Review on Poisonous Plants Detection Using Machine Learning

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Abstract: *Poisonous plants pose a significant threat to human and animal health, leading to various adverse effects ranging from mild discomfort to severe toxicity. Early identification of these harmful plants is crucial for preventing accidental ingestions and minimizing the associated risks. This project focuses on developing an efficient and accurate system for the detection of poisonous plants using machine learning techniques. The proposed solution leverages a comprehensive dataset comprising images of various plant species, categorized into poisonous and non-poisonous classes. Convolutional Neural Networks (CNNs) are employed for image feature extraction, allowing the model to discern subtle visual patterns indicative of poisonous plant characteristics. Transfer learning is applied using pre-trained models, enhancing the system's ability to generalize and adapt to diverse plant species.*

Keywords: Detection, Identification of plants, Leaf patterns, Poisonous plants classification.

I. INTRODUCTION

For years, toxicologists, botanists, and environmentalists have struggled to identify and classify dangerous plants. Accidental consumption of hazardous plants can have a variety of negative effects, from little discomfort to serious illness. Technological developments, especially in the area of machine learning (ML), have sparked an increasing interest in creating automated systems for the identification of toxic plants. The goal of this review paper is to present a thorough overview of the state-of-the-art in machine learning-based methods for detecting dangerous plants.

Traditional plant identification techniques mostly rely on human skill and frequently call for in-depth familiarity with certain botanical traits. These techniques take a lot of time, are arbitrary, and might not be useful for people without specific training. Machine learning, on the other hand, is an acceptable method to improve and automate the identification of toxic plants, offering a more practical and effective approach.

The objective of this review is to evaluate and compile the body of research on machine learning applications for identifying toxic plants. We examine several approaches that have been used in the creation of automated systems, such as ensemble learning, transfer learning, and convolutional neural networks (CNNs). We also look at the datasets that were used for validation and training, taking into account the difficulties posed by unbalanced data and the requirement for strong model generalization.

Additionally, the purpose of this review is to emphasize the usefulness of machine learning-based poison plant identification systems. As emerging technologies transition from lab settings to practical uses, we talk about whether they could be integrated into cameras, cell phones, and other fieldwork instruments. These systems' potential advantages in raising public awareness, averting incidences of plant poisoning, and enabling timely medical treatments are also examined.

Through a comprehensive analysis and synthesis of the present literature, this review paper aims to offer important insights into the state of machine learning applications for dangerous plant detection. By outlining future study directions and addressing the shortcomings of conventional methodologies, it adds to our understanding of how technology might be used to reduce the hazards associated with exposure to dangerous plants.

II. LITERATURE REVIEW

According to IM Hassoon et al. [1], in order to identify poisonous plants from their leaves, this research is composed of three stages: a pre-processing phase that prepares input pictures for the subsequent phase; second phase is the features extraction phase whose objective is to extract exact and relevant characteristics from the image; and in final phase the association between an object's grey level distribution space and statistical information is used to quantify the attributes of an object region that uses a cascade-forward neural network to classify plants as poisonous or not. 500 leaf images were obtained, 60% of them for training phase and the rest 40% for validation and testing. The reliability in this work is its capability to identify poisonous plants accurately. The proposed identification framework is achieved 99.5% of testing accuracy.

Regatte Sahithi Reddy et al. [2], for the suggested plant identification method, used the Mendeley dataset, which contains high-quality photos of 10 different species with several samples per species. They developed a software application which helps users to upload and submit plant leaves using the Flask framework. After classifying the supplied leaf image, the system provides information on the plant for that leaf. A CNN model is trained to accurately identify the plant to do this.

Eera Bhatt et al. [3], the author of this paper generated original data for the logistic classification model focused on specific properties of each iNaturalist image. After looking over the samples, visual observations were made and previous reading material comparing poisonous and non-toxic plants was used to pick the attributes for the models. They included the following features in the data: thorns, dark red stem, shiny, 3-leaf, white flower, green flower, and white flower. Using visually discernible variations between the toxic and non-toxic samples, we were able to identify these characteristics.

TH Noor et al. [4], the project is distributed into three stages. In first stage, a dataset of 2500 images of fifty Arabic plants was used in the Pre-Processing Stage out of which 80% images were used for training and the rest 20% of images were used for testing. The most popular six pre-trained architecture includes MobileNetV2, ResNet50, EfficientNetB0, InceptionResNetV2, Mobilenet, NASNetLarge, and Xception, were used in the next stage. The initial model used in this study was the Mobilenet, which was created by Howard et al. The Depthwise Separable Convolutions method is used in this model to extract features rather than the conventional convolution method..

MF Zuhri et al. [5], specifies that the Grey Level Co-occurrence Matrix (GLCM) model is one of numerous models used to analyze image textures.One technique that is frequently used as a guide to identify images in texture processing is the Grey Level Co-occurrence Matrix (GLCM). The precision of the GLCM feature extraction method is achieved using second-order feature extraction (d=2), which uses angles of 0°, 45°, 90 °, and 135 ° to determine the probability of a relationship between pixels that have exactly the same value as the pixel distance (d). Based on the outcomes of extracting different kinds of toxic leaves, the Neural Network approach was employed for the classification procedure.

As per the author, L Picek et al. [6][2022 last] the section consists of three parts. Using DNN as a deep feature extractor, the conventional picture classification approach makes it simple to automate the identification of plant species, and a classifier that uses a fully CNN.

Author RH Hridoy et al. [7][2021], specifies modern and cutting edge numerous features can be extracted using CNN models, that have been trained on huge benchmark datasets. In this work, transfer learning was utilized to recognize dangerous plants using pre-trained models including Xception, ResNet152V2, InceptionResNetV2, MobileNetV2, DenseNet201, and NASNetLarge. A pre-trained deep learning model called Xception is built using depthwise separable convolution layers and an extreme variation of the Inception architecture in which depthwise separable convolutions are used in place of the regular Inception modules.

K Malarvizhi et al. [8][2021], The contours approach, a data pre-processing technique, is used to convert the plant picture data set into a numerical data set with the required features as attributes. In addition, three machine learning algorithms—Support Vector Machine (SVM), Random Forest (RF), and k-Nearest Neighbour (k-NN)—are used for classification. The accuracy of each algorithm is compared, and the algorithm with the highest accuracy is employed for additional testing on real-time images.

DMC Dissanayake et al. [9][2021], The suggested methodology is divided into multiple phases, beginning with data collection, pre-processing, feature extraction, and classification. The five ML algorithms that their study has used are MLP, SVM, RF, CNN, and DT.The first area of concentration was MLP.They used four additional supervised machine

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learning algorithms after the MLP analysis. The accuracy of the suggested ANN model was 82.88% against the testing data set and 86.02% against the validation dataset. The remaining four algorithms, SVM, Random Forest, KNN, and DT, were employed in the second evaluation phase.

KS Gawli et al. [10][2020], In the project, they have used the Tensorflow framework to construct a customized CNN architecture, and we used CNN classifier for detection, which classifies images based on a set of regions of interest (ROIs). However, there are various challenges in applying CNNs to picture detection and recognition. Convolutional Layer, pooling, flattening, and completely connecting are the four primary layer working approaches of CNN Convolutional Layer. Using the tensor flow framework, the system achieved an accuracy of over 94.26% when evaluated on a dataset. The suggested approach was effective and really simple to use.

I Kharir et al. [11][2020], specifies steps for the proposed approach in a sequence order like image aquisition, pre-processing, image segmentation and feature extraction. The SVM model creates a clear decision boundary in an attempt to widen the gap between the two groups. The goal of SVM is to categorize data points by locating the hyper-plane in N-dimensional space, or n times the number of characteristics. The SVM model creates a clear decision boundary in an attempt to widen the gap between the two groups. Finding the hyper plane in N-dimensional space that classifies the data points is the goal of the support vector machine proposal. When the suggested methodology is tried using various sample leaf photos from various species, it typically yields positive results.

A Ahmed et al. [12][2020], The leaf form is used by the newly developed feature extraction technique in this study to detect the geometrical features. Additionally, three classification strategies will be used to evaluate the suggested methodology, and its results will be compared with the effectiveness of other methods that have been identified as different plant species in recent research. The SSA-SVM classifier, Salp swarm method, RBFNN, and SVM are the classification algorithms that are employed. RBFNN is a popular and highly accurate regression and classification algorithm used in difficult applications. Here, it has been applied to identify the best fit curve each leaf contour data point, enabling any combination of feature selection scenarios.

S Kaur et al. [13][2019], the full plant, leaf, flower, stem, or even the fruits can all be included in the photo. Pre-processing an image is a crucial step since it improves the image's quality for subsequent processing. This stage is essential since noise in images is common and might result in less accurate classification. To extract the region of interest (ROI), picture segmentation is a crucial and vital step in the image analysis process. One of the crucial phases in image processing and pattern analysis is feature extraction. The process of dimensionality reduction can also be applied to feature extraction. SVM is a very efficient and reliable approach utilized in classification. It includes supervised learning methods that are applied to regression and classification.

J Cho et al. [14][2019], selected three convolutional neural networks namely VGGNet16, ResNet50, MobileNet, to implement the proposed model as mobile application.1800 photos were randomly split into training, validation, and testing data in the ratio of 8:1:1 to assess the herb identification model. Based on data validation, an early halting procedure was used to avoid over-fitting during the learning phase. In order to streamline the picture data, every herb image was transformed into a grayscale image. Canny edge detection (CED) was applied, and the results of the VGGNet16, ResNet50, and MobileNet were compared before and after.

Y Sun et al. [15][2017], Mobile phones are used to acquire the BJFU100 dataset from natural scenes. Traditional methods don't operate as predicted to increase accuracy with increased network depth; instead, they cause issues like deterioration and disappearing gradient. Information can move deeper into the layers by skip connections introduced by the residual network, or ResNet. The stochastic gradient descent (SGD) approach trains the model parameter during the back propagation phase using the categorical crossentropy loss function as the optimization object. There are 80 training samples and 20 test samples out of the 100 samples in each class. With a test set accuracy of 91.78%, the suggested model ResNet26 shows that deep learning is a promising approach for large-scale plant classification in the natural world.

AHH Alsadi et al.[16][2017], Two methods were used to get the leaf images: (1) manually capturing ten leaves from each of ten distinct species. (2) The leaf-snap dataset, which comprises 188 tree species. During the testing phase, ten leaf photos from each of the ten species are used independently. Feed-Forward Neural Net: This kind of neural network design is called a "feed forward" network (newff), because the connections are "fed forward," meaning they don't form cycles like in recurrent nets.

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2) Vector Machines for Support: Support Vector Machines (SVM) are machines that are majorly used for classification; they are made up of related supervised learning methods. To provide a more defined boundary between two data sets, SVM creates a dual hyperplane in parallel.

H Yalcin et al. [17][2016], to classify various plant species, employed a pre-trained Convolutional Neural Network (CNN) model. The section covers the architecture of CNN model as well as the specifics of how it is used to identify various plant species. Connecting the nodes in the current layer to every node in the previous layer is one of the most significant issues when working with high-dimensional data, like photographs. With our method, each node is just connected to a particular area of the input volume rather than being connected to all of the nodes in the preceding layer..

R Rojas-Hernandez et al. [18][2016], apart from the general process like pre-processing, feature extraction, image normalization, contour extraction for plant classification, the author has proposed three new characteristics—vertical and horizontal symmetry, as well as centroid crossing distance—to the description of leaves. By identifying the leaf's leftmost and rightmost pixels, these can be retrieved. Additionally the leaf's highest and lowest pixels are identified (ymin and ymax, respectively). Two reference lines are provided to clarify the computation of the characteristics. As per the observation the SVM gave the worst results out of all the other algorithms.

H Zhou et al. [19][2016], There is a unique number assigned to each type of leaf. The CNNs were initially declared with random parameters prior to training. Essentially, there are four steps in the training process.

Add the sample sets to the network (Xp, Yp).Based on the connections and weights, compute the associated outputs Op.Determine the discrepancy between the ideal outputs (Yp) and the actual outputs (Op).Modify the weight matrix using the minimum error approach. Using the 25 tree species from the Leaf Snap Database, the suggested algorithm's performance is evaluated. 30% of the database's samples were selected for testing process, while 70% are used to train the classifier.

AC Siravenha et al. [20][2016],proposes a model Dataset and data samples: For training and classification, a total of 1865 texture samples were retrieved from the Flavia database, a leaf database comprising 32 plant species or classes .Analysis approaches: We employ a combination of techniques, including GLCM, 2D-DWT, and data normalization to extract a set of features or properties from leaf textures. This helps to prevent any deviations during the data transformation process. Training & Classification: Following data analysis, training or learning phase is applied to the normalized feature vectors prior to classification

SH Lee et al. [21][2015], the CNN model utilized in this research is based on the model that was presented in using the pre-training ILSVRC2012 dataset. Because a) recent research has shown that features extracted from the activation of a CNN trained in a fully supervised manner on large-scale object recognition works can be re-purposed to a novel generic task and b) deep model training calls for expertise. It consumes a lot of time as well.

HAC Priyankara et al. [22][2015], We suggest adding three new characteristics—vertical and horizontal symmetry, as well as centroid crossing distance—to the description of leaves. By identifying the leaf's leftmost and rightmost pixels (xmin and xmax, respectively), these can be retrieved. Additionally, we identify the leaf's highest and lowest pixels (ymin and ymax, respectively). The experimental findings show that the approach may be used with 20 different species and achieve an accuracy of 96.48%.

B Patil et al. [23][2013], proposes a method for the classification of plants by color, texture using SVM classifier. The plant classification model gives the input image module, feature extraction module, SVM classifier. Digital cameras can provide photos. The pre-processing stage begins whenever any image is considered before moving on to any other phase. Three features—the color histogram, edge histogram, and sobel edge direction—will be used by the feature extraction block to extract the features. Out of all the machine learning algorithms, SVM is the best. SVM uses methods for optimization to find the best class borders.

B Wang et al. [24][2013], The proposed method's identification performance is assessed using two leaf image datasets: the widely used Swedish leaf dataset, which comprises 75 samples of each of the 15 species of Swedish tree leaves; 25 training samples and 50 testing samples are used per species, and the nearest-neighbor classification rule helps to calculate the classification rate. The fastest and most constant match speed might be gained by using an offline database, which can continue to operate without a network connection

H Zang et al. [25][2012], SVM is a supervised classification method that was first presented by Vapnik et al. in 1979. It has strong performance against noisy and sparse data, performs well in higher dimensional spaces, and prevents over fitting, making it a useful classifier in a variety of scientific domains.

Since SVM primarily addresses binary classification issues, it must be adjusted to accommodate multiclass tasks. Two popular approaches are the One-Against-One (1v1) and One-Against-All (1vA) strategies. Due to the imbalanced training dataset, 1vA strategy's performance was affected in comparison to 1v1 approach. While the 1v1 technique does not have these issues, it must construct N(N-1)/2 binary classifiers in order to classify a dataset with N classes, which increases computational demands as the number of classes increases.

AC Siravenha et al. [25][2016],proposes a model Dataset and data samples: For training and classification, a total of 1865 texture samples were gathered from the Flavia database, a leaf database comprising 32 plant species or classes .Analysis approaches: We employ a combination of techniques, including GLCM, 2D-DWT, and data normalization to extract a set of features or properties from leaf textures. This helps to prevent any deviations during the data transformation process. Training & Classification: Following data analysis, training or learning phase is applied to the normalized feature vectors prior to classification.

N Kumar et al. [26][2012], in this proposed system the recognition process consists of classifying, segmenting, extracting, comparing.

For the great majority of valid input photos (those that pass the first leaf classifier), segmentation is successful.Based on our observations, the most common causes of segmentation errors are either the shadows the leaf casts onto the background, which seem as false positives.

III. LITERATURE SUMMARY

Sr No.	Citation	Year	Methodology/ Algorithms used	Observation
1	Hassoon, Israa Mohammed, and Shaymaa Akram Hantoosh. "CFNN for Identifying Poisonous Plants." Baghdad Science Journal 20, no. 3 (Suppl.) (2023): 1122-1122.	2023	Cascade forward neural network is used which is similar to feed-forward networks but CFNNs has a direct weighted connection from the input to the output layer	CFNN framework with TRAINLM training function is proposed for identification of the poisonous plants.
2	Regatte Sahithi Reddy, N. Ankitha, M. Lokesh, M. Anji Reddy. "Plant identification system using machine learning." IJCRT volume.11(2013): 2320-2882.	2023	The system gives plant information for that leaf after classifying the input leaf image. For this, an accurate plant identification model for the CNN is created.	In this study, to classify leaf species an application has been developed. It is based on a set of leaf attributes that leaf datasets have demonstrated potential for. 90% more accuracy was gained.
3	Bhatt, Eera, and Clayton Greenberg. "Plant Toxicity Classification by Image." Journal of Student Research 12, no. 1 (2023).	2023	Features from CNN's picture data were employed in the logistic regression model to categorize plants as harmful or non-toxic.	While the model's accuracy on training data was above 80%, its performance on validation data hardly outperformed a random chance accuracy.
4	Noor, Talal H., Ayman Noor, and Mahmoud Elmezain. "Poisonous Plants Species Prediction Using a Convolutional Neural Network and Support Vector Machine Hybrid	2022	CNN architectures, namely MobileNetV2, EfficientNetB0, Xception, InceptionResNetV2, NASNetLarge, and	SVM classifier yielded the best outcomes. CNN method combined with SVM produced good results with respect to accuracy, precision, and F1-

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	Model." Electronics 11, no. 22 (2022): 3690.		ResNet50, were used. SVM is employed for its ability to forecast data from two classes .	Score, with the classifier receiving scores of 0.92, 0.94, and 0.95, respectively.
5	Zuhri, Mohammad Faishol, S. Kholidah Rahayu Maharani, Affandy Affandy, Aris Nurhindarto, Abdul Syukur, and Moch Arief Soeleman. "Classification of Toxic Plants on Leaf Patterns Using Gray Level Co-Occurrence Matrix (GLCM) with Neural Network Method." Journal of Development Research 6, no. 1 (2022): 1-5.	2022	The GLCM algorithm is applied to check the textures. In order to extract a value from a picture, the model requires at least five attributes. The five characteristics are as follows: ASM, Entropy, IDM, Contrast, and Correlation.	The GLCM algorithm and shape features are used by the researcher. Shape features have helped to improve accuracy, with the Neural Network approach yielding the greatest accuracy rating of 96.15%.
6	Picek, Lukáš, Milan Šulc, Yash Patel, and Jiří Matas. "Plant recognition by AI: Deep neural nets, transformers, and kNN in deep embeddings." Frontiers in Plant Science (2022): 2788.	2022	Deep Neural Network (DNN) serves as a deep feature extractor and a fully CNN as a classifier.	The comparison of DNN classifiers demonstrates how modern CNN architectures have improved classification accuracy.
7	Hridoy, Rashidul Hasan, Fatema Akter, and Maisha Afroz. "An Efficient Computer Vision Approach for Rapid Recognition of Poisonous Plants by Classifying Leaf Images using Transfer Learning." In 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 01-07. IEEE, 2021.	2021	The CNN models that were already in use for this study were adjusted to identify toxic plants, and based on the issue.	The effectiveness of cutting-edge CNN models, including DenseNet201 (M5), Xception (M1), ResNet152V2 (M2), InceptionResNetV2 (M3), MobileNetV2 (M4), and NASNetLarge (M6), was assessed.
8	Malarvizhi, K., M. Sowmithra, D. Gokula Priya, and B. Kabila. "Machine learning for plant species classification using leaf vein morphometric." Int J Eng Res Technol (IJERT) 10, no. 04 (2021).	2021	Three ML techniques are used for classification: k-Nearest Neighbour (k-NN), Random Forest (RF), and SVM.	Random Forest classifier performed the best, with an accuracy rate of 90%. The accuracy of the other classifiers was at least 85%.
9	Dissanayake, D. M. C., and W. G. C. W. Kumara. "Plant leaf identification based on machine learning algorithms." (2021).	2021	The training phase evaluated the ANN model, which is depicted. For a proper comparison, the other four algorithms—SVM, RF, DF, and KNN—were also put through independent testing.	SVM and MLP methods performed satisfactorily when used with the suggested technique, and this strategy could suggest using those algorithms.MLP showed a low rate of under fitting and over fitting as well as a high learning rate.
10	Gawli, Kiran S., and Ashwini S. Gaikwad. "Deep learning for plant	2020	CNN was used which accepts input in the form	CNN classifier was used for classification. The system was

	species classification." JETIR 7, no. 11 (2020): 99-105.		of image frames. CNN layers are utilized to recognize fire occurrences from extracted frames and provide predictions in a time-efficient and highly accurate manner.	tested on dataset and attained an accuracy more than 94.26% with the help of tensor flow framework
11	Swu Vikaho, Dibya jyoti bora," Identification of Different Plants through Image Processing Using Different Machine Learning Algorithms" ResearchGate (2020)	2020	The goal of the suggested SVM is to identify the best hyperplane for classifying the two groups differently.The coordinate representations of each given observation are these support vectors.	We extract and enhance photos with the help of image processing techniques, converting them into some valuable information that is then processed in a SVM
12	Ahmed, Ali, and Sherif E. Hussein. "Leaf identification using radial basis function neural networks and SSA based support vector machine." (2020): e0237645.	2020	RBFNN, SVM, Salp Swarm, SSA-SVM algorithms were used.	SVM beat the RBFNN classifier, with an accuracy of 93% when employed with the chosen features.
13	Kaur, Surleen, and Prabhpreet Kaur. "Plant species identification based on plant leaf using computer vision and machine learning techniques." Journal of Multimedia Information System 6, no. 2 (2019): 49-60.	2019	Building a hyper plane in an n-dimensional space that clearly classifies input data points is how SVM classification is carried out.	Using the Swedish dataset, the system's average accuracy was 93.26%. 15 distinct plant species could be automatically classified.
14	Cho, Jaeseong, Suyeon Jeon, Siyoung Song, Seokyeong Kim, Dohyun Kim, Jongkil Jeong, Goya Choi, and Soongin Lee. "Identification of toxic herbs using deep learning with focus on the sinomenium acutum, aristolochiae manshuriensis caulis, akebiae caulis." Applied Sciences 9, no. 24 (2019): 5456.	2019	Three CNN learning models—ResNet50, MobileNet, and VGGNet16—were chosen in light of the potential for using the suggested model in a mobile application.	Using those photos, VGGNet16, ResNet50, and MobileNet were trained. The accuracies were VGGNet16: 93.9%, ResNet50: 92.2%, and MobileNet: 95.6%.
15	Sun, Yu, Yuan Liu, Guan Wang, and Haiyan Zhang. "Deep learning for plant identification in natural environment." Computational intelligence and neuroscience 2017 (2017).	2017	The residual network, or ResNet, adds skip links to enable more information to flow into the deeper levels (from the input or from earlier layers).	With a 91.78% accuracy rate on the test set, the suggested model ResNet26 proves that deep learning is a promising method
16	AlAsadi, Abbas H. Hassin, Eman Qais Anduljalil, and Amal Hameed Khaleel. "Leaf Recognition based on Neural Network Feed-Forward and Support Vector Machine Classifiers." (2017).	2017	The training and testing phases make up the bulk of the phase structure of the suggested leaf recognition system.	With a 91.78% accuracy rate on the test set, the suggested model ResNet26 proves that deep learning is a promising

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17	Yalcin, Hulya, and Salar Razavi. "Plant classification using convolutional neural networks." In 2016 Fifth International Conference on Agro-Geoinformatics (Agro-Geoinformatics), pp. 1-5. IEEE, 2016.	2016	For the purpose of classifying the types of plants from the image sequences gathered from smart agro-stations, a CNN architecture is suggested.	Based on 16 different types of plants, the experimental findings show that the CNN-based strategy is significantly effective with an accuracy of roughly 97.47%.
18	Rojas-Hernández, Rafael, Asdrúbal López-Chau, Valentín Trujillo-Mora, and Carlos A. Rojas-Hernández. "Plant identification using new geometric features with standard data mining methods." In 2016 IEEE 13th International Conference on Networking, Sensing, and Control (ICNSC), pp. 1-4. IEEE, 2016.	2016	It was suggested to add three new characteristics—vertical and horizontal symmetry, as well as centroid crossing distance—to the description of leaves. To extract these, find the leaf's leftmost and rightmost pixels .	It was observed that the SVM gave the worst results out of all the other algorithms
19	Zhou, Hong, Chenjun Yan, and Huahong Huang. "Tree species identification based on convolutional neural networks." In 2016 8th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), vol. 2, pp. 103-106. IEEE, 2016.	2016	This paper uses a model on the LeNet, which is made up of a fully connected multi-layer perceptron (MLP), two convolution layers, and two sub-sampling layers.	The results of the experiments show that the suggested strategy works well and completes the leaf classification task.
20	Siravenha, Ana C., and Schubert R. Carvalho. "Plant classification from leaf textures." In 2016 International Conference on Digital Image Computing: Techniques and Applications (DICTA), pp. 1-8. IEEE, 2016.	2016	Artificial neural networks (ANN) are among the machine learning approaches most commonly employed in plant categorization applications	The performance evaluation of many feature vector combinations and eleven wavelet bases. When compared to the GLCM approach, we found that the DWT contributed more to the rise in classification accuracy

IV. CONCLUSION

In conclusion, machine learning algorithms have given promising results in identifying the poisonous plants. Detecting poisonous plants using machine learning can be a valuable application with potential benefits for both human and animal safety. The use of advanced technologies, such as machine learning algorithms, can enhance the efficiency and accuracy of identifying poisonous plants in various environments

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