DeepHerb: A Vision Based System for Medicinal Plants Using Xception Features

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ABSTRACT The conservation of biodiversity is crucial as many plant species are critically under extinction. The traditional medicinal system, an alternative to synthetic drugs, promote healthy living and mainly depends on the wide repository of plants. A vision-based automatic medicinal plant identification system is proposed using different neural network techniques in computer vision and deep learning. The challenge lies in the unavailability of the medicinal herb dataset. The paper showcases a novel medicinal leaf dataset entitled DeepHerb dataset comprising of 2515 leaf images from 40 varied species of Indian herbs. The efficacy of the dataset is revealed by comparing pre-trained deep convolution neural network architectures such as VGG16, VGG19, InceptionV3 and Xception. The work concentrates on adopting the transfer learning technique on the pre-trained models to extract features and classify using Artificial Neural Network (ANN) and Support Vector Machine (SVM). The SVM hyperparameters are tuned further by Bayesian optimization to achieve a better performance model. The proposed DeepHerb model learned from Xception and ANN outperformed by 97.5% accuracy. A cross-platform mobile application entitled HerbSnap developed integrating the DeepHerb model identifies the herb image with a prediction time of 1 second per image and reveals the pertinent details of herbs from the database. 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.

INDEX TERMS Bayesian optimization, computer vision, deep learning, medicinal plants, support vector machine, transfer learning, Xception.

I. INTRODUCTION

India, a developing country is rich in biodiversity. Conservation of biodiversity ensures the sustainment of natural resources by boosting ecosystem productivity. More than sixty per cent of the population in developing countries rely on traditional therapeutic medicinal plants for curing many human ailments [1]. Though in the twentieth century, an impact on medicinal plants being poisonous and dose-dependent resulted in great danger to the usage of herbal medicines [2]. This impression moved people drastically towards surgical and allopathic treatments due to their quick response in treating the diseases. However, in recent years, low-cost and reduced chance of side-effects in herbal medicines drew the focus of pharmacopoeias in the world to characterize and encapsulate many of the active plant constituents, and also to synthesize nanomedicine as target action in new drug discovery. The amalgamation of traditional herb knowledge and modern technical approach will eventually upgrade the medicinal system to a greater extent.

WHO (World Health Organization) revealed that eighty per cent of the world depend on traditional herbal medicine as their primary medical care. As per the estimation, the contribution of plant drugs over the total drugs is 80% in India and China whereas 25% in the USA (United States of America). The knowledge of indigenous plants is well known by few experts, rural and native people and lacks easy access to its evidence. Hence, promoting the knowledge of herbs to the general public and researchers is important to promote healthy herbal life and prevent the extinction of the potential herbs [3].

The conventional method of identifying the Indian medicinal plants are time-consuming, tedious and a challenging

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work as it may be incorrect many a time for the reason that Indian herb wealth composes of more than 8000 species [4]. Classifying the herbs using the algorithms of computer vision show concern on categorizing the plant images into its distinct groups. The classification of plants using digital leaf images are challenging due to their similarities in inter-class and intra-class, the possibility of complex background and variations in many parameters such as illumination and colour. Thus, developing tools and solutions to analyze and interpret the patterns in the leaf images with significant results are essential. A model or system to accelerate the automatic recognition of Indian medicinal herbs is yet not concentrated in recent times by many researchers. Instead of relying on skilled botanists or Ayurveda (an ancient medicinal system of India) experts, automatic identification of therapeutic herbs will spring knowledge at ease to the general public and other stakeholders of medicinal plants.

The various trials exhibited by many scientists to classify plants using deep learning techniques [5]–[9]. Deep learning is a branch of artificial intelligence and machine learning, based on neural networks with multiple layers, can classify simple to most complicated problems [10]. In contrast to machine learning techniques, where feature engineering involves the manual selection of the feature extraction methods, deep learning automatically discovers the features from the given data [11]. The multi-layers in deep learning, use a large amount of data to exploit their architecture using the computation techniques with high performance to overcome the issues. The requirement of a large amount of data (millions) is expensive for any researcher to train the deep neural network from scratch.

Numerous applications in deep learning have proved good results towards the recognition of leaf images [12], [13]. Therefore, this research work concentrates to overcome several issues on the recognition and classification of plant leaf images by maintaining high accuracy and reduced prediction time for the system. The paper contributes to two novel approaches, firstly, building a deep learning model for the classification of medicinal herbs. Secondly, the custom medicinal leaf dataset which constitutes 2515 images to identify 40 species of Indian (Ayurveda) herbs. The paper projects two unique models out of six models incorporating the transfer learning approach on different pre-trained Deep Convolution Neural Network (DCNN) architectures (VGG-16, VGG-19, Inception and Xception) used exclusively to extract features. Of the six models, four models classify the extracted features using an Artificial Neural Network (ANN) and the other two use Support Vector Machine (SVM) and SVM with Bayesian optimization technique (to tune the SVM hyperparameters) as classifiers. The custom dataset used is very small to build any Convolution Neural Network (CNN) from scratch because CNN requires a larger dataset for better evaluation. Hence, using the transfer learning technique has proved as a better choice for training the CNN models with a dataset of a smaller size. This result in reduced training time as well as overcoming the overfitting issue.

The proposed model efficiently overcomes 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. To summarize, the major contributions proposed are:

(1) The custom dataset, built by collecting leaves from varied species of medicinal herbs available locally in the south India region. Several experiments carried over to standardize the dataset to achieve a high classification rate when applied to the proposed models. The proposed dataset attracts many researchers to build automatic image classification models using the artificial intelligence approach. The implemented system is analyzed using the Flavia dataset [14] and the custom dataset to compare the performance of the model.

(2) Extensive review from the related works helped to conclude on DCNN architectures such as VGG16, VGG19, InceptionV3 and Xception, classifiers such as ANN and SVM.

(3) The proposed model entitled DeepHerb model developed by extracting the Xception features and classified using ANN classifier shows high accuracy with less prediction time on real-time images.

(4) A mobile solution by developing a cross-platform mobile application labelled as ''HerbSnap''. The DeepHerb model is deployed into HerbSnap to classify the medicinal herbs with an accuracy of 95% (top-5 recognition rate) without any delay in recognising them. Table 11 describes the improved recognition time. A curated database (Traditional Medicinal Herb database) consisting of the pertinent details of the medicinal plants is integrated into HerbSnap to reveal the details of the recognized herbs.

The paper is organized as follows: Background study on transfer learning and CNN in section II. Section III describes the proposed methodology; the detailed findings are discussed in section IV. Section V concludes the work with future research ideas.

II. BACKGROUND STUDY

Automatic identification of medicinal herbs is essential and soon replace the manual recognition of enormous plant species by subject experts resulting in many benefits such as the reduced time and cost with acceptable classification accuracy. In the field of computer vision, solving problems using deep learning algorithms has become more prevalent. The study of an identification system for the plant has been carried over previously by many researchers. Analysis of digital images is essential in the research area of plant recognition [15]. The conventional approaches in machine learning techniques involve feature extraction algorithms, feature scaling and classification methods. The application of deep learning techniques on medicinal herb images includes no feature engineering but using convolution neural networks to extract the colour, vein, shape and edge features of a leaf image. Hence, for the classification, the selection of hand-crafted features extracted from the leaf image is eliminated.

The study shows the different classification techniques involved in two folds: to recognize the common/general plants using popular online leaf dataset by developing CNN from scratch and the other to identify the medicinal plants using custom dataset adopting the transfer learning approach using different DCNN architectures.

The CNN demonstrates an exceptional performance on many machine learning and image processing works [16] as it involves automatic extraction of both local and global features of an input image. A three-layer CNN model proposed to identify the plants using vein features from the INTA custom dataset for three different leaf species showed an acceptable accuracy of 92% [17]. A leaf identification system using five modules (2 convolutions and max-pool) followed by 3 Fully Connected Layers (FCL) of CNN architecture over general public leaf datasets such as Flavia with 97.9%, Leaf-Snap [18] with 86.3% and Foliage [19] demonstrated 95.8% accuracy [20]. Using the MalayaKew Leaf dataset, the five-layer network with two FCL in the CNN architecture built for the classification of leaves showed an accuracy of 97.70% and prove to have obtained a better representation of leaf features compared to the conventional approach [21]. A new three convolutional layer architecture built to extract features and classify using 2 fully connected layers accompanied by a softmax layer on the Flavia dataset showed an accuracy of 94.69%. Similarly, many references on building CNN from scratch on general leaf images depicted in Table 1 prove to be a good solution to replace the choice of multiple combinations of feature extraction techniques. But a large dataset is essential to achieve a high classification rate while performing real-time testing. Because to generalize all the patterns using limited dataset is difficult for any classifier. Also, limited dataset sufficiently representing its original distribution is considered as important in building the models [22].

Building new CNN architecture exclusively for medicinal herbs require a large custom-built herb dataset as the model may result in overfitting using the limited dataset. Currently, there is no availability of a public medicinal leaf dataset. Hence, there exists a huge demand to build one for developing a convenient system for medicinal plants. Although many data augmentation techniques such as horizontal flip, vertical flip, rotation, scaling and addition of noise are used to enlarge the dataset, the results may not be satisfactory. Another alternative approach for the above problem of a small custom dataset is Transfer Learning (TL) technique. The observations inferred from Table 2 summarizes the few works on the application of the transfer learning approach on medicinal plants. Also, the study reveals that the researchers have taken additional effort to build their dataset for model evaluation. The VGG-Net architecture used for feature extraction and SVM for classification on a custom dataset of Indian herbs showed an accuracy of 90.10%. But, no record of the prediction time and real-time testing [23].

The Inception-V3 architecture built along with SVM on a custom dataset showed an accuracy of 98%. The custom Indian herb dataset was constructed by extracting the images from google without maintaining the standard resolution [24]. The Bangladeshi herb dataset used VGG-16 architecture with an additional softmax layer to classify 8 classes, presented an accuracy of 95.13% [25]. The lack of standard images in the dataset has led to reduced accuracy. The AlexNet model with SVM showed an accuracy of 96.76% on 40 species of Indian herb dataset consisting of 2400 images. The dataset comprises 60 images per class (includes both front and back of each leaf face) where every sample image scanned are edited manually by using GIMP editor. Model evaluation time (training and testing), real-time testing and automation of editing the input images are not detailed [26].

The observations derived from Table 1 and 2, reveal that the features extracted from pre-trained convolution layers provide greater accuracy in recognizing the herbs and there exists a need to construct a standard medicinal leaf dataset just like the popular Flavia dataset built on leaves of general plants. The developed CNN models to be evaluated on real-time images for their efficacy on both accuracy and time. These studies motivate to propose a novel model using different DCNN architecture for extracting the leaf features. The proposed work will be a major contribution to the field of automatic identification of medicinal plants.

III. METHODOLOGY

The research focuses on automated identification of medicinal herbs using transfer learning technique in deep learning. Due to the unavailability of the herb dataset, efforts taken to construct a custom medicinal leaf dataset. Forwarding this dataset to build a CNN model in a traditional way result in reduced accuracy because the network requires a larger dataset (thousands or millions of images) for training, to provide competitive accuracy on real-time testing. The previous studies and review of the latest works prove that the use of transfer learning is a better approach to classify any images when the target dataset is limited in size.

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 pre-process and segmentation phase. The features of the leaf are extracted to obtain significant information by using the CNN architecture. Lastly, the features are classified using two machine learning techniques such as ANN and SVM.

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 (VGG, InceptionV3 and Xception) and classify the custom medicinal herb dataset after fine-tuning the model.

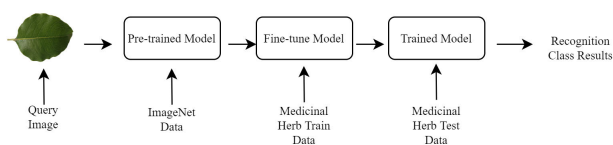### A. DEEP LEARNING ARCHITECTURES

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

TABLE 1. Summary of works on general plant dataset using CNN network.

References	Dataset	#Classes	#Samples	Accuracy (%)
Grinblat, G. L. et al., (2016) [17]	INTA (Instituto Nacional de Tecnologia Agropecuaria, Oliveros, Argentina)	3	866	92.60
Barre, P. et al., (2017) [20]	Flavia	32	1907	97.90
	Foliage	60	7200	95.80
	LeafSnap	180	28763	86.30
Lee, S. H. et al., (2015) [21]	MalayaKew (MK) Leaf	44	2816	97.70
Zhang, et al., (2015) [27]	Flavia	32	1907	94.69
Jeon, W. S., & Rhee, S. Y., (2017) [28]	Flavia	32	1907	99.60
Yalchin, H., & Razavi, S., (2016) [29]	TARBIL	16	4800	97.47

TABLE 2. Summary engaging different deep learning architecture using transfer learning on medicinal plant custom dataset.

References	CNN Network	Dataset	#Classes	#Samples	Accuracy (%)
Prasad, S., & Singh, P., (2017) [23]	VGG-Net in PCA	Custom	30	1500	90.10
		ICL	220	17000	90.70
Sabarinathan, C., et al., (2018) [24]	Inception-V3	Custom	50	1500	98.00
		Flavia	32	1907	99.28
		LeafSnap	150	7710	96.61
		ImageClef	126	6630	96.42
Habiba, S. U., (2019) [25]	VGG 16	Custom	8	8000	95.13
	VGG 19				92.75
	Resnet 50				89.63
	Inception V3				85.51
	Inception Resnet V2				87.33
	Xception				89.93
Dileep, M. R., & Pournami, P. N., (2019) [26]	Alexnet	Custom (AyurLeaf)	40	2400	94.87
	AyurLeaf-Alexnet				96.76

FIGURE 1. General representation of transfer learning on fine-tuned model.

in 2014 ILSVRC [30]. If Inception and Xception, are built on GoogleNet then VGG-16 and VGG-19 are built on VGG architecture. GoogleNet employs 7 million parameters whereas VGGNet with 180 million parameters. Fig. 2 shows the architecture of pre-trained models such as VGG–16, VGG–19, Inception V3 and Xception on ImageNet dataset widely used for many object detections tasks and implemented in our research work.

1) VGG-16 AND VGG-19
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

more memory usage, more parameters and expensive evaluation.

2) INCEPTION V3 AND Xception
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 seperable 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 batch
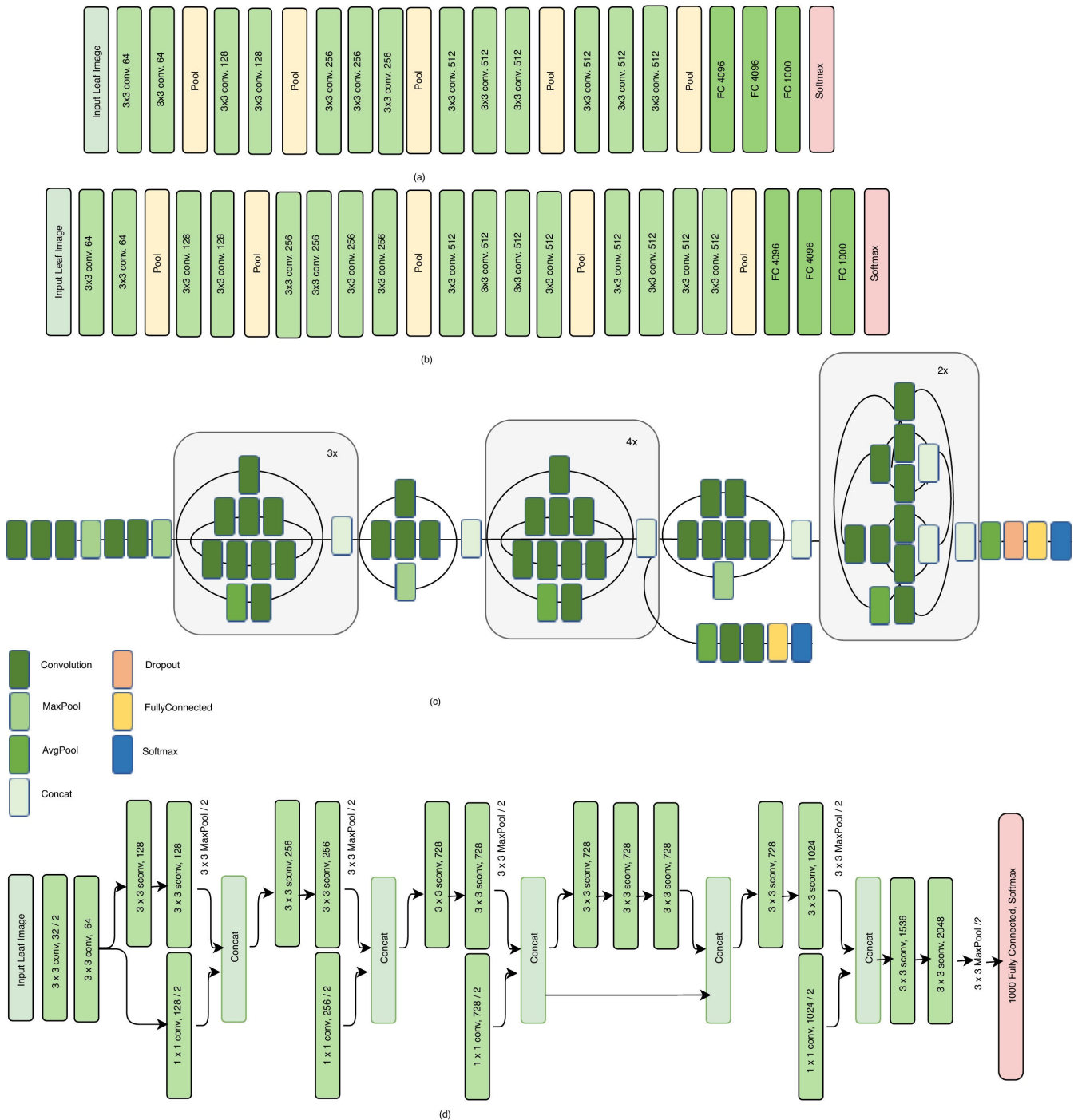
FIGURE 2. Representation of (a) VGG − 16 (b) VGG − 19 (c) Inception V3 and (d) Xception architecture.

normalizations. The implementation of this architecture is much simpler in Keras.

3) DEPTHWISE SEPARABLE CONVOLUTIONS

It is a substitute to traditional convolutions commonly known as ''seperable convolution'' in TensorFlow. The main limitation of general convolutions is that the convolution operations

are expensive. To illustrate, consider an input image with (100×100) dimension with 'c' number of channels. After applying the convolution filter of size $(d \times d)$, the number of convolution operations involved for 'n' kernels is given by $k^2 \times k^2 \times c \times n$. Here, k denotes the resulting dimension after the application of convolution. To overcome the above expensive convolution operation, the depthwise separable

convolution is initiated, consisting of two steps - depthwise convolution and pointwise convolution. It aims to decrease the memory requirement and computational complexity. In depthwise convolution, convolution computation is not carried over all the 'c' channels (d×d×c) rather it is (d×d×1). The first volume created has size (k×k×c), which is a convolution operation for one kernel or filter and not for *n*. In pointwise convolution, the traditional convolution is operated with size (1×1×n) over the volume (k×k×c). This result in the volume of shape (k×k×n). The above two steps reduce the number of operations to a factor proportional to 1 over n. The explicitness of Xception is that pointwise convolution is followed by depthwise convolution as shown in Fig. 3.
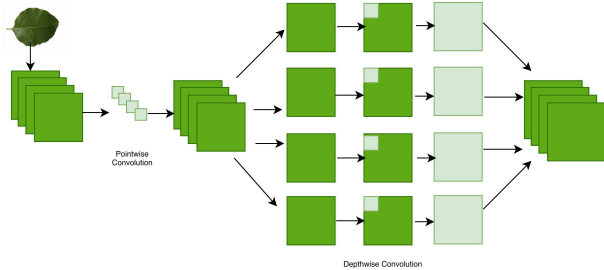
FIGURE 3. Concept of Xception architecture.

4) TRANSFER LEARNING (TL)

Transfer Learning is a new paradigm with increased attention lately in machine learning and deep learning to solve many domain problems [34]. When the target domain training data are insufficient to study the predictive models efficiently, TL influences supplementary data to learn from other linked source domains. The general approach of transfer learning adopted in this research is depicted in Fig. 4. In this paper, we fine-tune four widely known CNN models such as VGG-16, VGG-19, Inception V3 and Xception pretrained on ImageNet database. ImageNet is a huge dataset of labelled 15 million high-resolution digital images of about 22,000 classes. In these models, the knowledge obtained from the larger dataset i.e., ImageNet is forwarded to the proposed domain problem. All the above DL architectures have 1000 classes as output. The proposed transfer learning approach adopted for all the four CNN models on the custom medicinal leaf dataset (DeepHerb dataset) is in Fig. 5. The fully connected layers are removed from the source architecture, the features obtained from the convolutions of the source model are forwarded to the target model. The three different target models, artificial neural network with three new fully connected layers, a machine learning classifier - support vector machine and SVM along with bayesian optimization technique to tune the SVM hyperparameters are constructed to train and classify the DeepHerb dataset from the obtained features. The new fully connected layers in ANN consists of an equal number of classes as output as in the
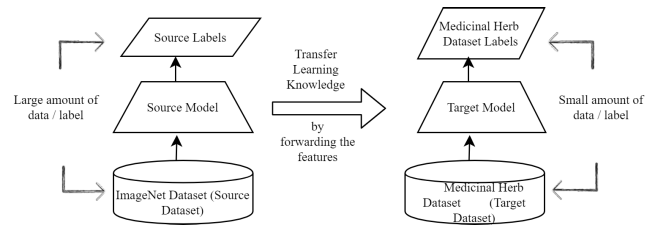

FIGURE 4. The general approach of transfer learning adopted in the proposed experiment.
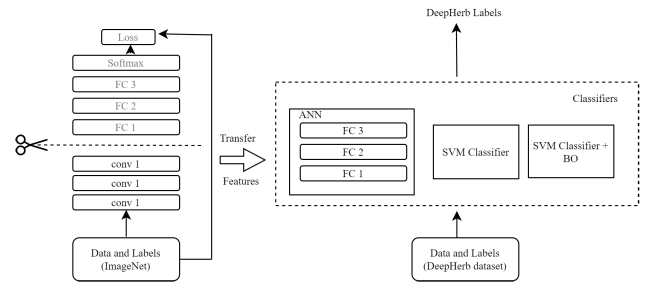

FIGURE 5. Proposed transfer learning approach on DeepHerb dataset.

custom dataset. The VGG-16, VGG-19, Inception V3 and Xception prediction layers are fine-tuned separately.

5) IMAGE SEGMENTATION

The leaf image captured or scanned is resized to 1600 × 1200 resolution and forwarded for segmentation to separate the foreground and background. The various OpenCV techniques are applied systematically to replace the background of the original image with white colour. Initially, a structured forest algorithm is applied to detect the edges, filters are applied to remove the salt and pepper noise, approximate contour and masking of foreground and background are followed by a grab-cut method to identify the sure background and foreground of the image. The complete process is automated by using the necessary libraries in python programming. The detailed steps carried out to segment the foreground and background of the query leaf image using the Python libraries such as Open CV2, Python image library (PIL) and NumPy are discussed in the algorithm and shown in Fig. 6 for *Nyctanthes Arbor-tristis* leaf.

Algorithm: Image segmentation

Input: Query leaf image I(m) with any lighter background

Output: A new leaf image with white background

Step 1: Resize the query input image I(m) to 1600 × 1200 pixels.

Step 2: Apply Gaussian blur technique to blur the image I(m) as shown in Fig. 6a.

Step 3: Detect edges using structured edge detection technique as shown in Fig. 6b.

Step 4: Filter out salt and pepper noise from I(m) obtained from step 3 as shown in Fig. 6c.

Step 5: Detect and draw the contour of I(m) as shown in Fig. 6d.

Step 6: Calculate the sure foreground and background area of I(m) as shown in Fig. 6e.

Step 7: Apply grab cut image segmentation technique to separate the leaf image from its background

Step 8: Place the segmented leaf image I(m) on a white background as shown in Fig. 6f.

6) THE DeepHerb MODEL

In this research, a new CNN model proposed by the name DeepHerb, classify the medicinal leaves from the custom-built DeepHerb dataset. The feature map consists of the features extracted from the pre-processed leaf image by using the pre-trained Xception model. Every leaf image initially undergoes image segmentation. To classify the feature vector the last separable convolutions and softmax classification layer of the original Xception are replaced by three new FCL with ReLU activation function. The dropout of 0.2, 0.2 and 0.1 respectively is introduced between each FCL and finally, a softmax classification layer is implemented to classify the 40 classes of the DeepHerb dataset.

Every input leaf image resized to size 400×300 and fed to Xception goes through the pointwise convolutions followed by depthwise convolutions, which result in a feature map of size $13 \times 10 \times 2048$. This feature map is then flattened and forwarded to the FCL ending in 40 softmax neural units (one neuron for every class in the dataset). To note that, Xception is not retrained but independent of the ANN network, trained separately. The proposed DeepHerb model in Fig. 7 proves as a state-of-the-art model for any classification problems. For the DeepHerb dataset, the model showcased an average testing accuracy of 97.5% and a prediction time of 44.10 seconds (excluding the image segmentation stage) for 521 test images.

7) SUPPORT VECTOR MACHINE (SVM)

The SVM is a classical supervised learning method with high capability in dealing with bigger dimensional space and non-linear data points [35]. SVM aims to keep the maximum marginal distance between the data points of the classes to be classified. This marginal distance indicates the farthest distance from the decision boundary. The position of the separating hyperplane is decided by the data points lying closer to the hyperplane.

In the research, two models are developed using an SVM classifier, where one model consists of an SVM classifier without application of Bayesian optimization technique and another model optimizes SVM hyperparameters (kernel and C values) using the Bayesian algorithm on the featured data to improve the accuracy and the execution speed. The C parameter, known as cost parameter controls the compromise between the correct classification of training data points and the smooth decision boundary. To provide the best predictive power of the model, the hyperparameter tuned for SVM are shown in Table 3. Bayesian optimization technique requires few iterations when compared to grid search optimization technique to reach the optimal values of the SVM hyperparameters such that its categorical cross-entropy loss shown

in (1) is minimized.

$$-\frac{1}{N} \sum_{i=1}^{N} log(P_{model}(y_i \epsilon C_{y_i})) \qquad (1)$$

where, N is the number of classes, P is the probability score of the model, C the class and y_i the datapoints.

TABLE 3. Hyperparameter tuned for SVM classifier.

Parameter	Value
Kernel	Linear
C	0.04

8) BAYESIAN OPTIMIZATION (BO)

In the world of machine learning, BO [36] is a sequential model-based optimization (SMBO) algorithm, one of the hyperparameter tuning techniques among manual search, grid search and random search techniques. BO differs from other techniques by improving the search speed using past performances. Hence, the future decisions are based on the past performance of the hyperparameters, which are not witnessed in random and grid search methods. The BO technique requires very few iterations to reach the optimal predicted performance values. It aims to minimize the objective function $f(a)$ by building a probability model to identify the hyperparameters needed to evaluate the true objective function. The three main components comprising of the minimization process: (a) Acquisition function $A(a)$; (b) Gaussian process model for objective function $f(a)$, specified by its mean and covariance function; (c) After each new evaluation of $f(a)$, the bayesian update process modifies the Gaussian model. The next evaluation point is identified by maximizing the acquisition function so that the Expected Improvement (*EI*) in the objective function is measured by discarding the values that increase it. The *EI* is given in (2).

$$EI(a, Q) = E_Q[max(0, \mu_Q(a_{best}) - f(a))] \qquad (2)$$

a_{best} is the least posterior mean location and $\mu_Q(a_{best})$ is the least value of the posterior mean.

9) SAMPLING MEDICINAL LEAF DATASET (DeepHerb DATASET)

A standard medicinal leaf dataset by the name, DeepHerb is built by gathering the medicinal leaves commonly found in different regions of Karnataka, the state in southern India. The images are captured using a mobile phone or a scanner. There exist similarities among the leaves of varied species in the dataset. The intra-class and inter-class complications found in different plants of the *Amaranthaceae* family is shown in Fig. 8. The intra-class similarity is due to variations such as maturity, illumination, colour, texture and shape. Fig. 9 shows the complete dataset that comprise of 2515 images with a resolution of 1600×1200. For the experiments, the dataset is divided into an 80:20 ratio for training
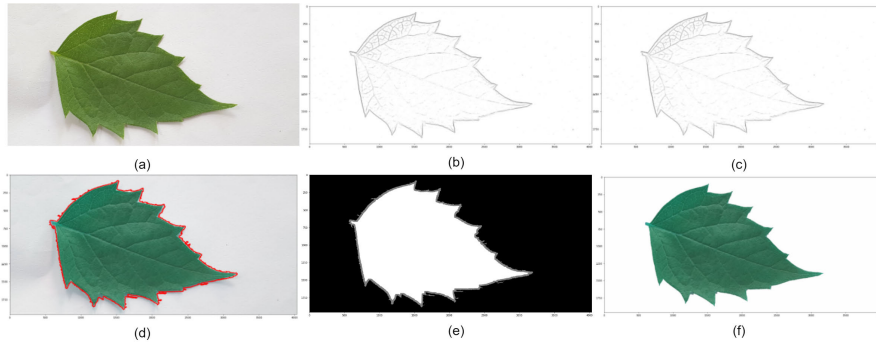
FIGURE 6. The steps involved to segment the background from the *Nyctanthes Arbor-tristis* leaf image.
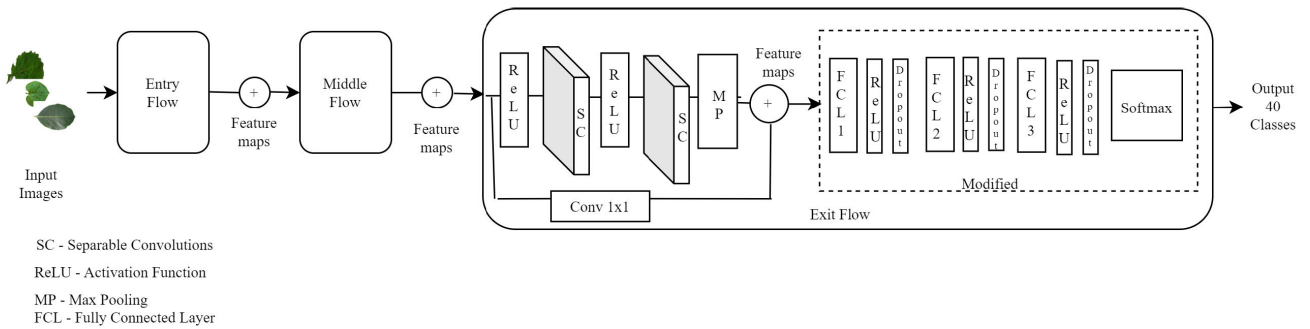

SC - Separable Convolutions

ReLU - Activation Function

MP - Max Pooling

FCL - Fully Connected Layer

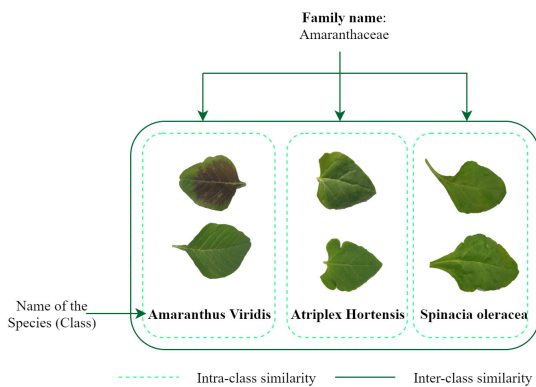**FIGURE 7.** The proposed DeepHerb model inspired by Xception architecture.

FIGURE 8. The intra-class and inter-class similarity in the DeepHerb dataset.

and testing. The scientific name of the species selected are: *Alpinia Galanga, Amaranthus viridis, Artocarpus heterophyllus, Atriplex Hortensis, Azadirachta indica, Bambusoideae, Basella alba, Brassica juncea, Carissa carandas, Citrus limon, Ficus Auriculata,Ficus Benjamina, Ficus religiosa, Hibiscus rosa-sinensis, Jasminum, Mangifera indica, Manilkara zapota, Mentha, Mercurialis Annua, Moringa oleifera, Muntingia Calabura, Murraya koenigii, Nerium oleander, Nyctanthes arbortristis, Ocimum tenuiflorum, Persea americana, Phyllanthus acidus, Piper betle, Plectranthus amboinicus, Pongamia pinnata, Psidium guajava,* *Punica granatum, Santalum album, Saraca asoca, Schefflera arboricola, Spinacia oleracea, Syzygium cumini, Syzygium jambos, Tabernaemontana divaricate* and *Trigonella foenumgraecum.*

The leaves of the above plants have medicinal values that benefit in treating many ailments in human beings. The different parts of the selected plants, such as bark, fruit and seeds are useful in preparing many types of medications. All these plants can be grown in local gardens without much effort. The knowledge of these Ayurveda leaves and tips to use them has to be spread widely to the public.

Here, the experiments are performed on both the medicinal leaf dataset (DeepHerb) and the publicly available Flavia dataset. The popular Flavia dataset [14] is used to compare the analysis of the proposed model against the custom dataset. Flavia dataset consists of 32 leaf species and 1907 clean images with fewer luminance variations.

IV. 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 and Xception 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 DeepHerb dataset. The features extracted

FIGURE 9. The varied species in the DeepHerb dataset.

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 DeepHerb dataset to classify the 40 different Indian herbs.

The work proposes four different kinds of source models such as CNN-VGG16, CNN-VGG-19, CNN-InceptionV3 and CNN-Xception for feature extraction. Three target models such as ANN, SVM and SVM+BO for classification. All six suggested models, M1, M2, M3, M4, M5 and M6 are described in Table 4. The model M1 extract features using VGG-16 and classifies them using ANN. VGG-19 in model M2 along with the ANN classifier. In model M3, InceptionV3 extracts the features with ANN as a classifier whereas, model M4 extract features using the Xception model and classify using ANN. The extracted features from Xception architecture is classified by the SVM classifier in model M5. The model M6 classifies the Xception features using the SVM classifier hyper-tuned by the Bayesian optimization technique.

All the CNN models are fine-tuned as per the parameters given in Table 5. To run the experiments, we used the Keras and TensorFlow deep learning framework using Python programming language. The images in the training set are augmented by rotating, horizontal and vertical flip, resize and adding some noise to images. The accuracy of all the CNN models for the DeepHerb dataset is analyzed.

The train set and test set of the DeepHerb dataset consists of 1994 images and 521 images respectively. The result-graphs (epoch vs accuracy score (%)) of four pre-trained models (M1 to M4) on DeepHerb dataset depicted in Fig. 10 shows that Xception architecture (model M4) outperforms all the others with a highest validation accuracy. Hence, further experiments are carried on classifying the Xception features in models M5 and M6, where Xception is used as the source model and SVM and (SVM + BO) classifiers as target models. The findings from the training and testing classification reports of all the models stated in Table 6 and 7 show that model M4 shows highest testing accuracy of 97.5% when compared to all other models. The bar graph (training and

TABLE 4. Description of the proposed models.

#	Model	Feature Extraction	Classifier
1	M1	CNN-VGG16	ANN
2	M2	CNN-VGG19	ANN
3	M3	CNN-Inception V3	ANN
4	M4 (DeepHerb)	CNN-Xception	ANN
5	M5	CNN-Xception	SVM
6	M6	CNN-Xception	SVM+BO

TABLE 5. Fine tuning parameters of CNN models.

Parameters	Value
Learning Rate	0.0001
Epochs	60
Optimizer	Adam
Batch size	8

testing accuracy vs model) in Fig. 11 reveals the efficacy of all six models on the DeepHerb dataset. This proves that the Xception features classified by ANN is better than SVM classifier for the DeepHerb dataset.

All the models are run on Google Colab Pro. Table 8 shows the training and prediction time of the models on the Deep-Herb dataset. The findings from the table show that model M5 and M6 trains faster compared to other models because SVM classifier consumes less computation time than ANN. Though the model M6 predicts faster, its testing accuracy rate (95.20%) is less when compared to model M4 recognition rate (97.5%). By analyzing the results obtained from Tables 6, 7, 8, and Fig. 11, the findings encourage to choose model M4 as the best model to classify the species in Deep-Herb dataset.

Further, the performance of both models (M4 and M6) is benchmarked using the Flavia dataset – a popular public dataset of leaves to compare their classification performance. Fig. 12 shows the comparison between accuracy and the models (M4 and M6) using both the datasets. The accuracy obtained by M4 (97.22%) on Flavia dataset is competitive

to model M6 (98.23%). But, for DeepHerb dataset, model M6 accuracy dropped to 95.02% where as model M4 performed well with an accuracy of 97.5%. Hence, model M4 is considered as the top performer and titled as "DeepHerb" model for our research. The state-of-the-art performance showcased by using the Xception features is ideal for any image classification problems where the dataset is of limited size.

TABLE 6. The classification report of training the CNN models on the DeepHerb dataset.

Model	Precision	Recall	F1-score	Accuracy (%)
M1	0.98	0.98	0.98	98.04
M2	0.98	0.98	0.98	97.54
M3	0.99	0.99	0.99	98.75
M4 (DeepHerb)	0.99	0.98	0.98	98.45
M5	0.99	0.99	0.99	99.17
M6	1.00	1.00	1.00	100

TABLE 7. The classification report of testing the CNN models on the DeepHerb dataset.

Model	Precision	Recall	F1-score	Accuracy (%)
M1	0.96	0.95	0.95	95.39
M2	0.97	0.96	0.96	95.97
M3	0.97	0.96	0.96	96.16
M4 (DeepHerb)	**0.98**	**0.98**	**0.97**	**97.50**
M5	0.94	0.93	0.93	92.90
M6	0.95	0.95	0.95	95.20

TABLE 8. Models evaluation time (seconds).

Model	Training (seconds)	Prediction (seconds)
M1	11253	32
M2	10870	29.8
M3	11373	28.2
M4 (DeepHerb)	13766	44.10
M5	1101	55
M6	7808	47.7

The top-1 training and testing accuracy obtained by DeepHerb model is 98.45% and 97.5% respectively for 40 classes. Some of the misclassifications are observed due to the similarity issues in DeepHerb dataset (1) Out of 8 images of *Trigonella Foenum-graecum*, 6 images are classified correctly and 2 misclassified as *Moringa Oleifera* and *Amaranthus Viridis* (2) Out of 10 images of *Piper Betel*, 7 are classified correctly and 3 misclassified as *Jasminum*. The prediction results of 9 misclassified herbs is detailed in Table 9. The remaining 31 herbs are classified correctly with an accuracy of 100%. Both the top-3 and top-5 prediction results of the model is 99.8%.

The DeepHerb model is integrated into the mobile application. The single image prediction time of the DeepHerb model through the mobile application is around 1 second which includes its image segmentation, classification and retrieval of top-5 images from the database.

The real-time testing of the DeepHerb model was carried on leaf images with different background colours. The image segmentation stage incorporated in the model efficiently worked on black, pink and off-white backgrounds. The real-time accuracy prediction rate is more than 95% for top-5 classification though more failures fall under top-1 and top-3 accuracy because herbs possess very close features, and image luminosity. Few query images captured under low light and slightly blur conditions are recognized in top-5 rather than in top-1 class prediction.

Table 10 shows the comparison of the DeepHerb model with other state-of-the-art techniques adopted to classify the plant leaves using the Flavia dataset. It is evident from Table 10 that the proposed system shows improvement when compared to other works. However, the P-Leaf Net model proposed by Beikmohammadi *et al.* [37] use image patches of the leaf instead of the complete image and 10000 epochs to store the highest accuracy weights. It shows the test accuracy of 97.72% on the Flavia dataset (1907 images) that is slightly higher than the accuracy scored by the DeepHerb model. Besides that, the accuracy of the P-Leaf Net model falls to 95.35% on the larger dataset (MalayaKew of 2816 images). The DeepHerb model, on the contrary, shows 97.22% on the Flavia dataset and testing performance of 97.5% on a larger dataset (DeepHerb dataset of 2515 images) with 60 epochs using whole leaf image as input. Comparing the performance of the DeepHerb model on both the datasets and its ability in real-time prediction exhibits significant improvement in recognizing plants. The above comparison proves that the amalgamation of features from Xception architecture and ANN classifier achieves improved prediction results.

Table 11 details the comparison of the techniques employed, dataset size, accuracy and prediction time of related works that have shown interest in building a mobile solution. The table further suggests the uses of the mobile application and their interest in developing an Android application for plant recognition. It is evident from the table that the camera module based prediction is much faster [38] in comparison to microcontroller based prediction [39]. The other works show no record of the recognition time of the system [40]–[42]. Though the accuracy obtained by the model in [39] is slightly more compared to the proposed system, it shows a high prediction time as it uses a microcontroller and LCD screen. The DeepHerb model, in comparison to other works, shows a fast recognition time of 1 second through its HerbSnap mobile application. To the best of our knowledge, the HerbSnap (cross-platform mobile application) integrated with the DeepHerb model is the first of a kind to identify the Indian medicinal herbs at low cost and time with a high testing accuracy rate of 97.5%.

10) TRADITIONAL MEDICINAL HERB (TMH) DATABASE
A curated TMH database is created from multiple web sources namely Wikipedia, medicinal plant websites, books and articles. The study reveals that current websites
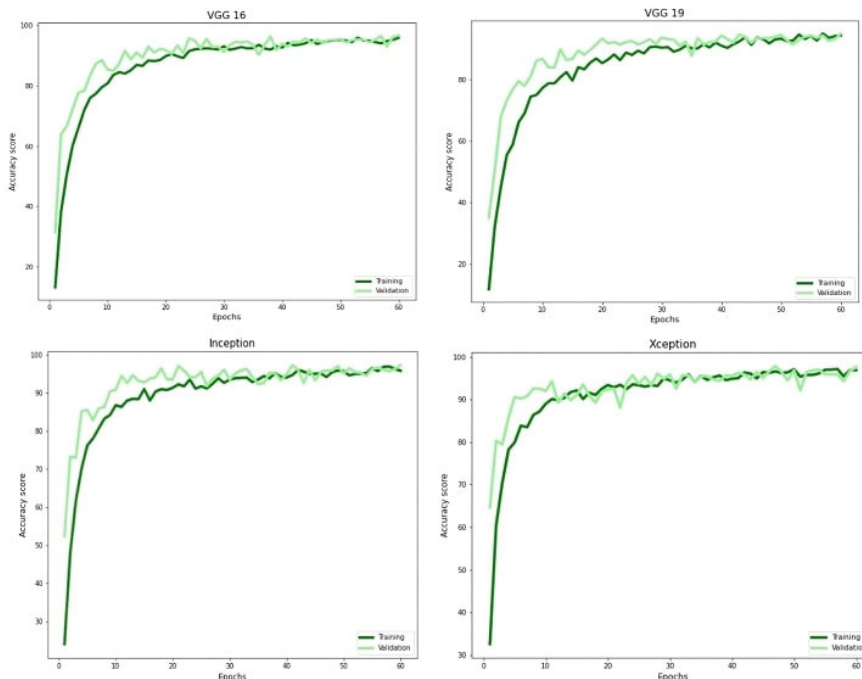
FIGURE 10. The training and testing accuracy vs epochs of ANN models on the DeepHerb dataset.

TABLE 9. The analysis of misclassified herb samples in DeepHerb dataset.

Medicinal plant	# Test samples	# Correctly classified	# Incorrectly classified	Error (%)
Artocarpus Heterophyllus	12	11	1	8
Bambusoideae	12	11	1	8
Ficus Benjamina	13	12	1	7
Mangifera Indica	13	12	1	7
Phyllanthus Acidus	13	11	2	7
Piper Betle	10	7	3	3
Schefflera Arboricola	12	11	1	8
Spinacia Oleracea	15	14	1	6
Trigonella Foenumgraecum	8	6	2	25
Total	108	95	13	2
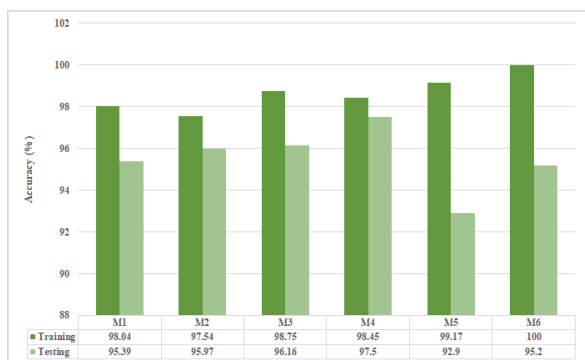
FIGURE 11. Training and testing accuracy of all six models on the DeepHerb dataset.
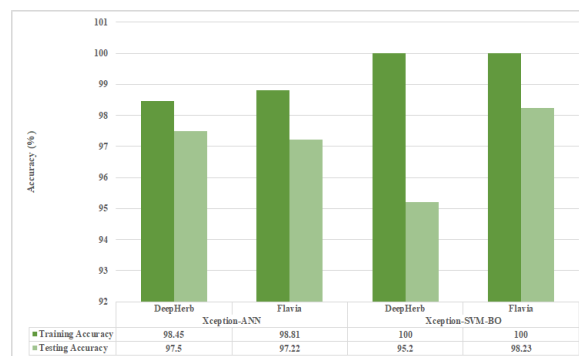
FIGURE 12. Training and testing accuracy of the DeepHerb model and M6 model (Xception-SVM-BO) on Flavia and DeepHerb dataset.

display few details of the medicinal plant like botanical name, common name and medicinal uses. More time is spent on gathering additional information associated with medicinal plants such as common name (s), botanical name, conservation status, growing weather condition (s) and many more for the selected 40 herbs in the DeepHerb dataset, which benefits the general public, researchers and experts to infer the additional knowledge easily.

TABLE 10. The comparative analysis of related state-of-the-art approaches on Flavia dataset.

Reference	Methodology	Accuracy (%)
Mahajan, S., et al., (2021) [43]	Morphological features + ResNet50 / SVM +Adaptive boosting	94.72
Beikmohammadi, A., et al., (2020) [37]	MobileNetV2 / SVM	97.72
Jasitha, P., et al., (2019) [44]	VGG16 / SVM	96.1
Wei Tan, J., et al., (2018) [45]	D-leaf / ANN	94.6
Ibrahim, Z., et al., (2018) [46]	HOG + LBP / SVM	97
DeepHerb Model (Proposed)	**Xception / ANN**	**97.22**

TABLE 11. The comparative analysis of HerbSnap mobile application prediction time with other works.

Reference	Feature Extraction technique	Classification technique	# Dataset samples	# Species	Accuracy (%)	Prediction time (seconds)
Husin, Z., et al., (2012) [39]	Morphological	Back Propagation Neural Network (BPNN)	2000	20	98.9	30
Prasvita, Desta Sandya and Herdiyeni, Yeni (2013) [40]	Local binary pattern and rotation invariant uniform pattern	Probablistic Neural Network (PNN)	1440	30	56.3%	No record
Begue, Adams et al., (2017) [41]	Base and derived features	Random Forest	720	24	90.1	No record
Cheng, Qian et al., (2018) [42]	Morphological + Hu moment invariant descriptors	BPNN+KNN	14000	220	92.8	No record
Muneer, Amgad and Fati, Suliman Mohamed (2020) [38]	Shape+Texture	Deep Learning Neural Network	1000	20	93	2
DeepHerb model (proposed HerbSnap mobile application)	**Xception**	**Artificial Neural Network**	**2515**	**40**	**97.5**	**1**
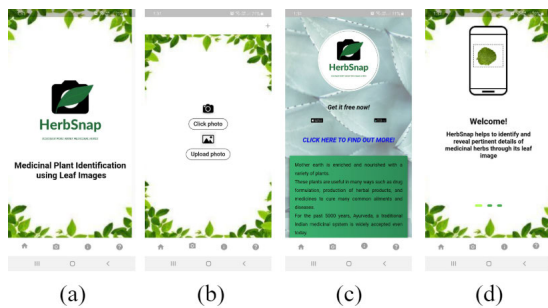
FIGURE 13. The screenshots of the HerbSnap mobile app main activities.

FIGURE 14. The screenshots of input herb image, prediction results and the pertinent details of the herb extracted from the TMH database in the HerbSnap mobile app.

11) THE "HerbSnap" MOBILE APPLICATION

The DeepHerb model integrated into the HerbSnap mobile application is available in both android and iOS platforms shown in Fig. 13. The mobile application is developed using Flutter, an open-source software created by Google to build cross platform mobile application for iOS, Android, macOS and Microsoft Windows. The proposed DeepHerb model (M4) consists of extracting the features of the input image by using the Xception architecture and classification using ANN to identify the medicinal herb. Currently, the app identifies and displays the TMH database for 40 different species of herbs presented in the DeepHerb dataset is shown in Fig. 14. The HerbSnap allow users to either capture a herb image (preferable on a lighter background) or upload a herb image captured from its camera module for prediction. It displays the predicted top-5 images along with the model confidence scores. The user can choose the best similar leaf image by clicking on one of the predicted top-5 images. The app fulfils the big gap in identifying the medicinal plant between the general public and the experts. Eventually, the knowledge of medicinal herb gathered from the HerbSnap mobile application and the TMH database will stimulate the

growth and uses of herbs in agriculture and help to conserve biodiversity.

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 four CNN models such as VGG16, VGG19, InceptionV3 and Xception with ANN as a classifier and two CNN models such as Xception-SVM and Xception-SVM-BO with SVM as machine learning classifier. Of the six models, the proposed DeepHerb model extracts the features from the Xception architecture and classifies the herbs using an artificial neural network classifier shows an average accuracy of 97.5% using the DeepHerb dataset.

The findings show that Xception architecture has outperformed when compared to the other three popular DCNN architectures. In this research, we claim that the combination of CNN features with ANN classifier works most appropriate because of the stability feature in ANN. The results obtained prove that Xception along with ANN showcase good accuracy results when compared to the model with Xception and SVM classifier fine-tuned by the bayesian optimization technique. The suggested DeepHerb model can further be used for any image classification problems. The work also proves that transfer learning is an efficient approach to build any neural network model with a limited dataset. However, failing to recognize the compound leaves and leaf images on the complex background is the limitation of the DeepHerb model.

Building the DeepHerb dataset involves tremendous human effort in collecting and standardizing the leaf images of forty different plant species. The dataset will be expanded further to concentrate more on rare and extinct species to attract more researchers to work for the betterment of herbal life in human society.

The proposed HerbSnap mobile application is an evidence of the base work of building an intelligent recognition system for Indian medicinal herbs using Flutter software. The Traditional Medicinal Herb (TMH) database is a small step towards building a curated database revealing multiple details of medicinal herbs, which attract many stakeholders of plants, including farmers.

The future scope of the work focuses on extending both the TMH database and DeepHerb dataset, providing easy access to the evidence of Ayurveda herbs to the world. Also, improving the classification technique to identify the very close classes, will support improving the real-time accuracy of the proposed system. The domain of medicinal plant seeks immediate attention, to identify and collect the rare and extinct herb species from remote places, as many herbs can be regrown and thus, provide a herbal solution to many ailments and improve the biodiversity of the country.

APPENDIX A

The herb samples collected and their pertinent details such as botanical name, medicinal properties and threat status.

Botanical name	Leaf image	Threat status	#Samples	Medicinal properties
Alpinia Galanga		Not extinct	50	Antimicrobial, anti-inflammatory, anti-HIV
Amaranthus viridis		Not extinct	122	Diuretic, anti-rheumatic
Artocarpus heterophyllus		Not extinct	56	Anticarcinogenic, antimicrobial
Azadirachta indica		Not extinct	63	Anthelmintic, antifungal
Atriplex Hortensis		Not extinct	82	Diuretic, antirheumatic
Bambusoideae		Not extinct	56	Antioxidant anti-inflammatory
Basella alba		Not extinct	103	Antidote, Aperient
Brassica juncea		Not extinct	34	Astringency, antioxidant
Carissa carandas		Not extinct	74	Astringent, antiscorbutic
Citrus limon		Not extinct	57	Antibacterial, antiperiodic
Ficus Auriculata		Critically endangered	50	Antidote
Ficus Benjamina		Not evaluated	64	Antioxidant, antimicrobial
Ficus religiosa		Not extinct	63	Purgative
Hibiscus rosa-sinensis		Not extinct	43	Antidiabetic, antioxidant
Jasminum		Not extinct	71	Aphrodisiac sedative
Mangifera indica		Not extinct	62	Antiseptic, astringent
Manilkara zapota		Not extinct	69	Antidiarrheal, antibiotic
Mentha		Not extinct	97	Analgesic, antibacterial
Mercurialis Annua		Not extinct	67	Emollient, purgative
Moringa oleifera		Not extinct	77	Antitumor, antipyretic
Muntingia Calabura		Not extinct	61	Antiseptic, antipruritic
Murraya koenigii		Not extinct	60	Anthelmintic, antifungal
Nerium oleander		Least Concern	62	Cardiotonic, diaphoretic
Nyctanthes arbor-tristis		Not Evaluated	40	Antioxidant anti-inflammatory

Ocimum tenuiflorum		Not extinct	52	Antioxidant, antimicrobial
Persea americana		Not extinct	75	anti-inflammatory anti-carcinogenic
Phyllanthus acidus		Not extinct	61	Emetic, purgative
Piper betle		Not extinct	48	Antimicrobial Antihistaminic
Plectranthus amboinicus		Vulnerable	48	Antioxidant, antiepileptic
Pongamia pinnata		Least Concern	61	Laxative, anthelmintic
Psidium guajava		Endangered	65	Antibacterial, anti-fungal
Punica granatum		Least Concern	79	Antimicrobial, anti-inflammatory
Santalum album		Vulnerable	58	Anti-inflammatory, anti-microbial
Saraca asoca		Vulnerable	68	Analgesic, astringent
Schefflera arboricola		Not extinct	58	Analgesic, anticonvulsant
Spinacia oleracea		Not Evaluated	72	Anti-diabetic, anti-bacterial
Syzygium cumini		Least Concern	39	Anthelmintic, antihyperglycemic
Syzygium jambos		Not Evaluated	56	Antibacterial, anti-inflammatory
Tabernaemontana divaricata		Not extinct	56	Antioxidant, anti-tumor
Trigonella foenum-graecum		Not extinct	36	Antibacterial, gastric stimulant

APPENDIX B

The part of the medicinal leaf dataset that support the findings of the study are available at doi: http://dx.doi.org/10.17632/nnytj2v3n5.1. The complete dataset will be available on request from the corresponding author.

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