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Vision-Based Classification of Significant Varieties of Immuno-Herbal Plant Leaves Using Modified Convolutional Model

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ABSTRACT

This study introduces an advanced AI-based model named **Deep Leaf Convv** designed to identify and classify medicinal plants such as *Argula*, *Giloy*, *Taro*, and *Ground Ivy*. Using an enhanced version of the VGG16 deep learning architecture, the model is optimized with 41 layers, including Batch Normalization and Dropout techniques, to ensure stability and accuracy while avoiding overfitting. By efficiently analysing plant features, this system offers a trustworthy and autonomous solution for distinguishing between different plant species. This paper has the potential to support healthcare, agriculture, and ethnobotanical research by streamlining the process of identifying plants with medicinal properties. The overall accuracy of 93.39% is achieved.

Keywords: *Immuno-herbal leaf, Deep learning model, Batch normalization, Classification*

1. INTRODUCTION

The emergence of a new corona virus, known as the SARS-CoV-2 has initiated a pandemic of COVID-19 (World Health Organisation, 2020). As the world looks towards science in search of an effective drug or vaccine, many countries started started exploring the role of traditional, complementary and conventional treatment methods. There are various prominent types and varieties of immune-herbal plants available nearby our living place such as Arugula, Basil, Amrita, Ground ivy, Giloy, Taro, and Safflower etc. The immuno-herbal plants are of significant use due to their efficacy evidence as antiviral, anti-inflammatory and immune modulatory agents for use in COVID-19 management and also for most of the chronic diseases. As research in COVID-19 treatment intensifies, exploring the potential roles of medicinal plants, lobbying and extrapolating from known scientific evidence on safety and efficacy could be highly beneficial.

Vision-based computing is a process of automatic extraction and analyzing of useful information from the images. When compared to human vision, the proposed methods arrive at more accurate results about the information gathered from the captured images. Computer vision and image processing approaches are broadly used in biological science, food industry, defense, material science, medical science and many other fields.

Instead of antiviral properties, most of the medicinal plants discussed here demonstrate anti-inflammatory effects supported by in-vivo preclinical evidence. At present, anti-inflammatory and immune-modulatory agents namely corticosteroids and IL-6 receptor antagonist have been utilised in COVID-19 management related to severe acute respiratory distress syndrome, in hopes to improve survival. The same concept can be applied to natural medicinal harvests.

The varieties of immuno-herbal plants namely Arugula, Ground ivy, Taro and Giloy play very significant role in increasing the immune power of human beings. The immuno-herbal plants exist with numerous varieties. Different varieties of significant arugula immuno-herbal leaf images are shown in Figure 1.

(a) (b) (c) (d)

Figure 1. Different varieties of arugula leaf images (a) Red dragon, (b) Garden tangy, (c) Astro and (d) Wasabi.

Arugula leaves are generally harvested small in size, averaging 7 to 10 centimetres in length, that have bright green color with smooth texture and prominent veining and frilled edges. The leaves tend to be deep green in colour with deep notches up and down both sides. Some leaves have full, round ends while others are more pointy. The arugula leaf is elongated with ridges, while spinach leaves are wide and oval shaped.

Red Dragon is a uniform, upright plant consisting of narrow, oak-leaf shaped leaves attached to branching, fibrous stems. Dragon's Tongue arugula has a crisp, slightly chewy consistency and a complex blend of peppery, grassy and vegetal flavors.

Garden Tangy is a fancy, large-leafed arugula that offers a milder, radish-like flavor that holds well even when cooked. Arugula is most often used in salads, soups, pasta, and on pizza. We grow our Garden Tangy Plants organically and guarantee them to arrive alive and thriving.

Astro organic arugula seeds produce a plant having leaves with less lobed and more strap-like. With a nutty, spicy taste that is sometimes pungent or peppery, arugula really perks up salads, sandwiches, and even pizza. It is very cold hardy, and has a milder flavor when grown in cool weather.

Wasabi arugula is a small plant, averaging 10 to 20 centimetres in height and contains many spoon-shaped leaves growing in a loose rosette. Wasabi arugula has an initially spicy, tangy bite, reminiscent of wasabi or horseradish, followed by subtly sweet, nutty, and slightly bitter undertones.

Different varieties of significant Ground ivy immuno-herbal leafs are presented in Figure 2.

(a) (b) (c) (d)

Figure 2. Various varieties of Ground ivy leaf images (a) English ivy, (b) Swidish ivy (c) Glacier ivy and (d) Needle ivy.

Ground ivy has shallow roots originating from nodes on creeping stems. Stems are square or four-sided and creeping. Leaves are round and scalloped along the edge. Leaves and stems have a strong mint-like odor. The plant has low-growing, fan-shaped leaves with scalloped edges having 1" diameter on square stems. The flowers are funnel shaped and blue-violet in groups of 2–3 near the tip of the stem. They are green to purplish green, orbicular and crenate along the margins.

English ivy is an evergreen perennial. It is also classified as a woody vine. English ivy can act as a ground cover, spreading horizontally and reaching 8 inches in height. But it is also a climber, due to its aerial rootlets, which allows it to climb to 80 feet high. The plant will eventually bear insignificant greenish flowers, but it is grown primarily for its evergreen leaves. In this regard, ivy can be classified as a foliage plant.

Swedish ivy house plants are nearly foolproof. This is one of the easiest types of ivy to grow indoors and needs little attention to thrive. This bushy plant has thick stems that grow upright at first, then trail over the sides of a container.

Glacier Ivy does double-duty as a lush groundcover, trellis plant or container-filler and a source of soft color all season long. The frosty-green and white variegated foliage is especially useful for creating contrast with dark foliage plants or bright vivid flowers.

Needle ivy plant has needlepoint and small evergreen climber with elegant, dark green leaves adorned with 3-5 sharply pointed lobes. The leaves are small but set close together. After a year or two of setting down roots, it will become vigorous in its spread. Spread of a single plant will easily reach six or eight feet, though it is quite easily kept smaller.

Diverse forms of significant Taro immuno-herbal leaf pictures are shown in Figure 3.

(a) (b) (c) (d)

Figure 3. Different varieties of Taro leaf images (a) Malanga taro, (b) Giant swamp, (c) False taro and (d) True taro.

Taro leaves are heart-shaped, wide, and medium to big in size, with an average length of forty centimeters and a width of twenty centimeters. The underside of the leaves is light green, while the surface is smooth and dark green. Veins also emerge from the central stem on the underside of the leaves. The rhizome gives rise to leaves that are up to 40 cm by 24.8 cm (153⁄4 in by 93⁄4 in). They have a light green underside and a dark green top. Growing between three and six feet tall, taro is a perennial herbaceous plant. The elongated, heart-shaped leaves resemble elephant ears and are bright green in color. About the size of a tennis ball, tubers are spherical and frequently have brownish skin and hairs. The flesh is pinkish purple, beige or white.

Malanga is very similar to taro and eddo and can be easily confused with them. In some areas malanga root is called eddo, cocoyam, coco, tannia, sato-imo and Japanese potato. The plant is grown for its tubers, belembe or calalous, which are used in a variety of dishes.

Giant Swamp Taro is an under-utilized but highly productive plant native to the North Sulawesi region of Indonesia. It can grow up to 5 metres tall and may produce tubers underground that are 2 metres in diameter and up to 3 metres in length.

The false taro leaves are up to 40 cm × 24.8 cm (153⁄4 in × 93⁄4 in) and sprout from the rhizome. They are dark green above and light green beneath.

Taro leaves have their size between medium to large, broad and heart-shaped, average size up to forty centimeters vertically and twenty centimeters horizontally. The leaves texture is dark green and smooth on top and light green underneath.

Different varieties of significant Giloy immuno-herbal leaf pictures are presented in Figure 4.

(b) (c)

Figure 4. Different varieties of significant Giloy leaf images (a) Turpenoids, (b) Alkaloids and (c) Lignans.

Geloy plants have elongated twining branches with heart-shaped betel-like leaves and yellow flowers. Succulent bark of this herb is grey or creamy white in appearance and wood is white, soft and porous. When stem is freshly cut it shows yellow tint. Aged plant stems grow up to 2 cm in diameter and have corky bark. Aerial roots erupted through nodal scars of branches. These plant have heart-shaped leaves with elongated edge.

Terpenoids are the largest group of plant specialized secondary metabolites. The chemical structures of these naturally occurring substances vary greatly. The plant has heart-shaped leaves with elongated edge similar to turpenoids but, differs in color and texture.

Alkaloids are **minute organic molecules, secondary metabolites of plants**, containing nitrogen usually in a ring; about

20% of plant species consist of alkaloids (Amirkia and Heinrich, 2014; Khan, 2016a). Alkaloids play major role in defence system of these plants against herbivores and pathogens.

Lignans:

Lignans are found in wide range of plant foods, including seeds (flax, pumpkin, sunflower, poppy, sesame), whole grains (rye, oats, barley), bran (wheat, oat, rye), beans, fruit (particularly berries), vegetables, and beverages like tea, coffee, and wine.

2. LITERATURE SURVEY

[Mulugeta, A. K. et al., 2024], presented a review that use deep learning approaches in classifying and recognizing medicinal plant species. The review analysed various studies in the recent past. The India led with 29% of paper contributions, followed by Indonesia and Sri Lanka. 67.7% and 96.7% respectively. Transfer learning was used in 83.8% of studies, and Convolutional Neural Networks was used in 64.5%. However, a global dataset for indigenous medicinal plants and the trustworthiness of deep learning approaches remain research gaps. The majority of papers are from India, Indonesia, and Sri Lanka, using a private dataset and transfer learning with a pre-trained model. The review provides insights into the challenges, limitations, and open areas of research in this field.

[Azgomi, et al., 2023] presented a paper on employing artificial neural networks and image processing to diagnose some apple fruit diseases. Usage of neural network and fruit categorization techniques to classify into four classes—scab, bitter rot, black rot, and healthy fruits—a low-cost method of diagnosing apple disease has been devised. Features of texture and color are used in the process. Features taken from the photos are fed into a multi-layer perceptron neural network. The best accuracy of 73.7% is attained.

[H. Mary Shyni, E. Chitra, 2022] presented a work on a comparative study of X-ray and CT images to find the presence of COVID-19 virus, using image processing and deep learning techniques. It is stated that the medical images with deep learning methods provided faster and more accurate results to detect COVID-19 disease. The article widely reviews the recent deep learning models for COVID-19 diagnosis. The articles discussed reveal that the convolutional Neural Network (CNN) is the most popular deep learning algorithm in detecting COVID-19 from medical images.

[M Koklu, et al., 2022] proposed a work on CNN-SVM research for grape-vine leaf categorization based on certain deep characteristics. Images of grapevine leaves are used in this study to do deep learning-based categorization. A unique self-illuminating mechanism is used to gather pictures of 500 vine leaves from five different species. Later, data augmentation techniques raised this figure to 2500. Using the chosen features, several SVM kernels are used for the classification. The system's categorization accuracy was found to be 97.60%.

[Malik, O. A. et al 2022], presented their research findings as an automated real-time medicinal plant types classification system for medicinal herbs in the Borneo region. The system consists of a computer vision, a knowledge base, auxiliary data and a mobile application. The EfficientNet-B1-based deep learning model achieved 87% and 84% Top-1 accuracies on a combined public and private datasets, respectively. The mobile application also provides crowdsourcing feedback and geo-mapping of species in the Borneo region. The proposed system shows promise in real-time plant species identification. It addresses challenges like small training samples and long-tile class imbalance. Techniques like class weighting and focal loss function improve model performance. However, performance accuracy drops when tested on real samples.

[Manjunatha Badiger, et al., 2022] proposed a work on leaf and stem disease diagnosis system based on image processing. Image processing methods are employed for disease detection that involves mathematical equation and mathematical transformations. Various transforms are performed on input images. These transforms will extract specific details from the picture. Before transforming, the image must undergo various operations namely feature adjustment which is also carried out mathematically. The work uses K-Means Clustering and Support Vector Machine (SVM) algorithm for disease detection.

[Aiswarya K, et al., 2022] presented a paper on plant disease diagnosis by Quantum Image Processing. The work proposed allows automation in order to create, establish quantum images and convert color pixel in well-defined ways. The model is independent of image rectification process and algorithm. the methodology make use of the same idea of energy metamorphose, related to 2D mapping in order to encode values of energy to group of quantum data.

[Azadnia, R. et al 2022], proposes a computer vision framework to recognize medicinal plants based on autonomous Convolutional Neural Network (CNN). The proposed framework works in two stages among which in the first stage CNN is used for feature extraction followed by second stage classifier stage for classifying features. Tested on different image definitions, the system achieved over 99.3% accuracy, effectively identifying medicinal herbs in actual-time as against to the traditional ways. The goal of the research was to use a DL algorithm and machine vision technology to create a real-time automated vision system for recognizing medicinal plants. Positive results have been obtained with the suggested automated real-time vision-based method for recognizing medicinal plants. It makes use of an enhanced CNN network that has classifier and convolutional blocks, which lowers parameters and boosts speed. With overall accuracy rates of 99.66, 99.32, and 99.45%, the model successfully recognized photos of medicinal plants at three different levels of definition, proving to be a useful substitute for conventional techniques.

[Abdollahi, J. et al., 2022] proposes a review on the medicinal herbs of Ardabil, which is a prime location for medicinal herbs, but many are endangered. To preserve biodiversity, researchers are making use of image processing and computer vision algorithms to identify medicinal plants. This study investigates using Convolutional Neural Network (CNN)-based techniques to identify Indian leaf species, focusing on rural medicinal plants using a pre-trained CNN architecture.

[Hassan Amin, et al., 2021] presented a paper on deep learning model on corn leaf disease classification. An end-to-end deep learning model is developed to identify healthy and unhealthy corn plant leaves. The developed model utilizes two pre-trained Convolutional Neural Networks (CNNs), Ef_cientNetB0, and DenseNet121 to grab deep features from the corn plant images. The proposed model achieved a classification accuracy of 98.56% which shows the superiority of the proposed model over ResNet152 and InceptionV3 that have resulted in a classification accuracy of 98.37% and 96.26% respectively.

[Roopashree, S. et al 2021], presents their research as a vision-based automatic medicinal plant identification system using neural network techniques in computer vision and deep learning. The DeepHerb dataset, consisting of 2515 leaf images from 40 Indian herbs, is used to identify plants. The system uses transfer learning techniques to extract features and classify using Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The DeepHerb model outperforms pre-trained models by 97.5% accuracy. The study also discusses DCNN architectures and classifiers like ANN and SVM. The DeepHerb model outperforms other popular DCNN architectures due to its stability features.

[Sweta Bhattacharya, et al., 2021] presented a review paper on Deep learning and medical image processing for coronavirus (COVID-19) pandemic. In this work, the state-of-the-art research works is summarized initially related to deep learning applications for COVID-19 medical image processing. Then, an overview of deep learning and its applications to healthcare found in the last decade is presented. Further, three use cases in China, Korea, and Canada are presented to show deep learning applications for COVID-19 medical image processing. Finally, several challenges and issues related to deep learning implementations for COVID-19 medical image processing are discussed.

[Xi Vincent Wang, et al., 2021] presented a review paper on robotic technologies during the COVID-19 pandemic. The current achievements of robotic technologies are reviewed and discussed in different categories. They are followed by the identification of the representative work's technology readiness level. The future research work trends and essential technologies namely artificial intelligence, 5G, Bigdata, Wireless sensor network, and Human-robot collaboration are highlighted.

[Dilbag Singh, et al., 2020] have proposed a work on Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. The chest CT images are utilized for early classification of COVID-19 patients. CNN model is used to classify the COVID-19-infected patients as infected or not infected. Additionally, the initial parameters of CNN are tuned using multi-objective differential evolution mode. Extensive analysis shows that the proposed model can classify the chest CT images with a good accuracy rate.

[Muneer, A. et al, 2020] proposes an efficient and automatic classification system for identifying Malaysian herbs used in medicinal or cooking areas. The system uses Support Vector Machine (SVM) and deep Learning Neural Network (DLNN) classifiers, with SVM achieving 74.63% recognition accuracy and DLNN 93% accuracy. The system has a processing time of 4 seconds for SVM and 5 seconds for DLNN, and 2 seconds for the mobile app. This research proposes an automatic visual recognition system for Malaysian herbs, improving accuracy by using 10 shape and texture features. The proposed algorithms are DLNN and SVM, with DLNN being more accurate than SVM. The system's accuracy is similar across different backgrounds, except for floral ones. However, limitations include not fully developing the mobile app for Android due to Python software limitations and the need for a faster processor for the system's operation.

[Syed Mohammad Abid Hasan, and Kwanghee Ko, 2016] have presented an article on depth edge detection using image-based smoothing and morphological operations. The principle of median filtering that has a renowned feature for edge preserving characteristics is used. The results are compared with some existing methods and stated that, proposed method gives better results. The work can contribute to promote applications namely, object detection, object segmentation, etc.

From the literature survey, it is observed that most of the work is supported out on detection of natural remedies of covid-19 virus. The work on detection of COVID-19 disease using X-ray and CT images using different classification models is also found. Also, the work related to various fabric defects detection is carried out. The works related to identification and classification of immune-herbal plants is not found in the state-of-the-art. Everyone knows that precaution is better than prevention. Hence, there is a need for development of methodology to identify different varieties of immuno-herbal plants. Thus, the motivation for the work related to "*Identification and Classification of Significant Varieties of Immuno-Herbal Plant Leaves Using Deep Leaf Convv Model*" to fight against covid-19 virus.

Problem Statement

In the state-of-the-art, the work on identifying the immuno-herbal plants is not found. The proposed work has more scope today to keep humankind away from covid-19 deadly viral disease. Hence, the work on "***Vision-Based Classification of***

Significant Varieties of Immuno-Herbal Plant Leaves Using Modified Convolutional Model" is proposed.

OBJECTIVES

To develop a methodology to classify:

immuno-herbal leaf images into different types as arugula, ground ivy, taro and Giloy.

Arugula leaf images into four varieties as Red dragon, Garden tangy, Astro and Wasabi

ground ivy leaf images into four varieties namely English ivy, Swidish ivy, Glacier ivy and Needle ivy.

Taro leaf images into four varieties as Malanga taro, Giant swamp, False taro and True taro.

Geloy leaf images into three varieties as Turpenoids, Alkaloids and Lignans.

Tree structure containing immuno-herbal plant leaves and their respective varieties is shown in Figure 5.

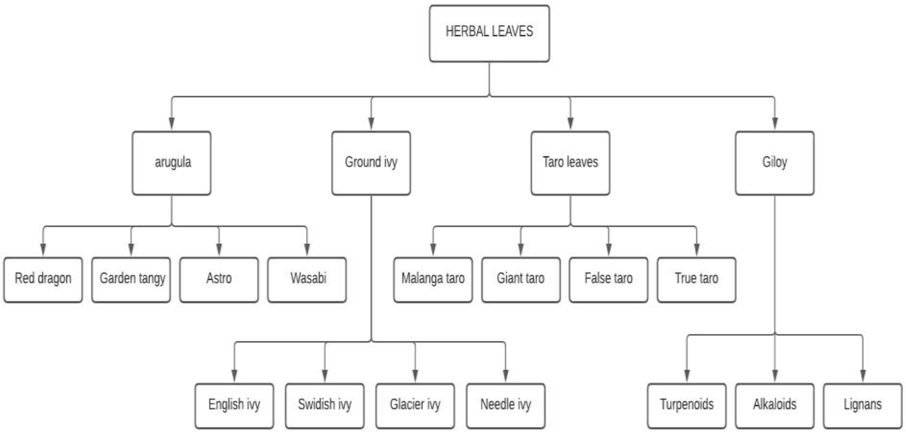

Figure 5. Tree structure depicting work carried out.

3. PROPOSED METHODOLOGY

Different Layers used in the proposed methodology are shown in Figure 6. This is a **deep model** with a total of 41 layers, significantly enhanced by the inclusion of Batch Normalization and Dropout, designed to provide better training stability and prevent overfitting for tasks like leaf classification.

Image acquisition

Images are acquired by visiting places and fields frequently using a high-resolution camera of 64 Mega pixels. Also, the images are collected from Google. The images are acquired with different light intensity considering different day timings. A distance of one meter is maintained during image capturing process.

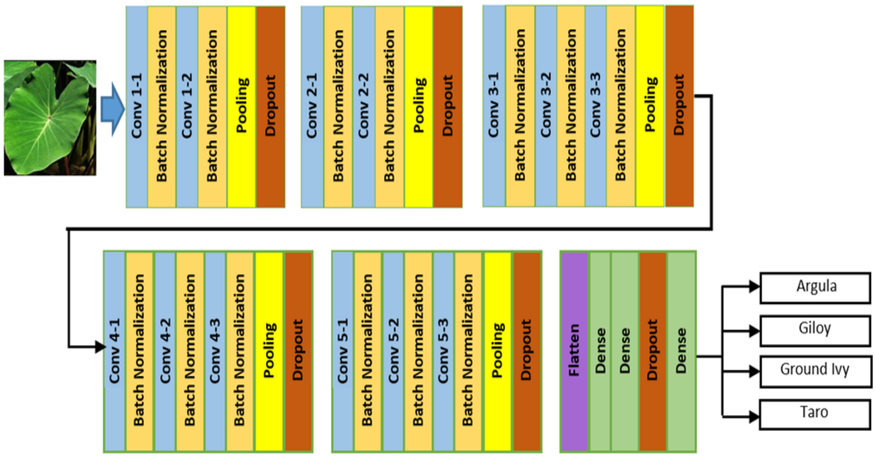

Figure 6. Different Layers used in the proposed methodology.

Convolutional Layers: There are 13 convolutional layers spread across 5 blocks, similar to VGG16. A **BatchNorm layer** is added after each convolutional layer, so there are **13 BatchNorm layers**.

Max Pooling Layers: There are 5 **MaxPooling2D layers**, one after each block of convolutional layers.

Dropout Layers: Dropout is applied after each convolutional block and after fully connected layers, totaling **6 Dropout layers** (5 after the convolutional blocks and 1 after the fully connected layers).

Fully Connected (Dense) Layers: There are 2 **Dense layers** (fully connected layers) with 4096 units each.

Flatten Layer: There is 1 **Flatten layer** that flattens the output from the convolutional layers before the dense layers.

Output Layer: There is 1 **final dense layer** for the output with num_classes units and a softmax activation.

4. KEY ENHANCEMENTS IN THE MODEL:

Batch Normalization:

Added after each convolutional layer and fully connected layer. This helps stabilize and speed up training by normalizing the activations, which reduces internal covariate shift.

4.2 Dropout:

Added after every convolutional block and fully connected layer to prevent overfitting, especially for smaller datasets like wheat classification. The dropout rates increase as the network gets deeper.

4.3 Increased Dropout in Fully Connected Layers:

A higher dropout rate (0.5) in the fully connected layers ensures that the model doesn't overfit, especially when working with large feature vectors extracted from earlier layers.

Additional Regularization:

These enhancements (BatchNorm + Dropout) together act as regularizes, improving the model's robustness and generalization on unseen data.

MODEL TRAINING ENVIRONMENT PARAMETER CONFIGURATION

The experiments in this paper were conducted on a system equiped with NVIDIA RTX 2060 with driver version 531.41 and CUDA version 11.8.The programming language used was Python version 3.8, with the deep learning framework PyTorch version 1.1. Pretrained weights were obtained from training on the public dataset PlantVillage. The datasets were trained for 30 epochs, with a learning rate set to 0.0001, input image size uniformly set to 224×223×3, momentum set to 0.9, batch size set to 32, and Adam optimizer used.

To evaluate various metrics of the model, the following metrics were adopted: accuracy, precision, Kappa parameter, recall, specificity, and F1-score. In the equations listed below, P (Positive) represents the true positive instances, i.e., the total number of samples belonging to the positive class in the dataset. N (Negative) represents the true negative instances, i.e., the total number of samples belonging to the negative class in the dataset. TP (True Positive) corresponds to the number of true positive instances, representing the quantity of instances correctly predicted as positive by the model. TN (True Negative) corresponds to the number of true negative instances, representing the quantity of instances correctly predicted as negative by the model. FP (False Positive) represents false positive instances, indicating the number of samples incorrectly predicted as positive by the model. FN (False Negative) represents false negative instances, indicating the number of samples incorrectly predicted as negative by the model.

$$Accuracy = \frac{TP + TN}{P + N} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{FP + TN} \tag{4}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

Table 1: Metric values for Different types of immuno-herbal leaf images.

	Accuracy	Precision	Recall	Specificity	F1 − score	Support
Arugula	0.92	0.93	0.94	0.94	O.80	71
Ground ivy	0.86	0.95	0.91	0.92	0.85	66
Taro	1.00	0.96	0.92	0.96	0.90	59
Giloy	0.96	0.92	0.88	0.91	0.89	66

5. RESULTS AND DISCUSSION

The experiments are conducted to compute the classification accuracies of different immuno-herbal leaf images. The classification accuracies of different types of herbal leaf images namely arugula, ground ivy, taro and Giloy are 92.5%, 94.2%, 93.5% and 95.2% respectively. The accuracies are shown in Figure 7.

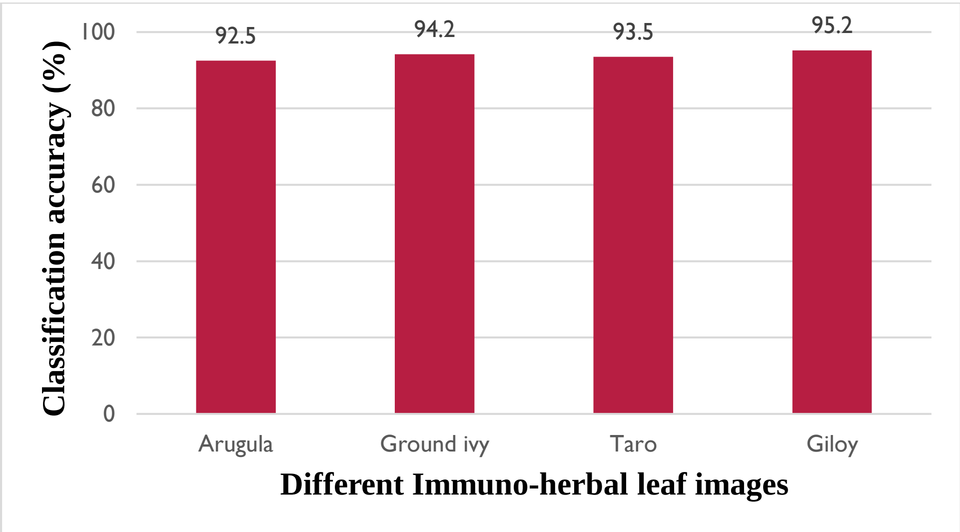

Figure 7. Classification accuracies of different immuno-herbal leaf images.

Further, the accuracies of varieties of arugula leaf images namely Red dragon, Garden tangy, Astro and Wasabi are computed and are shown in Figure 8. The overall accuracy of arugula herbal plant leaf images is 92.5%. Also, the classification accuracies of varieties of Ground Ivy, Taro and Giloy leaf images are obtained and are shown in Figure 9, Figure 10 and Figure 11 respectively.

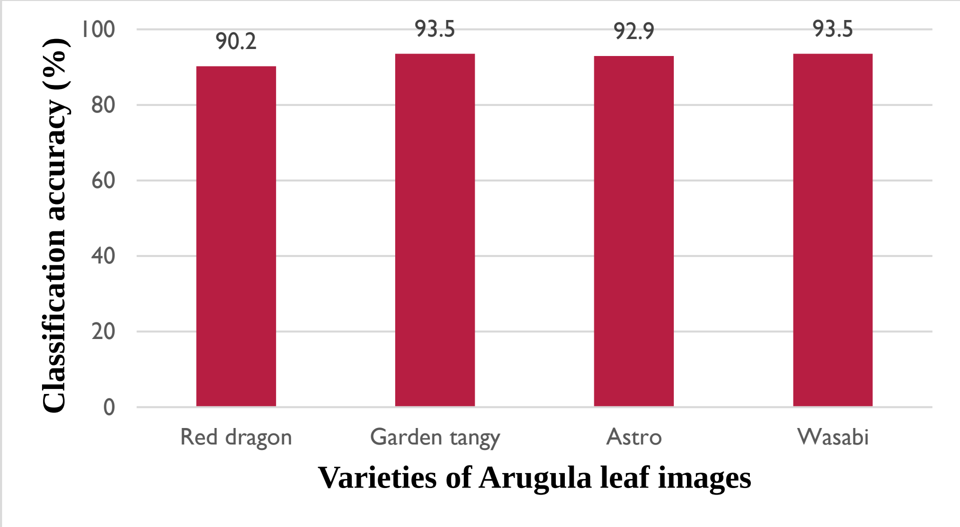

Figure 8. Classification accuracies of varieties of Arugula leaf images.

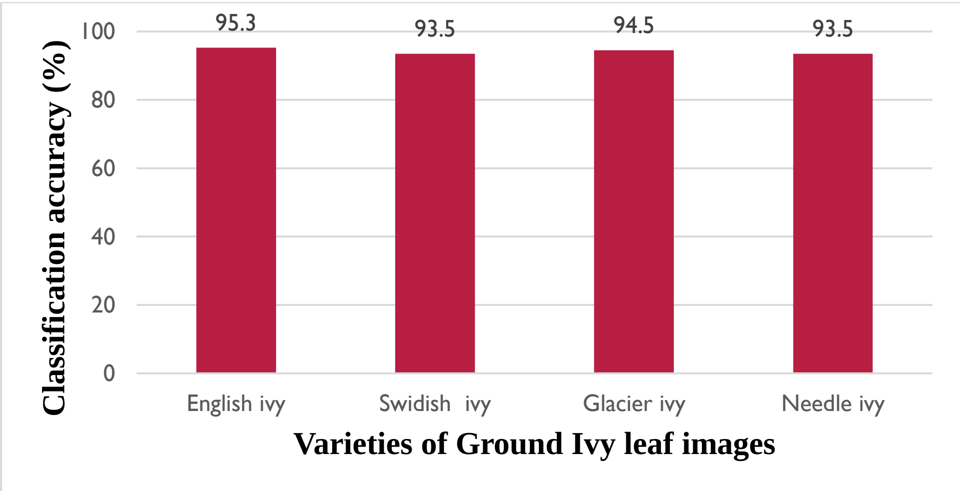

Figure 9. Classification accuracies of varieties of Ground Ivy leaf images.

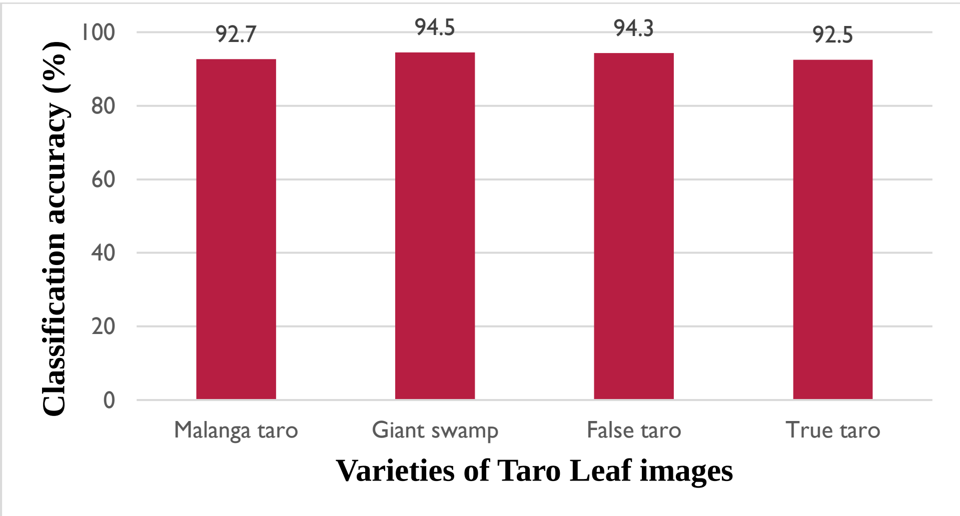

Figure 10. Classification accuracies of varieties of Taro leaf images.

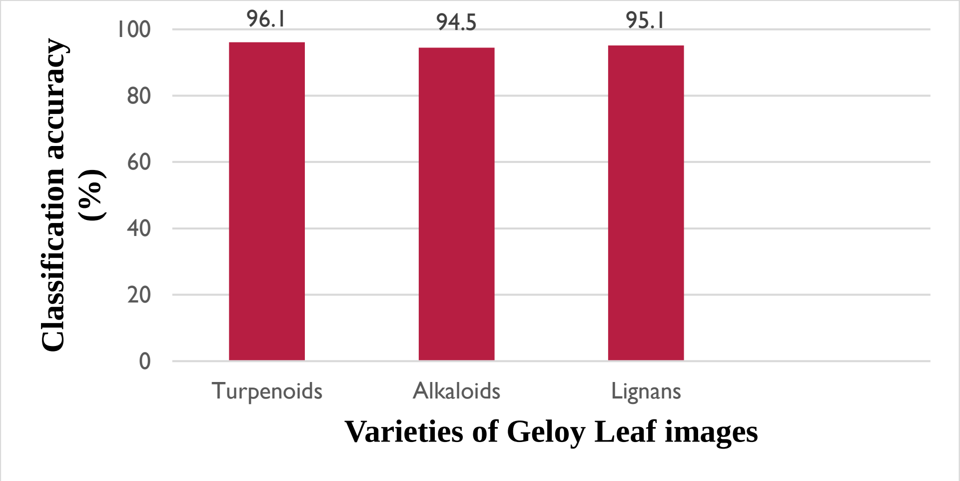

Figure 11. Classification accuracies of varieties of Geloy leaf images.

The confusion matrix and accuracy of the model is obtained for different epochs and the graph are shown in Figures 12 and 13. The proposed methodology has given better accuracy. The overall accuracy of 93.39% is obtained. The accuracy of Giloy leaf images is found to be maximum among all four types.

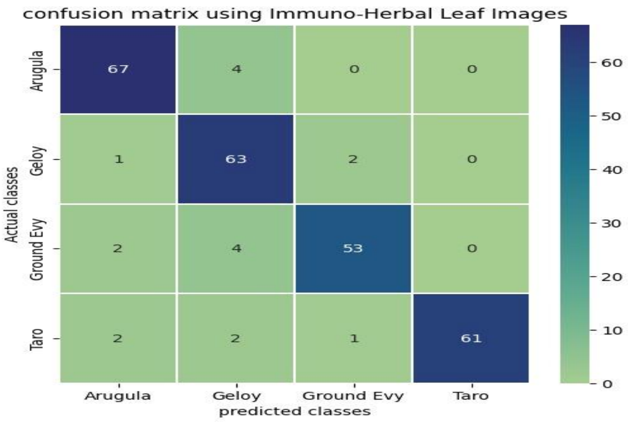

Figure 12. Confusion matrix

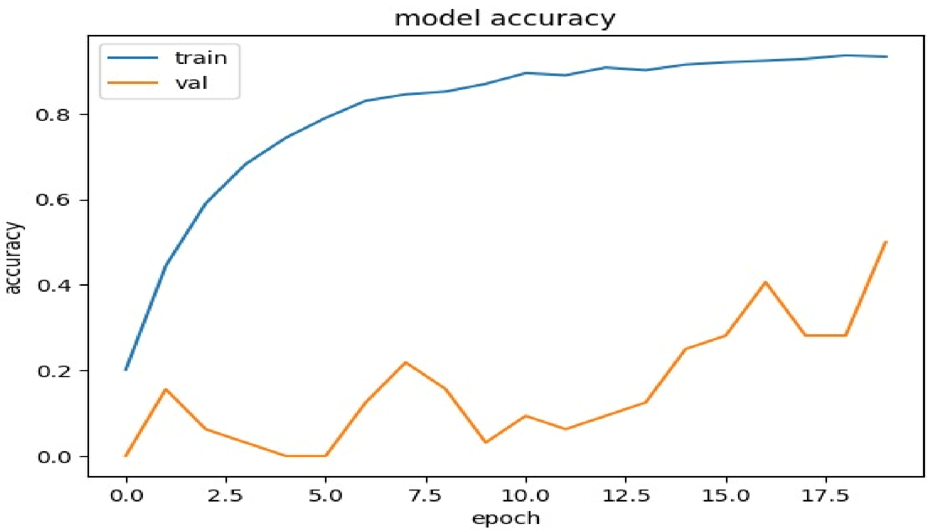

Figure 13. Graph showing Model accuracy for different epochs

6. CONCLUSION

Image processing-based approach is proposed and useful for plant diseases detection. This describes different techniques of image processing for several plant species that have been used for detecting plants for immunity booster. The proposed system focuses on utilizing the local immuno-herbal plants available. It creates awareness and helps society to gain natural immune power through the software tool developed, in order to withstand Covid-19 viral infections. The proposed methodology will also help people in society to keep themselves away from various infections other than COVID-19.

REFERENCES

[1] Mulugeta, A. K., Sharma, D. P., & Mesfin, A. H. (2024). Deep learning for medicinal plant species classification and recognition: a systematic review. Frontiers in Plant Science, 14, 1286088.

[2] Azgomi, Hossein, Fatemeh Roshannia Haredasht, and Mohammad Reza Safari Motlagh. "Diagnosis of some apple fruit diseases by using image processing and artificial neural network." Food Control 145 (2023): 109484.

[3] Shyni, H. Mary, and E. Chitra. "A comparative study of X-ray and CT images in COVID-19 detection using image processing and deep learning techniques." Computer Methods and Programs in Biomedicine Update (2022): 100054.

[4] Koklu, Murat, M. Fahri Unlersen, Ilker Ali Ozkan, M. Fatih Aslan, and Kadir Sabanci. "A CNN-SVM study based on selected deep features for grapevine leaves classification." Measurement 188 (2022): 110425.

[5] Malik, O. A., Ismail, N., Hussein, B. R., & Yahya, U. (2022). Automated real-time identification of medicinal plants species in natural environment using deep learning models—a case study from Borneo Region. Plants, 11(15), 1952.

[6] Badiger, Manjunatha, Varuna Kumara, Sachin CN Shetty, and Sudhir Poojary. "Leaf and skin disease detection using image processing." Global Transitions Proceedings 3, no. 1 (2022): 272-278.

[7] Aiswarya, K., and N. R. Sreekumar. "Plant Disease Detection Using Quantum Image Processing." In 2022 International Conference on Industry 4.0 Technology (I4Tech), IEEE (2022) pp. 1-6.

[8] Azadnia, R., Al-Amidi, M. M., Mohammadi, H., Cifci, M. A., Daryab, A., & Cavallo, E. (2022). An AI based approach for medicinal plant identification using deep CNN based on global average pooling. Agronomy, 12(11), 2723.

[9] Abdollahi, J. (2022, February). Identification of medicinal plants in ardabil using deep learning: identification of medicinal plants using deep learning. In 2022 27th International computer conference, computer society of Iran (CSICC) (pp. 1-6). IEEE.

[10] Amin, Hassan, Ashraf Darwish, Aboul Ella Hassanien, and Mona Soliman. "End-to-end deep learning model for corn leaf disease classification." IEEE Access 10 (2022): 31103-31115.

[11] Roopashree, S., & Anitha, J. (2021). DeepHerb: A vision based system for medicinal plants using xception features. Ieee Access, 9, 135927-135941.

[12] Bhattacharya, Sweta, Praveen Kumar Reddy Maddikunta, Quoc-Viet Pham, Thippa Reddy Gadekallu, Chiranji Lal Chowdhary, Mamoun Alazab, and Md Jalil Piran. "Deep learning and medical image processing for coronavirus (COVID-19) pandemic: A survey." Sustainable cities and society 65 (2021): 102589.

[13] Wang, Xi Vincent, and Lihui Wang. "A literature survey of the robotic technologies during the COVID-19 pandemic." Journal of Manufacturing Systems (2021).

[14] Singh, Dilbag, Vijay Kumar, and Manjit Kaur. "Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks." European Journal of Clinical Microbiology & Infectious Diseases 39, no. 7 (2020): 1379-1389.

[15] Muneer, A., & Fati, S. M. (2020). Efficient and automated herbs classification approach based on shape and texture features using deep learning. IEEE Access, 8, 196747-196764.

[16] Hasan, Syed Mohammad Abid, and Kwanghee Ko. "Depth edge detection by image-based smoothing and morphological operations." Journal of Computational Design and Engineering3, (2016): no. 3: pp. 191-197.

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