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# Herbal Plants Leaf Image Classification Using Deep Learning Models Based On Augmentation Approach

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**Abstract**

As the world grows daily, people are shifting towards renewable energy sources and natural resources for healthcare as remedies. Herbs are the natural source of medicine in place of synthetic drugs. Herbs are those kinds of plants used to cure the disease of humans or animals. Identification is the most critical aspect of using herbs as medicines. The problem of identification of these herbal plants is trying to be solved using Deep Learning (DL) models in this paper. Here the authors have successfully classified 25 categories of herbal plant leaf images using different deep learning models with the highest test accuracy of 97.68% on original data and 98.08% on augmented data. This research work is an extension of the previous research work by the same authors, titled "Herbal plants leaf image classification using machine learning approach", in which the six classical Machine Learning (ML) algorithms have been applied to original data and the highest classification accuracies of 82.51% has been achieved by using Multi-layer Perceptron (MLP) classifier.

***Keywords- Computer vision, Deep learning, Herbal plants, Image classification, Image processing, Machine learning, RGB image.***



## 1. Introduction

As the world is growing daily, humans are focusing more on natural resources for our different needs in everyday life and shifting more towards renewable sources of energy like solar energy, wind energy, nuclear energy, hydrogen fuel, etc. in place of the conventional petroleum oil, coal, and natural gases-based energy resources (Merino-Saum et al. 2018). This shift is due to the need for time because carbon emission has increased globally. The global average temperature is rising daily due to which many climate changes like heatwaves, drought, melting glaciers, rising sea levels, warming oceans, etc., are happening, and this affects all the creatures on the earth adversely (Emir and Bekun 2019). So, it is the responsibility of all humanity to make their efforts to reduce the carbon footprint by shifting more towards natural energy resources for our everyday needs. In this paper, the authors try to contribute little to adopting natural resources for medicines and herbs instead of synthetic drugs.

Herbs are parts of any medicinal plant which are used to cure and prevent animals and humans from diseases. In using the herbs for remedy, one must identify them first (Mahtab Alam Khan 2016). The

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identification of herbs is a most significant part of the process of using herbs as medicine. A person with prior knowledge of herb identification can identify herbal plants and tell their names to those who want to use that herb (Prasvita and Herdiyeni 2013). So, the whole process of identification is an expert's knowledge dependent. In this paper, the authors try to solve this herbal plant's classification problem from expert dependent to machine-dependent. Everyone has a machine like a smartphone in their hands, and they can click a few leaves image of a herbal plant, and the smartphone will tell the name of the herbal plant using the techniques used in this research paper. And when the classification is easy, the adaptation of herbs in place of synthetic drugs will be widely adopted.

The authors collect the herbal plants' images individually and manually. Then these images are trained through many Deep Learning (DL) models to classify the different categories of herbal plants (Panigrahi et al., 2018). The Train, Test, and Validation are being used in this paper to get good classification results via different DL models (Salazar et al., 2022). Eight other CNN models of DL have been used in this research for the classifications of herbal plants' leaf images.

Suppose a DL algorithm is applied to a set of data (in our example, herbal plants images) and has some prior knowledge about our data (in our case, what is the name of the plant of every class of leaves). In that case, generally, an expert gives this information, or a person who has prior knowledge of it tells the name of a plant. The DL algorithms can learn from the training data set (in our example, in every category, more than 150 images of leaves are being used for the training set) and give a prediction based on this learning to a new data set (we generally call it test data set), i.e., to which category the test leaves data set belongs to. In this way, we find the different accuracies and losses via different algorithms and the boxplot, and a confusion matrix has been drawn to show the outcomes.

The novelty of the proposed research work:

- To the best of the authors' knowledge, this is the first kind of herb leaf images database created by the authors, where a total of 6628 RGB images are divided into 25 categories of herbal plant leaf images.
- The eight deep learning models have been applied to these images, and all models' classification performance is measured through accuracies and losses (Tan, Lu, and Jiang, 2021). And the best CNN model has been identified successfully based on these measures.
- The higher misclassified categories have been identified, which is observed due to the similar texture of the classes.

The rest of this paper is structured as follows: Section 2 presents the literature review in which some existing works have been mentioned. The proposed methodology and each step are presented in Section 3. The data set description, and the experimental design is presented in Section 4. Section 5 presents the experimental results and their detailed analysis, where we have discussed the experimental results. Lastly, Section 6 concluded with present results in short and future research goals.

## 2. Literature Review

In this paper, the authors have implemented the six classical Machine Learning (ML) models to classify the same. This paper uses 25 categories of herbal plants leaf images (Gaurav et al., 2022). The highest accuracy which has been achieved is 82.51% by the MLP algorithms. Aman and Kumar, in their paper, collected images of 25 different flower plant leaf images and created a novel dataset of its kind (Bittu and Vipin 2022). Six classical machine learning techniques have been applied to this dataset, and the MLP classifier has achieved the best test accuracy of 89.61%. In similar works, Chitranjan and Kumar have created a novel dataset of 25 categories of vegetable plants leaf images, and Ojha and Kumar have developed a novel dataset of 25 types of Décor plants leaf images(Chitranjan and Vipin 2022)(Aparna and Vipin 2022). They have obtained test accuracies of 90.68 and 93.90%, respectively, by MLP classifier.

The authors have used modern computing devices and technology to build a deep neural network-based model named Medicinal Neural Network (Amuthalingeswaran et al., 2019). By using this model, the authors have the classification of four classes of medicinal plants. To train this model they have used 8000 images of these four classes. The proposed model has achieved good accuracy of 85%. In this paper, a new dataset of 10 kinds of medicinal plants in Bangladesh has been introduced by the authors(Akter and Hosen, 2020). To extract the high-level features, a three-layer convolution neural network is employed. The training was done on 34,123 images and the models were tested on 3,570 images, giving an accuracy of 71.3%. This paper analyses the benefits of various automated leaf pattern recognition procedures (Kumar Thella and Ulagamuthalvi, 2021). A proposed computer vision approach can entirely ignore the context of the image and provide an accurate and fast leaf recognition process.

Machine learning is artificial intelligence that detects medical image patterns (Erickson et al., 2017). According to the author, deep learning has become an advanced version of machine learning, which means it can identify complex features without requiring complex calculating algorithms. This paper presents a review of machine learning techniques that are used in the identification of leaf plant diseases (Wasike et al., 2021). The article provides an overview of the various methods and their advantages and disadvantages. This study aimed to explore the multiple aspects of machine learning in agriculture. Apart from these, there are multiple aspects in which ML can be used (Kumar and Sonajharia, 2017)(Vipin et al, 2021).

## 3. Proposed methodology

The flowchart of the proposed methodology is shown in Fig 1. Each methodology step will be discussed in detail in the further subsections.

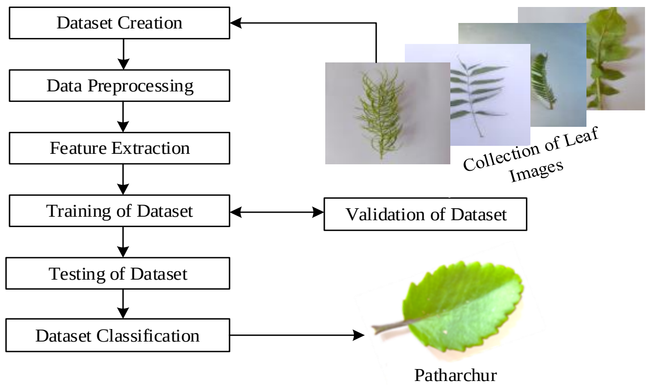



Fig.1. The flowchart of herbs classification

### *3.1. Divide dataset into train, validation, and test set*

The dataset is represented as $I = \{I_i, x_i\}_{i=1}^{n}$. Where, $i^{th}$ image in the dataset is denoted by $I_i$ . $x_i$ denotes all the categories of data in the dataset, $x_i \in X$ and $X = \{x_i\}_{i=1}^{n}$ for $i \in \{1,2,3 \ldots, n\}$ .Where $n$ is the number of categories in the herb dataset. Every image $I_i \in I$ is stored in the matrix $M$. Where $M_{i,j}$ represents the $i^{th}$ rows and $j^{th}$ column of the 2D matrix $M$. If tensors for deep learning are represented by $T$, then $T \in R^{h \times w \times c \times b}$ where $h, w, c,$ and $b$ represent the height, width, colour channel, and batch size, respectively. The required resized dataset $\{x_n^r, y_n\}$ obtained from resized function $Re(.)$ shown in (1).

$$I^r = \text{Re}(\{I_i^r, x_i\}_{i=1}^n, x_i\}_{i=1}^n, p \times q)$$

where $p \times q$ is the required resized dimension of each image $I_i \in I$ .

### *3.2. Divide dataset into train, validation, and test set*

The resized image dataset is represented by $I^r$. This dataset is divided into a training set, a validation set, and the Test dataset, namely $T_r, V_a, and\ T_e$ respectively. i.e., $T_r \subset X^r$, $V_a \subset X^r$, and $T_e \subset X^r$. Where $X^r = T_r \cup V_a \cup T_e$. And the augmented dataset is represented as $I^{ar}$. This augmented dataset is also divided into a Training set, Validation set, and the Test dataset, namely, $T_r^r, V_a^r, and\ T_e^r$, respectively, i.e., $T_r^r \subset I^r$, $V_a^r \subset I^r$, and $T_e^r \subset I^r$. Where $I^{ar} \in T_r^r \cup V_a^r \cup T_e^r$.

### *3.3. Deploying deep learning algorithms*

This step follows the model training and selection process. DL models are trained by a large set of training labelled data. This neural network has three main layers: the input layer, the hidden layer, and the output layer. The deep term in deep learning denotes the number of hidden layers in a model. Standard neural networks have 2-3 hidden layers, but a complex neural network can have more than 100 hidden layers. The different layers of the deep neural networks are as follows: rectified linear unit (ReLu) layer, convolution layer, backpropagation layer, Pooling layer, and fully connected layer.

*Model selection:* Let training set $T_r \subset X^r$ has been dived into $n - mini\ Batches$ as $\{MB = (X^{\{1\}}, y^{\{1\}}), (X^{\{2\}}, y^{\{2\}}), (X^{\{3\}}, y^{\{3\}}, \dots, (X^{\{k\}}, y^{\{k\}})\}$, where $T_r = \bigcup_{i=1}^k (X^{\{i\}}, y^{\{i\}})$ and $\bigcap_{i=1}^k (X^{\{i\}}, y^{\{i\}}) = \emptyset$. And each batch is used for training the DL model subsequently and carrying forward the propagation on $X^{\{i\}}$. Then the normalized computation cost on the size of the batch has forwarded for backpropagation using the current batch $(X^{\{i\}}, y^{\{i\}})$ and predicted labels $(\hat{y}^{\{i\}})$ to update the neuron weights of each layer. If training accuracy at $t^{th}$ epoch has $Acc_{Train}^t \approx Acc_{Train}^{t-1}$The then-current model will be selected $M_s$ for the prediction of test data $T_e \subset X^r$. Then set of prediction $Y_{Te}^p$ of test data can be obtained, see eq. (1).

$$Y_{Te}^p = \{\hat{y}_i\}_{i=1}^m = M_s(T_e) \tag{1}$$

Finally, the classification accuracy of the deep neural networks will be calculated for the $j^{th}$ iteration using the eq. (2)

$$Acc_j(Y_{Te}, Y_{Te}^p) = \frac{1}{m} \sum_{i=1}^m \begin{cases} 1; & y_i == \hat{y}_i \\ 0; & Otherwise \end{cases} \tag{2}$$

is $Y_{Te} = \{y_i\}_{i=1}^m$ and $Y_{Te}^p = \{\hat{y}_i\}_{i=1}^m$ are the set of actual labels and predicted labels for $m = |T_e|$ number of test samples.

Then mean accuracy can be calculated for all iterations as shown in eq. (3).

$$Acc_{avg} = \frac{1}{itr} \sum_{j=1}^{itr} Acc_j(Y_{Te}, Y_{Te}^p) \tag{3}$$

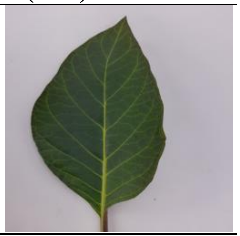
where $itr$ denotes the number of iterations of the same framework to get the various shuffling of the samples.

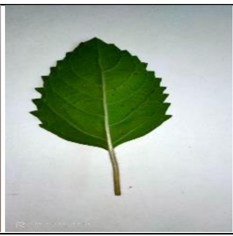
# 4. Experiments

## *4.1. Dataset descriptions*

The dataset description is shown in Table 1. It contains a total of 6,628 leaf images of 25 categories of herbal plants. Each class has more than 250 leaf images in it. All these images have been collected individually using a Samsung M12 smartphone camera. These images were taken on white cardboard separately. The front and back parts of leaves are taken randomly. The augmentation of these images has been done with the help of python code. After augmentation of five dataset types increased five times into 6628 X 5 = 33140 number of herbal plant leaves images.

Table 1. Sample image of all 25 categories of herbal plant's leaf with their details as Scientific/Botanical name(Common name): Number of images in the category

| | | | | |
|---|---|---|---|---|
|  |  |  |  |  |
| **1.** Calotropis gigantea (Akvana): 262 | **2.** Emblica Officinalis (Amla): 278 | **3.** Justicia adhatoda (Arusa): 267 | **4.** Cannabis sativa (Bhang): 269 | **5.** Clerodendrum infortunatum (Bhat): 259 |
|  |  |  |  |  |
| **6.** Eclipta prostrata (Bhringraj): 260 | **7.** Ageratum houstonianum (Bluemink): 254 | **8.** Capsella bursa-pastoris (Capsella): 266 | **9.** Tylophora indica (Dambel): 260 | **10.** Datura stramonium (Dhatura): 256 |
|  |  |  |  |  |
| **11.** Nyctanthes arbor-tristis (Harsingar): 289 | **12.** Cirsium arvense (Kantaiya): 272 | **13.** Pongamia pinnata (Karanja): 264 | **14.** Murraya koenigii (Meethaneem):256 | **15.** Plumeria pudica (Nagchampa): 272 |

| | | | | |
|---|---|---|---|---|
|  |  |  |  |  |
| **16.** Azadirachta indica (Neem): 289 | **17.** Vitex negundo (Nirgundi): 252 | **18.** Coleus barbatus (Patharchur): 254 | **19.** Mentha arvensis (Pudina): 277 | **20.** Putranjiva roxburghii (Putrajeevak): 261 |
|  |  |  |  |  |
| **21.** Catharanthus roseus (Sadabahar): 256 | **22.** Vernonia cinerea (Sahadevi): 257 | **23.** Asparagus racemosus (Shatawari): 260 | **24.** Ocimum sanctum (Tulsi): 267 | **25.** Verbesina virginica (Virginica): 271 |

### *4.2. Experiment design*

*Sampling & augmentation of dataset:* The research starts with collecting 25 categories of leaf images on the whiteboard with the help of a smartphone camera. After this, the abnormality of these images has been removed manually to eliminate the noisy, blur, and distorted images to create a proper dataset. The next task was the preprocessing, in which the photos were cropped and resized into 250x250 sizes. Each category of herbal plant images had been stored in separate folders. Each class has been divided into three parts: train, test, and validation. Finally, the herbal plant's classification has been done successfully with the output results in the form of accuracy and losses of different DL models. Dataset is augmented five times, and the same models are applied to this augmented data to improve the classification accuracy further. The five types of data augmentation used in this paper are flipping left-right, making images black & white, rotating them to some angle, skewing, and zooming.

*Deep learning models*: After this, the different DL models have been applied to these original datasets. Firstly the model gets trained with the help of the training dataset, and after that, the validation is done with the help of the validation dataset. Lastly, the test part happened on the test dataset. This paper uses the eight different DL CNN models to do the classifications, 1. ResNet-18 (Ayyachamy et al. 2019), 2. AlexNet (Alom et al. 2018) 3. VGG-11 (Gan, Yang, and Lai 2019), 4. SqueezeNet (Iandola et al. 2016), 5. GoogLeNet (Al-Qizwini et al. 2017), 6. ShuffleNet (X. Zhang et al. 2018), 7. ResNeXt-50 (Wang et al. 2018), and 8. DenseNet (K. Zhang et al. 2019)(Sharma, Berwal, and Ghai 2020).

*Evaluation parameters:* Training, validation, and test accuracies, as well as training, validation, and test losses, are the evaluation parameter for both standard data as well as on augmented data. These parameters are visualized using a line chart of accuracies and losses. While test accuracies and losses are shown using the box plot. The classification was visually shown using a heat map of the confusion matrix.

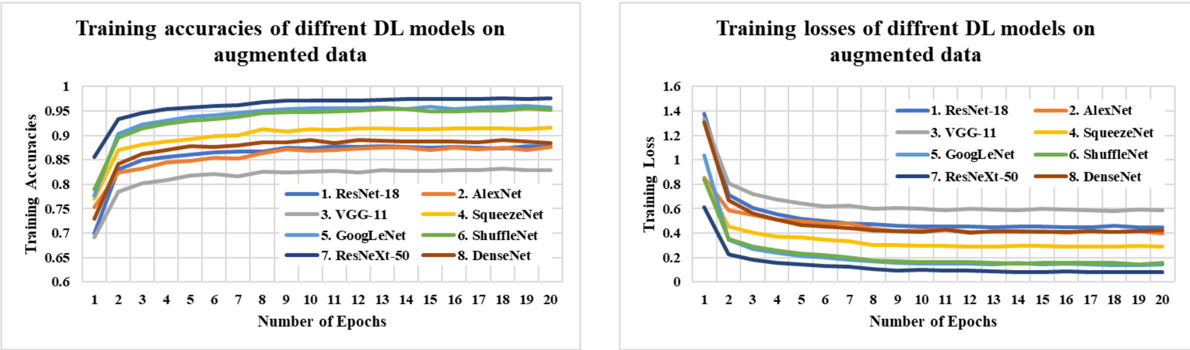
### *4.3. Hardware and Software requirements*

An Intel(R) Xeon(R) Silver 4210 CPU @ 2.20GHz 2.19 GHz Processor-based Workstation with 64.0 GB of Installed RAM, 64-bit operating system, Windows 10 Pro, Version 21H2, GPU Quadro RTX 4000 has been used as a hardware component for this research. While on the software end, Anaconda Navigator 2.1.1, JupyterLab 3.2, Python 3.9.7 64-bit, and Machine Learning Library from Scikit-learn have been used.

## 5. Results and Analysis

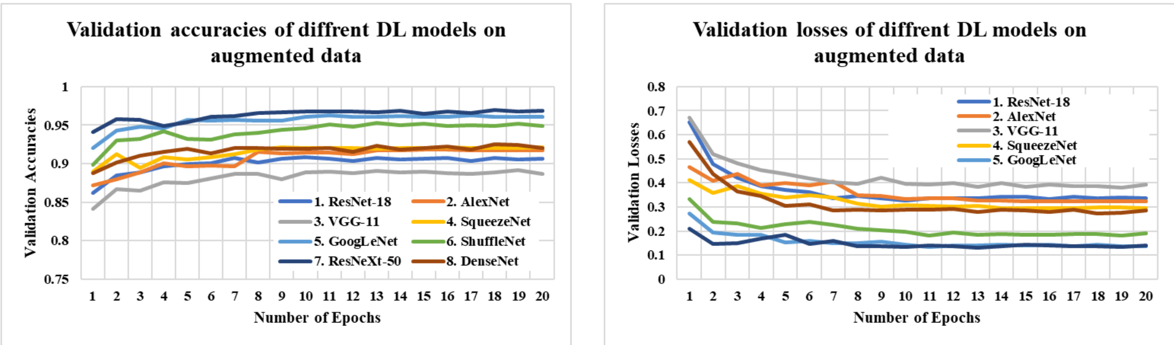
### *5.1. Results*

The training accuracies and losses, as well as validation accuracies and losses on the augmented dataset, are shown in Fig 2 and 3, respectively. On the original dataset, the same results have been demonstrated in Appendix-A.




(a) (b)

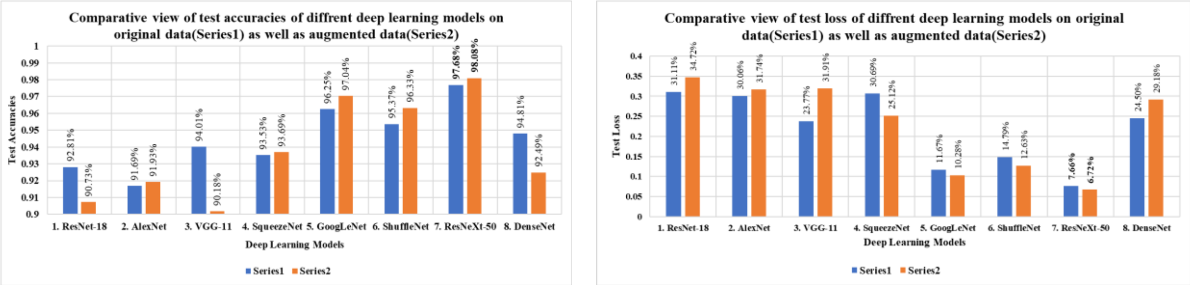
Fig. 2. (a)Training accuracies of models on an augmented dataset; (b) Training losses of models on an augmented dataset




(a) (b)

Fig. 3. (a)Validation accuracies of models on an augmented dataset; (b) Validation losses of models on an augmented dataset

The comparative view of the test accuracies and test losses on original and augmented data has been shown side by side in Fig 4.




(a) (b)

Fig. 4. (a) Test accuracy of DL models ; (b) Test losses of DL models

The heat map of the confusion matrix obtained in the output is shown in Fig 5. Here one can see that the maximum misclassification has occurred in class 20. Putrajeevak on the y-axis with class 3. Arusha, 9. Dambel, and 19. Pudina on the x-axis.

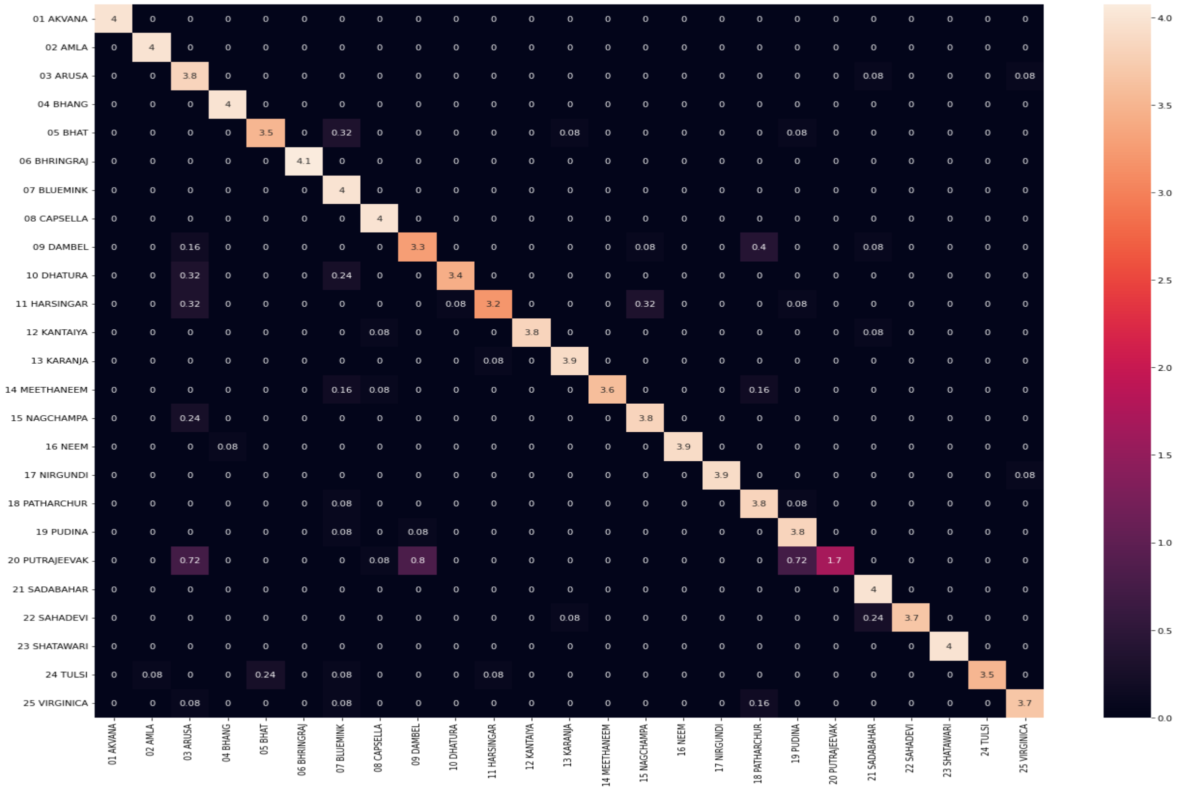



Fig. 5. Confusion matrix of classification performance of ResNext50 using the head map

### *5.2. Analysis of results*

Figs 2(a), 3(a), 6(a), and 7(a) show that the training & validation accuracies have a logarithmically increasing nature in the line chart on the normal dataset as well as the augmented dataset for 20 epochs on all eight deep learning models. While Figs 2(b), 3(b), 6(b), and 7(b) shows that the training & validation losses have a logarithmically decaying nature of line chart on normal data as well as augmented data. It is visible from line charts that as the epoch increases, the models become more and more stable. These results validate the quality of the datasets. Test and validation accuracies of ResNexXt-50 model are higher than all other models amongst these eight models after the model gets stabilized at the end of 20 epochs. At the same time, the VGG-11 model has the lowest validation and training accuracies at the end of 20 epochs.

Using ResNeXt-50 of DL models, we achieved the highest test accuracy of 97.68%, while with GoogLeNet(96.25%), we obtained the second-highest, and for ShuffleNet(95.37%) it is the third highest on the normal dataset. While on the augmented dataset too, ResNeXt-50(98.08%), GoogLeNet(97.04%), and ShuffleNet(96.33%) are the first, second, and third highest test accuracies models, respectively. These results conclude that the data augmentation has improved the test accuracy from 97.68% to 98.08% i.e., by 2.32% for ResNeXt-50 model, 0.82% for GoogLeNet, and 1.01% for ShuffleNet.

The same models, ResNeXt-50(7.66%), GoogLeNet(11.67%), and ShuffleNet(14.79%) gives the first, second, and third lowest losses, respectively amongst eight models on normal dataset and ResNeXt-50(6.72%), GoogLeNet(10.28%), and ShuffleNet(12.63%) are the first, second, and third lowest losses, respectively on augmented dataset. So, losses decrease by 12.27% for ResNeXt-50, by 11.91% for GoogLeNet, and by 14.60% by doing data augmentation.

And finally, from the heat map in Fig 5, we can observe that a few of the classes for which some misclassification occurred are categories 9. Dambel, 10. Dhatura, 11. Harshringar, 14. Meethaneem, 20. Putrajeevak etc., amongst these categories, maximum misclassification with itself and others is happing with category 20. Putrajeevak.

## 6. Conclusions

Using the classical machine learning algorithms in one of the old research works by the same authors on the same 25 categories of normal herbal plants leaf dataset, the test accuracy of 82.51% has been achieved by the MLP classifier. The lowest test accuracy model amongst the eight deep learning models on the normal dataset used in this paper is the AlexNet model, whose test accuracy is 91.69%, much higher than the highest performing machine learning MLP classifier (82.51%) in the previous research work. This result significantly improves classification accuracy when we use a deep learning model in place of the classical machine learning algorithms. So, DL models will be preferred over ML models for herb leaf image classification.

The training, validation, and test accuracies are highest. In contrast, the training, validation, and test losses are lowest for the ResNexXt-50 model on both normal and augmented data compared to the eight DL models used. So, ResNexXt-50 is the best DL model for herbal plants' leaf image classification among all eight DL models. While the second highest and third highest models GoogLeNet and ShuffleNet, respectively, also have good test accuracies compared to the ResNexXt-50.

For future research, we will try to include more classes of herbs in the dataset and further improve the test accuracies by applying another model or using concepts like Multi-view ensemble learning (Vipin and Sonajharia, 2015). At the same time, some of the most misclassified classes' accuracies will be improved by collecting more leaf images in that category in the dataset, extracting better features, and or applying better algorithms (Vipin and Sonajharia, 2014).

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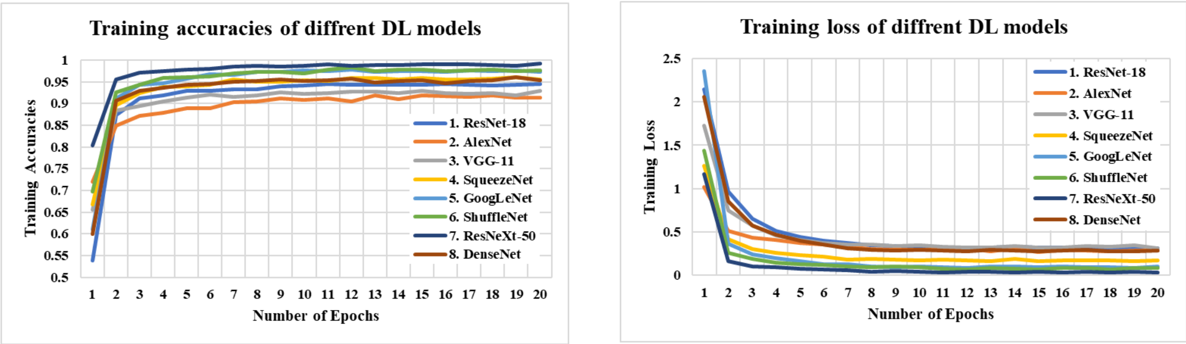
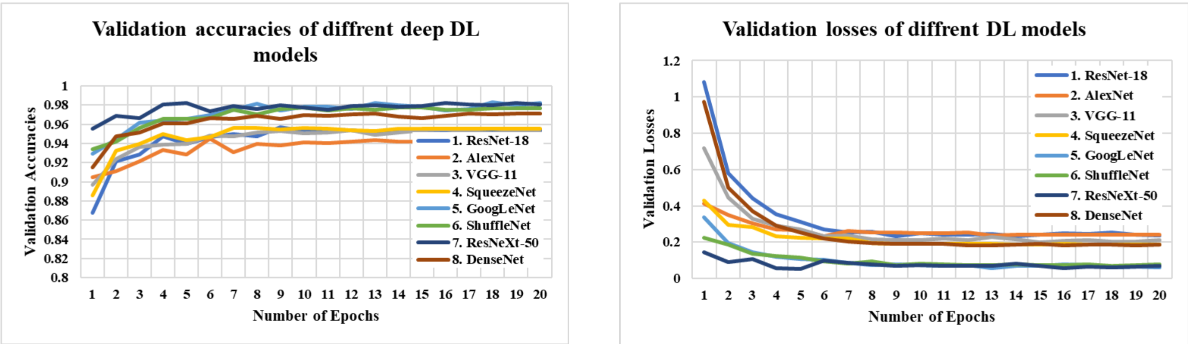
## Appendix A. The training accuracies and losses as well as validation accuracies and losses on the original dataset have been shown in Fig. 6 and Fig. 7, respectively.




(a) (b)

Fig. 6. (a) Training accuracies of models on the original dataset; (b) Training losses of models on the original dataset




(a) (b)

Fig. 7. (a) Validation accuracies of models on the original dataset; (b) Validation losses of models on the original dataset

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