

Software Proposal Document for project Wheat Impurities' Detection.

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Proposal Version	Date	Reason for Change
1.0.1	25-October-2020	Proposal First version's specifications are defined
1.0.2	27-October-2020	After notes of v1 and added Gantt Chart.
1.0.3	14-November-2020	After increasing our project scope.

Table 1: Document version history

GitHub: <https://github.com/BonyGeorge/Wild-Oat-Detection>.

Abstract

In the past centuries, Wheat planting has been deteriorated due to the growing of Wild Oat (Avena Fatua) plant and rust disease with it which on expansion do reduce the wheat production by 93% for every square-meter. Although it's going to be hard to differentiate between the two plants, we will detect both wild oats and rust in wheat by using image processing and deep learning at the beginning of the farming process, to decrease their appearance. Thus, if the farmer didn't recognize wild oats within the first 30 days of growing with the Wheat, it kills the crop and spread about 100 to 150 of the Oats seeds. Hence, detection in the early stages is a must. Pervasion in wheat fields can diminish yield by as much as 80%. Our target is to differentiate between both wild oat and wheat and decreasing rust disease.

1 Introduction

1.1 Background

It is important to protect the wealth of each crop to protect its quality and quantity, if they are using it for themselves or using it for profit from other countries and increasing their economic life style. Wild oat harm more than 3/4 from the crop as it prey on the food and water of the wheat plant :therefore, Wild Oats grow faster, longer, and healthier than wheat. It looks similar to the Wheat's color and shape ;thus, it is hard to be detected without a professional farmer's eyes as shown in [Fig 1 , Page 2]. If Wild Oats has been spread in the soil, it will harm not only the Wheat plant but also the soil, as it stays in it from seven to eight

years years according to the soil condition.



Figure 1: The left picture is Wheat and the right pictures is Wild Oats

Rust disease occurs each year, in Egypt and many other countries, by the occur due to the weather condition. Rust affect wheat in different places, as it does have different kinds and effects. There are three types yellow rust, which appear in the stripe, orange rust, which appear in in the leaf, and black rust, which appear in the steam. Rust have the flexibility to spread rapidly and reduce wheat yield and quality. Damage to wheat depends on the expansion stage at the time of infection and therefore the overall level of rust severity [Fig 2 , Page 2] [15] [30]. In Egypt, four sudden disease epidemics were recorded during the five elapsed decades (1967 - 1997). the primary yellow rust epidemic was recorded in 1967; however, the foremost important stripe rust epidemic occurred in 1995 particularly within the Northern and Southern Delta areas. Yield of the foremost common commercial wheat varieties were significantly reduced, causing yield losses from 10 to 70%, by yellow rust and therefore the national average loss in grain yield ranged from 14.00 – 20.50 you bored with the Nile delta region. It causes a substantial yield loss (reaching 23%) within the susceptible wheat cultivars under suitable environmental conditions, particularly within the northern parts of the Delta region [Fig 3 , Page 3] [17] [25].

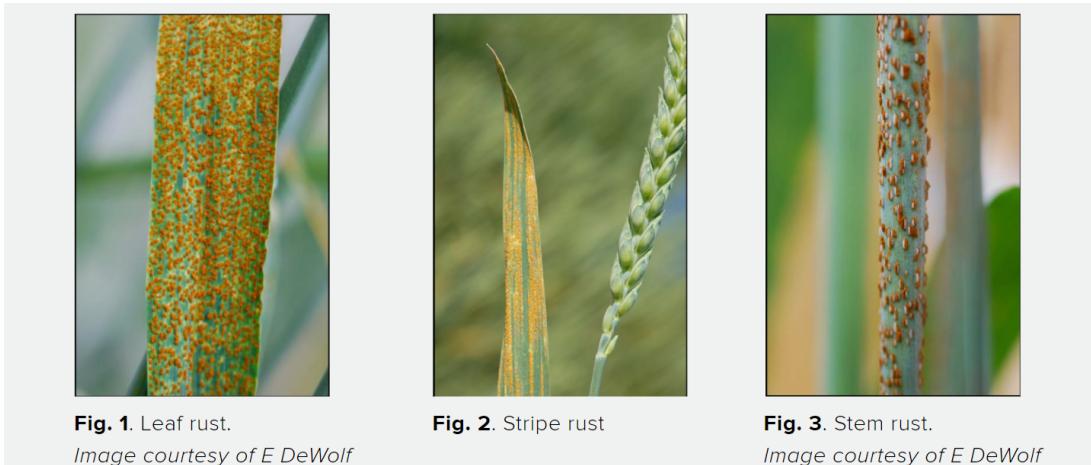


Figure 2: Types of rust

In-Season Wheat Rust Cycle

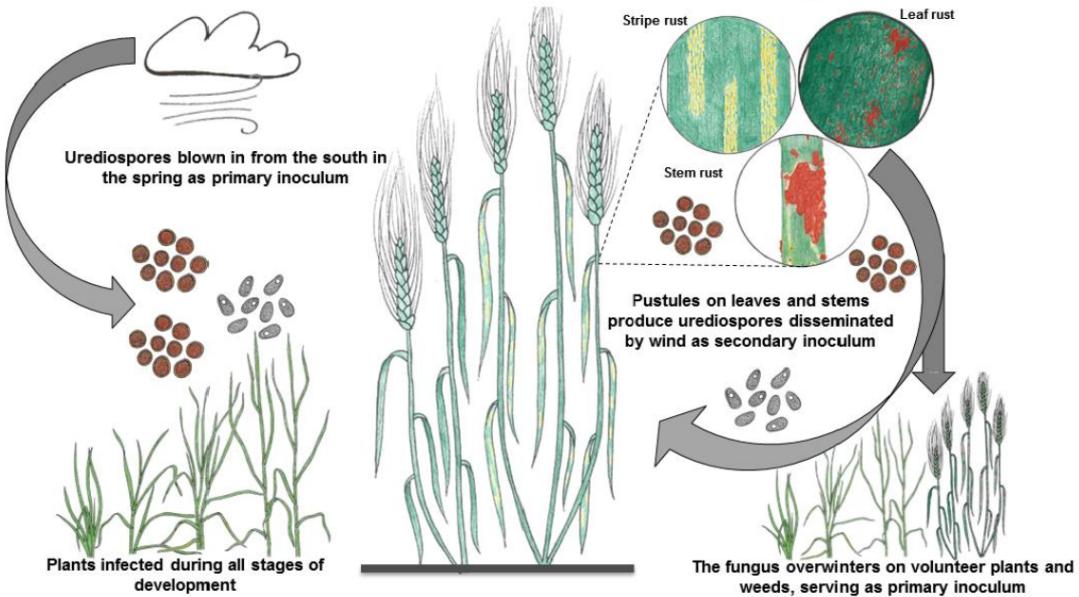


Figure 3: Rust appearance

Although that won't be a simple work as we don't have data set for Wild Oats, our aim in this project is to use camera detection to alert whether there are any Wild Oat or not. We will use camera that will area scan not line scan. Accordingly, it will be easier to be detected , as shown in [Fig 4 , Page 4]. We will also use Sensors to analyse the data of the weather to ability to predict, track, and control plant diseases. We will have three different phases which are data collecting, image processing, and deep learning to detect both Wild Oats and rust disease [12].

Area Scan Camera

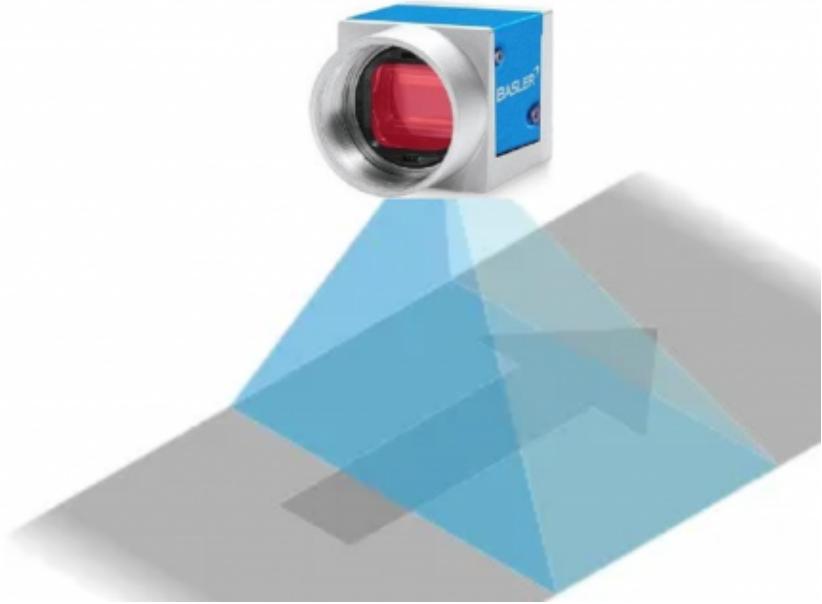


Figure 4: Scan Shape

The ideal growth conditions for yellow rust are temperatures of between 8-13 C for spore germination and penetration, and 12-15oC for further development and with free water. This makes yellow rust more of a spring disease. It should be noted, however, that whilst young plants will be susceptible, as they mature, they will develop “adult plant resistance. The impact of yellow rust within the field: The yield penalties from yellow rust in wheat can range from 5% to as high as 30% in high disease pressure scenarios (highly susceptible varieties in coastal regions/eastern counties). These penalties result from rust colonies within the leaf, draining carbohydrate from the plant and reducing green leaf area. Severe infections lead to poor root growth and drought susceptibility [Fig 5 , Page 5] [14].



Figure 5: Yellow Rust

Throughout many centuries all over the world, planting Wheat plays a very important role , as they plant with a very large scales ,for example planting wheat [1] ,as shown in the [table 2]. Countries depend on farming more than depending on importing their crops. Foreign Agricultural Service (FAS) Cairo stat that Egypt never export it only import as it uses more than what they plant.checks both wheat creation and the region gathered figures to remain unaltered from the USDA official MY 2019/20 measure of 8.77 MMT and 1.37 million hectares independently. [2]

General Authority For Supply Commodities (GASC) claimed that Egypt import about 6.49 MMT of milling wheat [Fig 6 ,Page 6]. Over the last six marketing years, GASC's largest foreign suppliers have been Russia (17.49 MMT) and Romania (7.02 MMT), followed by France (4.14 MMT), Ukraine (3.05 MMT) and the United States (1.17 MMT) [Fig 7 , Page 6][28] [2].

Rank	Country	Wheat Produced (Tones)
1	China	134,340,630
2	India	98,510,000
3	Russian Federation	85,863,132
4	United State of America	47,370,880
5	France	36,924,938
6	Australia	31,818,744
7	Canada	29,984,200
8	Pakistan	26,674,000
9	Ukraine	26,208,980
10	Germany	24,481600

Table 2: Statistics by Oishimaya Sen Nag on January 11 2019 in World Facts

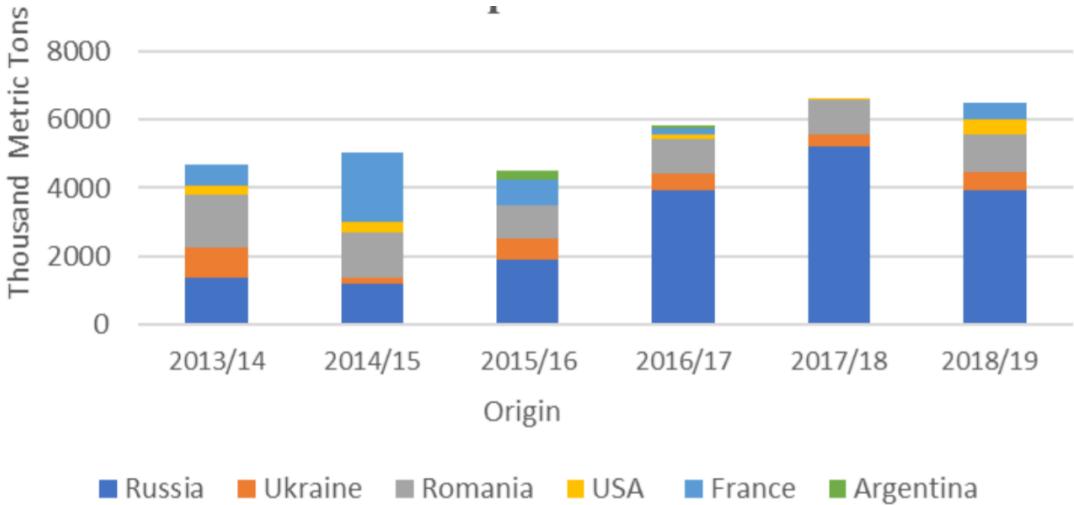


Figure 6: General Authority For Supply Commodities (GASC)

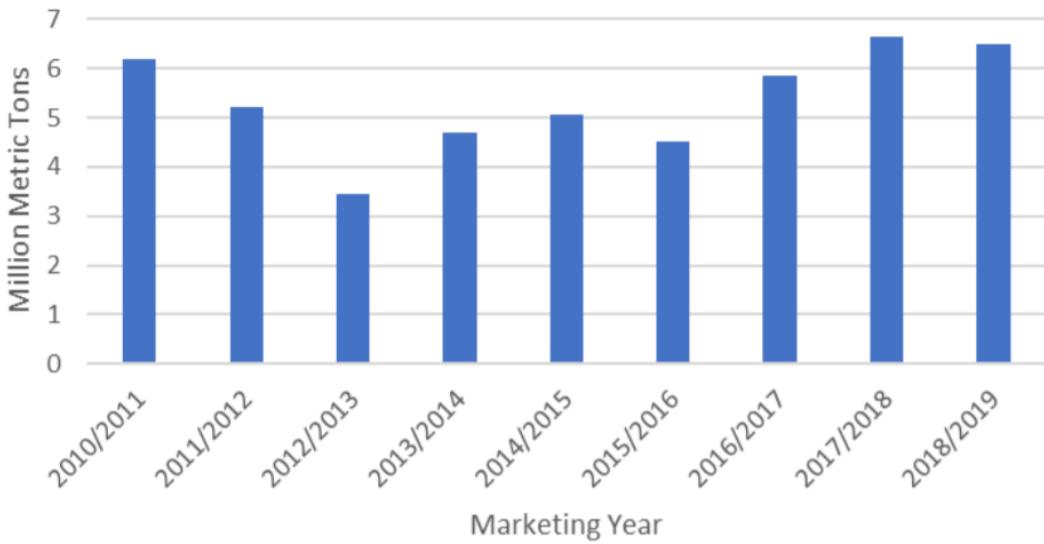


Figure 7: GAIN: Global Agriculture Information Network.

1.2 Motivation

1.2.1 Academic

The yearly expense to the [23] wheat industry of wild oats during 1999 was assessed to be \$80 million, with \$60 million being spent on herbicides and their application and \$20 million in lost yield. Wild oats are exceptionally serious and when left uncontrolled, can diminish wheat yields by up to 80 %. Most noteworthy yield misfortune happens when the plants develop simultaneously as the harvest. They produce an enormous number of seeds and up to 20 000 seeds/m² can be created by uncontrolled pervasion. Wild oats maintain a strategic distance from early herbicide applications as an extent of the seeds develop later than the yield. In United State, Wild oat goes after light, dampness and soil supplements, which straightforwardly diminish crop yields [32].

Wild oats have been constrained by social methods in western Canada, yet unfriendly climate conditions, measures for control of soil disintegration, moisture preservation, or insects control much of the time disturb the weed control program. The significant endurance instruments of wild oats are torpidity, which blocks fatigue of the seed gracefully by germination in any one year, and life span, which allows the seed to live for significant stretches under conditions which are horrible for germination [33]. The farmers solved the problem by using chemical methods in their fields, that was helpful so they can decrease the loss of their productivity. On the other hand, it decreases by default the nutrition value of the wheat[32] [9].

Crop pathogens with worldwide prevalence and potential for long distance migration and invasions into new areas may pose a heavy threat to food security regionally or globally (Brown and Hovmøller, 2002; Dean et al., 2012; Beddow et al., 2015). Crops like wheat, which are cultivated worldwide across diverse agro-ecological zones, provide an enormous niche for his or her pathogens at local, regional, and continental scales (von Broembsen, 1989; Brasier and Buck, 2001). Wheat pathogens are controlled to an oversized extent via ongoing and large-scale breeding efforts to boost disease resistance, which is economical, environment friendly and sometimes the sole available option (Singh et al., 2016). However, for years, the widespread use of rust-resistant varieties has substantially reduced losses caused by leaf, stripe and stem rust. additionally, since none of the rust fungi typically overwinter in Ohio and other parts of the Midwest, spores have to be blown up from the south so as for these diseases to develop, and in most years, this usually occur very late within the season, towards the highest of grain development. Some leaf rust are often found on volunteer plants within the autumn, but these fall infections appear to be of limited importance for the occurrence and spread of the disease within the spring. In Ohio, late May and early June are times when rust infection becomes critical and rust is more damaging on late-maturing varieties in years when cool, moist weather persists into mid-summer, extending the season [3] [15].

We will utilize the best calculation for picture acknowledgment ,which is Mask Region-based Convolutional Neural Network(Mask R-CNN) [19].It's realized that it is quicker than the typical CNN as it depends on a Region Proposal Network(RPN) which goes about as the spine in the prepossessing stage in the calculation [18]. The Mask R-CNN will assist us with separating between the plants types on the off chance that it is a wild oat and rust disease, it will send a ready notice to an Android based versatile application [29] so the client may realize that it isn't wheat and take it off the ground. To our knowledge no one tried to solve this problem until now; a lot of papers, experiments and reports had been made to compare Wheat and any other crop not solving the existence of Wild Oats with the Wheat.

1.2.2 Business

Wheat is that the most generally grown crop within the world, providing 20% of protein and food calories for 4.5B people. Its demand is additionally increasing with a growing world population (60% more by 2050 with a predicted population of 9B). However, wheat production is now facing variety of challenges from abiotic stresses, pathogens and pests thanks to climate changes. Among them, wheat yellow (or stripe) rust, caused by *Puccinia striiformis* f. sp. *tritici* (Pst), could be a devastating wheat disease worldwide, particularly in regions with temperate climates. This disease develops and spreads very quickly under favourable environmental conditions , a moderate precipitation in spring. it's estimated that yield loss caused by yellow rust disease is a minimum of 5.5 million tons p.a. at a world level [38].

Egypt was one of the exporting countries allover to world but ;nowadays, because of the growth of Wild Oats with the Wheat it made it one of most importing countries .Moreover in United States according to the report indicated by in article , yearly misfortunes to wild oat in North Dakota, the most plagued state, are from \$150 to \$200 million yearly [32] .

Yellow (stripe) rust *Puccinia striiformis* has caused severe losses on wheat in yield and grain quality in

China, because the largest acreage dedicated to wheat production, China has also the biggest area at risk of yellow rust epidemics.

Wheat yellow (stripe) rust caused by *Puccinia striiformis* f. sp. *tritici* (PST) is one among the foremost devastating diseases of wheat worldwide. In China, yellow rust has appeared in yearly epidemics since the widespread occurrence of the disease within the 1950s and has caused losses of quite 60 million tons . Severe levels of infection can cause yield losses of over 50% and significant reductions in grain quality. The three most vital weather factors affecting epidemics of stripe rust are moisture, temperature, and wind . When weather are relatively appropriate, the disease can spread rapidly over very long distances. Infection can occur anytime from the one-leaf stage to plant maturity provided plants are still green. The pathogen causing yellow rust infects the green tissues of plants of cereal crops and grasses. Such a disease utilizes water and nutrients from the host plants, which weakens the plants and therefore the wheat yield and quality are greatly reduced [44].

Since this issue is worldwide, this implies if it has been illuminated , the financial matters of every single nation that plant Wheat quality and amount will be improved. Also, Farmers will experience the ill effects of utilizing synthetic compounds and their installments, which drop the strength of the Wheat, and from difficult work for identifying the Wild Oats from their ranches. Along these lines, each nation will have financial development, increment the size number of harvest item and the well being quality and amount of the Wheat itself. Estimating the impact of utilizing the master frameworks on expanding the creation, and limiting the cost, will likewise be done once he master frameworks begin to be in the creation climate and are utilized as a choice help device [26].

1.3 Problem Statement

Wild Oats grow with the Wheat in the same time with their slight difference in appearance of their color and shape ,which make it difficult to detect them from each other. One of the main challenges that are facing is that Wild Oat data set isn't available online. As for rust disease, we have to differentiate between the three types of rust in their different parts of the wheat plant , to measure the strength and the wind speed we predict whether this wind contain rust or not , and to monitor the weather condition.

There are several problems that our aim is to solve. Our aim is to reduce the number of Wild Oats and rust in the Wheat to get high quality of wheat, increase the weight of crop each year, improve the quality and quantity of the Wheat, increase the gain of the farmer, minimize the farmer work to recognize the wild oats in the land, and cut off the usage of the chemicals that kills the Wild Oats but bring off the quality of the Wheat [9]. ,

2 Project Description

2.1 Objectives

- It's to motorize the area of Wild Oats & Wheat Rust inside the wheat plants with the most imperative possible accuracy by detecting it in the early stages it will reduce the spreading of the wild oat.
- Automate & Simplify the operation of the detection so anyone can use the device.
- Real-time detection of the wild oat & the wheat rust at it's early stages so we can prevent diminish from hurting the dirt, spreading it's seeds or diminishing sustenance estimation of the wheat and to have a healthy wheat.

2.2 Scope

1. The user will move with the camera in the field and the camera will capture images using Deep Learning approach.
2. Our cloud provider will begin processing these incoming images and classify them into healthy wheat, rusted wheat and wild oat.
3. The user will know that there is a wild oat or wheat rust here when the buzzer attached to the Raspberry Pi rings.

2.3 Project Overview

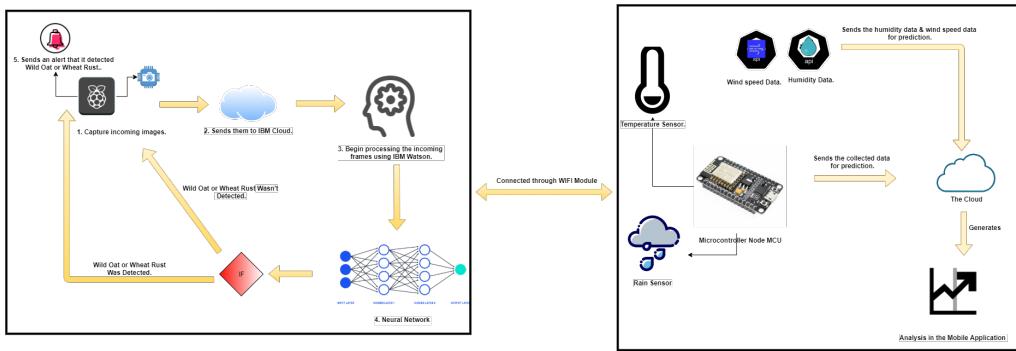


Figure 8: System Overview.

- First thing, the main machine will collect all the information from the input images(size, date and types), where these input images have different specifications. Then some pre-processing will occur by our system to normalize these images so all the images are going to have same size and dimensions and has full RGB channels. This phase is going to help us in the main processing phase when we need to use these input images. The main processing stage is where we have our data in a normalized sequence, so we can now begin to run the training phase of our model to begin feeding the algorithm with the images. Then comes our testing phase(Validation phase), where our model is ready to be evaluated and tested by the images. We used a layer or shape of Neural Networks [7] which is the Mask R-CNN deep learning approach to easily & faster detection of the wild oat & the rusty wheat from the healthy wheat plants within the field.

After our model is finally ready and tested it will be embedded in a Raspberry Pi which is connected to a camera module which will be detecting the wild oat using real-time camera recording [5] so it will keep recording and send them to the Cloud so our model can divide these videos into frames and give them labels, organize them and resize them to the suitable size for feature extraction.

If our model detected a wild oat or a rust in the wheat among the wheat field, it will make the buzzer attached to the Raspberry Pi to make an alert noise to show that a wild oat or rust in the wheat has been detected within this area.

- Our second device consists of a Node MCU micro-controller, which some sensors are connected to it. These sensors are Rain drop sensor and Temperature sensor. Also, the Humidity data and the Wind speed data we are going to get these data by using the Weather API.

After our weather monitoring system completely built it's going to detect a high speed wind which has fungicides by collecting the data from the sensors and compare it to a standard data, then it's going to predict if there is going to be wind, which will cause a wheat rust. Also, these data will be sent to our mobile application which has a dashboard to make analysis about these wind data.



Figure 9: Model Creation.

2.3.1 Dataset.

Our Dataset is divided into 3 main classes and 3 sub-classes the Wheat class, the Wild Oat class and the Wheat Rust class which contains three sub-classes; the Leaf Rust(Orange), the Stem Rust(Yellow) and the Wheat itself rust(Black), also it consists of non normalized data of type images.



Figure 10: Non Normalized Wheat Dataset.

2.3.2 Input.

Our input will be through incoming frames from the camera module to the Cloud data service.

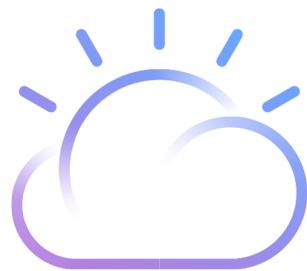


Figure 11: Cloud Service Provider.

2.3.3 Pre-processing.

Normalized data makes Neural Network works better. So, in the pre-processing stage our model must normalize the incoming frames by giving them same target size for all the images and divide them into batches.

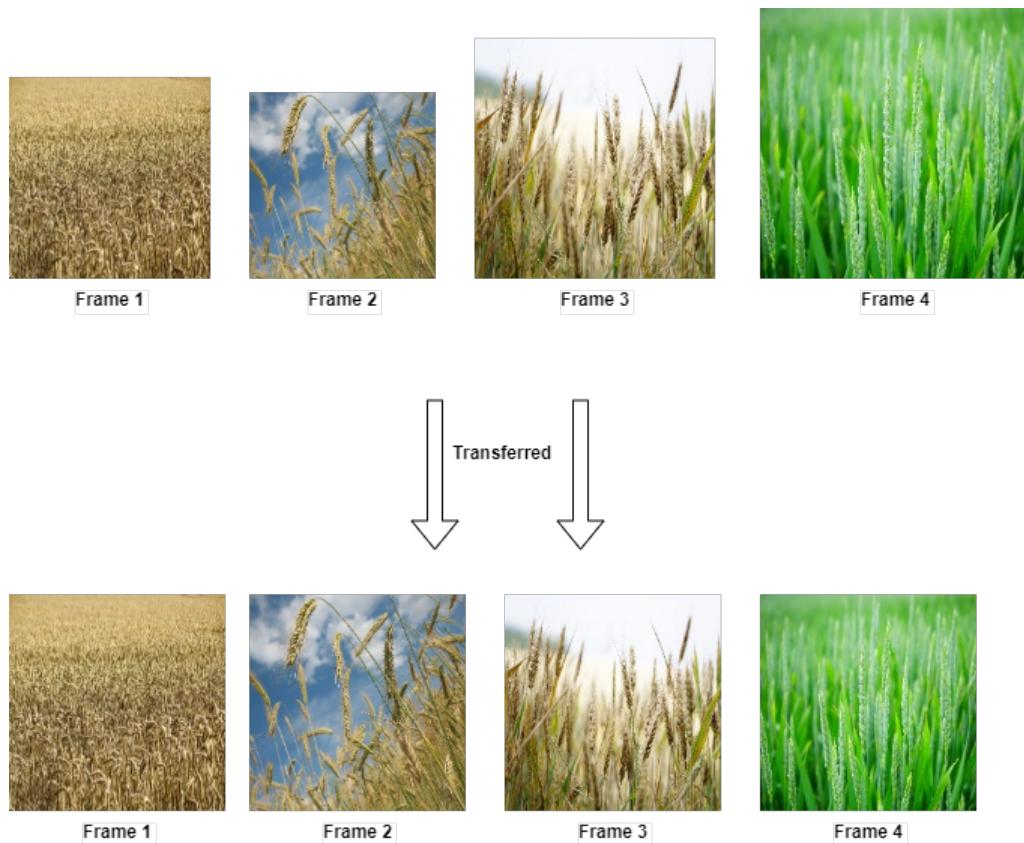
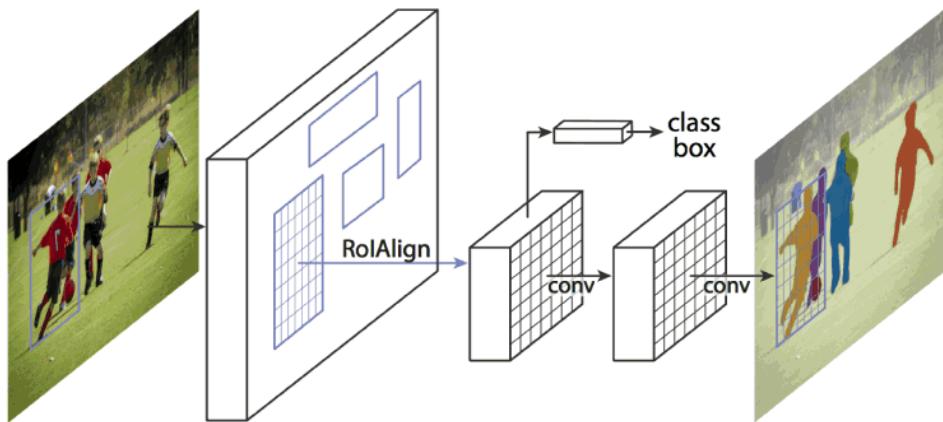


Figure 12: Images after being Normalized.

2.3.4 Main processing

The main processing phase is where we train our model with the dataset of type images so it can detect our incoming frames using TensorFlow and Keras python libraries [8] to use the Mask R-CNN for detection phase.



The Mask R-CNN framework for instance segmentation

Figure 13: Mask R-CNN Algorithm.

2.3.5 Output.

The output of our system will end in one of the two ways either,

- Our system doesn't detect a wild oat/wheat rust and continue capturing videos of the field.
- Our system detects a wild oat/wheat rust, then it will make the buzzer, which is connected to the Raspberry Pi rings.

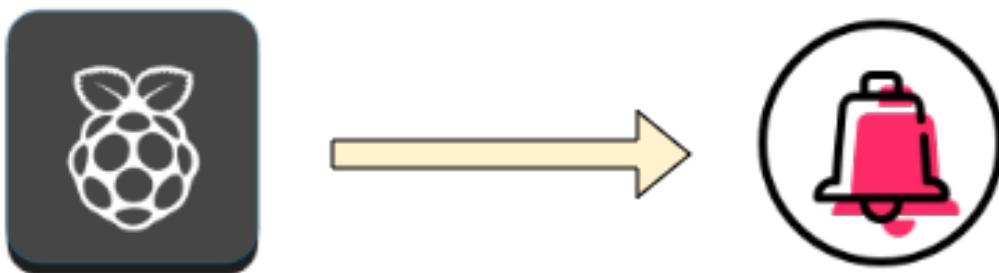


Figure 14: Alert by our Buzzer.

2.4 Stakeholder

2.4.1 Internal

#	Name	Job
1	Abanoub George	Full Stack Developer.
2	Ibrahim Fawzy	Back-end Developer.
3	Mai Mahmoud	Front-end Developer.
4	Nour Bahaa	Front-end Developer.

2.4.2 External

Our stakeholder is anyone who is willing to plant wheat and try to get its maximum nutrition value from it ;consequently, it will reach the highest productivity he can get from wheat planting and to protect his soil from anything that would harm the soil.

3 Similar System

3.1 Academic

1. Yin Shen et al. [35]: Impurities in wheat genuinely influence wheat quality and food security. They are primarily created during the operational cycle of consolidate gatherers. In this paper, developed six datasets of named pictures of wheat, to be specific ordinary bugs, wheat, grass, stalks, spikelets, and awns of wheat. The preparation set was made out of 25,200 pictures and the approval set comprised of 10,800 pictures. These datasets can be utilized to research programmed acknowledgment applications and testing on wheat. These datasets additionally give significant bits of knowledge into other grain debasements and started with handling these pictures so they can lessen the impact of movement, concealing, and contrasts in light before arranging and naming them. At that point they a strategy for the perceiving wheat debasements dependent on CNN, improved by Inception_v3 network that dissects the picture qualities of the pollutions in wheat. Their outcomes show that the WheNet network accomplished the most productive outcomes. It like wise shows a shorter preparing time, and its acknowledgment correctnesses for Top_1 and Top_5 of the test set are 98.59 % and 99.98 %, individually. The mean estimations to the both of the AUC and review pace of the planning on the acknowledgment of different pictures of pollutions are higher than those of the ResNet_101 and Inception_v3 organizations. Subsequently, the WheNet organization can be a helpful device in perceiving pollutions in wheat. Moreover, this strategy can be utilized to recognize pollutants in different fields.
2. Sarmad Hameed Imran Amin [13]: As the expansion in the total populace the interest of the wheat is likewise increments. So as to expand the development wheat in the wheat crop it is important to recognize the weed in the wheat crop and the fruitless land to limit the development of weed so the development of the wheat can be expanded. Automated Air Vehicle (UAV) is utilized for information obtaining of wheat crop in various stages so high caliber of RGB pictures can be caught. The proposed technique encourages the extraction of weed, wheat, and infertile land in the wheat crop field utilizing foundation deduction. The outcome shows that foundation deduction technique is useful for recognition the weed, desolate land, and wheat.

3. Mamoon Rashid et al. [27]: The activity of this examination is to channel the sick aspect of the leaf from the leaf images.(how to fathom) The creators proposed and actualized picture preparing strategy utilizing OpenCV for isolating the unhealthy aspect of the leaf from the picture of the leaf (Foreground Extraction, Edge Detection, Color sifting and Combination of Edge Detection with Color Filtering is accomplished for wheat images).This research utilized KNN and SVM for discovery of sicknesses and accomplished a precision of 88 % with SVM and 85 % with KNN on neighbor size of 5.
4. Varsha P. Gaikwad Vijaya Musande [11]: The most significant factor in decrease of value and amount of yield is because of plant sickness. Distinguishing plant ailment is a key to forestall agrarian misfortunes. The point of this paper is to build up a product arrangement which consequently identify and order plant infection.It includes four steps,step 1)Image acquisition,step 2)Image pre-processing,step 3)Image segmentation and step 4)Feature extraction (consider color,shape and size).For classification used is Neural Network based classifier. They took some images from internet to increase database.And they captured images using digital camera (canon A3500, 16 m pixels) foundation of all pictures were stifted utilizing deduction method and all images stored in Jpeg format.The result of accuracy is 80.21 % (neural network) and 89.23 % (support vector machine).
5. Xiaojing Niu et al. [22]: Wheat illnesses are hurtful to wheat creation, yet there are hardly any division calculations that can viably distinguish regular illnesses of wheat leaves.This paper proposes a programmed and solution with K-means clustering, first they start with the colour image is transformed to Lab colour space from RGB.Then Clustering is done by taking the absolute difference between each pixel and the clustering centre in Lab colour space.The data set collected from the Internet.The results shows that the segmentation accuracy for 1)powdery mildew, 2)leaf rust and 3) stripe rust (the three common diseases) is more than 90%, which proves the efficacy of our method.
6. Xia Jing Zongfan Bai [16]: The detection using remote sensing to Wheat Stripe Rust is significant for farming management.in request to improve location exactness of the disease seriousness of wheat strip rust.In this paper a detection method dependent on solar-induced chlorophyll fluorescence merged with mixed spectral index (this method based on detecting biochemical parameters).The data set was collected from thirteen differential spectral indices sensitive to the severity of wheat strip rust by using different two methods (Partial lesat squares"PLS", BP neural network). The results are 1) The models based on solar-induced are more accurate than that based on fifferential spectral index. 2) the prediction model of "Bp neural network" is better than PLS.
7. Sahil et al. [31]: It provides a description about the Avena fatua. The Avena fatua is viewed as one of the world's most exceedingly awful rural weeds and it is expanding in significance (CABI Crop Compendium 2011). It is a particularly genuine weed in grain harvests, for example, grain and wheat. A fatua attacks and brings down the nature of a field crop, commonly wheat or oat fields and vies for assets with the yields. It causes soil dryness and gives great conditions to maladies and bugs (for example frit fly, nematodes and smut). It also provides how to manage it by At the point when it is a weed of oat yields, for example, wheat, oats, grain it is hard to recognize A. fatua from the harvest until blooming. Consequently, the wild oat should just be taken out in the wake of blooming. Since A. fatua seeds can remain torpid in the dirt as long as 10 years, it is critical to eliminate plants before they produce seed. A. fatua seeds ought to be eliminated before processing to guarantee great grain quality. A controlled consume after collect can lessen the practicality of the A. fatua seeds that stay on the dirt surface. Numerous specific herbicides can be successful alone, in blends or groupings. Right planning and pace of herbicide application is basic to boost control. When utilizing any herbicide consistently read the name first and ask a consultant.

8. Ahmed A. Rafea [26]: This paper presents current endeavors in creating expert systems for crop management in Egypt. It incorporates the description of five expert systems (Tomatoes, Oranges, Lime, Cucumber, Wheat) to increase the production. To solve the problem they decided to make an expert system for each plant.the data-set collected from A Central Laboratory for Agricultural Expert Systems (CLAES) and by testing all expert systems the benefits 1) to measure the effect of using expert systems on the performance of the extension workers. 2)Assess the decision taking skills of the extension workers compared with decisions generated by the expert systems. To achieve the objective. The results after applying the methodology it can undoubtedly be seen that an improvement in the presentation has occurred, and the execution of the created master framework is a lot more better than the expansion laborers even after using the system.
9. Omar A. Almaghrabi [4]: Weeds are one of the serious issues in crop creation. They contend with crop plants for light, dampness, supplements and space. *Avena fatua* L. (wild oat) is viewed as the thirteenth most significant weed around the world. *A. fatua* has expanded enormously in the downpour fields and inundated regions of the nation just as somewhere else on the planet. It is a yearly grass what's more, is hard to kill in light of the fact that the seeds break before crop development and a significant number of the seeds are blasted through the dirt, when they are turned up close to the surface. the dataset collected from Giza129 grains were obtained from Agricultural Research Center, Giza, Egypt. Various concentrations were utilized (0.0, 0.05, 0.2, 0.7, 1.0, 2.0 also, 3.0 mM) for all germination test tests. Cleaned Petri dishes (9.0 cm) fixed with twofold layers of Whatman No. 1 channel papers were utilized for each treatment, three reproduces were taken, each comprising of 20 grains. The channel papers were watered varying by including 5 ml of refined water (for control) or on the other hand answers for be tried. So the result illustrate that the percentage of germination of wild oat was altogether hindered with increasing the concentration of phenolic compounds, and also Ferulic acid was the best compound which totally repressed the germination at a concentration of 3.0 mM of phenolic compounds.Simultaneously, wheat was somewhat influenced with the various convergences of the four phenolic compounds.
10. Bentolhoda Shahvand et al. [34]: *Avena fatua* is one of the most significant weeds in oats and summer crop cultivates that charge a high yearly expense for weed control all through the world.Wild oat is found in little grain oats, especially wheat.Lethargy breaking medicines included the use of various centralizations of sulfuric acid, warm water, gibberellin, stratification(chilling), scarification, different temperatures, rinsing, and the use of ethanol.So he results illustrate that the highest percentage of germination founded in the stratification period of 2 to 3 weeks at 2 to 5 °C in which germination rate over 70 % adding to The concentration of sulfuric acid illustrate that the highest seed germination 42% in treatment using concentration sulfuric acid 15%. Moreover, our discoveries shown that rising, warm water application, consistent temperatures were not viable treatment for wild oat dormancy breaking.
11. Mohsen Azadbakhta et al. [6]: Wheat leaf rust is one of the generally normal and damaging parasitic illnesses of wheat which dangers world wide food security. Plants contaminated by this sickness show different manifestations at various phases of improvement which can be all the while seen in different pieces of the tainted leaves and leaves can be in an assortment of tones, for example, yellow, orange or dark color. They used several spectral vegetation indices (SVIs) and ML techniques to solve the diseases detection problem. And Dataset used here is divided into five equally sized fold and the test fold is left aside and collected using an ASD FieldSpec.Finally the results illustrate that SVIs better than ML methods at all three LAI levels and the performances of the ML methods were improved with increasing LAI value.

12. Sumit Nema Aarju Dixit [21]: Farming is an antiquated occupation. Machine learning technique is utilized for wheat leaf infection location. Malady is restricting the development of wheat plant. Quality and amount of wheat plant is additionally decreased by it. For color space lab color space is utilized. Wheat leaf picture is captured by the computerized camera. After it the captured picture is handled to decide the infected and un-diseased status of each test leaf. To recognize the clusters of wheat leaf k-means clustering strategy is utilized. The classification technique back vector machine is utilized to perform activity on different wheat leaf tests. Bolster vector machine contains two datasets; one is preparing dataset and testing data. Comparison result appears the ailing and un-diseased leaf from the test information. Test comes about confirmed by terms; cruel, standard deviation, change, middle and mode.
13. Umamaheswari S et al. [41]: Decrease in crop yields because of weeds result from their multiferous methods of meddling with crop growth and crop culture. Weeds rival crops for at least one plant growth factors, for example, mineral supplements, water, solar energy and space and they frustrate crop cultivation activities. The goal of this paper is to introduce a start to finish system which works progressively by accepting pictures of homestead crops as information and produces a lot of bouncing boxes for each type of weed located in the image as output directly and the detection done using Convolutional Neural Networks(CNN) without any human assistance. their dataset was very small and in the future the system will be trained on a large dataset.Finally, The results can used by automated weed detection system under tasks in agriculture.
14. Adnan Farooq et al. [10]: Weed detection is very critical for sitespecific weed control in order to decrease the cost of farming as much as we can.To solve the problem they used Convolutional Neural Network (CNN) in three steps: 1)Data collection, 2)Generating labelled samples, 3)Classification. The dataset used by camera and each captured image has 61 band and band image of the hyperspectral cube has 1040 X 1320 pixels. The reesults illustrate that Convolutional Neural Network (CNN) architecture using higher number of bands reach higher classification accuracy.
15. Jinling Zhao et al. [44]: Yellow rust "stripe" which is scientific name known by (*Puccinia striiformis*) has caused a huge loss in wheat production and its quality, especially that the weather factors affecting diseases of yellow rust are wind,temperature, and moisture which is must happened in winter so its a big problem. They collect the dataset from the National Experimental Station for Precision Agriculture of China. They used a hyperspectral imaging spectrograph to detect the yellow rust there are 4 steps to complete the experiment by using this device: the first step is to collect the samples, second they measure chlorophyll content of leaves at different layers, third catch the samples with a black cloth, and Final step is collecting the hyperspectral data cubes as in the figure below, the camera lens is away from the wheat plants by 0.8 m. The results that they found at the final stage that the yellow rust infestation at different leaf layers.



Figure 15: Structure of hyperspectral imaging spectrograph.

16. Alexandre Pereira Marcos et al. [20]: Coffee "yellow-orange" rust attacks the coffee leaves from underside caused by a fungi affecting many productive coffee regions especially Brazil which is already known by the awesome coffee but the rust can cause danger in coffee production up by 50 %. They aim to build a model and train a convolutional neural network (CNN) to detect the rust infection in coffee leaves using tensorflow library. They created a dataset consists of 159 images of coffee leaves by a digital camera. as in this figure the upper picture is a sample of coffee leave and the lower regions indicating the presence of coffee leaf rust. The results illustrate that they can detect the infection with a high precision.

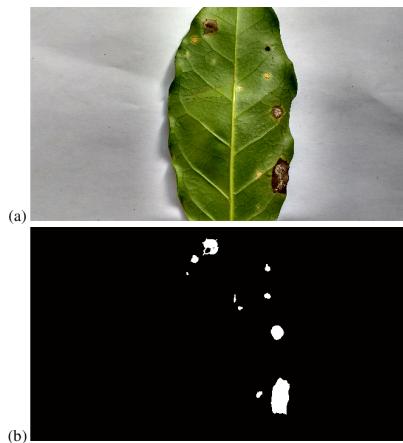


Figure 16: Rust infection as a black and white mask.

17. Jinya Su et al. [38]: Agriculture faced a lot of problems one the danger and important problem is yellow rust "strip" which is can destroy more than 40% of wheat crop. So They used an Unmanned air vehicle (UAV) to collect the dataset by using 4K HDR camera is adopted to take manually image for all wheat plots then used an algorithm (Multispectral image labeling). And They used the deep learning convolutional neural network (CNN) for semantic segmentation which is based on U-Net. The results explained that the first applied to segment wheat pixel is (white) from background black "left image" then rust regions (light blue) "middle image" then by using the algorithm the labelled dataset is applied "right image".

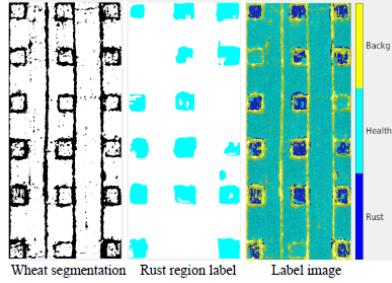


Figure 17: EXPERIMENTAL RESULTS.

18. Thomas Truong et al. [40]: fungal diseases in plants one of the factors that decreases the crops production in the world so in this paper they aims to protect crops by predicting future environmental conditions which raise the growth and expansion of fungal diseases. So in the figure below they build an IOT device for data collection cosists of (wind speed sensor, wind direction sensor, wireless internet module, solar charge, 12v battery, rain fall sensor, gps,circuit housing and Underground sensor connection) this device illustrate the operation of a single environmental data collection device in the field. The device sends its location to a website containing a Google Maps "JS" application program interface (API). The API takes the geographical information of the device and places a marker on the Google Map at the device location. The marker contains a link which leads to the Sparkfun database where the device measurements are retrieved. the result that this system will be used to improve the detection of fungal diseases and predict how the diseases will spread in the crop fields.

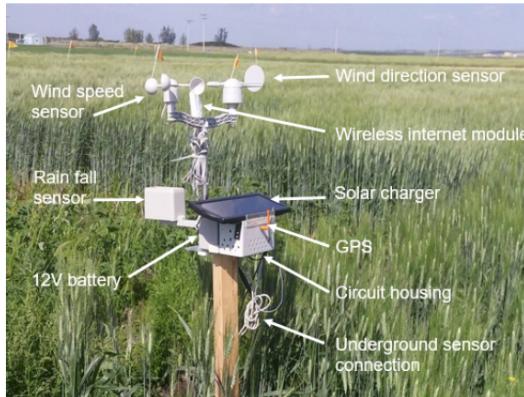


Figure 18: The environmental data collection device in the field.

19. X Shu et al. [36]: Wind is one of the popular of renewable energy and it is collected by wind turbine generator but the efficiency is low.The aim of this paper is to build a system can detect the wind signal and capture the energy of the wind to convert the energy to electricity for human.They reach the goal using conventional wind energy detection device based on "electromagnetic mutual repulsion" the piezoelectric sheet of flexural tension structure is deformed by electromagnetic force.The results they achieve their goal and the device succeeded to detect wind signal and capture the wind energy.

3.2 Business Applications

MyCorp Wheat [37]: it's an interactive tool that brings the crop diagnostics to the paddock. It consists of a lot of tools such as Diagnostic tool which diagnose a range of possible constraints based on the crop,

Variety selector which determine which wheat variety to grow in your country, CropCheck which aims to maximize crop yield and to optimize grain quality and profitability and MyEconomic tool which provides various treatment options for various pest and diseases in your corp.

4 What is new in the Proposed Project?

Our project is going to be used in detecting wild oat and rust in wheat, which has never been done before in our knowledge. Other projects was made to detect different things in wheat like impurities and black spikes. In other similar systems, they used VGGC but we are going to improve it by using Mask R-CNN algorithm. Mask R-CNN Deep Approach to seamlessly and easily discover wild oat from wheat plants and rust within the field. Once our model is able to be used, it will be installed in a Raspberry Pi that is connected to a camera module that can identify wild oat or rust by using real-time camera recordings that are new to our project, other related systems that use images. We're going to use the Raspberry-Pi camera module V2, this is the Arduino DIY webcam video camera. This camera module can record video at 1080p30, 720p60 and 640x480p90 resolutions, all functionality is provided in the current edition of the Raspberry operating system and is a high quality 8 megapixel Sony IMX219 image sensor specially built add-on board for Raspberry-Pi. In our project, we have a problem because we don't have a wild oat dataset, we're going to collect our own dataset. Once our weather forecasting system has been fully installed, it will detect a high-speed wind that has fungicides by gathering data from the sensors and comparing it to normal data, and then predict whether there will be wind that will cause wheat rust. These data will also be submitted to our smartphone application which has a dashboard to evaluate these wind data.

5 Proof of concept

We used MATLAB as a start to proof our concept [Fig 19 , Page 19]. We reached to a result but not the result that we actually wants to reach, as it only read and differentiation between folders images as it put every folder pictures separate than the other and set it in a fields-cells.

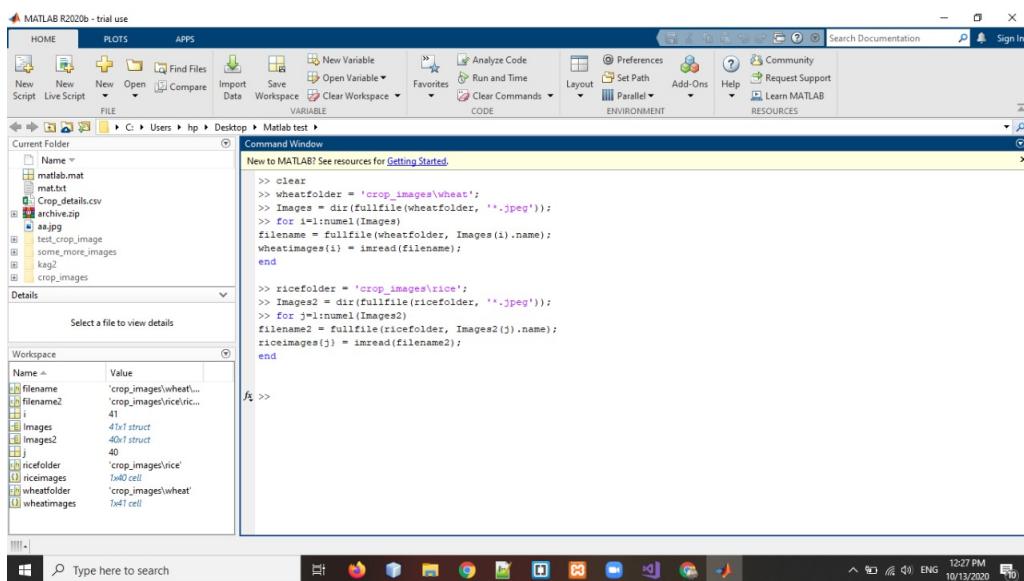


Figure 19: Storing the training images in the array's.

We implemented the two data sets for Wheat [Fig 20 , Page 20] and rice Fig [21 , Page 20] to see how the different in readings. We got different readings and more accurate percentage , as we re-organized and differentiate between the two data set.

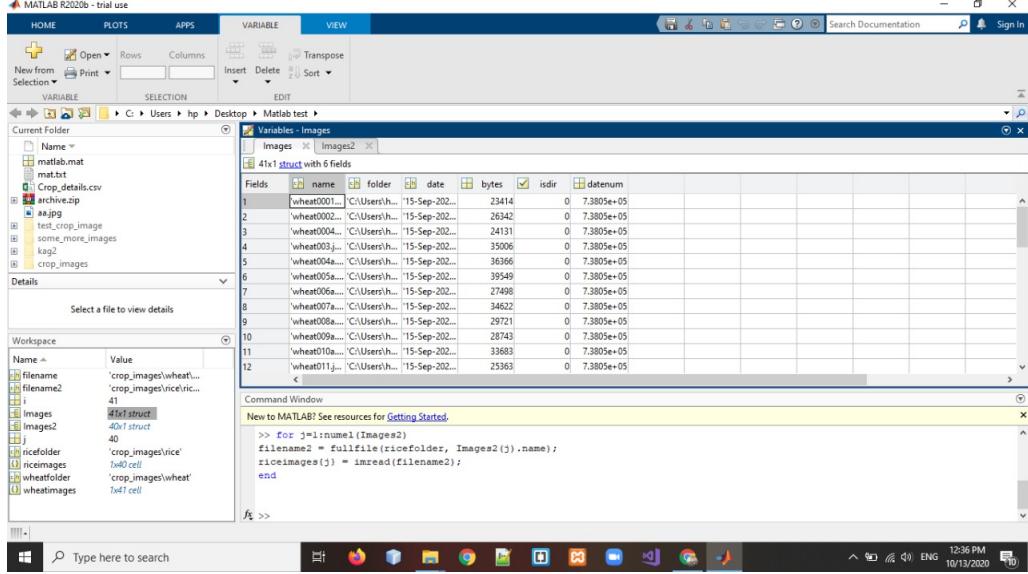


Figure 20: Wheat pictures stored in an array.

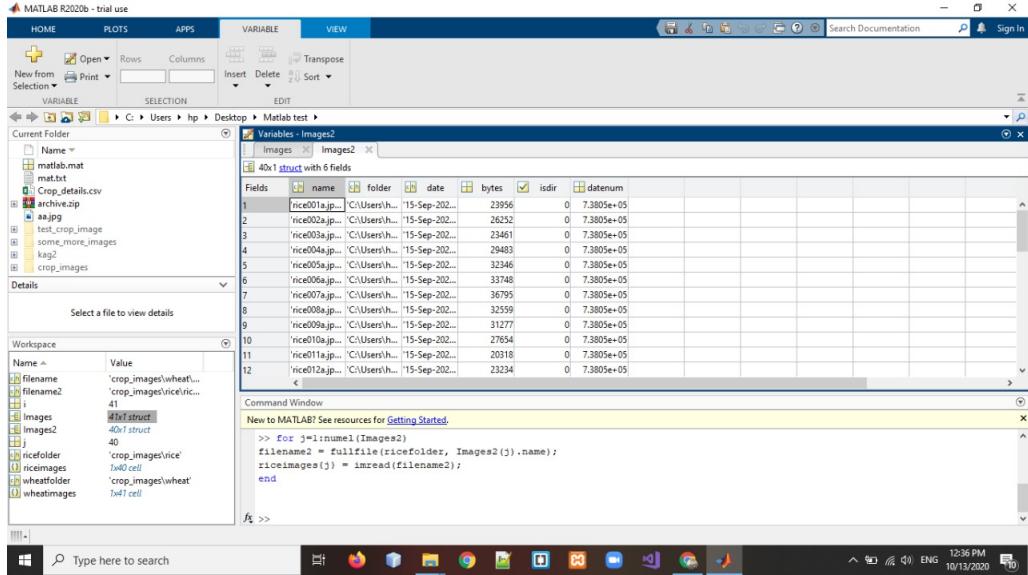


Figure 21: Rice pictures stored in an array.

As a Kaggle competitor used VGG19 Network, VGGC takes a (224224x3) picture fix as info and works in the spatial structure of the picture. It is not the same as past techniques[24]. There is no manual element extraction strategy in VGGC organization. The VGGC network is comprised of an information layer, 16 convolutional layers and two completely associated layers. So as to gauge scene enlightenment all the more viably, VGGC network streamlines the scholarly highlights. The starter analyses of this technique on pictures with spatially shifting brightening shows that our VGGC neighborhood enlightenment assessment capacity is steady, and the model has preferred speculation and power over the current model utilizing convolutional neural organization to anticipate scene lighting [43].

Here we used CNN algorithm to train and test our model [Fig 23 , Page 21]. Also he reached an accuracy of 65 % which is low. We used here Convolutional Neural Network which is also used in feature extraction from the images, which leads to higher accuracy than he got we reached an accuracy of 95 % and average accuracy among all the epochs of 87 % [42] [Fig 25 , Page 22] [Fig 26 , Page 23]. Also we tried to predict by selecting a single image to evaluate our model [Fig 24 , Page 22].

Plant Recognition using Convolutional Neural Network.

Problem Statement:
Recognition of whether the input image of the plant is rice or wheat.

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- Eng. Hager Sobeh
- Eng. Nour el-huda Ashraf

Importing main libraries

```
[3]: import tensorflow as tf
from keras.preprocessing.image import ImageDataGenerator
import numpy as np
```

Figure 22: Our Python Notebook.

Preprocessing on Training set (Image Augmentation)
We are applying some geometrical transformation to move the pixel to prevent overfitting(Zoom In, Zoom Out, Rotations).

```
[4]: train_datagenerator = ImageDataGenerator(rescale = 1./255,
                                             shear_range = 0.2,
                                             zoom_range = 0.2,
                                             horizontal_flip = True)

trainning_set = train_datagenerator.flow_from_directory('dataset/training_set',
                                                       target_size = (64, 64),
                                                       batch_size = 15,
                                                       class_mode = 'binary')

Found 252 images belonging to 2 classes.
```

Preprocessing the Test set

```
[5]: test_datagenerator = ImageDataGenerator(rescale = 1./255)
test_set = test_datagenerator.flow_from_directory('dataset/test_set',
                                                 target_size = (64, 64),
                                                 batch_size = 5,
                                                 class_mode = 'binary')

Found 113 images belonging to 2 classes.
```

CNN init

Figure 23: Training and Testing phase.

```

Skills Network Labs
File Edit View Run Kernel Help
PLANT-RECOGNITION.ipynb
Plant Recognition.ipynb
Plant Recognition using Convolutional Neural Network.
Problem Statement:
    - Using main libraries
    - Preprocessing on the image augmentation
    - Preprocessing the test set
    - CNN init
    - Convolution Layer
    - Pooling Layer (Max Pooling)
    - Adding a second convolution layer & pool layer
    - Flattening
    - Full Connection
    - Output Layer
    - Compiling the CNN
Training the CNN on training set and evaluating it on the test set.
Getting the Average accuracy among all stages.
Printing the Accuracy
Making a prediction

[17]: Avg_Acc = np.mean(history.history['accuracy'])
print(round(Avg_Acc * 100,2), '%')
0.78 %

Printing the Accuracy
[17]: import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'])
plt.title('Plant Recognition Model Accuracy.')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Accuracy'])
plt.legend(['Training', 'Testing'], loc='upper left')
plt.show()

[18]: from keras.preprocessing import image
test_image = image.load_img('dataset/single_prediction/wheat_or_rice_1.jpg', target_size=(64, 64))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
result = model.predict(test_image)
if result[0][0] == 1:
    prediction = 'Wheat Plant.'
else:
    prediction = 'Rice Plant.'

[19]: print(prediction)
Wheat Plant.

End of Notebook.
Activate Windows
Go to Settings to activate Windows.

Mode Command ⌘ Line 1 Col 1 Plant Recognition.ipynb

```

Figure 24: Predicting what plant of the selected image.

```

His last epoch accuracy.

In [14]: print('Test accuracy - {:.%}'.format(model.evaluate(X_test, y_test)[1] * 100))

2/2 [=====] - 1s 290ms/step - loss: 1.8974 - accuracy: 0.6471
Test accuracy - 64.70588445663452%

Our last epoch accuracy and Average accuracy .

Epoch 10/10
17/17 [=====] - 5s 314ms/step - loss: 0.0093 - accuracy: 0.9603 - val_loss: 3.0548 - val_accuracy: 0.5929

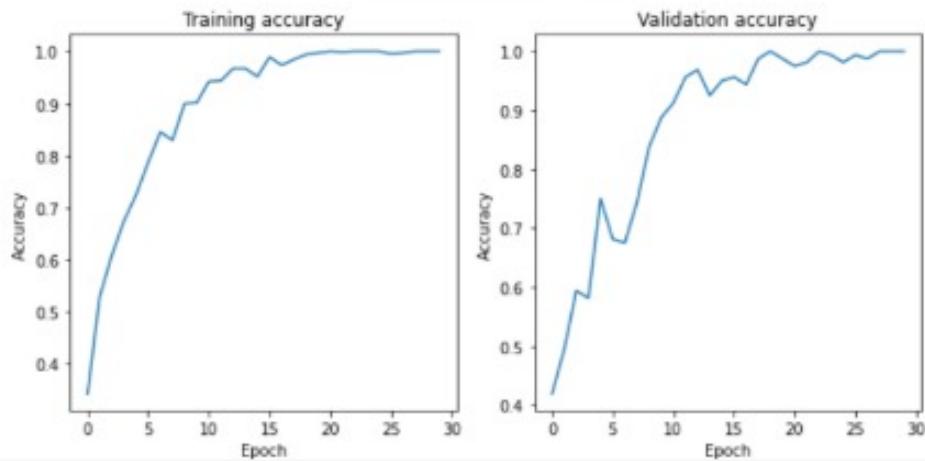
Getting the Average accuracy among all the stages (epochs)

: Avg_Acc = np.mean(history.history['accuracy'])
: print(round(Avg_Acc * 100,2), '%')
: 87.78 %

```

Figure 25: Last epoch accuracy & average accuracy in percentage.

His Accuracy.



Our Accuracy.

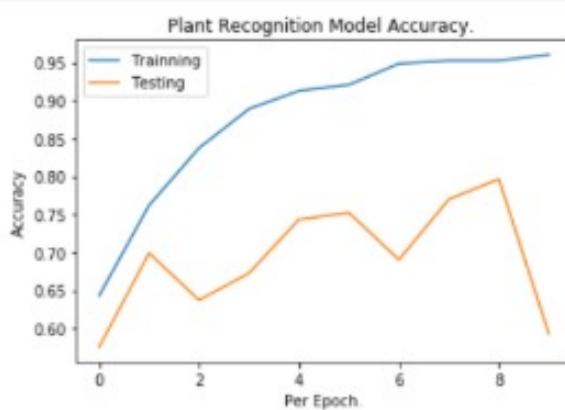


Figure 26: Plotting the training and testing accuracy's.

6 Project Management and Deliverable

6.1 Deliverable

#	Task	Date	Deadline
1	Proposal ideas.	15-July-2020	1-September-2020
2	Announce ideas for students.	2-September-2020	—
3	Proposal Evaluation.	Last week in October 2020	—
4	Submit Contribution paper.	First Semester	Second Semester
5	SRS Evaluation.	Third week of December 2020	—
6	SDD Evaluation.	Third week of February 2020	—
7	System Prototype.	Last week of April 2020	—
8	Technical Evaluation.	Last week of May 2020	—
9	Final Thesis.	Last 10 days of June 2020	—
10	Ceremony.	24-June-2021	—

6.2 Tasks and Time Plan

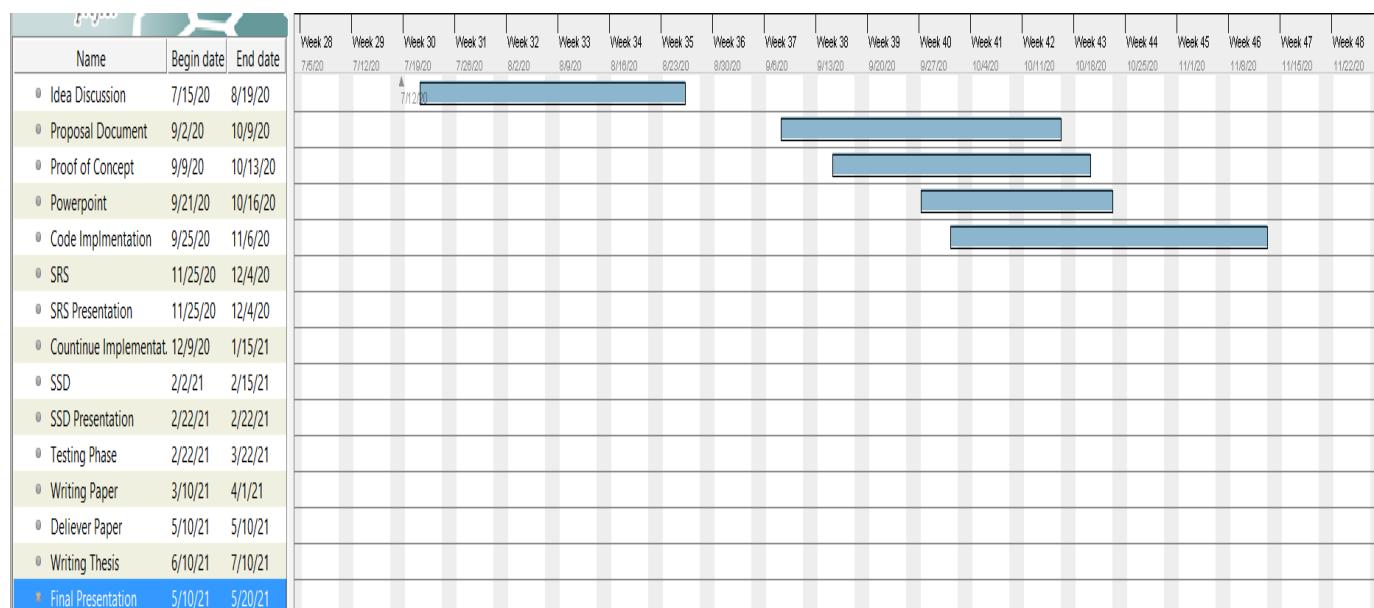


Figure 27: Our Gantt Chart part 1.

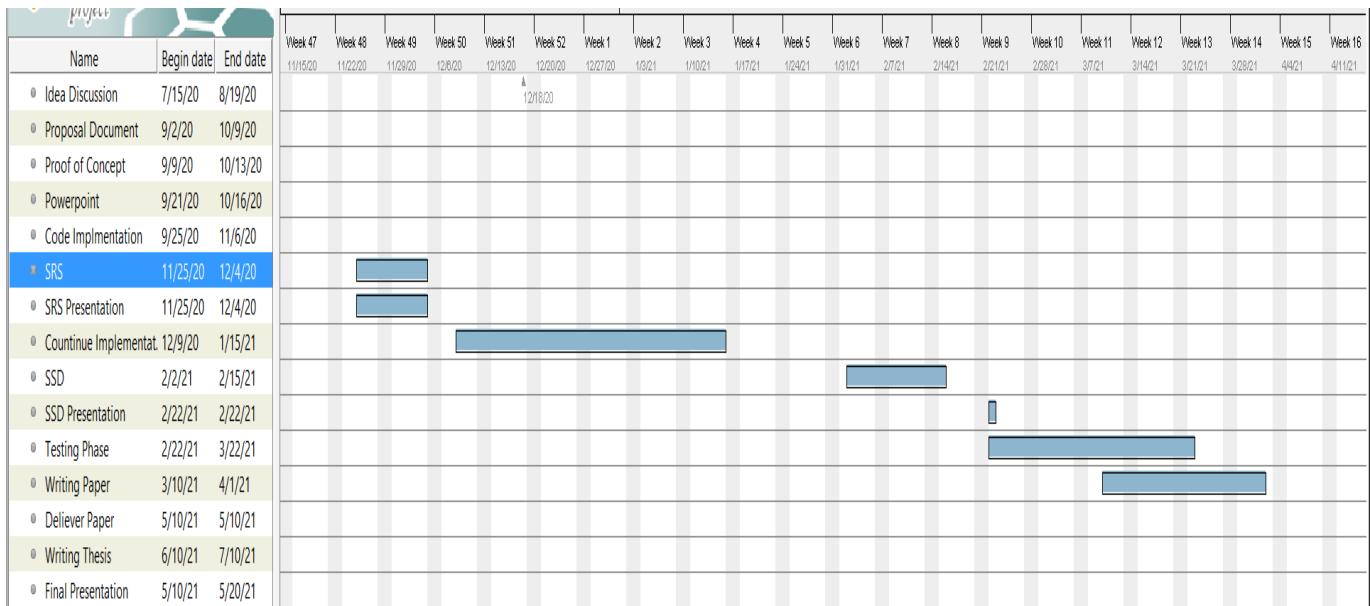


Figure 28: Our Gantt Chart part 2.

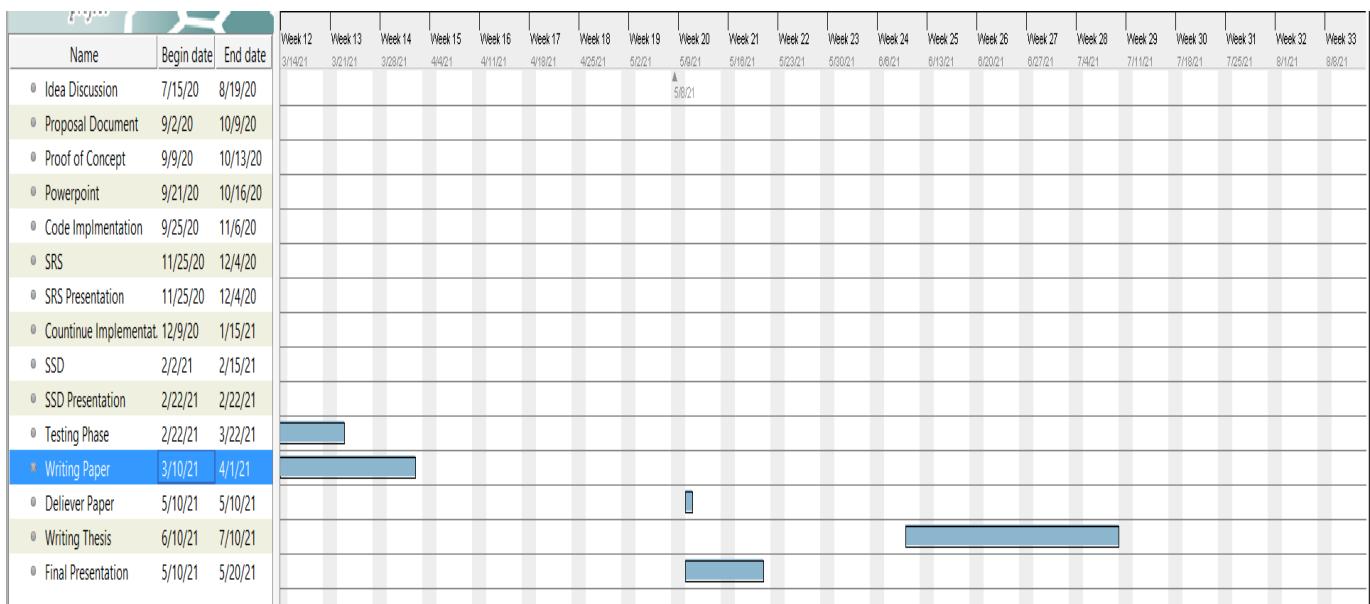


Figure 29: Our Gantt Chart part 3.

6.3 Budget and Resource Costs

#	Product	Cost
1	Raspberry Pi4 With Sensor Modules.	1,200 LE
2	Camera Module V2 Official 8 Megapixel HD.	850 LE
3	Small Buzzer.	5 LE
4	Raindrop Sensor Module – Water Sensor.	40 LE
5	WiFi Serial TTL Module "ESP8266-12E".	170 LE
6	Atmospheric Sensor - BME280 (Pressure/Altitude -Temperature - Humidity).	125 LE

7 Supportive Documents

- **Dataset :** We didn't find a data set in Kaggle for the Wild Oats ;therefore, We made an agreement with the Agriculture Research Center in Giza Government, in Cairo to collect it from them after a month. In the Agriculture Research Center, they plant Wheat earlier than any other farm.
- **Contact documents :**
- **Survey :** We will use the help of the Agriculture Research Center will will have it in the first of November , by Full-time Research manger Dr.Ahmed Sadea Uthman and the head of the laboratory center Dr. Abdo Ebead Ismael (01120244147) and (0107359267). [39]
- **Contacting authors :** We tried to contact the author of the article [35] to take their data set ; unfortunately, we didn't receive any respond back.

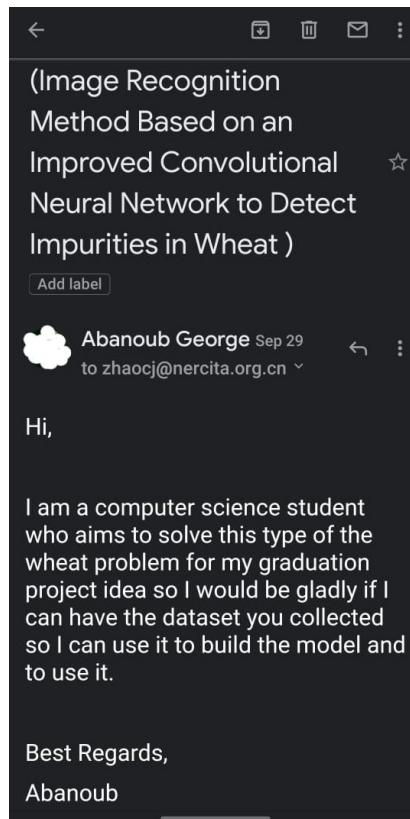


Figure 30: Trying to Contact one of the authors for their dataset.

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