Olive fruits identification using AI and Edge Computing

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LIST OF SYMBOLS, ABBREVIATIONS AND ACRONYMS

mAP	Mean Average Precision
AI	Artificial Intelligence
PA	Precision Agriculture
IoT	Internet of Things
IoU	Intersection over Union

ABSTRACT

Estimation of yield in olive production is very important in order to enhance the overall management and economic returns from olive orchards. Conventional methods of yield estimation are time consuming and most of the times they are prone to mistakes. This thesis presents a new method that applies image segmentation and artificial intelligence on the edge devices to enhance the estimation of the olive yield. This work suggests that with the assistance of adopting the U-Net architecture, it is conceivable to segment olives from photographs taken in-field, under natural light. The images were segmented manually to obtain a special dataset with binary masks that allow to clearly distinguishing olives from the rest of the background and, consequently, provide accurate predictions of olive yield. These images were used to train the U-Net model, and evaluated on dice score and the mean average precision (mAP). This thesis also presents the benefit of image segmentation over the object detection approach in managing the issues of natural orchard environment and the importance of data processing on the edge devices such as real-time data analysis and minimal data transfer. From the findings of this study, it was concluded that the proposed method has the potential of greatly improving the precision of the olive yield estimation while at the same time being a more efficient approach that could be used on a large scale in the management of the orchard. The trained algorithm was deployed on NVIDIA Jetson Nano and tested on field images. Positive results along with low latency makes this research a vital push in the government's already planned increase in local olive production. The research belongs to the agricultural technology domain, as it identifies how AI can be applied in practice in actual farms.

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

Agriculture lays the bedrock foundation for international economic security and the sustainability of people. This sustainability has its roots in both developed and underdeveloped countries as it sets the social and economic policies of these countries. In the vast field of agriculture, one key element is olive cultivation. Olive cultivation is not only significant for economic reasons, but also holds a majority stake in the sustainability of environment, in places such as close to Mediterranean region, and increasingly in the south Asia, specifically Pakistan. Given the recent focus of government on the increased spending on agriculture sector – especially olive cultivation – this thesis will delve into merging technological advancements, in the recently emerging field of Artificial Intelligence, with agricultural farming. Recently discovered techniques in the AI such as image segmentation, will be utilized for overall yield estimation of the olive fruit. This, coupled with the deployment on edge device (NVIDIA microcontrollers with built-in GPU) has the potential to maximize growth and modernize the newly emerging olive sector of Pakistan. Past decade has seen massive advancement in agricultural sector, through the use of technical innovations, aimed solely at increasing the productivity and bringing sustainability into farming. A prominent technological innovation is the application of artificial intelligence, mainly image segmentation, for yield estimation that has the potential to significantly improve the old agricultural practices and contribute to resource management.

1.1.1 Global and Local Context of Olive Cultivation

Olive oil market is a lucrative industry globally, where its market cap reaches upwards of $11 billion. This market is driven by demand of organic healthy fats by the consumers of mainly affluent countries. A prominent ingredient in the Mediterranean dietary lifestyle, olives are consumed in European countries such as Spain, Italy, and Greece. As of late, Pakistan government has decided to put significant resources to decrease dependence on imports. One such measure is the cultivation of olives, which the government deems as high value crop. High value crops integrated into the agricultural ecosystem aims to boost the efficiency of agricultural sector, and also reduce the imports. Currently Pakistan imports $ 3.5 billion worth edible oil [1]. Even though most of it is palm oil, the government with this spending on olive farming is hoping to cultivate a habit of healthy fats in the nation's diet. This planning by the government, has led to the plantation of millions of olive trees throughout the country [2]. Even though Pakistan is largely agricultural country, cultivation of olives is relatively new, with wild olives growing in the remote south western areas of Pakistan from centuries, intentional plantation of fruit is in adolescent stage. This adolescence in olive cultivation has caused problems in the expansion spending by the government due to lack of low-cost technologies to monitor and manage large scale olive yields, lack of precision devices and non-scalable infrastructure.

1.1.2 Technological Innovation in Agriculture

The arrival of AI in the field of computer technology has removed the bottlenecks for innovation in agriculture, in that it has shaped tools and techniques that can drastically increase the output of traditional farming with better precision and, in more energy efficient way. As previously discussed, image segmentation, a popular vision based deep learning technique has the potential to enhance yield production by order of magnitudes ten, which consequently leads to better plant health and management through optimized distribution of resources. In this thesis, we propose a solution, based on the image segmentation technique, that has the ability to estimate olive yield in field through edge deployment. As is the natural outcome of technological interference in traditional practices, the proposed solution is scalable, in accordance with the Pakistan's government's spending plans in this area. Keeping in mind the key factor of real-time analysis, this approach is operation first approach, analyzing data on site without the need for extra data transmission latency and expenses. Real-time data analytics is one of the reasons why agricultural yield has seen a massive boost in recent years

1.1.3 Research Significance and Objectives

The main goal of this research is to first design a reliable model that has the ability to predict olive crop yield and then validate the model's accuracy. Naturally a high accuracy model would be the acceptable solution. The model will predict by capturing images directly in the field. The final solution will equip farmers with practical understanding of their farm's yield. These operational insights will help farmers in planning their business strategy in the long run, while also supporting their daily agricultural decisions. Since this model is an offline model, edge deployment will significantly increase its reach, further into the areas where farmers typically complain of network connectivity. Thus this proposed solution provides decisive reinforcement to well-connected areas, while also developing remote agricultural areas.

1.1.4 Methodology Overview

For this research, a dataset of annotated images of olive trees was collected from a single source of olive plantation, albeit with different species. The images collected were then used for training the deep learning model, that can detect – more specifically segment an olive from the background – in its natural environment. Rigorous testing will be performed on both, the output of the model, and the input of the model (curated images) to establish a framework which incorporate diversity, and promotes robustness so that the proposed solution is applicable to other regions or even crop types.

1.2 Problem Statement

Optimization is a crucial step in enhancing the productivity of olive farming. This optimization relies on the precise yield estimation of olives on the trees. Conventionally, the yield estimation, either for olives or other fruits, relies on manual counting or statistical guessing based on initial counts. This exercise is laborious, time consuming and bares a heavy margin of error. Not only are these methods inaccurate, they're also inept at providing meaningful information in real time. As a result, the precision of agricultural decision making is critically hampered. Latest innovations in the field of AI offers valuable alternatives to this manual yield estimation problem, increasing both its accuracy and efficiency. Even though the AI models propose revolutionary results, their practical execution remain largely indebted to challenges. These challenges include biasness and computational constraints. A model's accuracy is as valid as the data the model was trained on. The biasness in data, often overlooked, is equally represented as biasness in the solution. Field conditions, time of the day, specificity of the species, all these factors contribute to the final output of the model when deployed in real scenario. Furthermore, the computational resources required for the AI models to run, vastly outdo the resources available for edge deployment (at least the cost effective resources since this is to be a scalable solution). The model, therefore, needs not just be free of biasness in its training, it should also be computationally optimized to work on low cost edge devices. Given these problems at hand, our approach aims to resolve these challenges through a reliable AI based system, which at its core uses a U-Net architecture (a deep neural network architecture where layers are shaped in U formation) to segment images of olives that are fed to it directly from a live camera feed mounted on a handheld contraption. We will make use of novel dataset free from biasness, to achieve not only high accuracy but also operational efficiency on resource constraint edge devices.

1.3 Objectives of the study

1.3.1 Develop an efficient image segmentation model

The main goal is to develop deep learning model, capable of segmenting field taken images of olive fruits. The key to our project lies in the utilization of U-Net architecture. U-Net is a convolutional neural network that was developed for applications such as medical image segmentation. One key feature of this architecture is its ability to generalize information based on a relatively small dataset. This provides accurate segmentation results for cell segmentation and other medical tasks. Efficiency of the proposed model is our primary concern, since the practicality of our solution is based on it. In this context, efficiency constitutes of several other aspects including:

Accuracy: One essential element is the high segmentation accuracy depending on the metrics adopted (dice score, mAP) whereby the more accurate segmentation is, the more reliable the model's predictions are in estimating olive yields.

Computational Efficiency: Due to this the said model is to be deployed on edge devices and, consequently, should work efficiently within the context of these comparatively underpowered devices. This entails the strategic redesign of the network design which will minimize the number of parameters as well as the several computational steps needed in order to process the various images.

Training Efficiency: The model should be capable of delivering high accuracy even when trained on a small dataset, primarily owing to the difficulty and cost associated with procuring large datasets in agricultural environments. There may be measures like data augmentation and transfer learning used to enhance the performance of the model in the eventual training regardless of the amount and variation of training data.

Generalization Ability: A pre-requisite is for the model to perform well on unseen data and hence it will be desirable for the model to perform well for olive images from different orchards under different conditions. In this way, the robustness of the model guarantees that, regardless of changes in the environmental conditions or characteristics of olive trees over time and geographical space, the use of the model would prove valuable in another geographic location in another year.

1.3.2 Optimize Model Performance for Edge Devices

Edge computing deals with processing data near the point at which it will be required within the sector of agriculture, specifically on the fields. Ai models when deployed on offline edge devices, assists in making real time decisions on device, without the extraneous back and forth between a central high powered computational server and the monitoring device. This also removes the need for high powered connectivity required for wireless communication. This is especially beneficial in context of agriculture where many a times the operations are situated in the rural areas with inadequate means of advanced IT solutions. Although edge devices are becoming increasingly powerful, they are still limited in certain areas like the amount of processing power, memory and energy they can use to perform AI modeling and computations hence the need for optimized AI models for such platforms.

To achieve this objective, several strategies will be employed:

Model Simplification: Reduction of the number of layers and hence the size of the model without causing a major impact on the designs functionality of segmenting olive fruits. Software techniques that can help in application are pruning, quantization and depth-wise separable convolutions.

Efficiency Enhancements: Applying software optimizations that will greatly reduce the computational load on the edge devices without the subsequent loss in output. This includes utilizing the above mentioned code features where the specific operating hardware supports them and incorporating the model into the use of special-purpose hardware platforms for machine learning jobs.

Resource Management: Finding ways and means through which the memory is kept optimally controlled and the power consumption is low in order to enable the device to work for as long as possible in the field without necessarily requiring frequent recharging. Although it is quite viable, the power consumption optimization fits into a different thematic area and will only be discussed briefly as a by-product of memory optimization.

Performance Evaluation: Extensively validating the model in a variety of operational scenarios to check intended stability, reliability, and accuracy with edge devices. This will include field tests to compare and get performance results under various environments and during day and night.

It is with this perspective that this paper set out to improve the image segmentation model to enable the development of a reliable and highly functional tool that can be implemented directly in olive orchards. This capability will put an end to the usual delays and guesswork when it comes to arriving at decisions about crop health, and it will do so in a manner that could help to dramatically improve overall crop yield while at the same time making agriculture more sustainable.

1.3.3 Improve Olive Yield Estimation Accuracy

The third aim of this thesis is to improve the yield forecasting from olives through the more efficient use of image segmentation based AI. When predicting the olive production, people have always used counting or even taking samples which is costly in time, laborious and very often accompanied with considerable mistakes due to random errors of counting and natural variation in the sample. It is hoped with the aid of the present study, which adopts a systematic and AI-based procedure to solve this problem, yield forecasting can not only be more accurate, but also deliver more reliable predictions than those previously used in prior literature.

The task of segmenting the market needs to be done accurately to the finest level if possible. Examining the level at which the model accurately segments the olive fruits from the images taken in their natural setting—the orchards—it is felt that the model aids in improved yield estimation. The analysis process guarantees the accuracy of segmenting olives, give proportionate counts of the fruits, and reduces miscalculations that emanate from manual estimations.

The use of learning processes for the development of artificial intelligent systems is also scalable in approach. This scale up ability is much easier to achieve in an AI-based system and could handle large amounts of input data or be applied to other multiple setting without much additional cost. This scalability helps towards ensuring that the higher accuracy is not only achieved in a small-scale or a pilot study but in the large agricultural operational environs as well.

Another advantage of the AI models is that they are capable of undergoing continuous improvement via feedback and output analysis. This way as the model is trained with new data in case of next growing seasons, it can possess updated information and inferences resulting in high accuracy over time. This would require manual interference by the user and then taking that into account to which an idea can be developed further once non-continuous feedback methods have been identified and a success rate established.

It is necessary to provide the conclusion that verification and validation are the key to maintaining the correspondence between the model results and the actual harvested yields. Not only does this verification process assess the progress in the alleviation of inaccuracy but also the reliability of AI-based techniques in the eyes of other stakeholders within the agricultural sector.

1.3.4 Validate Model Under Field Conditions

The fourth aim of this thesis is to further confirm the efficiency and effectiveness of the developed image segmentation model with actual field tests. It is especially important for this validation to learn whether the model is going to work not just on a theoretical level in controlled or simulated conditions but also in real pictures of orchards. Some elements of the field validation activities and considerations, include:

Firstly, the behaviors of the model should be at least as good as the baseline under all the conditions. It should perform comparably in a number of given settings involving light conditions when imaging the tree (for instance sunny, cloudy, shadowy), weather conditions (be it dry, or humid), and organization of the physical view (for instance, approaching/ receding distance between the tree and the camera, different angles of shooting, etc.). This makes the system resilient to the continuous changes that occur in the external atmospheric environment of outdoor agricultural production.

Secondly, there may be a need for operational testing that will happen on the edge devices. It is important to test the model operation on edge devices as the work is conducted in this environment, and the model is designed for this purpose. This includes the evaluation of the amount of resources that is being used per frame and the number of frames per second with less computational power of the computer hardware that it is being executed on. This step validates whether or not the model has the capacity to provide feedback and analysis on the ground – a crucial factor contending the decision-making process in agriculture.

And lastly, the results obtained need to be cross-checked with the ground truth. High-quality data collected from ground truths entails counting and measuring the yields to provide a ground truth standard to compare the model’s result. Apart from helping determine the accuracy, comparison also highlights contexts in which the model might suffer from weaker performance or shine in terms of effectiveness.

1.4 Significance of the Study

1.4.1 Advancement in agricultural technology

Our research entails the development and implementation of an accurate image segmentation model that applies artificial intelligence for the estimation of olive yield, which is a major technological innovation that falls under Agro-tech. In decision and design support systems in precision agriculture where the focus is on using technology to raise productivity, this research expands the applicability of AI approaches. Another subfield of agriculture that has benefitted from advancement is the area of agricultural technology that has depended on forms of mechanization, selective breeding and, in the current century, data management. Although artificial intelligence is itself still quite common in many ways, the application of it especially in real-time, on-site as is the case with edge devices is somewhat still nascent. This research presents a method of utilizing the U-Net architecture for image segmentation directly in the field: thus, it is one that not only effectively and efficiently replaces a time-consuming task or activity that would have otherwise require a large amount of manpower but does so just as accurately and much quicker.

Technological Integration: Therefore, this paper demonstrates how AI can be incorporated into the current farming practices to improve the decision-making systems. The dispensation under which images are processed and analyzed on the edge devices with little or no recourse to computational power or connectivity presents a huge boost in the application of smart systems in settings that are characterized by limited resources.

Innovation in Image Processing: The use of the image segmentation developed for the identification of olive yields with the aid of CNN presents an unexplored problem in the agricultural imagery. While for general object recognition it is possible to use models with less precise parameters, due to the fact that olives are small and often overlapping objects, the methods should be more accurate and be able to distinguish between similar textures, colors and shapes in a variety of conditions.

Real-time Data Processing: Thus this research offers a roadmap for real-time data analytics on the edge devices in the field of agriculture. This capability results in the identification of crop status at any given time, which is very helpful in making appropriate changes to enhance the yield that can be made on the crops such as in the area of harvesting and resource usage.

Sustainability and Precision: In addition, such technology enhances on precision hence making it sustainable. Thus, reliable yield estimates help to use water, fertilizers, and pesticides more effectively, minimizing their consumption and, consequently, the negative impact on the environment. This conforms to the general idea of precision agriculture which aims at improving the accuracy, efficiency and the sustainability of farming.

Thus, the improvement of agricultural technology presented in this work is not only a useful instrument for olive growers, but also an example for future innovations in other spheres of agriculture. It is an advancement towards the utilization of AI in the actual farming practices, thus, opening opportunities for more widespread use and innovation that will be useful for the whole agricultural sector of the world.

1.4.2 Improvement in yield estimation methods

In this thesis, a valuable addition to the agricultural yield estimation literature is made by enhancing the approaches for olive yield assessment through the application of an innovative deep learning-based image segmentation model. Conventionally, yield expectations are made based on sample data or average data of previous years, which is unsuitable and may not reflect actual conditions of the subsequent year. These methods are tedious, subjective and their application is not feasible for large organizations.

The introduction of an AI-driven approach, utilizing the U-Net architecture for image segmentation directly in the field, provides several improvements over these traditional methods:

Increased Accuracy and Reliability: This way the proposed approach minimizes the person's mistakes and enhances the precision of the crop overall count based on the pictures. This level of detail is crucial in monetary and business management modalities in olive farming since estimating the anticipated output can greatly influence the viability of farming ventures.

Timeliness of Data: With this model, one can estimate the yield while the crops are still standing in the field in real time or nearly real time. This information is particularly useful for decision making especially concerning matters of yield, which are best taken at the right time and crop yield is one of the activities that require timely decision making.

Scalability: While the manual sampling methods have to be done time and again in different areas and different orchards with extra workforce, the AI approach can be repeatedly used in large areas and different farms without incurring extra costs for labor. This scalability makes it suitable for the larger operations and can easily be incorporated into other agricultural management systems and is a standard way of estimating the yield in different geographical areas and for various crops.

Objective and Consistent Assessments: It is a systematic approach of estimating yield which is not influenced by the subjectivity of the human Counties. This objectivity is important for standardization of data collection and analysis since the former is important in longitudinal studies and the later in comparisons between different locations and times of the year.

Enhanced Decision-Making: This means that farmers and the entities involved in the farming business can be in a better place to make their decisions concerning the utilization of resources, the time to harvest and the market stand. It can therefore result in better efficiency, less wastage and therefore better financial results.

1.4.3 Resource Efficiency

The results of this study provide a considerable impact on the optimization of resources in the cultivation of olives. Most of the conventional farming systems are based on assumptions and presumptions when it comes to matters concerning the use of water, fertilizers, pesticides, and even labor. These approaches are often inefficient resulting in over-usage or under-usage with all the financial implications that are associated with over or under usage.

The integration of precise, AI-enabled yield estimation methodologies addresses these inefficiencies in several impactful ways:

Targeted Resource Application: This information can help in making proper decisions when it comes to the utilization of resources especially when it comes to different orchards or even different regions in the orchards. This precision minimizes wastage and provide assurance of proper use of the resources in the best way. For instance, knowledge of expected yield can assist in changing the quantity of fertilizer that is required, the scheduling of irrigation based on the crop water requirements and, controlling the amount of labor to be used in the farming process during the harvest time.

Reduction in Input Costs: It is in this light that through effective management of the agricultural inputs, farmers are able to cut down their expenses tremendously. Minimizing the overuse of valuable resources such as water and fertilizers enables the farmers to use them sparingly while applying them in the right measure "just in case." With accurate estimation of the expected yields, the farmers are able to save on costs, which would have been used to purchase the excess quantities of the inputs, and thus promote the conservation of the environment.

Improved Water Management: Water is a very important and at the same time a limited commodity in many agro based areas. This is due to the fact that efficient water use is critical in the regions where water scarcity is a challenge and olive trees are grown. AI in yield estimation helps in proper irrigation management which is very essential in the effective usage of water since the available water is well utilized in the production of high yields without wasting water.

Enhanced Environmental Sustainability: Besides the reduction of the cost of the inputs, efficient resource utilization presents other environmental repercussions. Reduced application of fertilizers and pesticides minimize possibilities of their drains off into water course and polluting water sources, while efficient use of water is beneficial for the conservation of this precious commodity. Also, efficient input use helps in decreasing the energy consumption in the production, transportation, and utilization of these inputs in agricultural activities thus lowering their carbon footprint.

Data-Driven Management Practices: It means that AI and data analytics in the estimation of the yield improve the management of the farm through the use of a scientific approach. This is due to the fact that this data driven approach not only focuses on the usage of resources but it also involves other decisions with regard to crop management as well as soil management and pest management. It forms the basis for the adoption of sustainable farm management practices that consider on environmental, economic and social aspect.

1.4.4 Environmental Impact

The research and application of an image segmentation model in this thesis are closely related to the protection of the environment and practicing efficient and eco-friendly farming. The environmental implication of this research is enormous since it presents several outcomes which not only affect the primary subject of olive farming but also other environmental concerns.

Reduction of Chemical Inputs: The yield helps in determining the exact amount of fertilizers and pesticides to be used on the farm hence reducing on their use leading to their conservation. This approach helps avoid the spread of chemicals into water bodies thereby reducing on eutrophication of water sources and affecting aquatic life. Thus, the suggested model also plays a role in decreasing the risks of soil degradation and loss of biological diversity stemmed from overuse of chemical pesticides.

Conservation of Water Resources: Irrigation water management is very essential in agriculture particularly in areas that are prone to drought and where olive trees are usually grown. AI model allows for more precise scheduling of irrigation depending on the crop's requirements and the expected output, which is the yield. This is control watering system that is used in the farming of trees in the orchards, this help in the conservation of water even as the water supply is decreasing, the use of water is properly made without affecting the health of trees in the orchards.

Mitigation of Carbon Footprint: Through efficient utilization of agricultural inputs and machinery the model can be said to have an indirect positive impact on the carbon footprint of olive cultivation. This implies that in the application of water, fuel, and energy for example fertilizers and pesticides, less will be utilized. Also, improved yield forecasts can assist in strategizing better handling and transportation, which would in turn lead to reduced energy use and greenhouse gas emissions connected with handling and transportation.

Promotion of Sustainable Agricultural Practices: This study is beneficial for the change in the direction towards more effective and eco-friendly cultivation by offering a tool which can increase the profitability and, therefore, the sustainability of olive groves. This makes it easier to estimate the yield for a given area and therefore efficiently manage resource such as land, water, and other inputs such as fertilizers and seeds, which can also entail the use of sustainable practices such as, conservation agriculture, integrated pest management as well as promotion of organic farming.

Long-Term Ecological Benefits: This thesis presents the most effective and beneficial precision agriculture technologies to increase the application of environment-friendly farming practices. Some of the long-term ecological implications include, improved soil quality, water quality, enhanced bio-diversity, and better and sustainable agricultural systems to deal with ecological changes and climate change effects.

1.4.5 Scalability and Adaptability

In this thesis, a remarkable improvement of the scalability and flexibility in the Agro-tech systems is demonstrated. This is crucial as it not only leads to the assessment of the model's appropriateness in various scenarios but also shows its possible use in other fields excluding the olive farming.

Scalability: The benefit of the AI model introduced in this thesis is modularity and, as a result, its scalability. The model can be implemented in many orchards of different sizes and without a proportional rise in human resources and expenses. This scalability is beneficial for the large scale farming enterprises and can be easily incorporated into other technologies used in farming. Thus, by using edge computing devices the model can process the data at the points of its collection, which does not require the constant connection and allows make the decision on the fly that is crucial for large and complex agricultural networks.

Integration with Other Agricultural Technologies: This design of the model makes it easy to integrate with other technologies used in agriculture such as GIS, drones and satellite imagery and the automated harvesting equipment. This integration capability promotes a more integrated approach to farming where all these technologies work together to improve on the farming output.

Customization for Local Conditions: This model can be tweaked to fit specific conditions of specific regions as far as agriculture is concerned and this is because there are many different conditions in different regions. Some of the factors that can affect the output of the model include; Climatic factors, type of plant species, the density of planting, and management practices used in farming. It is therefore important for the model's applicability and relevance that the various elements of the model can be tailored to the local data and conditions so that the technology remains useful and applicable in different agricultural settings across the globe.

Facilitation of Precision Agriculture: Thus, demonstrating the potential of the proposed method in various conditions, this thesis contributes to the further application of the precision agriculture technologies. Precision agriculture is based on the use of the right and timely information that models like the one presented in this paper can offer to manage the farming process. This control results in increased crop production, reduced negative effects on the environment and therefore increased income.

1.4.6 Economic Impact on Rural Communities

There is a great potential for the economic impact of the development and application of an AI-based image segmentation model for estimating olive yields on the rural communities that grow olives. This technology consequently affects the financial management of farming by increasing production, minimizing expenses, and possibly generating new income sources for small and big scale farmers. The consequence of these alterations is especially important in the rural zones due to the fact that agriculture is the main source of income there.

Enhanced Agricultural Productivity: Through giving proper and timely information on the olive yields, the model helps the farmers to plan on the right time to harvest the olives in order to get the best income out of it. This optimization may in turn enhance the overall production of the orchards, and the quality of the crops which enhance the income.

Cost Reduction Through Optimized Resource Use: The model helps in cutting down on costs that are incurred in the wrong utilization of resources such as water, fertilizers and pesticides, which are key costs in agriculture. If farmers use these inputs more wisely and where they are really needed, then costs can be reduced to the Minimum. Also, the accurate estimation of the yield enables the proper and efficient organization of labor, another vital cost input, particularly during the crucial period of the crop's life cycle, the harvest.

Stabilization of Income: Thus, the proper yield estimates help the farmers to make more precise decisions concerning the financial planning and risk minimization. Being aware of the expected yield in the beginning is crucial for farmers as it allows them to sell the goods at the right time and at the right price, consider futures contracts or other options. This can assist in providing a more stable source of income since the risk of price changes and the conditions of the market can be reduced.

Economic Diversification Opportunities: With proper yield data, farmers may venture into the other income generating activities like agro-tourism or value addition products like oil and other by products of olives. It can help to generate more income sources and to decrease the dependency on the sales of raw olives which are the prime source of earnings for the people engaged in olive farming.

Community Employment: As a result of higher yields and possibly increased farming activities as a result of reduced costs and increased returns from the orchards there is a possibility of job creation within the rural areas. Employment can be created not only in the farming sectors but also in the linked sectors like processing, marketing and distribution of the farm products which in turn can lead to enhancement of the economy of the particular region/district.

Sustainable Economic Growth: In the long-run, the use of the modern technologies in farming helps in the development of the economy in the rural regions. As agricultural practices become more efficient and profitable, there is a ripple effect on other local businesses and infrastructure, fostering overall economic growth and improving the quality of life in rural communities.

1.4.7 Contribution to Academic Knowledge

This thesis is significant and original piece of work that enriches the body of knowledge especially in the areas of agricultural technology and applied artificial intelligence. This contribution is several-fold, it identifies the shortcomings of the existing research, it presents new methods, and it lays the groundwork for future research. Advancement in Image Segmentation Techniques: This research provides theoretical contribution to the existing literature through proposing and optimizing image segmentation approaches, particularly the U-Net model for the agricultural context. Although U-Net has been widely used for medical imaging, applying it in agriculture and particularly under field conditions and on edge devices brings new problems and possibilities. This thesis presents these adaptations in light of the fact that most of the studies done in the literature are conducted in more controlled environments and therefore the changes needed for the applications to be used in less controlled environments are discussed.

Integration of AI with Edge Computing in Agriculture: This paper is relevant to the area of edge computing as it centers on the application of AI models on devices at the edge within the context of agriculture. It examines the particular issues concerning the processing of big data on devices with restricted capabilities which, in turn, contributes to the understanding of how AI can be integrated into such devices. This has implications to the Internet of Things (IoT) and other areas which involve edge computing.

Methodological Innovations: Thus, this thesis presents methodological advancements in outlining the procedure of the dataset generation, model training, and field validation in the context of olive orchards. These methodologies can be extremely useful for any scholar intending to replicate or build upon the presented AI applications in comparable agricultural or environmental conditions. The elaboration of the challenges and solutions encountered and applied contributes to the existing literature on the real-world application of AI.

Empirical Data on AI in Precision Agriculture: Thus, contributing to the literature on the efficiency of AI technologies in enhancing the yield estimations, this thesis provides quantitative data for further discussion on the benefits of digital tools in precision agriculture. The concentration on olives as a crop, which is less explored in this regard than other food items like fruits, particularly apples and oranges, is highly desirable.

Bridging Theory and Practice: This paper provides a link between theoretical research in AI and real-world agricultural problems revealing that theoretical concepts can be applied to solve practical problems. It is important for the academic community to understand the practical applications and the drawbacks of AI technologies and this research provides a view into the matter that can help in future work.

Future framework: Last but not the least, this research provides a total framework for future research in similar fields. It suggests future work directions to improve the AI models for better results, extend the study of similar models for other crops, or include more environmental data to improve the models.

CHAPTER 2: LITERATURE REVIEW

During the early stages of the fruit, fairly accurate estimations can be made about the size of the fruit and estimated yield it would produce. Even though it forms a large portion of the oil crop market, the studies done on the olives about their developmental stages are sparse. One such analysis, is done by [3] where the authors provide a comprehensive analysis of the transcriptome dynamics at early stage of fruit development. The study focuses on the cell division and expansion, known to be significant factors affecting size and yield of the fruit. The authors focus on the specific genes that play vital role in the cell cycle regulation and hormonal changes. Proper understanding of these characteristics are vital to the first part of our study, where we utilize these morphological characteristics in order to build a segmentation model. By including these biological insights about the early stage development, we efficiently create a foundational framework for our methodology as well as improving the chances of reliable prediction. Remember that a good model is the one with low biasness, and understanding the development cycle help us understand the diversity in our data collection method further on. Although not technically related, this study offered great insights into olive plantation.

2.1 Overview of image segmentation techniques

Keeping in mind our research area, in this paper [4], the authors present a review of the image segmentation techniques and methods focusing on the main topic of the study. They cover from basic techniques like thresholding and clustering to advanced techniques like edge detection and region growing based on machine learning. However, traditional machine learning has been the largest part of the industry until a few years before now and these techniques have become somewhat outdated or in other words, they need deep learning to enhance their performance. Segmenting the image automatically using color features, textures and edges would not work for our case study since olives, like many fruits, camouflage with the surrounding background. It resembles the surrounding leaves and tree in terms of its physical structure and this makes it hard for conventional learning methods to distinguish it from the background. Here, deep learning offers significant enhancements in the segmentation and detection of fruits.

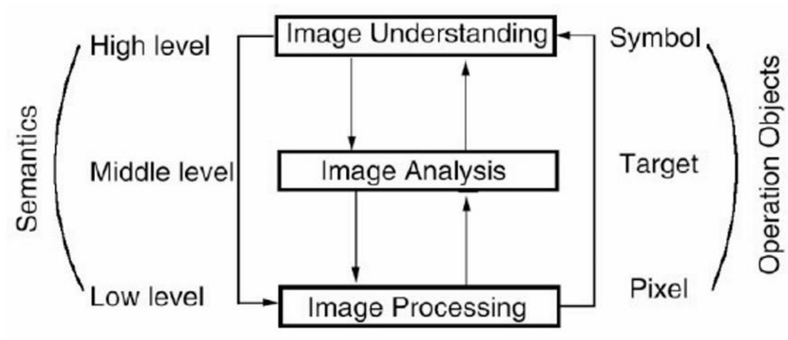

Figure 1 Three layers of image segmentation as discusses in [4]

For deep learning exploration in the context of yield estimation, a detailed literature review of deep learning methods is provided in [5]. The authors focus on models that use Convolutional Neural Networks (CNN) including Faster R-CNN, SSD, and YOLO that have been effective in fruit detection irrespective of the conditions. This is important for us to study as such models share the same problem with detecting fruits which include complex background, variable lightning, etc., all of which are a part of the olive detection problem. The study reveals that having a large annotated model gives a better opportunity to train a reliable model. This finding was useful in our strategy for creating a new annotated dataset in a natural setting. We want to design a model that would be as accurate and as reliable as the models described in the study above by applying the patterns identified in the study. As for our approach, we do not employ object detection, which is described in the discussed models, but segmentation. Thus, we provide a new perspective on the methods of image segmentation for fruit counting and yield estimation.

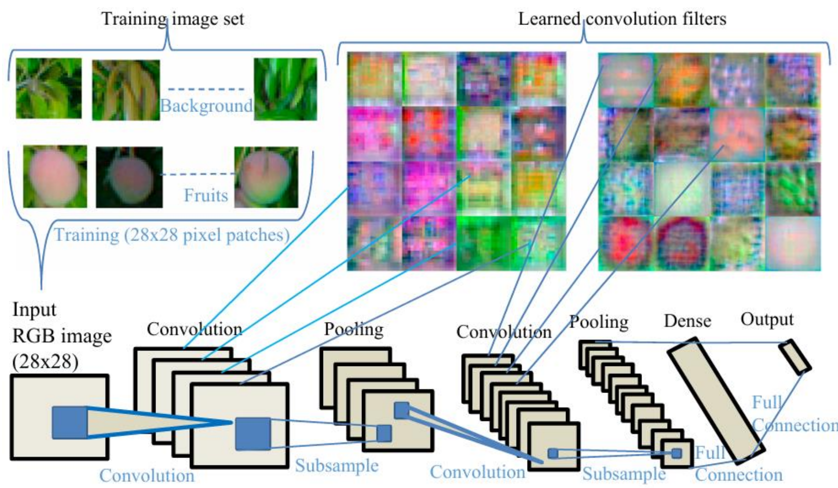

Figure 2 Conventional deep learning model architecture for feature learning [5]

2.2 Applications of AI in Agriculture

The work done by [6] uses a single shot detection method, where there is no need for the extraction of region proposals and classification hence making it fast and suitable for real-time operations. In terms of the accuracy, which is above 90 percent, and the processing time suitable for real-time applications, they have demonstrated the potential of CNNs in enhancing precision agriculture (PA) tasks. Some of these include data augmentation and transfer learning that enhances the model's performance in any environmental condition, which is ideal for olive yield estimation. This work offers a key reference for future work on incorporating advanced AI tools in the estimation of olive production, thus opening a new avenue for the use of deep learning in PA.

As an important work, which is related to the development of automated methods for olive yield estimation based on image segmentation, the study by [7] can be considered as the most relevant. They proposed multi-spectral feature learning approach for fruit segmentation in almond orchards with the classification accuracy of 88% which proves the applicability of machine learning techniques in agriculture. Despite the fact that their method incorporates unsupervised feature learning into a CRF model, this thesis will use supervised learning strategies. In particular, our work implies using a neural network that will be trained only on the images of olives on trees, manually labelled, and captured in the natural light conditions of the field. This approach is intended to use high-quality, annotated data to directly teach the model segmentation tasks with the help of a mask, without the need for an additional feature learning step. The fact that the proposed approach relies on a supervised learning model stems from the expectation that it will have a direct correlation between the input data and the annotated output that is expected to increase the quality of the olive yield estimates.

The study done by [8] performed olive fruit recognition using neural networks by following method:

First, the study employs the histogram analysis and the “Watershed” transformation to split and define various objects (olives, leaves, stems, etc.) in the picture. This assists in enhancing the segregation of data that is vital in analysis since it is done based on categories. Then, two neural networks are applied sequentially. The first network determines the location of olive fruits by shape, color and texture. The second network is in charge of checking on the Fruits identified to ensure that they do not duplicate, this is very vital for the counting and estimation of the size. Subsequently, the networks are fine-tuned on a set of images with labels and tested on other data sets to assess the model’s performance. The performance of the networks and the adjustments made on the networks are based on statistical methods and cross-validation techniques. The current paper presented potential in the field of image segmentation and how it can be applied in estimating the yield of olives. Authors used automatic segmentation based on probability distribution of pixel values as presented, which although very useful may not be very helpful in cases of different lighting conditions and without the use of a white background as done in the original paper. Hence, manual segmentation could be more preferable for such application. The distribution function for that normal distribution looks like this:

$$\emptyset_{\mu_i,\sigma_i^2}(x_c) = \int_{-\infty}^{x_c} \varphi_{\mu_i,\sigma_i^2}(t)dt = \int_{-\infty}^{x_c} \frac{1}{\sigma_i\sqrt{2\pi}} e^{\frac{-1}{2}\left(\frac{t-\mu_i}{\sigma_i}\right)^2} dt, \qquad x \in R$$

The work [9] is the foundational basis for our further study. This paper by Eduardo Assunção et al. provides a basis for integrating state-of-the-art image detection models such as the MobileDet model into edge computing for fruit detection in agriculture. The method and findings of this study are useful in demonstrating the ability of edge devices that are fitted with TPUs in executing sophisticated computational tasks on-site. The related works in the field of olive yield estimation are also described and compared to the methods based on lightweight, efficient, and accurate machine learning models that are applicable for constrained edge devices. The peach fruit detection study offers a real-world approach to fine-tuning and implementing these models utilizing Quantization aware training (QAT) which makes certain that the models will be accurate and efficient when used in real environments of agriculture. In addition, this reference emphasizes on the need of developing specific datasets and carrying out rigorous field trials that are essential to transfer the showcased technology to the small scale olive farming. This way, the thesis not only draws upon the best practices of the current state of affairs in the agricultural technology domain but also contributes to the development of future research agendas in precision agriculture and yield estimation within the context of edge computing.

The researchers of this study [10] captured images with the mobile phones' in-built cameras in different locations in Brazil, concentrating on the Arbequina olive cultivar. As shown in the figures below, a Color Checker chart was also incorporated into the frame to help with color matching.

Figure 3 Color checker used in capturing the dataset [7]

Several color correction methods were used in the study including Color Correction Based on ColorChecker that applies the ColorChecker for color correction, Adaptive Histogram Equalization that improves the contrast of an image by adjusting different regions of an image, useful in areas of variable lighting, and Histogram Equalization (HE) that redistributes the tonal levels in an image to enhance contrast. To increase the model's reliability, the study used the rotation of images and bounding boxes to teach the model many different orientations of the olives. The research established that all the proposed pre-processing techniques enhanced the detection performance when compared to the raw input images. Nevertheless, AHE was especially efficient in addressing the issues with the natural lighting changes. Moreover, the performance of the models was enhanced by data augmentation through rotation for all the preprocessing techniques. To elaborate on the research findings, adaptive Histogram Equalization (AHE) is a tool of image processing which aims at increasing the contrast of images. While standard histogram equalization is a global method, AHE is a local one. AHE is a time consuming technique as it is local in nature and applies contrast enhancement on small parts of the image one at a time. This can be a drawback especially in real-time applications where time is of the essence and processing must be done as quickly as possible. Further, while taking images of trees we realized that images taken under the trees are affected by lighting conditions and images taken from the side where light from the sun is intense. Thus, balancing the lighting for all parts of the image would be practically improbable in real time. Hence the decision to not incorporate AHE in our research.

Some useful findings for the considered task of olive yield estimation by using neural networks can be obtained from the study by Kundid Vasić et al. [11] that looks at the possibility of applying YOLOv7 for identifying small fruits including olives in natural conditions. The study also shows that YOLOv7 is capable of recognizing olives from pictures taken in natural light and with a relatively small set of images, the precision and recall are quite impressive. Specifically, the study uses a two-class labeling system to improve the model's ability to learn from images where olives are not clearly distinguishable or may be mixed with vegetation. Although our model depends on the mask annotations for image segmentation instead of object detection, the results obtained by Kundid Vasic et al. can be considered as relevant. Their approach's performance in detecting and discriminating small and partially occluded agriculture objects exemplify the applicability of advanced neural networks in the estimation of fruit yield, which is the premise of this dissertation.

Thanks to the recent developments in image processing and CNNs, the applicability of the two has extended to agriculture; for instance, Ponce et al. [12] implemented the classification of olive fruits. It is their work that offers high accuracy in the classification of olive-fruit variety and thus contributes to the understanding of the role of AI in the improvement of agriculture production. In this regard, this thesis uses convolutional neural networks in image analysis, similar to Ponce et al. (2019); nonetheless, the work of this thesis also encompasses the estimation of olive yield through image segmentation. The methods of image preprocessing and neural network training employed in their work served as the basis for the methodology employed here, which also depended on high quality image data and efficient image processing to ensure that the model's predictions were accurate.

Even though our approach is based on segmentation, the work [13] by Ahmad Aljaafreh et al. is related to the application of AI in agriculture, but uses object detection. This is important because both the methodologies focus on increasing the effectiveness and precision in the observation and management of agriculture. The study by Aljaafreh et al. reveals that YOLO models' application in real-time detection of olives is efficient, a testament to the usefulness of AI in solving practical problems in agriculture, including real-time analysis and automation. Despite the fact that the systems described in the papers are designed for object detection, the operational principles and the results obtained can be helpful for our project, which also relies on the use of AI for optimization but with the help of another approach. This is where one of the most important lessons learned from their work comes in, which concerns the ways they tackle the problems that are quite relevant to our work, such as the management of occlusions due to leaves and branches, as well as the issue of varying light conditions in natural environments. Their approach to data enhancement techniques and the steps they have taken for data labeling of the dataset is also quite insightful. Therefore, with the help of the same approaches we can improve the data gathering and the training of our segmentation models to make them more suitable for real field conditions. Also, their analysis of the integration of YOLO models into a robotic system for automated harvesting raises similar issues of real-time application of AI at the edge fitting well with our thesis on edge AI. Nevertheless, the particularities of the AI models and their uses are not the same, the issues and the possible approaches in the application of such technologies in the open environment settings are similar. Thus, although Aljaafreh et al.'s paper employs a different AI approach, the general possibilities, issues, and their solutions are relevant to this work as well. From their approach to the dataset management, model training, and real-time processing, we get the following useful foundation, which is going to help in the objectives of this research on olive yield estimation. This work also shows how some of the field-specific AI issues can be addressed and solved and the solutions can be applied to segmentation tasks as well.

In the following study done by Arturo et al. [14], images were captured in a Picual olive orchard located in Spain, using a DSLR camera for high resolution images. The use of nighttime photography with halogen spotlight is to avoid disturbing daily activities and to improve the quality of the images for analysis. Their approach includes image preprocessing to enhance image quality and constraint the search space. The olive fruits are identified using a CNN which determines whether sub-images contain an olive in their center. The process is carried out using the MATLAB platform and tools for image processing and deep learning. Images are converted into the LAB color space to facilitate a detailed analysis of luminance and color channels. Initial locations of olives or 'seeds' are determined using mathematical morphology and then only areas that have maximum reflection of light presumed to be olives are considered. In the following, the paper presents the details of the OLIVEnet dataset including the training and validation images. These architectures include CNN architectures like AlexNet, VGGNet, and Inception, which are trained using this dataset with information on their configurations and performance. The CNN that performed well in this work was the Inception-ResNetV2 which was able to accurately detect the olive fruits with high precision and recall. Opportunities and challenges of other CNN architectures are presented and compared with the proposed method for olive fruit identification.

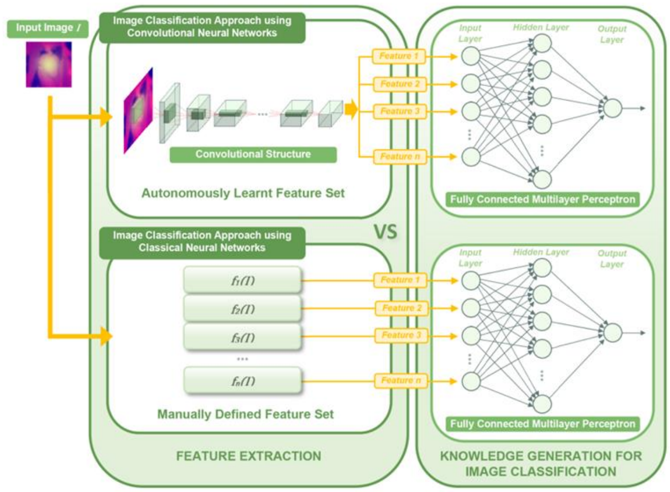

Figure 4 Architecture employed by Arturo et al.[13]

In the similar context, Figorilli et al. [15] present the work that uses CNNs with RGB imaging to categorize the olives for quality to enhance the production of extra virgin olive oil (EVOO). Thus, this research is crucial for illustrating how AI can be incorporated into the current agricultural processes to enhance productivity and quality of products. The approach used in this work incorporates the use of a conveyor belt system fitted with an RGB camera to take images of olives which are thereafter fed through a CNN model to classify the olives based on discernable features that relate to quality. The work's conclusions demonstrate the model's high efficiency in classification problems, thus, its applicability in industrial practices as a tool for manual sorting processes enhancement or replacement. This paper acts as a good starting point for future research in the area of using image processing and machine learning in agriculture especially in the area of quality control in agricultural products. Having completed our study, it is possible to apply the findings of this paper to the improvement of the olive crop quality from our yield estimation.

In similar vein on the subject of computer vision on olives, the study by Aquino et al. [16], proposes a new and unique approach of estimating the olive yield using machine learning and computer vision. While the existing studies mostly use meteorological-related indicators for yield prediction, this paper offers the way to analyze the data from orthographic images of olive trees with no reference to indirect variables as yield estimates.

Entire methodology relies on the neural network trained by several descriptors computed from the images; the count of the visible fruits, the area of the spilled fruit, dispersion and aggregation metrics. It is important to note that these descriptors are designed to imitate the perceptual analysis that an investigatory or a field expert is expected to perform. The same is proved using actual data of a super-intensive olive orchard to ensure that it works without significant yield overestimation margin of 2.64%. Understanding the application of advanced image processing techniques alongside neural network in predicting yield are invaluable knowledge pointers to my thesis that outlines the application of image segmentation in estimating yield on the edges of olive trees. While the present study's examination of fruit features and the subsequent inclusion of these findings into the model are useful, several similarities can be drawn between it and the segmentation strategies used in my work. Another related work presented in the paper [17] is quite novel. This research by Beyaz et al. uses digital images with 7200 dpi resolution and ANN check lists the Spanish olive cultivars with an asserted efficacy of 90% between the seven types. By means of LabVIEW Vision Assistant v2013 and the subsequent ImageJ software, the research team was able to capture the images in accordance with the physical measurements of olives and olive stones from both groups. This method is characterized by non-interference with samples and lack of necessity to segment samples manually to reveal traits for cultivars. These techniques are highly useful because they provide a faster and more practical solution compared to measurements involving genetics and manual labor, which may not work well outdoors. The methodologies and research findings of this paper help me to locate my thesis on estimation of olive yield based on image segmentation as it opens up the ways and horizon of using image processing in the agricultural field especially for increasing the sensitivity and specificity of olive based analysis. The use of ImageJ software for preprocessing dataset was influential in our research.

The paper [18], introduces a new and improved method in the segmentation of fruits and vegetables using mask R-CNN. In detail, it proposes a new strategy to enhance the edges of segmentation masks by using a score-based mask edge refinement algorithm. It is important in applications where high degree of accuracy in the identification of objects is necessary including the modern automatic checkouts in supermarkets and agricultural surveys. The authors employ a novel cosine similarity-based loss function to address this problem of missed details at the edges of objects which are typical with other segmentation models. Despite the fact that both projects are designed for segmenting agricultural objects, our approach is aimed at olive yield estimation, which can be considered as more specific compared to the wide range of fruits and vegetables analyzed in the paper. Also, we are going to focus on the applicability of our approach on the edge devices, which are often not connected to the network and work in limited conditions, while the paper discussed does not have this focus. Nevertheless, the findings of the paper are very much related to the work that we are conducting. The enhancement of the edge accuracy in the segmentation maps can be vital when estimating yields of olives, because it is important to identify every single olive. Such methodological advancements such as the use of a score-based edge enhancement seen in the paper could be modified for use in our model to increase its accuracy. For instance, incorporating this similar scoring system into the loss function of our model can possibly improve the olive segmentation outcome. Also, the evaluation of the models in the paper through advanced metrics such as dice score and mean average precision (mAP) will prove to be useful for future comparisons and validations.

CHAPTER 3: METHODOLOGY

3.1 Data collection

The procedure of data gathering is an essential component for the development and testing of the proposed models. This section outlines the process of data collection of olive tree images, which are the primary objects of interest in this work.

3.1.1 Selection of Olive Orchards

The data collection process was preceded by identifying olive orchards in Barani Agricultural Research Institute in Chakwal which is the only area where olive cultivation is popularly practiced with the aid of government spending. This center is established by the Government of Pakistan to enhance the olive cultivation and production in the country and to carry out research in this regard. The orchards used in this study were selected using some criteria such as the type of olive trees, density, and ease of access for imaging. The team ensured that they sought for permission to conduct the data collection from the right authorities to avoid disturbing the farming activities. The data was collected in the month of October to match the fruit ripe season as demanded by the research. The species of olives used in the study were Gemlik, Gohar, and Leggino and all of them are indigenous species of the area.

3.1.2 Imaging Equipment

The photographs were taken from a single phone camera, Samsung galaxy Note 5, to create a dataset that is as close to real life scenario as possible. The images were taken during day time on very sunny day to ensure adequate lighting. However, in a day light scenario, the images taken from under the tree have less illumination whereas the images taken adjacent to trees have high illumination. Through this approach we are hoping for a diverse dataset, capable of all lighting conditions on any particular day. Each image captured has a resolution high enough to clearly distinguish individual olives on the branches, which is crucial for effective segmentation later in the study. A total of 900 images were collected from the three species. Figure 5

Figure 5 : Subset of the collected dataset

3.1.3 Image Annotation

All images were manually labelled to generate a standard set of images for training of the segmentation models. On a touch screen computer with a stylus, binary masks were then applied to the pictures. In these masks, the regions that correspond to olives were painted in white, the rest of the regions – in black. This detailed annotation step was useful in preparing the ground for the optimization of the U-Net architecture in identifying olives and non-olives in the image dataset.

The following subsection explains the detailed guidelines applied for the annotation to meet the standards in the dataset for the thesis. The annotations were done using a Lenovo stylus pen on a touchscreen Lenovo computer hence enabling the subject to be well drawn. The software chosen for this purpose was Fiji; this is an image processing package developed from the open source ImageJ software and which deals with binary masks and has basic features like drawing, erasing, zooming and saving. Before the annotation process, the stylus pen was set to achieve high precision and the researcher ensured to gain proper understanding with the software's features in order to enhance efficiency.

Each image was then imported into the annotation system and properly orientated as well as having the right dimensions. The images were then scaled down to a level where the olives can be seen without them being pixelated while at the same time being able to be seen in relation to the tree branches. The boundary of each olive was drawn with the stylus pen by connecting the points using smooth lines without interruptions. Next, the olive was drawn and the fill tool was employed to color the enclosed space white in order to depict the fruit. After the filling, another round of review was done by zooming out so that any olive that was partly visible in the image or at the edges was accurately captured. Each finished mask was stored in a lossless format like PNG so that the binary data of the mask is not altered.

To ensure quality and standardization of the annotations, every image mask that was completed was checked to ensure that no olives were missed and no markings were made outside the olive area. Peer review was also done where possible to have another trained annotator look at the masks and give their input, thus adding another level of confirmation. Lighting and visibility issues were also on the forefront as they are inevitable in real life situations. Shadows or overexposure of some areas posed some challenge in the identification to make sure that olives that were in such areas are well outlined.

3.2 Image processing

In this section, we focus on the images' preprocessing methods that are crucial for the required setup for applying the U-Net model. This is the most important step as it prepares the raw images and their corresponding masks for training of the neural network model.

The first stage of the data preprocessing involves the following steps: defining the size of the images, in this case, 768 x 768 for the images with three color channels. Connections for the training images and their masks are set up, so that each picture has its corresponding mask. The training images and masks are then read in from the directories for the training images and masks and stored in lists for the next steps.

The training images are next opened and each image file is stored in a NumPy array of type float32. This resizing does not distort the aspect ratio and color which is very essential for segmentation of the image. Likewise, the masks are also preprocessed with a coherent prepossessing methodology. Every mask is read, and data type of the mask is changed into Boolean to meet the requirement of binary format. The masks are reshaped to the size of the training images and reshaped to have an extra dimension, thus, the masks become grayscale images. This step is very important to ensure that the mask format is matching the model's expected input format.

Both the images and the masks are then subjected to patch extraction once the resizing is done. Thus, it splits each image and mask into non-overlapping patches of the size 256×256 using patchify tool. It also helps in the management of the large images as well as the training process since it tackles parts of the images at a time which could be easier for the neural network to work with. This follows the model input dimensions, and downsizing is very important for the edge application.

By doing these preprocessing steps the raw images and its corresponding masks are then converted to a set of prepared data. This dataset is then prepared for the subsequent model training, validation, and deployment where accurate estimation of olive yield using image segmentation models is the main goal. Thus, this approach provides that data to be fed to the neural network is well arranged in a manner that enhances the effectiveness of the model in real-world problems. However, there is one more important step that has to be conducted before the data can be fed to the model and that is to preprocess the images one more time to a format that is suitable for feeding to the model. This step is very vital because it plays a significant role in determining the final results of the model. In the subsequent Section, we describe in detail certain properties of the model like the backbone, the pre-trained weights etc., which is why the discussed preprocessing is relevant. Each of the image matrices that this float32 value is a part of should be changed to match the pre-trained values of the weight matrix. For this preprocessing, we employed a very convenient function from the segmentation model library. Once the data has been pre-processed it is then piped into the deep learning training pipeline.

3.3 Implementation of U-Net Architecture

The U-Net is a CNN based algorithm proposed mainly for the segmentation of biomedical images. The method was presented in the paper of Olaf Ronneberger, Philipp Fischer, and Thomas Brox [19]. The architecture stands out because it requires few training images and provides correct segmentations.

Architectural Overview

U-Net is a type of encoder-decoder network that has a unique architecture that resembles the letter U as evident from the name. The encoder (or contracting path) encodes contextual information of the image and the decoder (or expansive path) localizes the object using the transposed convolution to upscale the lower resolution features from the encoder to higher resolution layers.

Encoder

Encoder is formed by two layers of three by three convolutions, each of the layers followed by a ReLU activation and then a two by two max-pooling layer with a stride of two. At each down sampling step the number of feature channels is doubled.

Mathematically, each layer in the encoder can be represented as:

$$C_i = ReLU(W * C_{i-1} + b)$$

where C_i is the output from the i^{th} convolutional layer, W and b are the filter weights and biases of the convolutional layer respectively and * shows the convolution operation and ReLU is used for non-linear activation.

Decoder

For the decoder, each step consists of the transposed convolution of the feature map followed by a 2x2 up-convolution that halves the number of feature channels, a concatenation with the correspondingly cropped feature map from the encoder path, and two 3x3 convolutions, each followed by a ReLU. The cropping is necessary due to the loss of border pixels in every convolution.

If U_i represents the up-sampled output, the operation can be described as:

$$U_i = UpConv(C_i)$$

$$C_{i+1} = ReLU(W * Concat(U_i, C_{i-encoder}) + b)$$

Here, UpConv is the transposed convolution that is applied for upscaling and Concat is the concatenation of the upsampled output with the encoder's feature map giving high resolution features.

Skip Connections

Skip connections are also incorporated in U-Net where the output of encoder layers is connected to the same decoder layers. These connections offer basic high resolution details to the decoder, which is very useful for accurate localization.

Final Layer

The last layer of the network consists of a convolutional layer with 1x1 filters and is used for feeding the feature vectors into the required number of classes. In binary segmentation cases, this would output two channels, which are then passed through a softmax layer to yield the probability of each class at each pixel:

$$S = Softmax(W * C_{final} + b)$$

where S is the segmented output, and C_{final} is the feature map from the final convolutional layer of the decoder.

Loss Function

The training of U-Net is usually done using a pixel-wise cross-entropy loss or a Dice coefficient loss. However, in our case we used the BCE Jaccard loss for its pixel level accuracy and performance on intersection over union. This loss function would be represented as

$$D(Y, \hat{Y}) = \frac{2\sum_{i=1}^{N} y_i \hat{y}_i}{\sum_{i=1}^{N} y_i^2 + \sum_{i=1}^{N} \hat{y}_i^2}$$

This architectural design and the custom configured elements of U-Net make it particularly adept for tasks where high localized precision is required and for our dataset with sparse binary masks, this works the best.

It must be noted here that U-Net architecture has several different variations, each designed for various purpose. What is described above is the basic U-Net architecture first proposed in the original paper, the others include Linknet, PSPNet, and FPN. These other models could be explored if the level of accuracy achieved by U-Net is subpar. In order to build U-Net architecture, we'll rely on a library called segmentation models that has pre-defined few of the starting parameters and we can change and update as we progress.

For the model to train our dataset, we need to define several parameters, namely, Backbone and Architecture. Backbone constitute the layers involved in the encoder and decoder part. As the number of layers' increase, the complexity of the model increases with it, and, the complexity is one-to-one related with the accuracy of the model. A complex model is able to learn more from the given dataset than a non-complex one, however, a complex model would end being hefty in size. For our final purpose, we need to deploy the model on a resource constraint device, therefore, we need to strike a combination between complexity and efficiency. We will choose EfficientNetb7 as the backbone of our model. It is dense model with 813 layers, making it fairly complex to train and run. This will give us the rough estimate of the accuracy and we would decrease the complexity as we move further. The goal, as stated previously, is to find the perfect balance between efficiency and accuracy. In order to decrease the complexity in favor of latency, we will utilize the previous versions namely EfficientNetb1 and EfficientNetb4, later being the more complex out of two.

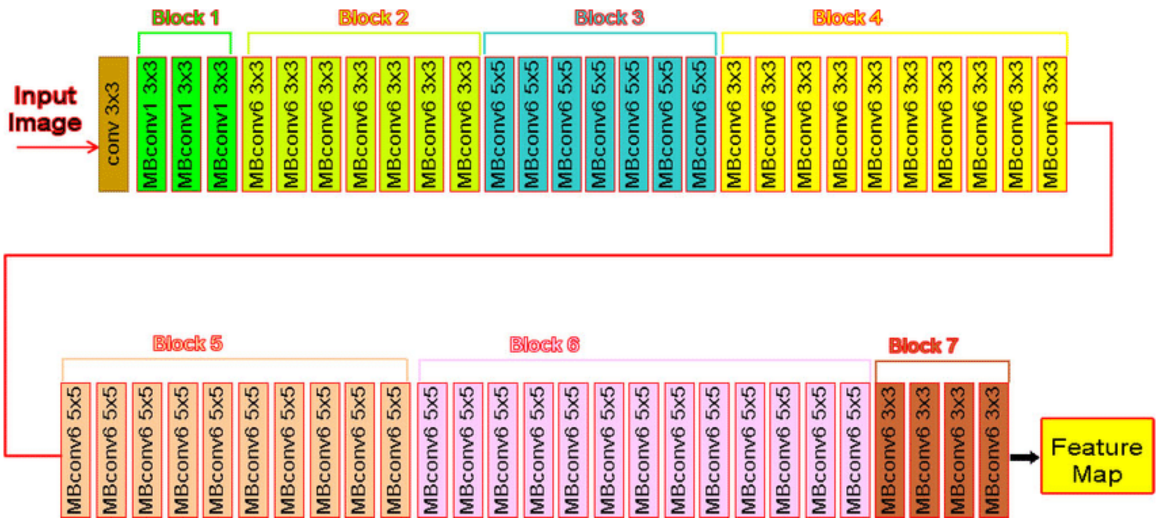

Figure 6 : EfficientNetb7 architecture

Architecture in this case refers to the kind of architecture we will use for segmentation. We will utilize the classic U-Net architecture with EfficientNetb7 layers. It must be noted that the model wouldn't be trained from scratch. Training such a complex model with a small dataset as ours would be meaningless, therefore, we will utilize transfer learning technique, where we use predefined weights for our backbone, trained on Imagenet dataset. We will freeze the encoder weights in order to not disturb the learned characteristics and will allow training of the decoder weights to adjust to our dataset.

3.4 Model training and Validation

There is one more thing that we have to do before we feed the data to be learned into the system which will help the model to generalize the features from training data much more efficiently. In order to enhance the training, set we will randomly transform the images in such a way that an image will not be the same in successive epochs.

This paper's dataset, as mentioned earlier, is the backbone of this research and comprises of over 900 high-quality images. These images show the different views of the olive trees with different light conditions to gather complete data set for model training. For each image the binary masks were generated: the olives are colored white and the background

– black. This segmentation helps the model to specifically identify the olives from the fruits as well as other objects in the background. But, as a result of the fact that there are natural fluctuations in the environment where olives are cultivated, it is essential to train the network with a dataset, which would resemble these fluctuations as much as possible. To this end, data augmentation was used to increase the sample size of the dataset used. These augmentations include rotation, translation, zooming, and horizontal flip. This augmentation increases the randomness of the data and is a good way to mimic varying angles of viewing and lighting of the images hence improving the performance of the model. The U-Net model applied in this work is enhanced through the integration of EfficientNetB7 as the main network architecture. The encoder network is initialized with the pre-trained weights from ImageNet which enhances the learning rate and performance of the network by applying transfer learning. This pre-training benefits the model in the following way: it allows the model to learn quickly the specifics of the task of olive segmentation through fine-tuning the pre-trained network with our dataset.

The training process started with the initialization of the encoder component of the U-net with EfficientNetB7 pre-trained weights. The decoder was initiated randomly and fine-tuned to learn for the purpose of segmenting only the olives. The training process incorporated a set of loss functions, the main loss function used dice coefficient, while the intersection over union (IoU) was used for the validation. Adam's optimizer was implemented as it has adaptive learning rate and generally converge faster during the training process. The initial learning rate was set to 0.001, with a decay strategy that decreases the learning rate by a factor of 0.1 at the point when the validation loss did not decrease anymore. In this regard, the intersection of the union of the model's predicted output and the ground truth output was used as the evaluation metric - namely Jaccard index.

This metric calculates the similarity of the predicted segmentation mask with respect to the ground truth, giving a numerical indication of the model's performance. The IoU score is a measure that shows the precision and accuracy of the model in segmenting the olive fruits; the higher the score, the better the segmenting is done. The model was trained and validated in several rounds to adjust the parameters and improve the model's efficiency.

To check the model's ability to perform well on new data that it has not seen during training, the validation set was used which was a different set from the training set. Once the training was done on the EfficientNetB7 model, we started training the less complex model, owing to the fact that we need to find the right balance between accuracy and complexity (which in turn governs the latency of the model). The two other backbones chosen for this purpose were EfficientNetB4 and EfficientNetB1. Both these backbones drop their level of complexity in favor of computational speed. These models contain 474 and 242 layers respectively.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Evaluation Metrics

In this section, the metrics that were used to evaluate the performance of the developed image segmentation model are described since the model is crucial for proper olive production estimation. For our analysis, we utilized two main metrics: namely Dice Score and mean Average Precision (mAP). These metrics were chosen to ensure that the efficiency of our segmentation model was assessed in its entirety, and that the model's effectiveness is credible in practical environments.

Dice Score:

The Dice Score is used to calculate the similarity between the predicted segmentation masks and ground truth labels. It is most useful for data sets with imbalance in class sizes. Given that ours is a sparse dataset, where each image represented by either 1 for mask or 0 for not, has high number of 0 pixels and very low number of 1 pixels. This makes each image an imbalance dataset such that each pixel is a data in each image. The dice score falls between 0 and 1 and the higher the score the closer the predicted labels are to the actual labels. This way, the coefficient can reflect the interrelation between precision and recall and becomes a suitable measure for the assessment of segmentation's quality in cases when the distinctions between objects (olive fruits) are not that clear.

The Dice Score is defined mathematically as:

$$Dice\ Score = \frac{2 \times |A \cap B|}{|A| + |B|}$$

where A represents the pixels of the predicted segmentation and B the pixels of the ground truth.

Mean Average Precision (mAP):

Average Precision (mAP) is another all-encompassing measure of the accuracy of object detectors and segmentation models at various levels of Intersection over Union (IoU). Since we are dealing with the single class segmentation, mAP gives a single measure that reflects precision and recall of the model at all levels from the most lenient to the strictest. This metric is vital in the evaluation of the model's capability to identify olives under different conditions and sizes.

The calculation of mAP involves:

1. Specifying the set of the IoU thresholds for the precision-recall trade-off analysis.

2. Computing Precision and Recall — for each IoU threshold, to calculate the ratio of true positive to the total positive, i.e., the ratio of correct identification of olive region to the total region identified by the model (Precision) and the ratio of true positive to the total positive in the actual image (Recall).

3. Voting in the form of Averaging of Precision — calculates the precision for each threshold and then takes the average of these to provide the mAP.

Thus, we use Dice Score and mAP to evaluate the overall pixel classification and the model's capacity to correctly segment olive fruits from the background in different situations. The combination of the two strategies enables us to validate the model's efficacy and preparedness for implementation in actual environments, thus creating a sound basis for accurate yield prediction. Collectively, these metrics give a more comprehensive picture of the model's effectiveness when dealing with actual images of agricultural fields.

4.2 Results of Image Segmentation

Model	**Dice score**	**mAP**
EfficientNetb1	0.78	0.79
EfficientNetb4	0.85	0.93
EffecientNetb7	0.80	0.91

Table 1 Segmentation results for three architectures

B1 scored 0.78 on the dice score, and b7 the biggest model scored 0.80 on the dice score, however, surprisingly b4 the middle ground was able to score the highest on the benchmark at 0.85, the trend continues for the mAP values as well where the best performing model was once again EfficientNetb4 with a mAP value of 0.93, followed by EfficientNetb7 with 0.91, not a huge difference only slightly lower than the best performing model, and EfficientNetb1 scored 0.79, a significant reduction in the value outlining a bad model performance. Even though scores do not differ much between EfficientNetb7 and EfficientNetb4, the fact that b4 is a significantly smaller model with vast computational efficiency than the b7 model, this score is rather surprising. Remember that we didn’t have a huge dataset to begin with in the first place, and these models have performed significantly better than expected. This surprising score might owe its existence to the fact that the model that didn’t have too many layers in its deep network was able to generalize the patterns better than the model that had too many layers causing it to overfit on the training data, hence, when exposed to test data, the performance reduced. A point can be made then about the significantly worse performance of b1 model despite having even smaller number of layers than b4, such that it should have generalized even better than b4, however, given the small dataset an even smaller number of layers cost accuracy. EfficientNetb4 hit the sweet spot of not overfitting and not underfitting either. For a very large dataset, EfficientNetb7 might have performed better than b4 since that much data needs a substantial amount of layers in the network to learn, and at that point complexity becomes directly proportional to accuracy of the model.

Images below show the results of three models. For each row, left most image refers to the actual image taken in the field, middle is the ground truth (manually created mask), whereas the right most is the actual image greyed overlaid with ground truth (in blue) and prediction of the model (in red). The images shown here form a part of the test dataset, that comprises of images with vastly varying lighting conditions, number of olives and the specie of olives. The accuracy of models across all these variable conditions is a testament to excellent learned patterns from the dataset. As previously mentioned, the variability in the dataset (as little bias as possible) allowed for such results.

4.2.1 EfficientNetb1

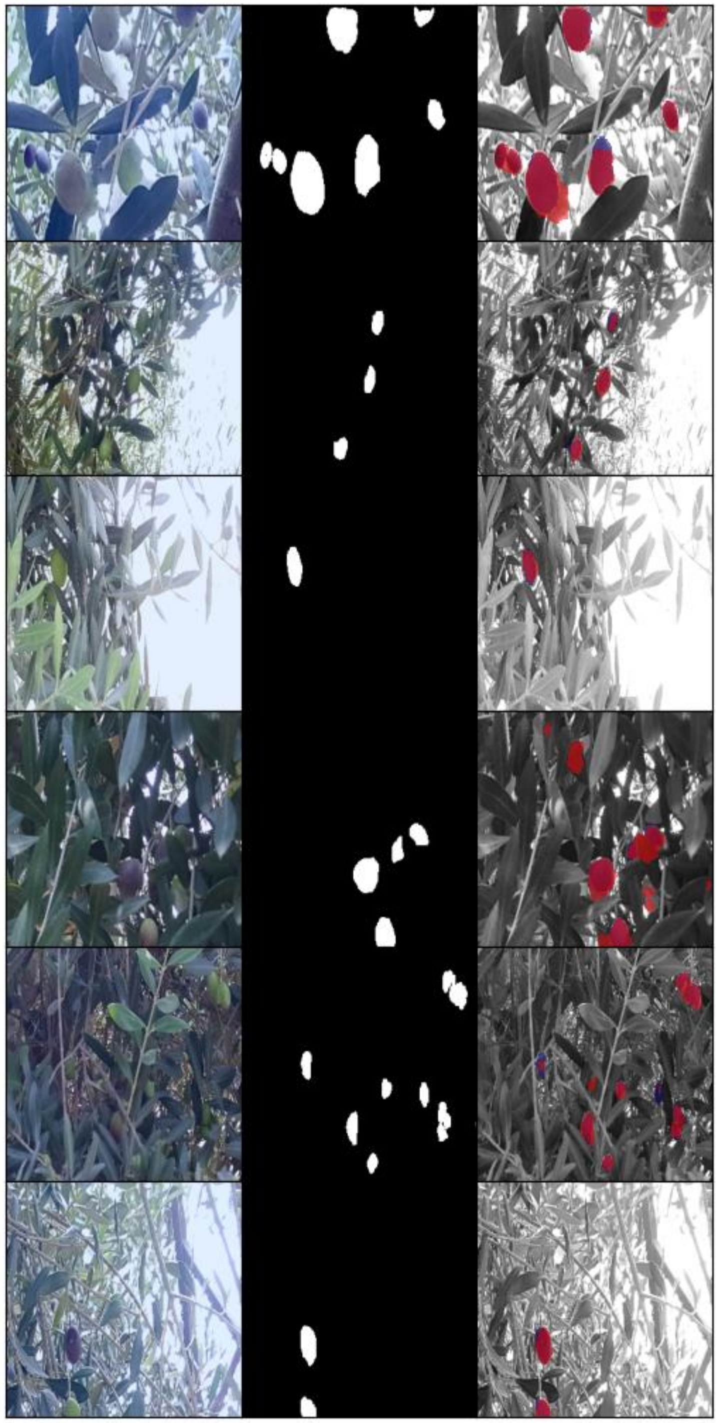

Figure 7 Original image(left), ground truth(middle), prediction overlaid(right)

4.2.2 EfficientNetb4

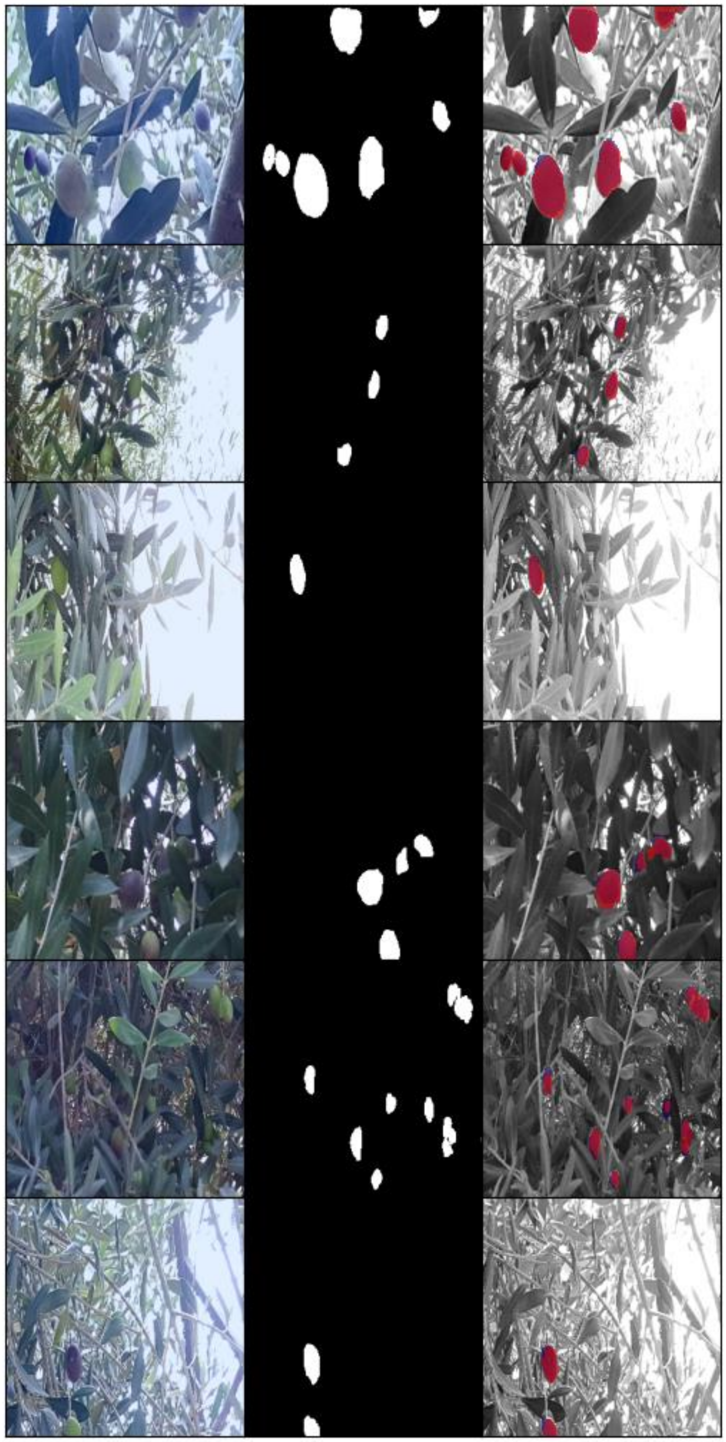

Figure 8 Original image(left), ground truth(middle), prediction overlaid(right)

4.2.3 EfficienetNetb7

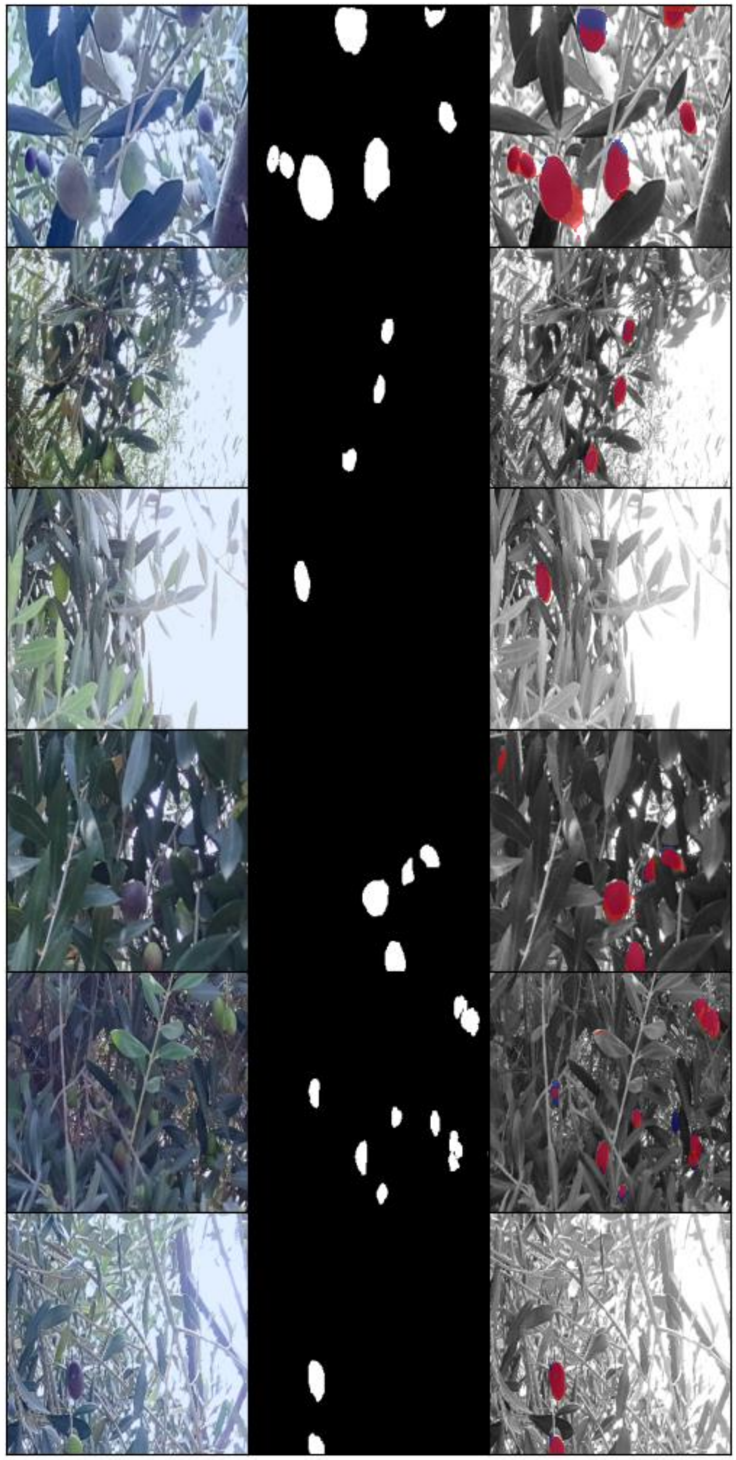

Figure 9 Original image(left), ground truth(middle), prediction overlaid(right)

4.3 Analysis of Model Performance

All three models performed fairly well and offer an opportunity to be deployed in the field. However, given the fact that EfficientNetb4 performed the best and is not the most complex model out of all these clearly suggest the way forward. A lot comes down to the metrics on which these performances were measured. From the segmentation results we can see that there isn’t too much difference between the all three models visually. However, visually we miss many nuance segments of the output. The dice score offers a generalized evaluation for the whole segmentation and includes every pixel result. As we can see, there isn’t a significant difference in the dice score metrics. That is because the dice score doesn’t really penalize the false positives or the false negatives. In terms of overall segmentation, dice result shows that models have learned fairly well, and are segmenting relatively closely, meaning nothing seems to be too far off. Therefore, a more penalty driven metric such as mAP was required. This way we can penalize the false positives a lot better. EfficientNetb1 performed drastically worse on mAP score, because of the fact that although it segments true positives fairly well, it also has a tendency to include false negative. It’s this false positive that the mAP penalizes severely. This trend follows in the all three models. The mAP score reduces drastically for a false positive, however, if the model has predicted a true positive such that the boundaries are a little lose, meaning that the size of olive might be slightly bigger in prediction than the actual olive, the mAP doesn’t penalize as severely. However, this error in the output can be fixed with erosion and dilation. Erosion refers to the shrinking of the predicted result, where the shrinkage depends upon the size of the kernel. Dilation, therefore, refers to the opposite of the erosion and works to expand the predicted olives’ boundaries. These are common computer vision techniques and have been used in many industries over the years. For our case, we used a combination of erosion and dilation, with the kernel size of 4x4 which gave us the best result.

At this point, we must highlight an excellent performance example from our best performing model, where the model performed better than the manual annotator. During our testing with the model using the test dataset, we came upon an example image where the ground truth for that image missed two instances of olives in that image. A mistake on part of the annotator, however, the model was perfectly able to segment those un-annotated olives. At first it looked like a bad prediction, however, careful examination revealed that it in fact was anything but a bad example.

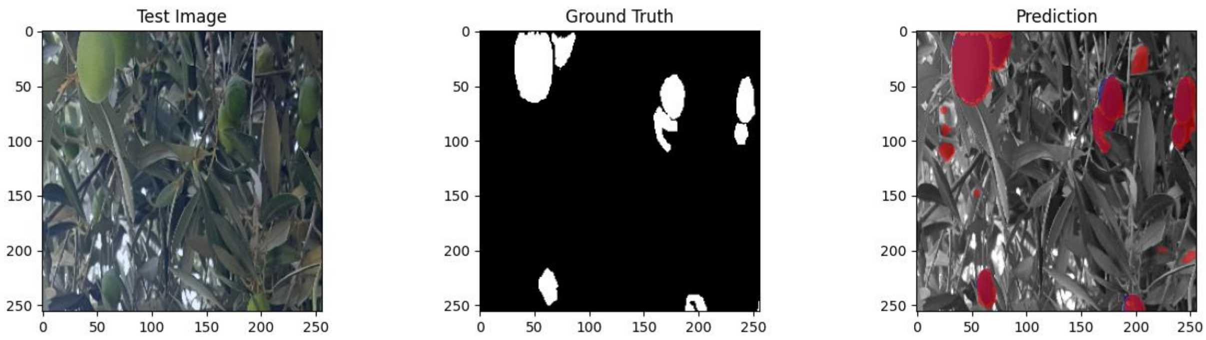

Figure 10 Model predicted three true positives not originally in ground truth

The extra red marks on the right most image, are the olives that the model predicted accurately, which were not present in the ground truth.

Similarly, there are examples where the model performed worse than expected. An example of such performance is:

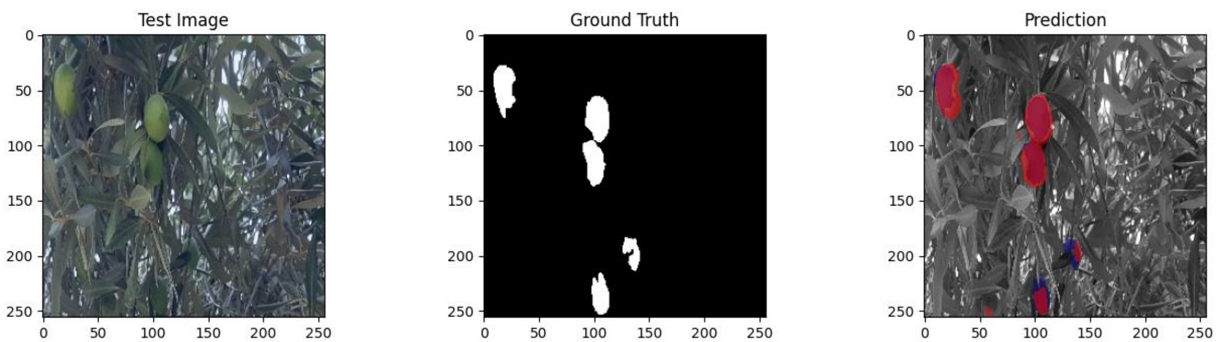

Figure 11 Example where model performed bad

In this case, the boundaries of the olives are way off. In three instances the boundaries are significantly larger than ground truth, creating false positive, however, related to the same true positive olive. And on two instances the model was too strict in its prediction of olives, creating false negatives. One instance of actual false positive is observed in the bottom. This is a complex image, where each olive is obstructed by either leaves or branches. In case of the branch the model offered a conservative prediction, however, for the clearly visible olives, the boundaries blend in to environment around it in such a way that the model couldn’t really predict the ending of the olive and the beginning of the leaves accurately.

4.4 Deployment on Edge device

Once the model was trained, it was deployed on the edge device. The edge device chosen for this thesis was NVIDIA Jetson Nano, due to its cheaper price factor. We wanted a device that scalable in terms of cost efficiency, meanwhile not being too conservative on computational efficacy. Jetson Nano is equipped with 4GB of GPU storage, plenty for our model. We were able to get an output of 20 fps with our largest model, EfficientNetb7, deployed. In order to deploy the model on to the edge device, it was necessary to convert it to its resource constraint variant tensorflowlite. This way the original model that was over 350Mbs in size, was brought down to 50Mbs. The Jetson Nano is equipped with 64GB of storage, therefore, no issues were observed in storing the model. The edge deployed solution was tested on a stream of test images. The reason for that is the timing of olive cultivation. Around the time of writing, field testing of olive detection using our method was not possible, owing to cultivation season.

CHAPTER 5: CONCLUSIONS AND FUTURE RECOMMENDATION

This thesis has successfully shown the application of image segmentation through the use of the U-Net architecture for estimating olive yield while running the application on edge devices. The process of creating a dataset of olives' images with the use of manual labeling was crucial for the training of our model. This specific approach, segmentation, was better suited to differentiate the instances of the olive fruits due to the complexity of natural orchard scenes. By comparing with the ground truth using dice score and mean average precision (mAP), it proved the reliability and precision of this model, which provided a possibility for the application of improving the traditional agricultural work by decreasing the workload and enhancing the working efficiency. This further proved the application of this technology in edge devices through real time processing of data with less need for data transfer, hence efficient use of computational resources and data management costs. The developments highlighted in this paper indicate that there is a general move towards better and efficient use of resources in the production of olive, which may result in better yields and profits among farmers.

The bad examples, such as the one discussed above, can be fixed with either a larger dataset than the existing one, or an even complex model with more layers. However, given the fact that we observed diminishing returns for the complex model, it can be suggested that a larger, more comprehensive dataset is required. The obstruction examples can be fixed with a kind of dataset examples where olive images are taken zoomed into single olives being obstructed by leaves or branches. This way a dataset of variable zoom level can constructed and the model would have a relatively easier time guessing the size and physical boundary of obstructed olives. For the EfficientNetb7 model, experimentations can be done on the hyperparameters with adjustable learning rate and batch size. Implementing regularization methods might improve the accuracy of EfficientNetb7 even further and help reduce the overfitting that we experienced.

It is possible to connect the given segmentation model with other IoT devices in the orchard, which include the moisture level sensors in the soil and climate monitoring tools.

There is a possibility that if the two are integrated then a more integrated approach to the management of orchards in terms of yield estimation and resource allocation could be implemented.

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