Identification of Lantana Camara Distribution Using Convolutional Neural Networks

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Declaration

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Abstract

Lantana camara is an exotic invasive plant that has been a major threat to the biodiversity of a number of countries around the world. This plant has introduced a number of hazards such as outpacing native trees and plants, changes in soil, devaluation of habitat, alteration of fire and more. This dissertation presents a novel method using Convolutional Neural Networks (CNNs) and image processing techniques to identify the distribution of *Lantana camara* plants with red, orange, or yellow colour flowers, in aerial images. The proposed method includes three stages for the detection of *Lantana camara* invaded places. The first step is the detection of possible flower patches in the aerial images. Second step is the recognition of *Lantana camara* flowers from the flower patches through classification of a convolutional Neural Network (CNN). The last step is marking *Lantana camara* flower presence in the original image. The resulting image is marked with *Lantana camara* flowers, which indicates the presence of *Lantana camara* plants in that image.

Thresholding in L*a*b* colour space has been employed for the first step to segment possible flower patches from aerial image. For the second step, the BVLC (Berkeley Vision and Learning Center) distributed AlexNet has been used as the CNN architecture. The CNN has been trained to classify 967 flower species at an accuracy of 55.2%. The accuracy of recognizing *Lantana camara* flowers by the CNN is 94.6%. The accuracy of identifying all *Lantana* camara flowers in the original image is 40.71%. The proposed model was able to identify the presence of *Lantana camara* in aerial images successfully.

Preface

This dissertation proposes a design to identify the distribution of *Lantana camara* in aerial images. Chapter 1 gives an overview of the dissertation. Chapter 2 describes the background and related work for this study. Chapter 3 and 4 explains the design and implementation of the proposed approach. Chapter 6 conclude the dissertation as a whole. In the chapter 3 and 4, the implementation of the Convolutional Neural Network (CNN) is based on the work done by Krizhevsky et al. and fine-tuning of the CNN has followed the work by Nguyen et al. The rest of the work apart from these was proposed by me and my supervisors.

Acknowledgement

I would like to express my deepest gratitude to my supervisor, Dr. Kasun De Zoysa, senior lecturer at University of Colombo School of Computing (UCSC), for the constant guidance and supervision he provided me to continue this research throughout the year. And also, I would like to thank my co-supervisor, Dr. P. V. K. G. Gunawardana, lecturer at UCSC, for all the directions, guidance and tremendous support he has given me to carry out my research successfully.

And my special gratitude goes to Mr. Prabash Kumarasinghe, lecturer at UCSC, for the continuous guidance, motivation and assistance he offered me through many ups and downs in this research.

I extend my thanks to Dr. Chamath Kappetiyagama, senior lecturer at UCSC, for giving me useful insights for the improvement of the research.

I also would like to give thanks to Mr. Chathura Suduwella, research assistant, at UCSC, for providing aerial images at different locations and for giving a hand on the research. And also, I thank Mr. Namal Jayasuriya, Ms. Samali Liyanage, Mr. Ashan Maduranga, Ms. Akarshani Amarasinghe, Mr. Charith Madusanka for their kind support given to me to carry out this research.

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List of Acronyms

CNN : Convolutional Neural Network

HSV : Hue - Saturation - Value color space

LBP : Local Binary Patterns

LMDB : Lightning Memory-Mapped Database

RGB : Red - Green - Blue color space

UAV : Unmanned Aerial Vehicle

Chapter 1 - Introduction

1.1 Background and Motivation

"Weed", is a notorious word among the people involved in the fields of agriculture, horticulture, forestry and botany. The word refers to a plant that grows undesirably and out of control in a geographically important area. The new shorter Oxford English dictionary on historical principles [1] describes the word as "a herbaceous plant not valued for use or beauty, growing wild and rank, and regarded as cumbering the ground or hindering the growth of superior vegetation... An unprofitable, troublesome, or noxious growth." It is a well-known fact that the potential global crop yields are significantly reduced in each year due to the presence of weeds. Therefore, a substantial attention has been focused on weed control [2-4], weed mapping [5] and weed identification [6-7] to overcome the situation.

Lantana camara, is a weed plant that has been getting attention for its invasive behaviour recently. Earlier the weed plant has been used as a flowering plant to embellish gardens. However, due to its toxicity it has become poisonous to surrounding plants, thus showing invasive behaviour by growing out of control. Now it has become one of the top destructive weeds in the world and has introduced a number of threats to the biodiversity of the environment [8, 9].

In Sri Lanka, *Lantana camara* has been spread over a variety of places of the country, after escaping from Royal Botanical Gardens in Peradeniya. Now it severely threatens a number of farmlands, cultivated areas and biodiversity rich places such as national parks.

Specifically, *Lantana camara* has been recorded as a major hazard in Udawalawa National Park in Sri Lanka [10]. This invasive plant has outgrown a number of native plants and trees, as other plants cannot compete with its toxicity. As a consequence, food sources for the animals in the national park has been reduced. The plant itself is also not edible for most of the animals. A larger number of elephants in Sri Lanka, for whom the national park is the home, have been desperately threatened by *Lantana camara* invasion. These animals need a large amount of food sources, which is not available in the national park as the park has grown out of sufficient food sources due to *Lantana camara* invasion. As a result, the elephants leave the national park boundaries and invade villages seeking for food. As a consequence, number of human-elephant conflicts have been reported in the areas around the national park.

For these reasons it is a crucial fact that *Lantana camara* plants needs to be removed in the national park. However, the national park consists of a large area that it is difficult to discover the invaded areas manually. Therefore, a mechanism is required to automate the *Lantana camara* seeking process. As a solution for this, a mechanism to identify the *Lantana camara* distribution with the use of its flowers has been proposed in this dissertation.

1.2 Research Problem and Research Questions

As discussed in the section 1.1, a mechanism has to be developed to detect the *Lantana camara* invasion of an area. The use of aerial images is a way that can cover a large area, therefore have been considered as the base media for detection. The research problem and the research questions to identify *Lantana camara* distribution in aerial images are formulated as follows.

Research Problem:

How to identify the distribution of *Lantana camara* plants in aerial images?

Research questions:

1. How applicable are Local Binary Patterns (LBP) and thresholding mechanism in localizing *Lantana camara* flowers?
2. How applicable is CNN in classifying *Lantana camara* flowers?

1.3 Methodology

To identify the distribution of *Lantana camara* a flower-based recognition mechanism is employed and experimented in this study. As the input for the proposed design, high resolution aerial images that captures a suspected *Lantana camara* invaded area is considered. These set of images can be acquired by a satellite, a manned aerial vehicle (e.g. a helicopter), an unmanned aerial vehicle (e.g. a quad-copter) or any other media that is able to take high quality images from above. The requirements considered for the aerial images are described in section 3.3.

The acquired set of images then go through a flower localization process. In this step, possible regions that are suspected to be *Lantana camara* is located. Two methods, namely Local Binary Patterns (LBP) and thresholding has been experimented for their performance. These mechanisms are further described in section 2.4. The thresholding mechanism in L*a*b* colour space has shown a significant performance in localizing *Lantana camara.* Thus, the next steps are performed upon the results of localizing flowers using the thresholding mechanism. The experiments carried out on the two methods, LBP and thresholding, and the results obtained are further discussed in section 5.2. The thresholding-applied images then go through morphological operations, dilation and erosion, in order to remove noise. The resulting image consists of clusters indicating the presence of possible flower regions of the original image. Section 3.4.2 give further details on the flower localization task. The clusters in the resulting image are calculated for their centers and a square around these centers are cropped. These cropped images indicate possible *Lantana camara* flower images.

These set of images then go through a classifier to be classified for its class. The classifier used in this study is a convolutional Neural Network (CNN). The CNN architecture, CNN components and the employed type of CNN is explained in details in section 2.5. The flower localization process was employed in the proposed methodology to reduce the number of cropped image patches needed to be fed into the CNN, thus improving efficiency. After these cropped images are classified by the CNN, the images that were classified as *Lantana camara* are taken and marked in the original image. Other images are not further considered. The mapping process is clarified in section 3.7. The end result of the overall design would be the original aerial image marked with *Lantana camara* flower presence. The presence of flowers indicates the distribution of *Lantana camara* plant in the considered area that is captured by the image.

1.4 Outline of the Dissertation

Chapter 1 gives a brief introduction for the research with sections describing the background, research problems, methodology and limitations. Chapter 2 presents a literature review on available attempts to identify the distribution of *Lantana camara,* related work on identifying *Lantana camara* leaf, studies that has been carried out to classify flowers and how CNNs are applied in plant identification. The design of the proposed methodology is discussed in chapter 3 and it gives details of different techniques used in achieving the main goal of the study. Chapter 4 explains how the techniques discussed in chapter 3 are implemented. The results of the proposed methodology and the evaluation process is presented in chapter 5. Lastly, chapter 6 discusses the conclusions of the results and evaluation process.

1.5 Delimitations of Scope

The proposed methodology has put its foundation upon the presence and visibility of *Lantana camara* flowers in an area that is invaded or suspected to have been invaded by *Lantana camara.* Therefore, the presence of flowers is a requirement for the design to be successful, which leads it to be most efficient in the flowering season of *Lantana camara.* The aerial images taken of an area should be of high quality and *Lantana camara* flowers in these images should be visible to an extent, where it is identifiable by a naked eye. The height, which the images are taken from, is not important as long as the images contain identifiable *Lantana camara* flowers as described previously. The images also need to be taken in soft shadow-less daylight. The media used for image acquisition is not an important factor for this study. However, the above-mentioned conditions must be met for the acquired images.

The method cannot be used in locating *Lantana camara* plants grown under a thick canopy layer as these plants are less likely to able to be captured as an aerial image. However, *Lantana camara* growth under a thick canopy layer is very rare due to the fact that the plant needs direct sunlight to grow well.

This proposed approach is more suitable at identifying the presence of *Lantana camara* in areas with flat lands with few trees.

1.6 Summary of the chapter

In this chapter, main components of the dissertation have been laid out. In here the research problem, research questions and hypotheses are introduced. Then the research was justified, definitions were presented, the methodology was briefly described and justified, the dissertation was outlined, and the limitations were given. On these foundations, the dissertation can proceed with a detailed description of the research.

Chapter 2 - Background & Literature Review

2.1 Introduction

This chapter provides an overview of the invasive plant, *Lantana camara,* and reported studies that are carried out for *Lantana camara* detection, identification of *Lantana camara* distribution, flower identification and plant identification using Convolutional Neural Networks (CNNs). Furthermore, this chapter provide details on image processing techniques experimented in this study as well as details about CNN, its components and the employed CNN architecture in the proposed methodology.

2.2 *Lantana camara*

2.2.1 Introduction

Lantana camara [11] is a flowering plant, which is native to American tropics. It had been widely planted as a garden plant. However, the plant has now spread over 60 countries around the world and is now very commonly considered as an invasive plant. The scientific classification of the plant is as follows.

- Kingdom: Plantae
- Order: Lamiales
- Family: Verbenaceae
- Genus: Lantana

Lantana camara is being referred by a number of names including big-sage, wild-sage, red-sage, white-sage, tickberry, etc. In Sri Lanka it is known as "Gandapana", "Baloliya" or "Rata Hinguru". The plant has been spread over Sri Lanka after escaping from Royal Botanical Gardens in Peradeniya. *Lantana camara* is considered as one of the worst invasive species in the world according to Global Invasive Species Database, which is maintained by the Invasive Species Specialist Group (ISSG) of International Union for Conservation of Nature (IUCN).

2.2.2 Characteristics of *Lantana camara*

Characteristics of *Lantana camara* plant and its organs are discussed in this section.

Plant

Lantana camara is a shrub that can grow up to 4 meters high. The shrub is vigorous that it can live a wide variety of environmental conditions. It also can survive many natural hazards such as floods, droughts, etc. The plant contains a toxic chemical that helps it to outgrow other plants [12]. Figure 2.1 shows a *Lantana camara* plant.

Leaves

The leaves of this are small and the characteristics of the leaf can be slightly different from environment to environment. The shape of the leaf can be elliptical or oval shaped. The apex of the leaf can be broadly rounded or pointed. The surface is hairy and deeply veined. The margins can be round toothed or regular toothed. A strong odour can be noticed when the leaf is crushed. Leaves are not edible for animals because of the toxicity. A sample image of *Lantana camara* leaves is shown in Figure 2.2.

Flowers

The flowers of the *Lantana camara* plant is very unique and colourful. Various colour combinations including colours such as red, orange, yellow, pink, purple, white can be seen in *Lantana camara* flowers. The flowers of this plant are small. They are tubular shaped and arranged in clusters. The colours of the flower change with age. The flowers can be seen almost throughout the year. An example of a *Lantana camara* flower is shown in Figure 2.3.

Figure 2.1 : *Lantana camara* plant [13]

Figure 2.2 : *Lantana camara* leaves [14]

Figure 2.3 : *Lantana camara* flowers [15]

Fruits

The fruits of this plant are very small and can be of colours green or dark purple (ripe). The plant produces around 12,000 seeds per year. The fruits of *Lantana camara* are edible. Figure 2.4 shows an image of *Lantana camara* fruits.

Figure 2.4 : *Lantana camara* fruits [16]

2.2.3 Invasive behaviour of *Lantana camara*

Lantana camara shows a strong invasive behaviour. As mentioned in section 2.2.2 it produces a large number of seeds throughout the year. Seed eating animals like birds distribute these seeds widely, which leads to the dispersal of the plant. Moreover, the plant can grow quickly in recently burnt areas, cleared areas for cultivation or areas where trees have been cut for timber. Due to the toxic chemicals it produces other plants cannot compete with it. Due to these reasons, the plant can invade areas widely.

2.2.4 Threats by *Lantana camara*

The invasiveness of this plant has led to a number of threats around the world [17,18]. Following are some of the threats by *Lantana camara.*

- Changes in soil
- Outpace native trees and plants
- Reduce food productivity for wild animals
- Devaluation of natural habitat
- Reduction in biodiversity
- Increase the risk of wildfire in forests

2.2.5 Removal of *Lantana camara*

Given the threats emerged by Lantana camara, it is often needed to be removed. There are number methods used for this. The use of fire and herbicides are very common approaches in removing *Lantana camara*. The use of heavy machinery or people to remove *Lantana camara* is also another effective method. A less common method of biological control has been recorded by Day et al. [19] and Cilliers et al. [20]. Here, they have introduced an insect species to control the growth *of Lantana camara*. Another method to control *Lantana camara* growth is re-vegetation. A plant that outgrows *Lantana camara* is introduced to invaded areas. Such method has been discussed by Fernando et al. [21] by mentioning *Panicum maximum* as a plant to control *Lantana camara* invasion.

2.2.6 Summary

Lantana camara is an invasive plant that has threaten the biodiversity of a number of geographically significant areas around the world. The toxic chemical that it includes has sustained for its invasive behaviour. Even though variety of methods for *Lantana camara* plant evacuation exist, finding places invaded places by *Lantana camara* in a larger area has been a major concern. The reason is that the plant can grow very widely and dense, which makes humans unable to reach those areas and find them. Therefore, a mechanism is needed to discover *Lantana camara* invaded areas without having humans to reach those places.

2.3 Related work

Plant identification has been a challenging task in computer vision and image processing. This task can be carried out by focusing on different organs of plants such as leaf, flower, bark or the plant as a whole and different plant features such as colour, texture, shape, contour or venation pattern. The most used organs are for plant identification are leaf and flower, as they show many unique and distinguishable features. The next four subsections discuss related work on different plant identification approaches as follows.

- Studies that have been carried out for identification of *Lantana camara* distribution using remote sensing.

- Studies that have been carried out for *Lantana camara* identification using leaf.
- Approaches for flower identification.
- Studies that have been carried out to identify plants via Convolutional Neural Networks (CNNs).

2.3.1 *Lantana camara* identification via remote sensing

There have been a few approaches to identify *Lantana camara*. One of these approaches include remote sensing, which detects the distribution of *Lantana camara* in larger areas. Kimothi et al. [22] have done a study to evaluate the utility of satellite images obtained from IRS LISS-IV and Cartosat-1 satellites to differentiate *Lantana camara* from other vegetation. The methodology they have followed used a maximum likelihood classification using extracted mean, contrast and variance features from the merged two satellite imageries. The results have shown 94.6% differentiation for *Lantana camara*. The availability of satellite images of IRS LISS-IV and Cartosat-1satellites is a limitation to countries other than India.

A similar approach has been taken by Fernando et al. [21] to identify the distribution of *Lantana camara.* This approach has also used satellite images and has done a Normalized Difference Vegetation Index (NDVI) calculation along with a supervised classification. The researchers have reported 92% accuracy for *Lantana camara* identification. However, they have mentioned that identifying *Lantana camara* mixed sites was difficult, because of the low image resolution of the satellite images.

Taylor et al. [23] has done a study to find the optimal band (hyperspectral wavelength) *Lantana camara* discrimination that can be used for hyperspectral imagery. The experiment has been carried out on Hyperion (a hyperspectral imaging spectrometer on the NASA Earth Observing-1 satellite) images, which consists of 155 bands. The two approaches, statistical analysis of the reflectance and the first derivative reflectance (FDR), have identified 86 and 18 optimal bands, respectively, to differentiate *Lantana camara* from 7 other co-occurring species. Reported accuracies are of 80%, 77%, 76% for all 155 bands, for selected optimal 86 bands and 18 bands, respectively. Despite the fact that this study has found a reduced number of bands to discriminate *Lantana* camara without a major decrease in the classification accuracy, the authors have mentioned that the selected optimal bands may be fixed to the evaluated environment.

In the study carried out by Priyanka et al. [24], the researchers have built spatial invasion distribution models for *Lantana camara* using three species distribution modeling algorithms known as Biomapper, GARP and Maxent. In this study, 108 environmental variables were considered as potential predictors and 33 were selected into predicting the distribution of *Lantana camara*. Evaluation of the models has been carried out on satellite data and open source maps. The Maxent model has outperformed other two models and has reported accuracies of 87%, 79%, 71%, 78%, 80% for very low, low, moderate, high and very high *Lantana camara* distributions, respectively. Although, the availability of the data for the selected environmental variables is a limitation of this research.

Masocha et al. [25] have proposed a methodology to map *Lantana camara* distribution using Support Vector Machines (SVM) and Neural Networks (NN) classifiers. These classifiers have used habitat and terrain position data and they have been evaluated for their performance, alone and combined with a GIS (Geographic Information System) expert system. The best accuracy of 83% has been reported by the combination of the neural network and the expert system. However, *Lantana camara* absent areas and areas with a low distribution of *Lantana camara* are misclassified due to insufficient spectral information.

2.3.2 *Lantana camara* leaf identification

To identify *Lantana camara* through leaf, a study has been carried out by Olsen et al. [26] using Histogram of Oriented Gradient (HOG) descriptors, which focus on leaf texture. They have used images of lantana camara leaves in its natural background for evaluation and have achieved 86.07% accuracy from the two-stage binary classification procedure they have proposed. Four classifiers have been experimented in this study, namely, Logistic Regression (LR), Linear Support Vector Machines (LSVM), Gaussian Support Vector Machines (GSVM) and Neural Networks (NN). NN has shown the best performance in the first stage binary classification. Thus, the output from the NN has been used for the second stage binary classification. The aforementioned classifiers have been used to experiment in this stage also. Here, LR has outperformed other classifiers. As authors have mentioned, the reason for this is that the input vector size is small in this stage.

Salve et al. [27] have used leaf shape descriptors to identify plants. The two shape descriptors, Zernike Moments (ZM) and HOG, used in this study have obtained 84.66% and 92.67% accuracies respectively. The evaluation has been carried out on a subset of "VISLeaf" dataset. However, the considered dataset only contains 10 leaf images for each of the 50 plant species (including *Lantana camara*). Furthermore, these images of leaves are not captured in its natural environment compared to the aforementioned study [26].

2.3.3 Flower identification approaches

There have been a number approaches to detect flowers in computer vision domain. Nilsback et al. [28] have followed a study to investigate the performance of a multiple kernel framework with an SVM classifier using four features, (local shape/texture, shape of the boundary, overall spatial distribution of petals, and colour) alone and combined. The experimentation has been carried out on 8189 images belonging to 103 classes. The methodology also includes a segmentation process to separate the flower from background. The results have shown the best accuracy of 72.8% for the combination of all features. This infers that the classification accuracy increases when more features are used.

Another flower classification approach has been taken by Guru et al. [29] using two texture features (grey-level co-occurrence matrix and Gabor responses) on a K-Nearest Neighbour (KNN) classifier. An HSV thresholding method has been used for flower region segmentation. Evaluation has been carried out on a dataset of 1250 flower images, which belongs to 25 categories. The use of combined features has shown 98.88% accuracy.

Sari et al. [30] have proposed a model for flower identification that addresses the effect of lighting conditions. For this, they have removed the L* channel and considered only a* and b* channels in the L*a*b* color space of the images. A texture feature extracted using Segmentation-based Fractal Texture Analysis (SFTA) also has been considered in this approach. For the classification these two colour and texture features have been utilized for a KNN classifier method. Evaluation has been carried out on a dataset consist of 400 images belonging to 10 categories. Images have been preprocessed to segment the flower region. Circular Average Filter (Pillbox) and Otsu's thresholding have been applied to achieve this task. The best accuracy recorded for this study is 73.63%.

A further approach using a Neural Network (NN) has been carried out for flower classification by considering colour features gained from normalized colour histogram and texture features gained from grey-level co-occurrence matrix by Siraj et al. [31]. This study has concluded that the number of images used in training affects the accuracy of the results and classification accuracy can be improved by duplicating images that are difficult to learn.

2.3.4 CNNs for plant identification

Convolutional Neural Network (CNN) is a deep feed-forward artificial network that has been effectively used in image recognition recently. A tree classification system called "Treelogy" has been introduced by Cugu et al. [32] by employing a CNN and an SVM. A leaf-based recognition has been followed on a dataset of 57 tree species with 5408 leaf images that are segmented out from the background. These images have been used to extract 15 hand-crafted features (e.g. mean, standard deviation, contrast, entropy, etc.) and a several combinations of them have been used to train a Linear SVM (LSVM). The Caffe framework [33], along with CaffeNet (a variation of AlexNet [34], which is further described in section 2.5.4) has been used as the CNN architecture and have been fine-tuned using the same set of images used for classification. The best accuracy of 90.5% has been obtained by the LSVM trained using both CNN feature vectors and hand-crafted features.

Another leaf-based plant identification approach has been taken by Lee et al. [35]. In this study, AlexNet [34] has been used as the CNN architecture and it has been used to learn leaf features. A Deconvolutional Network (DN) has been applied to visualize the learnt CNN features. The CNN has been fine-tuned using a dataset containing 2816 images of 44 species. For the training process two types of data has been used: 1) Leaf image as a whole with HSV colour extracted from the leaf area. 2) Cropped patches within the leaf area. Results show that the latter produced better results. The study deduces that the shape of the leaf is not a good feature for plant identification. This is due to highly activated features falls on the shape of a leaf, which leads to misclassification of leaves that are similar in shape. Meanwhile, they have concluded that the venation structure is a promising feature for plant identification. The study reports 99.5% accuracy for the Multilayer Perceptron classification based on CNN features, which were obtained using cropped patched within the leaf area. They have also inferred that CNN features provides a better representation when compared to hand-crafted features.

Ghazi et al. [36] have performed a study to identify plant species via three CNNs, namely, AlexNet [34], GoogleNet [37] and VGGNet [38], using images of different plant organs. Among these three CNNs AlexNet comprises the simplest architecture (with less number of layers), while GoogleNet and VGGNet consist of very deep architectures. VGGNet has the most number of parameter, which is 144 million in number. The evaluation of this study has been carried out on the dataset of LifeCLEF 2015 [39] which contains around 1.2 million images belonging to 1000 classes. Results of this study has concluded that GoogleNet and VGGNet exhibit higher performances, where GoogleNet performed the best accuracy of 78.44%. This implies that having more layers in the architecture provides more accuracy. However, the authors have mentioned that simpler networks with less layers and parameters will benefit in defining novel and computationally efficient networks.

The comparative study on CNNs for identifying plant species using flower images has been experimented by Nguyen et al. [40]. Three CNNs, AlexNet, CaffeNet and GoogleNet have been evaluated on extracted flower images of PlantCLEF 2015 [29]. The researchers have employed a saliency-segmentation-based approach to select the flower region of an image. The best accuracy of 67.45% has been obtained by GoogleNet for raw images. The authors have concluded that GoogleNet performed better because it has more layers than other two CNNs. And also, GoogleNet performs better than hand-crafted features based on Kernel Descriptor (KDES) techniques due to the fact that the descriptor is not flexible enough to reveal different features for flowers. Furthermore, the reason for obtaining a better accuracy for raw images compared to preprocessed images is explained as, sometimes preprocessing may disregard the flower itself as well as flower related information in its natural background.

2.3.5 Summary

In order to locate *Lantana camara* in larger areas, remote sensing technology has been an effective technique for many researches as mentioned in section 2.1, where images are taken from satellites and open source maps. However, these methods can be costly, may not provide images with sufficient spatial resolution or may not be available for some areas. As a solution for this Unmanned Aerial Vehicles (UAVs) or manned aircrafts can be used in high resolution image acquisition. Although, the usage of manned aircrafts is costly and can be inefficient compared to UAVs. In this case, UAVs are very flexible, easy to handle, less costly and can be operated even in risky environments. Since it can fly at lower altitudes, it can take high resolution images, where even small details of a plant can be detected. It can carry different sensors as per the user's need and can operate on its own with scheduled routes. However, UAVs have to take a number of images to cover a large area compared to satellites or aircrafts. Yet, UAVs would be the ideal solution for acquiring high quality images compared to above mentioned drawbacks in satellites, open source maps and manned aircrafts.

Giving consideration to the limitations of the approaches mentioned in section 2.3.1, these methodologies can be less successful in identifying *Lantana camara* in different situations. Therefore, an approach is needed to overcome all these restrictions.

To the best of our knowledge, there have been no study done to identify the distribution of *Lantana camara* with the use of leaf detection or flower detection. However, for identification of *Lantana camara* distribution, the use of flower detection can be much more efficient because of the unique features that *Lantana camara* flowers exhibit and the wide spread of flowers over the plant in its flowering season. In contrast, *Lantana camara* leaf, can show very few notable features to be helpful in being identified in aerial images, when surrounded with other plants (*Lantana camara* leaf can be very easily mistaken for leaves of other plants such as *Chromolaena odorata*).

In this dissertation, a novel approach to identify *Lantana camara* distribution is presented using a flower detection mechanism. Compared to the remote sensing methodologies discussed in section 2.3.1, the proposed method will be able to detect *Lantana camara* even when it is mixed with other plants or its distribution is very low in certain places. Therefore, the proposed methodology will be more effective when eradicating *Lantana camara*. In addition, the proposed methodology is not dependent on the site tested. Thus, when the conditions for the image acquisition are met, the methodology can be utilized in a wide variety of places around the world.

2.4 Image processing techniques

2.4.1 Local Binary Patterns (LBP)

LBP [41] is a powerful mechanism in object recognition where it shows robustness over differences in brightness, contrast, image rotation and image scale [42]. In this method, the calculation is done by comparing the intensity of each pixel with the intensities of the neighboring pixels and transforming this comparison to a binary number. This number is then converted into a decimal number. The neighborhood size can be different. Figure 2.5 shows how this process is carried out for one pixel considering a 3x3 neighborhood.

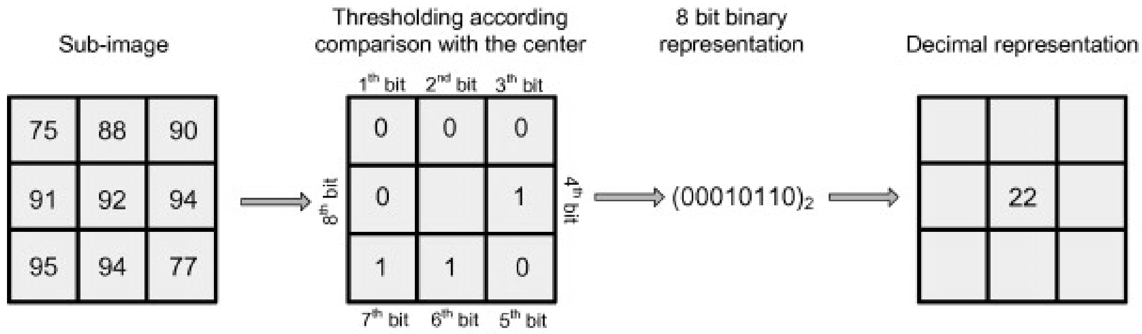
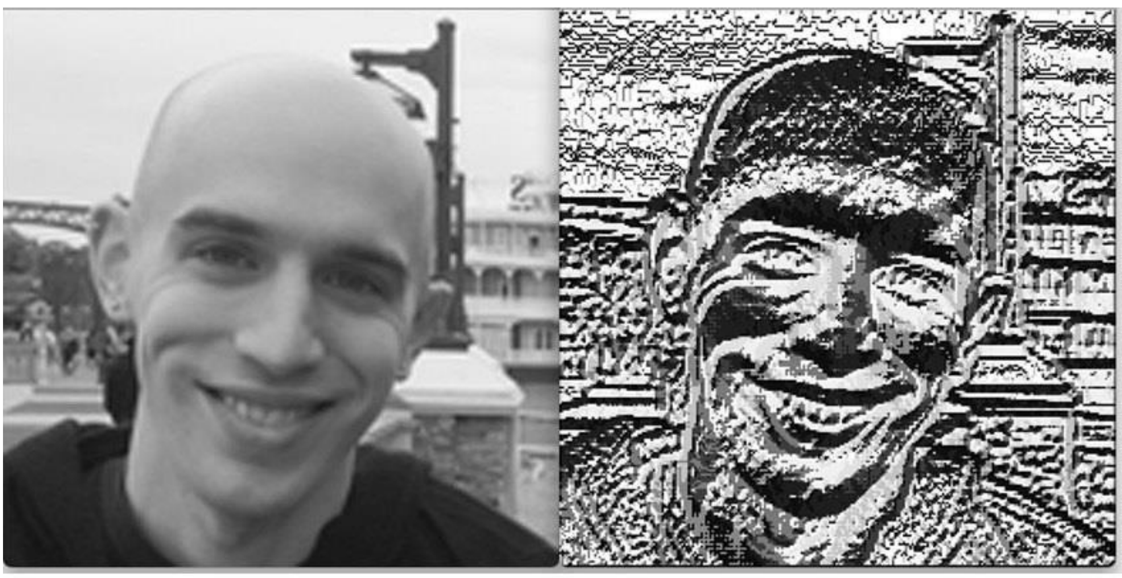


Figure 2.5 : LBP process [43]

In the example, the middle pixel is being considered and the neighborhood pixels are the pixels around it. The intensity of the middle pixel is taken as the threshold intensity and this intensity will be compared with the intensities of the neighboring pixels. If the pixel being considered has an intensity less than the threshold intensity it is given the binary value 0, otherwise it is given 1. After comparing all neighboring pixels, each pixel will get 0 or 1. These values are written as a binary number following a clockwise manner starting from the top left corner pixel. The resulting binary number is then converted to a decimal number and this number will be taken as the new intensity for the middle pixel. This process is repeated for all pixels in the image. Figure 2.6 represents an example of LBP computation on an image.



(a) (b)

Figure 2.6 : LBP computation applied to an image [44]. (a) Original image. (b) LBP applied image.

2.4.2 Thresholding

Thresholding [45] is a simple method that creates a binary image by comparing all pixel intensities with a fixed constant (threshold). If the pixel being compared has a higher intensity than the threshold it will be represented in white, otherwise will be represented in black (the representing colors can be changed as necessary). This is the basic concept behind thresholding. The optimal threshold values fall on the valleys of intensity histograms. However, the threshold selecting mechanism can be changed as per user's needs.

RGB thresholding:	Thresholding is done by using separate thresholds for the 3 color channels Red, Green and Blue. Only the pixels which have intensities less than (or greater than according to the situation) the threshold are selected for the results. These results for three color channels are then combined together using AND operator.
HSV thresholding:	In this method, a similar approach followed by RGB thresholding, is used for Hue, Saturation, Value (HSV) color space.
YC_BC_R thresholding:	A similar approach used for RGB, is used for the YC_BC_R color space.
L*a*b* thresholding:	A similar approach used for RGB, is used for the L*a*b* color space.

Figure 2.7 shows an example of applying thresholding mechanism to an image. Figure 2.7 (b) plots the intensity histogram of the original image. Peaks indicate that, there are a higher number of pixels are having intensity values at peaks and valleys represent that a lesser number of pixels are having intensities at the valleys. The threshold is selected at the valley between two peaks and shown by the line drawn in the middle. A threshold at a valley indicates a clear separation for the image.

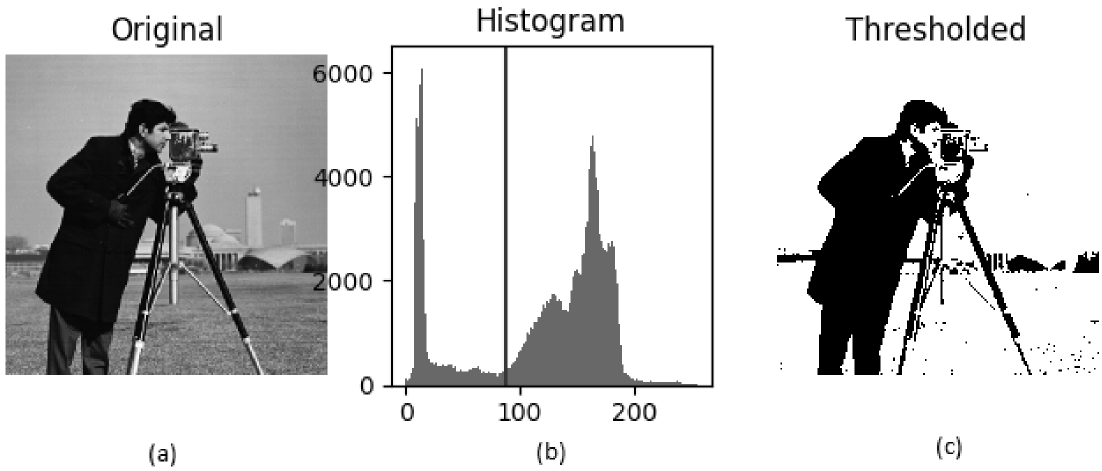


Figure 2.7 : Application of thresholding on an image [46] (a) Original image. (b) Intensity histogram. (c) Thresholded image.

2.4.3 Edge detection

Edge detection is an image processing technique to identify edges of objects in an image. More specifically this method identifies points with discontinuities of brightness or intensity. Intensities of an image continues smoothly throughout an object in an image and this smooth continuity drops at the edges of the object. Thus, this point can be considered as a edge point in the image. Edge detection has shown an important role in image processing, computer vision, machine vision, feature extraction, feature detection and image segmentation [47]. Figure 2.8 presents an image applied with Canny edge detection mechanism.

Figure 2.8 : Canny edge detection example [48]

2.4.4 Summary

The applicability of LBP method and thresholding method is experimented in this study. The edge detection mechanism is not experimented for this study due to the presence of large number of objects in considered images in this study. The edge detection method is less efficient in segmenting objects when there are thousands of same sized objects surrounded by edges, which is the case in the images used in this study.

2.5 Convolutional Neural Network (CNN)

2.5.1 Introduction

Convolutional Neural Network(CNN) has been an emerging technique used in areas such as image recognition [34], speech recognition [49] and natural language processing [50]. CNNs has been inspired by Neocognitron, which is a hierarchical, multilayered artificial neural network introduced by Fukushima et al [51]. The first application of CNNs has been recorded by LeCun et al. [52] for developing a CNN named LeNet for document recognition. The CNNs share the same weights and biases over a layer, unlike neural networks. They show translation invariant and space invariant characteristics [53, 54], thus performs better in recognition tasks. In the year 2014, most of the highly ranked teams have used a CNN in their work in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [55], which is a benchmark in object detection and classification. An example result of ILSVRC 2014 is shown in Figure 2.9.

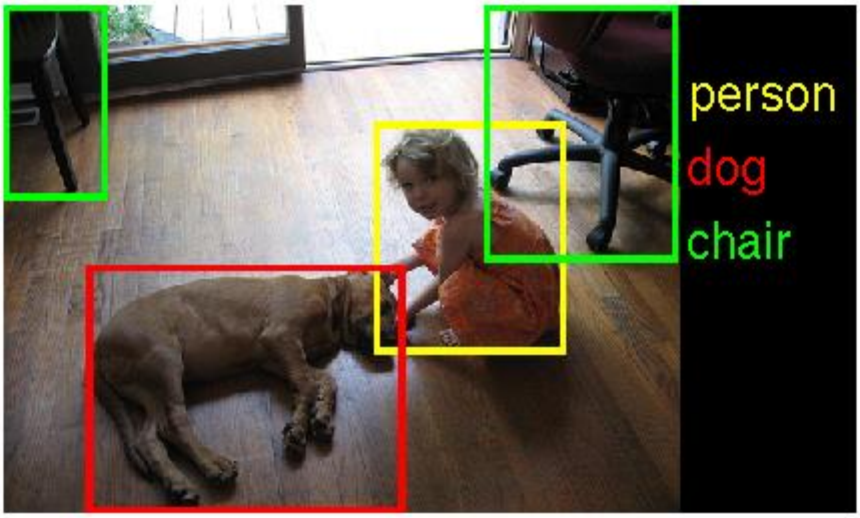


Figure 2.9 : Example classification of ISLVRC 2014 [56].

2.5.2 Suitability of CNN for image recognition

CNN has been an emerging technique for image recognition over neural networks. In neural networks, images are flattened to a single vector and to train this flattened vector, a set of fully connected layers are used. However, using this approach, important shape information is neglected as the images are flattened. To avoid this CNNs came in to the picture. In CNNs neurons are only connected locally, rather than having fully connected layers as in neural networks. Therefore, shape information is preserved and taken into consideration when feature maps are generated in each layer. Thus, this machine learning technique has shown a significant performance over other learning techniques in image recognition tasks.

2.5.3 CNN architecture

A CNN contains an input layer, a number of hidden layers and an output layer. Hidden layers of the CNN can consist of convolutional layers, pooling layers, ReLU layers, fully connected layers, dropout layers or loss layers. A combination of these layers builds up the CNN architecture. The task of each hidden layer is described as follows.

Convolutional : Layer — Each neuron in this layer is retrieved by a convolution operation applied on its input. The kernel used for each neuron is designed using same weights and a bias. Therefore, all the neurons learn exact same feature from the input. The output is called a feature map. A number of feature maps can be created as necessary.

Pooling Layer : — These layers are used immediately after convolutional layers. The input for this layer is a feature map. The feature map is divided into regions of same size and these regions are combined into a single neuron. Different pooling procedures are used in this, such as max pooling and L2 pooling. Suppose x_1, x_2, ..., x_n are the values of the neurons in a selected region, then max pooling and L2 pooling procedures are defined as follows.

$$\text{Max Pooling : } f(x_1, x_2, \ldots, x_n) = \max(x_1, x_2, \ldots, x_n) \quad (1)$$

$$\text{L2 Pooling : } f(x_1, x_2, \ldots, x_n) = \sqrt{\textstyle\sum_{i=0}^{n} x_i^2} \quad (2)$$

ReLU Layer : — In this layer, non-saturating activation function, $f(x) = \max(0,x)$ is applied to the neurons in the previous layer.

Dropout layer : — Dropout is a solution for the over- fitting problem. In this layer, some of the neurons get opted out in order to avoid them being specialized on training data. The neurons that get opted out is different for each iteration.

Norm Layer : — Performs normalization over a set of neurons.

Fully Connected : Layer — Neurons of this layer is connected to all neurons in the previous layer and computed their values just as a normal neural network. This layer comes after a set of multiple convolutional, pooling and ReLU layers.

Loss Layer : — This layer comes after the fully connected layer. It computes the inaccuracy of the predicted class from the actual class for classification problems. Calculation of loss can be computed using functions such as Softmax loss or Hinge loss (in classification problems), Euclidian loss (for Linear regression problems) and Sigmoid Cross Entropy loss (for multi-classification problems).

An example of a CNN architecture is shown in Figure 2.10.

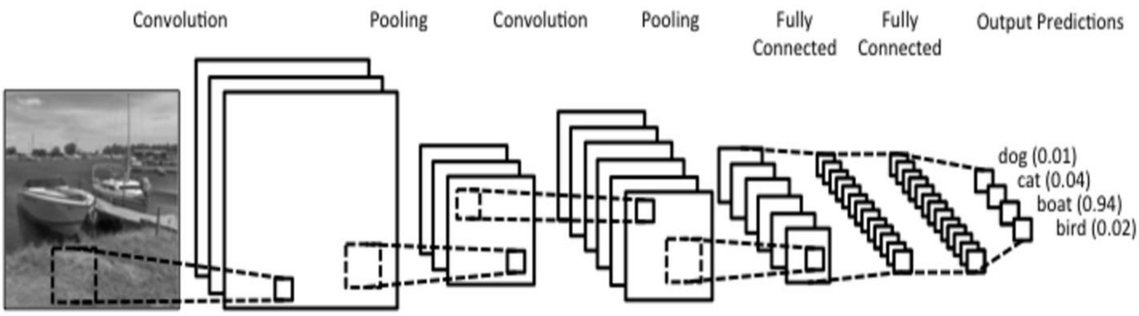


Figure 2.10 : An example of a CNN architecture [57].

2.5.4 AlexNet

AlexNet is a CNN designed by Krizhevsky et al. [34] to compete in ILSVRC [55] in 2012. They have achieved the least top-5 error rate of 15.3% for the classification of 1.2 million images to 1000 categories. AlexNet has marked a milestone in the ILSVRC history by achieving a significant decrease of the error rate over the state-of-art solutions at that time. The AlexNet architecture includes eight layers including five convolutional layers and three fully connected layers. The AlexNet architecture is shown in figure 2.11. AlexNet has been employed in the proposed design because of its simplicity, availability of resources and the wide community of users.

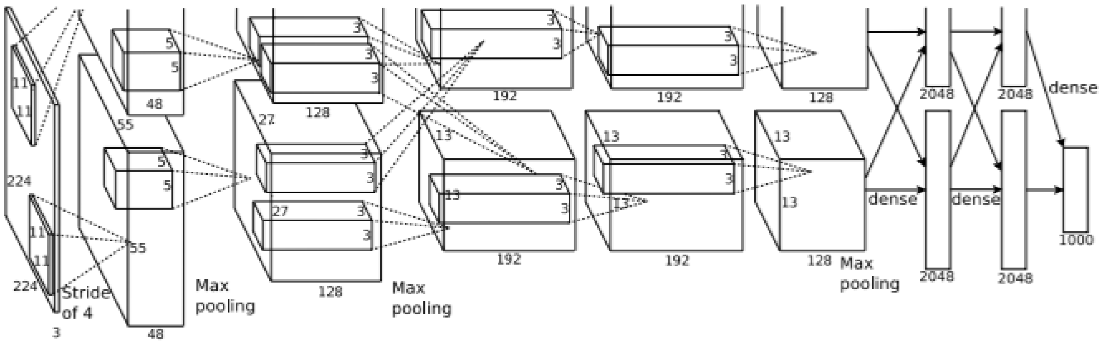


Figure 2.11 : AlexNet architecture [34]

2.5.5 Summary

Section 2.5 provided a detailed description of CNNs and it is concluded that CNNs provide a better classification in image recognition tasks due to its space and translation invariant characteristics and also due to its nature of focusing on local information of an image.

2.6 Summary of the chapter

This chapter discussed about the *Lantana camara* plant, its characteristics, threats to the environment and methods to remove this plant. Then it was highlighted the need of a mechanism to identify the distribution of this plant in larger areas. The previous work that has been done in order to identify *Lantana camara* plant is also stated. In addition, various approaches taken for the identification of plants through the use of leaves and flowers is discussed along with the utility of CNNs in plant identification. Furthermore, image processing techniques and convolutional neural networks were explained in detail at the last sections of this chapter. The next chapter gives full information about the proposed research design in this study.

Chapter 3 - Design

3.1 Introduction

This chapter gives the design details of the solution proposed for the identification of *Lantana camara* distribution. The chapter consists of six sections to describe the proposed model, the techniques and methods experimented in each stage of the model and considerable limitations of the model at each stage.

3.2 Proposed model

In order to identify the distribution of *Lantana camara*, several methods have been used as discussed in section 2.3. However, due to the limitations discussed in those approaches, a flower-based identification mechanism is proposed in this study. The reason behind focusing the flower is that, it is the most prominent organ that shows unique features compared to all other features of the plant. Figure 3.1 presents phases the proposed model for the research problem addressed in this study. A set of aerial images of an area, where the invasion of *Lantana camara* needs to be found, is considered as the input for this model. From these collection of images, possible flower regions are detected in the first stage. In the second stage a square around the detected flower regions are cropped, where the flower portion falls into the middle of the cropped area. In the next stage, these cropped patches are fed into a CNN, in order to classify them as *Lantana camara* or not. The patches that are classified as *Lantana camara* is then marked on the original image in the last stage. Each stage of the proposed model is explained in details and possible methods than can be followed to achieve them are discussed in the next sections.

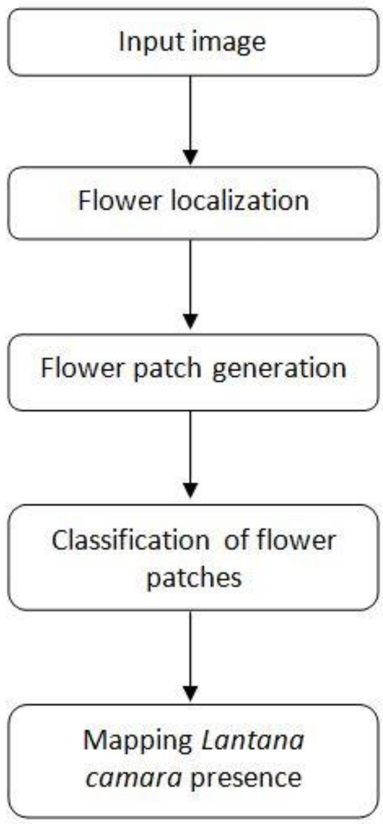


Figure 3.1 : Phases of the proposed model

3.3 Input image

A set of images taken of a *Lantana camara* invaded area is considered as the input images. These images should have following restrictions for the model to perform best.

- The area of the flower portion of an image should fall into a square of 50x50 pixels. If this restriction is not met, certain parameters of the design will have to be adjusted considering the image resolution.
- The images must be taken in soft light (shadow-less light).
- Camera angle is of less importance.

An example input image considered in this study is shown in Figure 3.2.

Figure 3.2 : Sample input image

3.4 Flower localization

A flower-based approach is considered as the solution in this dissertation disregarding the features of the whole plant or features of leaves, which are the most visible features (including flower features) in a *Lantana camara* invaded area. The reason behind taking no account of texture features of the whole plant is that, when the plant is mixed with other plants, the texture patterns can differ or not visible at all. On the other hand, the reason for neglecting the use of *Lantana camara* leaf is that, its leaves are very small to be detected in an aerial image and also, they do not show distinctive features which separate them from leaves of other plant species. Given that, the flower would be the best choice for detecting *Lantana camara* distribution. However, texture patterns of the whole plant and leaf features can contribute useful information to increase the accuracy of the proposed model, even though they are not taken into account in this dissertation.

In the flower localization step, possible spots that are likely to be a *Lantana camara* flower is recognized. The reason behind doing so is to increase efficiency by reducing the number of locations to be fed into the CNN. Otherwise, the image needs to be divided into hundreds of overlapping sets of smaller patches. Then these hundreds of image patches should be fed into the CNN for classification. Given that, the flower localization step reduces the number of patches need to fed into the CNN by identifying possible flower patches in the image. A set of image processing techniques were experimented in order to achieve this task. Section 3.4.1 and section 3.4.2 discuss the experimented methods in details.

3.4.1 Local Binary Patterns (LBP)

The input images go through the LBP mechanism explained in section 2.4.1. Figure 3.4 (b) represent the resulting image after applying LBP method to the input image. As it may seem, the result does not show important features for the flowers to be isolated from the background. However, when only the highest intensity values are selected and visualized as in Figure 3.4 (c), the result shows a clear separation of flowers from the background. That is, more connected dots in flower areas are visible when compared to the background. Yet, a salt-and-pepper effect appears on the resulting image. To remove this effect, erosion technique is applied. A disk-shaped kernel with the radius of 2 pixels is used in erosion operation. The reason to choose this kernel is that the majority of the noisy dots, which cause the salt and pepper effect are of the size less than the area of a circle with a radius of 2 pixels. The resulting image after applying erosion is presented in Figure 3.4 (d). Then a dilation operation is applied to the resulting image using a disk-shaped kernel with a radius of 10 pixels to join the dots and generate a cluster, which would become as nearly as the size of a flower. The resulting image after applying dilation is presented in Figure 3.4 (e). Although this procedure gives promising results, there are some limitations and considerations that should be noted when applying this process. These restrictions are as follows:

- The kernel size can differ on the quality of the image, because kernel is chosen in such a way to remove noise while preserving flower information. Therefore, kernel size should be adjusted accordingly before employing this method.
- The procedure might not provide sufficient results if the image quality requirements are not met.
- This method sometimes captures non-flower regions, because of the high illumination that they show compared to the background. However, these misidentified patches do

not make an effect on overall performance, because this method is employed to reduce the number of candidate regions in an image to be fed into the CNN.

- Not all flower regions are captured from this method. But this issue can be disregarded, because it is not the focus of this research to identify all flower regions, but to identify where a plant exists. Thus, not spotting all flower regions is tolerable as at least one flower segment is adequate to indicate the presence of a plant.

The whole process of localizing flower regions in an image using LBP is presented in the Figure 3.3.

Figure 3.3 : Flower localizing procedure with LBP

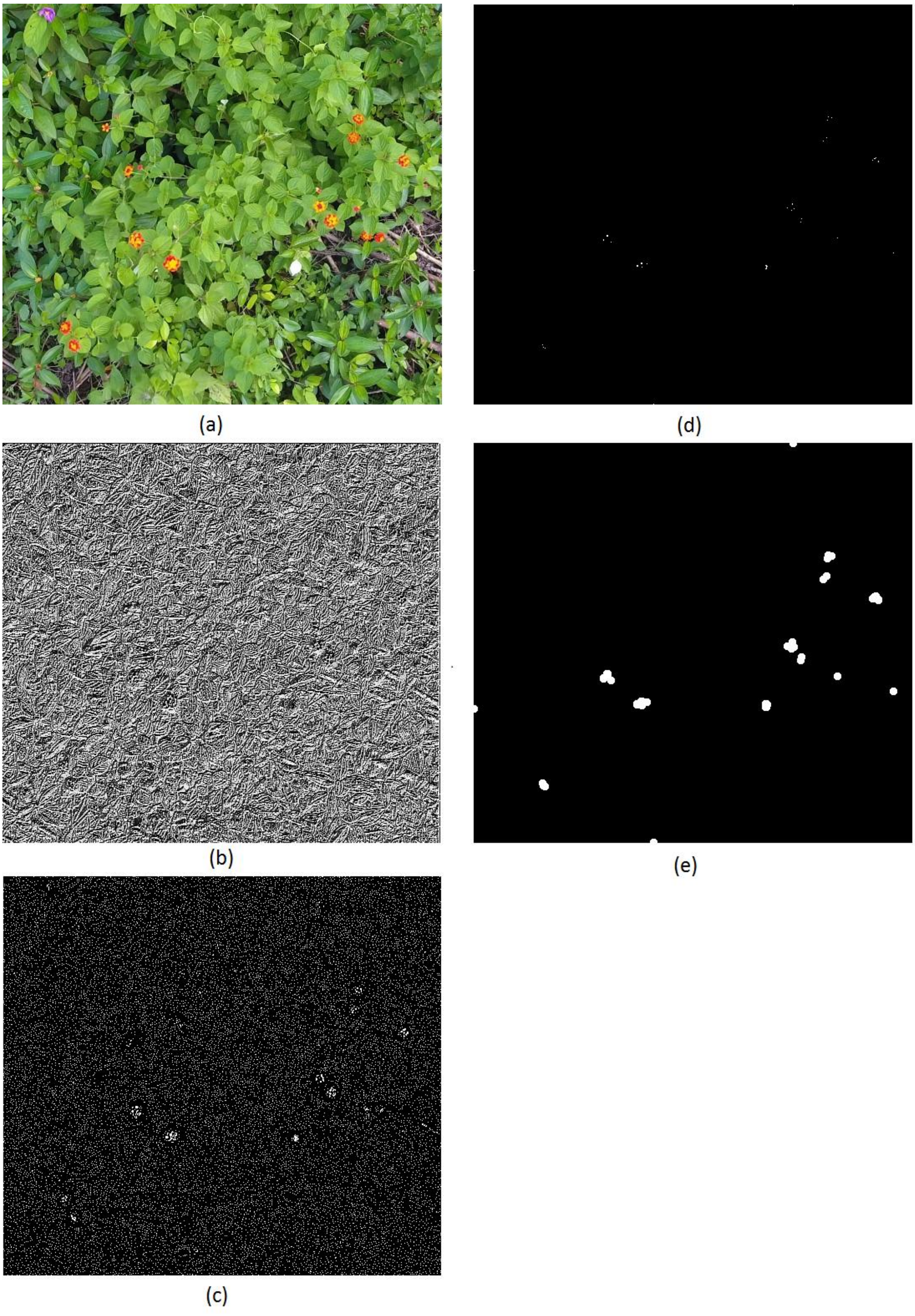


Figure 3.4 : Flower localization with LBP. (a) Original image. (b) Resulting image after applying LBP method. (c) Resulting image after considering highest intensities. (d)Resulting image after erosion. (e) Resulting image after dilation.

3.4.2 Thresholding

The applicability of thresholding mechanism is also experimented in this study to localize flower patches. The thresholding mechanism was explained with further details in the section 2.4.2. Figure 3.6 and figure 3.7 present the outcome of thresholding in RGB and HSV colour spaces, respectively. The results show that despite the variety of colours that *Lantana camara* exhibit, a set of common threshold values for each channel in the RGB and HSV colour space, can be found to flower segmentation.

For YC_BC_R thresholding and L*a*b* thresholding, a common threshold to segment flowers could not be found. This is due to the variety of colours that *Lantana camara* flowers consist of, which makes it difficult to agree upon a common threshold value to segment flowers of different colours.

However, there are some drawbacks of applying the thresholding method in flower localization.

Limitations

It can be seen in the second scenario of Figure 3.6, that the regions that has similar colours to the colour of the flowers, are also being detected. This is a critical situation when considering pink/purple *Lantana camara* flowers. The reason is that, pink/purple *Lantana camara* flowers display a colour, which can be easily found in the background. Therefore, when detecting pink/purple *Lantana camara* flowers, regions from background are also going to be detected. This fact could have been ignored if it only captures small areas with regard to the flower. But, the regions that displays pink/purple colour are very large compared to the flower. For example, sand roads and places with dried sticks and leaves show colours related to pink/purple, thus being captured by threshold mechanisms. Nevertheless, due to the fact that these areas do not show a uniform distribution in the image, a large number of clusters are segmented compared to the number of actual flower patches in an image, which leads to a reduced efficiency in the flower localization step.

Effective scenarios for thresholding

In spite of these limitations, thresholding mechanism is effective on localizing *Lantana camara* flowers of colours red, orange, red and orange, or orange and yellow. The reason is that these colours are less likely to be found in the background. And even if regions of these colours are found in the background, the case is trivial as these regions are not very large or distributed (most of the regions with these colours contains an object such as a flower or a plastic can, rather than a bigger area like a road). Thus, misidentified clusters of these colours would be very few and would not severely affect the efficiency of flower localization step.

The results of YC_BC_R thresholding and L*a*b* thresholding applied to orange *Lantana camara* flowers are shown in Figure 3.8. Out of the four thresholding mechanisms L*a*b* thresholding performed the best for segmenting red, orange, red and orange, or orange and yellow *Lantana camara* flowers.

Steps after thresholding

After segmenting possible flower clusters in an image, morphological closing operation (i.e. dilation followed by erosion) has to be carried out in order to fill the clusters that are not formed well. Next morphological opening operation (i.e. erosion after dilation) has to be performed to remove noises. A disk-shaped structuring element with the radius of 10 pixels used for these two operations. The size of structuring element should be adjusted according to the quality of the image.

The figure 3.5 shows the complete process of flower localization using thresholding mechanism.

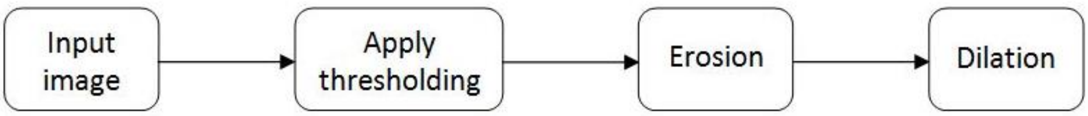
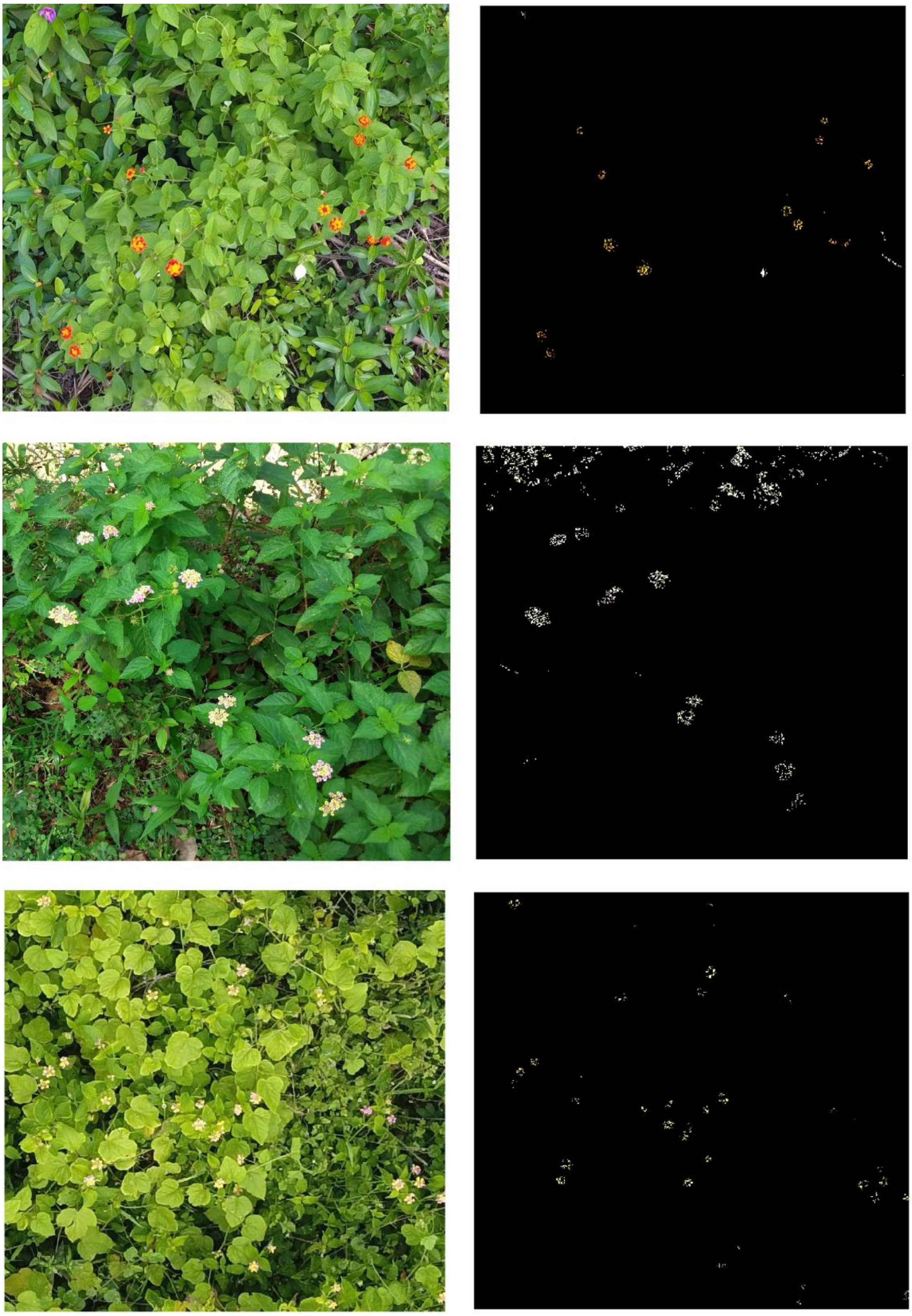
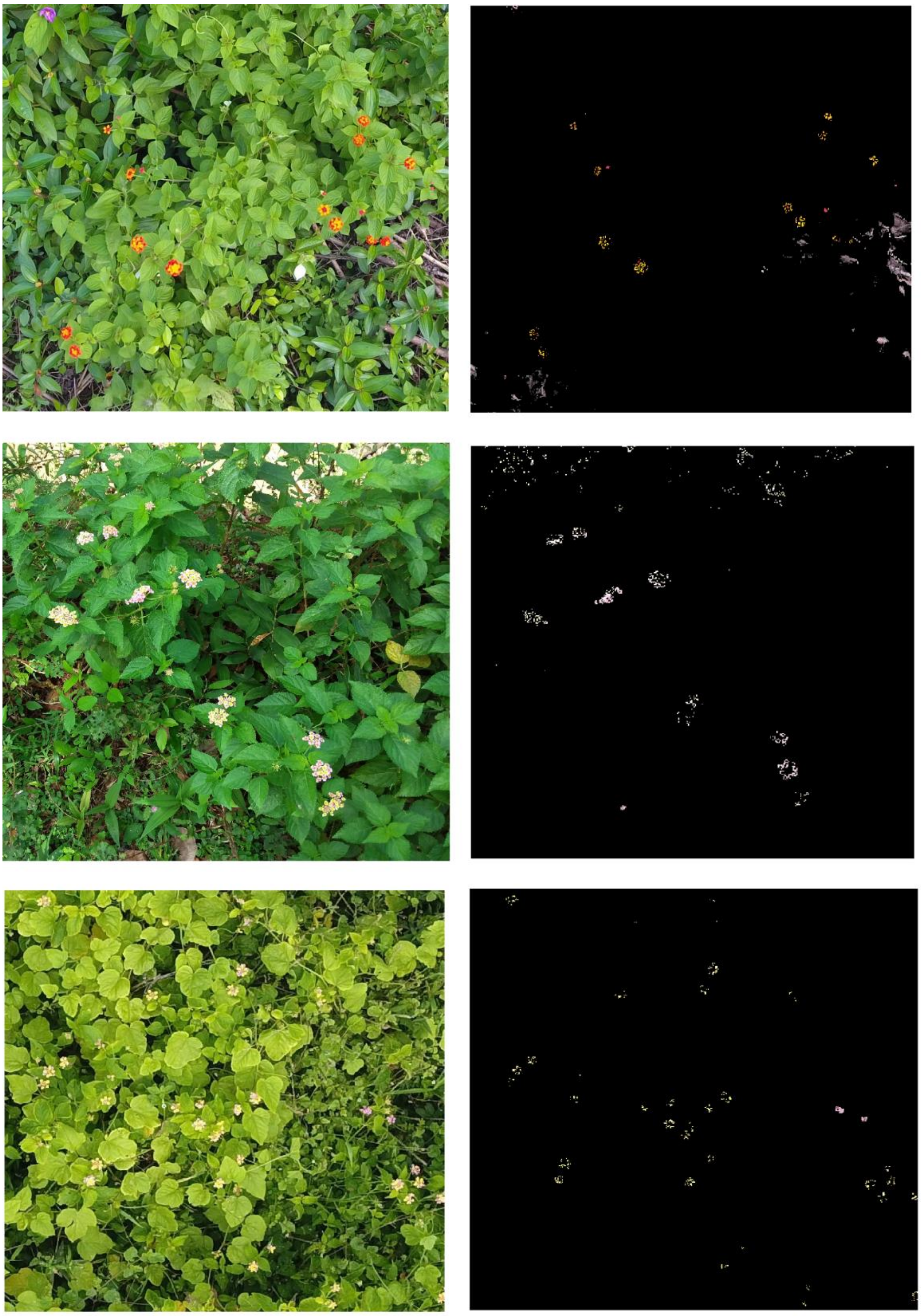


Figure 3.5 : Flower localizing procedure with thresholding



(a) (b)

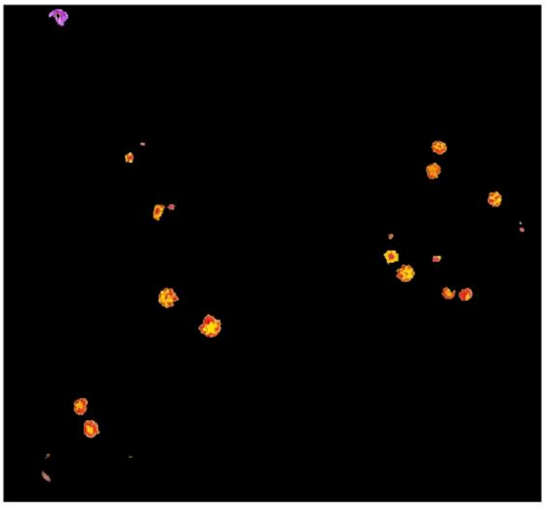
Figure 3.6 : RGB Thresholding. (a) Original images. (b) Resulting image.



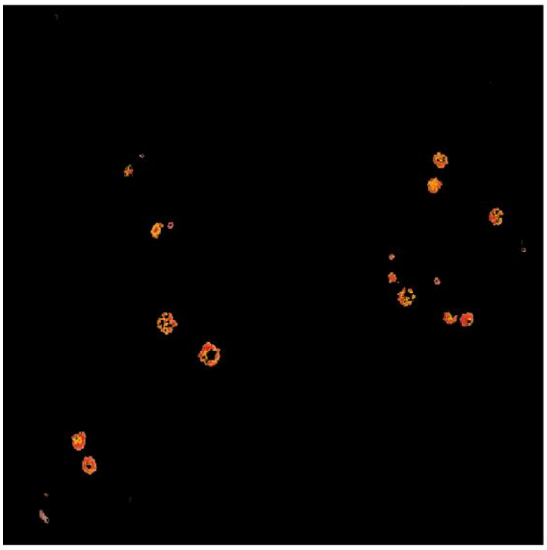
(a) (b)

Figure 3.7 : HSV Thresholding. (a) Original images. (b) Resulting image.

(a)



(b)



(c)

Figure 3.8 : Results of thresholding on orange *Lantana camara* flowers (a) Original image. (b) YC_BC_R thresholding result. (c) L*a*b* thresholding result.

3.4.3 Conclusion

Two mechanisms for flower localization were discussed in the section 3.4. It was concluded that both mechanisms are successful in discriminating *Lantana camara* flowers plants with red, orange, or yellow colour flowers, from the background. If the considered invaded area is certain to have *Lantana camara* plants with flowers of these colours, flower localization procedure which includes thresholding is more applicable. Out of the four colour spaces used in thresholding, L*a*b* colour space is chosen as the optimal solution as it performed better in discriminating red, orange, or yellow colour *Lantana camara* flowers. On the other hand, LBP included flower localization procedure is suited when the invaded area has *Lantana camara* plants with flowers of colours other than the mentioned colours as agreement on a global threshold for all colours is a limitation in thresholding.

3.5 Flower patch generation

As the result of the flower localization step, an image with a set of clusters to indicate the flower regions in it, is generated for each image. This image with clusters then go through a process to generate patches of flowers. To do this, the cluster center is calculated. Using this coordinate, a 100x100 pixels area is cropped around it and saved including its center coordinate details. In the following step, these saved image patches are fed into the CNN to be classified as *Lantana camara* or not.

3.6 Classification of flower patches

The generated possible flower patches from the aerial images should be then classified for its flower category. For this task, a classifier is needed to correctly recognize *Lantana camara.* The selected classifier is a CNN and the reason for employing a CNN for classification is justified in section 2.5.2. AlexNet [34] has been used as the selected architecture for its simplicity. The selected CNN has been trained to classify 967 flower species by using flower images (including *Lantana* camara) extracted from the lifeCLEF 2015 [39] dataset. The dataset is further described in section 4.3.1. The generated flower patches from the aerial images are fed into the classifier in order to classify the flower patches as *Lantana camara* or not.

3.7 Mapping *Lantana camara* presence

The classified patches of aerial images are used as the input of the mapping step. The patches that are classified as *Lantana camara* are taken into consideration and other patches are disregarded. The flower patches that are classified as *Lantana camara,* indicates that a *Lantana camara* flower exists in the location where the patch is taken. Therefore, using the center coordinate of each *Lantana camara* present flower patch, a 100x100 pixels square is drawn in the original aerial image where the patch is taken. The result of this step would be the original aerial image marked with squares around detected *Lantana camara* flowers.

3.8 Summary of the chapter

This chapter provided a detailed account of each step of the proposed model in this study. Section 3.1 provided a brief introduction for the chapter and section 3.2 provided an overview of the proposed model. Section 3.3 described the nature and the restrictions of the input image considered for the design. Flower localization phase and the applicability of LBP and thresholding mechanisms for flower localization are discussed in section 3.4. Furthermore, section 3.5 described the mechanism behind flower patch generation and section 3.6 narrated the utilization of CNN for the flower classification. Lastly, section 3.7 presented the mapping process of *Lantana camara* presence in the original aerial image

Chapter 4 - Implementation

4.1 Introduction

This chapter focuses on the implementation of the research design described in chapter 3. The chapter also discusses the tools and technologies utilized in the design. Furthermore, the details of the dataset used in training the CNN is given in detail.

4.2 Tools and technologies

4.2.1 MatLab

MatLab[1], which is short for Matrix Laboratory, provides a multi-paradigm numerical computing environment for complex matrix calculations, data visualization, developing and running algorithms, Graphical User Interface (GUI) generation and interfacing with programs written in other languages. It also provides collections of specialized functions and applications for solving problems in particular areas, such as signal processing, neural networks, wavelets, etc. This software tool is used in a wide variety of domains including, mathematics, statistics, science, engineering, computer science, etc. MatLab has been popular for its large community of active users and the detailed documentation it provides.

4.2.2 Caffe

Caffe[2], which is short for Convolutional Architecture for Fast Feature Embedding, is a deep learning framework developed by Yangqing et al. [33]. Caffe supports a number of deep learning architectures such as convolutional neural networks, fully connected neural networks, recurrent neural networks, etc. The framework is widely used in image classification and image

[1] https://in.mathworks.com/products/matlab.html
[2] http://caffe.berkeleyvision.org/

segmentation tasks [58-62]. Caffe provides an expressive architecture and an extensible code for development. It also provides a greater speed with use of CuDNN of Nvidia[3] for GPU. Moreover, it has a wide community of users and detailed documentation source, which would be much helpful for people who are new to Caffe.

4.2 Flower localization implementation

The implementation details of Local Binary Patterns (LBP) and thresholding methods that have been experimented for the flower localization task are described in this section. The code details are explained in MatLab.

4.2.2 Procedure with Local Binary Patterns (LBP)

LBP method

Figure 4.2 shows the implementation of the LBP method in Matlab. Image is read into *I2* variable. The width and the height of the image is saved in w and h variables. Then, for a selected pixel *J0*, its intensity is compared with all 8 neighboring pixels. If the neighboring pixel's intensity is more than the middle pixel's intensity the result is taken as 1 and otherwise taken as 0. All 8 results are saved in *I3(a, b)*, where *a* can take values *i-1, i or i+1* and *b* can take values *j-1, j or j+1.*These 8 results, which is a binary number when written in the clockwise order starting from *I3(i-1, j-1)*, are then converted into a decimal number. This decimal number is the new intensity value for the pixel being considered and is saved in *LBP(i, j)* for the LBP applied image.

[3] https://devblogs.nvidia.com/parallelforall/deep-learning-computer-vision-caffe-cudnn/

```
imname ='image.JPG';  % get the image name
I2=imread(imname);    % read image
figure, imshow(I2);   % display image

w=size(I2,1);       % get the width of the image
h=size(I2,2);       % get the height of the image
I3=ones(w,h);       % create a w by h matrix with ones

% LBP calculation
for i=2:w-1
  for j=2:h-1
     J0=I2(i,j);
      I3(i-1,j-1)=I2(i-1,j-1)> J0;
      I3(i-1,j)=I2(i-1,j)> J0;
      I3(i-1,j+1)=I2(i-1,j+1)> J0;
      I3(i,j+1)=I2(i,j+1)> J0;
      I3(i+1,j+1)=I2(i+1,j+1)> J0;
      I3(i+1,j)=I2(i+1,j)> J0;
      I3(i+1,j-1)=I2(i+1,j-1)> J0;
      I3(i,j-1)=I2(i,j-1)> J0;
     LBP(i,j)=I3(i-1,j-1)*2^7+I3(i-1,j)*2^6+I3(i-1,j+1)*2^5+I3(i,j+1)*2^4 ...
         +I3(i+1,j+1)*2^3+I3(i+1,j)*2^2+I3(i+1,j-1)*2^1+I3(i,j-1)*2^0;
  end
end
```

Figure 4.1 : Implementation of LBP method

Erosion and dilation

The resulting image after applying LBP is going through erosion and dilation operations respectively, in order to remove the noise appearing in the image. A disk-shaped kernel of the radius of 2 pixels is selected for the erosion operation and a disk-shaped kernel of the radius of 10 pixels is chosen for the dilation process to make the flower clusters to be nearly the size of the actual flowers in the original image. The result is an image with clusters that indicates possible *Lantana camara* flower locations. Figure 4.2 presents the implementation details of the Erosion and dilation operations.

```
% performing erosion
SE1 = strel('disk',2);

BW1 = imerode(BW, SE1);
figure,imshow(BW1);

% performing dilation
SE2 = strel('disk',10);

BW2 = imdilate(BW1, SE2);
figure,imshow(BW2);
```

Figure 4.2 : Implementation of erosion and dilation

4.2.2 Procedure with thresholding

Figure 4.3 shows the implementation for the L*a*b* thresholding. L* channel is considered as channel 1, a* channel as channel 2 and b* channel is considered as channel 3. The optimal threshold values are selected through experimentation. The results of the three channels are then combined using AND operator. The resulting image is given by the variable "thresholded" in the implementation shown in the figure.

```
RGB = imread('image.jpg');

% Convert RGB image to lab color space
RGB = im2double(RGB);
cform = makecform('srgb2lab', 'AdaptedWhitePoint', whitepoint('D65'));
I = applycform(RGB,cform);

% Define thresholds for channel 1 based on histogram settings
channel1Min = 0.196;
channel1Max = 99.285;

% Define thresholds for channel 2 based on histogram settings
channel2Min = 10.733;
channel2Max = 74.838;

% Define thresholds for channel 3 based on histogram settings
channel3Min = 13.648;
channel3Max = 88.121;

% Create mask based on chosen histogram thresholds
thresholded = (I(:,:,1) >= channel1Min ) & (I(:,:,1) <= channel1Max) & ...
              (I(:,:,2) >= channel2Min ) & (I(:,:,2) <= channel2Max) & ...
              (I(:,:,3) >= channel3Min ) & (I(:,:,3) <= channel3Max);
```

Figure 4.3 : Implementation for L*a*b* thresholding

Thresholding for RGB, YC_BC_R and HSV color spaces are carried out in the same way. The ranges of selected threshold values for each channel in RGB, HSV, YC_BC_R and L*a*b*color spaces are shown in Table 4.2. Table 4.1 gives details of the channels considered in each colour space and the maximum range of each channel. The optimal threshold values are found through experimentation. The values can be slightly changed. The experimentation was continued using L*a*b* as it showed better discrimination.

Colour space	Channel 1	Channel 2	Channel 3
RGB	Red (0 to 255)	Green (0 to255)	Blue (0 to 255)
HSV	Hue (0 to 1)	Saturation (0 to 1)	Value (0 to 1)
YC_BC_R	Y (0 to 255)	C_B (0 to 255)	C_R (0 to 255)
L*a*b*	L* (0 to 100)	a* (-100 to 100)	b* (-100 to 100)

Table 4.1 : Channel description for each colour space

Colour space	Channel 1	Channel 2	Channel 3
RGB	255 only	0 to 255	0 to 255
HSV	0.901 to 0.166	0.683 to 1	0.689 to 1
YC_BC_R	0 to 255	0 to 255	149 to 255
L*a*b*	0.196 to 99.285	10.733 to 74.838	13.648 to 88.121

Table 4.2 : Threshold value ranges selected for red, orange, or yellow colour *Lantana camara* flower discrimination

Morphological closing and opening

Morphological closing (dilation followed by erosion) and opening (erosion followed by dilation) are applied on the thresholded image, respectively. A disk-shaped kernel (structuring element) with the radius of 10 pixels has been employed for both operations. This process removes the noise from the image. The result is an image with clusters that represent the flowers found from the original image. The implementation details of these two operations are given in Figure 4.3.

```
imname = 'image.jpg';
img=imread(imname);

%thresholding the image using LAB color space
img_lab = LAB(img);
% defining structuring element
SE = strel('disk',10);

% performing morphological closing
BW1 = imclose(img_lab, SE);
% performing morphological opening
BW2 = imopen(BW1, SE);
```

Figure 4.4 : Application of closing and opening operations on L*a*b* thresholded image.

4.2 Flower patch generation

The resulting clustered image (BW2) from the previous step is taken as the input in this phase. As the first, step all the cluster centers are found and saved in the "centeroid_list" variable. Then, a 100x100 pixel square area is cropped around the cluster centers by iterating through all cluster centers. However, if an edge of the patch that is being cropped, falls out of the original image, then that patch is discarded. The reason is that the discarded patch is of a flower that falls on the edge of the original aerial image. Patches containing only a portion of a flower, should not be considered in evaluation, as these patches does not contain all the details to be identified by the CNN. All the cropped patches are saved by a name including the name of the original image it was cropped from and the top left corner coordinates of the patch in the original image. So that, this information can be used when marking *Lantana camara* presence in the original image after classification.

```
centroid_list = regionprops(BW2,'Centroid');

for i = 1:1:length(centroid_list)
    XData = centroid_list(i).Centroid(1) - 50; %getting the left most value
    YData = centroid_list(i).Centroid(2) - 50; %getting the top most value
    XEnd = XData + 100;  %getting the right most value
    YEnd = YData + 100;  %getting the bottom most value

   if XData >=0 && YData >=0 && XEnd <= h  && YEnd <= w
        I = imcrop(I2,[XData,YData,100,100]); %cropping an 100x100 image
        imshow(I);

        imname1 = strsplit(imname, '.'); % getting only the name
        k = char(imname1(1)); % getting the first cell that contains name

        %creating name
        name = strcat(k,'_',num2str(XData),'_',num2str(YData),'.jpg');
        imwrite(I,name); % saving cropped image
    end
end
```

Figure 4.5 : Implementation of the flower patch generation task

4.3 CNN implementation

This section discusses about the implementation details of the CNN and the classification task. Furthermore, the section also describes the dataset used in training the CNN and fine-tuning process of the CNN.

4.3.1 Dataset

A large number of images are needed in order to train a CNN to correctly classify flowers and a variety of flower species is also needed for a better discrimination of *Lantana camara* from other flowers. The lifeCLEF 2015 [39] dataset was chosen for the training task. The dataset contains 113,205 images of 1000 plant species centered on France and neighbouring countries. Each image belongs to one of the categories including branch, entire (indicates the whole plant), flower, fruit, leaf, leafScan (scanned or scanned-like leaf) or stem. The dataset also provides an XML file for each image including details such as plant species, plant genus, plant family, category, observed date, etc. as metadata. Images that belong to the flower category are extracted from this dataset and used for CNN training. The resulting dataset consisted of to 967 tree species with 28225 images for training and 8327 images for testing. Figure 4.5 presents the examples of the LifeCLEF dataset.

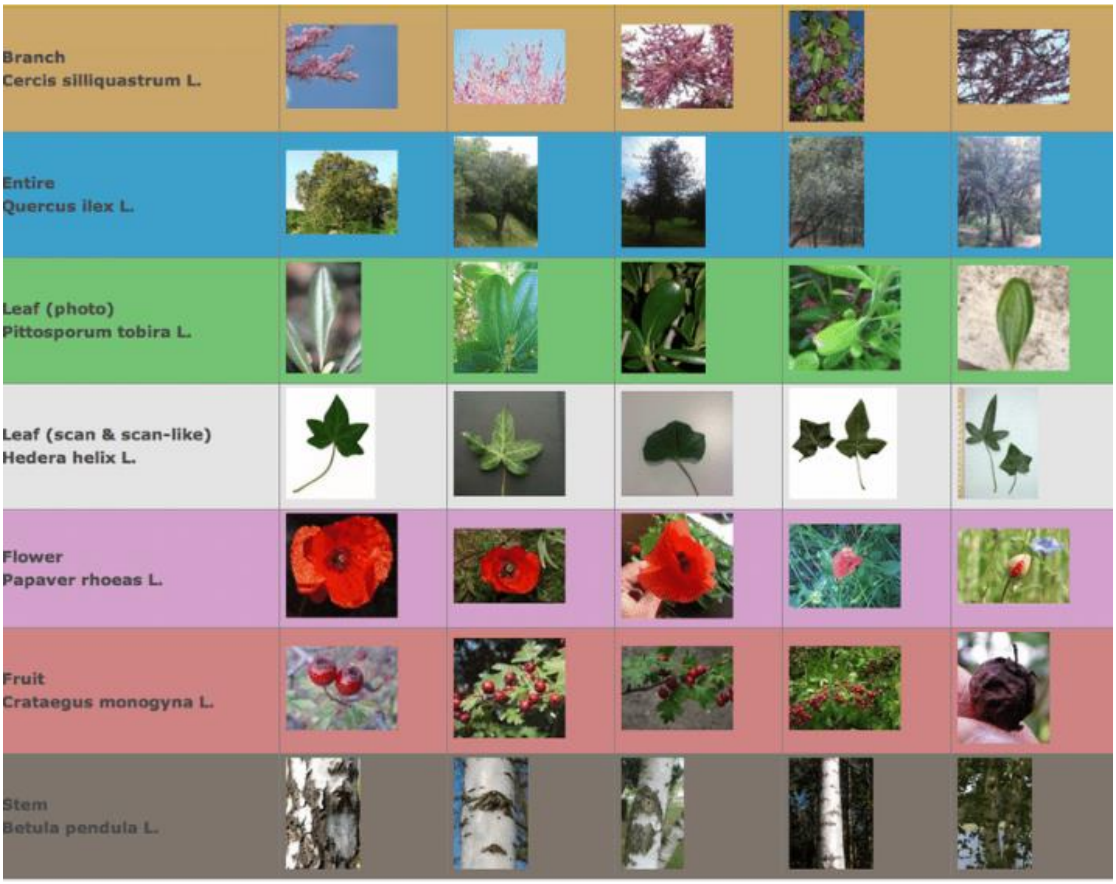


Figure 4.6 : Example of the LifeCLEF dataset [63]

4.3.2 Fine-tuned parameters of CNN

The AlexNet [14] CNN architecture is used for this study and the Caffe[4] deep learning framework is used to build the CNN. Pre-trained ImageNet [64] weights[5] for AlexNet were used as the initial weights. Following parameters of the original AlexNet architecture was changed according to Nguyen et al. [40].

- Test iteration: 1666
- Initial learning rate: 0.001
- Step size: 10000
- Batch size: 5 (test set)
- Number of iterations: 50,000

NVIDIA GeForce GT 430 graphic card with Cuda compatibility 2.1 was used in the machine used to train the CNN. However, AlexNet requirement is to use graphic car with Cuda compatibility 3.0+. Because of this restriction the default crop size of 227 was reduced to 198, which is the highest value that was possible to employ in CNN training. Furthermore, the number of nodes in the last layer (fc8) was changed to 967, as there are 967 classes of flowers used in training. Therefore, a multiclass classification is expected from the CNN. The reason for not using a binary classification is that, if a *Lantana camara* flower was misclassified as a different flower or a different flower was classified as *Lantana camara,* the misclassified classes can be tracked easily with the multiclass classification.

All the images are resized into 256x256 pixels before and converted into LMDB (Lightning Memory-Mapped Database) format before it is used for training. The required time for training is approximately 48 hours. Figure 4.7 shows a screenshot obtained of the training process of the CNN.

[4] http://caffe.berkeleyvision.org/
[5] https://github.com/BVLC/caffe/tree/master/models/bvlc_alexnet

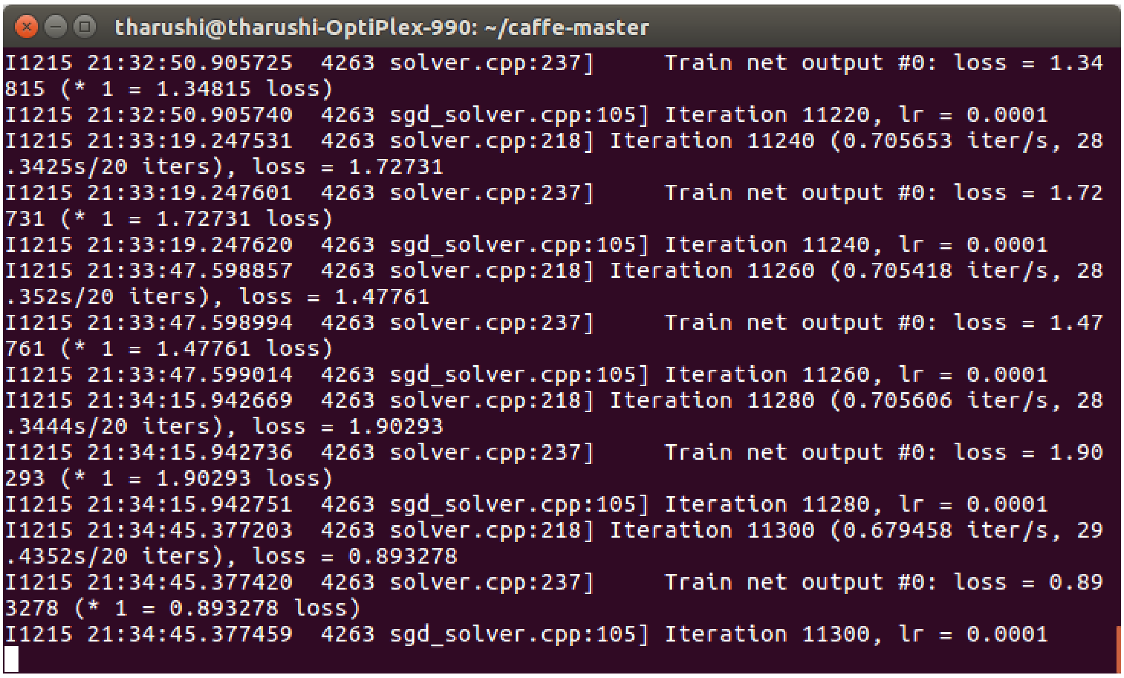


Figure 4.7 : A screenshot from the training process

4.3.4 Classification

The cropped flower patches are then fed into the train CNN and classified in order to find out the class, which they belong to. The results are saved in a text file.

4.4 Implementation of *Lantana camara* presence mapping

The text file containing names of cropped flower patches and their classified classes is considered as the input in this phase. If a flower patch is classified as a plant species other than *Lantana camara,* then that patch is neglected. If a patch is classified as *Lantana camara*, the name of that image patch is taken into account to get its coordinates on the original image that it was taken. Once the coordinate is read, a 100x100 pixel square is drawn at the found coordinate in the original image. The implementation of this phase is shown in figure 4.8.

```
imname='image.JPG';
img=imread(imname);

fid = fopen('results.txt'); %open the text file with classification results

while true
    %get line by line
    line_full = fgetl(fid);
    % dividing the name
    line_cells = strsplit(line_full, {'/',' ','.jpg','_',':'});

    n = char(line_cells(6));
    if strcmp(n,'LANTANA')  %takes only images classified as Lantana camara
        X = str2num(char(line_cells(4))); %get x coordinate
        Y = str2num(char(line_cells(5))); %get y coordinate

        %draw a rectangle of 100x100 pixels at (X,Y)
        img = insertShape(img,'rectangle',[X Y 100 100],'LineWidth',5);
        imshow(img);
    end
end
imwrite(img,'marked_image.jpg');
```

Figure 4.8 : Implementation of the mapping process

4.5 Summary of the chapter

In this chapter, the implementation details of the four phases of the proposed design was explained in a finer level. In addition, the details of the dataset used in CNN training and fine-tuned parameters of AlexNet architecture, that is used as the CNN in this study, was described.

Chapter 5 - Results and Evaluation

5.1 Introduction

This chapter discusses the results and evaluation of the proposed design under three sections. In the section 5.2, the two flower localization methods employed in this study are evaluated for their performance. The results of the classification by CNN is then evaluated in the section 5.3. Section 5.4 discusses the overall evaluation of the proposed design.

5.2 Flower localization

LBP method and L*a*b* thresholding technique in different color spaces has been experimented for flower localization. Table 5.1 and Table 5.2 shows the results for the LBP and L*a*b* thresholding methods respectively, experimented for 10 images. The two tables give information of the total number of flower patches existed in the aerial image, the number of flowers localized, and the sensitivity values for localization process in each image and for all images altogether.

Image	**No. of flowers in the image**	**No. of flowers localized**	**Sensitivity**
1	20	17	85.00%
2	40	12	30.00%
3	34	10	29.41%
4	41	17	41.46%
5	55	18	32.73%
6	48	20	41.67%
7	28	17	60.71%
8	34	21	61.76%
9	35	26	74.29%
10	24	17	70.83%
Total	359	175	48.75%

Table 5.1 : Accuracies for flower localization with using LBP

Image	No. of flowers in the image	No. of flowers localized	Sensitivity
1	20	19	95.00%
2	40	27	67.50%
3	34	28	82.35%
4	41	36	87.80%
5	55	51	92.73%
6	48	45	93.75%
7	28	28	100.00%
8	34	33	97.06%
9	35	35	100.00%
10	24	20	83.33%
Total	359	322	89.69%

Table 5.2 : Accuracies for flower localization with using L*a*b* thresholding

As shown in the results of the two methods, L*a*b* thresholding has achieved a higher accuracy of 89.69% in localization of flowers in contrast to the accuracy of 48.75% obtained by the localization procedure of LBP.

Figure 5.1 and Figure 5.2 present the results of the two flower localization processes applied for image 1 using LBP and L*a*b* thresholding techniques respectively. In Figure 5.1, a less number of flowers are localized and a number of unimportant regions were marked. This is due to the fact that, these regions contain objects that are of high intensities compared to the background, thus being noted by the LBP method. On the other hand, very few unimportant regions were marked in the background by the L*a*b* thresholding procedure as shown in Figure 5.2. The reason for localizing objects other than flowers by this method is that these objects contains a colour that are similar to the *Lantana camara* flowers being localized, thus being in the considered threshold range. However, the objective of flower localization phase is not to localize possible flower regions, but to reduce the number of patches to be fed into the CNN. For that, possible regions that could be *Lantana camara* is found by localization. Therefore, this will not be a major effect in overall performance as all these localized regions being classified by the CNN at the end. And these localized regions of background will not to be classified as the *Lantana camara* (refer section 5.4).

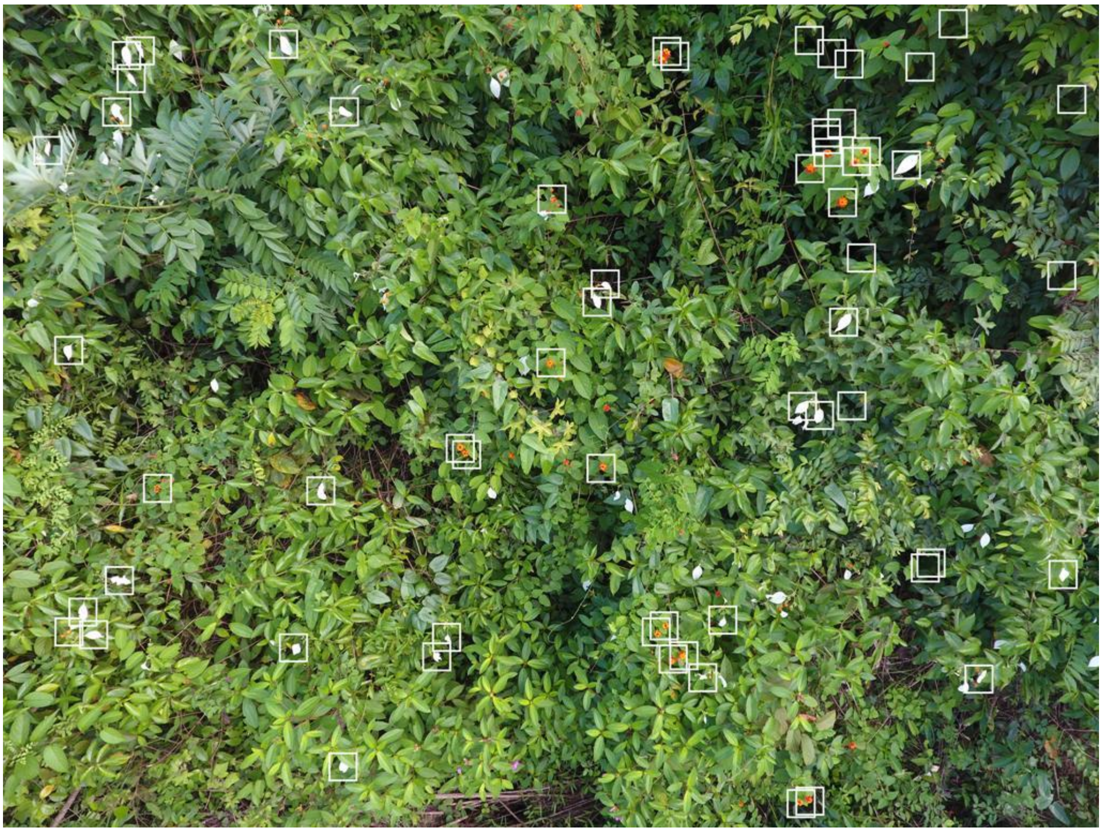


Figure 5.1 : Result of flower localization using LBP

Figure 5.2 : Result of flower localization using L*a*b* thresholding

5.3 Flower classification using CNN

The CNN was trained and tested by using the LifeCLEF dataset described in section 4.3.1. The multi-classification accuracy of 55.2% was achieved by the CNN where the random guess probability is 0.1% for the multi-classification of 967 classes. Confusion matrix for this dataset is shown in table 5.3.

Probability on random guess = $\frac{1}{967} \times 100\% = 0.1034\% \approx 0.1\ \%$

		Predicted class		
		Lantana camara	**Not *Lantana camara***	**Total**
Real class	***Lantana camara***	10	3	13
	Not *Lantana camara*	2	8312	8314
	Total	12	8315	8327

Table 5.3 : Confusion matrix for the CNN evaluated on the LifeCLEF dataset [39]

Evaluation measures for *Lantana camara* using the confusion matrix given in Table 5.3 are calculated as follows.

Precision = $\frac{10}{13} \times 100\% = 76.92\%$

Negative predictive value = $\frac{8312}{8314} \times 100\% = 99.9\%$

Sensitivity = $\frac{10}{12} \times 100\% = 83.3\%$

Specificity = $\frac{8312}{8315} \times 100\% = 99.9\%$

Accuracy = $\frac{8322}{8327} \times 100\% = 99.9\%$

However, the test dataset contains only a few *Lantana camara* images and a large number of other flower images. Therefore, The CNN was tested for 200 images of *Lantana* *camara* with dimensions around 500x500 pixels collected from the internet and obtained 97.5% accuracy. Figure 5.3 shows some examples from these images collected data from the internet.

Figure 5.3 : Example images tested for *Lantana camara* identification accuracy

5.4 Overall evaluation

For overall evaluation, images that have gone through L*a*b* color thresholding for flower localization is considered as the input for classification, because L*a*b* thresholding performed better in flower localization. The accuracies gained for six scenarios are shown in Table 5.4.

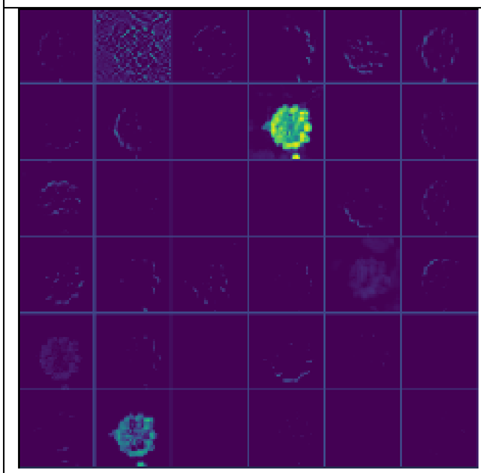
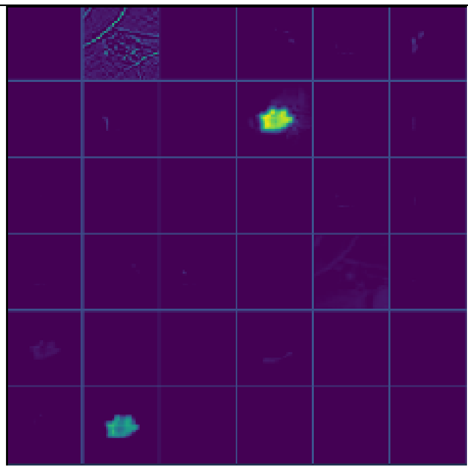
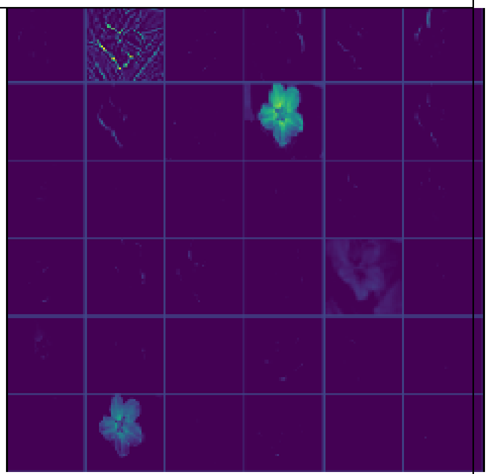
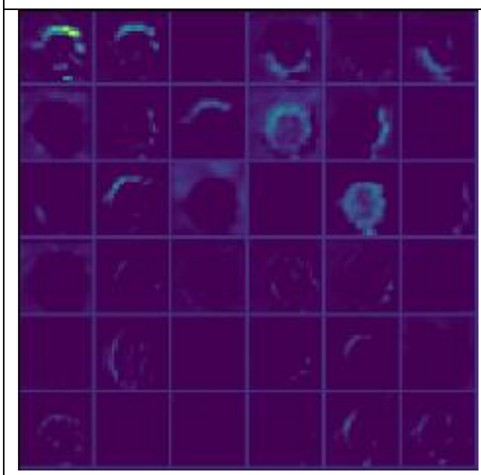
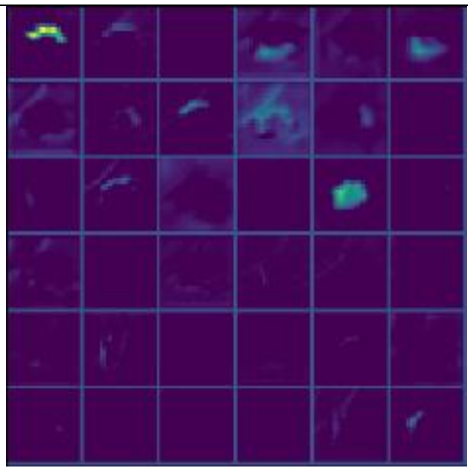
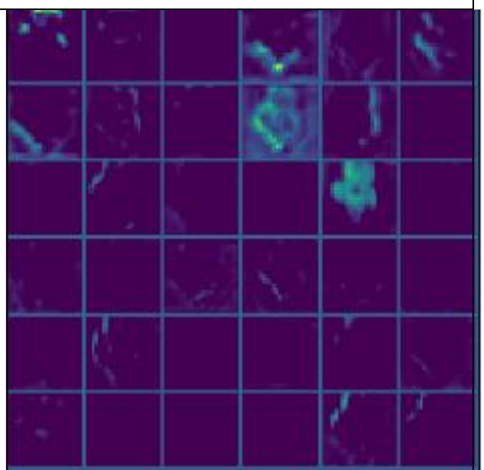
Image	Flower count in the original image	Localized flowers	Classified flowers	Classifier sensitivity	Overall design sensitivity
1	20	19	11	57.89%	55.00%
2	40	27	11	40.74%	27.50%
3	55	51	24	47.06%	43.64%
4	48	45	21	46.67%	43.75%
5	28	28	11	39.29%	39.29%
6	35	35	14	40.00%	40.00%
Total	226	205	92	44.88%	40.71%

Table 5.4 : Evaluation of the overall design

The classifier accuracies have dropped significantly for the localized images when compared to the 97.5% accuracy gained for *Lantana camara* identification. This due to the fact that the localized and cropped flower patches, that are fed into the classifier, are being largely misclassified as *Lysimachia arvensis*. The flower patch does not contain finer details of the *Lantana camara* flower to discriminate it from *Lysimachia arvensis*. Therefore, the feature vectors generated by the *Lantana camara* flower patch shows similarities with the feature vectors learnt by *Lysimachia arvensis.* 94.7% of the misclassified patches were classified as *Lysimachia arvensis*. The Table 5.5 visualizes the feature vectors generated by a *Lantana camara* flower used in training, a misclassified *Lantana camara* flower, a *Lysimachia arvensis* flower. It can be seen that the feature vectors generated for three flowers are similar to some extent, thus leading to the misclassification. This complication implies the need of refining the design to discriminate *Lantana* camara from other mistaken flowers.

As an important note to be mentioned, the flower count in the original image column in table 5.4 also includes flower patches that contains flower regions less than 50x50 pixels, which is not the requirement for input images mentioned in section 3.3. This may have been the reason for the drop of accuracy. However, it is not the objective of this study to find all flowers present in an image, but to mark the presence of *Lantana camara* in the image. The number of flower patches identified out of the number of flowers actually exist in an image is just an accuracy measure taken for evaluation. The result of an aerial image that has gone through the proposed design is shown in figure 5.4. As shown in the figure the proposed model has successfully marked the presence of *Lantana camara* in the image for a person to able to detect it.

It is important to draw the attention to the fact that none of the localized patches from background areas were classified as *Lantana camara.* To improve the proposed model, the refinements that can be made are explained in section 5.5.

Lantana camara (in training dataset)	Misclassified *Lantana camara*	*Lysimachia arvensis*
Image of the flowers		
		
Features learnt in Convolutional Layer 1		
		
Features learnt in Convolutional Layer 2		
		

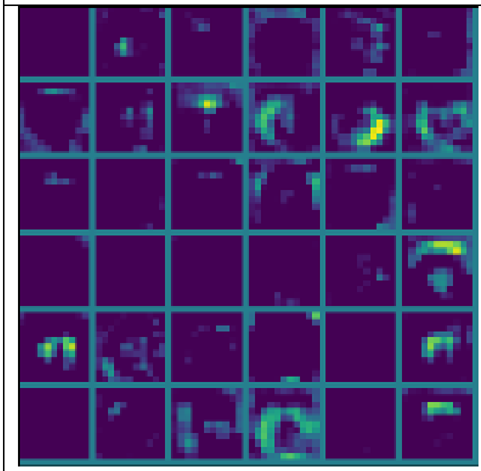
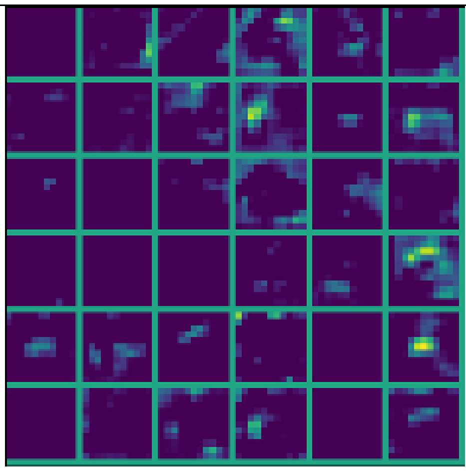
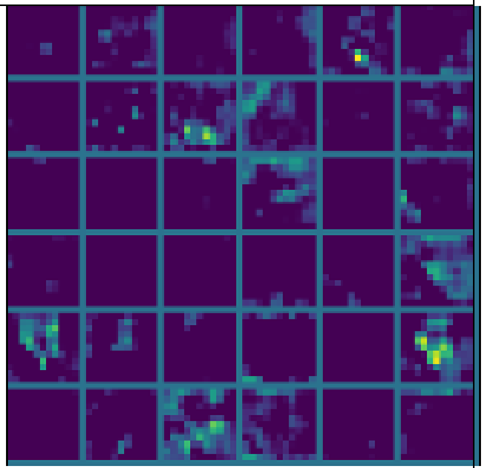
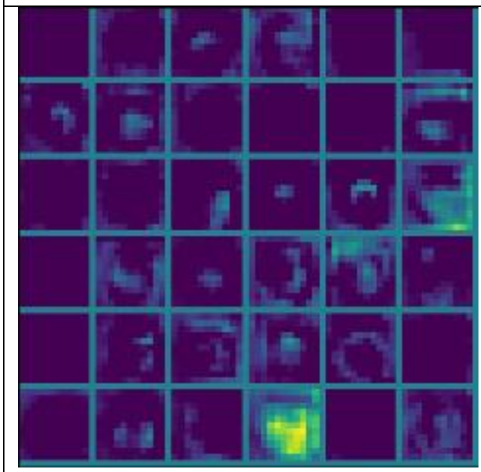
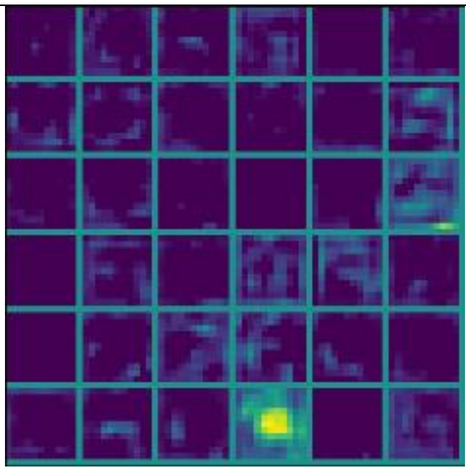
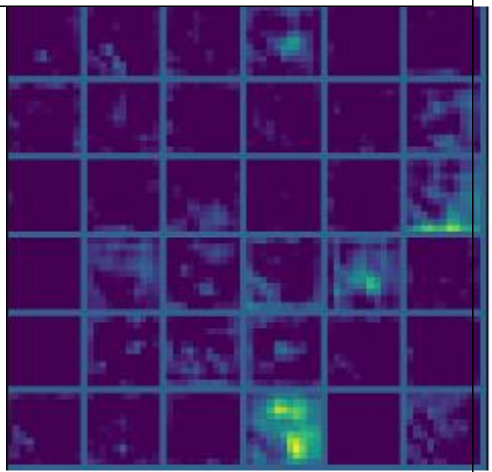
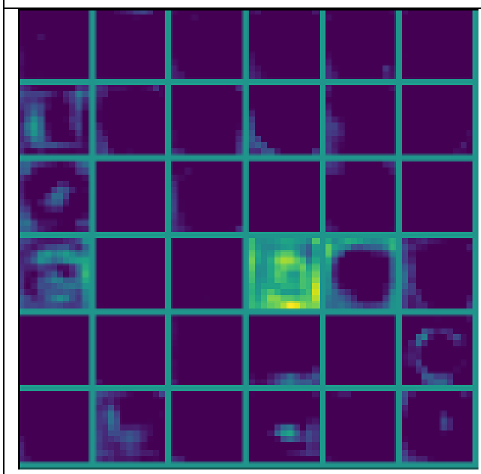
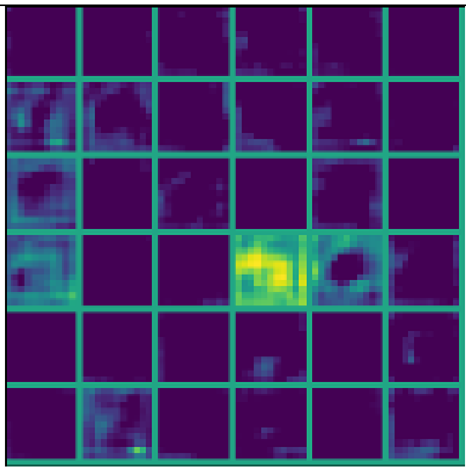
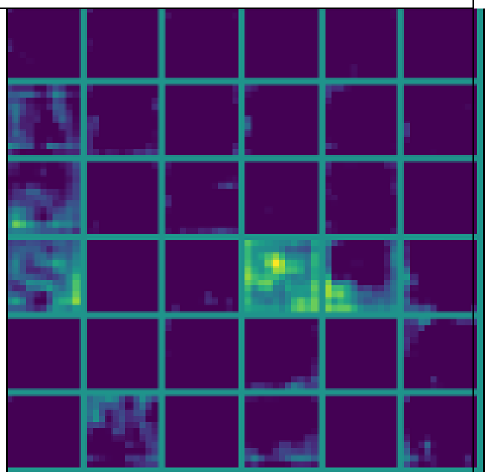
Features learnt in Convolutional Layer 3		
		
Features learnt in Convolutional Layer 4		
		
Features learnt in Convolutional Layer 5		
		

Table 5.5 : Features vector visualization at first five layers

Figure 5.4 : Result of an aerial image gone through the proposed design

5.5 Design improvements

The drop of overall accuracy is an important concern for the proposed design. The factors that can be considered to overcome this can be listed as follows.

Input data refinements

- High quality images are needed in order to capture the flowers at a level, that the details of the flowers are visible to the CNN to a certain extent.

Dataset refinements

- Restricting the training dataset by considering only the plant species available in the area/country that is being observed.
- Since the size of the flower at a pixel range is considered in this study, the flowers that are smaller than the *Lantana camara* can also be neglected and removed from the training dataset, because they will not be selected from the flower localization process

due to noise removal process applied on the image using dilation and erosion image processing techniques. Using this restriction, the confusion of *Lantana camara* with *Lysimachia arvensis* can be avoided as *Lysimachia arvensis* flowers are only 10-15 millimeters wide [65], which makes it very smaller than *Lantana camara* flowers.

Localization process refinements

- Relative size of flowers can also assist in rejecting flowers that are considerably larger than *Lantana camara*, so that these larger flower species can be omitted from the training dataset of the CNN. Noise removal in the localization process will not remove larger flowers in aerial images, therefore selecting them as candidate flower patches. To exclude them, the relative size of flowers compared to the size of the leaves surrounding the flower can be considered. A flower should not be considered as a possible *Lantana camara* flower, if the ratio of flower size to the leaf size is too large or too small compared to the ratio of the sizes of *Lantana camara* flower to leaf.

5.6 Summary of the chapter

In this chapter, the results of the LBP and L*a*b* thresholding mechanisms for flower localization process were evaluated in section 5.2 and concluded that L*a*b* thresholding performed better. The performance of the CNN was evaluated in section 5.3 and the overall performance of the proposed design was discussed in section 5.4. Section 5.5 described the refinements that can be incorporated with the proposed model.

Chapter 6 - Conclusions

6.1 Introduction

This chapter reviews on conclusions about the research questions and the research problem. It also discusses the major limitations considered in this study and provides future improvements that can be made for the study.

6.2 Conclusions about research questions (aims/objectives)

Two research questions were addressed in this study. The first research question concerned about the applicability of LBP and thresholding methods in flower localization. It was concluded that the thresholding mechanism performs better in identifying red, orange, or yellow colour *Lantana camara* flowers as it shows a clear separation of flowers from the background and captures a higher number of flowers compared to LBP method. The L*a*b* colour space was chosen in this study for thresholding because of its ability to separate flower regions in general and this method obtained an accuracy of 89.69% at localizing *Lantana camara* flowers. However, thresholding does not perform well in localizing different coloured flowers, because a global threshold range for all colours of *Lantana camara* flowers could not be agreed upon. In this case LBP can be used.

The second question addressed in this study is the applicability of a CNN in the flower classification process. The AlexNet [34] was employed as the CNN architecture. The classifier gained an accuracy of 55.2%, which considerably higher compared to the random guess accuracy of 0.001%. The trained CNN could predict *Lantana camara* at 94.6% accuracy. Therefore, it is concluded that a CNN is employable in the classification task.

6.3 Conclusions about research problem

To identify the distribution of *Lantana camara* in aerial images, a novel method including L*a*b* thresholding-based flower localization process followed by a CNN classification was proposed in this study. As discussed in section 2.3 there have not been reported any flower based remote sensing mechanism to identify the distribution of *Lantana camara* in related works. L*a*b* thresholding was successfully employed in localizing possible flower regions at n accuracy of 89.69%. The accuracy of identifying a *Lantana camara* flower by the proposed CNN is 97.5%. The accuracy of identification of *Lantana camara* flowers in an aerial image by the proposed design is 40.71%. The use of low quality flower patch images as the inputs for the CNN has drastically reduced the accuracy of the overall process. However, the result of the design, which is a copy of the original aerial image marked with *Lantana camara* presence, can clearly show the presence of *Lantana camara* in the aerial image, therefore indicating the distribution of the plant in each image.

6.4 Limitations

The image acquisition of an area, that is suspected to have been invaded by *Lantana camara,* is required to be done in the *Lantana camara* flowering season. Otherwise the proposed design would not provide effective results.

When acquiring aerial images of an area, the requirement is to have high quality images with *Lantana camara* flower portion fits into more than 50x50 pixels size in the captured images. Because flowers less than of this size would not contribute towards the identification of the *Lantana camara* distribution. Furthermore, images need to be captured in soft light conditions (shadow-less light).

The dataset being used to train the CNN should be included with exactly the plant species that are present or suspected to be present in the area or country, which is being considered for acquiring aerial images. So that, the misclassification is reduced.

The proposed design was experimented on an area where *Lantana camara* was appeared to be of red, orange, or yellow colours. Therefore, the utility of the design in identifying other colours of *Lantana camara,* needs to be further experimented.

6.5 Implications for further research

The flower localization process is needed to further experimented in different scenarios by considering different coloured *Lantana camara* flowers. Either one global solution for all colours or a set of solutions for each *Lantana camara* flower colour can be combined in order to generate a general solution.

Furthermore, the proposed design is needed to be experimented with images acquired in different lighting conditions. The proposed design can be improved in order to increase the overall design accuracy by suggested refinements given in section 5.5.

In addition, texture details that is appeared on *Lantana camara* plants in flowering seasons can also be included in the design for further improvements. Moreover, the use of infrared sensors to capture different radiations emitted by plants can be experimented to find out if there exists a unique pattern in emitted radiations by *Lantana camara* plants. This result also can be joined with the proposed design for a better prediction.

The mapping of the distribution can be further extended by indicating the results in a Google Maps like map. For this, location details should be recorded for each image during the image acquisition. Once these images go through the proposed design and marked for their *Lantana camara* presence, coordinates-to-pixels calculation can be done to find out the latitude and the longitude of the marked positions. These positions can be then marked in a Google Map like map. This would make the results more usable for people in need of viewing the invasion of the area as a whole.

Furthermore, mapping mechanism needs to be improved to a method that marks an area of *Lantana camara* presence. The evaluation method also needs to be improved accordingly. So that the accuracy of the design is calculated based on the area discovered as Lantana *camara*, not by the number of flowers correctly identified.

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