

**Developing a Seed Segmentation Algorithm Which Incorporates a Deep-Learning Architecture**

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# ABSTRACT

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# **CHAPTER 1: INTRODUCTION**

## 1.1 BACKGROUND TO THE PROJECT

Photometric analysis of seeds entails the concept of identifying and analysing key characteristics of each seed, identifying descriptive traits such as seed colour, seed texture or the angularity of the seed. However, with this, an imperative issue introduced is the consideration for the countless array of different plant species which the various seeds may originate from, and therefore the identification and analysis of each seed can be considered as an expensive operation in regards to time complexity.

The basis of this project explores this concern and aspires to develop an algorithm which is capable of automatically identifying the plant species for each individual seed that may be present in each seed image sample in the dataset, based on the data which the algorithm has learned from a given training dataset of seed images; hence a deep-learning approach. Imperatively, the automated system for the taxonomical analysis of the seed sample images should provide an interface for seed experts and non-experts to be able to perform necessary analytical operations on a large dataset of seed images in a timely manner.

However, a technical challenge that will be faced is the development processes involved with deep-learning strategies and techniques, this is largely due to the current lack of experience in regards to the development of this type of system architecture. On the other hand, this challenge contributes towards the motivations behind this project, as this project presents a great opportunity to learn more about the field of deep-learning and its applications within Computer Science.

Previous research in this field of study indicates that an approach for accommodating this concern would be to develop a system which is inspired by the cognitive functions of a biological brain, otherwise referred to as an artificial neural network (ANN) (Egmont-Petersen et al, 2001). However, a convolutional neural network (CNN) is a form of ANN which focuses solely on the functional replication of the visual cortex of a biological brain. Furthermore, research was also indicative of the fact that the performance of the system architecture is largely dependent on the data which is passed through as a parameter for the CNN, for example larger patches of seed image training data would likely improve the accuracy but decrease speed of the algorithm (Mori, 2017). In addition, the complexity of the developed deep-learning architecture will also contribute to the overall performance of the algorithm, for example more layers of convolutional tasks will lead to a higher time complexity for the system performance. To this end, research also suggested that this could be amended by developing the algorithm through the utilisation of the graphics processing unit (GPU) device, which would allow some of the deep-learning tasks to be parallelised and operate more efficiently (Mori, 2017).

To surmise, the primary deliverable of this project will be a seed segmentation and feature extraction algorithm using a deep-learning CNN system architecture, the success of which should provide seed experts and non-experts with the opportunity to analyse key characters of various seed samples with a high performance. The core of this project envelopes the concept of testing how accurate the system will be able to correctly estimate seed characteristics, while considering the speed of the system.

## 1.2 PROJECT AIM AND OBJECTIVES

Predominantly, the aim of this project is to develop a seed segmentation and feature extraction algorithm while utilising a deep-learning architecture. This algorithm will be designed to perform accurate feature extraction by learning characteristics from a provided training dataset, this data will then be utilised for the analysis of key characteristics of different plant species for the establishment of species identification, for example seed texture and seed colour.

Explained below are the objectives, which upon completion, will help accomplish this aim:

1. Experiment with existing deep convolutional neural network architectures and evaluate their effectiveness for the problem at hand.
2. Develop a customised deep convolutional neural network architecture such that the algorithm is capable of learning key characteristics from a given training dataset of images.
3. Develop the algorithm with the extraction of photometric features. The system should be capable of identifying key features of each seed foreground object that can be observed in the image to provide further analysis.
4. Develop the algorithm such that the system can be easily adapted and customised in the future by training the system with a new training dataset.
5. Adapt the algorithm using parallel programming and the Graphics Processing Unit (GPU). Parallelising some segments of the developed algorithm should theoretically enable a significant performance improvement in regards to the processing capabilities of the deep convolutional neural network that was developed. However, it should be noted that this objective is being considered as a STRETCH objective, and therefore development towards the completion of this objective will only begin when the prior objectives have been completed to a satisfactory standard.
6. Design and develop an easy-to-use graphical user interface (GUI) for any non-experts which may use this architecture. This is considered as a STRETCH objective and will only enter development upon prior objectives of the project being completed to a satisfactory standard.

# **CHAPTER 2: LITERATURE REVIEW**

The following section will be conducting a brief literature review of 10 different academic sources, aspiring to demonstrate recent research developments which can be considered as relevant to the proposed project.

## BENEFITS OF AUTOMATION AND COMPUTER-AIDED APPROACHES

A research study explores the concept of computer-aided image analysis techniques which are considered as contributing towards improving the insight of seed analysis, such as image acquisition and pattern recognition. Varma et al (2013) suggest that the combination of image analysis and human intelligence emulation is an important technology that will aspire to many applications in modern varietal identification and seed certification. It is proposed that a current major research area is the encapsulation of human intelligence, suggesting that development in image acquisition, pattern recognition and decision-making techniques will help to improve existing systems while providing a better return on investment and reduced costs.

Artificial Neural Network (ANN) is a methodology largely founded upon an attempt to replicate the methodologies performed by a biological brain to process data. However, a study was conducted which involved a comprehensive review of more than 200 applications of neural networks being incorporated into modern day system architecture. Egmont-Petersen et al (2001) argue that while ANNs are not automatically seen as the best solution towards most classification problems, they have been largely incorporated into various applications which inspired its creation: pattern recognition, psychology and neurophysiology. This study also suggests that a challenge for ANNs is the issue of the feature complexity and subtle discrepancies between images, such as variations in position, orientation and scale.

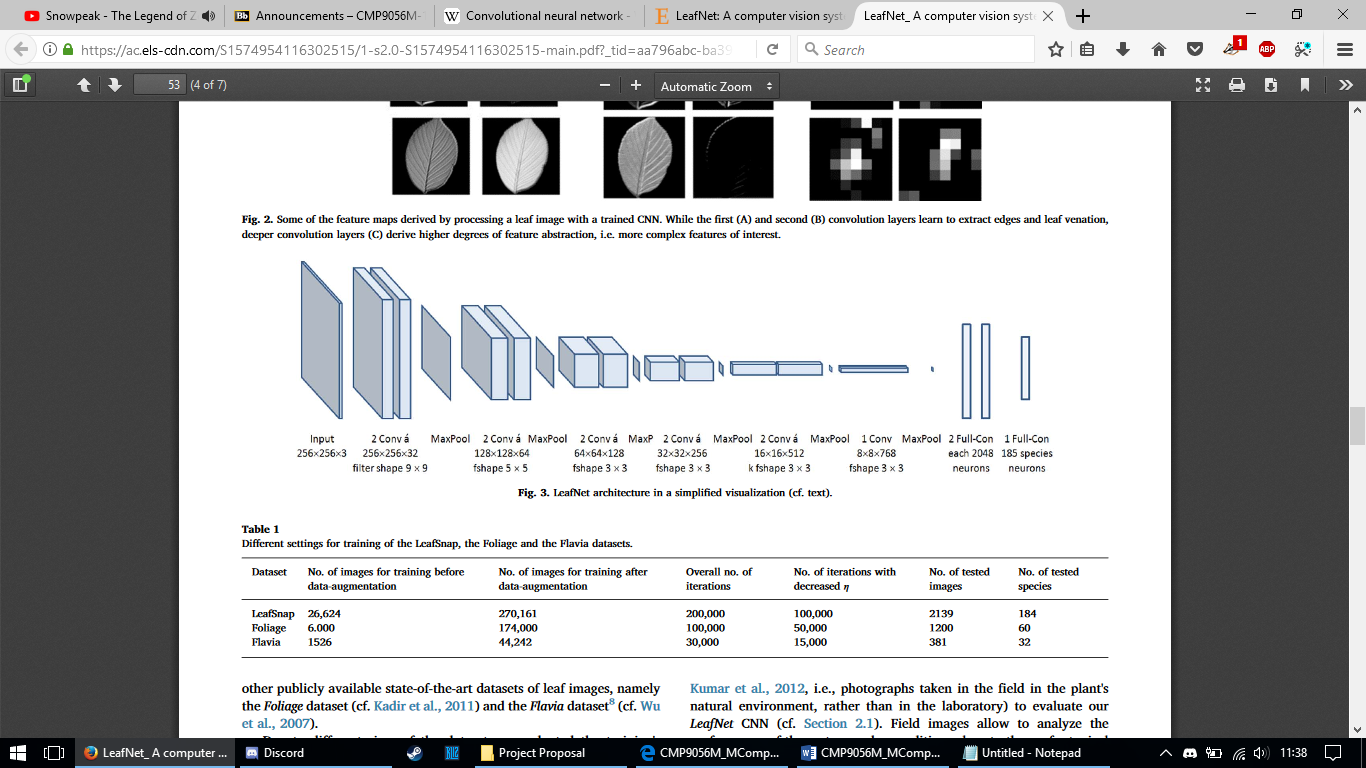
To surmise, taxon identification is an imperative step within plant ecological studies, the efficiency and reproductivity of which may benefit from automation of this task, as the process of manual plant species identification and analysis can be argued to be difficult, time-consuming and erroneous for non-experts. While the automatic system architecture of ANNs and deep learning impose the requirement of a large dataset, these methodologies are becoming popular approaches for pattern recognition. This approach could benefit this project, as it could allow reduced costs for any plant experts and non-experts that may use this seed segmentation and feature extraction algorithm.

## CHALLENGES OF DEEP-LEARNING SYSTEMS

The term “Big Data” refers to extremely large datasets that have been procured as a result of advancements in data storage capability, increase of computational power and more data volume accessibility. Sutton and Barlow (1998) suggest that deep-learning architectures provide the capability for effective analysis and abstraction of useful knowledge from both large amounts of data and data collected from difference sources. To this end, the utilisation of “Big Data” provides the opportunity for more patterns and correlations to be detected and analysed by the deep-learning model, hence; more data can provide a higher level of data abstraction. Furthermore, Gheisari et al. (2017) suggest that while this is the case, this also presents many challenges to be faced with the deep-learning model.

## EXISTING DEEP-LEARNING NEURAL NETWORK SYSTEMS

Convolutional neural networks (CNN) are a form of ANN which are largely inspired by the biological processes and organisation of the visual cortex of a biological brain. A CNN structure is largely comprised of an input and an output layer, with a variable number of hidden layers depending on the desired complexity of the system. The hidden layers can include convolutional, pooling or fully connected layers.



Barré et al (2017) developed a deep CNN system entitled “LeafNet” which was designed to learn discriminative features from leaf images and establish plant species identification. A recognised issue with current customised, specialised and hand-crafted identification systems is the expense of these approaches, whereas a deep CNN approach provide an alternative system architecture which permits adaption to different taxa by training the algorithm with different training data.

Similarly, Krizhevsky et al (2012) researched ImageNet classification with deep convolutional neural networks in an attempt to classify 1.2 million high-resolution images into 1000 different classifications. This system was designed with 5 convolutional layers accompanied with max-pooling layers and 3 fully connected layers. Overall, this study found that the test-data achieved an error rate of 37.5% and 17.0%, which was considered as a significant performance improvement when compared with the previous state-of-the-art methodologies.

Zhao et al (2009) developed an automatic mass peanut seed detection algorithm through appearance characteristics of each peanut seed. This entailed the process of performing component analysis for evaluating the contribution rate of each variable, which would subsequently be input as component parameters for the neural network model of the algorithm. Zhao et al (2009) found that the automatic mass peanut seed detection algorithm achieved a peanut seed variety recognition rate reached 91.2% and a quality recognition rate of 93.0%. This study surmised that the developed peanut detection algorithm through a machine vision approach possessed cost and speed advantages, and could be considered for the identification of peanut cultivars and quality.

Similar research follows the development of an automatic segmentation algorithm for fluorescence micrographs which incorporated a fast-learning neural network for the detection of fluorescent cells. Nattkemper et al (2002) suggest that the evaluation of a large number of micrographs by human experts is time consuming and nearly impossible due to the observer’s concentration naturally declining rapidly during the visual inspection of the noisy intensity images. Within this system, the detection of fluorescent cells as focus points is performed in the first module of the system architecture, this consists of a neural network of local linear map type (LLM) which is trained through a set of image patches that contain fluorescent cells.

In contrast, Chitra et al (2016) conducted a comparative study for alternative image analysis techniques. Overall, this study found that image processing techniques such as Histogram Thresholding present the advantage of not requiring any previous image information and emphasises on strong edges within the image, however this technique cannot be applied to multi-channel images and foreground objects can distort the image histogram. Furthermore, the Watershed Segmentation technique can efficiently merge essentials from both discontinuity and relationship based systems, yet this technique is known to create over-segmentation due to local irregularity within the image.

In conclusion, the research conducted suggests state-of-the-art segmentation techniques such as automatic Histogram Thresholding could automatically segment the seed objects away from other entities in the image without being required to learn commonalities in seed features from a large dataset of seed image samples. On the other hand, deep-learning architectural approaches such as the approach established by Zhao et al (2009) demonstrate potential of the technique by achieving a higher feature recognition accuracy rate of 91.2%. In conclusion, this research could be argued to show that a deep-learning approach for the system architecture could be a more accurate means for processing the sample seed images involved with this project, despite a higher time complexity.

## DEEP-LEARNING WITH A GRAPHICS PROCESSING UNIT (GPU)

Mori (2017) developed a real-time image processing algorithm for image-guided radiotherapy, the purpose of this study was to explore the implementation of different neural network models with different imaging modalities and consider the possibility of a real-time neural network architecture. In this study, a residual convolutional neural network (rCNN) is trained which is comprised of multiple sets of convolution, BN and ReLU layers, with the last layer being a convolutional layer with a single feature map and a input image. Mori (2017) found that while it was possible to develop the rCNN model in real-time image processing, it was also established that the image quality needs to be adjusted in consideration of the image size and the fluoroscopic frame rate, as in some cases the results suggested a performance which was under 30fps and therefore deemed unsuitable for real-time processing.

Similarly, further research indicates that while ANNs are becoming more popular in acoustic model training, the speed of the model performance can be improved by utilising the GPU device. To this end, a back-propagation (BP) neural network acoustic model for speech recognition is developed and utilised on the GPU device, therefore the application of an asynchronous implementation between the CPU and GPU alongside parallel reduction could be applied on some of the operations involved within the BP neural network. As such, Liu et al (2012) concluded that the training of the BP neural network was accelerated 26 times faster than using a single thread Intel Math Kernel Library implementation, this as a result enabled the opportunity for more data and more complex neural networks to be developed. Thus, this could suggest a performance improvement in regard to the recognition accuracy and speed of the algorithm that is going to be developed in this project if GPU-enabled processes are considered.

## SUPERPIXEL SEGMENTATION

Within the field of image processing, Ren and Malik (2003) define the principle of intra-region similarity as elements in a region which may have a similar brightness, texture and a low contour energy inside the region, whereas intra-region dissimilarity can be described as the elements in a region which may have a contrasting brightness, texture and a high contour energy inside the region. Superpixel segmentation can be derived as a popular image processing technique which operates by dividing the pixels of an image with similar visual characteristics into an atomic region, effectively replacing the original rigid structure of the pixel grid. Achanta et al (2012) describes Superpixel segmentation as an algorithm capable of capturing image redundancy and provide an effective means for computing image features. This in turn can reduce the complexity of any subsequence image processing tasks that may be applied in later phases of a system.

[image example of Superpixel segmentation on unrelated image].

Existing state-of-the-art image segmentation techniques such as mean-shift and graph-cut are able to procure a lower time-cost segmentation solution, however these techniques suffer from the weakness of allowing the superpixel size and shape to be inconsistent and have a high variance. To this end, Wang et al. (2017) perform a study entailing the development of a Superpixel algorithm which minimises the cost function through a minimum spanning tree cost function based on graph theory. This algorithm divides the superpixels by region growth based on the seed points that were pre-determined, using an energy function which considers both the colour difference and a distance factor. Overall, the conclusion of this study found that the algorithm was capable of generating superpixels with the same colour and size, the solution of which was found to be robust and capable of operating with different totals of superpixels and is capable of running consistently with either a small or large number of seed points.

## UTILISING PRE-TRAINED MODELS AND A TRANSFER LEARNING PARADIGM

## DATA AUGMENTATION

## CONVOLUTIONAL NEURAL NETWORKS

## VALIDATION METHODOLOGIES

## ACTIVATION METHODOLIGIES

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## SUPERVISED DEEP-LEARNING METHODOLOGIES

## NEUROSCIENCE BACKGROUND

# **CHAPTER 3: METHODOLOGY**

## 3.1 PROJECT MANAGEMENT

## 3.2 SOFTWARE DEVELOPMENT

## 3.3 TOOLSETS AND MACHINE ENVIRONMENTS

## 3.4 RESEARCH METHODS

# **CHAPTER 4: DESIGN, DEVELOPMENT AND EVALUATION**

# **CHAPTER 5: PROJECT CONCLUSION**

# **CHAPTER 6: REFLECTIVE ANALYSIS**

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# APPENDIX