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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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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.

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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, more generalized image classification tasks will be examined and lastly some popular CNN architectures will will be compared.

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 to the rice plant study. Which involved 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 increae in accuracy for this paper when comapared to Mohanty *et al.* (2016) can be explained by the improved 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.* (2019).

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

This paper found that when pitted against Resnet 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.

The feature that sets InceptionNet architectures apart from previous iterations of CNN 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. This aproach is commonly refered to as 'widening' the network.

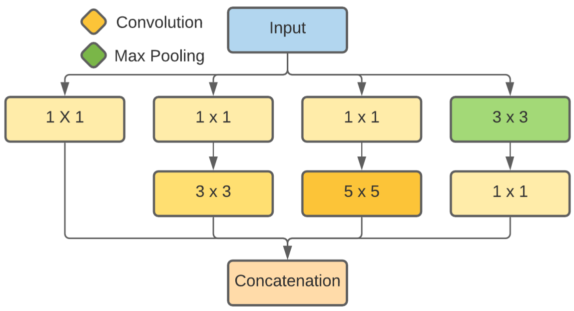

Figure 1: Inception Module Example.

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.

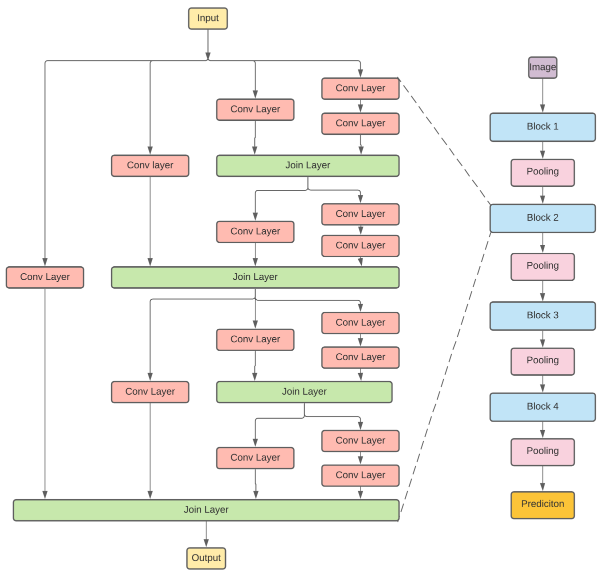

Figure 2: FractalNet Architecture.

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 even 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 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 Simonyan 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 possible answers 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 unrelated objects 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.

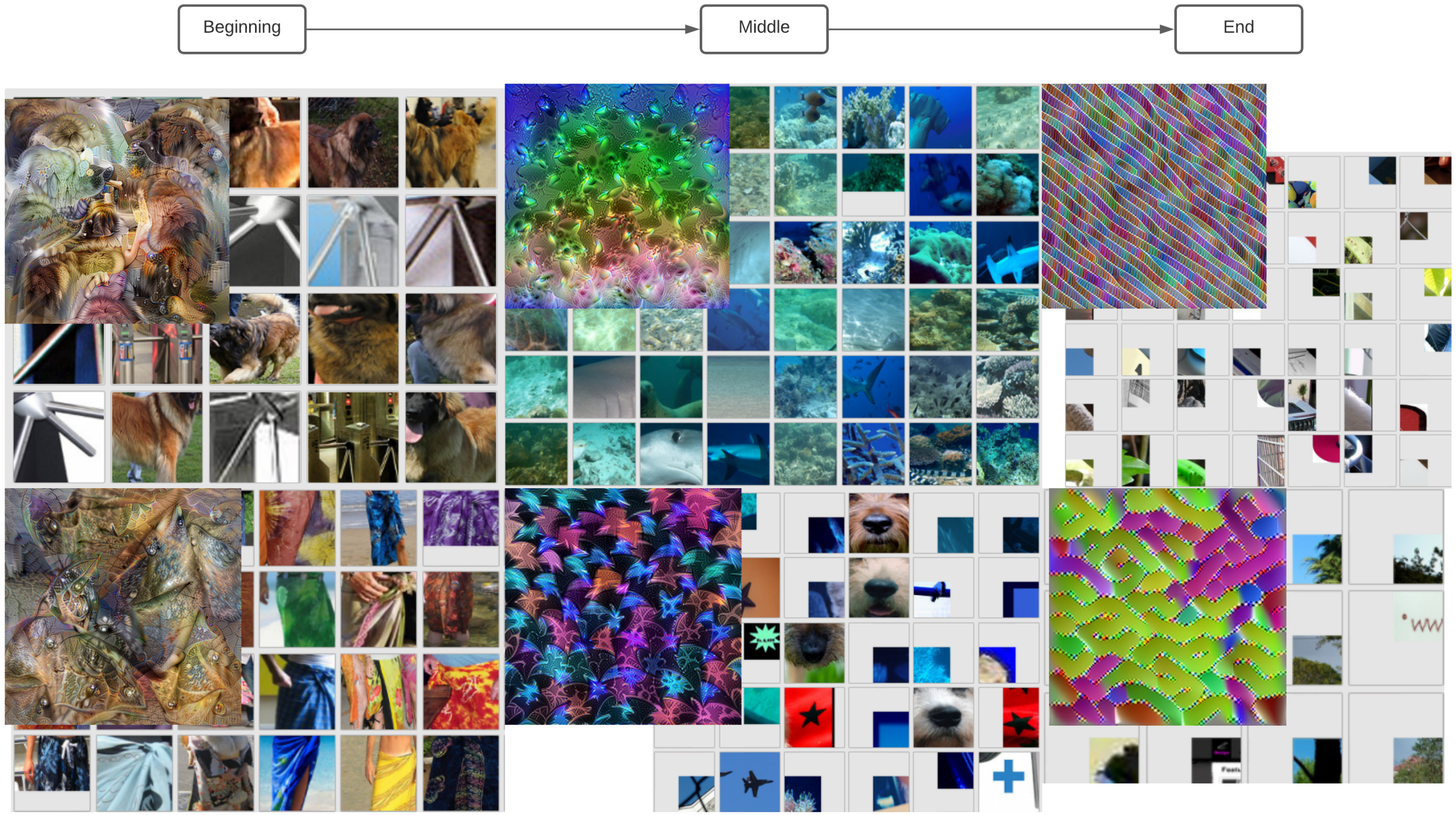

Figure 3: InceptionNet Filter Activation Maps

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 and 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

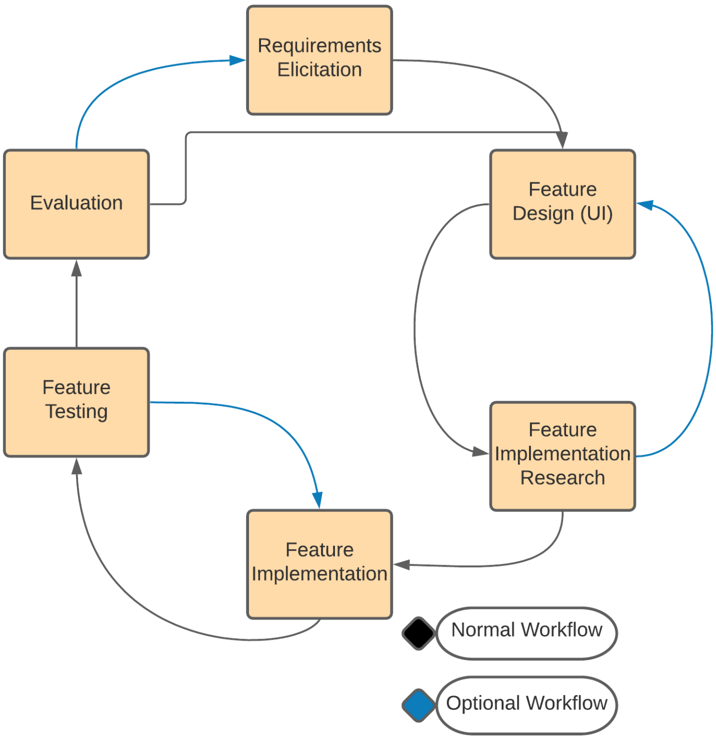

Figure 4: Development Lifecycle

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. Aditionally 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 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

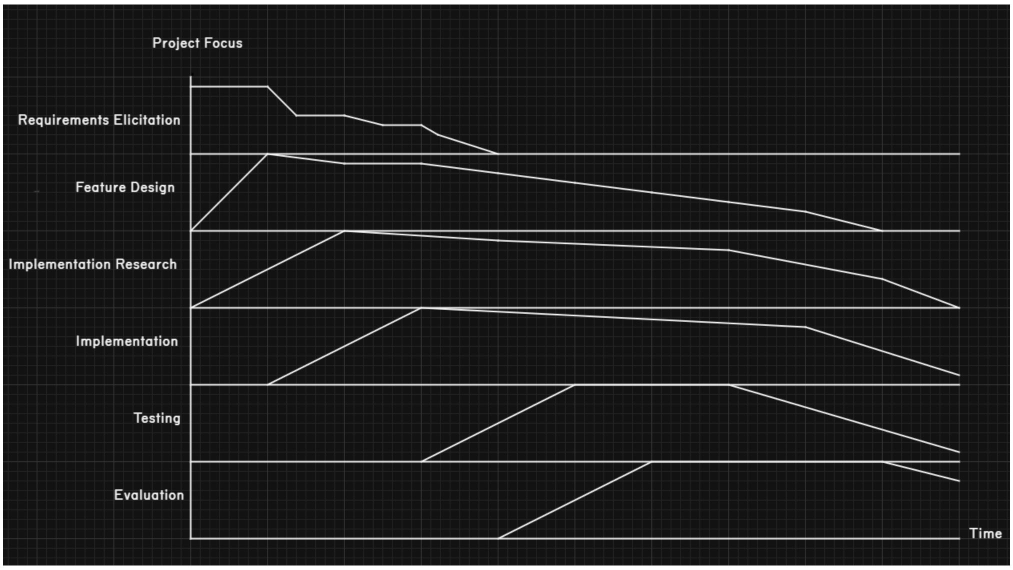

Figure 5: Project Focus Over Time

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.

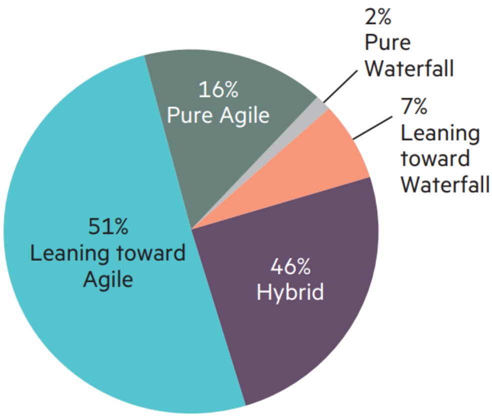

Figure 6: Primary development method used in organization across projects (601 respondents) diagram created by Hewlett Packard

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 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.

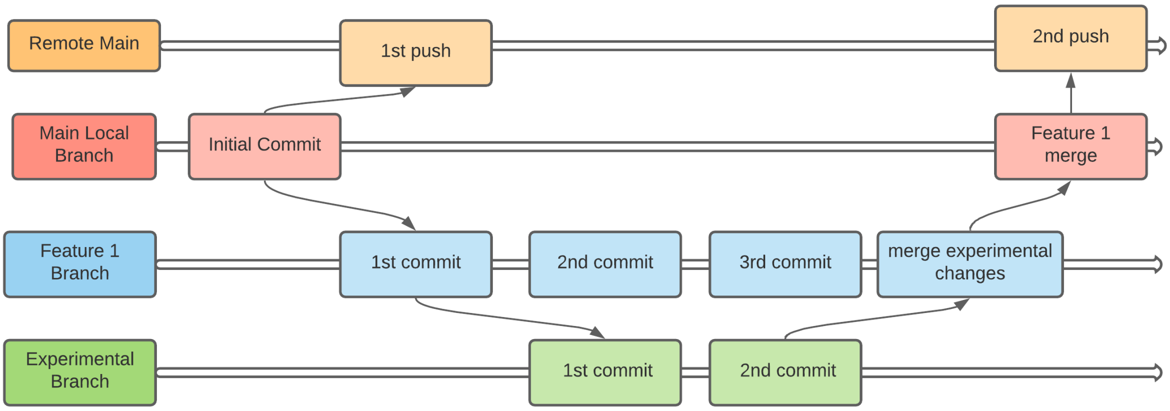

Figure 7: Example Workflow To Highlight Branch Usage

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

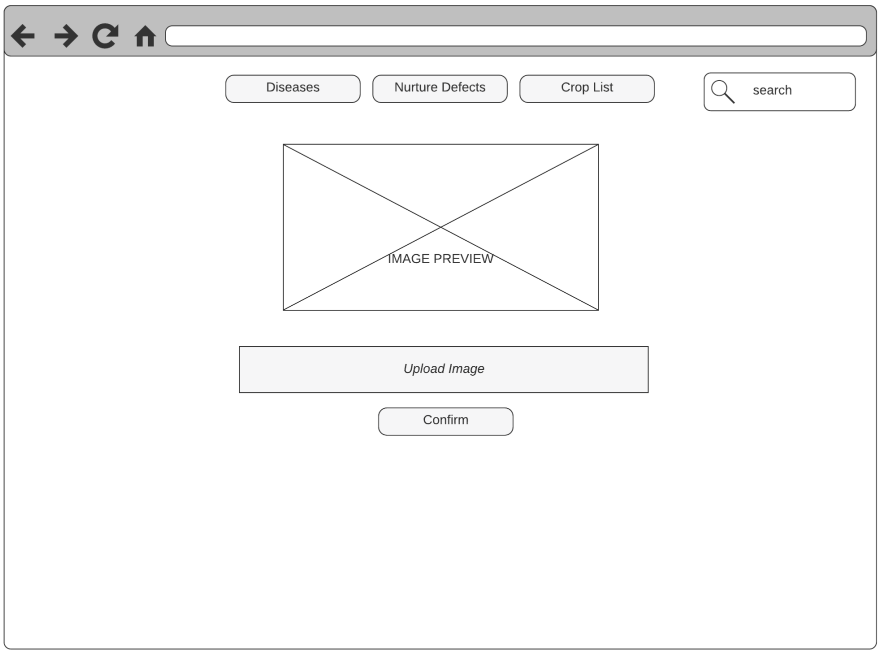

Figure 8: Homepage Wireframe

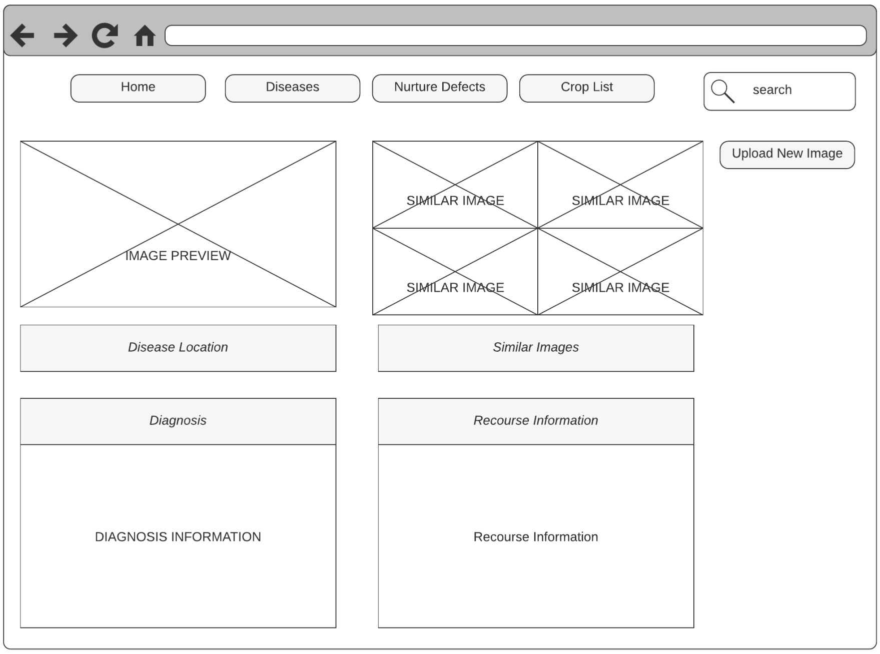

Figure 9: Defect Information Wireframe

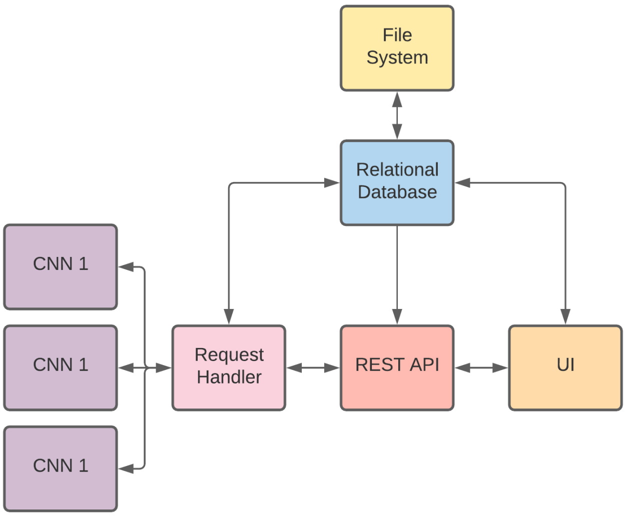

Figure 10: System Overview

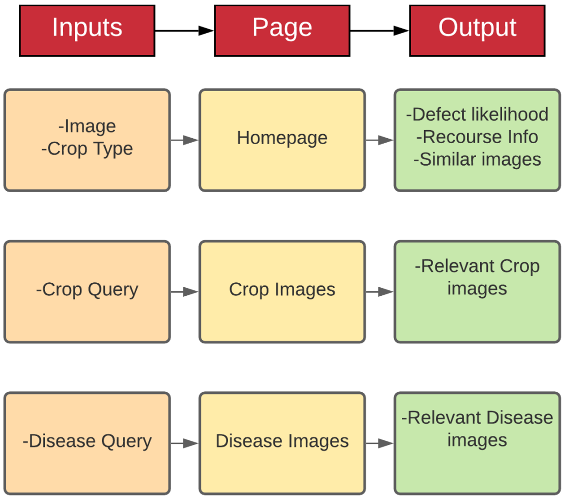

Figure 11: Input/Output overview

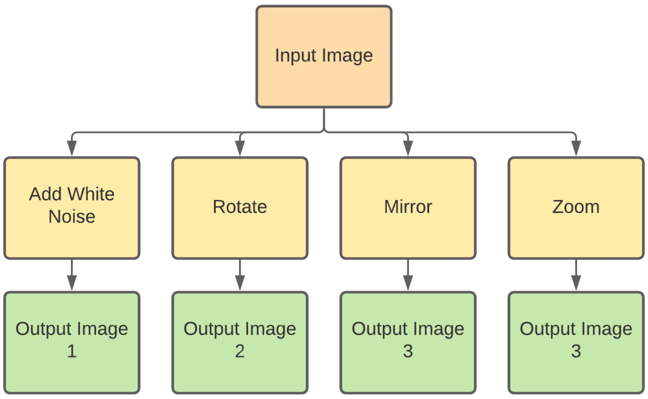

Figure 12: Input/Data Augmentation Methods

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 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

3.13 Justification of Implementation Choices

Chapter 4 - Results and Discussion

4.1 Main Results

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4.2 Evaluation Results

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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

REFERENCES

2021. URL https://yandex.com/images/.

ArabSat 5C - Internet by Satellite in Africa, 2021. URL https://www.globaltt.com/en/coverages-Arabsat5C_C.html.

best vegetables to grow - Explore - Google Trends, 2021. URL https://trends.google.com/trends/explore?q=bestvegetablestogrow&date=all&geo=US.

Digital Camera Market Share, Size, Trends and Forecast 2021-2026, 2021. URL https://www.imarcgroup.com/digital-camera-market.

File:Internet users per 100 inhabitants ITU.svg - Wikipedia, 2021. URL https://en.wikipedia.org/wiki/File:Internet_users_per_100_inhabitants_ITU.svg.

• Smartphone users 2020 — Statista, 2021. URL https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/.

G. Anthonys and N. Wickramarachchi. An image recognition system for crop disease identification of paddy fields in Sri Lanka. In *ICIIS 2009 - 4th International Conference on Industrial and Information Systems 2009, Conference Proceedings*, pages 403–407, 2009. ISBN 9781424448371.

Sungbin Choi. Plant identification with deep convolutional neural network: SNUMedinfo at LifeCLEF plant identification task 2015. Technical report.

Kaiming He, Xiangyu Zhang, Shaoqing Ren and Jian Sun. Deep Residual Learning for Image Recognition. Technical report. URL http://image-net.org/challenges/LSVRC/2015/.

Sachin D. Khirade and A. B. Patil. Plant disease detection using image processing. In *Proceedings - 1st International Conference on Computing, Communication, Control and Automation, ICCUBEA 2015*, pages 768–771. Institute of Electrical and Electronics Engineers Inc., jul 2015. ISBN 9781479968923.

Alex Krizhevsky, Ilya Sutskever and Geoffrey E Hinton. ImageNet Classification with Deep Convolutional Neural Networks. Technical report, 2012. URL http://code.google.com/p/cuda-convnet/.

Omkar Kulkarni. Crop Disease Detection Using Deep Learning. In *Proceedings - 2018 4th International Conference on Computing, Communication Control and Automation, ICCUBEA 2018*. Institute of Electrical and Electronics Engineers Inc., jul 2018. ISBN 9781538652572.

Gustav Larsson, Michael Maire and Gregory Shakhnarovich. may 2016. FractalNet: Ultra-Deep Neural Networks without Residuals. URL `http://arxiv.org/abs/1605.07648`.

Sharada P. Mohanty, David P. Hughes and Marcel Salathé. sep 2016. Using Deep Learning for Image-Based Plant Disease Detection. *Frontiers in Plant Science*, **7**, 1419. ISSN 1664-462X. URL `http://journal.frontiersin.org/article/10.3389/fpls.2016.01419/full`. (doi:10.3389/fpls.2016.01419)

Karen Simonyan and Andrew Zisserman. VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION. Technical report, 2015. URL `http://www.robots.ox.ac.uk/`.

Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky and Ruslan Salakhutdinov. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. Technical report, 2014.

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2015a.

Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke and Andrew Rabinovich. Going Deeper with Convolutions. Technical report, 2015b.

Smith J. Rosser A. Brown C. Schulte-Herbruggen B. Booth H. Sassen M. Mapendembe A. Fancourt M. Bieri M. Glaser S. Corrigan C. Narloch U. Runsten L. Jenkins M. Gomera M. Walpole, M. and J. Hutton. Enabling poor rural people to overcome poverty Smallholders, food security, and the environment. Technical report, 2013. URL `https://www.ifad.org/documents/38714170/39135645/smallholders_report.pdf/133e8903-0204-4e7d-a780-bca847933f2e`.

Zifeng Wu, Chunhua Shen and Anton van den Hengel. jun 2019. Wider or Deeper: Revisiting the ResNet Model for Visual Recognition. *Pattern Recognition*, **90**, 119–133. ISSN 00313203. (doi:10.1016/j.patcog.2019.01.006)

Sergey Zagoruyko and Nikos Komodakis. Wide Residual Networks. Technical report.

Heyan Zhu, Qinglin Liu, Yuankai Qi, Xinyuan Huang, Feng Jiang and Shengping Zhang. nov 2018. Plant identification based on very deep convolutional neural networks. *Multimedia Tools and Applications*, **77**, 29779–29797. ISSN 15737721. URL `https://doi.org/10.1007/s11042-017-5578-9`. (doi:10.1007/s11042-017-5578-9)

Appendix A - Project Proposal

Appendix B - Ethics Checklist