal Processing, 25(1), pp.205-221.
8. Da, X., Yu, K., Shen, S., Zhang, Y., Wu, J. and Yi, H., 2012. Identification of differentially expressed genes in a spontaneous altered leaf shape mutant of the navel orange [Citrus sinensis (L.) Osbeck]. Plant Physiology and Biochemistry, 56, pp.97-103.
9. Cope, J.S., Corney, D., Clark, J.Y., Remagnino, P. and Wilkin, P., 2012. Plant species identification using digital morphometrics: A review. Expert Systems with Applications, 39(8), pp.7562-7573.
10. Diago, M.P., Fernandes, A.M., Millan, B., Tardáguila, J. and MeloPinto, P., 2013. Identification of grapevine varieties using leaf spectroscopy and partial least squares. Computers and electronics in agriculture, 99, pp.7-13.
11. S. A. Riaz, S. Naz, and I. Razzak. Multipath deep shallow convolutional networks for large scale plant species identification in wild image. In 2020 International Joint Conference on Neural Networks (IJCNN), pages 17. IEEE, 2020.
12. Manasa, N., Herur, P., Shetty, P., Prarthana, N., & Venkatrao, P. (2019, June). Plant recognition using watershed and convolutional neural network. In 2019 3rd International conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 969-973). IEEE.
13. Hu, J., Chen, Z., Yang, M., Zhang, R., & Cui, Y. (2018). A multiscale fusion convolutional neural network for plant leaf recognition. IEEE Signal Processing Letters, 25(6), 853-857.
14. Amara, J., Bouaziz, B., & Algergawy, A. (2017). A deep learning-based approach for banana leaf diseases classification. Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband.
15. Yadav, S.; Sengar, N.; Singh, A.; Singh, A.; Dutta, M.K. Identification of disease using deep learning and evaluation of bacteriosis in peach leaf. Ecol. Inform. 2021, 61, 101247.
16. N, K.; Narasimha Prasad, L.V.; Pavan Kumar, C.S.; Subedi, B.; Abraha, H.B.; V E, S. Rice leaf diseases prediction using deep neural networks with transfer learning. Environ. Res. 2021, 198, 111275
17. Chen, J.; Zhang, D.; Zeb, A.; Nanehkaran, Y.A. Identification of rice plant diseases using lightweight attention networks. Expert Syst. Appl. 2021, 169, 114514. [Google Scholar] [CrossRef]
18. Joshi, R.C.; Kaushik, M.; Dutta, M.K.; Srivastava, A.; Choudhary, N. VirLeafNet: Automatic analysis and viral disease diagnosis using deep-learning in Vigna mungo plant. Ecol. Inform. 2021, 61, 101197.
19. HulyaYalcin, SalarRazavi, “Plant Classification using Convolutional Neural Networks”, IEEE International Conference on Agro-Geoinformatics, Tianjin, China, DOI: 10.1109/ AgroGeoinformatics.2016.7577698, Spet, 2016
20. AmalaSabu, Sreekumar K, “Literature Review of Image Features and Classifiers Used in Leaf Based Plant Recognition Through Image Analysis Approach”, International Conference on Inventive Communication and Computational Technologies (ICICCT), DOI: 10.1109/ICICCT.2017.7975176, March, 2017.
21. Lee, S.H., Chan, C.S., Mayo, S.J. and Remagnino, P., “How deep learning extracts and learns leaf features for plant classification”, Pattern Recognition, Vol. no: 71, 2017.
22. Ghazi, M. M., Yanikoglu, B., &Aptoula, E. (2017). Plant identification using deep neural networks via optimization of transfer learning parameters. *Neurocomputing*, *235*, 228-235.
23. J.G. Barbedo, “Factors influencing the use of deep learning for plant disease recognition,” Biosystems engineering, vol. 172, pp. 84-91, 2018. https://doi.org/10.1016/j.biosystemseng.2018.05.013.
24. Zhu, X., Zhu, M. and Ren, H., “Method of plant leaf recognition based on improved deep convolutional neural network”, Cognitive Systems Research, Vol. 52, Dec, 2018.
25. Garcia-Garcia, A., Orts-Escolano, S., Oprea, S., Villena-Martinez, V., MartinezGonzalez, P. and Garcia-Rodriguez, J., “A survey on deep learning techniques for image and video semantic segmentation, Applied Soft Computing”, Vol. 70, May, 2018.
26. Kaya, A., Keceli, A. S., Catal, C., Yalic, H. Y., Temucin, H., & Tekinerdogan, B. (2019). Analysis of transfer learning for deep neural network based plant classification models. Computers and electronics in agriculture, 158, 20-29.
27. wei Tan, S.W. Chang, S. Abdul-Kareem, H. J. Yap, and K.T. Yong. Deep learning for plant species classification using leaf vein morphometric. IEEE/ACM Transactions on Computational Biology and Bioinformatics, 17(1):8290, 2018
28. Grinblat, G.L., Uzal, L.C., Larese, M.G. and Granitto, P.M., 2016. Deep learning for plant identification using vein morphological patterns. Computers and Electronics in Agriculture, 127, pp.418-424.
29. Zhang, X., Qiao, Y., Meng, F., Fan, C., & Zhang, M. (2018). Identification of maize leaf diseases using improved deep convolutional neural networks. Ieee Access, 6, 30370-30377.
30. Ghasab, M. A. J., Khamis, S., Mohammad, F., &Fariman, H. J. (2015). Feature decision-making ant colony optimization system for an automated recognition of plant species. *Expert Systems with Applications*, *42*(5), 2361-2370.
31. Zhao, C., Chan, S.S., Cham, W.K. and Chu, L.M., 2015. Plant identification using leaf shapes—A pattern counting approach. Pattern Recognition, 48(10), pp.3203-3215.
32. Sabu, A., Sreekumar, K. and Nair, R.R., 2017, December. Recognition of ayurvedic medicinal plants from leaves: A computer vision approach. In 2017 Fourth International Conference on Image Information Processing (ICIIP) (pp. 1-5). IEEE.
33. Siravenha, A.C.Q. and Carvalho, S.R., 2015, August. Exploring the use of leaf shape frequencies for plant classification. In 2015 28th SIBGRAPI Conference on Graphics, Patterns and Images, 297-304.
34. Lehoucq, R. B., & Rowe, S. T. (2016). A radial basis function Galerkin method for inhomogeneous nonlocal diffusion. Computer Methods in Applied Mechanics and Engineering, 299, 366-380.

35. Chouhan, S. S., Singh, U. P., Sharma, U., & Jain, S. (2021). Leaf disease segmentation and classification of Jatropha Curcas L. and Pongamia Pinnata L. biofuel plants using computer vision based approaches. Measurement, 171, 108796.
36. Heba F. "Performance improvement of plant identificationmodel based on pso segmentation." International Journal of Intelligent Systems and Applications (IJISA) 8, no. 2 (2016): 53
37. Singh, Vijai. "Sunflower leaf diseases detection using image segmentation based on particle swarm optimization." Artificial Intelligence in Agriculture 3 (2019): 62-68
38. Sethy, Prabira Kumar, Nalini Kanta Barpanda, and Amiya Kumar Rath. "Detection & Identification of Rice Leaf Diseases using Multiclass SVM and Particle Swarm Optimization Technique.", 2019.
39. Kaur, Amanpreet, and M. D. Singh. "An overview of pso-based approaches in image segmentation." International Journal of Engineering and Technology 2, no. 8 (2012): 1349-1357
40. Chanda, Moumita, and Mantosh Biswas. "Plant disease identification and classification using BackPropagation Neural Network with Particle Swarm Optimization." In 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), pp. 1029-1036. IEEE, 2019.
41. P. Shunmugapriya, S. Kanmani, A hybrid algorithm using ant and bee colony optimization for feature selection and classification (AC-ABC Hybrid), Swarm and Evolutionary Computation, Volume 36,2017, Pages 27-36, ISSN 2210-6502,
42. C. S. Sumathi. et al. Hybrid Optimization for plants leaves Classification. International Journal of Computer Science and Technology. 2014.
43. Kanthan Muthukannan. et al. A GA_FFNN algorithm applied for classification in diseased plant leaf system. Multimedia Tools and Applications. 2018;77:24387-24403.
44. Jaspreet Kaur, et al. Artificial Neural Network Optimization by a Hybrid IWD PSO Approach for Iris Classification. IJEECS. 2017.
45. M. Ravishankar, et al. Hybrid feature selection using group search particle swarm optimizer for plant leaf classification. International Journal of Engineering & Technology. 2018; 5909-5916
46. Sajad Sabzi, et al. Using video processing to classify potato plant and three types of weed using hybrid of artificial neural network and particle swarm algorithm. Measurement. 2018;126: 22-36.
47. Siyuan Lu, et al. Fruit Classification by HPA-SLFN. WCSP. 2016.