

Quantifying target movement using neural networks

by

Aryan Singh Dalal

BTech, M.D.U, India, 2021

A Report

submitted in partial fulfillment of the
requirements for the degree

Master of Science

Department Of Computer Science
Carl R. Ice College Of Engineering

KANSAS STATE UNIVERSITY
Manhattan, Kansas

Approved by:

Co-Major Professor
Dr.Pascal Hitzler

Approved by:

Co-Major Professor
Dr.Ajay Sharda

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Abstract

Application rate errors when using self-propelled agricultural sprayers for agricultural production remain a concern. Among other factors, spray boom instability is one of the major contributors to application errors. Spray booms' width of 38 m, in combination with 30 kph driving speeds, varying terrain, and machine dynamics when maneuvering complex field boundaries, make controls of these booms very complex. However, there is no quantitative knowledge on the extent of boom movement to systematically develop a solution that might include boom designs and response boom control systems. Therefore, this study was conducted to develop an automated computer vision system to quantify the boom movement of various agricultural sprayers. A computer vision system was developed to track a target on the edge of the sprayer boom in real time. A YOLO V7 and V8 neural network models were trained to track the boom's movements in field operations to quantify effective displacement in the vertical and transverse directions. An inclinometer sensor was mounted on the boom to capture boom angles to validate the neural network model output. The results showed that the model could detect the target with more than 90 per cent accuracy, and distance estimates of the target on the boom were within 2 cm of inclinometer sensor data. Overall, this system can quantify the boom movement on the current sprayer. The data can be used to make design improvements to make sprayer booms more stable and achieve greater application accuracy.

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Acknowledgments

I would like to express my sincere gratitude to my co-advisors, Dr. Pascal Hitzler and Dr. Ajay Sharda, for their guidance and support throughout my graduate studies. Their mentorship and expertise have been invaluable in shaping my research, developing my critical thinking skills, and preparing me for the next steps in my academic and professional journey. I am also deeply grateful to the members of my committee, Dr. William H. Hsu for their insightful feedback and helpful suggestions. Their contributions have been instrumental in refining my research questions, improving my methodology, and ensuring the quality of my work. Without their support and encouragement, this research would not have been possible. Thank you.

Dedication

This work is dedicated to my parents who have been a constant source of love, support, and encouragement throughout my academic journey. Their unwavering belief in me has been instrumental in my pursuit of knowledge, and this achievement would not have been possible without their guidance and sacrifices. I am forever grateful for their unconditional love and the values they have instilled in me. This work is dedicated to honoring their unwavering support and expressing my deepest gratitude for everything they have done for me.

Chapter 1

Introduction

Agriculture plays a vital role in sustaining human life and ensuring food security for the global population. It serves as the backbone of economies, providing livelihoods for millions of people worldwide. As the world's population continues to grow at an unprecedented rate, the importance of agriculture becomes even more pronounced. However, this rapid population growth poses significant challenges and exerts immense pressure on agricultural systems. The world's population is expanding at an unprecedented rate, with projections estimating that it will reach 9.7 billion by 2050. This demographic surge raises concerns about the ability of agricultural systems to meet the escalating global food demand. Food security, defined as the availability, access, and utilization of sufficient, safe, and nutritious food, becomes increasingly challenging to achieve as the population grows. Ensuring an adequate and sustainable food supply for a burgeoning population necessitates innovative approaches to enhance agricultural productivity, efficiency, and resilience. The exponential increase in the global population has resulted in a surge in the demand for food, placing unprecedented strain on agricultural resources and infrastructure. With limited land available for cultivation, expanding

agricultural operations to meet the growing population's needs has become increasingly challenging. The strain on agricultural land has led to the intensification of farming practices, with the aim of maximizing crop yields within the available arable land. However, this intensification comes with its own set of challenges, including increased use of fertilizers, pesticides, and water resources, which can have adverse environmental impacts.

Due to the scarcity of agricultural land and the growing population, expanding agricultural operations is becoming more and more challenging¹.

In order to meet the ever-growing demands of a rapidly expanding global population, the implementation of smart and efficient agricultural practices becomes imperative. These practices are designed to maximize resource utilization and improve crop yields. One critical aspect of agricultural practices that warrants immediate attention is the issue of resource wastage, particularly in relation to spraying. Spraying, an indispensable procedure in modern agriculture, plays a pivotal role in regulating pests, diseases, and weeds, while simultaneously enhancing crop yield and quality.

However, traditional spraying methods often suffer from inaccuracies, leading to inefficient use of resources and an inadequate increase in crop yield. The ramifications of imprecise spraying are two-fold: significant economic losses and environmental damage. In the context of spraying, the misapplication of chemicals not only hampers crop protection efforts but also leads to resource wastage. Imprecise spraying methods employed today result in wasteful expenditure of the total budget allocated for spraying operations. Such unnecessary expenditure can be alleviated by adopting smarter practices that optimize spraying techniques, ensuring the precise application of chemicals to the targeted areas while minimizing wastage. A significant factor in achieving higher crop yields is minimizing the wastage of sprayed chemicals² that miss their intended target. Addressing this issue is crucial as spraying is a fundamental practice in agriculture that plays a

critical role in managing pests, diseases, and weeds, leading to improved crop yield and quality. It also offers opportunities for optimizing resource utilization and minimizing waste by enabling targeted treatment of specific areas or plants. However, ensuring the proper application of pesticides is essential. Over-application can result in environmental harm and excessive residue, while under-application may only provide partial effectiveness. Therefore, achieving the optimal balance in pesticide application is vital for maximizing the benefits while minimizing potential drawbacks. By implementing precise and accurate spraying techniques, farmers can enhance the efficacy of their pest management strategies, reduce environmental impact, and promote sustainable agricultural practices. One of the challenges that farmers face is to ensure a uniform spray distribution of chemicals on their crops. This is important because uneven spray dispersion can lead to economic repercussions in agricultural practices. To ensure effective weed and pest control, it is crucial to apply chemicals at the correct rates. By achieving the appropriate application rates, farmers can effectively manage weeds and pests, resulting in improved crop production and associated economic benefits. The accurate and precise chemical application plays a significant role in optimizing agricultural outcomes and maximizing the return on investment for farmers³. Traditional sprayers often lack precision in chemical application, resulting in the wastage of resources and a failure to effectively increase crop yields. The imprecise spraying methods can account for approximately 20 percent of the total budget allocated for spraying operations. This inefficiency not only leads to financial losses but also hinders the potential for optimal crop growth and productivity. To address these challenges, there is a need for advanced spraying technologies that offer improved accuracy and targeted application, enabling farmers to optimize resource utilization and maximize crop yield. The lack of control over boom movement during spraying is a primary

factor contributing to inaccurate application. When a boom is attached to a mobile vehicle navigating uneven and challenging terrains, it is susceptible to encountering vibrations, such as roll and yaw. These vibrations can result in unintended movements, compromising the precision and effectiveness of the spraying process. The occurrence of such movements during spraying operations can be detrimental and undesirable. These unintended movements of the spraying equipment can compromise the accuracy and effectiveness of the chemical application⁴. The vertical movements of a boom have a substantial impact on the uniformity of deposit density, affecting both the longitudinal and lateral distribution along the vehicle's path. As the height of the boom changes, the spray spread varies, leading to inconsistencies in deposit density. Additionally, horizontal fluctuations in the boom's velocity further contribute to variations in deposit density along the track. These factors highlight the significance of controlling and minimizing both vertical and horizontal movements of the boom to ensure consistent and uniform chemical application.

Boom movements primarily originate from the motion of the sprayer frame, which poses a challenge to precise spraying. To address this issue, a suspension system is commonly employed to establish a buffer between the boom and the frame. The suspension system is specifically designed to isolate the boom from the roll motion of the sprayer frame, effectively reducing unwanted movements of the boom during operation. This suspension system plays a critical role in minimizing the adverse effects of boom movements on the uniformity of deposit density during chemical application. By effectively dampening and attenuating the vibrations and oscillations transmitted from the sprayer frame to the boom, the suspension system ensures that the boom remains stable and maintains a consistent spraying position. This, in turn, enhances the accuracy and uniformity of chemical deposition, resulting in improved spraying efficiency and optimized

crop yield⁵. Despite the implementation of the suspension system, it is important to note that a significant amount of movement can still be observed. This indicates that the suspension system is not entirely capable of completely eliminating the boom movements. Further improvements and refinements may be necessary to enhance the effectiveness of the suspension system and reduce the residual movements of the boom. By addressing these remaining challenges, it is possible to achieve greater stability and precision in boom positioning, leading to improved uniformity in deposit density and more efficient chemical application in agricultural practices. To address this issue, innovative solutions and technologies are needed to minimize boom movement and ensure consistent and accurate application of chemicals onto the target areas, ultimately enhancing the efficiency and productivity of agricultural spraying operations. Given the detrimental impact of the aforementioned issues on both the environment and farming expenses, there has been a growing interest among researchers to seek computer science-driven solutions for optimizing and controlling sprayers' movements. The evolving complexity of contemporary agricultural practices has underscored the importance of computer vision technology, particularly in the field of spraying. By enabling machines to perceive and comprehend visual information from their environment, this technology essentially grants them a form of "vision," empowering the development of more accurate and efficient spraying systems. The integration of computer vision with agricultural machinery holds great promise in mitigating environmental damage, reducing farming costs, and enhancing overall spraying performance. As such, exploring computer science-based solutions in the context of spraying has become a pressing area of research, with the aim of revolutionizing agricultural practices and fostering sustainable farming techniques.

Chapter 2

Related Work

Agricultural operations often involve the application of chemical products through spraying methods, albeit with unintended consequences. One of the significant drawbacks of this practice is the deposition of chemical residues in the soil, resulting in detrimental effects on soil fertility and plant diversity. The presence of these residues poses a threat to the delicate balance of the ecosystem, impacting not only the immediate agricultural productivity but also the long-term sustainability of the land⁶ .

The use of chemical sprays, while intended to combat pests, diseases, and weeds, inadvertently introduces substances that can alter the natural composition of the soil. Chemical residues can persist in the soil for extended periods, leading to a decline in soil fertility and nutrient availability. This decline negatively impacts plant growth and development, compromising the overall productivity and quality of agricultural crops. The detrimental effects of chemical residues extend beyond soil health and can also have far-reaching consequences for the broader environment. Runoff from agricultural fields can transport these residues to nearby water bodies, contaminating aquatic ecosystems. This contamination poses risks to aquatic organisms, impacting their survival, reproduction, and overall

ecosystem health. Additionally, the persistence of chemical residues in the environment can contribute to the development of pesticide resistance in target pests, necessitating the use of higher chemical doses or the adoption of alternative, potentially less sustainable pest control methods.

However, precision spraying provides a promising alternative approach that offers a means to minimize pesticide losses and optimize their distribution across agricultural fields. By adopting precision spraying techniques, the application of pesticides is guided by specific characteristics and factors, ensuring targeted and efficient coverage⁷.

Precision spraying, also known as site-specific spraying or variable-rate spraying, leverages advanced technologies and data-driven insights to determine the precise amount and location of pesticide application. This approach takes into account various factors such as soil conditions, crop growth stage, pest densities, and environmental conditions. By tailoring pesticide application to these specific characteristics, precision spraying minimizes the amount of chemicals used while maximizing their effectiveness.

The key advantage of precision spraying lies in its ability to reduce pesticide losses. Traditional spraying methods often result in significant pesticide drift, where a portion of the applied chemicals is carried away by wind or volatilization, leading to environmental contamination and wastage. In contrast, precision spraying enables farmers to target specific areas or plants that require treatment, minimizing the potential for off-target drift and reducing the overall environmental impact.

Moreover, precision spraying optimizes pesticide distribution across the field, ensuring that the right amount of chemicals is applied precisely where needed. By employing advanced sensing technologies, such as remote sensing or ground-based sensors, farmers can gather real-time data on plant health, pest presence, and field variability. This data is then analyzed and

used to create application maps that guide the sprayer in delivering the appropriate pesticide dosage to specific areas, mitigating the risk of under or over-application

Over the past two decades, extensive research endeavors have been dedicated to the continuous improvement and adoption of precision spraying techniques. These efforts have played a pivotal role in advancing the state-of-the-art methods employed in this practice today. Numerous studies have been conducted with the objective of quantifying and understanding the movement of spraying boom and its subsequent impact on outcomes. These studies have been trying to employ sophisticated technologies and methodologies to accurately measure and quantify the movement of spraying equipment during application. By analyzing factors such as boom stability and vibrations, researchers aim to elucidate the relationship between equipment movement and spray outcomes. One of the challenges in agricultural spraying is to measure the movements and deformations of the boom, which is the part of the sprayer that holds the nozzles. These movements and deformations can affect the spray quality and coverage, as well as the stability and safety of the sprayer. Therefore, various evaluation techniques have been developed to assess the boom's behavior in field conditions. These techniques can be divided into two main categories: absolute and relative measurement methods. Absolute methods measure the boom's shape and displacement with respect to its own geometry or configuration. Among the absolute methods, the most commonly used one involves attaching small seismic accelerometers to the sprayer. This technique has several advantages over other methods. First, it does not alter the boom's behavior during measurement, as it does not add any extra weight or stiffness to the boom. Second, it allows for comparisons between different sprayers, as it provides a standardized and objective measure of the boom's performance.

In a separate study led by Nation, H.J.⁸ and their research group, the motion of the boom in both the vertical and horizontal directions was investigated using a set of transducers, specifically a seismic mass accelerometer. The primary objective of this research was to compare the extent of movement caused by factors such as rolling and yawing of the sprayer and to analyze which direction (vertical or horizontal) was more influenced by these factors.

The study aimed to provide insights into the reasons behind the boom's movement and quantify the relative magnitude of vertical and horizontal displacements. By employing the seismic mass accelerometer, the researchers were able to accurately measure and record the boom's motion in both directions. The data obtained allowed for a comprehensive analysis of the impact of rolling and yawing on the boom's movement. While the findings from this study contribute to the broader understanding of sprayer movement dynamics and can serve as a basis for further investigations aimed at developing strategies to mitigate and control boom motion. However, researchers did not present any specific findings of methods for stabilizing the boom aside from the suggestions mentioned in the paper. D. Pochi and D. Vannucci⁹ conducted a comprehensive research study to explore the movement of the boom by utilizing Potentiometric Transducers as a reliable method to record the motion. The experiment employed a strategic placement of sensors along a horizontal bar, which was carefully positioned parallel to the boom. The study was designed in two distinct parts, with the initial phase focusing on conducting controlled laboratory tests, while the subsequent phase involved extending the experiments to field conditions.

The laboratory experiments proved to be highly promising, demonstrating the efficacy of Potentiometric Transducers in accurately capturing the boom's movement. The results showcased the potential of this technology

in providing precise measurements. However, the field experiments presented some challenges, as the recorded data yielded less satisfactory outcomes in comparison. It is important to note that the field tests were limited to a relatively short test track, spanning only 6 meters. Furthermore, the primary objective of these field tests was to gather data predominantly influenced by soil unevenness.

The research conducted by D. Pochi and D. Vannucci provides valuable insights into the intricacies of measuring the movement of the boom. While the laboratory experiments displayed promising results, further investigation is required to enhance the accuracy and reliability of measurements in real-world field conditions.

A study conducted at Gembloux Agricultural University⁴ in Belgium aimed to investigate the movement of booms during spraying operations. The study involved equipping two vehicles with a radar speed sensor and a three-axis dynamic measurement unit. Each boom was instrumented with ultrasonic sensors and accelerometers. Sensor fusion techniques were employed to extract yaw, jolt, and deformation speeds by assuming that the boom's motion could be represented as a combination of high and low-frequency motions.

To evaluate the performance of the sprayers, tests were conducted on trailed sprayers with boom lengths of 22 and 24 meters, on different types of soils.

The results were analyzed to determine the frequencies at which yaw, jolting, and deformation occurred. Additionally, the coefficients of variation for ground deposit were calculated from the data obtained.

It is important to note that this study primarily focused on investigating horizontal movements and did not consider other factors that may influence sprayer performance. For instance, factors like uneven terrain, wind speed, and wind direction, which can affect both horizontal and vertical movements of the boom, were not taken into account. Moreover, the other

disadvantage of this method is its tediousness due to the requirement for precise positioning of the target before conducting trials. A more comprehensive research should consider these additional factors to provide a more comprehensive understanding of sprayer performance and its impact on ground deposit.

It has been observed that earlier mentioned studies predominantly relied on non-computer vision methods to assess boom movement. However, with the advancement of computer vision technology over time, it has demonstrated remarkable efficiency and accuracy when applied to agriculture-related machinery. For instance, A model that uses computer vision for real-time weed classification was introduced in a research by Chung-Liang Chang¹⁰ at the National Pingtung University of Science and Technology. The model achieved an amazing classification rate of 90 per cent. This computer vision-based approach was also expanded to include variable rate irrigation, allowing the management of deep soil moisture content at predetermined levels.

The detection and precise identification of diseases affecting grain crops is essential to guarantee the efficiency and sustainability of agricultural operations. For prompt response and mitigation of potential risks, fast and precise disease identification is essential, especially in pest outbreaks.

Currently, the traditional method of diagnosing plant diseases depends heavily on visual assessments, which is time-consuming and prone to bias and mistakes. Understanding the limitations of this approach, researchers have worked to come up with inventive solutions by utilizing the power of computer vision and artificial intelligence. The research's main goal is to automate plants' disease detection process, creating a path to greater accuracy and efficiency. In this approach, computer vision techniques and AI algorithms are used to analyze pictures and automatically identify signs of disease. The extraction and analysis of highly discriminative

characteristics are among the many important parts of this automated detection process that are essential for accurately identifying particular diseases. A significant advantage of this methodology is its ability to use classification models, which allows the classification of pictures into separate classes, including healthy or diseased.

Study conducted by Sachin and Patil¹¹ offers a comprehensive examination of image processing techniques for detecting plant diseases. As it is known, the difficulties in the field of plant disease image analysis are extensive and numerous. Accurate identification is made more difficult by the presence of cluttered backdrops and the lack of clear borders distinguishing symptoms.

Along with the variances in symptom presentation caused by various illnesses, the wide variety of capture conditions adds another level of complexity. The complexity is further complicated by the confluence of symptoms caused by several conditions as well as the occurrence of different disorders producing related symptoms. The effectiveness of current image analysis tools is significantly influenced by these dynamic elements combined, necessitating careful attention while developing illness detection strategies. Proposed study talks about how to use k-means clustering and Otsu's method for effective image segmentation, along with how to improve disease identification by using color, texture, and morphology characteristics. The study also looks at artificial neural networks (ANNs), especially how well self-organizing feature maps (SOFM) and back-propagation algorithms work for disease classification.

The study examines the collective potential of these advanced image processing techniques to revolutionize plant disease detection. Such findings highlight the crucial role that cutting-edge technologies play in enhancing precision and efficiency in agricultural disease management. In the end, this will lead to improved crop health and more sustainable agricultural practices.

The research aims to address the limitations of conventional visual diagnosis by automating the disease detection process by using advanced technological methods. This advancement has the potential to change the way disease management in agriculture, helping people make better choices and promoting sustainable farming. As a result, the integration of computer vision and artificial intelligence has the capacity to significantly improve disease identification accuracy and, subsequently, optimize crop health and yield.

The study previously mentioned serves as a prominent testament to the transformative synergy achieved through the integration of computer vision and machine learning within a diverse array of equipment applications. This paradigm shift engenders both cost-effectiveness and a remarkable enhancement of operational precision and efficiency. Building upon these groundbreaking revelations, our initiative is poised to leverage the fusion of computer vision and machine learning to address the intricate challenge of monitoring boom movement during sprayer operations in agricultural contexts.

Our project endeavors to unravel the intricate dynamics of boom motion in real-time scenarios by harnessing the advancements in these cutting-edge technologies. The incorporation of computer vision and machine learning holds the potential to revolutionize the accuracy and effectiveness of tracking boom movements, thereby ushering in a new era of improved agricultural practices. Through this proactive endeavor, we anticipate that the amalgamation of these technologies will not only optimize the utilization of resources but also unveil novel insights that can significantly propel the realm of precision agriculture forward.

Chapter 3

Methodology

3.1 System Setup

3.1.1 Camera Selectiton

The meticulous process of camera selection was undertaken with a dedicated focus on the ever-changing dynamics of the boom’s motion during sprayer operations. This selection process involved a careful evaluation of critical factors, including the appropriate focal length and the clarity of captured images. Particular emphasis was placed on the attainment of exceptional image quality across extended distances, as this capability is pivotal for accurately tracking and analyzing boom movements. Furthermore, a series of deliberate measures were implemented to enhance the camera’s ruggedness and resilience, enabling it to withstand and thrive in challenging environmental conditions such as dust-laden atmospheres, rain, and high temperatures. This strategic consideration aligns with the project’s commitment to maintaining the highest standards of image quality while ensuring that the camera remains functional and effective even in adverse settings.

The comprehensive strategy employed in the camera selection process underscores the intricate interplay between technical precision and environmental robustness. By carefully balancing these aspects, the Basler acA1920-50gc, which is a color camera and has a high 1920*1200 pixel resolution and 2.3 megapixels, was chosen after a careful selection procedure for its extraordinary high-resolution data collecting capabilities. The Basler camera, notable for its capacity to capture brisk action, achieves a maximum frame rate of 50 frames per second, highlighting the commitment to accuracy in capturing dynamic boom movement during sprayer operations.

The camera's capabilities are further enhanced by the thoughtful selection of the 35mm ruggedized Kowa lens (LM35HC-V 1" Ruggedized 35mm 5MP C-Mount Lens), which enhances picture acquisition while putting an emphasis on outstanding quality and endurance in difficult field circumstances. This seamless blending of the camera and lens improves the project's ability to precisely track and assess boom movement during spraying.

Utilizing the Basler camera's cutting-edge capabilities, a tactical improvement was added to support its toughness and longevity. The installation of a specialized camera housing, [Industrial Camera Enclosure CH50 - IP69](#), was required for this improvement, which gave the camera IP69 capabilities and a dust-proof shell. This housing improvement strengthened the physical integrity of the camera in addition to protecting it from dust and environmental elements, which was particularly useful in situations where the camera may experience physical impact from its surroundings. By adding this tough housing to the Basler camera, the system gets improved resilience and robustness, enabling it to perform consistently and produce excellent results in the dynamic and demanding environment of sprayer operations in the field.



Figure 3.1: *Camera Housing*

3.1.2 Data Acquisition System

Following this phase, which was crucial for the study's facilitation, we continued our advancement by finalising the system meant for the systematic collecting and subsequent processing of data inside the local infrastructure. To complete this assignment, a thorough set of requirements was created in order to efficiently expedite the selection process that followed. The system had to meet a number of requirements, but the most important one was that it must have enough storage to save all of the photos that were collected for the life of a sprayer's operational cycle. This need was based on the requirement to completely record the sequential steps of the sprayer's application method in order to support the efficacy and tenacity of our investigational efforts.

For the purpose of this study, we developed a data acquisition (DAQ) system consisting of various components. The system is powered by a dual-output power supply (E36234A, Keysight, Fountaingrove Parkway, Santa Rosa, CA), capable of delivering DC power. For this setup, the power supply was configured to provide 20V to activate the DAQ system. This power supply offers programmable input ranges and flexible connectivity

options. Use Figure as a point of reference [3.7](#).

To manage data recording and processing, we incorporated a fanless PC (LEC 2580-711A, Lanner Electronics, Mississauga, ON, Canada). This PC is equipped with a substantial 16 GB memory, Intel (R) HD Graphics 520, and an Intel Core i7-6600U CPU. Please see Figure [3.2](#) for a reference. Furthermore, the DAQ system accommodates connectivity with up to four cameras simultaneously, enhancing its versatility and capacity to capture crucial information. This carefully assembled DAQ system serves as a cornerstone for our study, enabling us to efficiently collect and analyze data related to sprayer operations.



Figure 3.2: *Fanless PC.*

3.1.3 LabView Program

During this phase, we used an instance of an application running on LabView to obtain video files captured by the camera, which will be further converted into frames, along with other meta-data files. This application provided a functional user interface to access the properties of the camera and other sensors. The main screen of the application is shown in [3.4](#) The

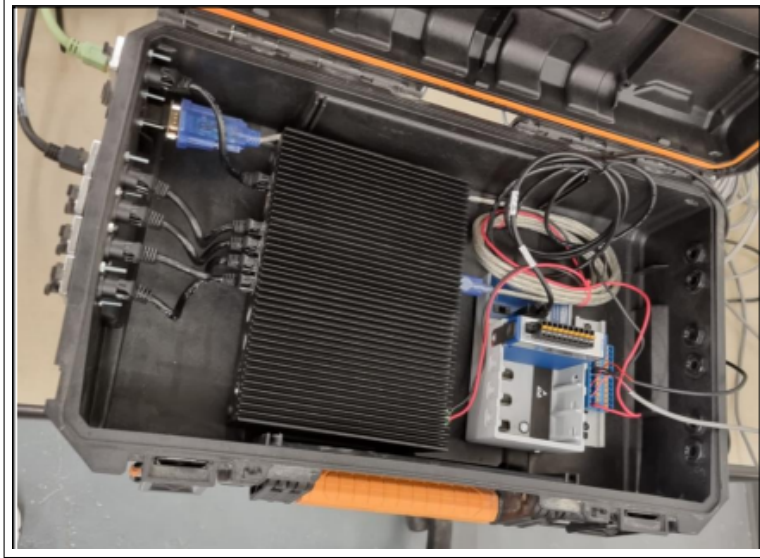


Figure 3.3: *Data Acquisition (DAQ) System set-up*

setting button on the top left corner reveals a tree-structured dialogue that is used to access and modify camera characteristics for all active cameras.

The camera Button is used to choose the active cameras in this system. The start button is used for initialization and stopping of the video, and the Save Button is used to save the image buffer with associated metadata into the Video file. However, if the start button is clicked without the buffer being saved, in that scenario, buffers are overwritten. The show Analog data button displays the analog value fetched using the TMM/TMS 22 inclinometer sensor on the top of incoming video stream data. Save Analog

Data and Save GPS Data button is used for logging results in a text file format and saving in a given path by using the data directory button, along with the video file. The Exposure Button and Gain Button are used to alter the exposure value and gain value in each frame, respectively. The GainAuto Button is used to access the automatic gain setting of the Basler camera. This is used in environments where the exposure is dynamic. BufferTime(s) takes a numerical value, which means the number of seconds in the picture buffer. Acquisition automatically comes to a stop when the

buffer is filled. FrameRate(FPS) depicts the number of frame would be captured in a second in a video.

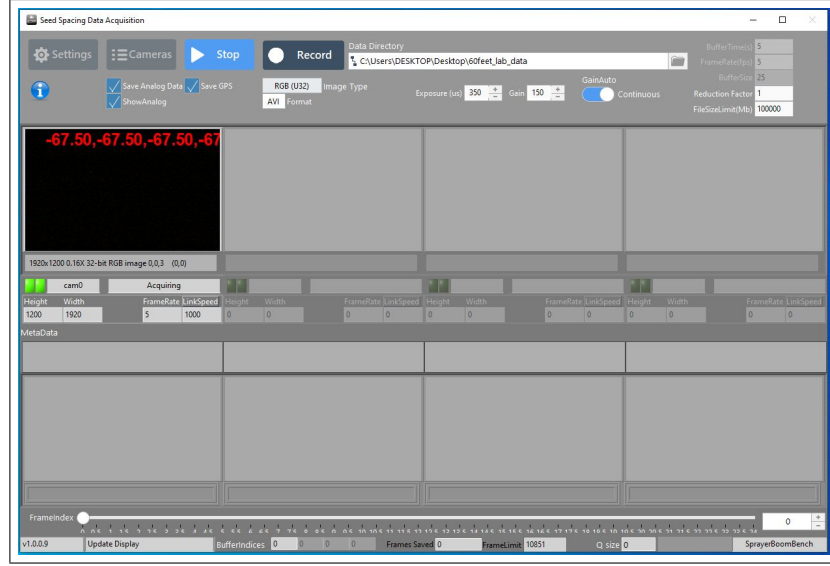


Figure 3.4: *LabView Program*

3.1.4 Sprayers

In the process of formulating our approach, we used the CaseIH Patriot sprayer, manufactured by CNH Industrial (CNHI), as a pivotal instrument for gathering the image dataset. This dataset was crucial in enhancing and improving the information gathered, which allowed us to design our technique.

We used the New Holland Guardian SP410F sprayer by CNHI for testing our developed methodology in the field. We used the methodology to collect the validation sensor data and compare it with system test data. It front boom sprayer that allows you to spray later into the growing season, easily maneuver at the headlands, and make on-the-go adjustments quickly and easily — all from the comfort of a cab specifically designed for the Guardian sprayer. The SP410F model has a horsepower of 412 and a tank size of either 1400 or 1600 gallons. The 2023 model of the SP410F has received

precision tech upgrades from Raven Industries, including Slingshot from Raven, and the IntelliSpray II, with data collected and aggregated by Raven’s Connected Workflow system. The sprayers are equipped with IntelliView 12 and Viper 4+ displays, allowing operators to monitor their sprayer’s vital functions including suspension information, liquid management controls, auto rinse functions, 4-wheel steering, tread width adjustments, and more.

3.2 Experimental Boom

A specialized boom structure was carefully developed for the lab environment to precisely replicate the whole range of boom movements, even under unfavorable circumstances. This innovative boom stand served as a practical solution for conducting the study in instances where the sprayer and field conditions were not readily accessible. Deliberate care was taken during the design and construction phases to accurately mimic the varied range of boom movements in all directions. This all-encompassing strategy made it easier to do partial behavioral analyses, gather data, and undertake rigorous testing in a controlled setting, thus strengthening the resilience and adaptability of the study project.

In order to facilitate comprehensive experimentation, the following design considerations were taken, refer Fig 3.6, a ten-foot boom section was seamlessly integrated into the central segment of the boom stand which elongated backward to provide support as a counter-weight. This boom section was attached with articulate joints that facilitated controlled movements along the horizontal axes, thereby enabling precise manipulation during tests. In conjunction with this, an [actuator](#) mechanism was strategically affixed at the inception of the boom to facilitate vertical

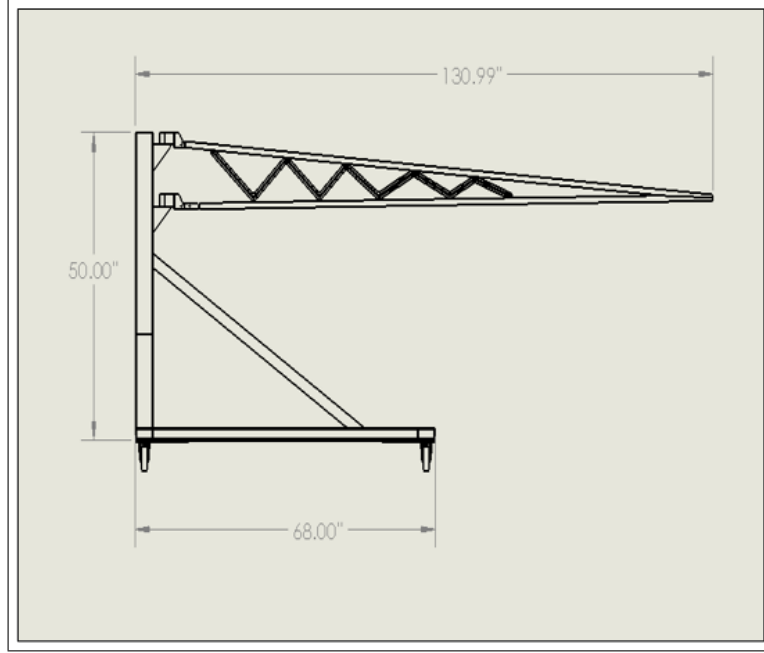


Figure 3.5: *Boom's dimesnison*

elevation, thereby granting the capacity for vertical axes motion. This mechanism was adeptly designed to operate within a vertical space, with the assembly standing at an elevation of four feet and being stably grounded by a secure base extending across 5.6 feet. This sophisticated integration of dynamic components allowed for intricate movement replication, thereby enhancing the accuracy and comprehensiveness of the investigation within a controlled laboratory environment.

3.3 Development

Let's take a first step in explaining the entire strategy we have taken to accomplish our study objectives before going into the finer details of our recently established technique. The approach incorporates a methodical process for identifying and measuring the boom's movement along all four dimensions. It includes identifying an object positioned at the rear end of the boom, which is then captured by a camera that is carefully positioned



Figure 3.6: *Experimental Boom*

at the other end. Through this process, we extract the precise coordinates of the identified object, allowing us to accurately determine its actual displacement. This sequential process serves as the foundation of our methodology, guiding us toward a comprehensive understanding and successful achievement of our research aims.

3.3.1 Aruco Marker

When delving into the realm of object detection, a natural starting point is to leverage the capabilities of the OpenCV library in conjunction with ArUco markers. ArUco markers bear a resemblance to Quick Response (QR) codes and are engineered as synthetic markers. They take on a square structure, featuring a prominent black border that encloses an inner binary matrix responsible for encoding a distinct identifier (ID). This black border plays a crucial role in facilitating rapid and accurate detection against varying backgrounds, contributing to the marker's robustness. The binary

matrix's coding not only enables error detection and correction mechanisms but also endows each ArUco marker with its own distinctiveness, even when multiple markers are present within the scene.



Figure 3.7: *Aruco Marker with 6x6 dictionary and Id no 3.*

The process of detecting ArUco markers involves two main steps. The first step entails identifying potential markers by examining the image and isolating square shapes using adaptive thresholding. Contours are then extracted from the thresholded image, and imperfectly shaped or non-convex contours are filtered out. Further filtration involves removing excessively small or large contours and those in close proximity. The second step involves verifying detected marker candidates by analyzing their internal coding. The canonical form of each marker is obtained through perspective transformation, and the Otsu thresholding technique is applied to distinguish black and white bits. Cells are created based on marker size,

and black-and-white pixel counts are used to identify the bits. Error correction techniques are applied if needed.

In the specific scenario of detecting the ArUco marker situated at the tip of the boom, within a video captured from a considerable distance of 60 feet, a range of influencing factors were observed to impede the successful detection process. Among these factors, one particularly significant challenge emerged from the substantial spatial separation between the camera and the target object of interest. This considerable physical gap caused the ArUco marker to appear diminutive in size within the video frame, subsequently introducing complexities in the accurate identification process.

Furthermore, the inherent practical limitations presented hurdles in addressing this issue. Attempts to enlarge the size of the ArUco marker beyond certain limits proved unfeasible due to constraints related to the boom's weight and overall balance. The prospect of using a larger marker raised concerns about the potential impact on the boom's movement dynamics, thus posing a risk of introducing inaccuracies in the detection process itself. Another critical factor that cast a shadow on the detection endeavor was the interference posed by the surrounding harvest yield. The presence of crops and their arrangement during the harvesting phase posed a potential obstacle, causing the ArUco marker to become obscured and concealed from view.

These challenges collectively underscore the intricate nature of detecting the ArUco marker under real-world operational conditions, emphasizing looking for alternative solutions that can overcome their limitations and meet the scope of the project while ensuring the highest accuracy.

3.3.2 Machine Learning

After conducting a thorough and exhaustive assessment of the limitations and deficiencies inherent in the previous methodology, a deliberate decision was made to adopt an alternative approach to advance the intended project. This strategic shift was driven by the necessity to overcome the constraints posed by the existing method and to ensure the successful execution of the designated task.

In the selection of the appropriate neural network architecture, taking into account the particular difficulties presented by the current situation. The possibility for the target item to be obscured, either by the crop yield in the area or because of partial visibility to the camera due to dynamic motions, is the biggest problem. Thus, a neural network that would be capable of navigating these challenging real-world scenarios while producing accurate and dependable detection results was carefully selected.

This multifaceted endeavor integrates cutting-edge neural network algorithms with a carefully constructed dataset, enhancing the neural network's capacity to decipher intricate visual nuances and patterns that denote the presence of the intended target object.

Our approach involved the systematic collection of an image dataset, followed by comprehensive annotation to facilitate the neural network's learning process. This prepared dataset enabled the neural network to effectively detect the desired target object.

3.3.3 Data Collection

Prior to commencing data collection, a pivotal determination was to ascertain the precise location of the target and camera on the boom. This selection was carefully coordinated to guarantee the liberty of the target and camera from any prospective influence with the boom's movement.

Additionally, preventive steps were taken to safeguard both, from the negative impacts of the nearby crop. These important factors were taken into account while choosing the end section of the boom’s uppermost segment to hold the target item and the last portion of the boom’s middle section to house the camera. These sites were carefully chosen because they offered more protection against crop-induced effects and outside disturbances, preserving the accuracy of the detecting procedure.

avast dataset was gathered that included a variety of picture situations with various brightness levels and grain characteristics. A total of 3490 photos made up this thorough collection, which carefully captured a variety of backdrops, including cornfields, wheat fields, soil patches, pastures, and buildings. With scenarios characterized by bright, hazy, and overcast weather, it was of utmost importance to capture photographs in various environmental and lighting situations. This vast dataset was purposefully curated in order to reflect the intricacy of agricultural operations in the actual world, where varying sunlight, ambient factors, and grain qualities all add to the complexity at hand. Sample images are shown in Fig. 3.8 depicting different backgrounds captured in different lighting conditions.



Figure 3.8: *Example of image dataset collected*

Once the dataset was finalized, it was passed to the manual labelers to

annotate the images using a bounding box with one class named target using a labeling tool called roboflow.com¹². The third phase involves data augmentation, an important step in expanding the dataset's diversity and adaptability, after attaining a significant amount of acquired data for trustworthy results. This procedure aimed to add a plethora of unique characteristics to the dataset, enhancing its ability to capture a large variety of conceivable scenarios. Auto-Orient, Resize, Auto-Adjust, and Contrast improvement by Adaptive Equalization Rotation, Exposure variation, Blur, and Shearing along both the horizontal and vertical axes were a few of the numerous attributes included. The collection was expanded to include a stunning 9,100 photos as a result of the careful assimilation of various features.

3.4 Object detection

Upon completion of data collection and subsequent pre-processing, attention shifted toward the realm of object detection and the selection of an appropriate neural network for training purposes. The decision to employ neural network training stemmed from the research's ultimate focus on spatial features, aligning with the study's broader objectives. We started by training the YOLO (You Only Look Once) algorithm, which was established in 2015, and serves as an object detection technique capable of identifying a diverse array of objects within an image. This approach redefines object detection by transforming it into a singular regression task, directly predicting bounding box coordinates and class probabilities from image pixel data. This integrated model has the capacity to simultaneously forecast multiple bounding boxes and class probabilities for the objects enclosed within these boxes. The structure of the YOLO model shares the

common structure in almost all its versions. For YOLOV7, A single-shot object detection model, the architecture fragments the input picture into a grid and estimates bounding boxes and class probabilities for each grid cell.

Three primary parts make up the architecture:

The E-ELAN (Extended Efficient Layer Aggregation Network) serves as the computational core within the YOLOv7 backbone, drawing inspiration from

prior work on network efficiency. It has been meticulously designed by evaluating critical factors such as memory access, I/O channel cost ratio, element-wise operations, and activation gradient pathways, all of which

significantly influence the model’s speed and accuracy. The proposed E-ELAN leverages techniques such as expansion, shuffling, and cardinality merging to continuously enhance the network’s learning capacity while

preserving the integrity of the original gradient pathways. The

CSPDarknet53 architecture, a customized version of the Darknet53 architecture, serves as the foundation for the YOLO v7 backbone. A neck is a structure that integrates the features that the backbone has extracted and transmits them to the head. The YOLO v7 neck employs a feature pyramid

network (FPN) to integrate the features at various scales and a bilinear upsampling layer to upsample the features from the backbone. The head is the component that predicts the bounding boxes and class probabilities for each grid cell. The YOLO v7 head uses three convolutional layers to predict the bounding boxes and class probabilities.

3.4.1 Training

In this study, we compared various different models and decided on using YoloV7 and YOLOv8n. The development of choice in finalizing YOLO models

was guided by the primary objectives of maximizing accuracy while minimizing the time required for object detection within a given frame, as

YOLO (You Only Look Once) works on the basis of Single-Stage Detection and divides the image into $N \times N$ grids, where N depends on multiple factors like size of the input image and scale of the object to be detected. It looks for the object in those grids once. These considerations were instrumental in tailoring the model to its specific requirements.

To facilitate the training of the YOLO models, a consistent methodology was applied. Initially, we partitioned the image dataset, consisting of a total of 9,485 images, into three distinct sections: training, testing, and validation, comprising 9,117, 220, and 148 images, respectively. The model's training primarily focused on a single class, referred to as "Target". To train the model, we used several parameters such as epochs = 400, learning rate of 0.01, and batch size of 16. Our evaluation process involved assessing the models' performance using key metrics, including MAP at 50 and MAP at 90 (Mean Average Precision), as well as measuring the time required for the detection of a single frame in milliseconds and analyzing the confidence level of the model in prediction with higher confidence being indicative of more reliable predictions. For YoloV7 metrics for MAP 50 and MAP 90 were 0.982 and 0.847 subsequently. For YOLOV8(n)

After the successful training of both neural networks within the same controlled environment, a comparative analysis was conducted on two distinct datasets. These datasets comprised images with varying backgrounds, specifically those featuring wheat and corn fields. Through this evaluation, it became evident that YOLOV8(n) exhibited a notably superior level of accuracy when handling images with either a wheat or corn background.

The assessment was performed to discern the networks' proficiency in detecting the target object under differing environmental conditions. In this context, YOLOV8(n) excelled, showcasing its robust performance and competence in various agricultural backgrounds.

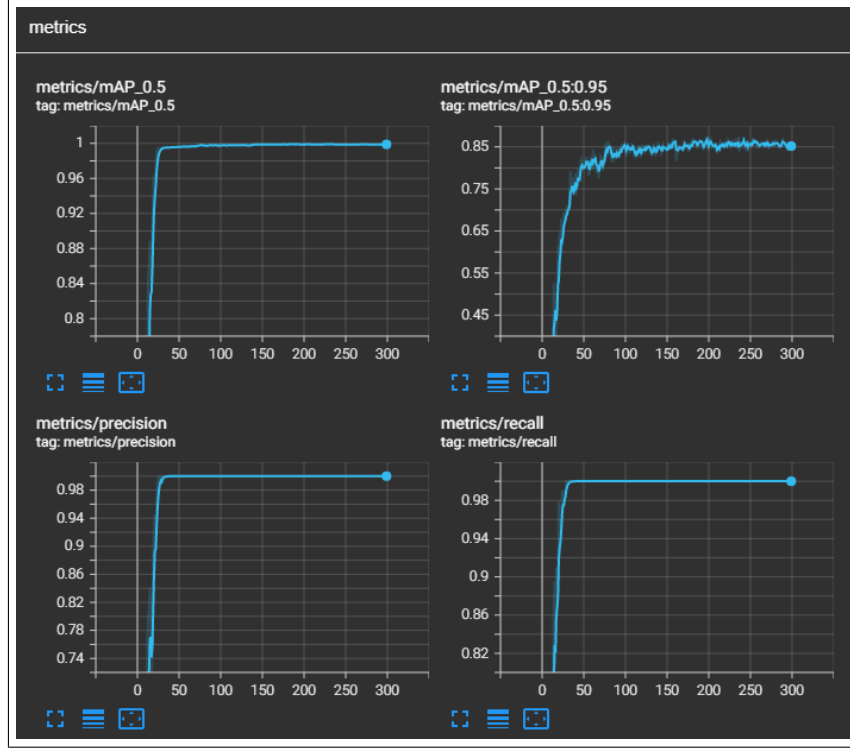


Figure 3.9: *YOLOV7 Training Results*

After establishing that YOLOV8(n) outperformed other models in terms of object detection accuracy, the next critical step involved assessing the model's speed in detecting images with agricultural backgrounds. These images, featuring both wheat and corn fields, were captured in two formats: RGB and Monochrome. To evaluate the network's efficiency, images were processed at two different resolutions, specifically Reduction 1 (retaining the original image size) and Reduction 4 (combining four pixels to form one, thus decreasing image clarity).

In this phase, a range of YOLOV8 models, including nano, small, medium, and large variants, were meticulously compared. Through this experiment, it was determined that YOLOV8(n) exhibited a higher confidence level in detecting each image while also requiring less time for processing.

Consequently, the test results unequivocally favored YOLOV8(n) as the model of choice to advance further, signifying its superiority in terms of

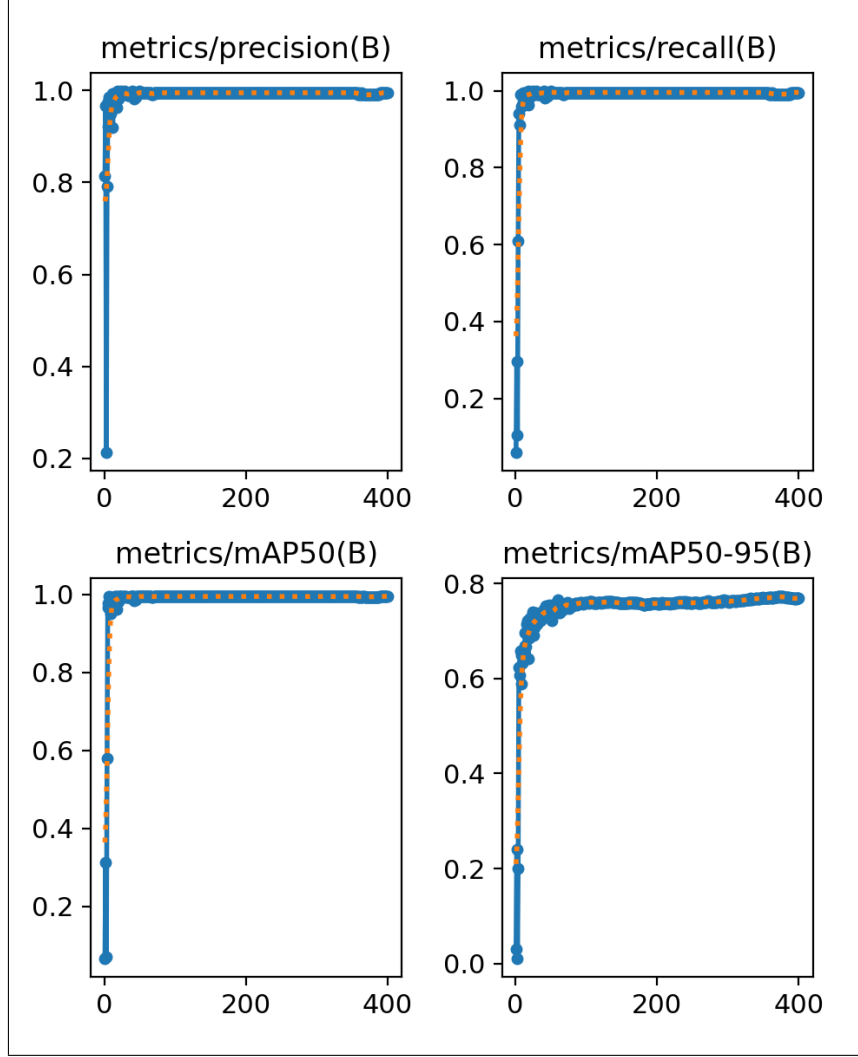


Figure 3.10: *YoloV8(n) Training Results*

both accuracy and efficiency in object detection within varying agricultural backgrounds and image resolutions.

3.4.2 Finetuning

Following the finalization of the neural network based on the aforementioned criteria, a detection test was conducted using approximately 1,000 images characterized by diverse lighting conditions and varying levels of clarity. During this evaluation, the network encountered challenges in detecting the target when confronted with blurred images resulting from

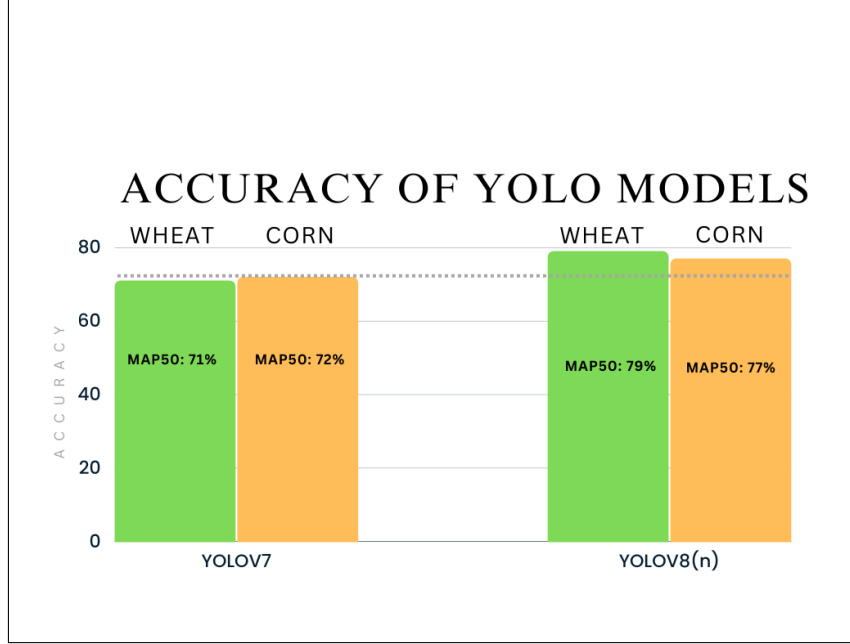


Figure 3.11: Comparison of YOLOV7 and YoloV8(n)

Image Resolution	Image Background	Model Parameter	Yolo 7	Yolo 8n	Yolo 8s	Yolo 8m	Yolo 8l
Reduction 1 (1920X1200)	Wheat	Speed (ms)	49ms	216ms	270ms	668ms	1831ms
		Confidence (%)	71%	79%	78%	82%	81%
	Corn	Speed (ms)	94ms	117ms	275ms	780ms	1358ms
		Confidence (%)	72%	77%	78%	79%	79%
	Color	Speed (ms)	33.6ms	126mms	428.9ms	982ms	836ms
		Confidence (%)	63%	67%	70%	71%	70%
	Monochrome	Speed (ms)	31.3ms	149ms	376ms	1083.4ms	2032.4ms
		Confidence (%)	82%	83%	83%	83%	83%
Reduction 4 (450X300)	Wheat	Speed (ms)	16.8ms	119.9ms	266ms	666.8ms	1348
		Confidence (%)	72%	77%	53%	80%	78%
	Corn	Speed (ms)	5.6ms	87.9ms	279ms	667ms	1812ms
		Confidence (%)	61%	74%	76%	70%	73%
	Color	Speed (ms)	5.6ms	8.2ms	387.2%	1705ms	2823%
		Confidence (%)	60%	61%	67%	66%	66%
	Monochrome	Speed (ms)	1.1ms	12.6ms	245ms	2215ms	3056.1ms
		Confidence (%)	72%	69%	69%	74%	77%

Figure 3.12: Comparison of time on YOLOV7 and YoloV8(n)

dirt accumulation on the camera lens, particularly when the sprayer was in motion.

To address this issue and enhance the network's performance, a strategy was employed. Images that the network failed to detect, primarily those affected by blurriness and lens contamination, were systematically collected. Subsequently, these challenging images were annotated to refine the dataset.

This improved dataset was then reintroduced to the neural network,

initiating a fine-tuning process.

The outcomes of this fine-tuning yielded promising results, with the network exhibiting enhanced detection capabilities, especially in the face of challenging conditions marked by blurriness and lens obstructions. This iterative approach significantly bolstered the network’s proficiency, resulting in an elevated overall detection rate across the complete image dataset.

3.5 Post-Processing

After finalizing the selection of the YOLO model, the subsequent phase of the project entailed determining the coordinates of the bounding box around the detected object in each frame. These coordinates were then compared to the coordinates of the very first frame, which served as the reference point, to calculate the actual horizontal and vertical movement of the sprayer. This vital step required converting the differences in coordinates into real-world distance metrics.

To achieve this, the project needed to establish the relationship between pixels and physical millimeters at specific distances. Frame sizes were measured at varying distances, starting from 10 feet and extending up to 60 feet, representing the camera’s proximity to the target in the experimental setup and the distance for the commercial sprayer, respectively. By dividing the width of the frame size by the corresponding number of pixels in that frame, the actual millimeter distance represented by a single pixel was determined. In the context of this project, two key distances were considered: 10 feet, reflecting the camera-to-target distance in the experimental setup, and 60 feet, which was relevant to the commercial sprayer scenario. As a result of these calculations, it was found that at 10 feet, one pixel equated to 0.53 millimeters, while at 60 feet, one pixel

corresponded to 3.19 millimeters. The actual movement of the boom in millimeters for each frame was determined by multiplying the Pixels Per Millimeter (PPM) by the difference in coordinates between the current frame and the initial frame, serving as the reference point. This calculation allowed for the precise quantification of boom movement in millimeters for each frame. This process was systematically repeated for every frame in the video sequence, enabling continuous monitoring of the boom's dynamic motion. The calculated movement data were efficiently stored in a pandas data frame, serving as a structured log to maintain and analyze the results throughout the project.

Chapter 4

Validation

The validation of the Model system developed in this study was a pivotal stage dedicated to thoroughly assessing the precision and efficacy of the system in the quantification of agricultural sprayer boom movements. The validation process employed a two-fold approach to ensure the model's accuracy. Firstly, manual readings were recorded while controlling the movement of the sprayer boom. This hands-on method allowed for a direct comparison between the system's output and the manually observed measurements, serving as a fundamental benchmark for accuracy. For carrying out validation tests with manual reading, tests were carried out on the experimental boom and sprayer boom.

The validation process involved a carefully planned sequence of steps to ensure the system's accuracy and effectiveness in quantifying the movements of the agricultural sprayer boom. Initially, the validation test commenced with the precise measurement of the initial position of the boom, which served as the reference point denoted as 0,0 for all subsequent measurements. This established a robust and standardized starting point for the validation procedure.

With the initial position accurately marked, the boom was systematically

moved in both horizontal directions, from right to left (in 4.1) and left to right (in 4.2). At the culmination of each horizontal movement, the final position was recorded to provide a basis for comparison with the model’s output. This step replicated real-world conditions, where the sprayer boom underwent dynamic changes during operations.

The true validation process included a comparison between the results generated by the Model model and the corresponding manual readings.

Multiple iterations of these comparative tests were conducted, each underlining the model’s consistency and accuracy. Remarkably, the results consistently demonstrated a high level of precision, with the system exhibiting an accuracy within the remarkable threshold of 1 centimeter.

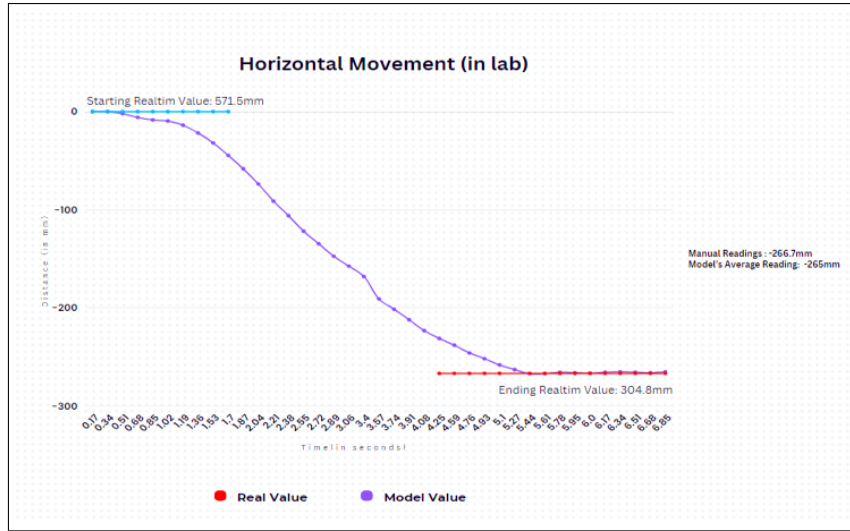


Figure 4.1: *In Lab validation test results 1*

In our pursuit of rigorous validation, manual readings constituted only one facet of the comprehensive process. In addition to these human-assisted measurements, the validation methodology incorporated state-of-the-art TMS/TMM22 inclinometer sensors, renowned for their exceptional precision with accuracy levels reaching as fine as 0.05 degrees. These advanced sensors proved to be indispensable tools in the validation arsenal,

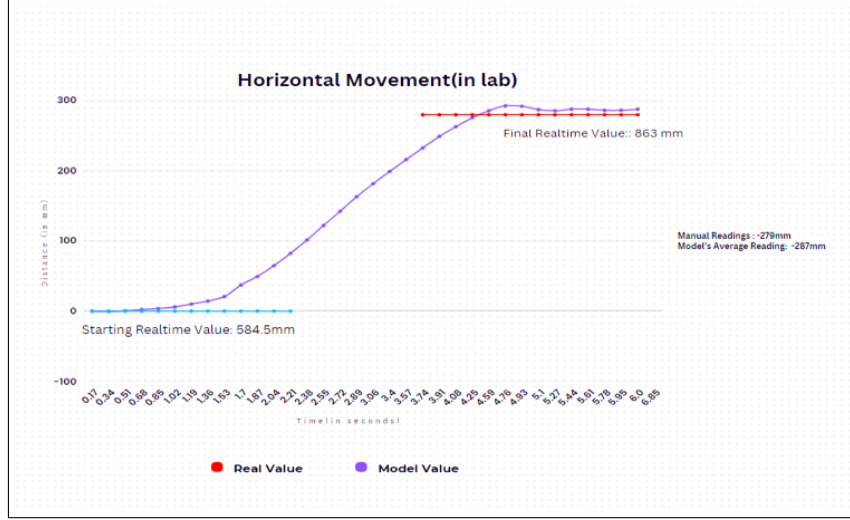


Figure 4.2: *In Lab validation test results 2*

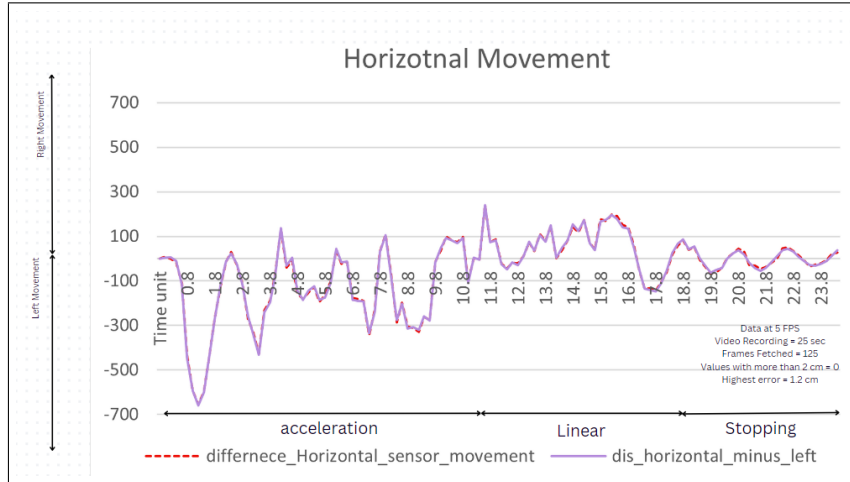


Figure 4.3: *Field validation test results*

offering an objective and quantitative approach to assessing the performance of the Model system.

The inclinometer sensors, strategically positioned at the inception of the boom, were adept at capturing the subtle angle deviations inherent in the boom's movement. For consistency and alignment with the model's 0,0 reference point, the initial reading from the sensor was designated as the pivotal point from which all subsequent readings were compared. This mirrored the modeling procedure, which initiated its measurements from the same origin.

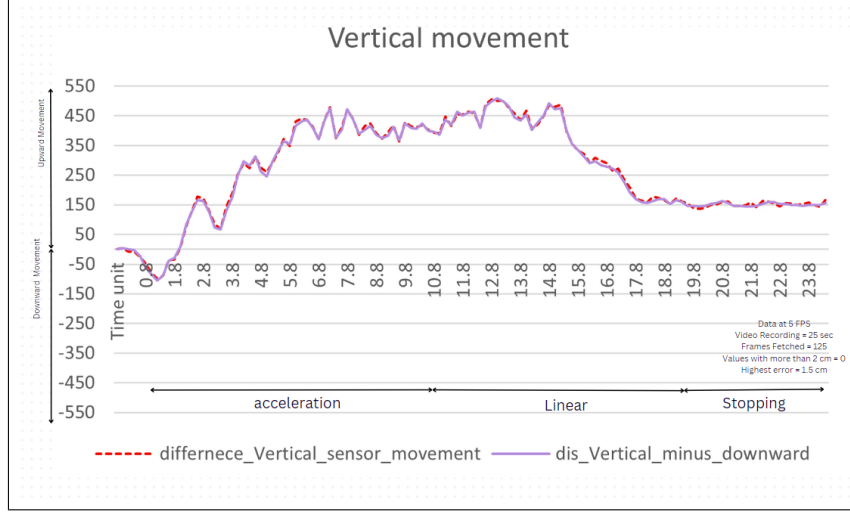


Figure 4.4: *Field validation test results 1*

Furthermore, it was of paramount importance that the validation tests replicated real-world scenarios. To achieve this, it was ensured that the vehicle operated under authentic agricultural conditions while spraying liquids, allowing the system to be assessed under conditions mirroring practical field use. The utilization of these advanced inclinometer sensors, coupled with the stringent validation criteria, collectively affirmed that the Model system not only met but indeed exceeded the exacting standards for the precise quantification of agricultural sprayer boom movements. The validation test confirmed that the model was accurate and followed the same footprint manual and sensor reading.

Chapter 5

Results

The primary objective of the computer vision model's development was to comprehensively and accurately monitor the intricate movements of the agricultural sprayer's boom as it operates in real-world field conditions. The model was engineered to not only detect but precisely track the boom's motion in its diverse and natural forms during the dynamic sprayer operations in the field. By effectively capturing the full spectrum of movement patterns exhibited by the boom, the model provides a robust and versatile solution for monitoring and analyzing agricultural sprayer performance, contributing to enhanced precision in modern farming practices. This capability marks a significant advancement in the field of precision agriculture and underscores the model's adaptability to varying environmental and operational scenarios.

Chapter 6

Conclusion

the developed computer vision model has demonstrated its effectiveness and reliability in tracking the dynamic movement of agricultural sprayer booms during field operations. The comprehensive validation process, which included manual readings and advanced inclinometer sensors, confirmed the model's ability to accurately quantify boom movements with a high degree of precision.

The model's proficiency in capturing the natural forms of boom motion is a notable achievement, as it enhances the monitoring and analysis of sprayer performance in real-world agricultural settings. This advancement is especially significant given the increasing importance of precision agriculture, where efficient resource utilization and crop yield optimization are paramount.

Chapter 7

Future Work

The future work in this project is focused on minimizing the current image processing time, transitioning towards real-time processing, and eliminating the need for operators to wait post-job completion for result processing.

This endeavor encompasses several vital aspects, including algorithm optimization, hardware enhancement, software refinement, model compression, edge computing, and real-time feedback implementation. By refining the computer vision algorithms and incorporating parallel processing techniques, we aim to accelerate the image analysis process. Upgrading hardware components, such as employing high-performance GPUs and specialized processing units, will contribute to faster image detection and analysis. Ongoing software enhancements will aim to reduce processing redundancy and streamline detection procedures. Model compression techniques will be explored to lessen the computational load on neural networks. Additionally, we will investigate edge computing solutions to facilitate on-site data processing, decreasing reliance on centralized systems. Finally, the incorporation of real-time feedback mechanisms will provide immediate insights to operators, enabling rapid adjustments during sprayer operations. These efforts collectively seek to optimize system

efficiency, making real-time image processing a reality, and enhancing the productivity and convenience of agricultural sprayer operations.

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