UNIVERSITY OF
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MComp Research Project

CMP9056M | Assessment Item 1

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Developing a Seed Segmentation and Feature Extraction Algorithm Which Incorporates a Deep-Learning Architecture

Introduction

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.

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.

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.

Existing Deep-Learning Neural Network Systems

Deep 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.

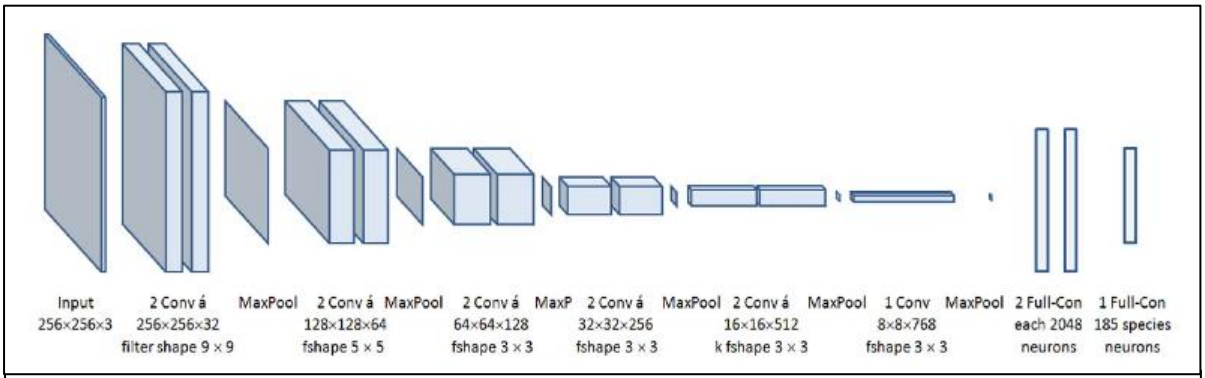


Figure 1. Image portraying the LeafNet CNN Layer Architecture (Barré et al, 2017).

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

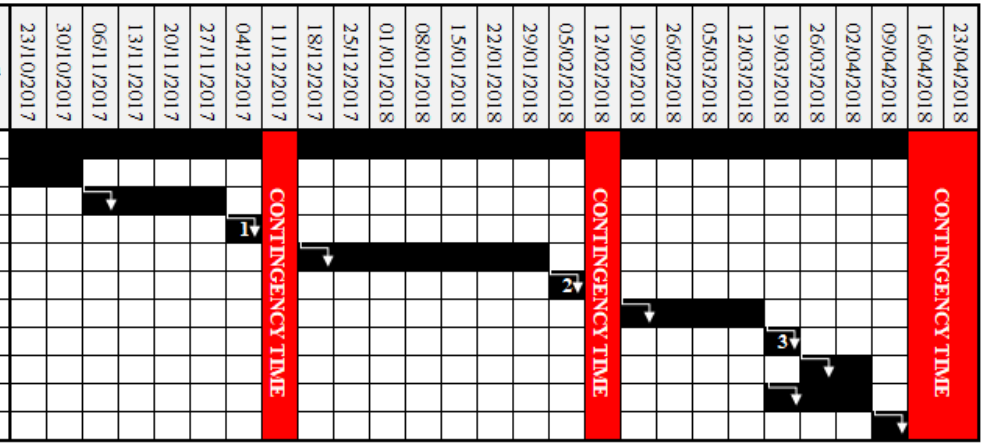
in real-time image processing, it was also established that the image quality needs to be adjusted in consideration of the image size and the fluoroscopic frame rate, as in some cases the results suggested a performance which was under 30fps and therefore deemed unsuitable for real-time processing.

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 regards to the recognition accuracy and speed of the algorithm that is going to be developed in this project if GPU-enabled processes are considered.

Project Plan

Gantt Chart

Task ID	Task Description	Start Date	End Date	Task Duration (Weeks)
1	Project Management, Thesis Write-Up and Further Research	23/10/2017	23/04/2018	27
2	Establish and Prepare a Sufficient Dataset of Seed Images	23/10/2017	06/11/2017	2
3	Develop and Experiment with Existing Deep CNN Architectures	06/11/2017	04/12/2017	4
4	Evaluate the Performance of the Architectures	04/12/2017	11/12/2017	1
5	Develop a Customised Deep CNN Architecture	18/12/2017	05/02/2018	7
6	Evaluate the Performance of the Architecture	05/02/2018	12/02/2018	1
7	Develop Photometric Feature Extraction	19/02/2018	19/03/2018	3
8	Design a Graphical User Interface (GUI) for the System	19/03/2018	26/03/2018	1
9	Develop the GUI for Non-Experts	26/03/2018	09/04/2018	2
10	Adapt the Developed Algorithm with GPU-Enabled Processes	19/03/2018	09/04/2018	3
11	Evaluate GPU-Enabled Performance of the Architecture	09/04/2018	16/04/2018	1



Key:	
1,2,3	Milestones
	Dependency

Methodology

An imperative task that will remain throughout the entirety of the project is the consideration for the project management that will be employed, this may involve but not limited to adapting the project plan as the project progresses or concurrently managing any additional research that may have been unforeseen during the early stages of the project. This task will also involve collating information and conducting a thesis write-up concerning the findings of this project, which will be finalised towards the end of the project lifecycle.

Prior to conducting significant development on the algorithm, a vital task to be completed is to ensure that a large, sufficient dataset can be established as the quality and quantity of the supplied dataset can be considered as part of the core of the neural network system architecture that will be developed. To this end, this task may require a total of 2 weeks to prepare as the dataset of seed images will need to be large and provide a satisfactory amount of variation so sufficient data can be learned for the neural network architecture.

As previously outlined, the core of this project will entail the development of neural network system architectures which can be used for the convolutional analysis of seeds that may be present in various seed image samples within the training dataset, hence this is reason as to why the tasks involved in achieving these objectives have been allocated the most project resources. Milestone 1 of the project will involve the development and experimentation of existing CNN architectures to establish their functionality for this project, whereas milestone 2 will largely be focusing on the completion of a new CNN architecture which has been optimised for this project.

By milestone 2 as defined in the project plan, an accurate, trained neural network model should have been fully developed and tested with a large dataset of seed image samples. By this point, the neural network model should have sufficient parameters for establishing species identification for each seed that may be contained in each image sample, however further photometric analysis operations will be developed for 4 weeks. Overall, the outcome of this task should provide the users of this algorithm with further analytical capabilities when processing each seed image sample, this task could entail the identification of additional seed features such as seed angularity, seed size and seed texture.

Assuming milestone 3 of the project plan was successfully achieved, this then infers that there is a possibility to extend the current system design and develop GPU-enabled processes alongside a GUI. The development of these two features will occur concurrently for a total of 5 weeks towards the end of the project, these STRETCH objectives embody the principle of aiming to improve the performance of the developed algorithm while also making the system more accessible for any non-experts that may use the system. Tools such as TensorFlow will be considered for the GPU-enabled algorithm design.

Risk Analysis and Contingency Plan

The following section presents an acknowledgement for all of the risks that have been considered to be significantly relevant to the project represented as a risk matrix, this section will prioritise risks that are specific to this particular project and will not be considering the handling of common risks such as the failure of hardware and equipment.

It should be noted that the risk quotient value has been calculated by: $impact\ level * risk\ likelihood$.

Risk Description	Risk Likelihood	Impact Level	Risk Quotient	Contingency Plan
The complexity of the developed deep learning architecture may be too high, therefore a parallel adaption of the developed system architecture may take longer than expected to complete within the planned project timescale.	0.80	2	1.6	The complexity of the deep learning architecture has been considered in the design of the timescale and management of the project, and therefore is the reason why the objective of developing the algorithm to run on a GPU is considered as a STRETCH objective. As a result, if the time remaining in the designed project timescale is not sufficient for this objective, then it should not concern the main deliverables of this project.
Tasks with dependencies featured in the project plan may require more time than anticipated to complete, this would then lead to potentially exponential delays for the subsequent tasks in the project plan. As a result, this could question the likelihood of the project being completed for the planned deadline.	0.60	5	3.0	At this stage of the project, it is likely that unforeseeable delays for the completion of some tasks with dependencies may occur, for example a task may just require more time than initially intended to complete. To counter this, the project plan has been designed with contingency time being allocated throughout the timescale of the entire project, whereby this time will be used as a means for finalising unfinished tasks and mitigate and completion delays for some of the tasks involved in this project.
The developed deep learning architecture may not be effective on every seed image sample and may struggle to successfully segment all of the seeds.	0.60	5	3.0	With this project, it is anticipated that the algorithm will not be able to acquire a 100% accuracy rate upon processing the entirety of the supplied dataset, this is in response to the type of results which were indicated from the research undertaken for this project.

				On the other hand, if the accuracy rate is significantly lower than expected, a possible cause could be a lack of input parameters for the algorithm or moreover a low training dataset of seed images, which would therefore limit the learning capabilities of the algorithm. If this is the cause, time will be allocated for seeking a new, larger dataset of seed images. However, if the cause is unknown, time will be allocated for mitigating the configuration of the deep learning architecture so that more effective results can be yielded.
Depending on the size of the training dataset that will be used for this project, the time complexity for training the deep learning architecture may be significantly higher and may take longer than expected to run. This can lead to difficulties in regards to debugging and executing the algorithm.	0.80	7	5.6	The hardware may prove to be insufficient in regards to processing power, and may take longer than necessary to fully process the large dataset of seed images. For example, the processing capabilities of the computers stationed in the University of Lincoln Computer Labs may be insufficient of a dataset of this magnitude. Therefore, additional time will be allocated for locating and establishing new hardware which would be able to process the large dataset of seed images more efficiently. However, if new hardware cannot be found, the project plan will be adjusted such that more time will be allocated for the processing of the input data, for example one option could be to contact the University of Lincoln technicians and seek permission to leave the algorithm processing the large dataset on-campus overnight.
The training dataset may be insufficient or may not provide a large enough variation between seed species and seed quality to be able to fully test the developed deep learning architecture.	0.40	8	3.2	The size of the dataset can be considered as part of the core of this deep learning architecture that will be developed. A small training dataset will limit the learning capabilities of the developed algorithm and will therefore also limit the accuracy performance of the deep learning architecture. If this is the case, a new, larger dataset of seed images will be sought and utilised to establish a greater compilation and variation of input data.

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