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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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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.

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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 aproach toAnthonys and Wickramarachchi (2009). Involved using image segmentation using 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 teqnique has subsequently been rendered redundant as this method requires a greater number of computational processes and acheives results that have been surpassed by CNN's. However, the image segmentation teqnique (with the purpose of isolating the leaf from the background) Is also sometimes used in CNN aproaches.

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-tuned[2] 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.*

[2]meaning 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

On 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 it's 49 templates (today known as filters) being designed by hand. And later goes on to to introduce 'Digit Recognition Using Constrained Automatic Learning' which allows some parameters of the network, including filter values to be updated automatically via backpropogation, 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 aleviates 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 backpropogation (for more on backpropogation see Cun Yann le (1988)) that led to, acheiving 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.

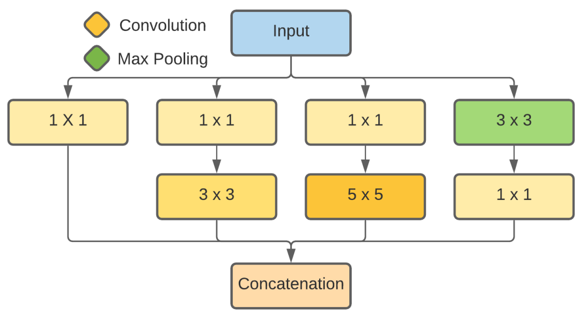

Figure 1: Inception Module Example.

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 it's 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 aproaches today. The relu funciton 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 paramters 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 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 aproach of further deepening the network to improve accuracy, citing their use of small receptive feild 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 initilaized. 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 apose to stochastic whereby the weights are updated after a single example. Data augmentation is also important in the aproach; each training image was cropped a . Their best performing ensemble of 2 VGG nets acheived 6.8% top-5 test error on the ILSSVRC test classification dataset. VGG Much like it's 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 classificaiton task. ResNets introduce the concept of the skip/shortcut/residual connection. Meaning ouptut 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%

Taking the residual connection further is the DenseNet. In this architecture we see a stack of dense blocks, in a dense block each layers output is concatenated with each proceeding layer, notably a ResNet adds the output of the previous layer whereas DenseNets concatenate. This has the benefit of preventing the network learning redundant feature maps and preventing the vanishing gradient problem. The network also employs 1x1 convoution layers to reduce input size to the more expensive 3x3 layers, much like the InceptionNet. After each dense block is a transition layer which consists of a 1x1 convolution operation and a 2x2 average pool with stride 2, the transition layer has the purpose of compressing the output volume. it is unusual to see average pooling used as it is typical to see max pooling, no justification is given for this choice. The authors also claim on the basis that models with over 25m parameters still see increase in accuracy that the DenseNet architecture prevents overfitting. For comparison the original ResNet contains 1.7m parameters.

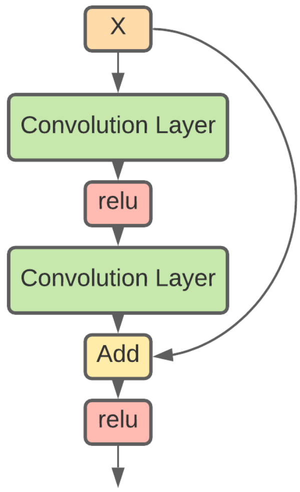

Figure 2: Residual Identity Block

An earlier but more distinctive 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 convoulutional operations occuring in parallel and finally being concatenated together. Aditionally 1x1 convolutions are employed to reduce the input volume to later convolutions and therefore improve training time and prevent bottlenecks. This aproach of adding more channels in a single layer is commonly refered to as ’widening’ the network.

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 prediciton as it is possible to take longer or shorter paths through the network. Longer paths being more accurate and more time consuming. Drop-out is also applied during training but at a coarser level than individual filters, rather, entire paths are dropped at join layers, leading to the creation of pathways of equally strong predictors. It is said in the paper they see their architecture as a more generic design that is not in it's final form as the best configuration of convulutional module and join layer has not been determined. The architecture can also be seen as a harness for creating an ensemble of networks of different depths.

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.

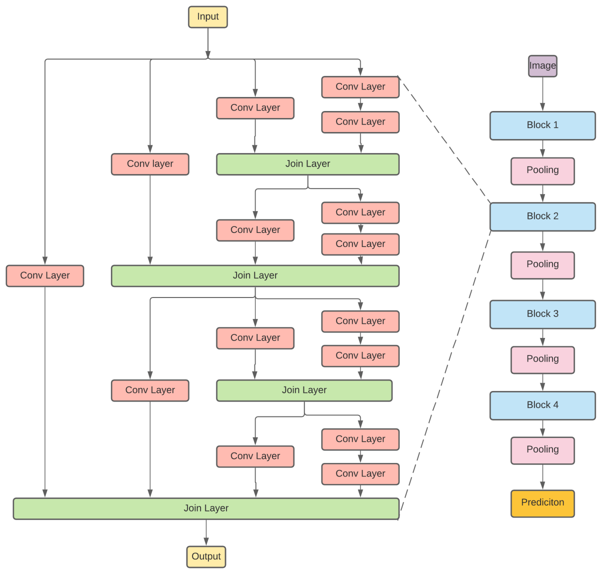

Figure 3: FractalNet Architecture.

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 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 convoutions.

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 gorup of) neuronal activation(s), that can correlate to some bias in the training data. And prevents neurons from becoming co-adaptive. This teqnique 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 VGGNetSimonyan and Zisserman (2015); both methods choosing to employ a dropout chance of 50%.

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.

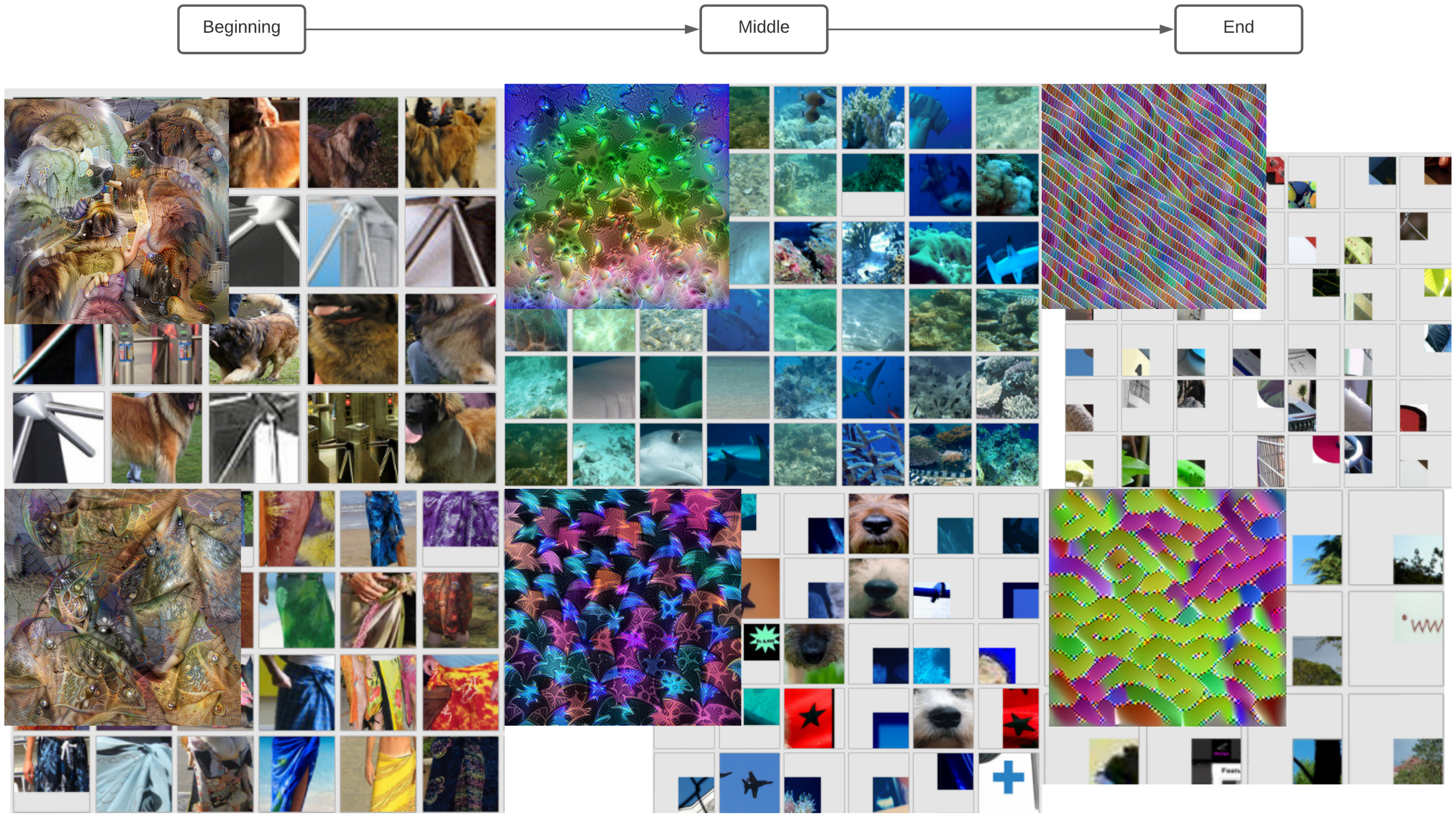

Figure 4: InceptionNet Filter Activation Maps (Examples taken from OpenAI Microscope)

2.3 Problem Definition

As it stands there are currently (09/02/2021) no easily found [1] 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 soley 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 & Objectives

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

2.5.1 Aims

- To aid gardneners 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 infomration 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 Gannt 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 by cyclical and focus on iterating over designs and prototypes. This will involve:

- Requirements elicitation.
  - This involves determening 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 apropriate technologies and libraries to achieve the design. This is nececarry 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 it's 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 nececarry to loop back on oneself to perform futher refinement. As illustrated by the diagram below. Throughout the project the focus of the workflow

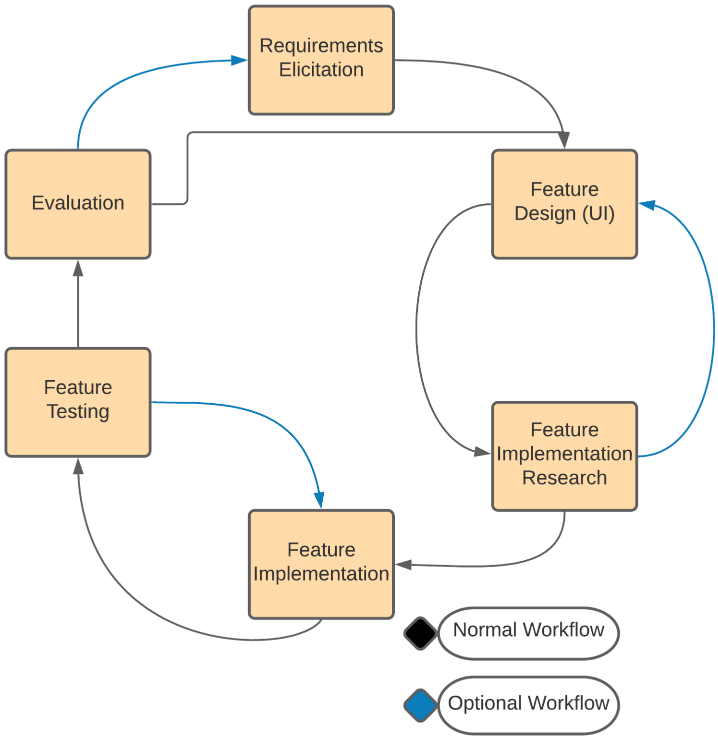

Figure 5: Development Lifecycle

will shift as illustrated by the diagram below.

The paper [CITE BIS OF INNOV] makes a compelling argurment 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 it's 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 flexebility to iterate on designs as one learns more about the technologies being used and gives the freedom to modify one's requirments in light of newly found research and technical limitations. Aditionally the nature of agile is to haves short lifecycles which has the virtue of 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 cycle[4].

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

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

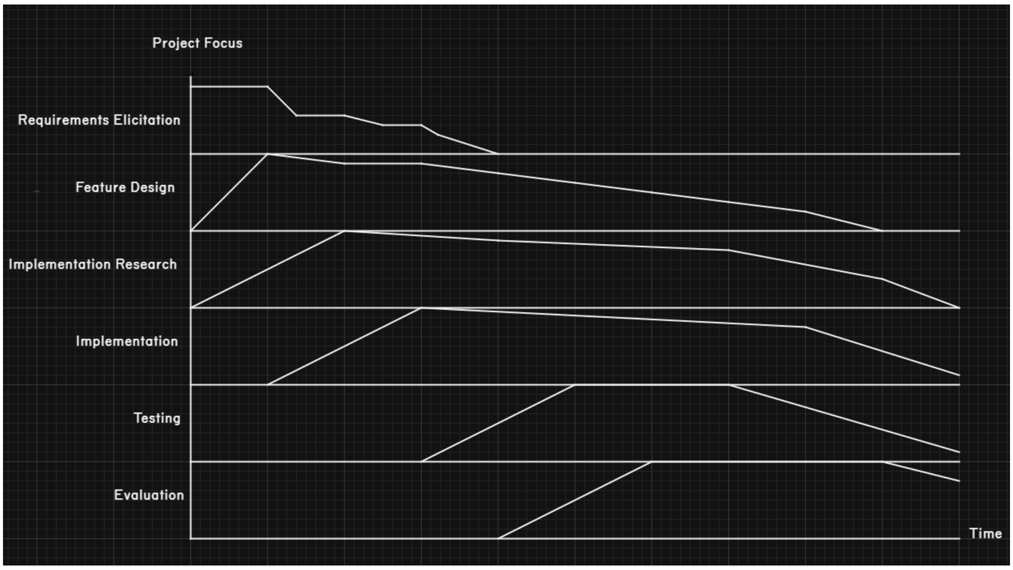

Figure 6: Project Focus Over Time

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.

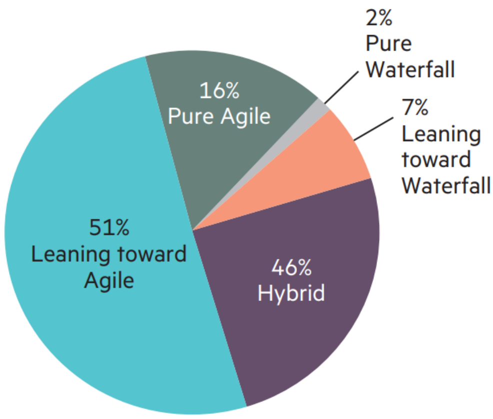

Figure 7: Primary development method used in organization across projects (601 respondents) diagram created by Hewlett Packard

3.2 Evaluation Design

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

3.3 Requirements Elicitation

As the scope of the problem domain is narrow in terms of interaction points for the user. Requirment elicitation will be driven by determining features that will build towards the solving the problem at hand. If for instance the problem was providing some kind of E-commerce website, project management application or social media website, the number of different features that could be employed in any one of these domains is vast and therefore one would need to consult the target audience and elicit the kind of requirements they would like to have. On the contrary, this project is far narrower in terms of points of interaction for the user. Therefore requirements will be determined on the basis of whether or not they contribute towards providing information about crop defects to the user.

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'. To determine which features will be prioritised one will employ the MOSCOW method (more on this later).

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 uitilized 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 acheivable.
  - 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 soloution space without disrupting the progress of the main branch. If the experimental implementation is successfull it will be merged with the main branch. It also allows the development of features in paralel, 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 seperate machine if nececarry and later be synced with the local main branch.

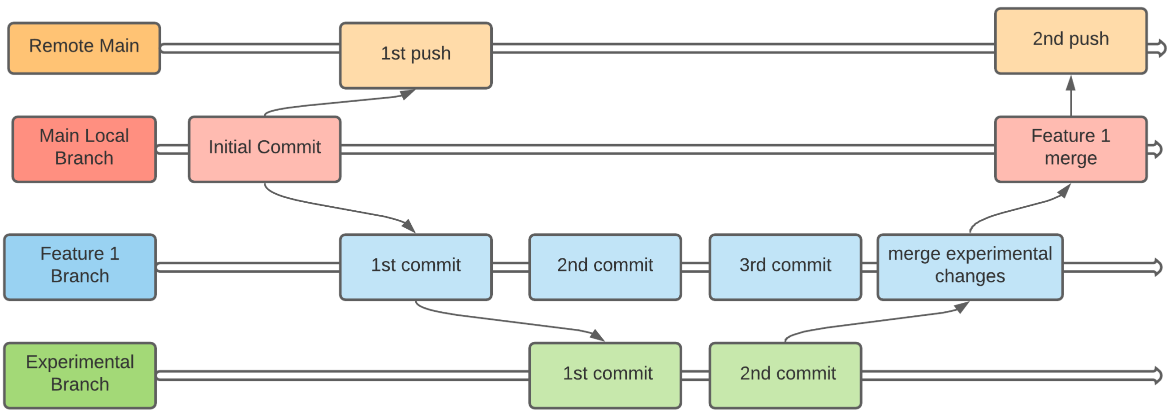

Figure 8: Example Workflow To Highlight Branch Usage

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 perfomance of the CNN incase they do not have suitable images of their own. The opinion data will be collected via online questionare.

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) $Accuracy = \frac{CorrectPredicitons}{TotalPredictions}$ Else if the samples are sqewed, the network could be a faliure 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 precice for a class when the predictions it does make are correct. Precicion cannot be used in isolation due to the fact that the network can have a high precicion for a class but still fail to identify the majority of images for that class. Succeeding soley 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 in to account the number of false positives. i.e. The number of images incorectly classified as the class in question. For example, if an image dataset contained three classes A, B, C, and the classfiier 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 $F1 = 2 \times \frac{1}{\frac{1}{precicion}+\frac{1}{recall}}$

3.9 Initial Designs

Firstly I have created a wireframe UI

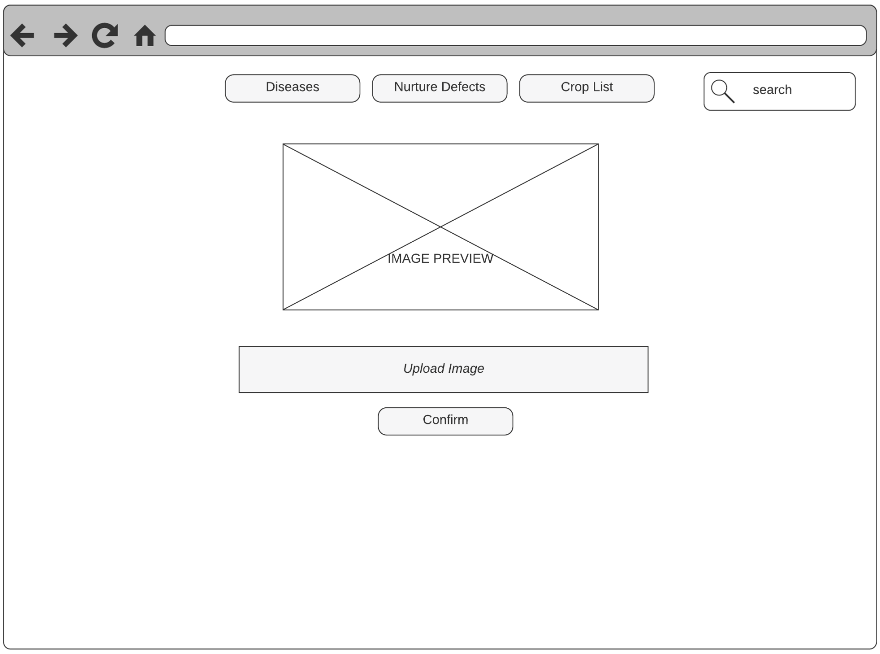

Figure 9: Homepage Wireframe

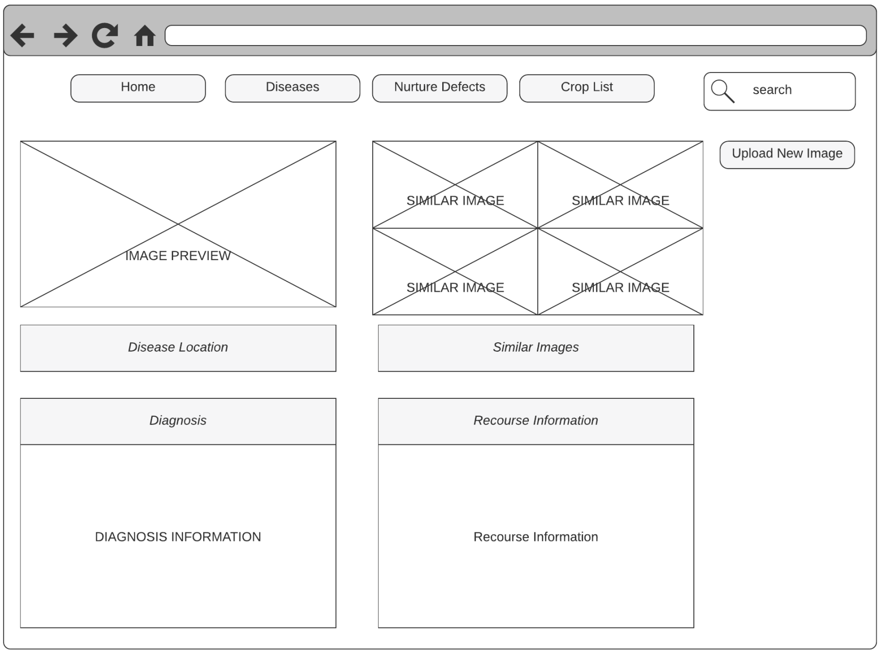

Figure 10: Defect Information Wireframe

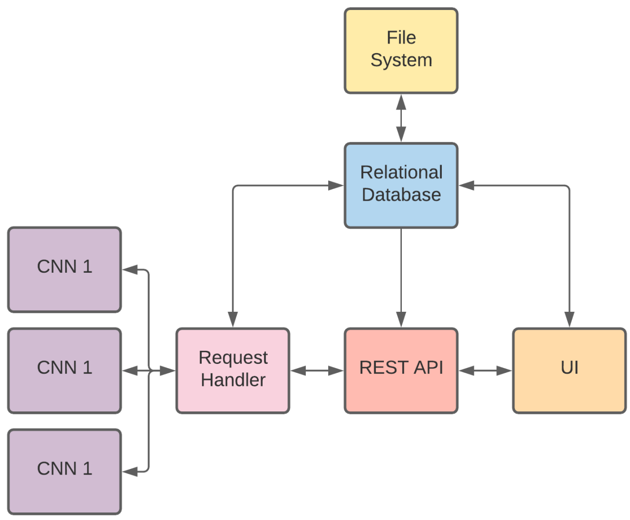

Figure 11: System Overview

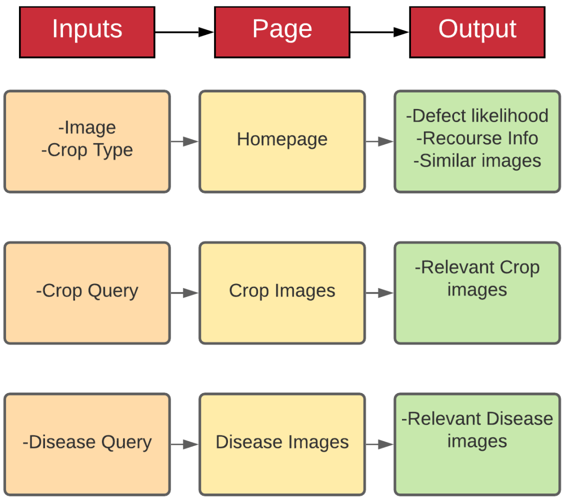

Figure 12: Input/Output overview

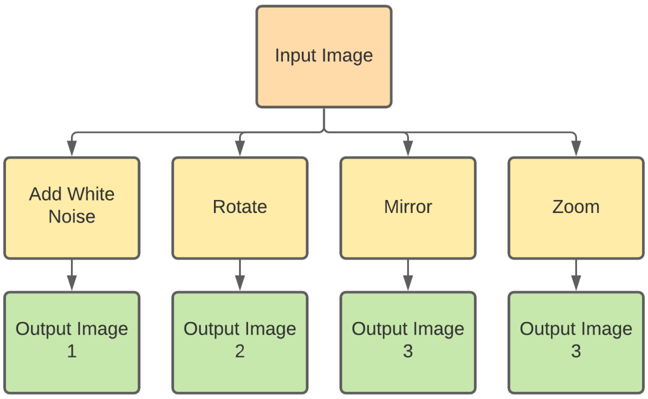

Figure 13: Input/Data Augmentation Methods

3.10 Employed Technologies & Justifications

- Vue.js
  - Vue.js allows for rapid creation of usable websites thanks to its webpack framework, which handles most of the boilerplate needed to handle routing and templates.
- Bootstrap
  - Bootstrap is a CSS framework that has predefined classes for styling HTML elements, this helps with the asthetics of the webpage. For a solo developer this can allow for more time to spent on making the functionality more robust instead of spending time on looks.
- 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 / Google Colab
  - This pthon environment allows for easy prototyping of code. In the case of Colab, it allows for the usage of google servers and GPUS which can be used to train neural networks. With the benefit of being able to then save the trained weights for usage elsewhere.
- Tensorflow & Keras

  - These pthon libraries allow for the creation of complex CNN architectures by abstracting away the underlying matrix/tensor multiplication of deep learning. Allowing for the programmer to declare relationships between CNN features such as convolutional layers, batch normalisation, dropout etc. Without having to construct their inner workings. It also allows for the creation of user defined layers, so adding in ones own bespoke functionality for a layer of the CNN is possible.

- numpy

3.11 Requirements

For assessing requirement priority one will employ the MOSCOW method [CITE Clegg, Dai; Barker, Richard]. This creates subcategory of requirments with the headings Must/Should/Could/Won't - have. The contents of the catagories can change during development in light of development progress. Items placed in the Won't-have category prevent the process of 'scope-creep'.

- 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 acheive 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 prvent 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

Data

The most important part of creating a CNN is the data it is trained on. The more properly labled data the network sees, the better. The most comprehensive dataset available (and the one which will mostly be used) is the Plant Village dataset. it contains 54303 images of healthy and unhealthy leaf images, in 38 catagories divided by species and disease. This dataset also contains pre-segmented[1][1] versions of all the images. This dataset was used in two seperate studies cited in the literature review.

Other datasets that may be used to pre-train the network before are the CIFAR10, CIFAR100 & ILSVRC datasets. These datasets are not specifically plant based, but may benefit the network to build initial feature maps. In Choi the authors used networks pre-trained on generic data such as the datasets mentioned. Experiments will be conducted to determine if this benefits classification accuracy

[1] meaning the background has been blacked out

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