A CONVOLUTIONAL NEURAL NETWORK (CNN) BASED APPROACH TO RECOGNIZE MEDICINAL PLANTS BY ANALYZING PLANT LEAF

W.D.L.S.A Costa

(179312U)

M.Sc. in Computer Science

Department of Computer Science and Engineering

University of Moratuwa

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Dissertation submitted in partial fulfilment of the requirements for the Degree of M.Sc. in Computer Science specializing in Software Architecture

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DECLARATION

Student Declaration:

I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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ABSTRACT

Sri Lanka is naturally gifted with a vast spread of flora and fauna throughout the country. Most of these plants can be used for therapeutic purposes like when in ancient days, our ancestors used them vastly and considered them to be one of the most highly efficient medical systems in the world at that time. However, with the dawn of modern medicine, indigenous medicine has been decreasing in usage due to factors such as the lack of knowledge about medical plants, the desire for fast recovery, and the reducing interest in traditional treatments due to their smells and appearances. Out of the above, the lack of knowledge about medical plants has been identified as the most contributing factor that demotivates the general public from using traditional medicine. Hence it is evident that a reliable and easy-to-use application to identify and analyse medical plants would be a timely solution to increase the use of traditional medicine in society today. The main objective of this research was to review the features used for leaf recognition, evaluate existing leaf-based medicinal recognition systems, and design a system that would address the loopholes in the available solutions. As such, the researcher carried out a comprehensive literature survey and reviewed existing classification methodologies like Support Vector Machine, Principle Component Analysis, Probabilistic Neural Network and Conventional Neural Network to assess what the best methodology for the above task would be. Due to its feature-extraction capability and high levels of accuracy, Conventional Neural Network was selected as the best approach for this study. Based on the selected method, the researcher designed and developed a feasible application that is capable of finding medical plants by the features of its leaf and medical values. Once the system was built, the researcher distributed surveys and conducted interviews in order to critically test and evaluate the application among industrial experts as well as general users. An overall recognition rate of 85% was recorded by the system, which was well-appreciated by the experts. However, recommendations like probable scope expansions and the need for higher response times were also suggested in the feedback received.

Keywords: medicinal plant identification, Conventional Neural Network, medical plant values, identification of leaf properties

ACKNOWLEDGMENT

First and foremost, I thank and praise Almighty God without whose love and blessings this research would never be completed.

I thank my loving wife and my parents who were always there for me at every step of the way with their prayers and words of encouragement. I also thank my sister and Dilshan who were always there to lend me their support.

I thank my supervisor Dr. Indika Perera, for agreeing to supervise my project, and for his patience, support and guidance.

Finally, I would like to thank Trisha, Tiran, Vilochane, Ryan, Niroshani, Bimsara, Shashi and Dulanjaya for their never-ending support, suggestions and help.

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Chapter 1

INTRODUCTION

1.1 Introduction

This chapter illustrates the background of the project and gives an overview of the problem domain, explaining why the researcher has a specific interest to conduct a research in the field of medicinal plants, as well as the motivation and objectives of this study.

1.2 Introduction to Medicinal Plants

The World Health Organisation (WHO) has defined a medicinal plant as a plant used for therapeutic purposes. It is also described as a plant, which in one or more of its organs, contains substances that can be used for therapeutic purposes or which can be utilised in producing useful drugs. Furthermore, the same species of plants can have different medicinal values if they grow in different places due to the considerable impact from variable properties such as soil, minerals and climate.

1.3 Project Background

Plants are considered to be an essential part of the ecosystem of the planet. Some of them are edible while some of them also have a medicinal value, which can be used for curative purposes. In ancient days, our ancestors had the knowledge and were smart enough to identify the medicinal plants which grew in their backyards or alongside the roads, and they used this knowledge to cure various diseases. However, in modern days people are unlikely to consume herbal medicines mainly due to factors such as the lack of knowledge about medicinal plants, the need for fast recovery and the reducing levels of interest in traditional treatments due to their smells and appearances.

According to published statistics, there are over 3,210 kinds of species of plants in Sri Lanka and it is undoubtedly a difficult task to identify a plant accurately from such a huge range. As asserted by the report of the Regional Meeting of the WHO in 2009, the inability to identify medicinal plants accurately is one of the facts that make most herbal remedies unsafe. The lack of proper knowledge about medicinal plants may result in using them mistakenly for therapeutic purposes.

According to Liwen Gao and Xiaohua Lin, it is understood that when it comes to identifying medicinal plants accurately, it requires a great amount of professional skills as well as time[1]. The existing recognition systems have a great dependency on the knowledge accumulation and experimental skills of humans, and most of them are time consuming. Therefore, there is a clear need of a fast, reliable and convenient plant-recognition method.

1.4 Objectives

The main objective of this research is to design and implement a Convolutional Neural Network (CNN) for identifying medicinal plants by its leaf. Along with this main objective, following sub objectives will be achieved.

- Carry out a comprehensive literature survey on existing researches and review the following:
  - The features used for leaf recognition
  - Existing leaf-based medicinal recognition systems and technologies
- Select suitable tools and technologies that will enhance the performance of the prototype.
- Test the prototype to ensure its quality and ability to recognise leaves by identifying a sample set of medicinal plants.
- Critically evaluate the prototype by questionnaires and experts in order to ensure that the aim of the system has been met and submit the draft report.

- Prepare and submit the final project report, including the final terms of reference, literature review, design, methodology, implementation, source code and prototype evaluation.

1.5 Research Question

How to use a Convolutional Neural Network (CNN) based approach to identify medicinal plants by its leaves.

1.6 Motivation

It is strongly believed that Sri Lanka is gifted with a vast number of medicinal plants. Hence, having a good knowledge of herbal plants would be a great asset to the nation. In addition, it is understood that several unfortunate incidents have occurred due to the lack of awareness among medical practitioners and the public when it comes to identifying herbal plants from an adulterant. A very common instance is that the "Ranawara" tree is most often confused with another plant with yellow flowers. The people who used this as a medication ended up in hospitals due to the poisonous substance in the leaves. On the other hand, people spend a quite a lot of money on western medicine while they are unaware of the fact that they could find medicinal solutions easily if they look around in their own backyards or alongside the roads. Hence, the researcher believes that developing an intelligent application which could address these issues would be a worth and timely effort.

1.7 Organization of the report

This section contains a brief summary of each chapter of the report and illustrates how the rest of the chapters have been organized within the context of the report.

1.7.1 Chapter 02

This chapter presents the findings of the literature survey on leaf recognition, methodologies that have been adopted by the existing systems and the importance of various technologies in recognizing leaves.

1.7.2 Chapter 03

Methodology is presented within this chapter. First it explains a high-level view of the system architecture and then it proceeds with detailed descriptions of each layer of the system.

1.7.3 Chapter 04

This chapter on implementation illustrates how the methodology described in the previous chapter was implemented. Implementation of each layer is further discussed in this chapter.

1.7.4 Chapter 05

This chapter on testing discusses the approaches carried out by the researcher for testing the application. This also presents the test results obtained for various test scenarios carried out by the researcher. It also discusses the evaluations carried out by domain experts and general users in relation to the project. Therefore, these results along with the researcher's evaluation are presented in this chapter

1.7.5 Chapter 06

The chapter concludes the report by stating how the aims and objectives were fulfilled, listing down the limitations of the prototype, key findings and future enhancements.

1.8 Summary

This chapter addresses the difficulty of recognising medicinal plants which have similar characteristics and highlighted the importance of a reliable and easy-to-use intelligent application to identify medicinal plants and their therapeutic values. The next chapter will contain a comprehensive literature review of the plant recognition approach along with the methodologies and classification methods used in similar existing systems in order to suggest a feasible approach for the development of a new and improved intelligent medicinal analysing system.

Chapter 2

LITERATURE REVIEW

2.1 Introduction

In the previous chapter, an introduction to and the motivation behind this project was presented. This chapter contains a comprehensive literature review on existing leaf recognition systems followed by a critical analysis. In the following analysis, researcher presents the existing computational models used in plant analysing systems, and a critical evaluation on each to identify their respective strengths and weaknesses.

2.2 Introduction to Plant Anatomy

Plants can be classified into two main categories such as flowering plants (angiosperms) and non-flowering plants.

2.2.1 Flowering Plants

Flowering plants are mainly divided into categories based on the number of its seed leaves such as Monocots and Dicots [2]. According to botanical clarifications, "Monocots refer to the plants which have a single seed leaf called cotyledon while Dicots have two seed leaves also known as cotyledons. In addition to that, leaf veins and floral parts can be used to separate monocots and dicots from each other. Monocots have leaf veins which form a parallel pattern while Dicots have leaf veins which form a net pattern." In terms of floral parts, Dicots have multiples of four and Monocots have multiples of three as showed in Figure 2.1[2]

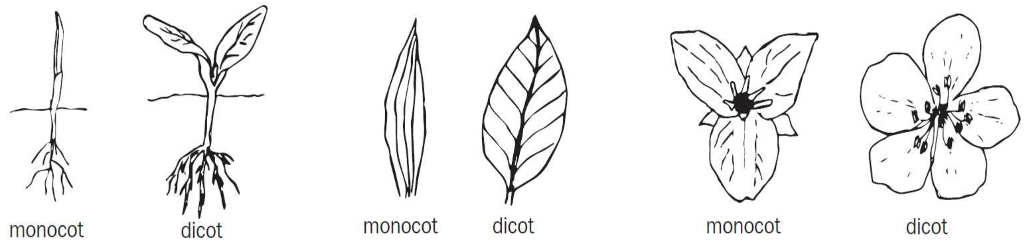


Figure 2.1:Seedings, leaf venation and floral parts are shown

2.2.2 Non-Flowering Plants

Non-flowering plants can be divided into two subcategories: with seeds and without seeds. Gymnosperms are plants with seeds while Bryophyte are plants which do not have a seed [2].

2.2.3 Leaf Arrangement

Leaf arrangement is the easiest set of features to observe in a plant. It can be divided into three categories namely opposite, alternate and whorled (Figure 2.2). An 'alternate' leaf arrangement is characterised by a single leaf per node while 'opposite' refers to two and only two leaves at a node on opposing each other. Leaves are said to be 'whorled' if there are three or more leaves per node arranged in a circular pattern as stated in [2].

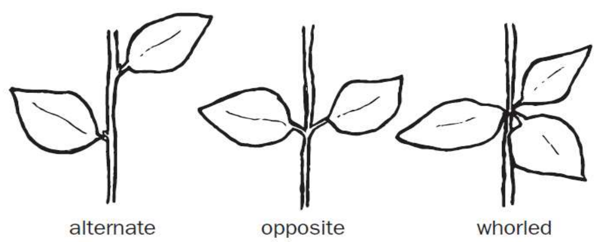


Figure 2.2: Leaf Arrangement

2.2.4 Leaf Type and Leaf Shape

Leaf Types are categorised by a number of definite segments. As explained in Scientific Literature, “a simple leaf has only one definite segment between the stem and the end of the blade as in Figure 2.3, while compound leaves are divided into definite and distinct segments called leaflets. Compound leaves are further separated into pinnately compound leaves and palmately compound leaves. Pinnately compound leaves have leaflets arranged on opposite sides of the leaf axis while leaflets of the palmately compound leaf radiate from a central point, like fingers radiating from the palm of a hand” [2].

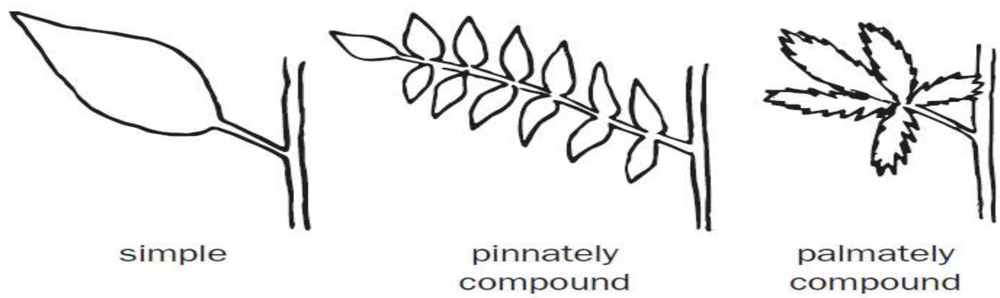


Figure 2.3:Leaf Types

As stated in [2], another important characteristic to identify leaves is to investigate the shape of it. There are many shapes of leaves and seven commonly used shapes are presented in this chapter. “Elliptic leaves are broadest in the middle and narrower at either end. Linear leaves are long and narrow with the sides being close to parallel to each other. Lanceolate leaves are much longer than wide, with the widest point below the middle of the leaf. Spatulate leaves look kind of like a spatula, with the tip being rounded and gradually tapering to the base. Ovate leaves are egg-shaped while oval leaves are round to oval, lacking a pointed tip. Cordate leaves are heart-shaped.” [2].

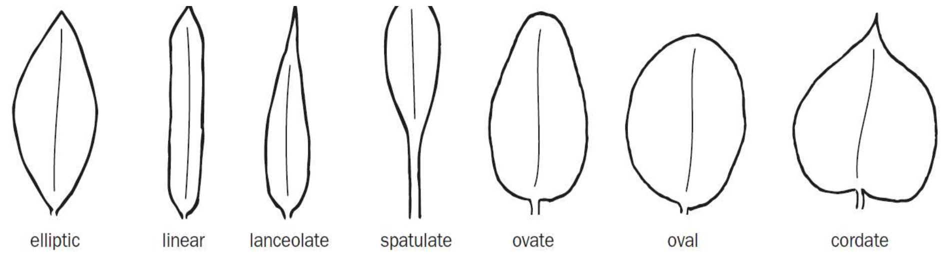


Figure 2.4:Leaf Shapes

2.3 Pre-processing and Feature Extraction

2.3.1 Introduction to Pre-processing and Feature Extraction

In many cases it is necessary to extract features of the plant leaf. Before extraction of the feature, a pre-processing will be conducted which means removing noise and other disturbances from the image. The main purpose of this stage is to improve the feature details and make sure the image is ready for classification. Once the noise and other disturbances are removed from the image it is converted to a grey-scale image.

Features make each leaf different and unique and as such, it is considered to be an important classification parameter. Therefore, feature-extraction is conducted in the next stage. In this process, features can be detected using the shape, texture or venation of a plant as illustrated in Figure 2.5 in detail.

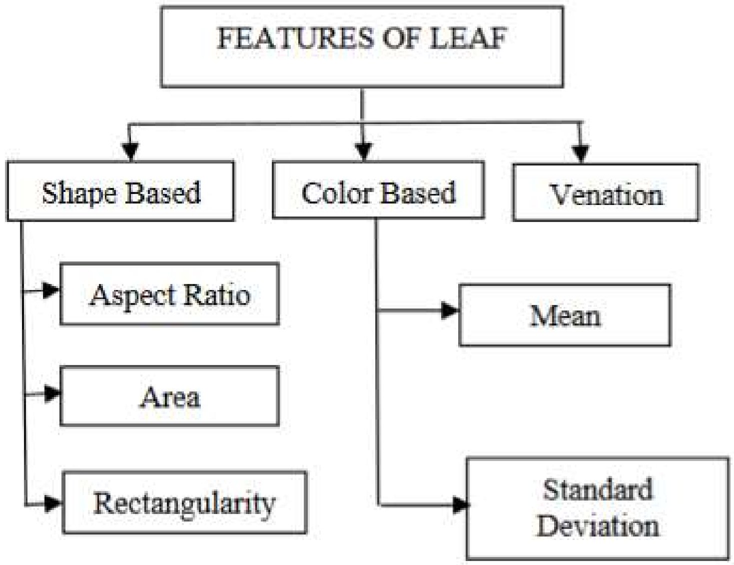


Figure 2.5:Types of leaf features [3]

2.3.2 Shape based calculations

According to [3] there are three shape-based calculations. Aspect ratio, Area and Rectangularity.

The following are formulas used for the calculations:

Aspect Ratio = Length of the Leaf/Breadth of the leaf

Length is calculated by taking the Euclidean distance of two tip points long the axis and breadth is calculated by taking the Euclidean distance long the minor axis. This is explained in Figure 2.6.

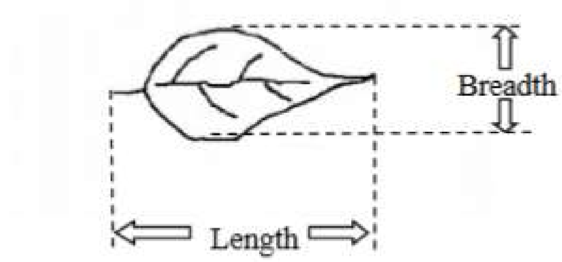


Figure 2.6:Leaf length and Leaf Breadth[3]

According to [3] Area and Rectangularity are calculated as follows:

Area=Area of pixel ∗ Total no of pixels present in a leaf

Rectangularity=L*WA

L = length, W = width and A = area of the leaf.

Rectangularity is the measurement which checks the similarity between a rectangle and the leaf.

2.3.3 Colour-based Calculations

Colour features need to have a Mean (sum of the average of the total pixels) and Standard Deviation. Calculation is illustrated in Figure 2.7.

$$Mean\ \mu = \frac{\sum\sum \mathbf{I}(\mathrm{x},\ \mathrm{y})}{\mathrm{M*N}}$$

$$\text{Standard deviation}\ \sigma = \sqrt{\left(\frac{1}{\mathrm{M*N}}\sum\sum(I(x,\ y)-\mu)^2\right)}$$

Figure 2.7:Mean and Standard Deviation of the pixels of the leaf

2.3.4 Venation-based Calculations

If the leaves are identified using the vein pattern, morphological operations can be used for this purpose such as opening by using structuring elements.

2.4 Image Processing using Raspberry Pi Processor

According to [4], in this approach, a 12-megapixel camera is used to capture high resolution images. The difference here is that it is an optical-based approach where digital image processing techniques are implemented. Once the images are captured, they are passed into Raspberry Pi to extract related information of the leaf's features. Features include image motion, shape aspect ratio, skewness and compactness. Then pre-processing is conducted in order to remove noise and any disturbances, enhance the image for a better view and sharpen the image to capture the sharp edges of the plant leaf. Once this step is completed, a software application was developed to compare the extracted features with an image database and to figure out the identity of the leaf. For this purpose, the dissimilarity factor was used and the class with the least dissimilarity factor was selected as the matching class for the input image. Figure 08 illustrates the flow of this approach. In the future work section, the researchers of this study have mentioned that classification should be performed with neural networks to achieve high accuracy levels.

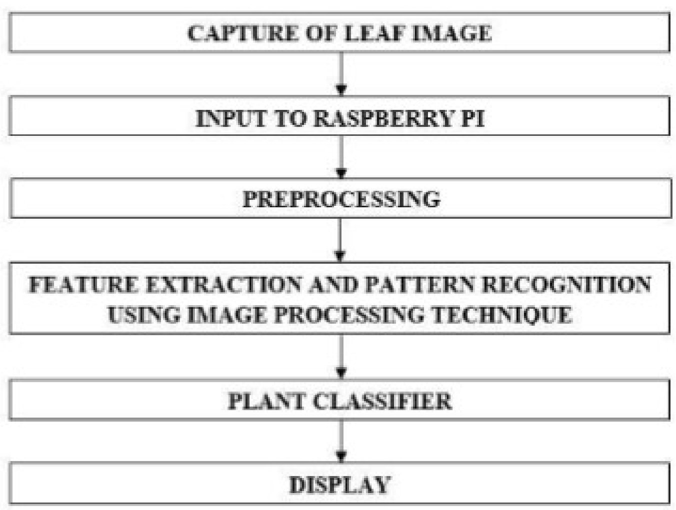


Figure 2.8:A block Diagram for Raspberry Processor used Image Processing[4]

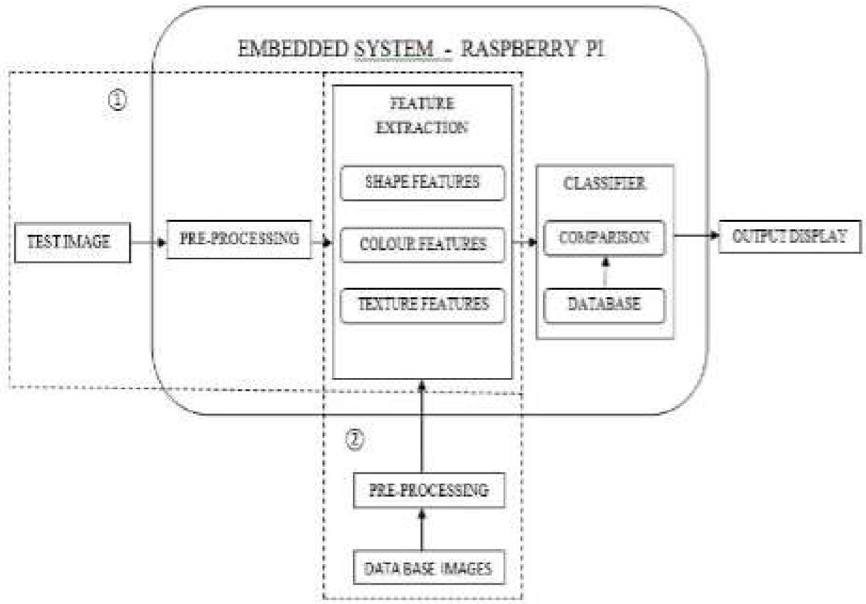


Figure 2.9:Overview of using Raspberry Processor for Image Processing[4]

2.5 Classification Methods

2.5.1 Principal Component Analysis (PCA)

PCA is a widely used tool in computer vision where its main objective is to reduce the dimensionality of data while retaining as much information as possible. Moreover, this is achieved with the use of projection that maximises the variance and conversely minimises the mean squared reconstruction error. Even though PCA outperforms many other techniques in image processing, there exist pitfalls such as computational cost and dimensionality. The following are the key aspects of the recognition process of PCA.

2.5.2 Kernel PCA

Kernel methods are a class of algorithms for pattern analysis. According to [5], Kernel methods are widely used in image processing where it has highly contributed in pattern recognition. Nevertheless, Kernel PCA is an outstanding approach which applies PCA on the mapped training samples.

2.5.3 Colour PCA

Colour is a vital aspect in some recognition processes. As stated in [6], a recognition rate which is 4.4% higher than the traditional PCA approach has been obtained by incorporating a colour aspect with PCA. Nevertheless, the use of three-color components in extracting patterns has improved recognition accuracy over traditional PCA. Furthermore, colour is one of the main features in recognising a flower. Therefore, this approach can be followed in the process of recognising medicinal flowers in order to achieve a higher accuracy level.

The drawback with PCA is that it contains unnecessary information such as poses and lightings, and this unnecessary information affects the recognition accuracy which leads to a conclusion that PCA is not the optimal rule for discrimination.

2.5.4 Bag of Visual Words Approach

According to [7] , the use of “bag of visual words” has been investigated in flower-classification. Furthermore, the ambiguities which lie between flower categories can be controlled by developing a visual vocabulary that clearly represents the various aspects (colour, shape, and texture) that distinguish one flower from another. Some flowers cannot be distinguished either by colour or shape alone. A combination of these aspects has to be used in distinguishing flowers. However, flower species often have multiple values for each of the stated factors. A vocabulary has been created in order to give an accurate representation of these properties. “The shape of individual petals, their configuration, and the overall shape of the flower can all be used to distinguish between flowers. Nevertheless, some flowers have characteristic patterns on their petals. These patterns can be more distinctive thus can be used in distinguishing flowers".

Vocabularies for each aspect are combined into a joint flower vocabulary. As a result of combining these features in a flexible manner, a high-performance rate could be expected. Comparatively, shape and texture have also impacted the performance rate. Eighty images each from seventeen species were used as the image sets for the investigation, resulting in an excellent performance. Finally, it was concluded that the 'bag of visual words' model approach for flower-classification outperformed petal-detectors, flower-detectors and many other detectors and descriptors [7].

2.5.5 Knowledge-based Approach

This approach uses both knowledge about the external world and the computer vision task. Nevertheless, according to [8], visual modelling and recognition is one of the four critical areas in the knowledge-based approach. It sets milestones in developing effective techniques for describing and storing natural objects. Furthermore, the approach is required to support recognition for such objects. Since the researcher's research area also addresses one of the natural objects, the recognition is supported by the knowledge-based approach.

2.5.6 Using Grey Level Co-Occurrence Matrix

As asserted in [9], in this approach, images are taken using a high-resolution camera and immediately pre-processed afterwards in order to remove noise and distortions from the image. Later, the image is converted to greyscale for the Grey Level Co-occurrence Matrix (GLCM) calculation. GLCM calculations are generally considered to be very high values and requires a large amount of computational power and resources. Hence, GLCM computational values were normalised so 1s and 0s could be used. This method is applied to texture feature values of the input leaf and performed for all the images stored in the database. Finally, a least difference value of class is selected as the most similar image class to the input leaf. The following text features were used for this: Inverse Difference Moment, Entropy, Sum Average and Difference

Variance. For classification, the average of above was used and it could reach to a success rate of 94 percent. The following is an overview of this approach.

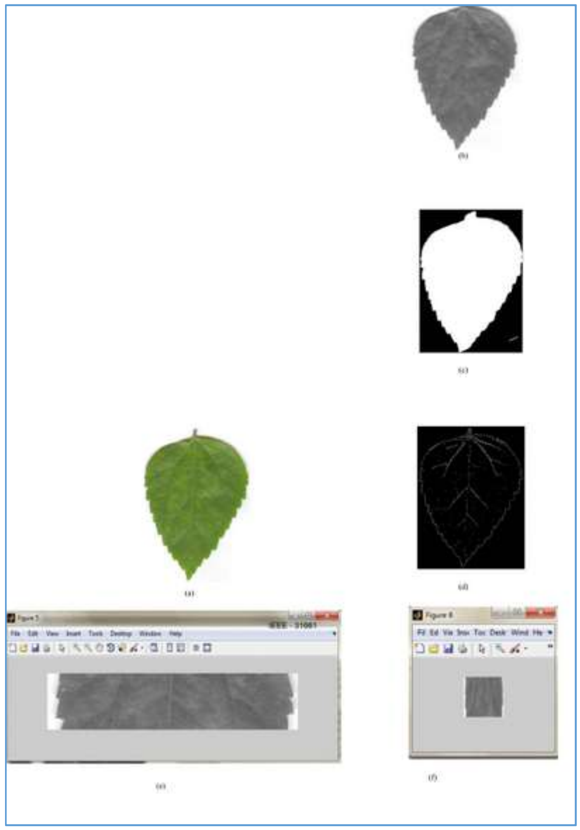


Figure 2.10:A GLCM based approach[9]

2.5.7 Support Vector Machine

SVM is a decision machine which is widely used as a machine learning technique [10]. Moreover, it maps input data into a high-dimensional feature space defined by a kernel function which returns the inner product between the images of two data points. Furthermore, the ability of applying SVM to a data set directly without a feature extraction process, once it is designed and used, is a key aspect of SVM. Thus, it is widely used in object recognition [10].

2.5.8 Probabilistic Neural Networks

According to [3], a Probabilistic Neural Network (PNN) is another classification algorithm and its main advantage is that it takes less time to train data. It derives from the Radial Basis Function (RBF). There are three main layers in a PNN namely, Input Layer, Radial Basis Layer and Competitive Layer. During the Input Layer, a calculation is performed in order to find the similarity of the input vectors and trained vectors. This vector value shows how similar the input vector is to its train vector value. Later, this value is summed in the second layer. As asserted in [3], during the Radial Basis Layer, the distance between the row weight vectors of the weighted matrix and the input vectors are calculated. Instead of training the weight, values are assigned. The new vectors are added into the weight matrix without changing the existing one. During the Competitive Layer, it finds which class its input values belong to, based on the probability. The maximum is 1 and for the rest of its classes it is 0.

2.5.9 Convolutional Neural Networks

According to [11], a Convolutional Neural Network (CNN) is a multi-layered network structure derived from the traditional neural network method. It mainly includes an input layer, a convolution layer, a pooling layer, a full connection layer and an output layer. It has the ability to perform feature extraction and mapping using training and it's a very fast way. Its strength lies in its high levels of accuracy when it comes to classification and prediction.

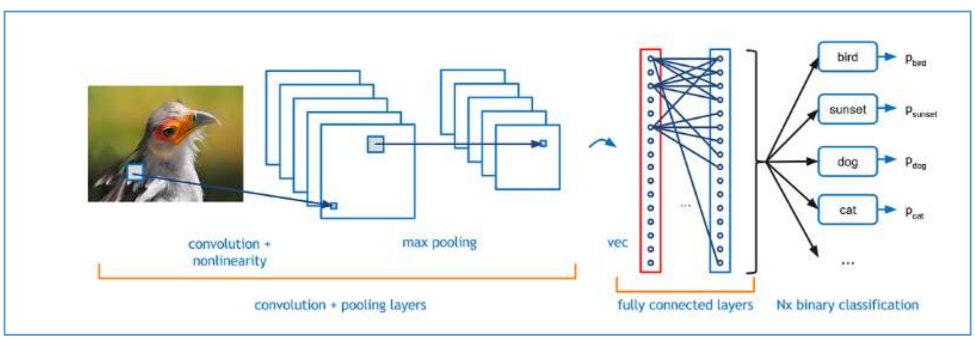


Figure 2.11: A sample Convolutional Neural Network [12]

2.5.9.1 Convolutional Neural Network Architectures

2.5.9.1.1 LeNet-5

This was introduced in 1998 and consists of 7 layers. Initially, it was used to identify digits on cheques by providing 32 X 32 grayscale images. The constraint here is that it requires a lot of computer resources if the accuracy level is to be increased [12].

2.5.9.1.2 AlexNet

AlexNet was inherited from Lenet but it has filters after every layer and stacked convolutional layers. In addition, it consists of convolutions, max pooling, dropout, data augmentation, and ReLU activations [12].

2.6 Summary

This chapter illustrated a comprehensive analysis on the research area. First, it gives a clear understanding of the leaf anatomy and the importance of an automated leaf analysing system. Afterwards, the researcher has discussed pre-processing, feature extraction and existing classification methodologies. The researcher has provided detailed views on how Raspberry processors were used after features extraction and computed dissimilarity, while some of the related work had initiated analysing with GLCM. Furthermore, Probabilistic Neural Network (PNN) and Support Vector Machine (SVM) were rated as highly accurate methods for classification. In the next chapter, the researcher will present a suitable overall architecture as the design methodology for the proposed application.

Chapter 3

METHODOLOGY

3.1 Introduction

In the previous chapter, a comprehensive literature survey on existing leaf recognition systems was followed by a critical analysis of these systems. In this chapter, a suitable methodology to implement the application is presented after investigating existing applications of the same calibre.

3.2 Overview of the Proposed approach

This section provides a very high-level view of the proposed approach. The following is the high-level design that addresses the events: taking a snap of the plant leaf, uploading it to be recognised, training the system, validation and testing the system, and finally identifying and displaying the plant details with its medicinal values.

In this approach, the researcher has proposed a service layer which has access to a CNN. Front End is a mobile application where a user can send take a snap of the desired plant leaf and send it for verification and later be able to view the related medicinal details, if applicable, back in the mobile application.

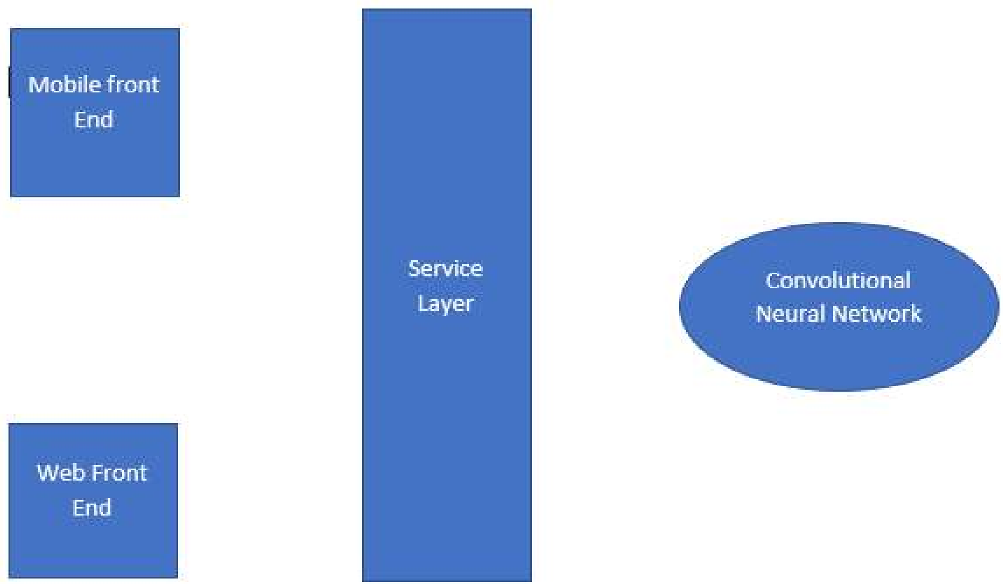


Figure 3.1: Overview of the Proposed system

In this application, there are three main layers: Front End Layer, Service Layer and Image Processing Layer. The Image Processing Layer is divided into three main modules: training, validation and testing.

3.3 Front End Layer

This layer possesses functionalities initiated by the user. The front end can either be a web or mobile. For this application, the researcher selected a mobile front end where the user has the ability to verify a plant using a mobile device. However, the image has to be focused to plant leaf and it should not be blurred or disturbed – the accuracy of the recognition depends on this. In order to verify if the image is focused well and in good quality, a validator is run at the front end. Once the validator confirms that the image is of good quality, it will be sent to the Service Layer for the identification process.

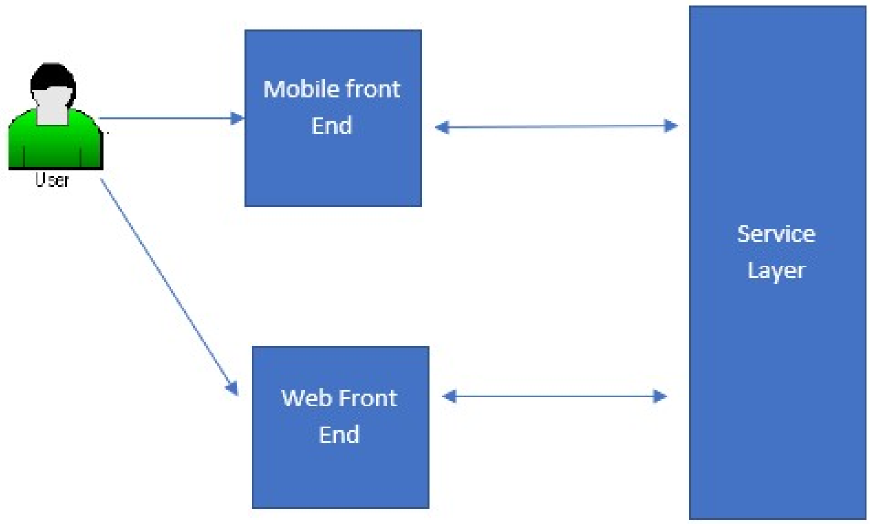


Figure 3.2:Front End Overview

3.4 Service Layer

This is a web service which has access to the image processing module. It accepts requests from the mobile/web front end and redirects them to the image processing layer to get analysed. With this approach, this application can be used globally. When a plant leaf is verified by the CNN, it performs a search operation in the Medicinal Plant Database to find its medicinal values and passes that information to the front end as illustrated in Figure 10.

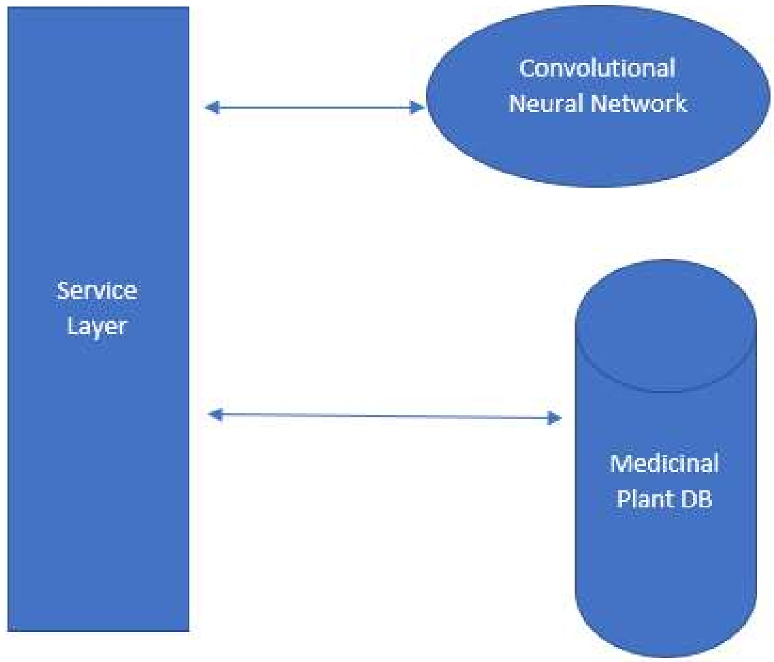


Figure 3.3:Overview of the service layer

3.5 Image Processing Layer

This is an overview of the image processing layer which identifies if a given image is of a medicinal plant or not. For this layer, the researcher has implemented a CNN.

The principle benefit of a CNN over a Traditional Neural Network is its low computational cost. As an example, A Traditional Neural Network needs 900 inputs for a 30X30 pixels image. A reasonably powerful machine can handle this but once the images become much larger, the number of parameters and inputs needed increases to very high levels, and this is the main disadvantage of using a Traditional Neural Network. This drawback can be overcome by using a CNN as it is designed in such a way where some generalisability has to be sacrificed for a much more feasible solution.

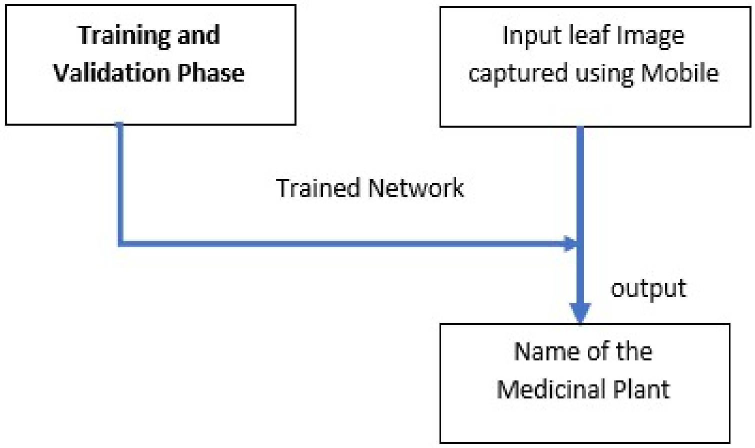


Figure 3.4:High level view of the Image Processing part

In the Literature Review chapter, the researcher discussed the various classification methods such as Principal Component Analysis (PCA), Support Vector Machine (SVM), Probabilistic Neural Network (PNN) and Convolutional Neural Network (CNN). After considering every classification method, the researcher selected CNN for the proposed medicinal plant leaf analysing application.

When using a CNN, the accuracy of the classification can reach up to 99%. Therefore, in this design, the researcher proposes **AlexNet** to be used as the CNN architecture since it is shallower than the other architectures and easy to use. The network is eight layers deep and has the ability to classify images into 1000 categories. In the Implementation chapter, a detailed view of this will be presented.

3.6 Prototype Development Methodology

Considering the fact that a system development methodology plays an important role in the software development process, the researcher selected a development methodology for the prototype development. The selection of a suitable development methodology is important for the success of any software project. Therefore, the researcher selected evolutionary approach over linear sequential approach for developing the prototype, considering the following factors:

- The linear sequential approach suggests a sequential approach to software development that progresses through analysis, design, coding, testing and maintenance of the project. Conversely, the evolutionary approach is iterative in nature and focuses on producing an executable product as early as possible. This ensures that the final product meets its targeted functionality.

- Unlike the sequential method, the evolutionary method allows constant reviewing of activities.

- The evolutionary approach testing is conducted throughout the development life cycle, thereby ensuring the software quality.

3.7 Summary

This chapter summarised the design of the proposed intelligent medicinal plant leaf recognition system. Furthermore, a high-level view of the system as well as an in-depth representation of the system have been illustrated in this chapter. As stated above, the designs consist of 3 main layers which will be developed in the Implementation phase of the project, namely the Front-End Layer, Middle Layer and Back End Layer. The Front Layer can either be a mobile or web application. With this approach, it makes the application more flexible so the users can connect via a mobile or a web application. The Middle Layer is supposed to handle all the web requests and it is designed to be implemented as RESTFUL API. Finally, the Backend Layer will be using a Convolutional Neural Network with AlexNet as its architecture and significant facts were provided to justify why Alex Net was selected over other CNN architectures.

Chapter 4

IMPLEMENTATION

4.1 Introduction

In the previous chapter, the researcher described the proposed methodology and its architecture. The vital combination of sub-layers which were the base for implementation of the application were also illustrated. This chapter explains the implementation process of each layer along with a technical analysis of the selected development languages. It also discusses the problems encountered during the Implementation phase and the solutions found.

4.2 Technology Stack Overview

It is vital to select a proper development language prior to the application implementation. Hence, in the following section the researcher discusses the reasons for selecting MATLAB 2017b as the back-end development language, C#.NET for the development of the Web Service and Android for the frontend development.

4.2.1 Language Selection for Front End Development

When selecting the frontend development language, the researcher took into consideration a few factors such as using open source programming languages as much as possible, likelihood of less response times and the ability to add more user-friendliness options. After considering Windows Mobile, Android and IOS, Android was selected.

4.2.2 Language Selection for Middle Layer Development

The Middle Layer will be a RESTFUL web service. For this purpose, the researcher selected ASP.Net as the programming language. Considering the time constraint, it is important that the language selected supports rapid development and it is known that C#.NET supports rapid development better than Java.

4.2.3 Language Selection for Backend Development

Matrix Laboratory, simply known as MATLAB, is used for various purposes. It is a very popular environment for algorithm development, data visualisation, data analysis, and numeric computation. Moreover, it is more efficient in solving technical issues than traditional programming languages. The ability to integrate MATLAB code with other languages and applications is a benefit of using MATLAB. Since the researcher has selected C#.NET as middle layer development language, a connector related to the backend development language is required in order to integrate the modules. MATLAB Builder NE, which will be discussed in the following section, provides a simple approach to integrate MATLAB with the .NET Framework. Therefore, considering the aforementioned facts and the ease of use in rapid development, the researcher has selected MATLAB as the back end developing environment.

4.3 Connectivity of Middle Layer and Back End

The MATLAB Builder NE was used to integrate MATLAB and C#.NET. This is an extension to MATLAB compiler. It can be used to convert MATLAB functions to the .NET methods written by the researcher. By using this extension, it is possible to call MATLAB functions from a .Net environment.

4.4 Implemented Layers

This section contains a detailed description of how the design aspects were covered in the Implementation phase. It also contains a high-level view of the system followed by the sub-layers which were implemented.

4.4.1 Front End Layer

The frontend layer was implemented with Android. Using a front end, a user can take a snap of a plant leaf, upload it to the system for verification and find its therapeutic information. The following is a screenshot of the front end:

Figure 4.1:Front End of the Application

4.4.2 Middle Layer

The Middle Layer is designed in such a way where any client application has the ability to access the plant analysing layer by making web requests. Hence, it is an advantage. In the proposed application, the researcher implemented a Mobile Front End to communicate with the web service.

4.4.3 Backend Layer

The backend layer is implemented using MATLAB. Using MATLAB, a Convolutional Neural Network was developed for this purpose. Among many convolutional network architectures such as AlexNet, GoogLeNet, ResNet and VGG, AlexNet was the selected CNN architecture for this implementation.

4.4.3.1 Dataset Preparation

Images that were captured using a mobile camera were saved under different labels (total 16 labels) where the labels represent the name of the plant (i.e. 16 different plants). The number of images for training were increased by performing data augmentation. (i.e.) Each image was rotated 45˚, 90 ˚ and 135 ˚ and resized to 227 in width and 227 in height. 78 images were used from the datasets and stored for testing. For training and validation, 1020 images were stored.

Since AlexNet is a pretrained Convolution Neural Network architecture for classification, 1000 categories of images composed of 8 layers were used. The researcher performed transfer learning in order to train the network for 16 categories since there were 16 different plants to be classified.

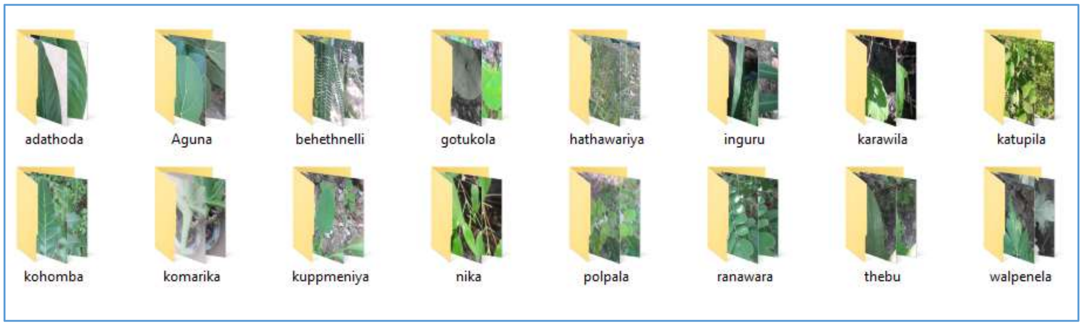


Figure 4.2:A view of the training dataset

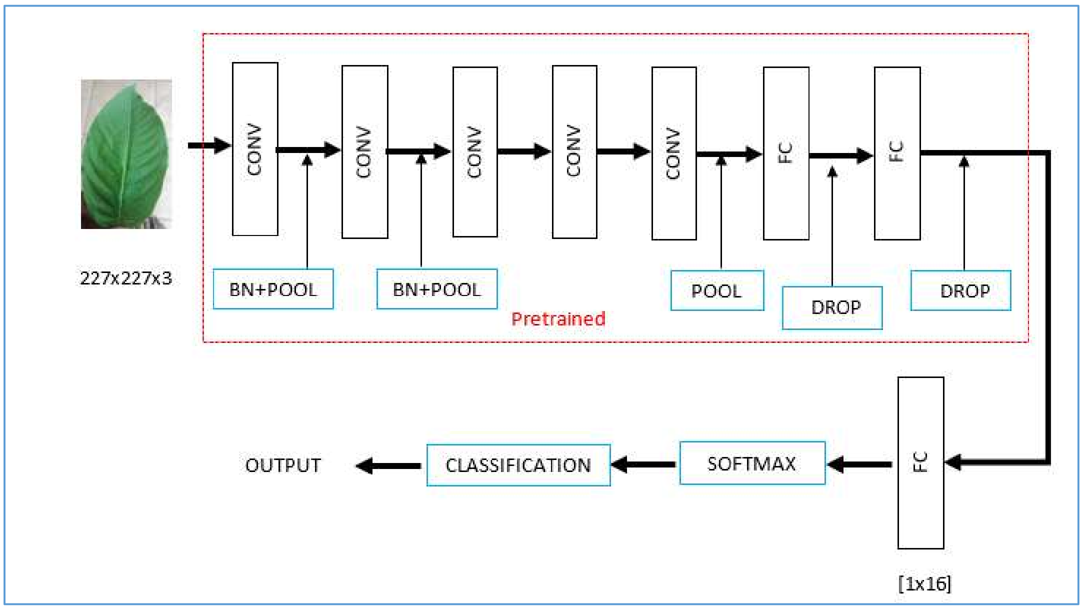


Figure 4.3:Overview of the Convolutional Neural Network used

4.4.3.2 Training Module

During the training phase, the validation had to be performed by taking 30% of images from the training datasets to predict the accuracy of the network. During the training process, loss was calculated along with accuracy. The datasets are divided into mini-batches and trained, and the loss is calculated for each mini-batch. Finally, the training is terminated based on the number of epochs given as an input. After each layer except the last layer, a ReLU activation function was performed.

With maximum accuracy and minimum loss, the trained network will be used to classify the new images that are given as an input.

```
%% define layers
net = alexnet;

inputSize = net.Layers(1).InputSize
layersTransfer = net.Layers(1:end-3);
numClasses = numel(categories(imdsTrain.Labels))

layers = [
    layersTransfer
    fullyConnectedLayer(numClasses,'WeightLearnRateFactor',20,'BiasLearnRateFactor',20)
    softmaxLayer
    classificationLayer];

%% options of training
options = trainingOptions('sgdm', ...
    'MiniBatchSize',10, ...
    'MaxEpochs',6, ...
    'InitialLearnRate',1e-4, ...
    'ValidationData',imdsValidation, ...
    'ValidationFrequency',20, ...
    'ValidationPatience',Inf, ...
    'Verbose',false, ...
    'Plots','training-progress');
```

Figure 4.4:Training Module- Define Layers

```
%% training
[netTransfer,tr] = trainNetwork(imdsTrain,layers,options);
save([output_path,'transfer_',pretr_net,'.mat'],'netTransfer','tr');
%% Testing accuracy
imdsTest =  imageDatastore('dataset_test', ...
    'IncludeSubfolders',true, ...
    'LabelSource','foldernames');

[YPred,scores] = classify(netTransfer,imdsTest);
idx = randperm(numel(imdsValidation.Files),4);
YValidation = imdsTest.Labels;

accuracy = mean(YPred == YValidation)

err_idx = find(YPred~=YValidation);
num_plot = ceil(sqrt(length(err_idx)));
figure;
for i = 1:length(err_idx)
    err_I = readimage(imdsTest,err_idx(i));
    subplot(num_plot,num_plot,i),imshow(err_I);
    label = YPred(err_idx(i));
%     title(string(label));
    title(sprintf('Pred:%s; True:%s',string(label),string(YValidation(err_idx(i)))));
end
```

Figure 4.5:Training Module

4.4.3.3 Classification Module

In the classification module, once the image is received it is resized into 227 X 227 and then passed for classification. The following code snippet shows how it happens. With this approach, it was noticed that response time was low, and the system identified the image quickly.

```
%% load testing dataset
img_resized = imresize(img,[227,227]);      %resizing image for the network input dimension
%% load network
model = load(net_path);
net = model.netTransfer;
tr = model.tr;

%% testing
[YPred,scores] = classify(net,img_resized);

figure;
imshow(img);
title(sprintf('Predicted Label: %s; \t True Label: %s',YPred,class));
```

Figure 4.6:Image Resize and Classification

4.5 Summary

This chapter discussed how the methodology described in the previous chapter was converted into a functioning prototype. The layers illustrated in the Methodology phase were implemented with some changes to the design considering the performance and time constraint aspects. This chapter further contained a brief overview on the technologies selected for the front end, middle layer and back end development. The researcher concluded the chapter with providing proofs of the implementation of the application.

Chapter 5

TESTING AND EVALUATION

5.1 Introduction

This chapter focuses on testing methodologies followed and the evaluations carried out by the system stakeholders, along with a self-evaluation by the researcher. It is important to carry out comprehensive testing and evaluation to ensure the quality of the product. Furthermore, the Evaluation section of this chapter addresses the functionality of the system, the prototype developed and the researcher's approach to the problem domain.

5.2 Testing

Testing is carried out in order to uncover errors of the application using various scenarios. For this application, a comprehensive testing phase was carried out and the researcher carried out cross-validation to ensure that the system meets the expected behavioural and performance aspects.

5.2.1.1 Cross-Validation

Cross-validation is mainly used in situations where the test results can be predicted. The use of cross-validation involves partitioning a sample set of data into a training set and a test set. Analysis is performed on the training set and it is validated on the testing set. Cross-validation is performed when there are unknown images in a data set, and a training data set to which the unknown images can be fit in. However, in order to obtain meaningful results, it is required that the training set and test set are acquired from the same population.

5.3 Testing Results

The system was tested using 16 different types of medicinal plants namely Adathoda (*Justicia adhatoda*), Aguna (*Alangium lamarkii*), Behethnelli (*Phyllanthus emblica*), Gotukola (*Centella asiatica*), Hathawariya (*Asparagus racemosus*), Inguru (*Ingiber officinale*), Karawila (*Momordica charantia*), Katupila (Flueggea leucopyrus), Kohomba (*Munronia pinnata*), Komarika (*Aloe vera*), Kuppameniya (*Nepeta Cateria*), Nika (*Vitex negundo*), Polpala (*Aerva lanata*), Ranawara (*Cassia auriculata*), Thebu (*Costus speciosus*) and Walpenela (*Cardiospermum halicacabum*). Testing was carried out for 96 images taken randomly and some of the results are presented in Table 5.1 below.

Table 5.1:Basic Test Cycle for Plant Leaves

#	Test Case	Uploaded Medicinal Plant Image	Predicted Medicinal Plant Name	Test Result
	Recognition of Aguna (*Alangium lamarkii*)		Aguna	Pass
	Recognition of behethnelli (*Phyllanthus emblica*)		behethnelli	Pass
	Recognition of gotukola (*Centella asiatica*)		gotukola	Pass

	Recognition of hathawariya (*Asparagus racemosus*)		Could not identify	fail
	Recognition of inguru (*ingiber officinale*)		inguru	Pass
	Recognition of karawila (*Momordica charantia*)		karawila	Pass
	Recognition of katupila (Flueggea leucopyrus)		katupila	Pass
	Recognition of kohomba (*Munronia pinnata*)		kohomba	Pass
	Recognition of komarika (*Aloe vera*)		komarika	Pass

	Recognition of kuppameniya (*Nepeta Cateria*),		kuppameniya	Pass
	Recognition of nika (*Vitex negundo*)		nika	Pass
	Recognition of polpala (*Aerva lanata*)		polpala	Pass
	Recognition of ranawara (*Cassia auriculata*)		ranawara	Pass
	Recognition of thebu (*Costus speciosus*)		thebu	Pass
	Recognition of walpenela (*Cardiospermum halicacabum*).		walpenela	Pass

Table 5.2:Critical Testing for Aguna

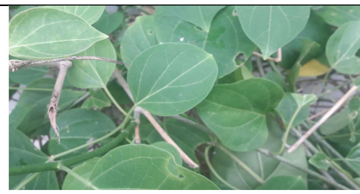
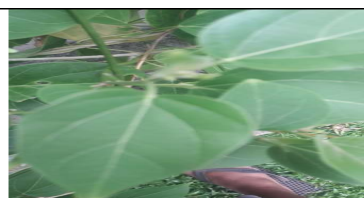
Test Case	Uploaded Aguna Image	Predicted Medicinal Plant Name	Test Result
Multiple images in photo		Aguna	Pass
Multiple images in Photo		Aguna	Pass
Not Well Focused		Aguna	Pass
Blurred image		Ranawara	Fail
Yellowed Leaf		Walpenela	Fail

Table 5.3:Critical Testing for Kohomba

Test Case	Uploaded Kohomba Image	Predicted Medicinal Plant Name	Test Result
Not Well Focused		Kuppameniya	Fail
Blurred image		kohomba	Pass
Blurred image		kohomba	Pass
Blurred image		Kohomba	Pass
Blurred and Yellow		ranwara	Fail

Table 5.4:Critical Testing for Kuppameniya

Test Case	Uploaded Kuppameniya Image	Predicted Medicinal Plant Name	Test Result
Multiple images in photo		Kuppameniya	Pass
Blurred image		Kuppameniya	Pass
Blurred image		Gotukola	Fail
Not Well Focused		Kuppameniya	Pass
Not Well Focused		Kuppameniya	Pass

Table 5.5:Critical Testing for Ranawara

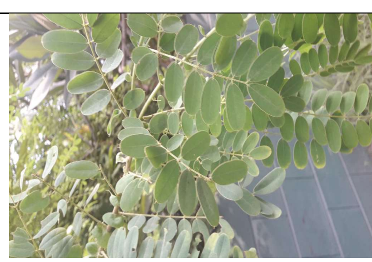
Test Case	Uploaded Ranawara Image	Predicted Medicinal Plant Name	Test Result
Not Well Focused		Ranawara	Pass
Not Well Focused		Ranawara	Pass
Multiple images in photo		Ranawara	Pass
Multiple images in photo		Ranawara	Pass
Multiple images in photo		Ranawara	Pass

Table 5.6: Critical Testing for Katupila

Test Case	Uploaded Katupila Image	Predicted Medicinal Plant Name	Test Result
Not Well Focused		Katupila	Pass
Not Well Focused		Katupila	Pass
Not Well Focused		Katupila	Pass
Multiple images in photo		Katupila	Pass

Multiple images in photo		Katupila	Pass

Table 5.7:Critical Testing for Thebu

Test Case	Uploaded Thebu Image	Predicted Medicinal Plant Name	Test Result
Not Well Focused		Thebu	Pass
Not Well Focused		Thebu	Pass
Not Well Focused		Thebu	Pass

Not Well Focused		Gotukola	Fail
Not Well Focused		Thebu	Pass

Table 5.8:Critical Testing for Hathawariya

Test Case	Uploaded karawila Image	Predicted Medicinal Plant Name	Test Result
Not Well Focused		karawila	Pass
Not Well Focused		Kohomba	Fail

Not Well Focused		Hathawariya	Fail
Not Well Focused		Walpenela	Fail
Not Well Focused		Karawila	Pass

Truth data

Classifier results	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Classification overall	Producer Accuracy (Precision)
Class 1	4	0	0	0	0	0	0	4	100%
Class 2	0	4	0	0	0	0	3	7	57.143%
Class 3	0	1	5	0	0	0	0	6	83.333%
Class 4	2	1	0	6	0	0	0	9	66.667%
Class 5	0	0	0	0	6	0	0	6	100%
Class 6	0	0	0	0	0	5	0	5	100%
Class 7	0	0	0	0	0	0	3	3	100%
Truth overall	6	6	5	6	6	5	6	40	
User Accuracy (Recall)	66.667%	66.667%	100%	100%	100%	100%	50%		

Overall accuracy (OA): 82.5%

Kappa[1]: 0.796

Figure 5.1:Confusion Matrix for Randomly Selected Seven Classes

5.4 Test Results Summary

In order to get a quick idea of the test results, the researcher has provided a summary as follows:

- Recognition Rate = Number of correct matches / (Total number of images)
- Recognition Rate for Aguna = 80%
- Recognition Rate for Kohomba = 80%
- Recognition Rate for Ranawara = 100%

Average Recognition Rate (Aguna, kohomba, Ranawara) = (260/3) *100 = 86.33%

5.5 Performance Measure of the Classification

In addition, using the Confusion Matrix as shown in Figure 5-1, the performance measures of the classification have been presented below.

Number of plant classes considered = 7

Precision of the dataset = 86.73%

Recall of the dataset = 83.334%

F1 Score = 2*(Recall * Precision) / (Recall + Precision)

F Score of the Dataset = 85.03%

For the training dataset, the accuracy measures are as follows:

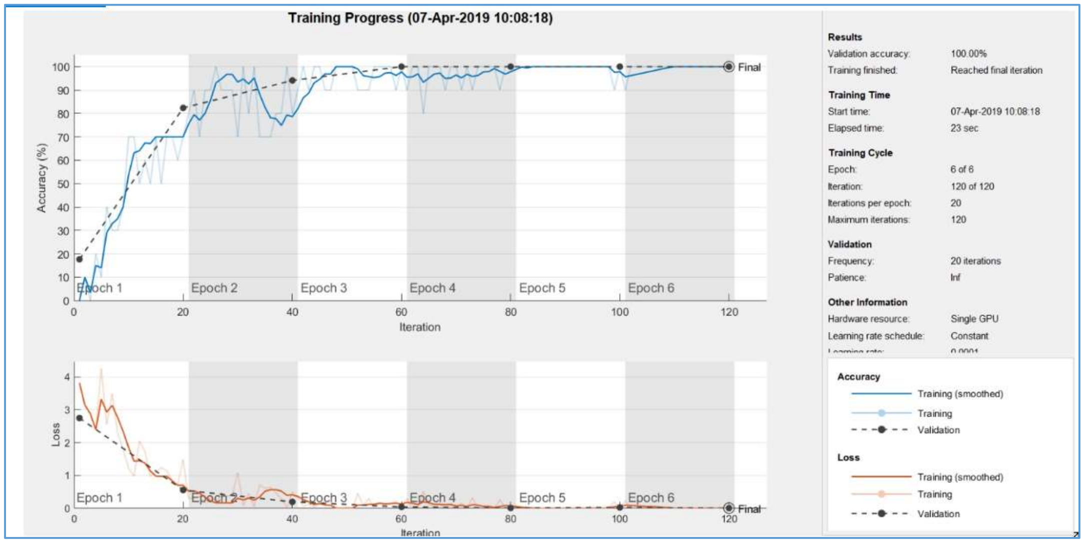


Figure 5.2:Accuracy Measures for the Training Dataset

5.6 Evaluation

Evaluation is important in ensuring a better designed and user-friendly system so that complexity is reduced for the user. Furthermore, the importance of the concept of the project and its novelty, the effectiveness of adopted approaches in solving the problem domain, and usability and usefulness are some of the key indicators which determine how successful the system is. Moreover, the future scope of the system is also based on the success of these aspects.

5.6.1 Evaluation Approach and Selected Evaluators

The researcher selected questionnaires and interviews as the main approach of obtaining feedback for the evaluation. The evaluation was carried out by a group of experts. As these stakeholders of the system include botanists, Neural Network specialists and most importantly general users, the questionnaires were prepared accordingly. Considering the fact that the majority of general users lack technical knowledge, the questionnaire was made straightforward without any jargon so that the evaluation carried out by the users would be effective. The evaluation by experts in subject areas related to the system was focused on the importance of solving the problem, the researcher's approach in solving the problem and the usability of the system.

5.6.1.1 Evaluation Criteria

The evaluation criteria were divided into two categories, one for the experts in the subject areas and the other for general users. Evaluation carried out by the experts was based on the concept of the project, the level of satisfaction of the solution given for the problem domain, accuracy of the system, suitability of the CNN-based approach in solving a problem of this nature, limitations of the prototype developed and the future scope of the system. Conversely, the evaluation carried out for the general users was straightforward where the evaluation was mainly based on the user-friendliness of the system, and the usability and usefulness of the system.

5.6.1.2 Evaluation results of the selected criteria

5.6.1.2.1 Experts' evaluation

The following sections summarise the valuable feedback provided by the experts in the area related to the project.

Table 5.9:Expert Evaluation1

Expert Field	Botanist
Concept of the project	*"This is a novel and useful application of technology in the plant identification process. The applications that the research proposes are highly applicable in plant taxonomy sites."*
Satisfactory level of the solution given for the problem domain	According to this evaluator, the system can not only be used in medicinal plant recognition but can also be applied to

	other plants provided that the relevant information is fed into the system.
Accuracy of the system	The evaluator was satisfied with the accuracy but suggested that more botanical details of the plants be added in order to increase the identification parameters and minimize misidentification.
Limitations of the prototype developed	The botanical details need to include more parameters to increase the accuracy and usage of the system.
Future scope of the system	*"This project could be developed into a system of national importance if botanical details can be highlighted more."*

Table 5.10:Expert Evaluation2

Expert Field	Botanist
Concept of the project	*"It is a useful area of study since it allows clear and easy identification of medicinal plants."*
Satisfactory level of the solution given for the problem domain	*"The researcher has a clear understanding of what has been developed within the limited scope of the study."*
Accuracy of the system	The accuracy of the system was stated as good since many samples have been used. However, negative testing should also be carried to ensure further accuracy of the system.
Limitations of the prototype developed	*"I am not sure of MATLAB's capability of handling huge sets of data, so this could be an issue when dealing with large-scale organisations."*
Future scope of the system	*"The scope is currently limited to recognising medicinal plants, but it can also potentially be used for other*

	commercial (e.g. as a gardening aid) or research (e.g. developing new medicine using plant extracts) purposes."

Table 5.11:Expert Evaluation3

Expert Field	Lecturer
Concept of the project	*"The concept focuses on the system being used by an expert in the subject area – this is useful, but it might be difficult to operate by a beginner."*
Satisfactory level of the solution given for the problem domain	*"Good effort. The researcher seems to have done a good literature survey. If the scope was to be expanded, it would require more research in those domains."*
Accuracy of the system	*"Obtaining an average of 85% accuracy with the given parameters is quite good, but the accuracy would have to be determined again if more parameters and testing scenarios are added."*
Limitations of the prototype developed	The response time was higher than expected by the expert.
Future scope of the system	The expert highlighted that the scope can be further expanded to assess other types of leaves for other purposes as well. It was also suggested that the use of newer technology and equipment could be useful to the system in future, so the system should be easily upgradable.

5.6.1.2.2 User Evaluation

The following section summarises the evaluation performed by the general users where the user-friendliness, usability and usefulness of the system were given more consideration.

User-friendliness of the system - Majority of the users were pleased with the user-interface. They considered the system to be user-friendly as they required little effort to get the desired result although they lacked the technical knowledge to do so. Furthermore, most of them were not knowledgeable on medicinal plants nor were they aware of the need for leaf recognition. Therefore, the user-friendliness was a key factor which led general users to embrace the system.

Usefulness of the system – Majority of the users were of the opinion that the system is very useful in identifying plants in the area of exporting flora and fauna through the department of customs. Furthermore, they indicated that Sri Lanka can eventually use this kind of system to patent plants/herbs used in Ayurveda and then start exporting these medicines in large scales.

Usability – The usability aspect can be enhanced further by giving the user the option of recognising a new leaf which is not in the system.

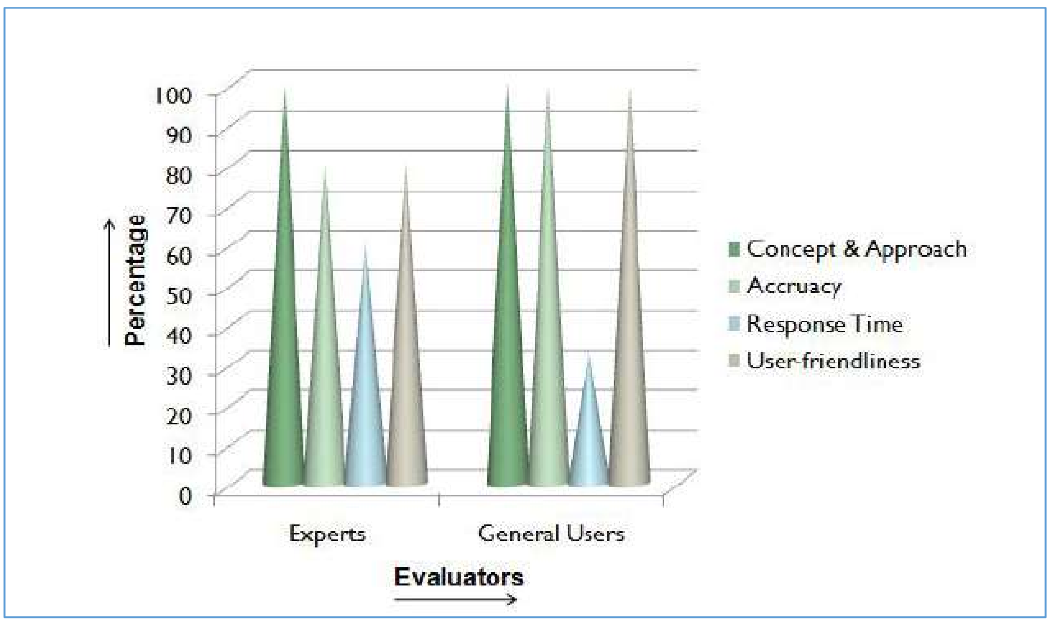


Figure 5.3: Evaluator and User Feedback

As showed in the above graph, a majority of users were satisfied with the concept, approach, accuracy and user-friendliness of the system.

5.6.1.2.3 Self-Evaluation

This section contains a critical evaluation carried out by the researcher on his own work. The researcher is thoroughly satisfied with the project as he has been able to turn the vision, he had two years ago into reality. Throughout the entire two years of project work, the researcher has gained considerable knowledge on the domain of the study as well as its technical aspects, with significant guidance given by the supervisor and experts in the subject areas related to the project.

The concept of the project proposed by the researcher was an outcome of being impressed by the heritage of natural sciences. At the initial stages of the project, the researcher carried out a comprehensive literature survey which laid the foundation for the development of the entire system. It also guided the researcher in selecting the best feasible approach for the problem domain. Having read valuable research journals, the researcher gained in-depth knowledge on a variety of subject areas related to computer vision. Furthermore, the books on medicinal plants helped the researcher in gaining valuable information regarding medicinal plants and their uses.

The knowledge gained from the literature survey and the approaches based on it helped the researcher to convert the system design into a functioning prototype. The evaluators' comments about the system proves the fact that this application has been a success, while the comments on drawbacks of the system encourages the researcher to enhance the system and get it to a commercial standard. Thus, the researcher is satisfied with the overall outcome of the prototype as he was able to meet the targeted functionality with a high accuracy level of 85%.

5.7 Summary

This chapter illustrated the testing process chosen by the researcher and the test results generated by the system. The tests were carried out in a range of conditions where white backgrounds were considered. The system obtained a recognition rate of 85%

for the input images, where 15 images from each plant type were used as the training data set. It also dealt with the most vital aspect in the software development process, which is the evaluation aspect. The section of evaluation addressed the project concept, functionality aspects of the developed prototype and the researcher's approach towards the problem domain. The next chapter will conclude the project report by stating how the aims and objectives were met, problems encountered during the development lifecycle, future enhancements and most importantly, key learnings from the undertaken task.

Chapter 6

CONCLUSION

6.1 Introduction

The previous chapter discussed the comprehensive testing and evaluation carried out in determining the success of the system. The researcher has now reached the end of the journey by successfully completing the phases of literature review, design, methodology, implementation, testing and evaluation of the project. This chapter concludes the project report by illustrating how the aim and objectives stated initially in the project have now been met. Furthermore, it sums up the further enhancements to be made, limitations of the prototype and the key findings of the project.

6.2 Achievement of Aim and Objectives

The researcher has developed and evaluated a feasible intelligent system which accurately recognizes medicinal plants by analysing its leaf. Therefore, the researcher believes that the initial aim of the project has been met successfully.

6.3 Achievement of Objectives

Carry out a comprehensive literature survey followed by a review

Chapter 2 consists of a comprehensive literature survey which was carried out in order to find out the leaf features used for plant recognition. It also highlighted the impact of leaf recognition in identifying medicinal plants. It was found that:

- The shape, colour and texture are the most common features that are used to recognise a plant by its leaf. However, the evidence from existing systems suggests that colour, shape or texture alone cannot be utilised to obtain a higher recognition rate.

- Existing leaf analysing systems have noise reduction, feature extraction and use SVM, PCA, PNN as classification methods. In this application, a CNN with AlexNet was used in order to achieve a high level of accuracy for identifying medicinal plants by its leaves.

Select suitable tools and technologies that will enhance the performance of the prototype

This objective was achieved in the implementation stage. Chapter 4 provided an overview of the technology stack of the application.

Design and implement the proposed prototype of "intelligent leaf analysing system for medicinal plants" according to best practices.

A high-level view of the system was given in Chapter 3 and contains a detailed description of each module in the proposed system. In Chapter 4, a detailed description has been provided regarding the implementation approach.

Test the prototype to ensure its quality and ability to recognise leaves by identifying a sample set of medicinal plants

Chapter 5 of the report discusses the testing phase of the prototype, which fulfils this objective.

Critically evaluate the prototype by questionnaires and by experts in order to ensure that the aim of the system has been met and submit the draft report

The latter part of Chapter 5 discusses the evaluation phase of the prototype, which addresses this objective.

6.4 Problems Encountered During the Research

- It took a large amount of time to do a comprehensive literature survey and review each method used in many existing plant identifying systems in order to get a detailed idea of the research scope.

- It took a considerable amount of time to get in touch with MATLAB and build a neural network as well.

- Moreover, during the implementation phase, the researcher had planned to use CNN GoogLeNet instead of CNN AlexNet with the intension of achieving a better accuracy rate. However, with the large amount of memory required for GoogLeNet, it was decided to use AlexNet.

- Another problem faced by the user was in integrating MATLAB with the .NET Framework. However, after much effort on the part of the researcher, the connection was made, and the results were obtained successfully.

6.5 Limitations

1. This application is limited to 16 types of medicinal plants. As illustrated in survey, most of the users requested it to be available for many medicinal plants.

- The researcher used cross-validation in testing the system. To reduce variability, it is desirable to conduct multiple rounds of cross-validation for a particular leaf. Due to the lack of time available, the researcher could not conduct multiple cross-validations for leaves.

6.6 Future Enhancements

- Based on the evaluations carried out, the researcher suggests that the system can be expanded to recognise more types of plants by analysing the leaf.

- The user interface can be improved to give more flexibility by adding new features. For instance, users can be given the option of training the system with a newly added set of leaf images.

6.7 Key findings

- A CNN can be used in the area of plant recognition with a high accuracy rate of recognition.

- In the evaluation of the application, it could reach a precision of 86.73%, recall of 83.33% and 85.03 for F measure.

- AlexNet outperforms GoogLeNet as it is a deeper network than GoogLeNet, uses more GPU memory and makes it heavier. AlexNet is shallower than GoogLeNet so it is easier to train.

6.8 Conclusion

This chapter summarises the entire effort made by the researcher in making this application a successful story. It discusses the overall achievements of the project, problems encountered during the entire lifecycle, limitations of the system, and further improvements that can be made. It also highlights the knowledge and experience gained by the researcher while undertaking a project of this nature. The most rewarding and challenging experience for the researcher was having to conduct a comprehensive research on both the botanical and technical aspects of the problem domain. Furthermore, it was a privilege to have been able to carry out the project under the constant guidance of a supervisor who had an in-depth knowledge in the technical aspect of the subject area. In conclusion, the researcher identifies his effort as a vital step towards making the current process of medicinal plant recognition more effective in the future by introducing a CNN based approach to recognise medicinal plants by its leaf.

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