

# Agri Robot

by

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## Introduction

### Overview

Agriculture is essential for any society, playing a vital role in the growth of a country's economy and its development. While some countries are utilizing latest agricultural approaches, majority still rely on traditional methods and techniques that are labor intensive and time consuming. The use of traditional approaches is failing to serve the high demand we are facing nowadays due to population growth. These problems highlight the urgent need for the use of new technologies to address these challenges. In this project we are proposing a cutting -edge solution that utilizes an AI model specifically YOLO (You Only Look Once), to detect crop ripeness and crop disease based on their leaves using an equipped rover with a camera and soil sensor that transfer data captured and display it on website interface providing a real-time insight into the conditions of crop. The proposed approach can significantly mitigate the issues that agriculture sector is facing, ultimately enhancing productivity and sustainability in food production.

### Background

Agriculture has been a keystone for human civilization for centuries. Evolving from primitive or subsistence farming to complex systems that feed billions. Traditional agricultural methods were born from local knowledge using basic tools, cultural and traditional everyday practices, sustaining communities for centuries. These methods and approaches often prioritize biodiversity and sustainability, relying on techniques such as crop rotation and organic fertilizers.

However, traditional agriculture approaches face huge challenges nowadays including soil degradation, climate change, and increasing population which as a result increased demands for food. Despite its strengths, traditional farming approaches are increasingly unable to meet the exponentially growing global food requirements. Issues such as nutrient depletion, deforestation, and soil erosion are prevalent as farmers strive to maintain productivity without the use of modern technology. The reliance on manual labor and simple tools limits efficiency and scalability, making it difficult to compete with industrialized agricultural practices that emphasize high yields through mechanization and chemical inputs[[1].](#_bookmark74)

Although agriculture sector is the backbone for Lebanon’s economy, contributing substantially in Lebanese Gross domestic product (GDP) reaching up to 80% of economic output [2] ;this sector faces systemic challenges ranging from water scarcity, infertile soils, inadequate access to technology, climate change pressures, and more. Thus, advancing agriculture through technology adoption is critical for Lebanon’s economic growth and sustainability which is a must.

There are various types of machines used in agriculture some of which are seeding machines that automate the sowing of seeds, ensuring optimal depth and spacing. Transplanting machines that move plants from a dense nursery growth stage to a more spread-out growth stage. Harvesting machines are designed for efficiently cutting plants from their roots. Robots equipped with sensors and end-effectors to identify and pick ripe produce. Weeding and pest control units that use precision application of herbicides

or mechanical methods to manage weeds and pests. monitoring and scouting drones or ground vehicles that gather data on crop health, moisture levels, and other critical parameters.

To address these challenges, there is a pressing need to integrate new technologies into agricultural practices. Innovative methods such as precision agriculture, which utilizes data analytics using IoT devices and sensors to optimize resource use, can significantly improve productivity while minimizing environmental impact. Technologies like drones for crop monitoring, robotic harvesters for labor-intensive tasks, and advanced irrigation systems can transform traditional farming into a more efficient and sustainable practice.

In this project we seek to demonstrate a proof-of-concept precision agriculture solution using robotic systems and sensors. The project aims to develop a rover equipped sensing for soil health analytics and 2 AI models for computer vision that can traverse farmlands and gather agricultural insights without needing a large workforce.

### 2.2- Objectives:

The objectives of this project are as follows:

* Promote sustainable farming practices to reduce soil erosion
* Increase Agricultural yield
* Offer remote monitoring to crop
* Automate collected sensor data
* Achieve real-time detection and classification.
* Detect with low latency

### 2.3- Motivation :

The recent escalation of conflict in Lebanon-Israeli War 2024, has had vast devastating impacts on the agricultural sector in specific and the environment in Lebanon in general . This war resulted in over 10,800 hectares of land stated Dr.Hadi Jaafar professor and chair of Department of Agriculture in American University of Beirut ,where areas four times larger than Beirut ,burned and significantly damaging crops and irrigation infrastructure, increasing the need for innovative solutions to restore and enhance the agricultural landscape is more urgent than ever. The fires impacted primarily shrubland and grassland while also inflicting extensive damage on forested areas along the 120km southern border, penetrating up to 10km inwards in some areas [[3].](#_bookmark74)

The cornerstone of Lebanon’s agriculture economy ,olive harvest with approximately 25% of agriculture lands are dedicated to olive groves primarily in south which due to the conflict it has been severely damaged .Lebanon and southern regions are known for producing the highest quality of olive oil globally Lebanon exported $ 30million USD worth olive oil in 2016 (EU-funded study ) .



*Figure 1 Burnt Areas in South Lebanon(October 2024 assessment ) -Data Source :European Forest Fire Information System*

In addition to agriculture in the Beqaa Valley the war led to damage to this crucial agriculture region disrupting export routes jeopardizing potato harvests such that Lebanon exports over $20 million USD worth annually mainly from Beqaa region in addition to cereal production with over 10,000 ha planted annually producing more than 40,000 ton of wheat and this disruption eventually impact the live hood of both farmers and market stability .

The approach proposed in presents an opportunity to address both immediate challenges posed by recent conflicts and long-term sustainability goals in Lebanon's agriculture sector. By utilizing advanced technologies for land monitoring that could help in damage assessment, crop monitoring, and precision agriculture, this initiative aims to not only restore but also enhance the resilience and productivity of Lebanon’s agricultural landscape in the wake of devastation supporting Lebanon's agriculture sector recovery.

### 2.4- Applications:

In this section, we will state the different settings and applications where the rover robot can be effectively deployed, highlighting the importance of applying this advanced technology in those applications, revolutionizing the traditional farming practices, thus ultimately contributing to a more efficient future in agriculture. The following is a list of applications where our rover can be implemented:

* Large Farms: enables farms to make the most out of their resources by constantly monitoring soil quality, fruit ripeness, and crop health real-time. By providing necessary and important data eventually increasing crop yield fertilization, and reduced wastage, and reduced operational costs. This, in turn, leads to more robust crops and higher productivity. Recent years show a significant growth in studying and inspecting how crops are grown and monitored in large field areas using autonomous techniques their operations and reducing environmental impact.
* Small Tight Farms: Numerous problems and constraints face farming systems nowadays which include small land sizes, unorganized crops, the decrease in the number of resources, and the increase in the degradation of quality of soil limits crop production and threatens overall food security. Different climate change circumstances such as frequent and extreme weather events and conditions magnify these problems Implementing this approach in smallholder farms represents a promising solution to the challenges these farms encounter. Our proposed approach offers real-time insights about soil conditions and crop health, and ripeness. Additionally, it increases the aware of small farm holders of plant conditions by providing soil data from sensor, which enables them to take necessary measures. Our approach provides tailored solutions to the specific challenges. Encountered by smallholder farms, ultimately enhancing crop production, food security, and the overall well-being of smallholder farmers.
* Greenhouses: advanced technologies integration, connected devices, and data- driven solutions in smart greenhouses can automatically monitor temperature, humidity, soil moisture, and ripeness of existing plants. This enables precise resource management, conserves water and nutrients, and ultimately contributes to cost reduction. Overall, applying such rover in greenhouses fits with modern agricultural practices and offers advantages to the quality of crops, efficiency of resources and increasing profitability.
* Vertical Farms: The use of this project, utilizing state of the art technology, including sensors, analysis of data, and automation maximizes the ability to adjust environmental variables such as light, temperature, humidity, and nutrient levels. This approach that allows optimal conditions combined to the specific needs of each crop results in an accelerated growth and enhanced productivity. According to a study done in, vertical farming has a huge potential in sustaining the production of food and all related services in urban and crowded areas, ultimately contributing to sustainable and economically viable agricultural practices.

While there are various applications for implementing this project, the ones highlighted above hold particular reference in today's modern problems of agricultural landscapes. Development and innovation are urgently needed in a world where the population continues to grow to sustain the daily increasing needs of supplies, ablate the amount of food being wasted, and supply access to food for all people especially those who are suffering from hunger and malnutrition. However, the potential use for this system extends far more than just its current applications. This system shows a huge promise in revolutionizing traditional farming methods by ensuring and enabling sustainable practices. Ongoing research and development indicate a growing range in the potential uses that could optimize agricultural practices in the future.

## Literature Review

### Introduction:

The integration of robotic technology in agriculture has been a growing area of interest in recent years. This integration has emerged as a solution to address the increasing demands for efficient food production. Recently, the evolution and progress in robotics and AI enabled the development high-end rovers equipped with sophisticated sensors and computer vision systems that provide some insights whenever we want wherever we are. In this chapter we will explore some of the latest conducted of research on robotic rovers in agriculture, focusing on their capabilities in soil data collection and computer vision in this field.

### Existing Work

In 2024, Tzani et al [[4]](#_bookmark74), investigated in assessing fruit quality and emphasizing its importance on agriculture sector and its effect on producers ,distributors ,consumers and countries economy .Stating that Artificial intelligence can aid and assess the quality of the fruits using images captured .The author presents a Deep learning model specifically vision transformers (ViT) to evaluated fruits using feature extraction .The ViT model proposed is trained on diverse set of fruit datasets enabling it to differentiate between rotten and ripe or good fruit based on its appearance rather than predefined quality attributes .The model achieved a high including the following : 99.50% percent accuracy for apples , 99% percent for cucumbers, and lastly 100% for grapes. Other fruits including the following: kakis, oranges, and tomatoes also resulted in high accuracy rates ranging from 98% to 99.50%. However, the model exhibited slightly lower performance in identifying guavas, lemons, limes, mangoes, pears, and pomegranates, with accuracies around 97% to 97.50%. The proposed approach solved an important problem that usually in traditional agriculture methods required extensive manual inspection. The ViT model proposed that abled automating fruit quality offered a scalable solution that can benefit various sectors.

In 2023, Li et al [[5]](#_bookmark74) , Li et al. indicated that the rapid development of computer technology has greatly facilitated international agricultural modernization and improved the efficiency of agricultural production. In this respect, Li et al. have suggested the Strawberry R-CNN, a new model proposed especially for the intelligent identification and counting of strawberries within their natural environment. The model proposed is built based on a refined existing model, namely the Faster R-CNN architecture, through several key modifications aimed at improving recognition accuracy. The original VGG16 backbone in Faster R-CNN was replaced by an improved multi-cascade network structure for the extraction of features, making it more capable of obtaining rich location data and fine details often lost in their higher-level abstractions. The experimental results of the proposed model showed that the mean precision of the Strawberry R-CNN model is 0.9019 for ripe strawberries and 0.8447 for immature, or in other words, unripe strawberries, with a mean average precision (mAP) of 0.8733. this approach underlines the potentials of advanced deep learning techniques for improvement in agricultural practices by enhancing automation and precision in crop management.

In 2024, Zhao et al [[6]](#_bookmark74) , conducted an approach using a lightweight version of YOLOv5 algorithm specifically YOLO-Granada , authors used this model to detect pomegranate fruit using an intelligent management systems for pomegranates orchards seeking to improve yields and address labor shortages .The paper states that currently most solutions use deep learning to detect pomegranate however deep learning is not effective in detecting small targets and large parameters , and it has slow computational speed so they suggested using YOLOv5 and for the pomegranate feature extraction they utilized a lightweight ShuffleNetv2 network .The results showed that the YOLO- Granada reached 92.2% accuracy percentage which is slightly lower than that in original YOLOv5 model which is 92.9% .On the other Hand YOLO-Granada achieved 17.3% increase in detection speed after compressing model parameters ,floating -points operations and overall size to 54.7% ,51.3% and 56.4% from the original network respectively .

In addition, the approach used showed a real time capability by processing 8.66 images per second. Moreover, the authors explored the development of an Android based application utilizing Nihui convolution neural network framework for detecting pomegranate real -time.

In 2023 Wang et al [[7]](#_bookmark74) , proposed an improved target detection algorithm based on YOLO v5n using K-means++ clustering algorithm to update the scale and aspect ratio of the anchor box so it can adapt to cherry tomatoes shape .Then they used coordinate attention mechanism (CA) to expand receptive field range reducing the interference that the model may face due cluttered background such as dead leaves , branches ,..etc that may affect the recognition of cherry tomato maturity. After that they replaced the traditional loss function with bounding box regression loss with dynamic focusing mechanism (WIoU) loss function. To address the boundary box regression balance problem between high-quality and low-quality data the authors introduced outlier degree and dynamic nomontonic mechanism. The results of the provided approach indicated that the improved model achieved a 1.4% increase in both recall and precision with respect to other YOLO models also the model achieved average accuracy mAP of 95.2% and average detection time of time 5.3ms which makes it highly suitable for deployment in embedded systems and mobile devices. The proposed approach provided rapid and accurate target recognition for cherry tomatoes.

In 2023 Pickett et al [[8]](#_bookmark74) , conducted a comparative between unmanned aircraft systems and agro-terrestrial (ground-based) surveying ,in this paper the author’s compared the accuracy, precision, time, and cost efficiency of using a small unmanned aircraft system (sUAS) for aerial surveying versus traditional ground-based (agro-terrestrial) surveying methods in an agricultural field. the researchers conducted both aerial and ground-based surveys on a 14-hectare field in Arkansas. concerning the aerial surveying they used a DJI matrice 300 RTK sUAS with a 45-megapixel camera. while the ground-based survey they used a utility vehicle equipped with a Trimble r8s GNSS receiver, collecting data at three different track spacings (7.62 m, 15.24 m, and 30.48 m). they also used statistical methods to compare the elevation data from the two approaches.

After conduction different experiments on different track spacings the author’s states that ground surveying is more widely adopted and requires less technical expertise with high accuracy in ground vegetation and low processing time also it can survey at night unlike aerial surveying .In addition ground-based surveys is more time-consuming, however, the ground-based surveys provided more detailed and accurate measurements. The authors suggest that ground-based approaches could be better than sUAS for applications that require higher accuracy, such as formal land surveys, as professional land surveyors are typically interested in absolute accuracy.

In 2024 Ozkan et al [[9]](#_bookmark74) , discusses the use of drones stating that it’s relatively new technology in agriculture and that there is limited amount of credible published research data evaluating the performance of drones compared to ground-based approaches providing the challenges and limitations in utilizing this method .Stating some of its limitations such as the frequent need to charge covering few acres per hour compared to ground sprayer for pesticides .In addition the author demonstrates the significant challenge of using drones due to it’s limited weight requirement stating FAA restrictions on drones, such as: “a drone must weigh 55 pounds or less including its payload” and drones can be flown only from 30 minutes before sunrise to 30 minutes after sunset while ground-based approaches can be used at night .

In 2024 Das et al [[10]](#_bookmark74) , proposed an agriculture rover to address the growing demand for sustainable agriculture practices .The agriculture rover is used for soil analysis and YOLOv5 model for detecting tomato ripeness .The soil analysis was done using NPK (Nitrogen ,Phosphorus and Potassium ) sensor which can give farmers insight about soil health and take necessary measures accordingly .The authors used dataset containing 500 images taken from tomato field and divided them accordingly : 350 images for training set , 100 for validation ,and 50 for testing set .

The model approach proposed resulted in 0.8518% for precision and 0.7624% recall providing a real demonstration for successful integration of computer vision into agriculture rover for crop insights and soil analysis conducting extensive field trails to assess efficiency of the rover in crop detection .

In 2020 Rajendran et al [[11]](#_bookmark74) , proposed IoT and AI integration to combat farmers agricultural loss due to plant disease ensuring there need for early pant disease identification mechanism .The observation for each and every individual plants in the farm for detecting early signs of diseases is labor intensive and time consuming .The authors utilized rover equipped with a camera and gps module to capture images of plant leaves through farms and greenhouses .The dataset employed is “Plant Village” plant disease was prepared by Hughes containing 60,000 images of more than 35 diseases of 16 plant species some of which are Pepper, grapes strawberries the four diseases that theses species suffer from are Black rot and Black measles in grapes , bacteria spot in pepper and leaf scorch in strawberry .The 2 deep learning models used in this approach are VGG16 and InceptionResNetV2 .The approach proposed resulted in 97.56 % training accuracy and 93.21 % for validation accuracy using VGG16 while in InceptionResNetV2 the training accuracy reached 98.32 % and validation accuracy reached 95.24% it’s worth noting that number of parameters in VGG16 is 134,289,223 Unlike InceptionResNetV2 having 58,091,591 having less than the half of the parameters in VGG16 .

In 2024 Karim et al [[12]](#_bookmark74) , integrated an edge device namely Nvidia Jetson Nano that can be utilized in rover with Deep learning model to leverage crop yield and detect crop disease precisely and utilized a python GUI (PyQt5) to interface the collected data .The proposed approach involved the use of modified MobileNetV3Large to detect crop disease early also the author performed a comparative analysis comparing the performance of the purposed approach some of which are :MobileNetv3Small

,DenseNet21 ,EfficientnetV2B1 .The proposed approach reached the highest training and test accuracies of 99.66% and 99.42% outperforming previously mentioned models.

In 2024 Ahmed et al [[13]](#_bookmark74) ,investigated the performance of two lightweight object detection models in the application of deep learning for precise tomato disease detection focusing on four categories : healthy , splitting rotation , sun-scaled rotation and blossom end rot .The two dataset were compared on custom tomato disease dataset .Initially the authors trained both models without data augmentation to establish a baseline and then utilized diverse data augmentation techniques from Roboflow to expand the dataset content .After data augmentation both models were re-trained and all disease categories were analyzed .The results showed that the models had significant improvement in accuracy after data augmentation .In addition the results showed that YOLOv8l reached 79.2% precision 70.1% recall 78.9% mAP50 55% mAP50-95 achieving higher accuracy compared to YOLOv5l which reached only 69.8% precision 62.3% recall 67.9% mAP50 49.5 mAP50-95 before data augmentation . Furthermore, the results improved after data augmentation such that YOLOv8l 91.6% precision 83.1% recall 88.5% mAP50 60% mAP50-95 while YOLOv5l only reached 89.3% precision 74.4% recall 85.2% mAP50 58.5% mAP50-95 .The results indicates that YOLOv8l outperforms YOLOv5l.

In 2024, Mac et al [[14]](#_bookmark74) , investigated the use of soft computing methods on autonomous intelligent agriculture particularly on systems for autonomous greenhouse navigation integrating fuzzy control algorithm with deep learning based models for classification that identifies illnesses in tomato plants through images of their leaves .This paper utilizes upgraded Deep Convolutional Generative Adversarial Network (DCGAN) which generates augmented images of diseased tomato leaves from the original samples there by enhancing the training dataset significantly .To identify which deep learning model is the optimal one in this application the author did a comparative analysis between various deep learning models some of which : VGG19, Inception-v3, DenseNet-201, and ResNet-152 .The approach proposed resulted in the following accuracies : 92.32%, 90.83%, 96.61%, and 97.07%, respectively using “original Plant Village “ dataset. The use of augmented dataset created by the proposed DCGAN, significantly increased the accuracy of ResNet-152 model reaching accuracy of 99.69% after it was 97.07%. The proposed approach increased the accuracy of DCGAN favoring the performance of deep learning models for monitoring greenhouses plants and detecting diseases.

### Summary Table:

*Table 1: State of the Art Research Comparison*

|  |  |  |  |
| --- | --- | --- | --- |
| Title | Authors | Year | Method Used and Outcomes |
| A General Machine Learning Model for Assessing Fruit Quality Using Deep Image Features | Tzani et al | 2024 | Deep learning model based on ViT with the purpose of assessing quality of fruits using images .The results showed the following accuracies: 99.50% for apples, 99% for cucumbers, and 100% for grapes, while other fruits like kakis, oranges, and tomatoes had high accuracy rates that ranged from 98% to 99.50%. It showed a bit of a lower performance for guavas, lemons, limes, mangoes, pears, and pomegranates, with accuracies ranging between 97%  and 97.50%. |
| Strawberry R-CNN: Recognition and counting model of strawberry based on improved faster R- CNN | Li et al | 2024 | The model is Strawberry R-CNN, extending the architecture of Faster R-CNN that performs the counting and intelligent recognition of strawberries The experimental results showed that Strawberry R- CNN achieved an mAP of 0.9019 for ripe strawberries and 0.8447 for immature ones, with a mAP of 0.8733, and counting accuracies of 99.1% for  ripe and 73.7% for immature strawberries. |
| YOLO-Granada: a lightweight attention Yolo for pomegranates fruit detection | Zhao et al | 2024 | YOLOv5-Granada pomegranate detection in an intelligent management system of a pomegranate orchard. They results reported that YOLO-Granada achieves a slightly reduced accuracy compared with the original YOLOv5 model-92.2% versus 92.9%. model parameters compression, floating-point operation compression, and size, respectively, to 54.7%, 51.3%, and 56.4%, increased detection speed by 17.3% for the YOLO-Granada model |
| A Lightweight Cherry Tomato Maturity Real-Time Detection Algorithm Based on Improved YOLOV5n | Wang et al | 2023 | The target detection algorithm used is based on YOLO v5n using K-means++ clustering algorithm , The results showed that the improved model outperformed other YOLOv5 model by increasing recall and precision by up to 1.4% also achieves an average accuracy mAP of 95.2%, with an average detection time of time 5.3ms, hence very suitable to be deployed in embedded systems and mobile devices. |

|  |  |  |  |
| --- | --- | --- | --- |
| Title | Authors | Year | Method Used and Outcomes |
| Small Unmanned Aircraft Systems and Agro-  Terrestrial Surveys Comparison for Generating Digital Elevation Surfaces for Irrigation and Precision Grading | Pickett et al | 2023 | The aerial surveying, they used a DJI matrice 300 RTK sUAS with a 45-megapixel camera. while the ground-based survey they used a utility vehicle equipped with a Trimble r8s GNSS receiver, collecting data at three different track spacings (7.62 m, 15.24 m, and 30.48 m).The results showed that ground surveying is preferred due to its high accuracy in measuring ground vegetation, lower processing times, and the ability to conduct surveys at night. While ground-based surveys are more time- consuming, they provide greater detail and precision |
| Designing and  development of agricultural rovers for vegetable harvesting and soil analysis | Das et al | 2024 | Agriculture rover is used for soil analysis and YOLOv5 model for detecting tomato ripeness. The model approach proposed resulted in 0.8518% for precision and 0.7624% recall. |
| Drones for  Spraying Pesticides Opportunities and Challenges | Ozkan et al | 2024 | The author discusses the use of drones stating some of its limitations such as the frequent need to charge covering few acres per hour compared to ground sprayer for pesticides and its limited weight requirement stating FAA restrictions on drones, such as: “a drone must weigh 55 pounds or less including its payload” and drones can be flown only from 30 minutes before sunrise to 30 minutes after sunset while ground-based approaches can be used at night |
| Automated Plant Disease Detection using Deep Learning Architectures with Autonomous rover | Rajendran et al | 2020 | The rover equipped with a camera and gps module to capture images of plant leaves through farms and greenhouses was used with 2 deep learning models VGG16 and InceptionResNetV2 .The results showed  97.56 % in training accuracy and 93.21 % for validation accuracy using VGG16 while in InceptionResNetV2 the training accuracy reached  98.32 % |
| Enhancing agriculture through real-time grape leaf disease classification via an edge device with a lightweight CNN architecture and Grad-CAM | Karim et al | 2024 | Nvidia Jetson Nano edge device was used to detect crop disease precisely and utilized a python GUI (PyQt5) to interface the collected data , the model used is modified MobileNetV3Large to detect crop disease early. The results were compared with MobileNetv3Small,DenseNet21,EfficientnetV2B1and the proposed method reached the highest training and test accuracies of 99.66% and 99.42% outperforming |

|  |  |  |  |
| --- | --- | --- | --- |
| Title | Authors | Year | Method Used and Outcomes |
| Improved Tomato Disease Detection with YOLOv5 and YOLOv8 | Ahmed et al | 2024 | Rover equipped with a camera and gps module was used to capture images of plant leaves through farms and greenhouses, farm for detecting early signs of diseases the results showed after data augmentation such that YOLOv8l 91.6% precision 83.1% recall 88.5% mAP50 60% mAP50-95 while YOLOv5l  only reached 89.3% precision 74.4% recall 85.2% mAP50 58.5% mAP50-95 .The results indicates that YOLOv8l outperforms YOLOv5l. |
| Intelligent agricultural robotic detection system for greenhouse tomato leaf diseases using soft computing techniques and deep learning | Mac et al | 2024 | Deep Convolutional Generative is used with the following models VGG19, Inception-v3, DenseNet- 201, and ResNet-152 to detect tomato disease. The results showed the following accuracies : 92.32%, 90.83%, 96.61%, and 97.07% and after using DCGAN, significantly increased the accuracy of ResNet-152 model reaching accuracy of 99.69% after it was 97.07%. |

### Alternative Design :

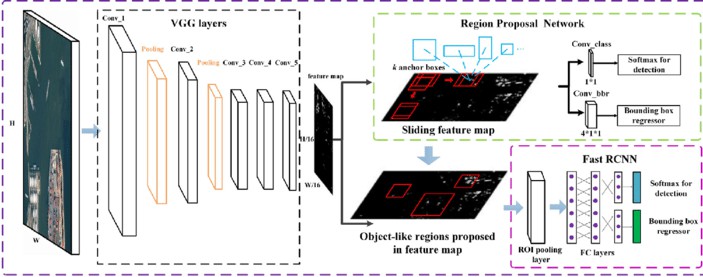
In this section, the different design approaches and tools that could be adopted for our project in relation to the 3 phases, which are divided as follows (phase 1: AI model development, phase 2: rover design and prototyping, and phase 3: website development) are going to be explored. This may enhance the effectiveness of our project by exploring different or various design approaches and tools and ensuring that they align with our objectives. This section focuses on the illustration of different methodologies and technologies that can be embedded into our project framework, making it flexible for adaptation and optimization of strategies. We have to make sure that with the choice of different options, our final design will satisfy not only the technical needs but also the practical needs of farmers and landowners.

#### Concerning the AI Model :

* + 1. Faster R-CNN :

Faster region-convolution neural network is two stage object detection model that is built upon previous models R-CNN .This model combines the benefit of deep learning

,convolution neural networks and region proposal network (RPN) that automatically generate the region proposal at the first .The Architecture of Faster R-CNN is divided into backbone networks that are considered as feature extractors commonly it included a pretrained Convolution Networks like shown in figure 3 below :



*Figure 2 Faster R-CNN Architecture [17]*

Where in the architecture presented above VGG was used from which the input image is processed to generate a feature map that captures hierarchical representations of visual information.

The feature map is smaller than the input image, though it retains essential semantic information, which is important for both region proposal and object classification tasks.

Once the region proposals are generated , the results are inputted to an ROI pooling layer which is used to extract a fixed length of vectors for each of the proposals Then the vectors are fed into two parallel fully connected layers which are divided as follows : one for object classification and the other is used to refine the bounding box coordinate While it’s had good characteristics in object detection it can underperform compared to other architectures as shown in table 2 below:

*Table 2 Yolov8 and Faster RCNN Comparative Analysis[18]*

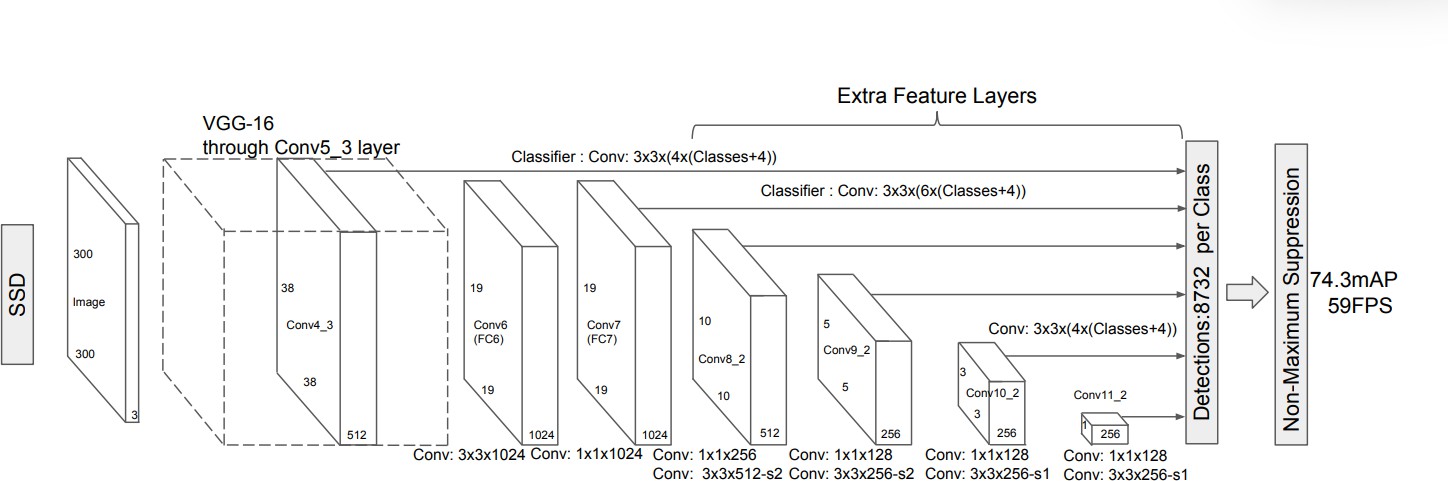
|  |  |  |  |
| --- | --- | --- | --- |
| Algorithm | mAP@50 | GPU latency (ms) | Customization |
| YOLOv8 | 0.62 | 1.3 | Customizable |
| Faster R-CNN | 0.41 | 54 | Limited |

Although Faster RCNN offers efficiency and accuracy in detecting objects yet YOLO provides lower latency approach as shown in table 2 where YOLOv8 reached 1.3 ms whereas Faster R-CNN needed 54ms greater than that offered by YOLO by more than 50 times one of the reasons that YOLO architecture achieves lower latency is due to the fact that YOLO is one stage while Faster R-CNN is two stage architecture . Despite the fact that in our project low latency for faster detection is important , accurate detection is important too and after comparing the latencies of both architectures we compared mAP@50 which is mean Average Precision that measures the precision and recall of a model at an Intersection over Union (IoU) threshold of 0.50 the YOLO architecture provided higher value reaching 0.62 compared to Faster R-CNN which reached only

0.41 which implies that YOLO architecture suits our proposed project and complies with our objective compared to Faster RCNN.

* + 1. SSD :

Single shot MultiBox Detector is single -stage object detection model unlike Faster RCNN which implies that SSD identifies targeted objects in an image after single forward pass of the network. The SSD discretize the output space of bounding boxes into a set of default ones but with different ratio aspects and scales at each feature map location enabling the model to predict bounding box offsets and class scores simultaneously for multiple object having various sizes. As previously explained model SSD consists of previously trained CNN such as VGG16 present in figure 4 below :



*Figure 3 Single Shot Mutibox Detection Architecture[19]*

which is used to processes an input image and generate feature maps. In addition, further convolutional layers are involved, reducing their size successively thereby allowing the model to detect of objects ranging from small to big by size. A key feature of SSD is its use of multi-scale feature maps; it uses the output from various layers of the base network to capture information across multiple resolutions which improves the detection of objects of different sizes. For every default box that is generated at each feature map location, SSD predicts the class confidences-the probabilities that each box contains some specific object class-and the bounding box adjustments to refine the position and size of these boxes for a better alignment with the objects detected. The SSD combines the localization loss, which was measuring exactly how well our predicted bounding boxes match ground truth, with the confidence loss assessing the accuracy in class prediction. At the end SSD uses Non-Maximum Suppression (NMS) which is used to remove redundant boxes to retain just the most confident predictions that finalize detections.

While SSD is a single-stage object detection which have lower inference with respect to other multi-stage object detection models yet it has some pitfalls that prevent it from being the optimum model for this project the model will be compared according to performance and accuracy.

Where Kaliappan examined the performance of both models YOLOv8 and SSD for precision poultry farming management and the results are shown below in Table 3 :

*Table 3 YOLOv8 versus SSD comparative analysis[20]*

|  |  |  |
| --- | --- | --- |
| Metrics | YOLOv8 | SSD |
| Precision | 0.9677 | 0.89 |
| Recall | 1.0 | 0.65 |
| mAP@50 | 0.987 | 0.77 |

While both YOLO and SSD showed nearly similar precision yet YOLO outperforms SSD recall and in mAP@50 mean Average Precision that measures the precision and recall of a model at an Intersection over Union (IoU) threshold of 0.50 which makes SSD have low accuracy compared to YOLOv8 model .The tradeoff between speed and accuracy of SSD makes it less efficient for our application in this project were precise detection is required to detect small crops or subtle signs of disease on leaves

Now concerning the performance of SSD model , YOLO v8 can process up to 155 Frames per second While SSD can only reach at most 46 frame per second as shown in in table 4 below:

*Table 4 Performance comparison between YOLOv8 and SSD[21]*

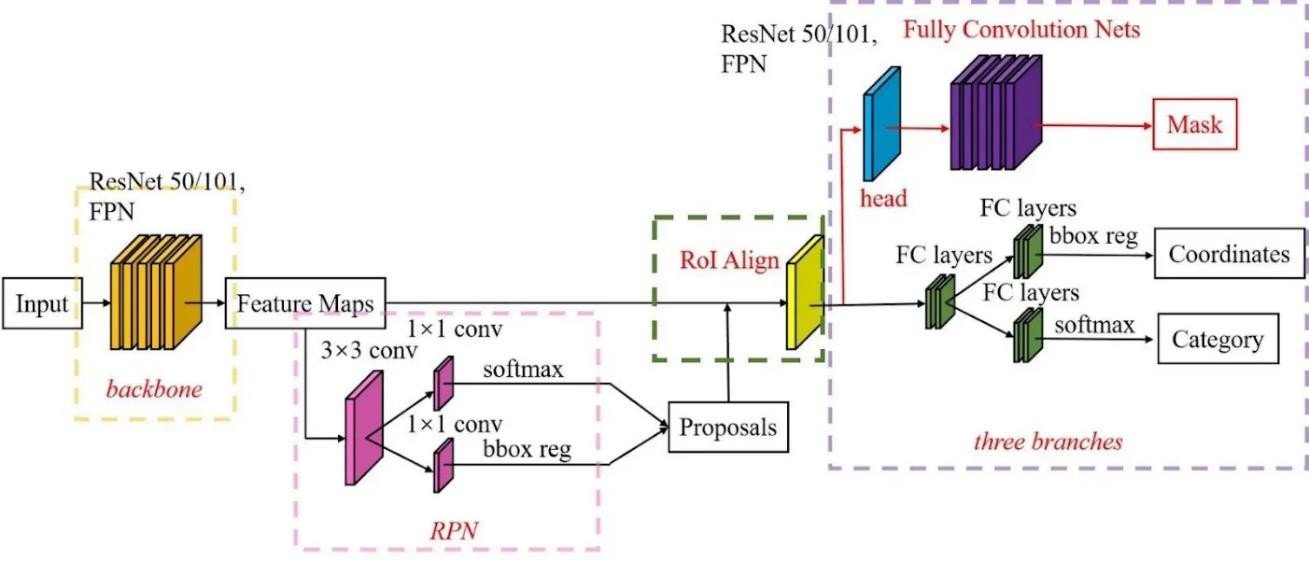
|  |  |
| --- | --- |
| Model | Frames Per Second (FPS) |
| YOLOv8 | 40-155 |
| SSD | 22-46 |

The low accuracy and low real time processing speed of SSD compared to YOLOv8 prevent us from choosing SSD such that other architectures offer higher accuracy and higher processing speed reaching 155 FPS .This implies that SSD is not suitable for real-time crop health monitoring making it unsuitable for our project .

* + 1. Mask R-CNN :

Mask region convolution neural network is an extension of Faster region convolution neural network object detection used for instance segmentation and object detection.

This model can detect an object in an image and generate high-quality segmentation masks for every detected instance. This allows the delineation of object boundaries at the pixel level. Starting with its backbone which is usually a pre-trained network like RestNet50 shown in Figure 4 below :



*Figure 4 Mask R-CNN Architecture[22]*

Which is used to process the input image for high-level features.To handle objects of different sizes effectively, an ( FPN ) Feature Pyramid Network is incorporated that builds a multi-scale feature pyramid by providing features in different resolutions.Then, the Region Proposal Network generates region proposals by sliding on the feature map to predict bounding boxes and object scores for potential objects in an image, outlining regions of interest. Instead of using traditional ROI Pooling or in other words Region of interest pooling, Mask R-CNN uses Region of interest Align (ROIAlign) , which relies on bilinear interpolation to ensure the exact alignment of the extracted features with the proposed regions which enables it to avoid misalignment and increases the segmentation accuracy. Mask R-CNN extends this further by adding a mask branch parallel to the existing branches for classification and regression of bounding boxes, by predicting a binary mask for each proposed region to outline the exact pixel-level boundaries of detected objects. The final output from the network would include a bounding box, class labels, and pixel-wise masks for every detected object allowing instance segmentation with great details combined with the usual object detection.

While Mask R-CNN is a extended version of faster R-CNN and its capable of object detection and instance segmentation yet it has some pitfalls that prevent it from being the optimum model for this project the model will be compared according to performance and accuracy

Sapkota in his attempt to compare between YOLOv8 and Mask R-CNN for instance segmentation in complex orchard environment to segment apple fruitlet ( unripe or immature fruit) resulted in the following :

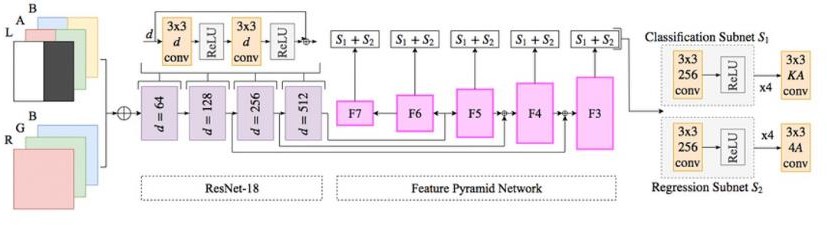
*Table 5 Comparative Analysis between Mask R-CNN and YOLOv8[23]*

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Model | Precision | Recall | mAP @0.5 | Inference Time(ms) | Frames Per Second(FPS) |
| YOLOv8(single -class) | 92.9 | 97 | 0.902 | 7.8 | 128.21 |
| Mask R-CNN(Single-Class) | 84.7 | 88 | 0.85 | 12.8 | 78.13 |
| YOLOv8(Multi-class) | 90.6 | 95 | 0.74 | 10.9 | 91.74 |
| Mask R-CNN(Multi-Class) | 81.3 | 83.7 | 0.700 | 15.6 | 64.10 |

Where YOLOv8 outperformed Mask R-CNN in both multi and single class dataset .in addition YOLOv8 had higher precision , recall and mean average performance at 0.5 threshold with lower inference time and more real time processing speed reaching in this example 128.21FPS which implies that Mask R-CNN is not the optimum model for our application that have similar objective to the above experiment .

* + 1. RetinaNet :

Retina Net is name is inspired by its ability to detect objects with high accuracy across a range of scales, mimicking human retina and how it perceives visual information .It’s a one-stage object detection model ,designed to effectively handle the challenges of imbalanced data and varying object sizes through its architecture that includes the following : a backbone network, a Feature Pyramid Network (FPN), and two task- specific subnetworks for classification and regression. The backbone network, usually Rest Net similar to one presented in figure 6 below :



*Figure 5 RentinaNet Architecture[24]*

Where RestNet-18 that is used to extracts feature maps from the input image at different scales. The Feature Pyramid Network (FPN) enhances this by creating a multi-scale feature pyramid that allowing the model to detect objects of various sizes; it does this through a top-down pathway that up samples higher-resolution feature maps and lateral connections that merge these with lower-resolution maps. The classification subnetwork predicts the probability of an object being present at each spatial location for each anchor box, while the regression subnetwork refines the bounding box coordinates. A key innovation in RetinaNet is its use of Focal Loss, which addresses class imbalance by focusing more on hard-to-detect objects, thereby improving overall detection performance. The output of RetinaNet consists of bounding boxes and class probabilities for detected objects, making it effective in various applications, particularly those involving dense or small-scale objects.

Although it provides significant features the inference time compared to YOLO models is slow and the reliance on anchor boxes can complicate the dedication of overlapping object that are found in crop fields [[25]](#_bookmark74)

#### Concerning the Website Development :

In this section, we will look at the various design alternatives for the website tools of our project, including the basic blocks of the frontend, backend, communication protocols, database, and cloud platform. We considered several frontend frameworks for user interface, evaluated different backend solutions to handle data robustly, and explored different communication protocols for dependable data exchange between the rover and the web application. Further, database systems were analyzed for the performance of storing and retrieving data, and cloud platforms were analyzed in terms of their scalability and integration capabilities. This in-depth exploration shall help identify the best technology combination to enhance system performance and the user experience

#### Frontend Development

Frontend development includes the graphics face along with the overall design aimed at customers in terms of experience. It serves as the bridge between the users and the software features. In our web interface, the frontend will be applied to view the data from the rover and interact with the rover in a live manner; this will be important in achieving the user usability. In order to decide which front-end technologies, we should use, whether React, Vue.js, or even Angular, we considered its impact on performance, maintainability, and user satisfaction. We evaluate these frameworks to find which one would be most suited for the project.

React is a free popular JavaScript library whose primary aim is to create user interface for particularly single page applications. By utilizing a component-based approach, it allows developers to create scalable reusable UI elements which in turn result in better code maintenance. Given that React is popular and supported by a vast community with a variety of state management solutions like Redux and Context API it would definitely be favorable for developing an agricultural rover’s interface that requires a lot of performance.

Vue.js is a JavaScript-based framework for building user interfaces, it’s single page applications and complex web applications targeting end users. It is ranked up as one of the most learnable programming languages due to its ease of use and integration capabilities with other applications. Its template syntax is easy to understand and the data binding is a reactive data which makes management of states very easy. In our project, this would enable the swift creation of a flexible frontend making interaction with Flask based backend seamless[[29].](#_bookmark73)

Angular is resolves complex single page applications through its architectural approach based on HTML and Type script. It has the features such as dependency injection and two-way data binding but is harder to learn compared to others frameworks. But due to their strong conventions and tooling it increases productivity of bigger teams.

For our interface, it would can use to construct the orderly frameworks that can be well scaled on data streams and user inputs

*Table 6 Frontend Comparison Table [29]*

|  |  |  |  |
| --- | --- | --- | --- |
| **Feature/Aspect** | **React** | **Vue.js** | **Angular** |
| **Type** | JavaScript library | Progressive JavaScript framework | Complete framework |
| **Learning Curve** | Moderate | Easy | Steeper |
| **Architecture** | Component-based | Component-based | Modular and service-oriented |
| **Performance** | High performance with virtual DOM | Great with lightweight core | Good, but can be complex for large apps |
| **Community Support** | Large community and ecosystem | Growing community, focus  on simplicity | Strong support and large ecosystem |
| **Use Cases** | Dynamic, complex UI | small to medium projects | large-scale applications |
| **Integration** | Easily integrates with various backends | Simple integration with REST and GraphQL | Well-suited for RESTful services |
| **Development Speed** | Fast development | Rapid development | Slower |

#### Backend Development

While choosing the backend framework to be adopted for the Web interface of our argi- robot project, we considered some of its specific needs, such as real-time data processing and ease of integration with AI models. Two of the key’s considered frameworks were Django and Flask.

Django is a high-level web framework intended for big and complex projects. It has integrated all the tools that a professional might need, such as an admin panel and authentication system, which by default can really speed up the development of big features. Although Django could provide its services in our present project, due to its comprehensive nature, it gives birth to unnecessary complexity within the system, making it a bit heavier than required. As our project deals with real-time data gathering and instantaneous feedback concerning soil and plant health, Django's overhead will possibly offset performance we want for seamless data exchange between the rover and the web interface[[30].](#_bookmark73)

On the other hand, Flask is a microframework quite good for small to medium projects, considering the flexibility and modularity. It lets the developer selectively integrate only those libraries that best meet the project's specific needs. In fact, Flask is a good choice in the scope of our argi-robot project, since it will be based on lightweight and speed considerations, crucial to real-time applications. The framework allows for quick exchanges between the sensors on the rover and the AI model; hence, it will be able to update data on the website at the same speed. This ensures users have timely insights concerning the condition of the soils or crops, hence giving valuable input for decision making.

*Table 7 Backend Comparison Table [30]*

|  |  |  |
| --- | --- | --- |
| **Feature/Aspect** | **Django** | **Flask** |
| **Framework Type** | Full web framework | Micro-framework |
| **Architecture** | Monolithic, with built-in components | Lightweight, modular |
| **Complexity** | High | Low |
| **Flexibility** | Less flexible | Highly flexible |
| **Performance** | Slower due to its comprehensive nature | Efficient with low latency in data transmissions |
| **Real-Time Processing** | Less suitable for applications requiring immediate feedback | Excellent for real-time applications |
| **Use Case** | applications needing extensive features | projects focused on efficiency and responsiveness |
| **Data Handling** | Slower data exchanges | Quick and efficient data handling |

#### Real time Communication:

Real-time performance in communication is crucially relevant to the success of the project due to the fact that any delay in data transmission may affect decision-making at any level of agricultural management arising from sensors and cameras timely. Three protocols were evaluated: HTTP, WebSocket, and MQTT as the primary means of communication.

#### HTPP:

The HTTP protocol follows in its design the principle of a Request-Response model. In this case, some client requests sent by an active client elicit responses from a passive web server. The classic method under which this process normally functions is the serving of HTML/CSS files to a client's browser. While HTTP works for simple data retrieval and authentication, such as user registration and login, loading of static content

like images and stylesheets, it does have significant limitations, especially with regard to our argi-robot project.

HTTP is most suitable for basic data acquisition operations and identity verification assignments throughout the project. Nevertheless, relying on HTTP alone has considerable drawbacks because HTTP is a request–response protocol, and the communication pattern is based on the request–response model, which increases the latency and overhead. This is the major limitation of HTTP presents in our project, which relies on real-time monitoring of data to efficiently manage agriculture. This will make the system slow, since refreshes the data are always late because of the request- response nature of HTTP. For example, soil levels would get updated after a long time, which could delay automated fertilizers adjustments or postpone critical diagnostics related to plant health.

#### WebSocket:

WebSocket mainly talks about how a client and a server will be able to share content through the full-duplex pipe. That is, two directions of data interchange, where the client and the server are also participating, exchange information with and within one another in turns over time. The response-method update approach of this bidirectional communication technique has several benefits over an application that needs real-time capability at a lesser cost than HTTP polling.

WebSocket can be effectively used for creating the real-time user interface on the website which is used for monitoring. Permanent connections between the server and the client provided by WebSocket let adding immediacy in updating of sensor data, video streams further improving the farmer experience during crop observation and monitoring. However, when used independently the WebSocket also poses its own difficulties, it could experience inefficiencies and yet escalate the complexity in receiving multiple data streams from the robot and other sensors; this would impact performance when expanded to more extensive agricultural systems.

#### MQTT:

MQTT (Message Queuing Telemetry Transport) is an IoT real time messaging protocol used by devices for communication. It designed to perform well under low bandwidth, high latency or unreliable networks. It uses publisher–subscriber model of messaging where one or more publishers can send messages to a broker that forwarding them to subscribers. It is well-used in IoT environment because of its efficiency and simplicity for use.

In our project, the best way to use MQTT is when receiving sensor information from the robot to a specific broker. This protocol again shines in the quick generation and dissemination of readings such as soil moisture and temperature with ability to support multiple subscribers including the monitoring website. However, one disadvantage in using MQTT by itself is the fact that some of the clients you want to carry out web- based interactions are unable to achieve two-way communication required in a personalized dashboard application. This means that although the sensor data may be transmitted efficiently the users and their interaction with the system may have to be compromised unless further additions of layers are made[[31].](#_bookmark73)

*Table 8 Communication Comparison Table [31]*

|  |  |  |
| --- | --- | --- |
| **Protocol** | **Advantages** | **Disadvantages** |
| **HTTP** | Easy to implement | Slower due to request- response model |
| Compatible with existing web technologies. | Less efficient for frequent data updates. |
| **WebSocket** | Full-duplex communication | Complicated to implement and manage. |
| Low latency which fits for real-time data transfer. | Requires-additional infrastructure to maintain persistent connections. |
| **MQTT** | Suitable for continuous data streams | May not handle large payloads |
| Lightweight |
| Great for IoT applications and sensor data. | More complex setup |
| Publish-subscribe model allows flexible  communication. |

#### Database:

The rover collects data through sensor camera streaming, which send them to website with a database solution to store and monitoring them. This approach will keep the farmer informed about the most recent crop health status and soil conditions in real time and comparing them to historical data, with a view to enhancing decision making and resource management.

This project is based on two major sources of data: sensors and cameras. The quantitative data about the agricultural environment includes soil moisture, temperature, and nutrient levels from sensor data. On the other hand, the cameras and video feeds provide visual information about the ripeness of crops, presence of diseases, and general health of the plants. The amalgamation of sensor and video data requires careful consideration of how this information will be processed and stored. For that reason, the choice between SQL and NoSQL databases becomes very important.

SQL databases, such as MySQL and PostgreSQL, are structured in how they store data. A key feature of these types of databases is that data must be inserted according to a previously predefined schema. This makes them suited for well-defined data types, such as user profiles or historical records of agricultural practices. Because they are ACID compliant, SQL databases provide substantial integrity for transactions occurring in user authentication or other critical events. However, SQL databases is restrictive in terms of

scalability and flexibility. As the volumes increase and there is a need for real-time processing of sensor data, the schema of SQL databases will prove to be a challenge.

NoSQL Databases, such as MongoDB or Cassandra, are meant for unstructured or semi- structured data and, therefore, will be best suited for the wide ranges of data generated from sensors and cameras. These databases allow for quick changes to be made in the data model with very minimal downtime, thus meeting the dynamic changing in agricultural monitoring. Another key feature of NoSQL databases is that they can scale up very quickly, and it can easily distribute data across multiple servers, something quite important as our project grows[[32].](#_bookmark73)

*Table 9 Database Comparison Table[32]*

|  |  |  |
| --- | --- | --- |
| **Feature/Aspect** | **SQL Database** | **NoSQL Database** |
| **Data Structure** | Structured Data; schema predefined. | unstructured and semi-structured data, Schema-less |
| **Sensor Data Storage** | Used for structured sensor data | Excellent towards diversified formats of sensor data. |
| **Camera-Data Storage** | The data from videos is store in metadata and take it reference | Store large volumes of video files along with metadata. |
| **Real-time-Data Handling** | Slower update for data changes very frequently | Optimal performance for frequented data changes and analytics on real-time data |

#### Cloud Platforms:

Selecting the right cloud platform and services to support the deployment and growth of the argi-robot in different markets is very crucial for the project’s success. In this section, our analysis revolves around AWS, Google Cloud Platform (GCP), and Microsoft Azure, and on their specific characteristics as far as our project is concerned Amazon Web Services (AWS) is a cloud platform that offers a variety of functionalities that are very useful for our agricultural rover project. It works well with Elastic Beanstalk for managing and scaling Flask apps, Amazon S3 to host the React UI and Amazon Document DB for the database management of MongoDB. Due to the vast range of tools offered by AWS, the integrations are seamless performances are better. Furthermore, the scalability that AWS provides enables us to convert resources on the go based on the amount of data received from the rover's sensors and cameras. Because AWS implements appropriate measures that help secure sensitive agricultural data, it is also beneficial for our project.

Google Cloud Platform (GCP) is best known for the efficient data processing, analytics and machine learning, which is very helpful for our agricultural rover project focused on data collection. Google App Engine makes the deployment of Flask backends quick with automatic scaling, while Cloud Storage helps in hosting the React UI and in datasets created by the rover. Through the integrated functionalities offered by GCP, it is possible to perform great amounts of sensor data screening for analysis and derive useful agricultural information. Thanks to the AI-powered components integrated into GCP, our app has the ability to analyze data and create accurate predictions, which streamline operations everywhere.

Microsoft Azure provides a broad range of cloud products such as analytics, computing and storage. Azure App Service makes it easy to deploy our Flask application and offers easy scalability options, while Blob Storage helps in providing scalable solution for deployment of the static files and for sensor data storage. Moreover, since Azure Cosmos DB has built-in support for MongoDB APIs, it can meet all our database management needs. The Azure IoT Hub takes added advantage of the strong integration and additional connectivity features of the rover by extending our capability to manage and analyze the data generated by the rover’s sensors. Thus, this added IoT functionality may simplify and improve our agricultural operations[[33].](#_bookmark73)

*Table 10 Cloud Platforms Comparison Table[33]*

|  |  |  |  |
| --- | --- | --- | --- |
| **Feature/Aspect** | **AWS** | **Google-Cloud Platform (GCP)** | **Microsoft Azure** |
| **Core Strengths** | Different service  offerings and scalability. | data analytics and  machine learning tools. | integration with  Microsoft products and services. |
| **Deployment Services** | AWS Elastic Beanstalk for Flask, S3 for React. | Google App Engine for Flask, Cloud Storage for React. | Azure App Service for Flask, Blob Storage for React. |
| **Database Options** | Amazon Document DB (compatible with MongoDB). | MongoDB Atlas or Cloud Fire store. | Azure Cosmos DB (supports MongoDB API). |
| **Scalability** | Highly scalable infrastructure | Easily scalable for various workloads. | Scalable solutions suitable for enterprise applications. |
| **Pricing** | Pay-as-you-go. Free tier available with limited usage (e.g., 1 million IoT messages/month) Pricing varies | Pay-as-you-go. Free tier with limited resources (e.g., 1 GB storage, 100 MB BigQuery queries/month).  Pricing varies | Pay-as-you-go. Free tier with limited usage. Pricing varies based on services used |
| **Security** | Strong security features | Robust security protocols | Different security features |
| **Best Use Case** | Good for full-stack applications needing many  services integration. | Ideal for projects needs advanced analytics and  machine learning. | Best for applications with strong Microsoft  integration needs. |

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#### Concerning the Rover Design and Prototyping :

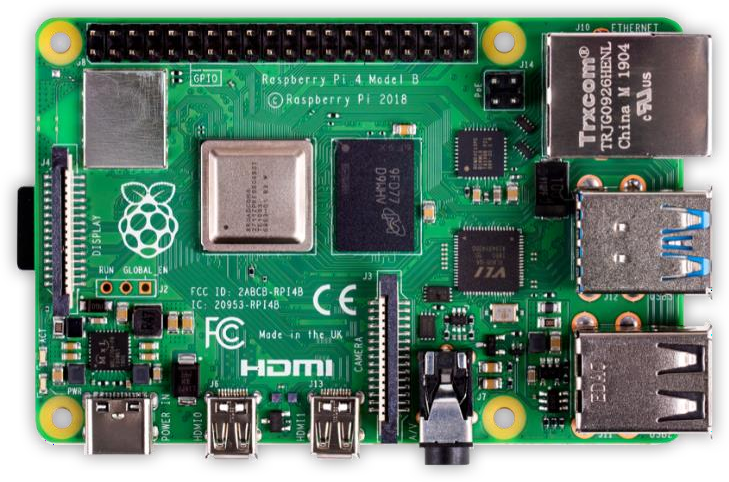
To ensure the best performance and adaptability to our project, we explored multiple options for controllers, cameras, sensors, motors, wheels, and relays. We carried out a detailed study of different controllers. Furthermore, we conducted an analysis of the potential of each of the camera options to provide quality images for AI analysis. We explored several sensors which in turn were mechanisms used for soil monitoring. We select motors that are both torque and efficient while we considered multiple wheel designs. These aspects were intended to optimize the rover's performance and adaptability to crop production systems.

### Controllers:

Controllers are key elements of every branch connected to our rover, which controls the flow of information and communication between hardware resources, including sensors, cameras. In this project, we analysis different controller’s type: Raspberry Pi, Arduino, and ESP modules. Each kind of controller has unique characteristics. The controllers provide easy and efficient communication between rover parts, thereby significantly enhancing real-time data collecting, feedback activities, and consequently quick and sure responses that are key to effective agricultural monitoring and decision-making.

Our target is to select a controller that can manage the data obtain from sensor reading and send it to website to analysis and store it. To enhance the rover’s functionality, we are going to select a controller that can execute motor functions for both the movement of wheels and deploying sensors into the soil. The controller should process data coming for camera and send it to the website for ai model analysis or the model will be embedded in the controller itself. It should facilitate real-time monitoring and analysis which will enhance the rover performanc

Raspberry Pi

Raspberry Pi 4 Model B is considered a powerful computer, providing significant upgrades in performance over others models with different variants of 1GB, 2GB, 4GB, and 8GB of RAM, and the support of dual-band Wi-Fi with frequencies of 2.4 GHz and 5 GH, and support pf Bluetooth 5. It has 40 GPIO pins for interfacing many different sensors and devices—everything on a single board capable of carrying strong computing and connectivity needs.

*Figure 6 Raspberry Pi 4 Model B*

For our project, Raspberry Pi 4 can be used in data collection and processing by connecting different sensors. It can serve as a web server for the visualization of real- time sensor data and remote supervision and control. It also has high resolution camera modules that help in taking pictures of crops for visual examination in health checks and pest infestation analysis. More importantly, Raspberry Pi can support the integration of ai model for predictive analytics and automation tasks like detect crop disease, thereby vastly improving the capability and effectiveness of the rover in agricultural management.

ESP32

The ESP32 is a very powerful microcontroller, well known for its built-in Wi-Fi and Bluetooth capabilities, thus mainly used in IoT applications. The ESP32 has a dual-core processor running up to 240 MHz and many GPIO pins, so it really can handle different tasks quite efficiently. The npk sensor are part of a project that needs to gather real-time environmental data. These kinds of data can be locally processed or sent to the cloud for monitoring and analysis. This project allows for automation of actuator control based on sensor readings, thus relieving the task associated with crop health and resource management.

*Figure 7 ESP32 microcontroller*

Integration of the ESP32 with Arduino brings flexibility into our project. In this respect, the ESP32 would be the main processing unit, while Arduino boards can be used to interface with specific sensors or actuators that require more pins or power. Such a setup allows for a modular structure in which the ESP32 takes care of communication and data processing, while Arduino boards handle physical interaction. Such collaboration eases the development process and enhances the comprehensive functionalities of the agricultural rover, allowing complex features like the integration of artificial intelligence models for predictive analytics and automation.

ESP8266

The ESP8266 is a small, low-cost Wi-Fi microcontroller that has recently gained much popularity for IoT applications due to its user-friendliness and advanced features. The ESP8266 makes it very convenient for developers to easily connect devices to the internet with an 80 MHz processor and a built-in Wi-Fi module. This technology can be applied in our project for data acquisition from various sensors and its transmission to a cloud platform or website in real time for monitoring. It will provide an appreciable rise in automation with regard to the irrigation systems and other agriculture activities that are controlled by actuators like pumps or motors through sensor data.



*Figure 8 ESP8266 microcontroller*

The addition of the ESP8266 brings greater capability to this project and eases development at several levels. In this setup, the ESP8266 is the main communication module, which handles Wi-Fi and allows data transfer, while the Arduino boards are used for auxiliary sensors and actuators that might require more GPIO pins or special interfacing capabilities. Integration allows the rover to have a modular and adaptive framework that allows it to acquire advanced capabilities in data acquisition and remote management while simultaneously allowing the integration of streamlined artificial intelligence models for enhancing real-time decision support.

Summary Table :

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Feature | Arduino Mega | Raspberry Pi 4 Model B | ESP32 | ESP8266 |
| Advantage | Large number of I/O pins | Higher processing power (1.5  GHz) | Dual-core processor for higher  performance | Simple solution |
| High processing power | Multiple RAM  options (2GB, 4GB, 8GB) | Built-in Bluetooth support | Smaller size |
| Good for complex applications | Dual micro- HDMI ports for 4K output | More GPIO pins (typically 34) | Easier to use for basic applications |
| Supports multiple sensors/actuators | More USB ports (2  USB 3.0, 2  USB 2.0) | Supports more communication protocols (I2S,  CAN, etc.) | Good community support and  libraries |
| Greater number of I/O pins | Better low- power modes for battery applications | Sufficient performance for most IoT tasks |
| Disadvantage | Larger size may not fit all projects | Larger size may not fit all projects | Slightly more complex to set up | Only single- core processor |
|  | Higher power consumption | Higher power consumption | Higher power consumption | Limited GPIO pins |
|  | More complex to set up | More complex to set up for beginners | No Bluetooth supports |
|  |  | More expensive |  | Fewer advanced features |

Camera

Integration of the camera into our rover will significantly increase the functionality of the system with visual monitoring and data acquisition. Cameras can be deployed in agriculture for applications like crop health assessment, surveillance, or monitoring of the environment. The camera provides insights regarding the growing conditions and detects quite a few issues at an early stage, including ripeness and diseases. The selection of the camera is depending on the controllers we select and also on the resolution and quality it gives. We will discuss various camera options to select the one which enhance the rover’s functionally

Raspberry Pi Camera Module

The Raspberry Pi Camera Module is the best choice for our rover because it has better image quality and is perfectly compatible with Raspberry Pi boards. Resolutions of up to 12 megapixels and the ability to record video provide detailed visual representations of crops, hence facilitating effective monitoring and assessment of their health. Moreover, it works well with many models of Raspberry Pi; thus, its integration in our application should be easy.



*Figure 9 Raspberry Pi camera*

To communicate with the Raspberry Pi Camera Module, one can make use of the dedicated camera interface—CSI on the Raspberry Pi—which allows for easy configuration and programming using libraries like picamera.

ESP32 CAM:

The ESP32-CAM is an effective and cost-efficient option; it includes a camera module with an ESP32 microcontroller, making it a particularly suitable choice for our project. It supports Wi-Fi, which allows live video streaming or sending of pictures to a server to enable remote surveillance. It is an important feature, especially in the immediate analysis of data and informed decision-making within agricultural methodologies. Interfacing the ESP32-CAM with an Arduino is actually possible by programming the ESP32 using the Arduino IDE; it inherently has camera and Wi-Fi functions, so that was pretty easy to implement on our rover system.



*Figure 10 ESP32 Camera*

USB CAM

In our project we can use Arduino microcontroller to build a highly precise system for controlling the USB cameras which would allow for live data feed from cameras placed at different locations of the agricultural field. It will be possible to combine pairs of transmitter and receiver radios to develop a wireless configuration so as to enable the Arduino to switch on industrial or commercial cameras depending on the signal criteria. This flexibility allows proper configuration of the triggering methods; from grounding the trigger pin to applying voltage depending on the model of the camera.



*Figure 11 USB camera*

This system does not only help to find the best position for cameras in complex conditions but also increases data acquisition effectiveness for crop monitoring, 3D

measurements, remote sensing and other, which will certainly lead to agribusiness growth and our better analysis and decisions in this field. The figure shows the simple connection between Arduino board and camera

*Table 11 Cameras Comparison Table*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Camera Option** | **Resolution** | **Connectivity** | **Integration Ease** | **Advantages** | **Disadvantages** | **Price** |
| **Raspberry Pi Camera Module** | Up to 12 MP | CSI  (Raspberry Pi) | Easy with Raspberry Pi | High image quality, video recording | Only works with Raspberry Pi | 14.79$ |
| **ESP32- CAM** | 2 MP (up  to 5 MP) | Wi-Fi | Easy with Arduino | Small, affordable, and supports streaming | Lower resolution compared to others | 13.99$ |
| **USB CAM** | Varies (up to 1080p) | USB | Moderate | Flexible, easy to find, and offers good  quality. | Requires additional hardware (USB host  shield) to work | 18.5$ |

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