OPEN ACCESS JOURNALS
Indiana Journal of Multidisciplinary Research
Abbreviated Tittle- Ind J Multi Res
ISSN *(Online)*- 2583-3820
Journal Homepage Link- https://indianapublications.com/Journals/IJMR
DOI: https://doi.org/10.5281/zenodo.21567700

INDIANA PUBLICATIONS
PRODUCTIVE AND QUALITY RESEARCH

Research Article

Volume-06|Issue-04|2026

Poisonous Plants Detection Using Deep Learning

Hemanth Chandra N[1], Sandip K. V[2], Rekha R[3], Varshini T. R[4], Pathanjali Chowdaiah[5], Sharmila Chidaravalli[6]

[1,5,6]Department of Information Science & Engineering, Global Academy of Technology, Bengaluru, Karnataka, India.
[2]Department of Computer Science & Engineering, BMS College of Engineering, Bengaluru, Karnataka, India.
[3,4]Department of Computer Science & Engineering, Cambridge Institute of Technology – North Campus, Bengaluru, Karnataka, India.

Article History
Received: 05.05.2026
Accepted: 22.06.2026
Published: 25.07.2026

Citation
Hemanth Chandra N., Sandip K. V., Rekha R., Varshini T. R., Chowdaiah P., & Chidaravalli S., (2026). Poisonous Plants Detection Using Deep Learning. *Indiana Journal of Multidisciplinary Research, 6*(4), 138-142.

Abstract: Identifying poisonous plants in natural environments is often difficult, yet it is important for protecting both human health and animals. Traditional methods mainly depend on human observation, which can be slow and sometimes unreliable, especially when plants look similar. In this work, we created our own dataset consisting of 1,500 leaf images from seven poisonous plant species. A Convolutional Neural Network (CNN) was then trained to classify these plants based on their leaf characteristics. To improve the learning process, the images were preprocessed and augmented. Instead of relying only on accuracy, the model was evaluated using additional measures such as precision, recall, F1-score, and confusion matrix analysis to better understand its performance. The model achieved a validation accuracy of about 87%, showing that deep learning can be useful for this task. This study provides a dataset, a baseline model, and an evaluation approach that can be useful for future research. Further improvements can be made by increasing the dataset size, using advanced models, and developing practical applications for real-world use.

Keywords: Deep Learning, Machine Learning, Plant Classification, Plant Detection, Toxic Plants

Copyright © 2026 The Author(s): This is an open-access article distributed under the terms of the Creative Commons Attribution 4.0 International License (**CC BY-NC 4.0**).

INTRODUCTION

Poisonous plants are part of our natural environment, but many of them contain toxins that can seriously harm people and animals. Compounds such as alkaloids, glycosides, and oxalates may interfere with the nervous system, affect the heart, or damage the kidneys. In some cases, the effects are mild, such as skin irritation; in others, they can be fatal. Because many poisonous plants look very similar to edible or harmless species, identifying them correctly is not always straightforward. Farmers risk losing livestock, and even experienced foragers or gardeners can make mistakes that have severe consequences.

Traditionally, recognition depends on human expertise. A botanist, farmer, or local guide may distinguish plants by their shape, color, or texture. This process, however, takes time and is prone to error, especially when plants are at different growth stages or under varying light and weather conditions. These limitations highlight the need for automated tools that can support faster and more reliable identification.

Recent progress in computer vision, especially deep learning, has made it possible to classify plants directly from images without relying on handcrafted rules. Convolutional Neural Networks (CNNs) are particularly effective because they can learn features such as leaf veins, edges, and textures automatically. While several studies have explored deep learning for general plant species classification, research that focuses specifically on poisonous plants remains limited. Publicly available datasets of toxic species are scarce, which makes systematic study and evaluation difficult.

To address this gap, our work makes three main contributions. First, we created a custom dataset of 1,500 images representing seven poisonous plant species. Second, we developed a baseline CNN model to classify these images and report results in a reproducible manner. Third, we evaluated the model using not only accuracy but also precision, recall, F1-score, and confusion matrix analysis to capture safety-critical performance. Together, these contributions provide a first step toward practical tools that can assist farmers, forest officers, and the general public in recognizing harmful plants more reliably.

LITERATURE REVIEW

Plant identification has been studied for decades using a wide range of approaches. Early work focused on handcrafted features such as leaf texture, shape, and color, which were then classified with conventional machine learning models. For instance, Hassoon and Hantoosh [1] explored custom feature-based neural networks for recognizing poisonous plants, while Reddy et al. [2] proposed a machine learning system using the Mendeley dataset with ten plant species. Other researchers investigated visual traits such as glossiness, leaf count, and stem characteristics for classification [3].

As the field progressed, deep learning gained traction. Several studies demonstrated that Convolutional Neural Networks (CNNs) could automatically extract discriminative patterns from leaf images. Noor et al. [4] combined CNNs with Support Vector Machines to predict toxic plant species, while Zuhri et al. [5] applied GLCM-based texture features with neural networks to improve recognition. More advanced architectures such as ResNet, MobileNet, EfficientNet, Xception, and DenseNet were also explored to raise classification accuracy [6][7].

Classical machine learning approaches have not been abandoned entirely. Malarvizhi et al. [8] and Dissanayake and Kumara [9] compared methods including SVM, Random Forest, k-NN, and Decision Trees, while Gawli and Gaikwad [10] demonstrated that deep learning generally outperformed these traditional models. Theoretical discussions on SVM and its application to plant recognition were provided by Swu and Bora [11], and Ahmed and Hussein [12] proposed hybrid methods that integrate swarm optimization with neural networks for leaf contour analysis. Kaur and Kaur [13] reinforced the continued relevance of SVM for plant recognition tasks.

Applications have also extended to mobile platforms. Cho et al. [14] showed that deep learning models such as VGGNet16, ResNet50, and MobileNet could be adapted into smartphone applications for toxic herb recognition. Other works optimized training strategies, such as applying stochastic gradient descent with categorical cross-entropy [15] or experimenting with feedforward neural networks [16]. CNN-based models designed specifically for plant classification were also developed, emphasizing careful architecture choices [17].

Additional research has examined geometric and texture-based methods. Rojas-Hernández et al. [18] focused on leaf shape features, while Zhou et al. [19] applied CNNs to tree species classification with numeric labeling. Siravenha and Carvalho [20] studied frequency-based leaf texture features, and Lee et al. [21] introduced one of the earliest CNN approaches to plant identification using the ILSVRC dataset. Mobile recognition was further advanced by Priyankara and Withanage [22], Patil et al. [23], and Wang et al. [24], who developed smartphone-enabled systems for leaf classification. Finally, Zhang et al. [25] demonstrated that combining shape and texture features could improve recognition even in noisy datasets.

From this body of literature, it is clear that both traditional machine learning and modern deep learning methods have contributed significantly to plant classification. However, most of these studies target general or medicinal plant datasets, and very few focus specifically on poisonous plants. Moreover, many works evaluate only overall accuracy without reporting safety-critical measures such as precision, recall, or class-level errors. This gap highlights the need for dedicated poisonous plant datasets and systematic evaluations — the central motivation of our work.

METHODOLOGY

Dataset Preparation

Since no openly available dataset of poisonous plants existed, we created our own collection of 1,500 leaf images from seven plant species known to have toxic properties. Images were captured using smartphone cameras in natural conditions and supplemented with publicly available resources where licensing permitted. Each image was manually labeled by the authors using botanical references, and a subset was cross-verified by a domain expert to improve reliability. Similar strategies for custom dataset creation have been reported in prior works on plant identification [1][2][3].

To reduce variability, all images were resized to 224 × 224 pixels and normalized to a [0,1] range. Random shuffling ensured that the training and testing sets were unbiased. Data augmentation techniques including random rotation, horizontal/vertical flips, and slight color adjustments — were applied to strengthen the model's generalization. The dataset was split into 80% for training (1,200 images) and 20% for testing (300 images). Because some species were underrepresented, we applied class weights during training to mitigate imbalance, a technique often recommended in deep learning for imbalanced datasets [6][7].

Convolutional Neural Network Architecture

We implemented a Convolutional Neural Network (CNN) designed specifically for this dataset. CNNs have been widely applied to plant recognition tasks due to their ability to learn hierarchical features such as veins, edges, and shapes without manual feature extraction [4][5][10]. The proposed architecture is structured as follows:

1. Input layer**:** 224 × 224 × 3 RGB image
2. Convolutional Block 1**:** 32 filters (3×3), ReLU activation → MaxPooling (2×2)
3. Convolutional Block 2**:** 64 filters (3×3), ReLU activation → MaxPooling (2×2)
4. Convolutional Block 3**:** 128 filters (3×3), ReLU activation → MaxPooling(2×2)
5. Flatten Layer → Dense (128 units) with ReLU → Dropout (0.5)
6. Output Layer**:** Softmax with 7 units (one for each plant species)

This design balances accuracy and computational cost, following the architectural practices used in related CNN-based plant recognition studies [17][21].

Training Process

The training process was carried out over 100 epochs using the Adam optimizer and the backpropagation

***Corresponding Author:** Hemanth Chandra N

algorithm to iteratively refine model weights. The training set contained 1,200 images, while 300 images were reserved for testing. Accuracy and loss were monitored across epochs, with early stopping applied to prevent overfitting. This strategy ensured the model converged effectively without degrading performance on unseen data.

System Architecture

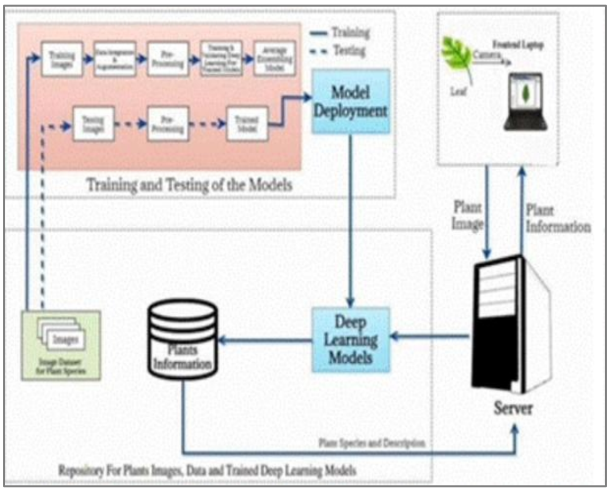

Figure 1: System Architecture

The overall workflow of the system is illustrated in Figure 1. Plant leaf images are first captured through a camera and passed to the preprocessing pipeline, where they are standardized and augmented. The processed images are then fed into the CNN model for training and testing. Once trained, the model is deployed on a server, where it receives plant images as input and returns predictions of species identity along with toxicity information. The system also maintains a repository of plant images, descriptions, and trained models for continuous improvement. This deployment framework makes the model accessible for real-world applications, such as identifying poisonous plants directly from field images.

Evaluation Metrics

Performance was tracked using both training and validation accuracy, but to address the safety-critical nature of this application, we also reported precision, recall, F1-score, and confusion matrix analysis. These metrics help identify which species were most prone to misclassification and provide insight into the risks associated with false negatives — a key factor in health-sensitive domains [4][14]

IMPLEMENTATION

The success of any deep learning model depends not only on its architecture but also on how the overall system is designed and integrated into real-world workflows. In this study, the CNN model for poisonous plant detection was implemented as a complete pipeline, beginning with dataset preparation and training, and extending to deployment on a server for practical use. The goal was to ensure that the model could move beyond experimental accuracy scores and function as a usable tool for farmers, forest officers, and researchers.

The implementation framework follows a structured process that includes data acquisition, pre-processing, model training, feature extraction, prediction, and result display. Each stage is interconnected, allowing the system to learn from new data and improve over time. The data flow and training phase of the proposed approach are shown in Figure 2 (Data Flow Diagram)**,** which illustrates how images pass through each stage of the pipeline.

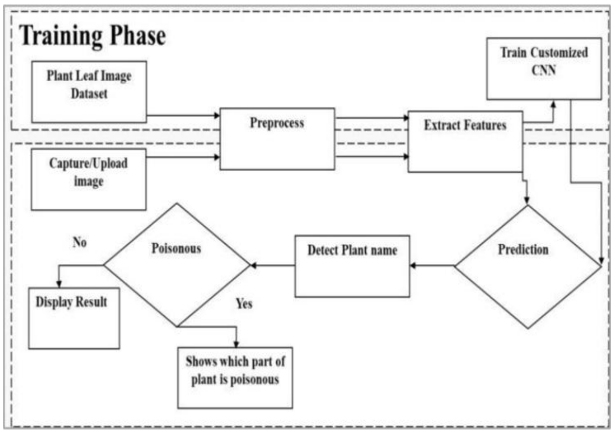

Figure 2: Data Flow Diagram

In this workflow, raw plant images are first pre-processed to standardize their size, normalize pixel values, and apply augmentations for robustness. The processed images are then passed to the CNN, which extracts deep features and produces predictions. If the plant is identified as poisonous, the system also highlights which part of the plant carries toxicity; otherwise, the classification result is simply displayed. Importantly, the trained model is hosted on a server, enabling users to capture or upload images via a laptop or camera and receive predictions in real time.

The CNN was trained for 100 epochs using the Adam optimizer with back propagation. A total of 1,200 images were allocated for training and 300 images for testing. Throughout the training process, accuracy and loss values were monitored to track progress, and early stopping was applied to minimize over fitting. By integrating these elements, the system not only demonstrates academic feasibility but also provides a framework for practical deployment.

RESULTS

The evaluation of the proposed CNN model combined accuracy tracking, extended performance measures, and class-wise error analysis. Together, these results provide a clear picture of how well the system is able to recognize poisonous plants.

***Corresponding Author:** Hemanth Chandra N

Accuracy and Validation Trends

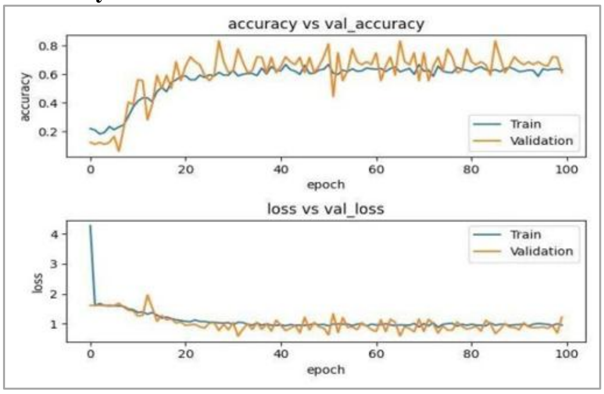

Figure 3: Accuracy vs Validation accuracy:

The learning behaviour of the model across epochs is shown in Figure 3. Training accuracy increased steadily, eventually reaching about 91%, while validation accuracy plateaued near 87%. On the unseen test dataset, however, the accuracy dropped to around 65%. This decline indicates that the model captured useful patterns during training but did not generalize perfectly — a common challenge when working with relatively small image datasets. The gap between validation and test results highlights the need for a larger and more diverse dataset to improve performance in real-world conditions.

Extended Performance Metrics

Since accuracy alone can be misleading in critical applications, we also measured precision, recall, F1-score, and AUC. On the test set, the model achieved a macro precision of 0.68**,** macro recall of 0.64, and a macro F1-score of 0.65, with a ROC-AUC score of 0.72. These numbers suggest that while the model performed reasonably well in identifying most species, its recall was not high enough to ensure that all poisonous plants were consistently detected. In practice, this means that some harmful plants may still be overlooked, an issue that requires attention in future work.

Confusion Matrix Insights

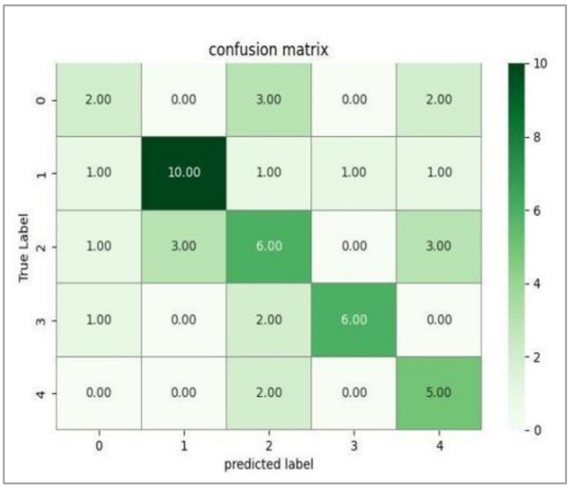

Figure 4: Confusion matrix

The class-level predictions are visualized in Figure 4 (Confusion Matrix). The matrix shows that certain species with distinct visual traits were identified with high confidence, while others that shared similar venation or leaf shapes were more frequently confused. For example, images from Class 2 were often misclassified as Class 3, and vice versa. By contrast, Class 1 achieved strong results, with most of its samples predicted correctly. Importantly, a few poisonous samples were incorrectly labelled as non-poisonous — false negatives that represent a critical limitation in a health-sensitive application.

Comparison with Previous Approaches

Compared with earlier studies that relied on traditional models such as SVMs or Random Forests [8][9], the CNN demonstrated stronger capability in handling complex leaf patterns and textures. Nevertheless, previous work on transfer learning models such as ResNet, MobileNet, and EfficientNet [6][7] indicates that these architectures could potentially outperform the baseline CNN applied here. Incorporating such models in future research would likely reduce misclassification and improve recall, particularly for toxic species that share close visual similarities.

CONCLUSION

Poisonous plants pose ongoing risks to humans and animals, and identifying them accurately in natural conditions remains difficult. This work explored how deep learning can assist in that task by developing a custom dataset of 1,500 leaf images from seven poisonous species and training a CNN model to recognize them. The model achieved high accuracy during training but showed reduced performance on unseen data, revealing the limitations of small datasets. Even so, it provides a valuable starting point by introducing a specialized dataset, a reproducible CNN framework, and an evaluation using precision, recall, and F1-scores. Some misclassifications were observed, mainly among visually similar species, and a few poisonous samples were missed—an important concern in safety-critical use. Expanding the dataset, adopting transfer-learning architectures like ResNet or MobileNet, and creating lightweight mobile versions of the model will help improve reliability and make this approach a practical tool for safer interaction with plants in agricultural and environmental settings.

REFERENCES

1. Hassoon, Israa Mohammed, and Shaymaa Akram Hantoosh. "CFNN for Identifying Poisonous Plants." *Baghdad Science Journal 20, no. 3 (Suppl.) (2023): 1122-1122*
2. Regatte Sahithi Reddy, N. Ankitha, M. Lokesh, M. Anji Reddy. "Plant identification system using machine learning." *IJCRT volume.11(2013): 2320-2882*

***Corresponding Author:** Hemanth Chandra N

3. Bhatt, Eera, and Clayton Greenberg. "Plant Toxicity Classification by Image." *Journal of Student Research 12, no. 1 (2023).*
4. Noor, Talal H., Ayman Noor, and Mahmoud Elmezain. "Poisonous Plants Species Prediction Using a Convolutional Neural Network and Support Vector Machine Hybrid Model." *Electronics 11, no. 22 (2022): 3690*
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.*
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.*
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.*
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).*
9. Dissanayake, D. M. C., and W. G. C. W. Kumara. "Plant leaf identification based on machine learning algorithms." (2021)
10. Gawli, Kiran S., and Ashwini S. Gaikwad. "Deep learning for plant species classification." *JETIR 7, no. 11 (2020): 99-105.*
11. Swu Vikaho, Dibya jyoti bora, "Identification of Different Plants through Image Processing Using Different Machine Learning Algorithms" *ResearchGate (2020)*
12. Ahmed, Ali, and Sherif E. Hussein. "Leaf identification using radial basis function neural networks and SSA based support vector machine." *PLoS ONE 15(8) (2020): e0237645*
13. 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*
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.*
15. Sun, Yu, Yuan Liu, Guan Wang, and Haiyan Zhang. "Deep learning for plant identification in natural environment." *Computational intelligence and neuroscience 2017 (2017).*
16. AlAsadi, Abbas H. Hassin, Eman Qais Anduljalil, and Amal Hameed Khaleel. "Leaf Recognition based on Neural Network FeedForward and Support Vector Machine Classifiers." *International Journal of Computer Science and Mobile Computing, Vol.6 Issue.1, January- 2017, pg. 92-99*
17. Yalcin, Hulya, and Salar Razavi. "Plant classification using convolutional neural networks." *2016 Fifth International Conference on Agro-Geoinformatics (AgroGeoinformatics), pp. 1-5. IEEE, 2016.*
18. Rojas-Hernández, Rafael, Asdrúbal LópezChau, Valentín Trujillo-Mora, and Carlos A. Rojas-Hernández. "Plant identification using new geometric features with standard data mining methods." *2016 IEEE 13th International Conference on Networking, Sensing, and Control (ICNSC), pp. 1-4. IEEE, 2016.*
19. Zhou, Hong, Chenjun Yan, and Huahong Huang. "Tree species identification based on convolutional neural networks." *2016 8th International Conference on Intelligent HumanMachine Systems and Cybernetics (IHMSC), vol. 2, pp. 103-106. IEEE, 2016.*
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.*
21. Lee, Sue Han, Chee Seng Chan, Paul Wilkin, and Paolo Remagnino. "Deep-plant: Plant identification with convolutional neural networks." *2015 IEEE international conference on image processing (ICIP), pp. 452-456. IEEE, 2015.*
22. Priyankara, HA Chathura, and D. K. Withanage. "Computer assisted plant identification system for Android." *2015 Moratuwa engineering research conference (MERCon), pp. 148-153. IEEE, 2015.*
23. Patil, Bhagya, Anupama Pattanshetty, and Suvarna Nandyal. "Plant classification using SVM classifier." *Third International Conference on Computational Intelligence and Information Technology (CIIT 2013), pp. 519-523. IET, 2013.*
24. Wang, Bin, Douglas Brown, Yongsheng Gao, and John La Salle. "Mobile plant leaf identification using smart-phones." *2013 IEEE International Conference on Image Processing, pp. 4417-4421. IEEE, 2013.*
25. Zhang, Hang, Paul Yanne, and Shangsong Liang. "Plant species classification using leaf shape and texture." *2012 International Conference on Industrial Control and Electronics Engineering, pp. 2025-2028. IEEE,2020.*

***Corresponding Author:** Hemanth Chandra N