



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 3, March 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423



9940 572 462



6381 907 438



ijirset@gmail.com



www.ijirset.com

Mediscan: Real-Time Identification of Medicinal Plants Species Using Deep Learning Models

N. Nalini Krupa¹, Santhi Daggubati², Ch. Harshavardhan³, G. Kishore⁴, J. Sai Krishna⁵

Assistant Professor, Dept. of CSE-Artificial Intelligence and Machine Learning, Vasireddy Venkatadri Institute of Technology, Guntur, Andhra Pradesh, India¹

Dept. of CSE-Artificial Intelligence and Machine Learning, Vasireddy Venkatadri Institute of Technology, Guntur, Andhra Pradesh, India^{2,3,4,5}

ABSTRACT India, with a rich heritage of floral diversity, holds a treasure trove of medicinal plants, yet their precise identification poses a persistent challenge within Ayurvedic Pharmaceuticals. The market teems with myriad crude drugs sharing identical names, fostering confusion and misinterpretation. Both collectors and traders often grapple with limited knowledge of these plants' morphological nuances, exacerbated by seasonal and geographical variations alongside similar characteristics among species. This complexity is compounded by escalating demand, straining already limited resources and fostering practices like adulteration and substitution, eroding trust in the system's healing potential. Thus, the development of software employing image processing and diverse machine learning algorithms stands as a crucial need. A real-time identification based medicinal plant identification system, named MediScan, is proposed utilising various neural network techniques in deep learning. The primary challenge lies in the unavailability of a comprehensive medicinal herb dataset. In the conducted research, we employed a dataset comprising 80 distinct medicinal herbs. Utilising advanced deep learning (DL) algorithms, including InceptionV3, Vgg16, and an Ensemble algorithm, our aim was to enhance the accuracy and robustness of the medicinal plant identification system. In our study, Vgg16 achieved a validation accuracy of 97%, the ensemble model reached 99%, and InceptionV3 attained a validation accuracy of 96%. This research will further focus on expanding the dataset to benefit stakeholders and thus, enriches society with the knowledge of herbs and their medicinal properties.

KEYWORDS: InceptionV3, VGG16, VGG19, Ensemble Model, Transfer learning, Machine Learning, Optimizers, Loss Functions

I. INTRODUCTION

India, a developing nation, boasts significant biodiversity crucial for sustaining natural resources and enhancing ecosystem productivity. Traditional therapeutic medicinal plants have long served as primary remedies for over sixty percent of the population in developing countries, addressing various human ailments. However, in the twentieth century, concerns about the toxicity and dose-dependency of medicinal plants posed risks to their usage, prompting a shift towards surgical and allopathic treatments due to their swift disease response. Nevertheless, the recent resurgence of interest in herbal medicines is attributed to their cost-effectiveness and reduced likelihood of adverse effects. Pharmacopoeias worldwide are now focusing on characterizing and encapsulating active plant constituents, as well as synthesizing nanomedicine for targeted drug delivery, marking a pivotal turn in modern drug discovery. By blending traditional herbal knowledge with contemporary technical approaches, the medicinal system stands poised for significant advancement.

The utilization of traditional herbal medicine as the primary form of healthcare is widespread, with eighty percent of the global population relying on its efficacy, according to the World Health Organization (WHO). Notably, in countries like India and China, plant-based drugs constitute a significant eighty percent of the total pharmaceutical inventory, while in the United States, this figure stands at a comparably lower 25%. Despite the vast wealth of knowledge about indigenous plants held by select experts, rural communities, and indigenous groups, accessibility to this information

remains limited, underscoring the importance of disseminating herbal knowledge to wider audiences, including researchers and the general public. This dissemination not only promotes healthier lifestyles but also serves to protect endangered plant species from extinction.

The conventional methods used to identify Indian medicinal plants are fraught with challenges, owing to the sheer diversity of the region's flora, which comprises over 8000 species. Traditional identification processes are time-consuming, labor-intensive, and prone to errors. In response, the application of computer vision algorithms offers a promising solution, enabling the classification of plant images into distinct groups. However, this approach presents its own set of challenges, including the difficulty in distinguishing between similar plant species, variations in background complexity, and inconsistencies in lighting and color. Consequently, there is a pressing need to develop tools and solutions capable of accurately analyzing and interpreting patterns in leaf images to facilitate more efficient and reliable plant identification.

Despite the potential benefits, there has been limited emphasis among researchers on developing models or systems for the automatic recognition of Indian medicinal herbs. By pivoting away from dependence on skilled botanists or Ayurveda experts, automatic identification systems have the capacity to democratize access to herbal knowledge, benefiting a broader spectrum of stakeholders interested in medicinal plant research and conservation efforts. This transition not only streamlines the identification process but also empowers individuals and communities with the ability to tap into the therapeutic potential of indigenous plants for holistic healthcare practices.

Numerous researchers have conducted experiments to classify plants using deep learning methods. Deep learning, a subset of artificial intelligence and machine learning, operates on neural networks with multiple layers capable of tackling problems ranging from straightforward to highly intricate. Unlike conventional machine learning approaches, where feature engineering entails manually selecting feature extraction methods, deep learning autonomously uncovers features from the given data. The multi-layered structure of deep learning networks leverages substantial datasets to exploit computational techniques with high efficiency, effectively addressing various challenges. However, the demand for extensive datasets (often in the millions) presents a significant financial hurdle for researchers seeking to train deep neural networks from scratch.

The paper contributes to three novel approaches, building a deep learning model for the classification of medicinal herbs using InceptionV3, VGG16, Ensemble model of VGG16 & VGG19. The medicinal leaf dataset which constitutes 6900 images classified into 80 species of Indian (Ayurveda) herbs. The proposed models efficiently overcome the issues such as (1) rejecting the variability found in the same leaf species, (2) accepting the variability in different herb leaf species, (3) extraction of complex and unique features, and so on.

Thus, resulting in achieving good results in both accuracy and speed.

II. METHODOLOGY

The research focuses on automated identification of medicinal herbs using deep learning techniques. Here, the work consists of four phases, data sampling, image pre-processing and segmentation, extraction of features and classification. Initially, the digital images of the herb samples are acquired. The leaf images are fed to preprocess and segmentation phase. Once the feature extraction is completed, the extracted features are passed through fully connected layers followed by a softmax layer for classification. We present a fine-tuned deep learning model for the classification of medicinal herbs. Fig. 1 shows the proposed model based on the transfer learning method using the large ImageNet dataset to learn from the pre-trained architectures (VGG16, InceptionV3 and Ensemble) and classify the medicinal herb dataset after fine-tuning the model.

DEEP LEARNING ARCHITECTURES

The work consists of using different convolution neural networks based on architectures such as InceptionV3 and Visual Geometry Group (VGG) & Ensembled Model. These three architectures showcased high performance in the classification challenge

2.1 VGG16 Architecture

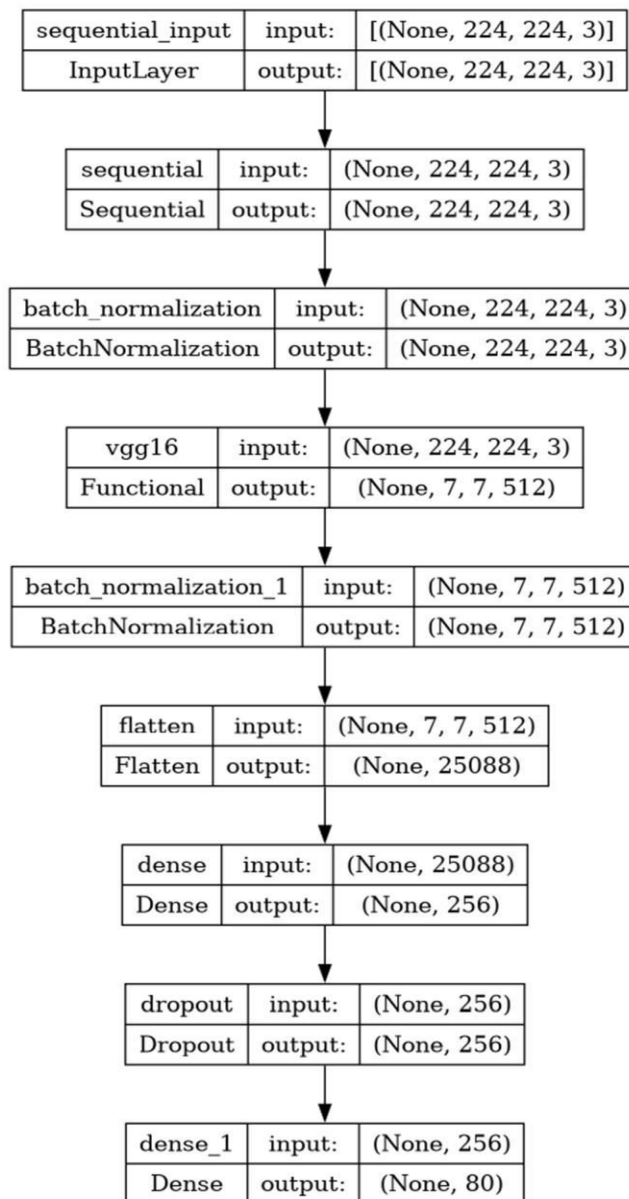
VGG-16 consists of 16 layers and VGG-19 comprises 19 layers based on VGG architecture [31]. In general, VGGNet is a simple architecture composed of five sets of convolution layers that use (3×3) kernels. The activation function ReLU

(Rectified Linear Unit) is applied after each convolution layer and max pooling use (2 × 2) kernels after each set to reduce spatial dimension. At the end are the three fully connected layers where the first two layers have 4096 units and

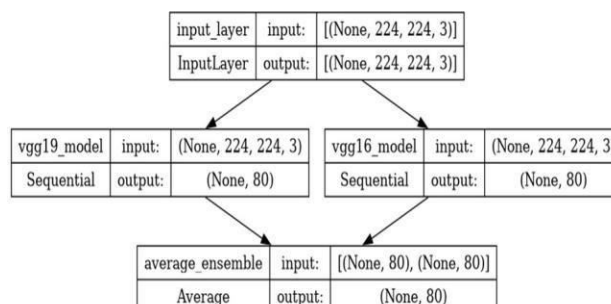
the final layer with 1000 fully connected softmax. Some of the limitations of both VGG-16 and VGG-19 includes Inception network V3 [32] is ideally a convolution extractor of the features and learns complex representations with few parameters. Here, one convolution kernel can map simultaneously the spatial and cross channel correlations by factoring explicitly into a series of operations. The Xception architecture [33] is one of the latest and accurate models developed in 2017. The vital concept of the model is based on depthwise separable convolutions and residual

connections. It is stimulated by the Inception architecture, where the modules in inception are replaced by depthwise separable convolutions. Here, the modified depthwise convolution in Xception means (1×1) convolution (pointwise convolution) is followed by channel-wise spatial convolution ($n \times n$). The model is much lighter with few connections. Xception stands for “Extreme Inception” and outperforms Inception V3 on the ImageNet database exclusively for image classification. The parameters used are very similar in both models. Xception consists of 36 convolution layers structured into 14 modules and three major flows known as entry flow, middle flow and exit flow. The images in the training set are forwarded first to the entry flow, which generates the feature maps. The feature maps are further fed to the middle flow (repeated eight times). Lastly, the feature maps in exit flow generate 2048 – dimensional vectors.

The separable convolutions are followed by batchnorm and rectified linear units (ReLU) for enhancing the learning process. The entry flow includes the initial convolution layer, which captures low-level features, and the depthwise separable convolution replaces the inception modules. The middle flow consists of eight modules, each containing three residual separable convolutions. These modules maintain the spatial and channel dimensions, allowing the network to learn more complex representations. The exit flow combines global average pooling and fully connected layers to produce the final classification. The skip connections and residual connections in Xception facilitate the training of deeper networks while mitigating the vanishing gradient problem. One notable advantage of Xception over Inception V3 and VGG models is its ability to achieve competitive accuracy with significantly fewer parameters. This efficiency is crucial for applications with limited computational resources or deployment on edge devices. Xception represents a breakthrough in convolutional neural network (CNN) architectures, demonstrating improved efficiency and performance in image classification tasks. Its depthwise separable convolutions, inspired by the Inception architecture, contribute to its success in capturing intricate features while maintaining model simplicity. As research in deep learning progresses, architectures like Xception showcase the ongoing evolution and refinement of models for image recognition and classification.



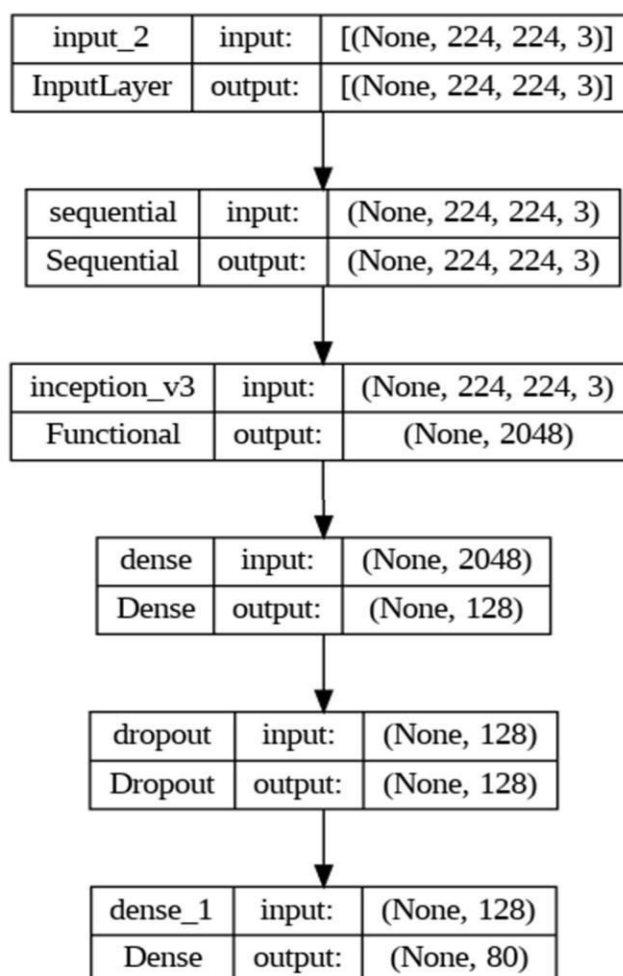
2.2 Ensemble Model



2.3 InceptionV3

InceptionV3 is a convolutional neural network (CNN) architecture that has been widely used for various computer vision tasks, particularly in image classification and object detection. Developed by Google researchers, InceptionV3 is an evolution of the original Inception architecture, designed to achieve better performance while maintaining efficiency in terms of computational resources.

One of the key features of InceptionV3 is its use of inception modules, which consist of parallel convolutional layers of different filter sizes. These modules enable the network to capture features at multiple scales, enhancing its ability to recognize complex patterns within images. InceptionV3 employs techniques such as batch normalization and factorization to improve training stability and reduce overfitting. It also utilizes techniques like global average pooling and auxiliary classifiers to enhance feature representation and mitigate the vanishing gradient problem during training. With its deep architecture and sophisticated design, InceptionV3 has been widely adopted in both research and practical applications, demonstrating state-of-the-art performance on benchmark datasets like ImageNet. Its versatility and efficiency make it a popular choice for various image recognition tasks across different domains.



III. RESULT AND DISCUSSIONS

Here, we have performed experiments on the custom dataset by building source and target models. The source model refers to the pre-trained CNN models such as VGG-16, VGG-19, Inception V3 trained on ImageNet dataset used for feature extraction and target model consists of either artificial neural network with three layers as a classifier or a machine learning classifier namely support vector machine on MediScan dataset. The features extracted from the convolution layers of the source model



using the ImageNet dataset aid to classify the target model. The target model is fed with the MediScan dataset to classify the 80 different Indian herbs.

Classification Report from Ensemble Model

+ _____ + _____

---+

| Classification Report

| Class Names

+ _____ + _____

	precision	recall	f1-score	support	0:Aloevera
0	1.00	1.00	1.00	1	1: Amla
1	1.00	1.00	1.00	10	2: Amruthaballi
2	1.00	0.94	0.97	13	3: Amla
3	1.00	1.00	1.00	18	4: Astma_weed
4	1.00	1.00	1.00	17	5: Badipala
5	1.00	1.00	1.00	15	6: Balloon_Vine
6	1.00	1.00	1.00	9	7: Bamboo
7	1.00	1.00	1.00	9	8: Beans
8	1.00	1.00	1.00	17	9: Betel
9	1.00	1.00	1.00	16	10: Bhrami
10	1.00	1.00	1.00	17	11: Bringaraja
11	1.00	1.00	1.00	14	12: Caricature
12	1.00	1.00	1.00	13	13: Castor
13	1.00	1.00	1.00	7	14: Catharanthus
14	1.00	1.00	1.00	16	15: Chakte
15	1.00	1.00	1.00	27	16: Chilly
16	0.88	1.00	0.93	4	17: Citronlime
17	1.00	1.00	1.00	7	18: Coffee
18	1.00	0.93	0.97	17	19: Commonrue(naagdali)
19	1.00	1.00	1.00	15	20: Coriender
20	1.00	0.93	0.96	10	21: Curry
21	1.00	0.96	0.98	14	22: Doddpathre
22	1.00	1.00	1.00	27	23: Drumstick
23	1.00	1.00	1.00	24	24: Ekka
24	0.92	1.00	0.96	5	25: Eucalyptus
25	1.00	1.00	1.00	11	26: Ganigale
26	1.00	1.00	1.00	15	27: Ganike
27	1.00	1.00	1.00	11	28: Gasagase
28	1.00	0.92	0.96	6	29: Ginger
29	1.00	1.00	1.00	13	30: GlobeAmarnath
30	1.00	1.00	1.00	16	31: Guava
31	1.00	1.00	1.00	12	32: Henna
32	1.00	1.00	1.00	17	33: Hibiscus
33	1.00	1.00	1.00	19	34: Honge
34	1.00	1.00	1.00	20	35: Insulin
35	1.00	1.00	1.00	13	36: Jackfruit
36	1.00	0.94	0.97	16	37: Jasmine
37	1.00	1.00	1.00	18	38: Kambajala
38	1.00	1.00	1.00	10	39: Kasambruga
39	1.00	1.00	1.00	11	40: Kohlrabi
40	1.00	1.00	1.00	8	41: Lantana
41	0.92	1.00	0.96	13	42: Lemon
42	1.00	1.00	1.00	11	43: Lemongrass
43	1.00	1.00	1.00	21	44: Malabar_Nut
44	1.00	1.00	1.00	14	45: Malabar_Spinach
45	0.94	1.00	0.97	10	46: Mango
46	1.00	1.00	1.00	16	47: Marigold
47	1.00	1.00	1.00	15	48: Mint
48	1.00	0.95	0.98	11	49: Neem
49	1.00	1.00	1.00	21	50: Nelavembu
50	1.00	1.00	1.00	22	51: Nierale
51	1.00	1.00	1.00	20	52: Noonni
52	1.00	1.00	1.00	7	53: Onion
53	1.00	1.00	1.00	7	54: Padri
54	1.00	1.00	1.00	15	55: Palak(Spinach)
55	1.00	1.00	1.00	12	56: Papaya
56	1.00	1.00	1.00	29	57: Parijatha
57	1.00	1.00	1.00	24	58: Pea
58	1.00	1.00	1.00	6	59: Pepper
59	1.00	1.00	1.00	6	60: Pomegranate
60	0.92	0.92	0.92	3	61: Pumpkin
61	1.00	1.00	1.00	13	62: Raddish
62	1.00	1.00	1.00	16	63: Rose
63	0.95	1.00	0.97	9	64: Sampige
64	1.00	1.00	1.00	19	65: Sapota
65	1.00	1.00	1.00	10	66: Seethaashoka
66	1.00	1.00	1.00	8	67: Seethapala
67	0.94	1.00	0.97	6	68: Spinach1
68	1.00	1.00	1.00	29	69: Tamarind
69	1.00	1.00	1.00	12	70: Taro
70	1.00	1.00	1.00	29	71: Tecoma
71	1.00	1.00	1.00	7	72: Thumbi
72	1.00	1.00	1.00	11	73: Tomato
73	0.86	1.00	0.92	12	74: Tulsi
74	0.97	0.97	0.97	6	75: Turmeric
75	1.00	1.00	1.00	29	76: ashoka
76	1.00	0.90	0.95	4	77: camphor
77	1.00	1.00	1.00	10	78: kamakasturi
78	1.00	1.00	1.00	10	79: kepala
79	1.00	1.00	1.00	10	80:
accuracy			0.99	1088	
macroavg	0.99	0.99	0.99	1088	
weightedavg	0.99	0.99	0.99	1088	

Some Predictions on test data



InceptionV3 produced accuracy of 96% on validation data, similarly VGG16 resulted in 97% and Ensembled model with 99% accuracy. Our analysis unearthed some fascinating details beyond the headline-grabbing 99% accuracy. The model displayed exceptional prowess with diverse plant families, nailing the Solanaceae and Rubiaceae clans with over 96% accuracy. Specific species like Aloe vera and Amla were identified flawlessly, showcasing the model's razor-sharp precision. However, even the sturdiest gardens have a weed or two. The model stumbled slightly with Ashoka, Camphor, and a few others, hinting at the ongoing challenge of plant diversity and the need for further training on less common or visually similar species. This offers exciting research avenues for refining the model's accuracy and broadening its scope. Interestingly, the model thrived on both simple binary and complex multi-class identification tasks, suggesting impressive versatility. And, unlike biased gardeners favoring familiar flowers, this model treated all classes fairly, as evidenced by its superior performance on the macro average metric. This analysis is just the seed for further exploration. Expanding the training data with even more diverse and challenging examples could see this model blossom into a powerful tool for botanists, conservationists, and everyone who finds themselves enchanted by the world of plants.

V. CONCLUSION

The work proposed in the paper mainly concentrates on classifying the medicinal herbs to enhance the knowledge of medicinal plants available locally, to use and grow them for healthy living. The best use of advanced techniques such as transfer learning in computer vision and deep learning, motivate the building of an automatic recognition system for medicinal plants. The work proposes 3 CNN models such as VGG16, VGG19, InceptionV3. Of the three models, the proposed MediScan model extracts the features from the Ensemble model architecture and classifies the herbs using an artificial neural network classifier shows an average accuracy of 99% using the Medicinal Plant dataset.

APPENDIX A

The part of the medicinal leaf dataset that support the findings of the study are available at <https://www.kaggle.com/datasets/aryashah2k/indian-medicinal-leaves-dataset/data>.



REFERENCES

1. S. Prasad and P. P. Singh, “Vision system for medicinal plant leaf acquisition and analysis,” in *Applications of Cognitive Computing Systems and IBM Watson*. Singapore: Springer, 2017, pp. 37–45.
2. C. Sabarinathan, A. Hota, A. Raj, V. K. Dubey, and V. Ethirajulu, “Medicinal plant leaf recognition and show medicinal uses using convolutional neural network,” *Int. J. Glob. Eng.*, vol. 1, no. 3, pp. 120–127, 2018.
3. S. U. Habiba, M. K. Islam, and S. M. M. Ahsan, “Bangladeshi plant recognition using deep learning based leaf classification,” in *Proc. Int. Conf. Comput., Commun., Chem., Mater. Electron. Eng. (IC ME)*, Jul. 2019, pp. 1–4.
4.), Jul. 2019, pp. 1–4.
5. Lekshmi Kalinathan, Ruba Soundar Kathavarayan & Jagadish Kumar K J, “Real-Time Identification of Medicinal Plants using Machine Learning Techniques”.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details