Recognising Ayurvedic Herbal Plants in Sri Lanka using Convolutional Neural Networks

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Date Received: 25-05-2020 Date Accepted: 24-06-2020

Abstract

Different parts of ayurvedic herbal plants are used to make ayurvedic medicines in Sri Lanka. Recognising these endemic herbal plants is a challenging problem in the fields of ayurvedic medicine, computer vision, and machine learning. In this research, a computer system has been developed to recognise ayurvedic plant leaves in Sri Lanka based on a recently developed machine learning algorithm: convolutional neural networks (CNNs). Convolutional neural networks with RGB and grayscale images and multi-layer neural networks with RGB images have been used to recognise the ayurvedic plant leaves. In order to train neural networks, images of 17 types of herbal plant leaves were captured from the plant nursery of Navinna Ayurveda Medical Hospital, Sri Lanka. As CNNs require a large number of images to train it, various data augmenting methods have been applied to the collected dataset to increase the size of the dataset. Backgrounds of images were removed and all images were resized to 256 by 256 pixels before submitting them to a neural network. The results obtained were highly significant and CNN with RGB images was able to achieve an accuracy of 97.71% for recognising ayurvedic herbal plant leaves in Sri Lanka. The study suggests that CNNs can be used to recognise ayurvedic herbal plants.

Keywords: deep learning, traditional ayurvedic plants, convolutional neural networks, multi-layer neural networks, image recognition, computer vision

1. Introduction

Ayurveda is a holistic healing system which was developed in the Indian subcontinent thousands of years ago. The word Ayurveda has derived from AYU and VEDA. ‘AYU’ and ‘VEDA’ mean life and Science or knowledge respectively (Indigenous-Medicine, 2017). Simply it means Science of Life. It encourages the use of herbal and non-toxic plants. It’s a simple and profound system of understanding health and diseases (Indigenous-Medicine, 2017). Ayurveda medicines are extracted from nature. They use natural leaves, roots, flowers, barks and natural products, etc. Among them, natural leaves play an important role to make ayurvedic medicines. Many of the people in the current generation cannot identify these valuable herbal plants and they cannot obtain the vital information about these plants. In order to protect these valuable endemic plants from danger, it is required to collect information about these plants and make the people aware about these ayurvedic plants.

Image recognition can be considered as one of the main fields of computer vision and machine intelligence. Leaf image recognition is a sub-field of image recognition. Leaf image recognition using computer vision and machine learning methods have been carried out rarely in the world. Complex image processing methods are used for recognition of leaf images due to the variations of leaves in

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plants. With the development of computer vision and deep learning (Aarshay, 2016; Bengio, 2009; Cope, 2012), most complex problems in image recognition have been solved and have been able to obtain models that are more accurate than the solutions obtained in classical image processing methods.

Machine Learning (Bishop, 2007) is a subfield of artificial intelligence that provides computers the ability to learn without being explicitly programmed. Here it is not needed to provide the algorithm manually to the computer as in a conventional computer program. Machine learning focuses on the development of computer programs that can learn themselves in a changing environment and adapt to the new environment.

Leaf image recognition is one of the main focused areas in the research field of computer vision due to its usability. There are many leaf recognition systems all around the world. These systems correctly identify only leaves which are in that specific country or region. Therefore, these recognition systems do not properly work for ayurvedic plants which are grown in Sri Lanka. Further, there is no proper leaf recognition system developed in Sri Lanka to identify ayurvedic plants. Lack of a proper computer system to recognise ayurvedic plants in Sri Lanka, is identified as the main problem in this study and it is addressed by a deep learning method: convolutional neural networks (CNNs). This method has been able to produce a high accuracy of recognising ayurvedic plant leaves in Sri Lanka.

Kumar et al. (2012) developed a system to recognise 184 tree species of the northeastern United States. This system requires a single leaf specimen that is photographed on a solid light-colored background. The recognition process consists of classifying, segmenting, extracting and comparing with a prototype tree species. In order to identify the correct match the nearest neighbor method was used and achieved an accuracy of 96.7%.

Wu et al. (2007) suggested Probabilistic Neural Network (PNN) with image and data processing techniques to implement a general purpose automated leaf recognition system for plant classification. Two leaf features are extracted and orthogonalised into 5 principal variables and they are used as the input of the PNN. The PNN was trained using 1,800 leaves and it was able to obtain an accuracy of more than 90% to classify 32 types of plants.

Kulkarni et al. (2013) suggested a leaf recognition system using Radial Basis Probabilistic Neural Network (RBPNN) and which was combined with Zernike movements. They have chosen 32 leaf types from the ‘Flavia’ dataset. This dataset also contains leaf images with a solid white-colored background. Images were first preprocessed and then extracted the features: shape features, vein features, color features, Zernike moments and texture features. Next RBPNN was trained using these extracted features. This system was able to obtain an accuracy of 93.82% and this was achieved with only 40 leaves per species. The advantage of using this method is that it does not require many samples of images for each plant as in the deep learning methods.

Bylaiah (2014) implemented a classification system based on Support Vector Machine (SVM) classifier. MATLAB was used as the main tool for the implementation. First, the RGB images were converted to grayscale images and then median filter was applied to the grayscale images. Next, a binary conversion and a segmentation were applied to these images. After that these preprocessed images were taken as the input and extracted the features: shape, area, major axis, perimeter, convex hull, minor axis length ratio of major axis length. These features were used to obtain the SVM to classify plants based on the shape-related features of leaves. This system could obtain only an accuracy of 85%.

Bhardwaj et al. (2013) conducted a plant leaf recognition system using Moment Invariant and Texture Analysis. Further, they have used MATLAB as their implementation tool. This system consists of six main steps. They are inputting leaf images, image enhancement, high-frequency feature extraction, image segmentation, parameter calculation and classification of leaves. Fourteen different plant types were selected and more than three hundred images were used for their experiment. Here also, they have used leaf images with a solid white colored background. In the image preprocessing step, the RGB image was converted to grayscale image and then it was converted to a binary image. After that, the binary image was smooth out and then filtered leaf contour was taken from the binary image. Image segmentation method was used to remove unwanted parts from the image. In the feature extraction phase, some physical features and moment invariant were extracted. Image moment is a certain particular weighted average (moment) of the image pixel intensities or a function of such moments. In the implementation stage, they have implemented the nearest neighbor classifier for leaf recognition. They have measured seven features descriptors of different plant leaves and stored in a dynamic matrix. This system has achieved an accuracy of 91.5%.

Charini et al. (2015) implemented an Automated Leaf Recognition System for Plant Classification. To evaluate the algorithm they have used a dataset which consists of 1,907 leaf images from 32 different types of plants. They also selected leaf images with a solid white-colored background. First they inputted the RGB images into the image preprocessing phase. RGB images were converted for that to grayscale images and then the grayscale images were converted into black and white images. After that, they have extracted edges of the preprocessed images. In the feature extraction step, geometrical features and textural features were extracted. Textural features are divided into two minor parts which are named as Local Binary Patterns (LBP) and Features based on Co-occurrence Matrix. After that Linear Discriminant Analysis (LDA) was used to reduce the feature dimensions of the preprocessed leaf images. LDA selects the most dominant features which have a higher class discrimination power. Then classification was done by K-Nearest Neighbor Classifier. The highest accuracy obtained was 92.1±1.9.

Wijesinghe and Marikar (2011) suggested an Automatic Detection System for the identification of plants using herbarium specimen images. Here they also used MATLAB as the implementation tool. The main objective of this study is to identify and classify individual species of Stemonoporus, a genus of Dipterocarpaceae, by image processing using Probabilistic Neural Networks (PNNs). Seventeen temonoporus species were selected for this experiment and a set of 79 herbarium images were collected from the National Herbarium at the Royal Botanical Garden, Sri Lanka. After that collected images were preprocessed. RGB leaf images were converted into grayscale images and then grayscale images were converted into binary images. In the feature extraction phase, leaf length, width, area and perimeter were extracted. Length and width of the leaf images were extracted using distance tools and the shape of the leaf was extracted using edge detection tools in MATLAB IPT. Then a neural network was implemented and trained using those preprocessed image sets. The overall classification accuracy utilizing the proposed technique for the test set was 85%. Compared with other systems it has good classification accuracy. But they have used a very small number of leaf images for one plant species. It is not good practice to train a neural network with a small number of images. Then it could be a reason to perform neural networks very poorly.

In (Sethulekshmi, and Sreekumar, 2014) the algorithms that have been introduced to automate the leaf recognition for plant classification in the past decade and achieved good performances are discussed. In this study, the researchers well investigated the properties of features (descriptors) applied in these algorithms and compared different feature extraction methods, a different combination of features and a number of classifiers applied for leaf identification process.

Sana et al. (2005) developed an Android based application to identify the medicinal herbs of Indian origin. The identification is done through a texture extraction algorithm called Gray-Level Co-occurrence Matrix (GLCM). The authors have mentioned that they have achieved satisfactory results; however, they didn't include the accuracy of the method in the research paper.

Chaki and Parekh (2011) proposed an automated system for recognising plant species based on leaf images. Plant leaf images corresponding to three plant types are analyzed using two different shape modeling techniques, the first based on the Moments-Invariant (M-I) model and the second on the Centroid-Radii (C-R) model. Neural networks are used as classifiers for discrimination. The data set consists of 180 images divided into three classes with 60 images each. Accuracies are ranging from 90-100%.

Zhang et al. (2016) introduced dimensionality reduction method based on local discriminative tangent space alignment (LDTSA) for plant leaf recognition based on leaf images. The proposed method can embrace part optimization and whole alignment and encapsulate the geometric and discriminative information into a local patch. The experiments on two plant leaf databases, ICL and Swedish plant leaf datasets, demonstrate the effectiveness and feasibility of the proposed method. The algorithm obtained more than 90% accuracies for both datasets.

All of the previously completed research studies, features of images were manually extracted from the leaf images and then applied a machine learning algorithm to recognise the images. Only one research of them was able to exceed the accuracy level of 95%. The advantage of the proposed method that uses a convolutional neural network for recognising ayurvedic plant leaves is that it does not need to extract features manually. However, to train the system it requires a large number of images of each plant and needs high-end computing facilities to train a CNN.

2. Material and Methods

2.1 Data collection

Images were collected from plant nursery of Navinna Ayurveda Medical Hospital. We have selected 17 types of herbal plants in Sri Lanka. They are Ashoka (අශෝක, *Saraca asoka*), Balunakuta (බලුනකුට, *Stachytarpheta indica*), Maha midi (මහ මිදි, *Premna latifolia var. viburnoides*), Bulu (බුළු, *Termininalia bellirica*), Ekaweriya (ඒකාවේරිය, *Rauvolfia serpentina*), Gas Thippili (ගස් තිප්පිලි, *Piper longum*), Heen Araththa (හීං අරත්ත, *Alpinia calcarata*), Heen Bin Kohomba (හීං බින් කොහොඹ, *Andrographis paniculata*), Kalu Waraniya (කලුවරණියෙ, *Justicia gendarussa*), Kapparawalliya (කප්පර වල්ලිය, *Plectranthus amboinicus*), Magul Karanda (මගුල් කරඳ, *Pongamia pinnata*), Mara (මාර, *Albizia lebbeck*), Mee (මී, *Madhuca longifolia*), Nika (නික, *Vitex negundo*), Pranajeewa (ප්‍රාණ ජීව, *Codariocalyx motorius*), Rath Handun (රත් හඳුන්, *Pterocarpus santalinus*), and Wal Thippili (වල් තිප්පිලි, *Croton hirtus*). In order to collect the data, leaf images were collected in two formats. Those were scanned images (scanned from a scanner) and captured images (camera images).

The scanned images were taken with high resolution (1,200 dpi) and RGB type. In order to maintain the original quality of the images, images were outputted in TIFF format. In here live leaves were brought and were scanned using an HP scanner. Captured images were taken from Nikon D90 camera with lens 18-105 mm and with several mobile phones. When taking the captured images, we have collected both still images and videos of herbal plant leaves. Then videos were converted into images by using a video editing software. All these images are in JPEG format.

Figure 1. Two sample scanned images.

Figure 2. Two sample captured images.

2.2 Data preprocessing

Background of each image was removed and set the background to white color. After removing the background from an image they were re-sized to 256 by 256 pixels. While images were re-sizing, it was necessary to maintain a fixed aspect ratio for the scanned images. These images have different sizes of width and height, so image padding was used after the removal of the background of the scanned images. It was helped to maintain a fixed aspect ratio after resizing the images. This limitation of the image size was made due to the capacities of hardware that we have used for our study were not capable enough to process larger sized images. These sizes were determined after testing several predefined networks using different sizes of leaf images.

Captured images didn't have similar backgrounds because different backgrounds were captured while images were being taken. First backgrounds of the captured images were removed and put a white background around the leaf. Since different images have different widths and heights, after the removal of backgrounds image padding was used to maintain the same sized images. Then captured images were resized to 256 by 256 pixels without changing the aspect ratio of that image. The size of an image is restricted to 256 by 256 due to the capacities of hardware available. This size was also determined after testing several predefined networks using different sizes of images of leaves.

Figure 3. Original scanned image (left) and image after background removal (right).

The scanned image dataset was then separated into 3 datasets for the purpose of training, validation, and testing to the ratios 70:15:15 respectively.

2.3 Data augmentation

294 scanned images and 281 captured images were collected from the plant nursery of Navinna Ayurveda Medical Hospital. However, this number of images is not sufficient to train a deep neural network. Therefore to increase the size of the dataset, two data augmentation methods were used. The first data augmentation used in the experiment is the rotation of images. We obtained 10^o, 20^o, 30^o and etc. rotated images of the original image up to 360^o. After the rotation, backgrounds of images were filled with white color and images were resized again to 256 by 256 pixels. The second data augmentation method is, taking the mirror image of the original image. The following image flipping methods were used to obtain the mirror images of the original.

- Flip image in horizontally
- Flip images in vertically
- Flip image in horizontally and vertically

After applying these data augmentation methods, sizes of the datasets for each plant were increased as in the following Table 1.

Table 1: The number of images created for each plant.

Plant name	Scientific name	Number of images
Bulu (බුළු)	*Termininalia bellirica*	1,224
Magul karada (මගුල් කරඳ)	*Pongamia pinnata*	1,152
Mara (මාර)	*Albizia lebbeck*	1,440
Maha midi (මහ මිදි)	*Premna latifolia var. viburnoides*	1,280
Nika (නික)	*Vitex negundo*	1,200
Rath hadun (රත් හදුන්)	*Pterocarpus santalinus*	1,248
Ekaweriya (ඒකාවේරිය)	*Rauvolfia serpentina*	1,200
Heen araththa (හීං අරත්ත)	*Alpinia calcarata*	1,296
Heen bin khomba (හීං බින් කොහොඹ)	*Andrographis paniculata*	1,296
Kappara walliya (කප්පර වල්ලිය)	*Plectranthus amboinicus*	1,200
Prana jeewa (ප්‍රාණ ජීව)	*Codariocalyx motorius*	1,200
Wal thippili (වල් තිප්පිලි)	*Croton hirtus*	1,152
Gas thippili (ගස් තිප්පිලි)	*Piper longum*	1,232
Ashoka (අශෝක)	*Saraca asoka*	1,280
Mee (මී)	*Madhuca longifolia*	1,200
Kalu waraniyaa (කලුවරණිය)	*Justicia gendarussa*	1,248
Balunakuta (බලුනකුට)	*Stachytarpheta indica*	1,232

Multi-layer perceptron - Multiple layer neural network is called as a multilayer perceptron (MLP). A multilayer perceptron is built using artificial neurons. The leftmost layer is the input layer and neurons in this layer are called input neurons. The rightmost layer is the output layer and neurons in this layer are called output neurons. The middle layers are called hidden layers. These networks may contain a single hidden layer or multiple hidden layers (Figure 4).

Convolutional neural network (CNN) - Convolutional neural network (CNN) is a popular deep learning technique for visual recognition tasks because of its proven quality of performance in image classification with less image preprocessing (Hubel and Wiesel, 1968; Krizhevsky et al., 2012; Srivastava et al., 2014). In machine learning, a CNN is a type of feed forward artificial neural network (Figure 5). They are widely used in the field of pattern recognition within images and videos. A CNN consists of several layers. These layers can be of three types, namely convolutional layers, pooling layers and fully-connected layers. When these layers are stacked together, a CNN architecture has been created. The neurons of the CNN layers are arranged in 3 dimensions (width, height, and channels). The channel is 3 for color images and it is 1 for grayscale images.

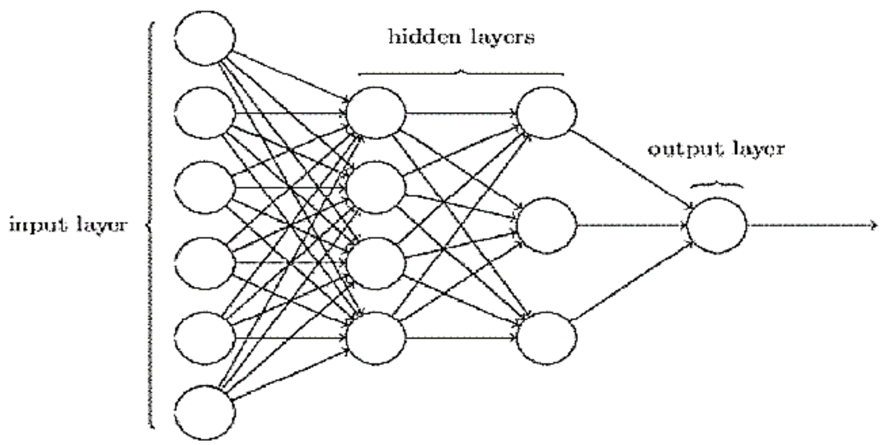

Figure 4. A MLP with two hidden layers.

Values of pixels of images were passed as the input to the CNN. As in MLP, the output layer consists of a 'softmax' layer.

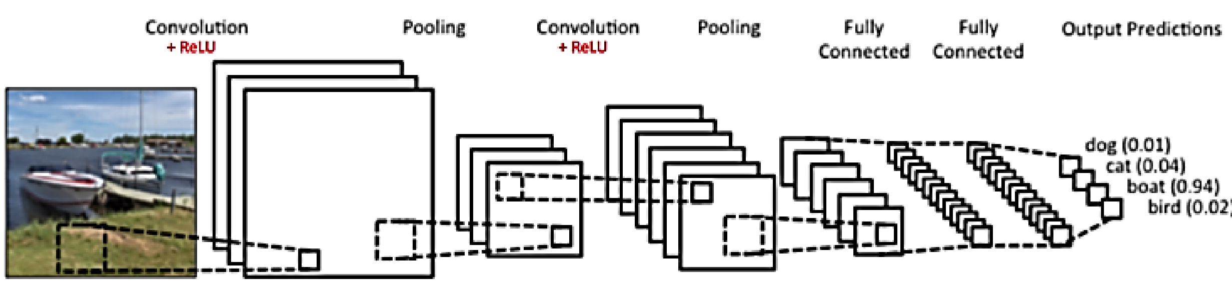

Figure 5. Convolutional Neural Network (CNN).

Implemented MLP-The implemented MLP architecture consists of 256×256 neurons in the input layer and 5 hidden layers of size 256 neurons (Figure 6). In the output layer, 17 neurons were used as there are 17 ayurvedic plant categories in the dataset.

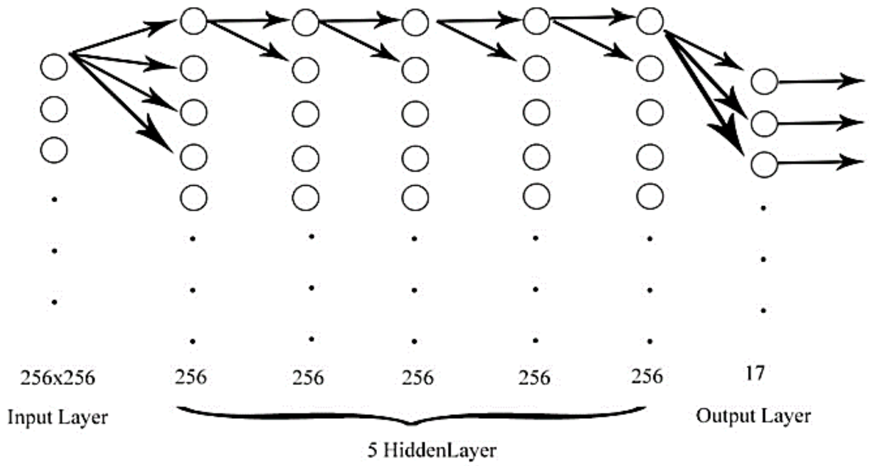

Figure 6. Basic architecture of the implemented MLP.

The pixel values of each image were passed as the input to the MLP and the output consists of a ‘softmax’ layer of size equal to the number of ayurvedic plants (17) to be classified. This ‘softmax’ layer produces probabilities for each type of ayurvedic plant of being a particular leaf belonging to that type.

MLP network was trained for 15 epochs because the network shows less convergence after 15 epochs. Here, we have used a base learning rate of 0.001, solver type as Stochastic Gradient Descent, Momentum of 0.9 and Weight Decay of 0.0001.

Implemented CNN-We have created and tested a new convolutional neural network (Figure 7) based on AlexNet (Krizhevsky et al., 2012). Here, two separate CNNs were implemented for RGB images and grayscale images. Same CNN architecture was trained for both systems and the only difference is the first CNN was trained for RGB images and the second CNN was trained for grayscale images.

The implemented CNN architecture consists of 256×256 neurons in the input layer, 5 convolutional layers, 5 max-pooling layers and a fully connected layer. Finally, the outputs of the fully-connected layer are connected to a softmax layer of size 17.

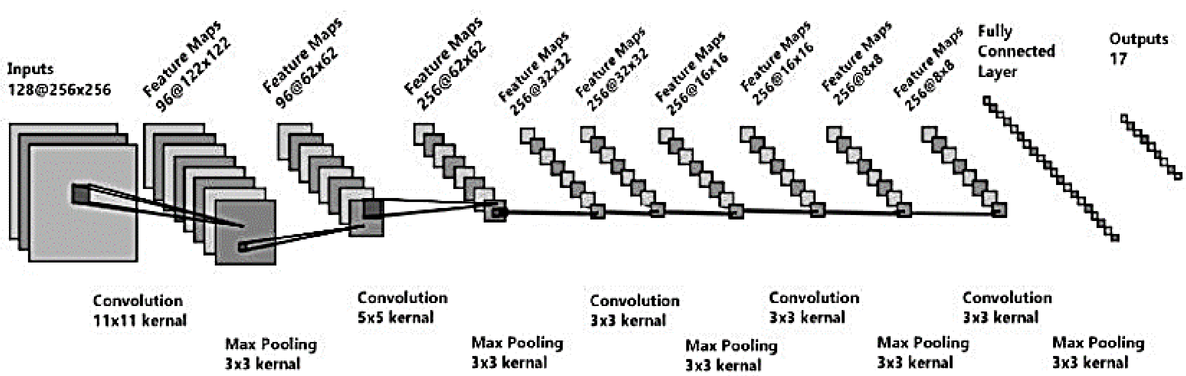

Figure 7. Basic Architecture of the implemented CNN.

The CNN networks were trained for 20 epochs because the network shows less convergence after 20 epochs. Here, we have used a base learning rate of 0.01, solver type as Stochastic Gradient Descent, Momentum of 0.9 and Weight Decay of 0.0001.

Libraries/Frameworks used in the implementation-The following libraries and frameworks were used to implement the deep neural networks mentioned earlier.

Caffe - Caffe is a deep learning framework made with expression, speed, and modularity in mind. It is developed by the Berkeley Vision and Learning Center (BVLC). Caffe is an open source machine learning framework (Jia et al., 2014). Caffe is based on C++ and CUDA which provides computation on GPU and CPU. It also binds with Python and MATLAB for training and deploying general-purpose convolutional neural networks and other deep learning models. This framework is mostly focused on computer vision, speech, multimedia, and it has a larger community support. Caffe is used in some industrial applications as well as some open source deep learning products like NVIDIA DIGITS.

NVIDIA DIGITS - NVIDIA DIGITS is an open source deep learning tool which was developed by major graphic processor NVIDIA (NVIDIA DIGITS, 2015). DIGITS is based on Caffe implementation. It mainly focuses on computer vision applications. DIGITS provides easy ways to add and create image databases for the network training, validation, and testing. DIGITS has real-time training processes' visualization of the network as a graph. That graph indicates the complete performance of the trained network and it is easy for developers to visualize their trained network. High utilization of GPU computations can be considered as one of the major advantages of Digits. This can be easily used because complex coding is not necessary for this process and it is easy to set up and to run. It uses a web browser as the interface and it is running as a web server. DIGITS was selected as the network training framework in this research due to GPU utilization, good support for computer vision and the real time visualization of network training.

The hardware and software used for this study were GPU Computer with Intel Core i7 CPU, DDR3 16GB of Memory and NVIDIA GeForce GTX 960 processor (2GB) and Tesla K40 GPU; Ubuntu 14.04 (64 bit); NVIDIA DIGITS 5 and MATLAB R2012.

3. Results

This section includes the models that have been trained and tested for the selected dataset and their accuracy for validation and testing, the real-time monitoring of network training was used which is provided by NVIDIA DIGITS to represent the results in the trained model. In this project, an image dataset was created by us, and we haven’t used any common datasets like MINST and CIFAR. Therefore the results should be interpreted by keeping the reliability on the dataset that has been created. Test data that we have used for testing is a completely separate dataset from validation and training.

Multi-layer perceptron (MLP) - This section includes the result that we were able to obtain by using an MLP for the classification of ayurvedic herbal leaves. Here we have used solid white-colored background images to train the system.

The MLP that we have trained performed somewhat well in the validation dataset by obtaining 58.70% accuracy (Figure 8). Classification of the test dataset was poor compared to other methods that we have used.

Convolutional neural network (CNN) - Using this CNN model we were able to obtain the best validation of 97.71% compared to the MLP network that we have tested. Here also we have used solid white-colored background images to train the system.

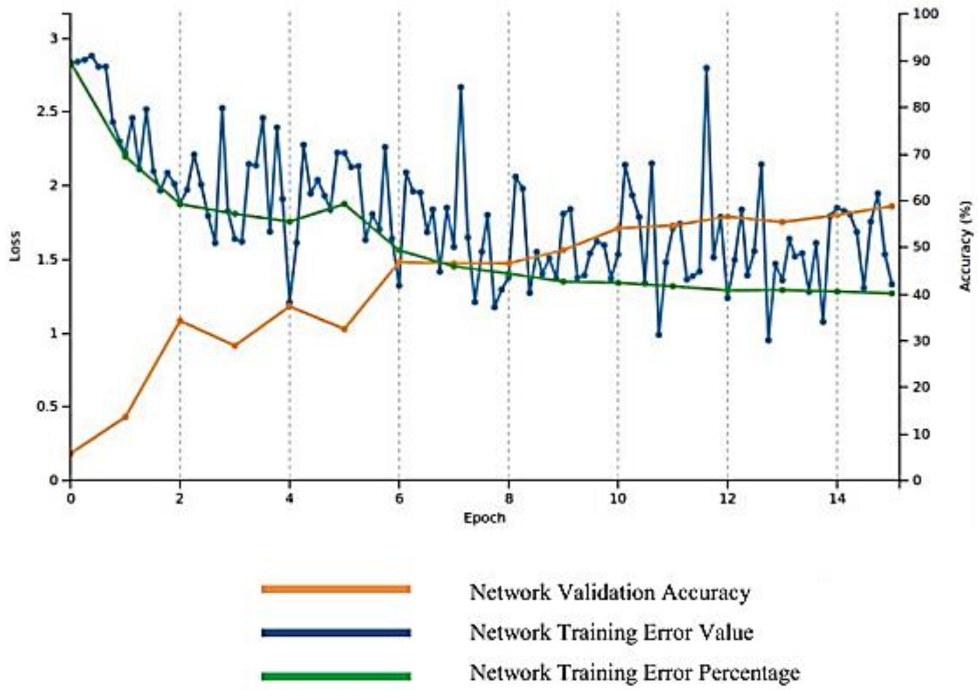

Figure 8. Real time monitoring plot of MLP training phase with validation.

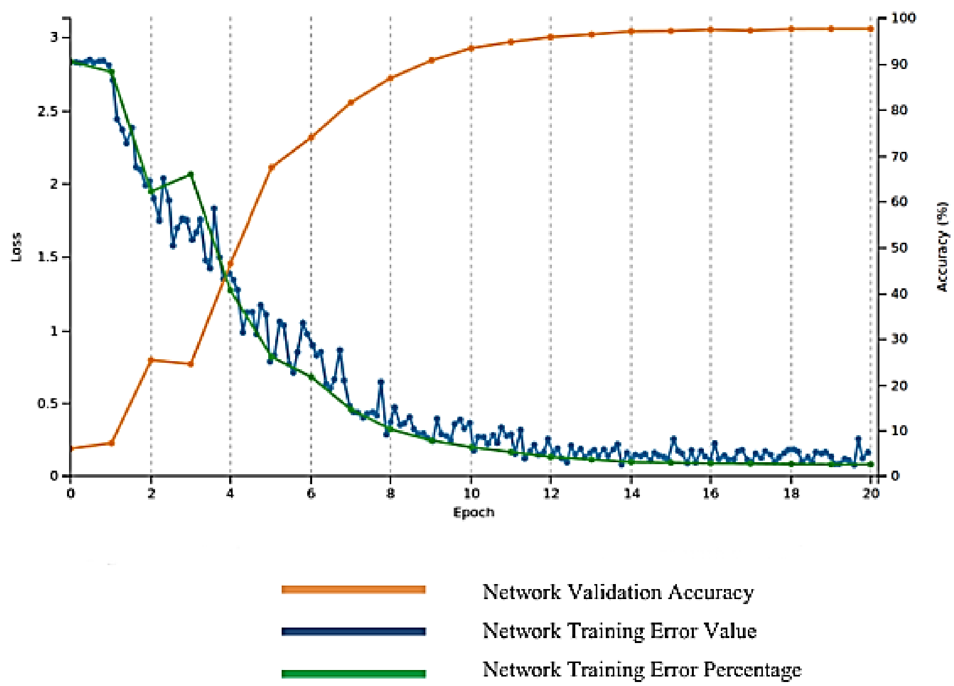

Figure 9. Real time monitoring plot for CNN training phase with validation.

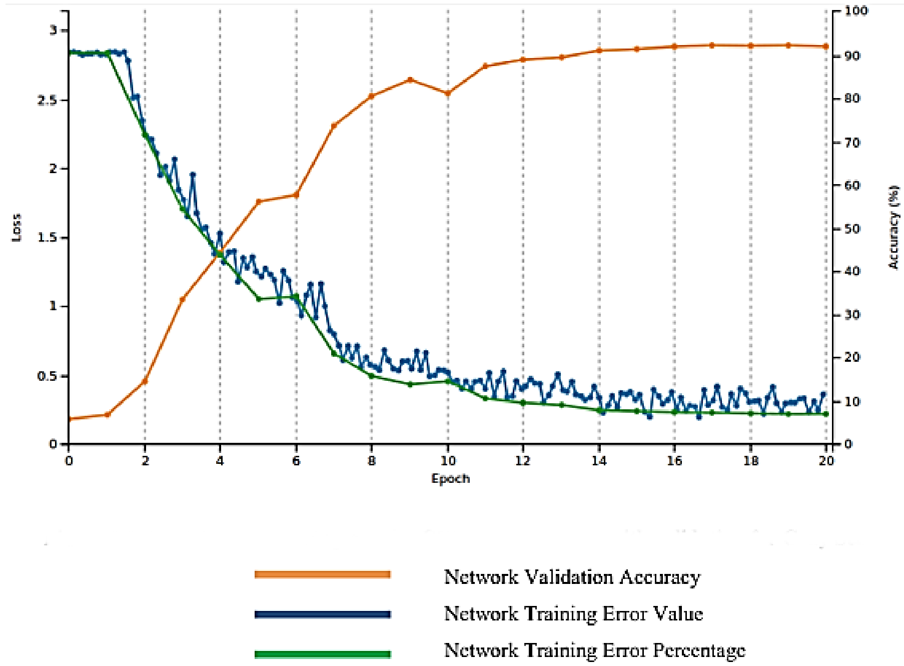

Figure 10. Real time monitoring plot for CNN training phase with validation for grayscaled images.

Convolutional neural network (grayscale images)-We have created and tested a new convolutional neural network based on the implementation of AlexNet but the main difference was, here grayscale, solid and white-colored background images were used to create the CNN. Using this model we were able to obtain a validation accuracy of 92.17% compared to other MLP networks that we have tested (Figure 10).

4. Discussion

We can clearly observe that both convolutional neural networks outperformed multi-layer perceptrons in validation and testing datasets. MLP with the same number of network parameters consumes more computation power and the time for network training process than convolutional neural networks. Among those two CNN networks, CNN trained with RGB images is performed better than that of CNN trained with grayscale images. This testing accuracy can be considered as a higher accuracy obtained for classification of ayurvedic plant leaves when compared to previously carried out studies. This deep learning based computer vision method also needs minimal image preprocessing to conduct the classification of ayurvedic plant leaf images. We have used a limited dataset for this study with a limited variation of scanned leaf images.

5. Conclusion

The main goal of this study was to find a deep learning approach for classification and detection of ayurvedic plant leaves in Sri Lanka. In this study, we implemented a convolutional neural network to classify ayurvedic plant leaves with notable accuracy. The tested network has higher accuracy than other methods that have been used for plant leaf classification.

We were also able to review previous work regarding the plant leaf recognitions with respect to our problem domain. In this study, we have implemented three classification systems for solid white-colored background images (scanned images). For captured images, we have implemented ‘Detectnet’ using NVIDIA DIGITS to directly detect the leaf parts of the images but the system was failed and it couldn’t identify leaf part and background part correctly. This is due to the time limitation, technologies that we have used and the complexity of the methods that can be used for the detection of images in and regions of images.

In the next stage of the research, it will be extended to implement both detection (of the leaf parts of the image) and classification at the same time (i.e. online detection and classification) and the final product will be implemented as an Android/iOS app in a smartphone. Hence, the smartphone users are able to identify valuable Ayurvedic herbal plants in Sri Lanka without the help of an expert of this area.

Acknowledgment

Our sincere appreciation goes to the Director and the staff of Plant Nursery of Navinna Ayurveda Medical Hospital who helped us to collect the images of Ayurvedic plant leaves.

We gratefully acknowledge the support of NVIDIA Corporation with the donation of the Tesla K40 GPU used for this research.

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