An Effective Convolutional Learning Model with Fine-Tuning for Medicinal Plant Leaf Identification

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Abstract: In this work has successfully presented the custom CNN model and AYURNet approach for Classification. We used a convolution neural network (CNN) to solve this problem of Multi-Class Classification of Plant Leaves of some Andhra Ayurvedic Plants. The convolution layer part of CNN was used for feature extraction and the fully connecteddense layer part of CNN was used for Multiclass Classification. Using the known best practices, a very simple and elegant CNN model was designed and built using Keras to solve the Plant leaf Multi-Class Classification problem. The model was trained on the training dataset for 200 epochs. Using the weight parameters obtained in each epoch, the model was tested against the validation dataset. Training accuracy and Validation accuracy were compared at each epoch and the model with the best weight parameters was chosen. The logic used to choose the AYUR-Best model was high accuracy above the chosen threshold of 99% and the least possible difference betweentraining accuracy and validation accuracy. This was to ensure that the accuracy of the model was very high while ensuring that there was no overfitting. The model chosen using this method performed very well on the test dataset too and it resulted in an accuracy of 99.88%. Similar high accuracies were achieved by leveraging popular pre-trained models like DenseNet169, EfficientNetB6, InceptionResNetV2, ResNet152V2, VGG16 and Exception, but it is seen that the respective models are heavy with a large number of parameters when compared to the custom CNN model described in this work. Due to the small size of the Custom CNN model, it is suitable for the development of the mobile application for Ayurvedic plant species identification based on the respective leaf images..

1 INTRODUCTION

The survival of human society is largely dependent on the ecological resources on this planet. For instance, the natural habitat and natural resources around us are being utilized for various human needs. In particular, human society has more dependencies on plant habitat. Hence, there is a tremendous magnitude of discoveries in the biological sciences, which enables humans in understanding the complexity in the biodiversity of plant life. Taxonomists and botanists conduct their exploratory expeditions to explore the natural habitat of plant life, which leads to enormous amount of information regarding the plant life in the natural habitat. This leads to vast museums, libraries, biological gardens (Bisby, 2000),(Edwards, Lane, et al. , 2000) and herbariums. In recent years, we have witnessed the revolution of digital world and virtualization, particularly, the development of virtual herbariums. Virtual herbariums contain all the information of plant species in the form of text, images, videos and other multimedia modalities. Classification and retrieval of information from such virtual herbariums is a challenging task. Image processing and pattern recognition techniques can be explored to devise methods for automatic classification and retrieval of information from virtual herbariums. Ayurvedic health care system uses medicinal plant resources like leaves, flowers, barks, fruits and roots for the preparation of medicines to prevent and cure common diseases, so it is very much essential to possess knowledge about the taxonomy and usage of medicinal plants. Though there are some experts who possess knowledge about the taxonomy of medicinal plants, their knowledge is generally restricted to only those plants, which are available in their respective regions. The recent developments in ayurvedic medicine have proved that the ayurvedic medicines are very effective for certain diseases and do not have

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any side effects. Since medicinal plants can be grown naturally and made available for a common man easily, it is appropriate to provide knowledge about medicinal plants and their usage. It is very difficult for a common man to possess a complete knowledge about all the medicinal plants and their usage as there are millions of species in the nature, which have medicinal value. Also, sometimes, even an expert in ayurvedic medicine may fail to classify certain species correctly due to intra-class dissimilarity and inter-class similarity. Therefore, it is obvious that one can think of an automated system to correctly classify plant species in a large collection. In view of this, in this work, we made an attempt to propose a medicinal plants classification system based on leaves by exploring some novel feature extraction techniques to characterize plant leaves and efficient representation technique to effectively classify medicinal plants.

2 RELATED WORK

A new technique was presented to find the ideal structure of CNN for texture recognition. Dixit and Ujjawal has suggested a strategy of texture classification using CNN and optimized with the whale optimization algorithm. This method applies WOA's ideas to optimize convolutional layer filter values and dense layer weight and bias values. For the testing purpose, this method was applied on three distinctive benchmark datasets viz. Kylberg v1.0, Brodatz, and Outex_TC_00012. The outcome demonstrated that the model performed fair enough when compared with the existing methods and accomplishes classification precision for the Brodatz dataset. This method proves CNN is more powerful and is a successful technique in texture recognition (Dixit and Ujjawal, 2019). Mehdipour Ghaz et al. By optimizing the transfer learning parameters, authors presented a method of plant identification using a deep neural network. Three amazing and famous deep learning designs, namely Google Net, AlexNet, and VGGNet, are utilized for the purpose. Transfer learning is utilized to improve the pre-trained models. To reduce over fitting, increase procedures are applied on image transforms such as rotation, translation, reflection, and scaling. Moreover, the networks' parameters are balanced and various classifiers are combined to improve overall execution. The results of the plant identification campaign LifeCLEF 2015 shows that the general validation accuracy of the top system has improved by 15% and the general inverse position value of the test set has improved by 10%. The framework recently got exceptionally a 2 nd place in the Plant CLEF 2016 (Ghazi, Yanikoglu, et al. , 2017). The recognition of plant species mainly depend upon the leaf characteristics. CNN was introduced to improve the recognition capacity of plant leaves in the complex environment. Xiaolong Zhu et al. have suggested a improved deep convolutional neural network for identification of leaves. These techniques has taken advantage of the Inception V2 with Batch Normalization (BN) instead of convolutional neural layers. In addition, the first image is cut to a predefined size in numerical order, and the segmented images are continuously loaded into the proposed network successively. After the precise classification via SoftMax and bounding field repressor, the divided snap shots with unique labels are spliced collectively as a final output snap shots. Research results show that this method is more accurate than Faster RCNN when it comes to recognizing leaf species in complex backgrounds (Zhu, Zhu, et al. , 2018). The proposed strategy used a deep belief network (DBN), and the process of preparing the network included unsupervised feature learning followed by fine-tuning of the supervised network. Samadhi et al. Presented a supervised deep learning-based method for detecting changes in radar images with synthetic apertures (SARs). From a general point of view, the prepared DBN produces a change location map as the output. Studies on DBNs exhibit that they don't create a perfect strategy without a proper dataset. Then it provides a dataset containing the appropriate amount and various information to train the DBN using the input images and the images obtained by applying morphological operators. The disadvantage of deep learning algorithms are time-consuming. Test results show that the method has acceptable implementation time in addition to the desired execution and precision (Samadi, Farnaam, et al. , 2019) Ubbens et al. recommended using deep learning to apply on rosette plants. Extended the capabilities of Deep Convolutional Neural Networks to perform leaf counting tasks. Deep learning systems generally require a large and diverse data set to train a generalized model without providing pre-designed algorithms to perform the task. This paper has introduced a new way to extend plant phenotypic datasets using rendered images of manufactured plants. It has been shown that the demonstration of the leaf counting task can be modified by expanding the dataset with high quality 3D synthetic plants. The ability of the model to generate an arbitrary distribution of phenotypes has been shown to mitigate the problem of dataset changes when training and testing on multiple datasets. After all, when training neural networks to do the job of counting leaves, real and synthetic plants are importantly interchangeable (Ubbens and Jordan, 2018). Preserving plants has become a vital task. It is very important, as few plants have incredible medicinal properties. Plants can be recognized by leaves, bark, seeds, fruits, flowers, etc. Lochan et al. proposed a method for detecting and classifying plants using a high-speed region-based convolutional neural network. Methodology that takes into account is identification of plants by leaf characteristics. The plants considered are medicinal plants that can be introduced in individual locations such as Himalayan and vegetable gardens. Author used a regional convolutional neural network (RCNN) to identify plants. The system uses a fast RCNN model that uses a convolutional system to extract features and classifies using support vector machine (Lochan, Naga, et al. , 2020). Yang et al. presented a method for recognizing semantic image information via MultiFeature Fusion and SSAE-based Deep Network. Effectively used the Convolutional Neural Network in the field of visual recognition and data augmentation techniques for small datasets to get the right number of training datasets. The author uses low-level features of the image to help extract advanced features that are naturally learned from deep networks in order to obtain successful emotional features of the image. At this point, the Stack Sparse auto-encoding system is used to sense the emotions caused by the image.

Finally, a semantically enlightening high-level phrase containing the emotions of the image is delivered. Experiments are performed using dimensional space IAPS and GAPED datasets and discrete space art photo datasets (Yang and Xiaofeng, 2020). Taxon identification is an important step in many plant biology studies. Pierre Barré et al., introduced semi-automatic system that can significantly improve your productivity and reproducibility. However, in most cases, it relies on a hand-crafted algorithm to extract a previously selected set of characteristics to distinguish between the types of selected taxa. As a result, such frameworks are limited to these taxa and also require the involvement of experts to provide taxonomic knowledge for the reproduction of such tailor-made systems. The purpose of the study was to set up a deep learning framework for learning to distinguish features from leaf images, as well as a classifier for identifying plant species. In contrast, the results with Leaf Snap show that learning highlights via a convolutional neural network improves the feature representation of leaf images, as opposed to handmade features. The analysis uses published Leaf Snap, Flavia, and Foliage datasets (Barré, Stöver, et al. , 2017). It is extremely challenging when the leaf images are similar in size, shape and texture. J. Hu et al recommended a method of multiscale fusion convolutional neural network for plant leaf recognition. First, the input image using the random biprimary interpolation task is reduced to a low resolution image. At this point, these input images of different scales are stepped into the MSFCNN design to learn identifiable points at different depths. In this phase, the fusion of features between the two different scales is confirmed by a join operation that connects the maps captured with images of different scales from the channel view. In addition to the depth of MSFCNN, multiscale images are dynamically processed and the corresponding highlights are combined. Third, the final layer of MSFCNN sums all the identification data to get the final predictor of the plant species in the input image. Test results show that the presented MSFCNN method is superior to some state-of-the-art plant leaf detection methods in the Malaya KewLeaf and LeafSnap datasets (Hu, Chen, et al. , 2018). Authors have suggested DPCNN and BOW methods for leaf recognition. The work focuses predominantly on feature extraction, particularly on textural feature extraction. Currently, new methods of leaf recognition rely on the word of bag (BOW) and entropy sequence (EnS). First, EnS is attained by a dual-output pulse-coupled neural system and later improved by BOW. A linear coding strategy with locality constraints was used for sparse coding and SVM used as classifier. Some representative datasets and existing techniques were assessed to understand the the impact of the methods implemented. Finally, the results showed the accuracy of the method is superior to that of existing methods (Wang, Sun, et al. , 2017). Though Leaves are helpful markers in identifying the plants, a significant downside is that numerous biological and environmental factors are likely to easily harm them. A method of fragmented plant leaf recognition presented by Chaki and Jyotismita uses fuzzy-colour, Bag-of-features, and edge-texture histogram descriptors with multilayer perception. Divided leaf images cannot be perceived based on the feature of shape. A unique methodology was brought in by using the combination of edge-texture histogram and fuzzy-colour to recognise divided leaf images. Initially, by using bag-of-feature, the images that were similar in appearance were recognized. To produce the feature vector, the consolidated element was utilized at that point. Since less information was given by the divided leaves, the method also aimed at achieving fragment size threshold. Using a multi-layer-perceptron classifier, the effectiveness of the proposed approach was considered. Since divided image public database is not available, a technique was developed to produce fragmented leaf image from the whole one (Chaki and Jyotismita, 2019). In general, Agriculturists and farmers have been facing repeated challenges in agriculture, one of it is being the diseases faced in rice. The extreme case of rice sickness is being no harvest. So, we need a more cost effective, Simpler and Automatic technique to identify sickness in rice. Using deep transfer learning Chen and Junde presents a technique to detect rice plant diseases. An outstanding result in classification and image processing is demonstrated by deep learning approach for settling the task. Taking advantage of both, the inception and Dense Net pretrained on the image net modules were chosen to be used in the network. Using this technique results in best performance in comparison with other state of the art methods. It achieves an average result of at least a public dataset. This average accuracy becomes high for the prediction of class for rice disease images even when different diseases were considered. The validity of suggested approach was shown by the test outcome. It is applied for the effective rice disease detection (Chen and Junde, 2020). Computer Researchers helped botanists by creating the plant identification systems to identify and perceive strange plant species more quickly. For the use of plant predictive modelling, different studies so far focused on algorithms or strategies that amplify the use of leaf databases. A technique of learning leaf features were presented by Lee and Sue Han. Leaf characteristics legitimately form the basic input data representations using CNN, and gain a knowledge of selected features on a Deconvolutional Network (DN) approach. The most typical feature undertaken in this research was veins of leaf. A multi-level representation of leaf data shows a hierarchical transition from a lower level trait abstraction to a higher level in relation to species. These results shown are consistent with the various botanical implications of leaf features. The results provides insight into the technology of hybrid feature extraction models that further enhance the discriminating ability of plant classification systems (Lee and Han, 2017). To resolve the issue of plant identification from patterns of the leaf veins, Grinblat et al., has proposed a deep convolutional neural network (CNN). In specific, three diverse legume species are considered, namely soybean, red bean and white bean. The presentation of a CNN evades the utilization of feature extractors which are handcrafted as it is standard in best in class pipeline. Moreover, this approach of deep learning altogether improves the precision of the pipeline. We additionally show that the announced accurateness is reached by extending the depth of the model. At last, by studying the models with a basic visualization method, we can disclose pertinent vein designs (Grinblat, Guillermo, 2016). Ferentinos et al has utilized leaf images of diseased and healthy plants. convolutional neural network models were created to detect disease in plants through methods of deep learning. A large dataset images were trained using 25 to 58 classes, including disease-free plants. The research undertaken has proved the model an remarkably helpful tool with good accuracy rate. The work carried can further be extended to work on real time plant disease (Ferentinos and Konstantinos, 2018). Based on venation fractal dimension and outline fractal dimension a new method is proposed portraying the features of plant leaf Du, Ji-xiang et al. Initially to separate leaf vein and edge, and get multiple veins, multiple threshold edge detection technique was used. Later, 2 dimensional fractal dimension of the multiple vein picture and leaf edge image will be calculated, and also adopted a fresh ring projection fractal image for shape of the leaf. Then, to classification and recognition of plant leaves, two kinds of fractal dimension characteristics are utilized. The test results showed the adequacy of the fractal dimension characteristic technique(Du, Xiang, et al. , 2016). Atabay et al., has presented a method of convolutional neural network with a new architecture applied to leaf classification. A new CNN design was introduced and applied on leaf classification. The utilization of the recently introduced Exponential Linear Unit (ELU) instead of Rectified Linear Unit (ReLU) as the non-linearity function of CNN was investigated. The structure has been analysed on Flavia and Swedish leaf datasets and the classification outcomes show that the presented CNN is effective for leaf classification (Atabay, Agh., 2016). For an effective weed management, data on the weed species in farming land is very important. By using a convolutional neural network, a method is proposed to recognise the plant species images in colour Dyrmann et al., 10413 images of weed and crop species at initial stages of growth is tested and trained having 22 species to build the network from scratch. These pictures used from six distinctive datasets, which have varieties like resolution, lighting, goal, and soil type. Also incorporates pictures taken under controlled conditions concerning camera stabilization and illumination, and pictures shot with cell phones which were hand-held in fields with distinctive soil types and changing lighting conditions. For these 22 species, A classification accuracy of 86.2% is achieved by the network (Dyrmann, Mads, et al. , 2016). Authors have reviewed with the upsides and downsides of each technique with respect to input information (Crop type) Iniyan et al. In developing countries like India, economy is depending majorly on agriculture. Expansion in agro-items influences the GDP of the country to a decent degree. To expand the profitability in farming, early identification of sicknesses is required. In the developmental work, we have to limit our discussion and detect the crop issues using technologies like machine learning. with the help of artificial neural network and support vector machine (Iniyan, et al. , 2020).

3 PROPOSED SYSTEM

In this chapter, a custom CNN architecture for APLC and an innovative AYUR-Best model approach to achieve the highest classification accuracy have been proposed. For experimentation, a comprehensive results analysis takes place using the custom leaf dataset. Classification of plant species is important to be able to take full advantage of the benefits provided by the respective species. Given the huge number of plant species, the classification of plant species requires knowledge and expertise. An expert botanist has the skill to classify plant species based on morphological characteristics. Manual techniques to classify plants are time-consuming and demand expert knowledge. Classification of plant species based on leaf images has become an active area of research. Due to advances in image processing and artificial intelligence techniques, it is possible to solve the complex problem of APLC. CNN's have gained popularity for the last 10 years with the availability of supporting hardware and software platforms. The problem chosen in this work is medicinal plant species identification by the classification of respective leaf images. It is not always possible for humans to come up with explicit patterns and features that can be fed as input to computer programs for image classification of non-geometric figures like leaves. CNN's are a good fit for solving this problem since theycan come up with models that can identify some patterns and features which may not be understandable and interpretable by humans but can do a good job of image classification. A large data set of images of leaves of various plants to be classified was first collected. A CNN architecture was designed which resulted in a model that was able to classify the chosen leaves with targeted accuracy.

3.1 Pre-processing

The only preprocessing step required in this work was to rescale the leaf images from 4000x3000x3 pixel size to 150x150x3 pixel size. This image rescaling could have been done as a part of the main Keras code itself. The only reason for implementing it separately in the local system using python was to reduce the size of images before uploading them to google drive. This is to increase the speed of upload from the local system to google drive. This is also keeping in view of the upper limit of 15GB free storage availability in google drive.

3.2 Building the CNN Model

The ML techniques of leaf image classification rely on data from hand-crafted features. The leaf images are run through several pre-processing steps. Hand-crafted features are a set of features extracted and derived from leaf images by researchers, to help the machine differentiate one leaf class from another. This feature data is collected from several leaves belonging to various plants. The leaf feature data andthe corresponding leaf labels are fed to relevant ML classification algorithms and training is done. So, the usual steps involved are pre-processing, feature extraction, and classification. Some of the classification algorithms used are the Multiclass support vector machine (MSVM) and the Random Forest classifier. Upon training, the classification algorithms can predict the leaf label based on the input feature data of the new leaves which were previously not part of the training dataset. In feature engineering, hand-crafted features are the set of features that the researchers assume will help humans implicitly differentiate one image class from another. We are still not at a stage where we can fully decipher how the human brain recognizes and identifies objects. So the better option thought by researchers for classification was to let the machine itself figure out what features would be best suitable for classification when it is given a set of training images of various classes. Deep CNN is better suitable for this task of image classification and has been used in the leaf image classification work described in this work. The basic concept behind CNN is to create a model that best maps the input training images to the corresponding known image labels. This model created based on the training imageset and labels, is then used for image class prediction. The model consists of convolutional layers and max-pooling layers followed by a multi-layer DNN. Convolutional layers are filters that act as feature identifiers or feature extractors. After the Convolutional layer, we usually have the Max-Pooling layer which helps in down-sampling of the feature representation received from the preceding Convolutional layer. The multi-layer neural network consists of fully connected layers also known as Dense layers. Classification of images is a very complex task. The image data involved is not linearly separable. A simple mathematical function is not enough for achieving this image classification task. The extremely complex relationship between the input image data and output labels is needed for this purpose. These cannot be expressed as direct mathematical formulas. The solution lies in coming up with a combination of basic building blocks that can model the required extremely complex relationship. The building blocks are the artificial neurons. Artificial neurons are mathematical functions that are the summation of products of inputs and weights. That means they are weighted aggregations of the inputs. A non-linear activation function like sigmoid, ReLU, or Tanh is then applied to this sum to introduce non-linearity. A DNN consisting of layers of several such artificial neurons is built. As per the Universal Approximation Theorem, such a kind of deep artificial neural network can be tailored to approximately represent any complex relationship between a set of inputs and outputs.The final layer of this network is the output layer which is used for prediction. In this case of image classification, it is the image class or label which is predicted. This process of modeling the neural network is not a simple exercise. It is a complex engineering exercise that involves trying out several CNN architectures for the problem at hand. Study and usage of known best practices are done for faster convergence to the solution. To start with, the weight parameters associated with the various neurons in the network are initialized with some values. The inputs to this network are numerical pixel data corresponding to the images. The input data is processed through the network and the prediction is done at the output layer. A comparison of the predicted output classes is done with the known true classes of the training data set of images. It is highly improbable that the prediction would be perfect in just one forward pass through the network. The difference between the predicted values and the true values is calculated using loss functions. If there is a loss or difference, then it means that the neural network model does not correctly define the relationship between the input and output. The task at hand is thus to minimize theloss and improve the model so that predicted values are as near to true values as possible. The way to improve the model is to adjust the weight parameters. This is done using the learning process. The updates to weights should not be done randomly. The weight adjustment should be done in a principled way based on the loss function. It is mathematically proven that the weight adjustment should be based on the derivative of the loss function for the weight. The derivative of loss for weight is known as the gradient. By moving in a direction opposite to the gradient, we can reduce the loss. This is known as Gradient Descent. In DNNs, the derivative of loss function needs to be calculated for all the weights corresponding to all the artificial neurons starting from the first layer till the output layer. The paths over which the derivatives of various weights for loss needs tobe calculated using the chain rule may be complicated. These computations of derivatives of all the weights in the network can be done efficiently using the backpropagation method. In the backpropagation method, the computation is done backward from the outward layer for reuse and efficiency. This processing of inputs through the network and the backpropagation of weights is done until the required accuracy is achieved. Since the amount of input data required to train these networks is large, we do not wait until all the input data is processed. The weight updates are done after a certain batch size of data processing is complete. When the processing of the full input training data set is complete, it is known as the completion of one epoch. Several such epochs are required before the required prediction accuracy is achieved. If the chosen model architecture does not achieve the required accuracy even after training for a large number of epochs, then another suitable architecture needs to be designed and the training process needs to be repeated. This exercise needs to be carried out until the desired accuracy is achieved. After the training of the model is completed and the desired training accuracy is achieved, the evaluation of the model against previously unseen test data needs to be done. Only when the test accuracy similar to training accuracy is achieved, the model is considered as successful. Sometimes, much less accuracy may be achieved during testing when compared to training. This is due to overfitting. Overfitting means that the model has memorized the training data instead of coming up with a proper relationship that will achieve similar accuracy on any test data. In such cases, changes to the model will again be required. CNN modeling aims to come up with the simplestpossible network design which will give the highest possible accuracy for the chosen image classification task. For the

APLC task, we designed the CNN model as shown in figure 1.

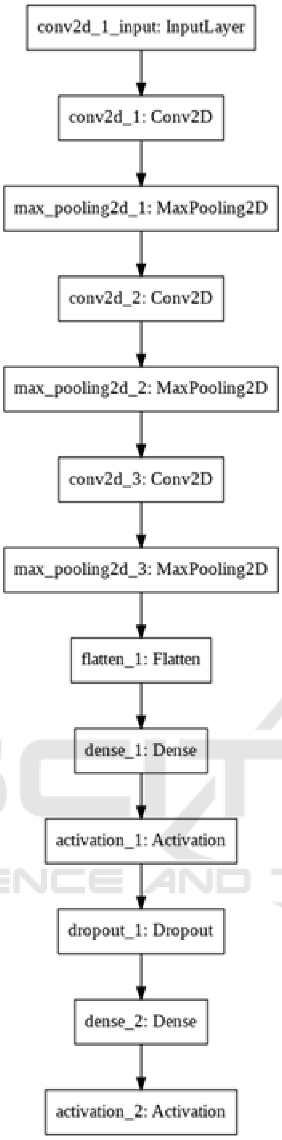

Figure 1:Graphical Description Of The CNN For Ayurvedic Leaf Image Classification

For the sake of simplicity, this CNN is designed as a sequential model with a linear stack of layers. Several hyperparameters are used in the design of the CNN model. These hyperparameters can be tuned to improve the accuracy of the CNN model. One of the hyperparameters is the activation function. These activation functions in neural networks are nonlinear. Without the non-linear activation functions, the output of the neural network would just be a linear transformation of the input even if the networkis deep with many layers. A linear transformation cannot solve complex problems involving non-linearly separable data. The representation power of the Universal Approximation Theorem and thus the DNNs is owing to the non-linear activation functions. The usual activation function that comes to mind in the case of a neural network is the sigmoid function. One problem with the sigmoid function is that it saturates when it reaches its peak value or bottommost value during training. This means that the derivative of the function becomes zero. When the neuron gets saturated, the weight update stops happening and learning gets affected. This is whatis known as the vanishing gradient problem. One of the other problems with the sigmoid function is that it is computationally expensive since it contains the exponential function.

The recommended default activation function for CNN is ReLU. ReLU is the short form for the rectified linear unit. It is represented in Equation 1. When the input value is positive, then the ReLU function will output the input value itself. If the input value is negative, then the ReLU function will output zero. ReLU is thus better than sigmoid function in the sense that it does not saturate for positive values and it is easy to compute. In the proposed CNN model, ReLU is used as the activation function for both the convolutional layers as well as the fully connected hidden layers.

This model was designed based on the known best practices and several trials with various CNN architectures. Figure 2 shows the model summary of the proposed network with the details of the number of parameters involved.

$$f(x)=\max(0,x) \tag{1}$$

Softmax is used as the activation function in the output layer.

3.3 Choice of Loss Function

The whole idea behind CNN modeling is to find the approximate relationship which is as near as possible to the true complex relationship between input and output. In ourcase of training the CNN model for leaf classification of multiple classes, the inputs are images of leaves of different known classes and the outputs are the leaf class labels of the respective leaf images. During the training process, we get the predicted output. For the training dataset, we know the true output. To assess the correctness of the model, we find the summation of the difference between the true output and the predicted output. This difference is calculated using a loss function. During the training, the loss is calculated using the loss function for all the data in the training dataset and it is summed up. It is this loss value that helps us choose the model which better approximates the relationship between the input data and output. It is obvious that the lower is the loss value, the better is the model. Some of the loss functionsused in neural networks are squared error loss, cross-entropy loss, and KL divergence.For this case of multi-class classification problem of leaves where we are using softmax function as the activation function in the fully connected output layer, the loss function which we chose is the categorical cross-entropy.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 148, 148, 64)	1792
max_pooling2d_1 (MaxPooling)	(None, 74, 74, 64)	0
conv2d_2 (Conv2D)	(None, 72, 72, 64)	36928
max_pooling2d_2 (MaxPooling)	(None, 36, 36, 64)	0
conv2d_3 (Conv2D)	(None, 34, 34, 64)	36928
max_pooling2d_3 (MaxPooling)	(None, 17, 17, 64)	0
flatten_1 (Flatten)	(None, 18496)	0
dense_1 (Dense)	(None, 128)	2367616
activation_1 (Activation)	(None, 128)	0
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 6)	774
activation_2 (Activation)	(None, 6)	0
Total params: 2,444,038 Trainable params: 2,444,038 Non-trainable params: 0		

Figure 2:Summarry of the Cnn fort Ayurvedic Plant Leaf Image Classification

3.4 Learning

Artificial neurons in the neural network consist of inputs, weights, bais, and activationfunctions. Once we chose a neural network model to tackle a problem, we need tofind the weights and bais which are the parameters that define the model. The values of these parameters are not known at the time of choosing the model. The best possible parameter values need to be found through the process of learning. To start with, the parameters for the chosen model will be initialized with some values. The inputs are then processed by the model and the outputs are predicted. During the training process, the inputs are the training dataset for which the outputs are known. The predicted output would not match with the known output after the first pass through the network. The loss function is used to find the difference between the actual known output and the predicted output. The aim of the learning process to minimize the loss such that we arrive at the parameter values which results in predicted output to be as near to the known output as possible. This will result in the required model which will best describe the relationship between the input and the output. For the complex relationship between the inputs and the outputs, it is just not possible to determine the values of a large number of parameters by guesswork or trial and error method or brute force search method. The purpose of the learning algorithm is toarrive at those values of the parameters which minimize the loss. This is hence an optimization problem that involves computing the parameters as efficiently as possible. The algorithms used for solving this problem are mostly based on calculus and linear algebra. Some of the popular learning algorithms are Gradient Descent, Adagrad, RMSProp, and Adam. The optimization algorithm used in this work for compiling the model is Adam. Adam is the short form for adaptive moment estimation. This algorithm was proposedby Diederik P. Kingma from OpenAI and Jimmy Lei Ba from the University of Toronto. Adam combines the advantages of two other optimization algorithms named AdaGrad and RMSProp. Adagrad is a gradient based optimization algorithm and a short form for the adaptive gradient. Adagrad performs small updates to parameters associated with dense features and it does larger updates to sparse features. Thus, it allows the learning rate to adapt based on the parameters. It, however, has the problem of shrinking of learning rate as the training progresses. This problem is overcome in another optimization algorithm named RMSProp by dividing the learning rate by exponentially decaying average of squared gradients. RMSProp chooses a different learning rate for each parameter. RMSProp is the short form for Root Mean Square Propagation and was proposed by Geoffrey Hinton. Adam's optimization algorithm used in the work described in this work combines the advantage of AdaGrad"s ability to deal with sparse gradients and RMSProp"s ability to deal with non-stationary objectives.

3.5 Evaluation

In the leaf classification problem described in this work, the dataset is perfectly balanced. Since the dataset was created exclusively for this work, it was made sure that the count of images in the training, validation, and test dataset of different classes of leaves is exactly equal. Since the count of images of different classes are exactly equal, the dataset is perfectly balanced. The advantage of a balanced dataset is that accuracy can be used as the metric to evaluate this model. The advantage of accuracy as a metric is that it is very easy and intuitive to understand. Both the overall accuracyas well as per class accuracy have been calculated for this model. The formula for calculation of accuracy is given in equation 1.

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of prediction}} \quad (1)$$

3.6 Methodology

In this work, the self-created data set of leaf images of six different species of locally available ayurvedic plants are used. For each of the six plant species, 1000 leaf images are taken. The total dataset size is hence 6000 leaf images. For each of the 1000 plant species images, the data set is split into training, validation, and test dataset in the ratio 70:15:15. The training and validation data set are used by our keras cnn program while building and training the model. The leaf images are rescaled to 150x150x3 pixel size. The rescaled leaf images are uploaded to google drive in the standard folder format as expected by the designed keras cnn program. The keras cnn program is coded in the google colab environment. The google driveis mounted locally to the google colab environment so that the leaf image dataset on the google drive is accessible to the keras cnn program. Keras cnn program is trained using the training dataset for 200 epochs. For every epoch, the training accuracy of the model is calculated. With the parameter weights calculated for each epoch, the

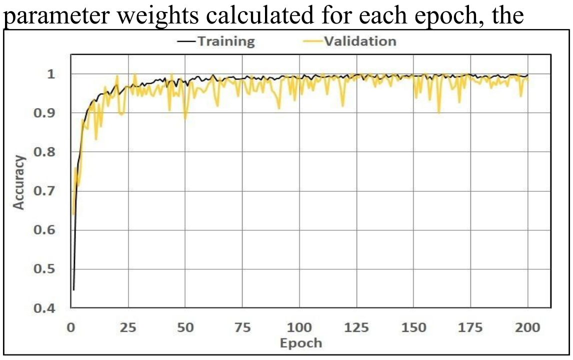

Figure 3:Model Accuracy

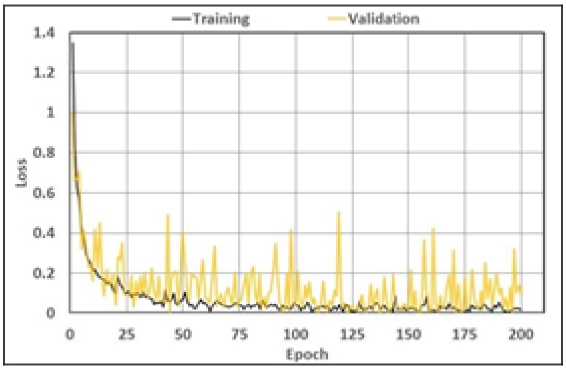

Figure 4:Model Loss

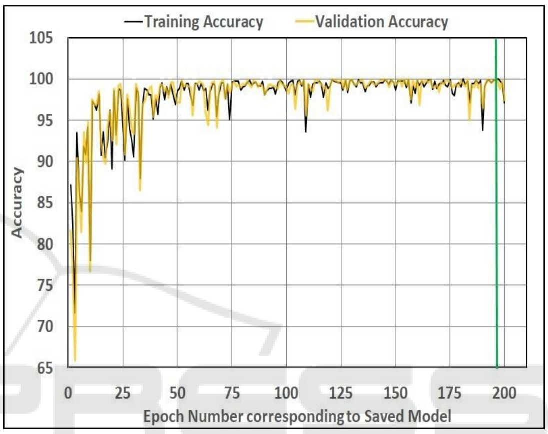

Figure 5:Training Validation accuracy-Checkpoint Saved Models

model is evaluated against the validation dataset and the validation accuracy is calculated. Using the checkpointing capability provided by keras, the model with parameter weights is saved at the end of each epoch. While the training is in progress, the training loss, training accuracy, validation loss and validation accuracy for each epoch is monitored.

4 RESULTS AND DISCUSSIONS

To start the process of plant species identification, the first step involved collecting the dataset. A qualitative study was conducted to identify suitable medicinal leaf dataset sources and determine the dataset format. The selection of a dataset is influenced by several factors, including the nature of the problem, the availability of data, the diversity of the data, and the relevance to the application. In order to generalize our approach, we used the benchmark dataset of medicinal plant leaf classification, i.e., Mendeley Medicinal Leaf. The dataset, representing images from 30 different medicinal plants, was selected for this study. The selected dataset contained a total of 1835 leaf images. A system's performance is affected by factors like the dataset size, class distribution, and data quality. To address this concern, data preprocessing was employed to clean the dataset. Figure 6 depicts some of the leaf samples of the Mendeley Medicinal Leaf Dataset.

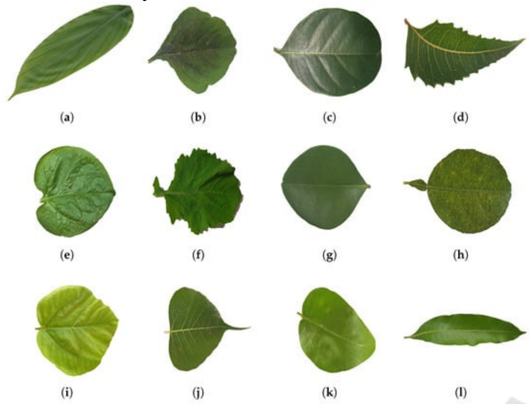

Figure 6: Showcases a sample of the medicinal leaf dataset images, illustrating the diverse range of plant images incorporated for classification purposes. (a) Alpinia Galanga (Rasna), (b) Amaranthus Viridis (Arive-Dantu), (c) Artocarpus Heterophyllus (jackfruit), (d) Azadirachta Indica (neem), (e) Basella Alba (Basale), (f) Brassica Juncea (Indian mustard), (g) Carissa Carandas (Karanda), (h) Citrus Limon (lemon), (i) Ficus Auriculata (Roxburgh fig), (j) Ficus Religiosa (peepal tree), (k) Jasminum (jasmine), (l) Mangifera Indica (mango).

The custom CNN model described in this work for APLC was freshly designed, trained and tested using the AYUR-Best model approach. It is also possible to leverage pre-trained CNN models for Ayurvedic leaf image classification. This method of reuse of pre-trained CNN models is known as Transfer learning. There are many popular pre-trained CNN models available in TensorFlow. As a part of the work presented, a comparison of the described CNN model is done with repurposed CNN models based on pre-trained models like DenseNet169, EfficientNetB6, Inception ResNetV2, ResNet152V2, VGG16 and Xception. The results are presented in Table 2. The observation is that classification accuracy achieved on the test dataset is similar for the custom CNN model (developed using the AYUR-Best model approach) and the repurposed CNN models. The custom CNN model (developed using the AYUR-Best model approach) is better in terms of the number of parameters and the size of the respective saved model. When compared to the repurposed CNN models, the number of parameters in the custom CNN model is the lowest and the size of the respective saved model is the smallest.

5 CONCLUSION AND FUTURE ENHANCEMENT

This work has successfully presented the custom CNN model and ayurnet approach for aplc. The motivation behind the work was to come up with an automatic computer vision based system to identify locally available ayurvedic plants. In this work, the part of the plant chosen for plant identification is the leaf. Theleaves of various plants are distinguishable from each other due to morphological differences. Leaves are the most easily available part of the plant and are available throughout the year. Several previous works done about plant leaf classification were reviewed. We used a convolution neural network (cnn) to solve this problem of multi-class classification of plant leaves of some andhra ayurvedic plants. The convolution layer part of cnn was used for feature extraction and the fully connected dense layer part of cnn was used for multiclass classification. Using the known best practices, a very simple and elegant cnn model was designed and built using keras to solve the plant leaf multi-class classification problem. The model was trained on the training dataset for 200 epochs. Using the weight parameters obtained in each epoch, the model was tested against the validation dataset.

Training accuracy and validation accuracy were compared at each epoch and the model with the best weight parameters was chosen. The logic used to choose the ayur-best model was high accuracy above the chosen threshold of 99% and the least possible difference between training accuracy and validation accuracy. This was to ensure that the accuracy of the model was very high while ensuring that there was no overfitting. The model chosen using this method performed very well on the test dataset too and it resulted in an accuracy of 99.88%. Similar high accuracies were achieved by leveraging popular pre-trained models like densenet169, efficientnetb6, inceptionresnetv2, resnet152v2, vgg16 and xception, but it is seen that the respective models are heavy with a large number of parameters when compared to the custom cnn model described in this work. Due to the small size of the custom cnn model, it is suitable for the development of the mobile application for ayurvedic plant species identification based on the respective leaf images.

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