



Bournemouth
University

FACULTY OF SCIENCE & TECHNOLOGY

BSc (Hons) [Degree Title]

May 2021

What's Wrong With My Crop? Using Convolutional
Neural Networks to Detect Crop Defects

by

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Final Year Project

Abstract

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A good abstract should be accurate, self-contained, concise, specific and clear. A quick way to assess the quality of your abstract is to check whether it answers the questions why, how, what and so what.

Researching the efficacy of using CNN's (Convolutional neural networks to identify crop defects) and creating a suitable platform for users to interact with the network.

It is easier to write the Abstract the last.]

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This is your opportunity to mention individuals who have been particularly helpful. Reading the acknowledgements in the past dissertations in the project library will give you an idea of the ways in which different kinds of help have been appreciated and mentioned.]

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Chapter 1 - Background and Lit Review

1.1 Context

the application area / industry / domain

1.2 Technological Aspects

lorem ipsum

Chapter 2 - Introduction

2.1 Context

With the increased availability of smartphones Sta (2021), digital cameras Ima (2021) and Internet access Wik (2021) Glo (2021). Coupled with the increased interest in home food cultivation Goo (2021) and the large number of people reliant on food grown in smallholdings Walpole and Hutton (2013). The ability to identify defects with crops using technology has potential to be impactful to many people.

2.2 Literature Review

Firstly, existing research regarding image classification of plants and plant diseases will be explored. Secondly, an analysis of CNN architecture development.

2.2.1 Disease Detection Usage Of CNNs

In 2009 a study was conducted using deep learning to identify three different disease classes on rice plants. The results showed over 70% classification accuracy on 50 sample images. The method employed used segmentation, followed by image feature extraction using three different algorithms to extract color, shape and texture information from the image. The feature data was input to a classification algorithm whereby the output would be one of the three disease types or no disease present. Anthonys and Wickramarachchi (2009)

In 2015 another experiment (using similar approach to Anthonys and Wickramarachchi (2009)). Involved using image segmentation using K means clustering and other image processing techniques, to find features in the image and create a one dimensional binary feature vector, to be processed by an ANN. Khirade and Patil (2015) The accuracy of detecting powdery mildew, yellow rust and aphids on wheat were 86.5%, 85.2%, 91.6% and 93.5% respectively. This non CNN technique has subsequently been rendered redundant as this method requires a greater number of computational processes and achieves results that have been surpassed by CNN's. However, the image segmentation technique (with the purpose of isolating the leaf from the background) is also sometimes used in CNN approaches.

A year later and there have been great successes in identifying crop disease with CNN's. In

2016 a paper was published running experiments on a 38 class crop disease dataset over 14 crop species and 26 diseases (or absense thereof). Resulting in 99.35% accuracy on a held-out test set (using GoogLeNet). Mohanty *et al.* (2016). This study utilized two established CNN architectures, namely AlexNet Krizhevsky *et al.* (2012) & GoogLeNet. Szegedy *et al.* (2015a) With GoogLeNet achieving a higher F1 score in almost all cases. This study also highlighted the effectiveness of using colour images when training the models. In all experiemnts, the color or segmented image models performed better as appose to grey scale images. A suprising aspect of the results is the fact that the segmented image models almost always permed worse than the colour image models, with the best performing model being trained on colour, non-segmented images. This may be due to some bias being present in backgrounds of the dataset images. Or it may be more effective to not perform segmentation on the images prior to training.

Then in 2018 InceptionNetV3 (a later iteration on the GoogLeNet i.e. InceptionNetV1 architecture) is used on a very similar if not the same dataset of 38 class crop diseases (this paper cites the number of crop species to be 13 appose to 14) and 26 diseases. Resulting in a slight increase in accuracy of 0.39%, to 99.74% classification accuracy. Kulkarni (2018) Prior to training the models, the training images were segmented to give the crop leaves a black background. Notably this study began with pre-trained InceptionV3 models and fine tuned them by training a seperate model for each type of crop. This allowed a system whereby the network is fed an image, it determines the crop, then it passes the image to the specific network tailored to that crop species. Unfortunately there are no results available of experiments with non-segmented data to compare with the Mohanty paper. Interestingly the author (Omkar Kulkarni) states 'The pre-processing of image is essential for removing noise and segmentation of the image which helps in improving the accuracy of CNN model'. However, the results table [APPENDIX LINK] produced by Mohanty *et al.* (2016) show non-segmented images acheiving higher accuracy. The increase in accuracy for this paper when comapared to Mohanty *et al.* (2016) can be explained by the better performing InceptionNet architecture

A study performed in 2015 by Sungbin Choi Choi which involved plant species identification from a multi-image observation query. Found that an ensemble of CNN's performed with better classification performance. The study utilized an ensemble of fine-tuned² GoogLeNet architectures.

This paper Zhu *et al.* (2018) performed experiments for plant species identification and justified that 'using CNN's can provide better feature representation compared to hand-crafted features.'

From the reviewed sources it is aparent that the best performing architectures have employed the Inception Szegedy *et al.* (2015b) module. which is consistent with the findings of Wu *et al.*

²meaning pre-trained on generalized data and then improved with domain specific data

(2019). This paper found that when pitted against Resnet He *et al.* and InceptionNet varieties the Inception-ResNet-v2 was the best performing well known architecture. However the researchers crafted a bespoke architecture using inception modules that slightly outperformed the Inception-Resnet-v2.

2.2.2 Existing CNN Architectures

One of the first major pioneering works in the field of machine vision has been Cun *et al.* (1989) which designed a CNN architecture to be used for character recognition and printed on a chip. With all of its 49 templates (today known as filters) being designed by hand. And later goes on to introduce 'Digit Recognition Using Constrained Automatic Learning' which allows some parameters of the network, including filter values to be updated automatically via backpropagation, removing the problem of having to design all of the filters manually. Manually designing filters can be seen as introducing some priori information to the network. Which also alleviates the problem of having a scarce amount of data. A noteworthy step when training their network is the final stages of training whereby they waited for their model to converge at a minima (minimizing loss, i.e. error) which took 23 learning passes, then trained it for a further 5 passes on a dataset that quote "had undergone slightly different preprocessing", resulting finally in a 5% error rate at classifying handwritten digits. Later in the work of creating LeNet5 LeCun *et al.* (1998) we see the invention of fully automated parameter tuning via backpropagation (for more on backpropagation see Cun Yann le (1988)) that led to, achieving 0.8% error rate at identifying hand written digits. This was in part made possible by the increased amount of data available to train the network.

Following from LeCun we see the next popular architecture (winner of the 2011 ImageNet Large-Scale Visual Recognition Challenge (ILSVRC)) that is often used as a benchmark in later papers AlexNetKrizhevsky *et al.* (2012). A noteworthy aspect of its design is the choice to change from using the tanh activation function that we find in ? to the relu activation function, which has been adopted in all state of the art approaches today. The relu function is linear so we see a decrease in training time by virtue of using a function that is less computationally expensive. They found that due to the large number of parameters in the network, it had a tendency to overfit the training set. To mitigate this, data augmentation is used including reflections and zooming in on only parts of

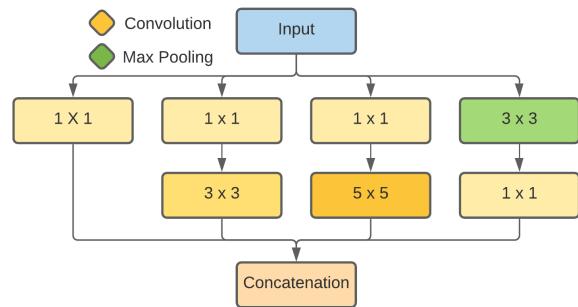


Figure 1: Inception Module Example.

the image such as corners/middle. Other augmentation included normalizing the RGB intensity across the image as it stated that 'object identity is invariant to changes in the intensity and color of the illumination'. This network also employs dropout as discussed later. When training the model stochastic gradient descent is used, whereby the parameters of the network are updated based on the loss of each training example. We also see mention of the concept of 'fine tuning' a network, whereby one takes a network that is pre-trained on a generalized dataset and then further trains it on domain or dataset specific input. Furthermore, we see evidence for the virtue of using ensembles of CNN's to reduce classification error. Finally the paper concludes stressing the importance of depth for classification accuracy citing a 2% reduction in classification accuracy for top-1 performance if any convolutional layers are removed. However a later paper Zagoruyko and Komodakis has established that 'widening' networks can be just as or more effective than deepening. The concept of widening can also be used to explain the effectiveness of InceptionNets.

Another major improvement in CNN architecture comes in the form of VGGNet (Visual Geometry Group) Simonyan and Zisserman (2015). In this paper they studied a range of different network depths. They take the approach of further deepening the network to improve accuracy, citing their use of small receptive field filters (3x3) as the main key to their success. This logically follows as the smaller the receptive field, less weights need to be tuned. This fact coupled with using a moderate amount of filter channels (512 at most) allows for more conv layers. Earlier designs were using larger filters especially in the first layer namely Krizhevsky *et al.* (2012)&Sermanet *et al.* (2013). To aid in training their deeper network variations, pre trained layers of shallower networks are used as the initial and final layers, with the middle layers remaining randomly initialized. When training the network min-batch training is employed whereby the weights of the network are not updated until a batch of training examples has been seen, as opposed to stochastic whereby the weights are updated after a single example. Data augmentation is also important in the approach; each training image was cropped a . Their best performing ensemble of 2 VGG nets achieved 6.8% top-5 test error on the ILSVRC test classification dataset. VGG Much like its predecessor AlexNet, employs max pooling layers and Relu activation function.

Continuing the theme of deepening networks we are introduced to the ResNet He *et al.* Winner of the ILSVRC 2015 classification task. ResNets introduce the concept of the skip/shortcut/residual connection. Meaning output from an earlier layer is added to the output of a layer some convolutions ahead of it. The emergent result is performance no longer degrading with greater network depths. A reason for this, is less feature information is lost through the convolution operations. Due to the fact that every conv operation reduces the volume of input, information is lost after each operation. The skip connection mitigates this by adding earlier information to later layers.

With an ensemble of ResNets it's top-5 err on the ILSVRC test set was 3.57%

An earlier but more different when compared to earlier iterations of design, comes in the form of InceptionNet/GoogLeNet Szegedy *et al.* (2015b). Part of their philosophy when creating the network was to make something that could perform well on hardware that was more widely available quote "the models were designed to keep a computational budget of 1.5 billion multiply-adds at inference time, so that they do not end up to be a purely academic curiosity." Szegedy *et al.* (2015b). The feature that sets InceptionNet architectures apart is the different varieties of Inception Module. An inception module is multiple convolutional operations occurring in parallel and finally being concatenated together. Additionally 1x1 convolutions are employed to reduce the input volume to later convolutions and therefore improve training time and prevent bottlenecks. This approach of adding more channels in a single layer is commonly referred to as 'widening' the network. Also we see feature information concatenated before being passed to the next module.

As it stands, there are few, (if any) papers exploring the efficacy of the novel fractalNet architecture Larsson *et al.* (2016) for crop disease detection or on any other dataset aside from the commonly used CIFAR10 & 100.

The inventors of the fractalNet performed experiments that justified their use over ResNets. Demonstrating results that showed improved classification accuracy. Another feature of the fractalNet architecture is the ability for the user to choose between speed of prediction and accuracy of prediction as it is possible to take longer or shorter paths through the network. Longer paths being more accurate and more time consuming.

Research has been conducted in 2016 Zagoruyko and Komodakis that determined 'wider' networks perform better than their deep narrow counterparts. They found that their 16-layer deep network had the same accuracy as a 1000 layer thin deep network with a comparable number of parameters. With the wider network being faster to train.

A key feature of CNN design is size and number of filters. In all examples mentioned (Resnet, InceptionNet, AlexNet etc), filter size is always odd and square. For instance 1x1, 3x3, 5x5 and so on. Size of filter will determine the size of the feature the filter will encode for. Number of filters

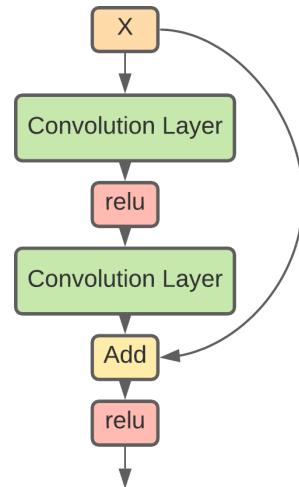


Figure 2: Residual Identity Block

will determine the depth of the convolution output. It is noteworthy that the Resnet50 architecture He *et al.* uses almost entirely 3x3 size filters. Whereas, the Inception module employs a mixture of 1x1 through to 5x5 convolutions.

A technique known as dropout is a feature that has been employed in increasingly deep networks to prevent overfitting and was first introduced by Srivastava *et al.* (2014). The principle behind its operation is randomly dropping paths between neurons during training. This ensures that predictions do not become overly reliant on a single (or group of) neuronal activation(s), that can correlate to some bias in the training data. And prevents neurons from becoming co-adaptive. This technique was employed in AlexNet Krizhevsky *et al.* (2012) whereby they used dropout in the first two fully connected layers of their model. They found that using dropout prevented overfitting but made training take twice as long. This exact method whereby dropout is used in the first two fully-connected layers is seen again in VGGNet Simonyan and Zisserman (2015); both methods choosing to employ a dropout chance of 50%. [REMOVE?] which performed experiments on several different architectures, concluding the efficacy of deepening networks to achieve higher classification accuracy. .

Another aspect of CNN's is the process by which they progressively narrow down the possibilities until they arrive at their conclusion. This is done by encoding loose abstract forms that relate to groupings of objects in the early layers and gradually arriving at very generalized forms such as horizontal lines or sine waves in the later layers. So to give an example drawn from the AI microscope [CITE AI MICROSCOPE] . In an early layer we may find a neuron that encodes for two semantically unrelated objects, yet objects that have a form in common such as dogs and turnstiles, a middle layer may encode for things under the sea or star shaped objects. Final layers encode for more generic features such as diagonal lines or squares. In the case of the dog and the turnstile, one can observe that a 'branch' of a turnstile is equateable to the leg of a dog and the 'console?' of the turnstile be equateable to the dogs body.

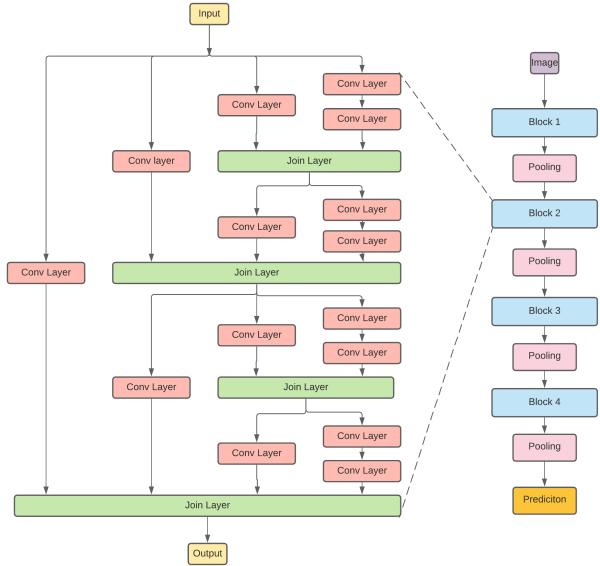


Figure 3: FractalNet Architecture.

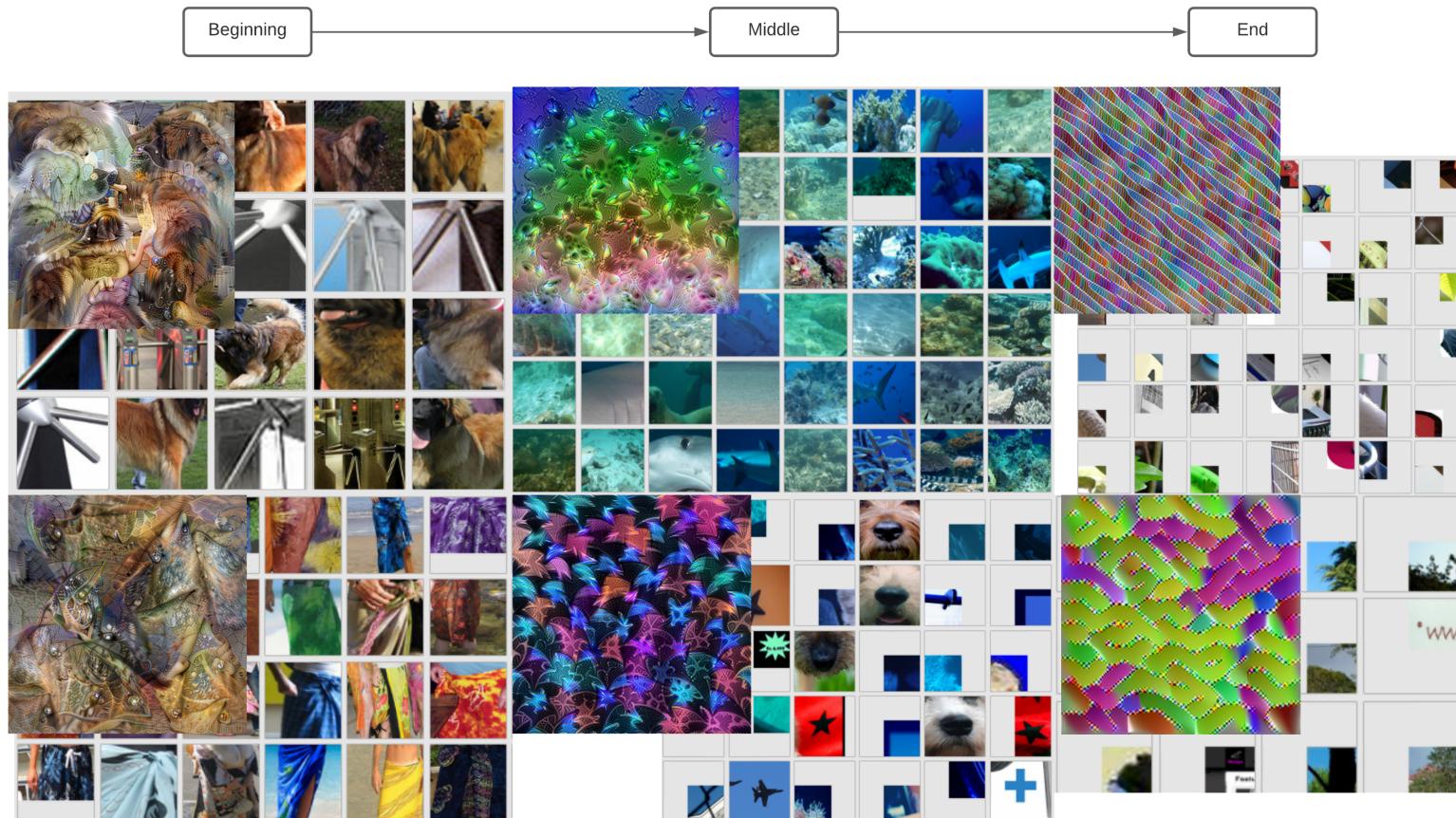


Figure 4: InceptionNet Filter Activation Maps

2.3 Problem Definition

As it stands there are currently (09/02/2021) no easily found¹ web interfaces for interacting with a crop defect identification service.

Although there exists very capable publicly available image classification networks. Yan (2021) There is no bespoke application catering solely to crop defect identification, that has the benefit of providing recourse information to the user.

2.4 Proposed Solution

To provide a web service that interacts with a convolutional neural network (CNN) backend to diagnose crop defects such as, nurturing problems e.g. lack of water/nitrogen/C02, too hot/cold. And external threats such as crop disease/pest infestation. The interface will be simple and intuitive as possible. The UI should minimise points of interaction and streamline the process of uploading a crop image to be analysed. The web service will return information regarding the percentage likelihood of each kind of crop defect, including images that are of similar nature to the one analysed.

2.5 Aims and Objectives

These should be SMART with clear success criteria defined specific, measurable, achievable, realistic, Timebound

2.5.1 Aims

- To aid gardeners and smallholders in identifying crop defects.
- To aid gardeners and smallholders in taking relevant recourse.

2.5.2 Objectives

- Provide a way for a user to upload an image to be analysed.
- Display information regarding the likelihood of each kind of defect.
- Display recourse information alongside defect information.
- Have gallery of images filtered by crop and disease type.

¹(i.e. not present in the first 3 pages of a google search for 'crop defect identification' and 'What's wrong with my crop')

2.6 Risk Table

Table 2.1: Risks Table

ID	Name	Likelihood	Impact	Control Mechanisms		
1	Improper Time Management	med/low	high	Follow the Gantt chart		
2	HDD/storage failure	low	high	All work will be backed up to github		
3	Illness/Injury	med	med	Should the need arise I will apply for an extention	to the due date.	
4	RSI (repetetive strain injury)	med	low	Work with proper postureand set up workstation properly.And take frequent breaks		
5	Eye strain	med	low	Ensure room is well lit when working on a screen.		
6	Incorrect Task Prioritisation	med	med	Iteratively re-asses the work being done and compare it to the mark scheme.		
7	Postural problems	med	low	Work with proper postureand set up workstation properly.And take frequent breaks		

(ID, name, likelihood, impact, control mechanisms / accept)

2.7 Overview

Introducing rest of dissertation (with cross references to sections)

Chapter 3 - Methodology

3.1 Project management methodology

I will use a Feature Driven Agile method. Meaning the workflow will be cyclical and focus on iterating over designs and prototypes. This will involve:

- Requirements elicitation.
 - This involves determining the needs of the user and defining requirements to meet those ends.
- Feature design (UI).
 - Features will be designed at first using wireframe models. Then on later iterations, colour and shading will be added alongside further usability considerations such as highlight on hover etc.
- Feature implementation research.
 - This step involves determining the appropriate technologies and libraries to achieve the design. This is necessary to realize the constraints that are imposed by the implementation method and know to what extent the design is feasible.
- Feature implementation.
 - Writing the code to create the feature.
- Feature testing.
 - Initially testing will be done manually with valid values until later iterations whereby extraneous values will be introduced. Once the feature is in its final iterations a unit test will be introduced.
- Evaluation.
 - Does the feature meet the requirements and fulfill the needs of the user?

This workflow will consist of a single cyclical workflow, with two nested "sub workflows" whereby upon completion of a step, it is sometimes necessary to loop back on oneself to perform further refinement. As illustrated by the diagram below. Throughout the project the focus of the workflow

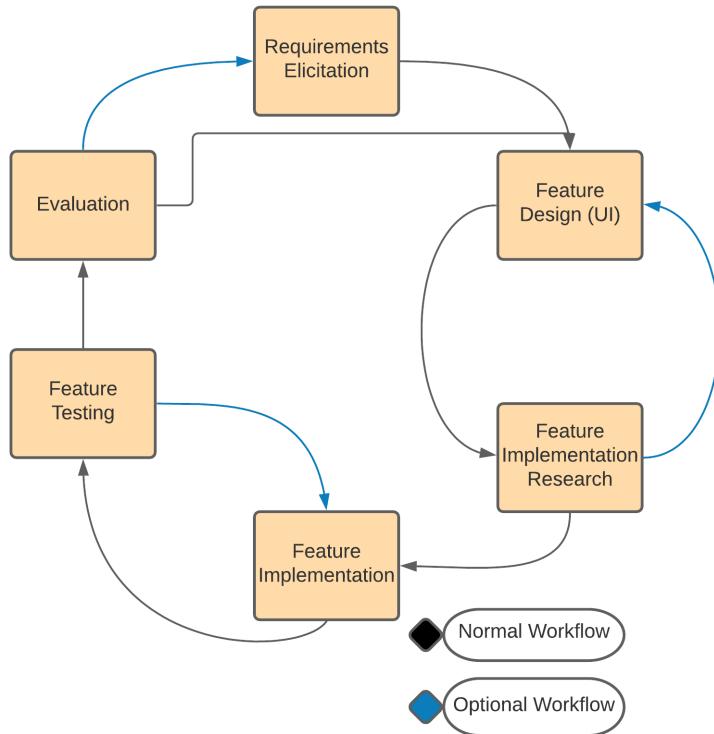


Figure 5: Development Lifecycle

will shift as illustrated by the diagram below.

The paper [CITE BIS OF INNOV] makes a compelling argument for the usage of agile methodologies over more linear project management methodology (PMM) styles such as waterfall. Agile focuses on design being done 'on an ongoing bases in smaller chunks' [CITE BIS OF INNOV]. It is also highlighted that agile allows development to respond to feedback and change. In fact agile has customer, designer and developer feedback baked in to its formula in the form of regular team meetings, especially if using the SCRUM 'flavour'.

For a lone developer Agile with Kanban is the PMM of choice as it allows the flexibility to iterate on designs as one learns more about the technologies being used and gives the freedom to modify one's requirements in light of newly found research. Additionally The lifecycle is short to give frequent milestones. This allows one to better track progress of the project by being able to see how many tasks have been completed on the Kanban board during the development cycle⁴.

Using Kanban to track tasks makes sense for a single developer as opposed to using feature driven development. As this allows for non-programming tasks to be tracked in the same way as programming tasks.

⁴Granted tasks alone are not the be-all, end-all metric but it does give some idea of progress

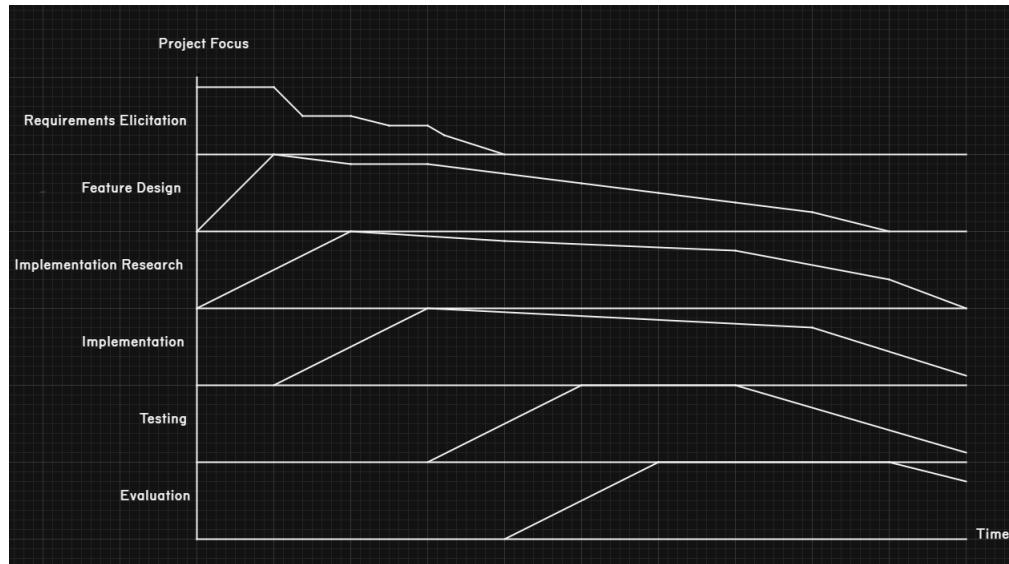


Figure 6: Project Focus Over Time

Furthermore, agile is a worthwhile methodology to use and familiarise oneself with as it has become the new norm in industry. As shown by a study conducted by Hewlett Packard.

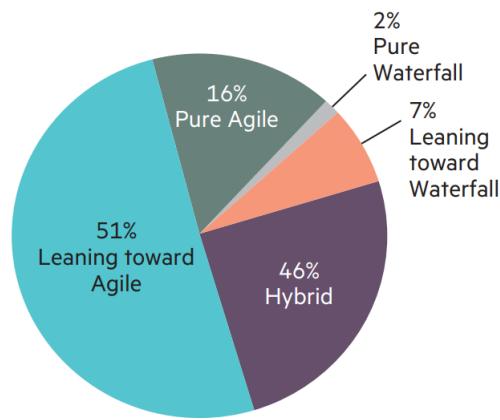


Figure 7: Primary development method used in organization across projects (601 respondents)
diagram created by Hewlett Packard

3.2 Evaluation Design

(what method(s), used how, with what and how many participants?)

3.3 Requirements Elicitation

How will requirements of the software be determined.

3.4 Feature management

To track the creation and completion of features, a Kanban board will be used. This will include columns for 'To do', 'Doing' and 'Done'.

3.5 Design Methods

- Requirements Elicitation
 - To better conceptualize the needs of the user. Use case diagrams and activity diagrams will be utilized.
- User Interface
 - Wireframes will be utilized to establish interface element placement i.e. layout.
 - More detailed mockups will be created when the earlier wireframes are constructed as prototypes and the concept is proved achievable.
 - A colour picker will be utilized to define the colour scheme.
 - In later iterations of the design, once there is a functioning UI, usability will continue to be refined with the help of existing usability research, to guide the usage of font/colour/highlight on hover/font size etc.
 - Additionally once a desktop friendly layout has been established, work will begin on optimizing a version for mobile.
- Back-End
 - UML will be used to show the overall design of the system through structural diagrams. These will show the interfaces of the classes and how they will interact with one another.

3.6 Testing methods

3.7 Version control

I will be using Git and Github. This will allow the creation of branches to explore experimental parts of the solution space without disrupting the progress of the main branch. If the experimental implementation is successful it will be merged with the main branch. It also allows the development of features in parallel, with any conflicts in their implementation being resolved at

the merge stage. The inclusion of a remote repository allows for work to continue on a separate machine if necessary and later be synced with the local main branch.

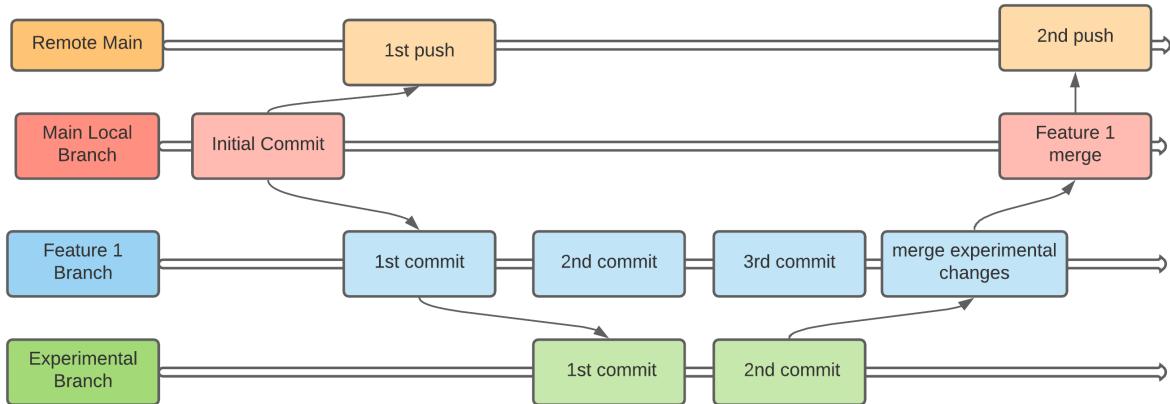


Figure 8: Example Workflow To Highlight Branch Usage

3.8 Evaluation methods

3.8.1 User Interface

The main method that will be utilized to determine the quality of the user interface will be the System Usability Scale (SUS) which can be seen here. (CITATION) The evaluator will be given remote access to the webservice. They will also be provided with some sample images to test the performance of the CNN incase they do not have suitable images of their own. The opinion data will be collected via online questionnaire.

3.8.2 Convolutional Neural Network (CNN)

Metrics for the evaluation of the CNN will be:

- Time to train the network on available hardware
 - The constraint here being if the network cannot be trained on the available hardware in under sixteen hours. Purely for practical considerations.
- Accuracy of CNN predictions. (which will be most effective when there are equal numbers of samples belonging to each class) $Accuracy = \frac{CorrectPredictions}{TotalPredictions}$ Else if the samples are skewed, the network could be a failure at detecting a specific under-represented class, yet still score high accuracy.
- Precision. This is the number of correctly predicted images out of all predictions of that class. $Precision = \frac{CorrectlyPredictedforClass}{TotalPredictedforClass}$ The network is precise for a class when the predictions

it does make are correct. Precision cannot be used in isolation due to the fact that the network can have a high precision for a class but still fail to identify the majority of images for that class. Succeeding solely on the fact that the images it has classified are correct.

- Recall. Is the correct number of predictions for a class out of the number present of that class. $Recall = \frac{CorrectPredictedforClass}{No.PresentForClass}$ This metric can also not be used in isolation due to the fact it does not take into account the number of false positives. i.e. The number of images incorrectly classified as the class in question. For example, if an image dataset contained three classes A, B, C, and the classifier labeled all images A. The recall for A would be 100 percent.
- F1 score. This metric tries to find the balance between precision and recall and can be expressed as $F1 = 2 \times \frac{1}{\frac{1}{precision} + \frac{1}{recall}}$

3.9 Initial Designs

Firstly I have created a wireframe UI

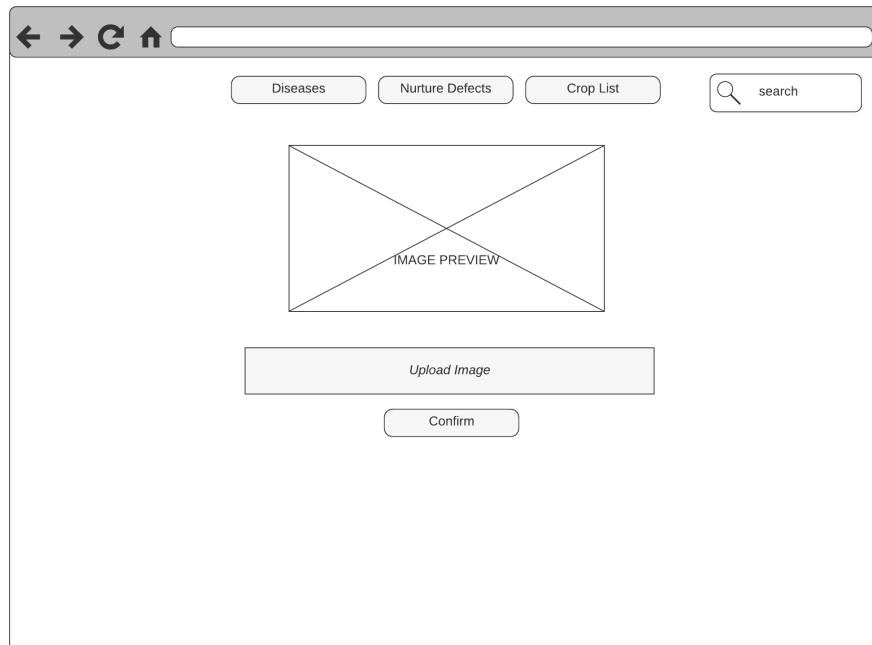


Figure 9: Homepage Wireframe

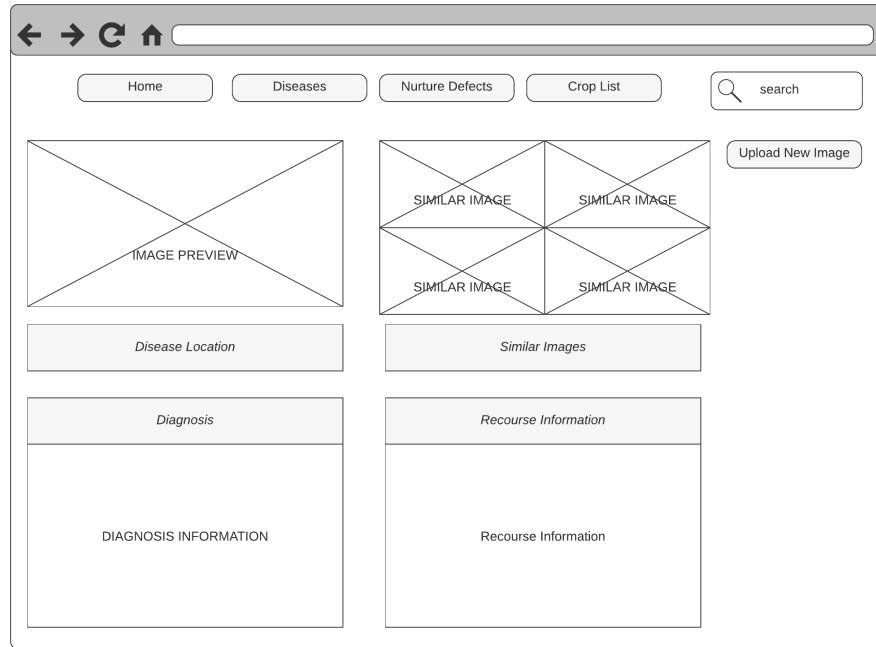


Figure 10: Defect Information Wireframe

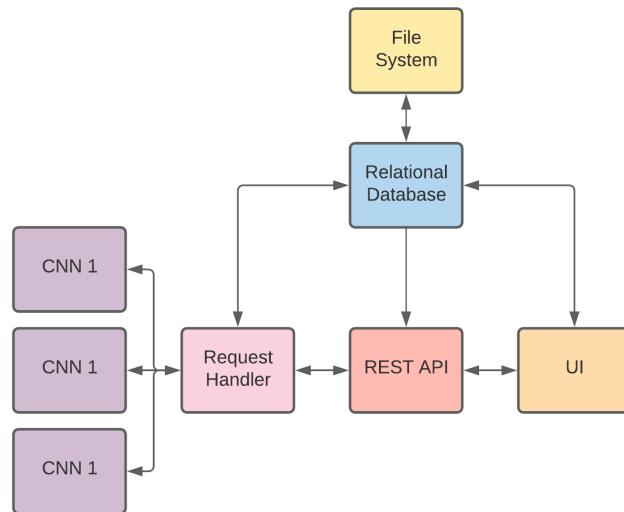


Figure 11: System Overview

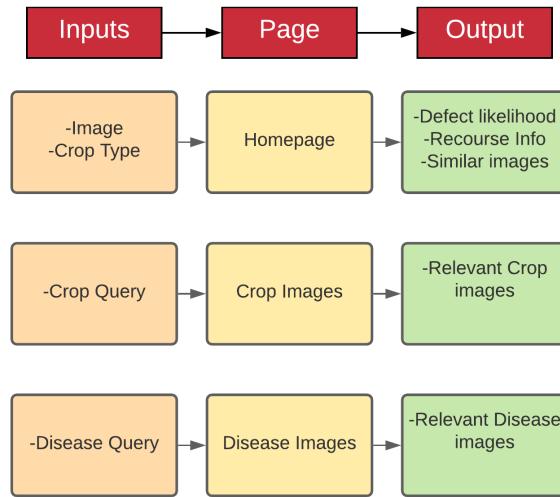


Figure 12: Input/Output overview

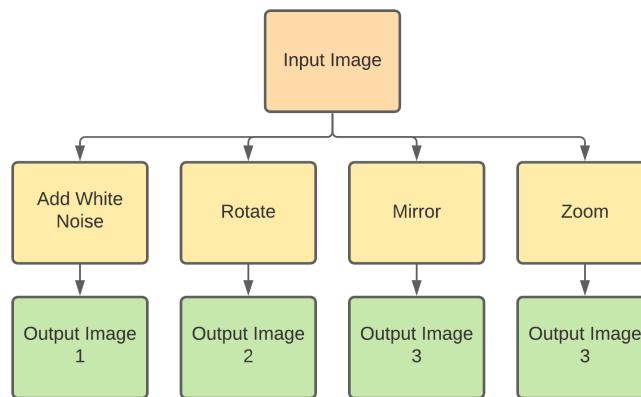


Figure 13: Input/Data Augmentation Methods

3.10 Employed Technologies

- Vue.js
- Bootstrap
- MySql
 - The SQL database will mainly be responsible for storing filepaths to images. This gives the ability to use an SQL statement to fetch certain groups of images for display or training.
 - The database will also store recourse information.

- Jupyter Notebook
- Tensorflow & Keras
- numpy

3.11 Requirements

- Must Have
 - Ability for user to upload an image
 - CNN that is capable of classifying at least 2 different defects across 2 different plant species.
 - An API that allows communication from the UI to the CNN
 - API must be able to receive images.
 - API must return defect information.
 - API must return recourse information.
 - API must return relevant images to the detected defect.
 - have a working REST API. The API will provide information regarding the likelihood of each kind of crop defect, when served an image via a link to a relational database. In addition to other metrics such as similar images and time to compute. The API will be robust enough to handle the receipt of erroneous requests.
 - A python backend that will handle image classification using a CNN.
 - A UI that will allow the user to upload an image to be analysed.
 - The UI will display information regarding the likelihood of each kind of possible defect.
 - To display the relevant images that fit the description of the most likely defects.
 - To display recourse information to rectify the defect.
 - Collecting, cleaning and pre-processing the image data.
 - Artificially grow the dataset by performing translations/rotations/adding noise to the images to make the training data more comprehensive.
- Should Have
 - A page to allow users to see a gallery of images sorted by defect type.

- A page to allow users to see a gallery of images sorted by crop type.
 - The CNN should be able to classify at least 7 different defects across at least two different plant species.
 - The CNN should achieve at least 80% accuracy at classifying all different classes of defect in a held out test set that contains an equal number of each class.
 - Regularisation techniques to prevent the NN overfitting.
- Could Have
 - Ability for users to add additional information about the crop to determine the defect.
 - Won't Have

3.12 Testing and Implementation details

3.13 Justification of Implementation Choices

Chapter 4 - Results and Discussion

4.1 Main Results

lorem ipsum

4.2 Evaluation Results

lorem ipsum

Chapter 5 - Conclusion

5.1 Section One

a dissertation is a substantial document, it is convenient to break it up into smaller pieces. In this template we therefore give every chapter its own file. The chapters (and appendices) are gathered together in `dissertation.tex`, which is the master file describing the overall structure of the document. `dissertation.tex` starts with the line

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Appendix A - Project Proposal

Appendix B - Ethics Checklist