Faculty of Electronics & Computer Technology and Engineering

An Automatic Fish Counting System Based on Machine Vision in Aquaculture Technology

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An Automatic Fish Counting System Based on Machine Vision in Aquaculture Technology

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in partial fulfillment of the requirements for the degree of
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DEDICATION

I would to dedicate to my beloved father, mother, sister and little sister. Also, I would like to thanks to all my friends that had been with me all the time.

ABSTRACT

The Automatic fish counting system is a fish population that monitor in aquatic areas that automated by using a technology method. This system can identify and count various fish species precisely and effectively by utilizing the advance technologies including computer vision. The creation of an automated fish counting system based on machine vision in aquaculture technology has the potential to revolutionize fish farming methods by offering an accurate and efficient method for fish population monitoring. This system typically consists of a camera that have placed in a specific area to record the fish that pass through. However, the issues involved in fish counting in aquaculture may not all be fully addressed by the fish counting techniques now in use. The traditional manual fish counting methods are time-consuming, labor-intensive, and prone to human error, making them ineffective in large-scale or real-time applications. Thus, the main purpose of this project is to evaluate the performance of the fish counting platform accuracy using a statistical approach. Furthermore, this work is to design a fish counting system based on a computer vision platform that determine the fish grading and quality. The automated technology offers a more accurate and efficient solution for aquaculture farms, allowing for the accurate and rapid measurement of fish populations. A system of this type would assist a wide range of stakeholders, including fisheries managers, aquaculture operators, environmental researchers, and conservationists, by allowing them to make accurate decisions and implement effective strategies based on precise fish population data.

ABSTRAK

Sistem pengiraan ikan automatik ialah populasi ikan yang memantau di kawasan akuatik yang diautomasikan dengan menggunakan kaedah teknologi. Sistem ini boleh mengenal pasti dan mengira pelbagai spesies ikan dengan tepat dan berkesan dengan menggunakan teknologi termaju termasuk penglihatan komputer. Penciptaan sistem pengiraan ikan automatik berdasarkan penglihatan mesin dalam teknologi akuakultur berpotensi merevolusikan kaedah penternakan ikan dengan menawarkan kaedah yang tepat dan cekap untuk pemantauan populasi ikan. Sistem ini biasanya terdiri daripada kamera yang telah diletakkan di kawasan tertentu untuk merakam ikan yang melaluinya. Walau bagaimanapun, isu-isu yang terlibat dalam pengiraan ikan dalam akuakultur mungkin tidak semua dapat ditangani sepenuhnya oleh teknik pengiraan ikan yang kini digunakan. Kaedah pengiraan ikan manual tradisional memakan masa, intensif buruh, dan terdedah kepada kesilapan manusia, menjadikannya tidak berkesan dalam aplikasi berskala besar atau masa nyata. Oleh itu, tujuan utama projek ini adalah untuk menilai prestasi ketepatan platform mengira ikan menggunakan pendekatan statistik. Tambahan pula, kerja ini adalah untuk mereka bentuk sistem pengiraan ikan berdasarkan platform penglihatan komputer yang menentukan penggredan dan kualiti ikan. Teknologi automatik menawarkan penyelesaian yang lebih tepat dan cekap untuk ladang akuakultur, membolehkan pengukuran populasi ikan yang tepat dan pantas. Sistem jenis ini akan membantu pelbagai pihak berkepentingan, termasuk pengurus perikanan, pengendali akuakultur, penyelidik alam sekitar dan pemuliharaan, dengan membenarkan mereka membuat keputusan yang tepat dan melaksanakan strategi yang berkesan berdasarkan data populasi ikan yang tepat.

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CHAPTER 1

INTRODUCTION

1.1 Background

The creation of an automated fish counting system is based on machine vision in aquaculture technology it has the potential to revolutionize fish farming methods by offering an accurate and efficient method for fish population monitoring. In order to assess the accuracy, dependability, and practicability of the automatic fish counting system, this project will also incorporate field trials and validation of the method in actual aquaculture settings.

The project background will include a thorough evaluation of existing literature, research, and technologies related to fish counting and machine vision in aquaculture. This will include an evaluation of several image processing approaches, machine learning algorithms, and hardware components for fish counting. The research will also include field trials and validation of the automatic fish counting system in real-world aquaculture settings to assess its accuracy, reliability, and practicability.

1.2 Addressing Global Aquaculture

Figure 1.1 Global Aquaculture of fish farming

The practice of raising fish, crustaceans, mollusks, and other aquatic animals in controlled habitats for food, entertainment, and conservation is known as aquaculture, also referred to as fish farming. The increased demand for seafood has been addressed, and pressure on wild fish stocks has been reduced. Aquaculture has the potential to improve economic growth and food security, but it also faces a number of global issues that need attention. This is where the tracking and counting is important for this project. By Monitoring fish populations is necessary to preserve their viability and stop overfishing. Fisheries managers can set catch limits, enforce fishing laws, and create sustainable fishing techniques to conserve fish stocks and their ecosystems by using accurate tracking and counting of fish populations. This ensures that fish populations don't become so low that they can no longer replenish themselves and that present and future generations may continue to rely on them for food and a living.

1.3 Problem Statement

Figure 1.2: A traditional method is to manually count different type of fish

The issues involved in fish counting in aquaculture may not all be fully addressed by the fish counting techniques now in use. To accomplish precise and effective fish counting in various aquaculture settings, an integrated system that integrates cutting-edge machine vision techniques, fish behavior analysis, and real-time data processing is required. Fish can vary in size, shape, and color, and there are also variances in lighting, water quality, and fish behavior, all of which make it difficult to count fish using machine vision. A crucial issue that needs to be solved is creating a reliable and also able to do fish counting system that can handle these difficulties. The modern method is different from the old technique in that acoustic surveys employ specialized sonar equipment to broadcast sound waves into the water and measure their reflections off fish and other objects. By analyzing the returning echoes, scientists can calculate the number of fish, their size distribution, and their behavior. However, in the traditional technique, they must physically count fish in aquaculture, which is time-consuming, labor-intensive, and prone to human mistake. Handling the fish may cause stress, compromising their health and growth.

1.4 Project Objective

The main purpose of this project is to create a dependable and accurate system that can use computer vision methods to count the number of fish in a specific setting or aquatic ecosystem. The goals are as follows in further detail:

a) To design a fish counting system based on a computer vision platform that determine the fish grading and quality.

b) To evaluate the performance of the fish counting platform accuracy using a statistical approach.

1.5 Scope Project

The scope of this project is as follow: -

I. Designing and constructing a hardware setup for fish counting in aquaculture tanks that includes cameras, light, and picture recording devices.

II. Evaluating the system’s accuracy, efficiency, and dependability in various aquaculture environments and under diverse conditions

III. Integrating the hardware configuration with the fish counting algorithm to create a fully automated system.

1.6 Contribution of the project

The automatic fish counting system can contribute in a various way such as the method eliminates the need for manual fish counting, which is time-consuming, labor-intensive, and prone to human mistake, by leveraging machine vision techniques and deep learning algorithms. The automated technology offers a more accurate and efficient solution for aquaculture farms, allowing for the accurate and rapid measurement of fish populations. Furthermore, the technology delivers up-to-date information on stock levels, growth rates, and general fish health by continuously capturing and analyzing fish photos. This real-time data collecting promotes better aquaculture management decision-making by enabling for timely interventions and adjustments as needed.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

In the current era of advanced technology, object counting relies on image processing to obtain a specific amount of analyze data or elements from images. Because it takes so long to manually count objects, it can cause eye fatigue and produce inaccurate results. There are many studies that have been done by also shows an automated fish counting that is feasible to maintain track of the fish and analyze their behavior under environmental circumstances for their growth.

2.1.1 Fish Marketing

Figure 2.1 : Fresh fish in local area in Malaysia

Table 2.1: The Export value and the quantities for Malaysia fish

YEAR	EXPORT VALUE (USD '000)	EXPORT QUANTITY (TONS)	PRICE PER KG (US$/KG)
2022	0	94,387	0.00
2021	256,160	112,007	2.29
2020	237,678	128,489	1.85
2019	237,832	87,099	2.73
2018	199,327	82,107	2.43
2017	181,150	76,857	2.36
2016	173,185	116,576	1.49
2015	175,573	84,655	2.07
2014	140,380	59,567	2.36
2013	131,397	61,689	2.13
2012	124,519	74,775	1.67

The aquaculture sector of Malaysia's economy is heavily dependent on the fish farming business. Malaysia has a thriving fish farming industry thanks to its vast water resources, pleasant temperature, and long coastline. The market largely concentrates on freshwater aquaculture, where a variety of species are raised in ponds and cages, including tilapia, catfish, and carp. These freshwater species serve the domestic market by supplying a consistent flow of reasonably priced, fish that is grown nearby.In addition to helping to provide food security, Malaysia's fish farming business is crucial to the nation's economy. It creates employment possibilities, particularly in rural areas, and supports the agricultural industry's general expansion. Fish farming also lessens the need for wild-caught fish, preserving natural fish populations and safeguarding marine habitats. Malaysia has a well-established fishing marketplace that offers to both domestic and international markets, which provides export opportunities. Malaysian fish and fisheries products, including prawns, tuna, and numerous species of fish, are sold to countries all over the world. The country benefits from its strategic location and worldwide market access.

To summarize is that the government's dedication to environmentally friendly aquaculture methods and ongoing technological breakthroughs are likely to fuel the industry's continued expansion. Fish farming in Malaysia will continue to play a vital role in addressing customer demand for locally produced and sustainable seafood while guaranteeing the long-term stability of the business.

2.2 Fish Farming

Figure 2.2: Red Tilapia Fish farming

The practice of raising fish and other aquatic organisms in cages, ponds, or other controlled conditions is known as fish farming, often known as aquaculture. Fish are kept in a controlled setting that resembles their natural habitat, providing them with optimal growth and reproductive circumstances. There are several fish species including the popular one such as salmon, tilapia, trout, and catfish, can be farmed. Depending on the species and the desired end product, farming practices might be different

Pond culture, in which fish are bred in enormous artificial ponds, is a typical practise in fish farming. These ponds are intended to preserve water quality and create favourable circumstances for fish growth. Another method is cage culture, in which fish are housed in floating cages or net pens in natural bodies of water such as lakes or coastal areas. This strategy allows for a more natural atmosphere while still maintaining some amount of control.

Overall, fish farming is an important industry that contributes to global food security, economic development, and sustainable resource management. It helps to conserve wild fish stocks by minimising reliance on fishing from natural environments.

2.3 Traditional Fish Counting system

Figure 2.3: Traditional method of fish traps and nets

The Traditional way to determine on the region and type of fish being calculated have difference type of method. which are Visual Counts that use a technique of a person stands in one place and counts the number of fish passing by visually. This is frequently done at a dam or a fish ladder when fish are forced into a small passage to make it easier to count them. Next is, the method of fish traps and nets that are useful for catching and counting fish. Fish are counted and then released back into the water after being caught in a trap or net that has been set up in a certain area.

2.3.1 Advantages and Disadvantages

The traditional fish counting system has both benefits and drawbacks. The first benefit is that the cost-effective may not require a sizable investment in technology or equipment and may be less expensive than modern technologies. The portable field can also be used in the field without the need for complicated equipment or a power source. Last but not least, the conventional fish counting system is quite simple and straightforward, making it simple to adopt.

The process takes too long, especially when there are a lot of fish to count, which is the primary disadvantage. The second is that current technologies, such as underwater cameras or a sensor, would not be able to provide as much information about fish populations as conventional approaches. Last but not least, the conventional approach may be intrusive since electro fishing or the use of nets may be intrusive and may harm fish populations, particularly if improperly carried out.

To put it briefly, the traditional fish counting methods have been in use for a while, more and more people are finding the accuracy and popularity of current technologies, such as automated counting methods and underwater cameras.

2.4 Modern Fish Counting

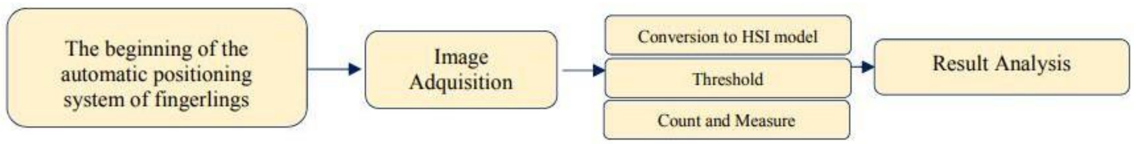


Figure 2.4: Block diagram from a modern method

Because of the recent advent of a modern fish counting technique, the way we monitor and estimate fish populations has undergone a radical change. Older methods of counting fish, such as hand visual surveys, required a long time and were frequently inaccurate. As a result of technological advancements and the application of cutting-edge scientific approaches, fish counting has improved in efficiency, accuracy, and non-intrusiveness.

The use of underwater cameras and image recognition software is one example of a modern technique to fish counting. Underwater cameras are deliberately positioned in bodies of water to capture high-resolution photographs or films of fish in their natural environment. This technology eliminates the need for human observers and generates a steady stream of data, allowing researchers to acquire reliable population estimates over time.

The use of acoustic telemetry is another novel technology. It entails attaching miniature acoustic transmitters that emit distinct signals to fish. Scientists can use this technique to study fish behavior, migration patterns, and population dynamics. It gives useful information on fish movements, habitat preferences, and population size without requiring direct observation or disturbance.

2.4.1 Fish Grading

The research from [22] on the grading fish is an important operation in the fishing industry. In this study, a method for automating fish grading based on multispectral photography is described. The photos were captured with a Multispectral Imaging System developed in-house. The accuracy of a convolution Neural Network (CNN) was reached. Furthermore, for comparison purposes, machine learning algorithms such as Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), and Support Vector Machine (SVM) were applied to the preprocessed dataset.

According to [22] is of worth since it contains a collection of multispectral photos from three distinct grades of tuna. This fish sample came from a well-known fish exporting firm. As a result, each grade and multiple samples were obtained using machine learning techniques. illustrates the number of samples gathered from each category, with quality decreasing as the grade. The acquired image was in.jpg file format, and each image was 1024x1280 in size. Meanwhile, figure 2.5 depicts the RGB image corresponding to each grade. Figure 2.6 shows the acquired multi spectral image of different spectral bands in nm 505, 740, and 850 for the same materials.

Figure 2.5: RGB image of each class

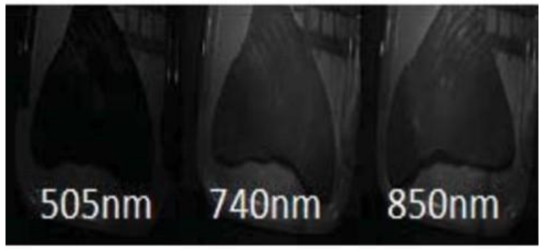


Figure 2.6: Multispectral image from different bands

2.4.2 Fish Growth Rate

According to [23], in order to get the desired result more accurately, the stocking density was modified to a very intensive (320 fish/decimal) aquaculture technique. Estimating the amount of feed required in terms of the percentage increase in size and weight at a certain growth stage in proportion to time (SGR) is critical. Because the initial and final weights are considered in the commonly used SGR calculation equation, the result is not precise enough to understand the growth of fish in the intermediate stages. As a result, the creation of a relationship between water quality parameters and fish growth at various stages in relation to intensive farming is likely to be effective.

The study's goal of this [23] was to examine tilapia development and production while estimating the specific growth rate (SGR) of tilapia with a focus on many intermediate sample phases. The experiment was carried out in tanks fed with sinking and floating feed in an intensive aquaculture system. Furthermore, by focusing on cultural techniques, this study aimed to quickly increase tilapia production. As a result, this approach of intensive fish culture will allow marginal fish farmers to produce a big volume of fish while still earning the predicted earnings from a small plot of land.

2.5 Counting Framework

2.5.1 Data pre-processing

The dataset of the research [5] that the 1200 images were created by intercepting seconds and deleting fuzzy and geographically situated comparable images from films. The photos are scaled to 800 600 to aid training. Furthermore, the training set, validation set, and test set are divided in the ratio of 6:2:2, with the original numbers being 720, 240, and 240, respectively. To boost the model's generalization ability, the training set size was increased from 720 to 3600 by adding salt-and-pepper noise, Gaussian noise, and performing vertical and horizontal flips.

As a result of the data augmentation, a total of 4080 photos are obtained, and the final numbers of training, validation, and test sets are 3600, 240, and 240, respectively. The dataset is categorized into three density classes based on fish counts: sparse (120), medium (120-200), and dense (>200). Following augmentation, the dataset contains 1258 images with sparse density, 1666 images with medium density, and 1156 images with dense density.

2.5.2 LFCNeT

According to [5] constructed based on density map regression, which can facilitate training a streamlined network structure. Fig. 2.7 shows the general structure of LFCNet. The whole model is divided into three parts: encoder, decoder and generation head. In Ghost module, the first number in each bracket represents the size of the convolution kernel and the second number represents the number of kernels. After the encoder, the decoder consists of three C3 modules and three transposed convolutional layers.

In C3 module, the first parameter is the convolution kernel size in C3 block, the second parameter is the number of kernels, and the third set of parameters is the dilated rate of C3 block. The first parameter in transposed convolution is the convolution kernel size, and the second parameter is the number of kernels. After three transposed convolution layers, the resolution of the generated density map is consistent with the input of the model. Finally, the generation head is connected to the decoder and the predicted density map is calculated via 1 ×1 convolution

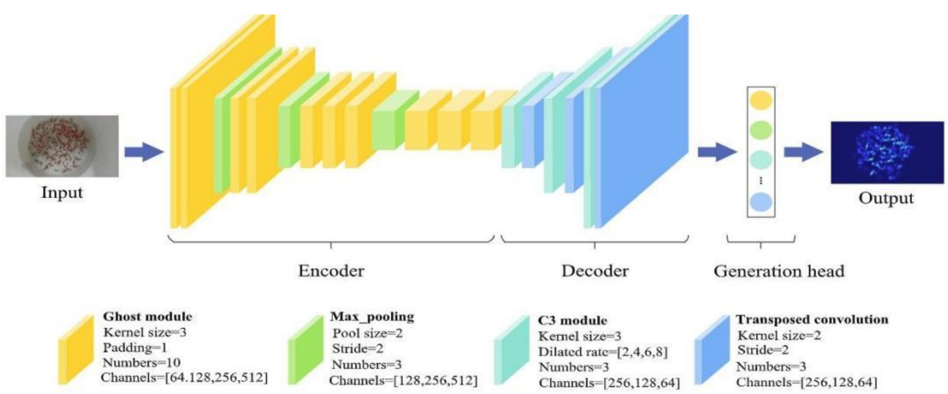


Figure 2.7 The structure of LFCNet.

2.5.2.2 The Encoder to extract fish features

The first ten convolutional layers and three pooling layers are chosen in this process as the encoder's fundamental architecture. However, as the number of layers increases, so does the computational effort. The Ghost module is a lightweight alternative to regular convolution, and its primary purpose is to compress the network while keeping the number of channels constant. As a result, the standard convolution layers are replaced with Ghost modules to build the encoder, which can ensure both accuracy and efficiency at a cheap cost.

2.5.2.3 The Decoder for improving the quality of density map

LFCNet's decoder recovers detailed data from the feature map using three C3 modules and three transposed convolution layers. In this method, the computational cost is decreased while the density map's quality is improved. The six dilated convolution layers are used in CSRNet to broaden the receptive field. However, the model with extensive use of dilated convolution is heavy for embedded devices and reduces efficiency at the inference stage. Furthermore, the dilated convolution has a gridding effect that can degrade performance.

This result of the efficient extraction of more detailed information by C3 modules and transposed convolutions. Figure 2.8 depicts the LFCNet and CSRNet counting results of the same samples in different settings. According to [5] that the first column contains four original fish photos from three different density levels, whereas the second, third, and fourth columns have the matching Ground truth, density maps generated by LFCNet and CSRNet, respectively. The genuine values and model-predicted values are shown in the upper left corner of the density map. Both models perform well in sparse and medium scenes, demonstrating the viability of density map regression-based methods for fish counting.

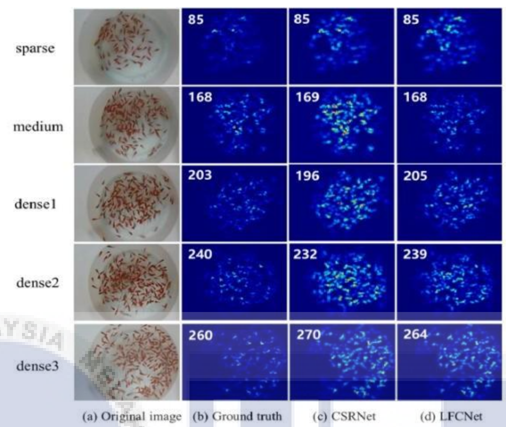


Figure 2.8 Visualization of counting results. The number in the upper left corner is the predicted value, LFCNet is closer to the Ground truth

2.6 Accuracy

Figure 2.9 the original shrimp images

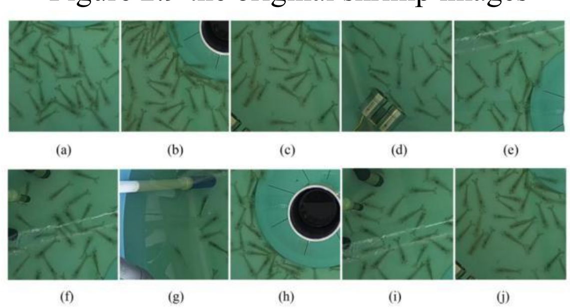


Figure 2.10 the difference shrimp image after extracting the region of interest

There have been numerous studies done on this problem before because it might be difficult to notice and count tiny sizes fish. The researcher of [10] study on the automatic shrimp counting method, the region of interest should be set to a region chosen from the image that is the focus of the image analysis and is circled for further processing because they indicated that the size of the shrimp images had a pixel resolution of 1600 × 1600. They can display the original shrimp image and the shrimp image after extracting the region of interest, respectively, by cropping to exclude the backdrop from the region of interest in the shrimp image.

The result of a local shrimp image counting is that the photos of local prawns in the test set, and it was assessed using a variety of evaluation indicators. The evaluation metric outcomes of the counting model for the test set are shown in figure 2.11. The suggested LightYOLOv4 from the researcher of [10] the local shrimp counting model was tested with a total of 5234 shrimp. 4931 and 422 prawns were correctly and improperly recognized, according to the data. P was 92.12%, R was 94.21%, F1 was 93.15%, and mAP was 93.16% in this instance. These evaluation indicators all show that the proposed meth is effective. When recall and precision both peaked at some time, precision began to rapidly decline. the average precision (AP) of the shrimp detection was 93.16%.

Based on the trained local prawn counting model, the test set detection results. Shrimp that was correctly detected are indicated in the figure by the yellow box, while those that were incorrectly detected are indicated by the red box, and those that were not detected are indicated by the purple box in the web version of the image. Several shrimps were accurately identified, whereas one shrimp that was moving quickly and had a physique that was unusual for a shrimp one with a skinny shape and hazy eyes.

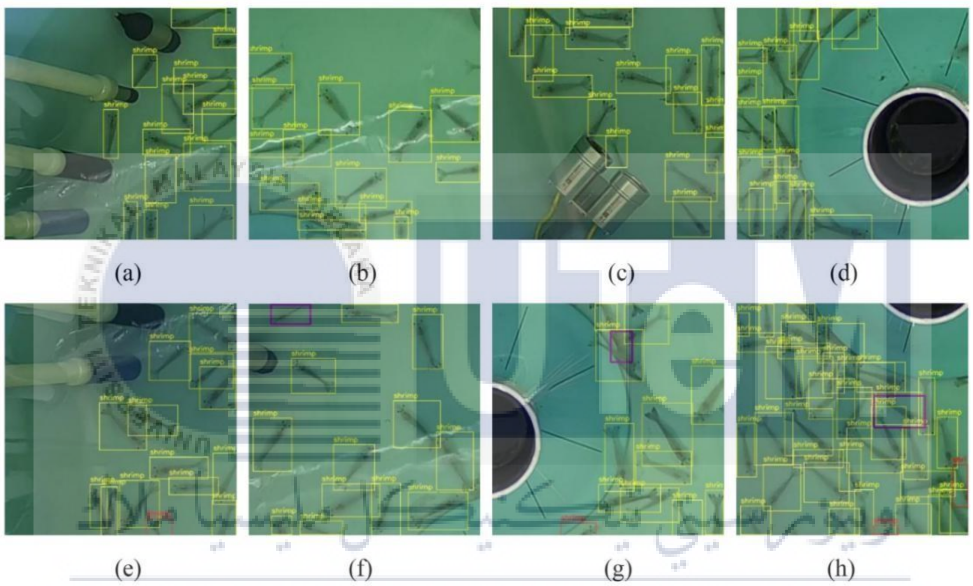


Figure 2.11 Local shrimp images (a)to(d) with correct detections and (e)to(h) having false or missing detections

2.7 Summary

To summaries the review of literature, a fish counting system is a technological instrument that counts and monitors fish populations in aquatic environments. Its primary purpose is to gather data for scientific research, fisheries management, and environmental monitoring. The system employs a variety of approaches and instruments to properly track and measure fish counts. Other ways include using video cameras or underwater sensors to identify and track fish movements. Some systems also use machine learning algorithms to analyze data and identify fish species. These systems help to preserve aquatic ecosystems, safeguard endangered species, and ensure the sustainable use of fish resources by providing accurate and timely data on fish populations.

CHAPTER 3

Methodology

3.1 Background Method

The overall approach and goals of the automatic fish counting system are highlighted in this technique. The flowchart, block diagram, and method used to per-process, fish detection, fish counting, data analysis, and results display will be covered in greater detail in this chapter's overview. The system uses computer vision and image processing skills to automate the counting process, eliminating the need for manual counting methods and minimizing human error.

3.2 Research Design

A quantitative research design is a method for gathering and interpreting numerical data in scientific studies that is systematic and organized. Its objective is to quantify, measure, and analyse phenomena, variables, and variable relationships. Thus, the quantitative technique is utilized to collect and analyse numerical data in order to test hypotheses, detect trends, and draw objective conclusions in this an automatic fish counting.

The experimental design focuses on the structure and organization of experiments to test hypotheses and evaluate the effectiveness of interventions or treatments. An experimental design in the context of the automatic fish counting based system project may include using appropriate statistical to compare the results of the experimental groups and determine if there are significant differences in fish counting accuracy or other performance metrics. The following step is to identify and control any other potential variables or confounding factors that may have an impact on the results. This could include regulating ambient circumstances, standardizing data gathering techniques, or using covariates in the study.

3.3 Research Flowchart

Flow charts are basic diagrams that outline a process so that it might be readily communicated to others. They can also be used to define and analysis a process, creating a step-by-step image of it before standardizing or improving it.

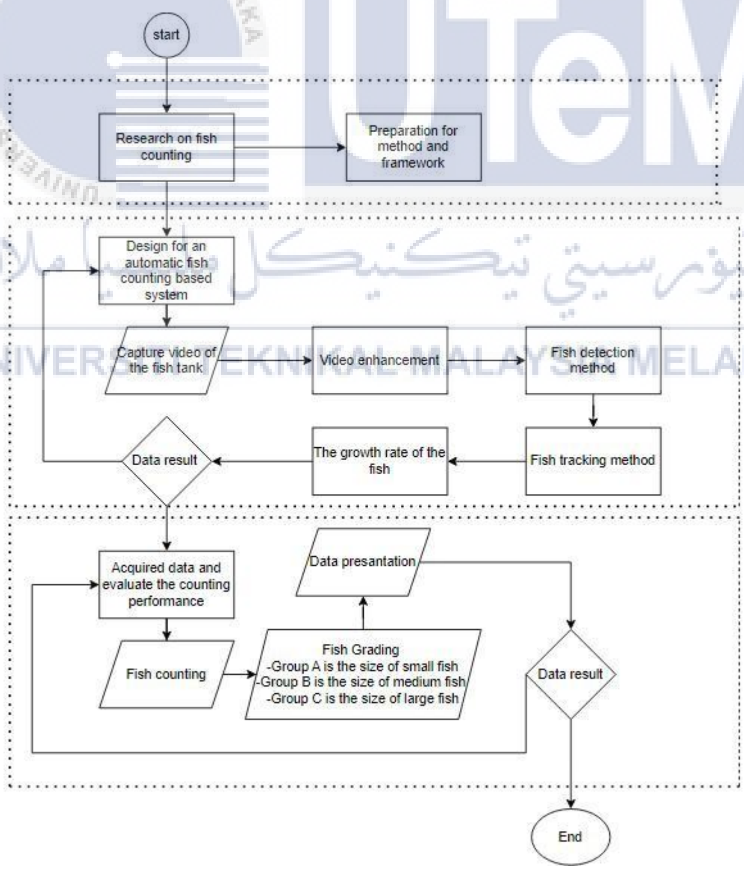


Figure 3.1: The flowchart of the process on each phase

3.3.1 Block Diagram

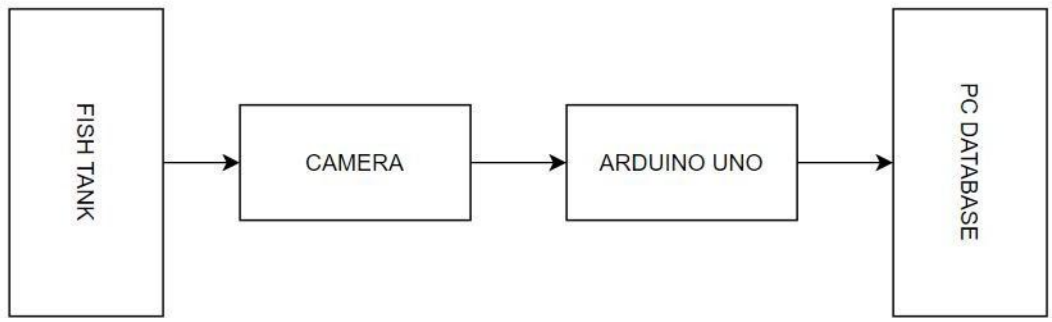


Figure 3.2: Block diagram for Automatic fish counting

In this figure, 3.2 showed that the process of automatic fish counting in a physical form. The first step was the fish tank where the fish were tracked. A fish detection module was crucial for the automatic fish counting system. Next, a camera that is connected to the Arduino UNO will record a real-time footage or collected data images of the Goldfish in the given area. The recorded data was subsequently passed into a pre-processing step. Advanced algorithms were used in fish recognition and tracking to recognize and track individual fish in the collected footage or image data. To distinguish one fish from another, these algorithms examined several visual or aural aspects of the Goldfish, such as size, shape, color, or unique patterns. The Goldfish that were recognized and tracked were then labeled with identifiers that can be display at the output. Then, for the Arduino UNO will take data from the camera of an image and give the output data to the computer.

Finally, the output of the counting and analysis block was displayed to the user via a user interface block. The user interface could be a computer screen that displayed the fish count information in a human-readable way. Additionally, the user interface included the customization, such as the frame per second, the counting number of goldfish and size of each classes.

3.4 Circuit Layout

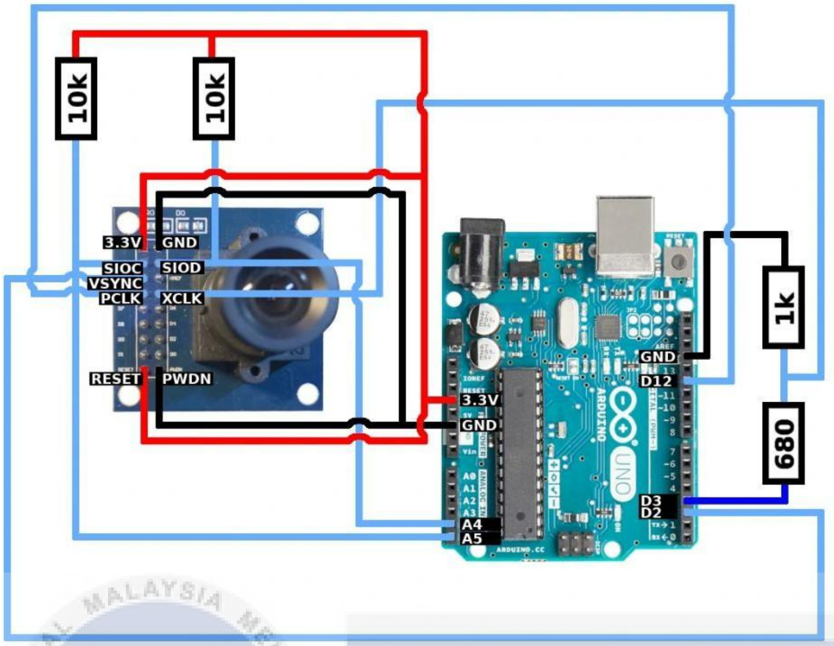


Figure 3.3: The circuit layout for the camera

The figure 3.3 shows is for the connection of Arduino camera to Arduino Uno. A voltage divider is used to convert the Arduino's 5V signal to 3.3V for the camera. This is because the OV7670 camera module is not 5V tolerant, this is required. The input clock that drives the camera is XCLK. Arduino has a maximum output frequency of 8Mhz. The camera module requires 30Mhz for maximum speed, although eight is sufficient to convey a little image to the computer.

The camera sends a 3.3V signal to the Arduino. This connection can be formed without the need of a voltage divider. As a result, vertical sync is required to determine when a new frame begins. Otherwise, it appears to Arduino as a continuous pixel stream with no beginning or finish.

3.5 Coding

```python
def classify_size(width, height):
    # Define size classification thresholds based on your criteria
    big_threshold = 100.0  # Adjust this threshold based on your criteria
    medium_threshold = 50.0  # Adjust this threshold based on your criteria

    # Classify object size based on width and height
    if width >= big_threshold and height >= big_threshold:
        return "big"
    elif width >= medium_threshold and height >= medium_threshold:
        return "medium size"
    else:
        return "small size"
```

Figure 3.4: Classify the fish grading

```python
if FLAGS.count:
    # Count objects found
    counted_classes = count_objects(pred_bbox, by_class=True, allowed_classes=allowed_classes)
    # Loop through dict and print
    for key, value in counted_classes.items():
        print("Number of {}s: {}".format(key, value))
        # Loop through detected objects and print their sizes
        for i in range(len(pred_bbox[0])):
            class_name = class_names[int(pred_bbox[2][i])]
            box = pred_bbox[0][i]
            box_width = box[2] - box[0]
            box_height = box[3] - box[1]
```

Figure 3.5: Identify the counting system


```python
# Format bounding boxes from normalized ymin, xmin, ymax, xmax ---> xmin, ymin, xmax, ymax
original_h, original_w, _ = original_image.shape
bboxes = utils.format_boxes(boxes.numpy()[0], original_h, original_w)

# Hold all detection data in one variable
pred_bbox = [bboxes, scores.numpy()[0], classes.numpy()[0], valid_detections.numpy()[0]]

# Read in all class names from config
class_names = utils.read_class_names(cfg.YOLO.CLASSES)  # Adjust this line based on your configuration

# By default, allow all classes in .names file
allowed_classes = list(class_names.values())

# If crop flag is enabled, crop each detection and save it as a new image
if FLAGS.crop:
    crop_path = os.path.join(os.getcwd(), 'detections', 'crop', image_name)
    try:
        os.makedirs(crop_path)
    except FileExistsError:
        pass
    crop_objects(original_image, pred_bbox, crop_path, allowed_classes)
```

Figure 3.6: Detection for the goldfish

Figure 3.4 depicts the fish grading classification. First, a threshold must be established to identify which sort of class will meet the requirements. As a result, the big_threshold is set to 100, the medium_threshold to 50, and the small_threshold to less than 50. The next step is to grade the fish using the height and breadth to check if it satisfied the parameters I established.

Figure 3.5 depicts identifying the counting system. Then it counts the classes that I provide, which are goldfish classes. The display that says "Number of ()s: " will then be printed.format(key, value)) and it also loops over the following photos to detect and print their sizes.

Finally, in figure 3.6, is the goldfish detection. The first step is to create the bounding boxes from the original image of y-max, y-min, x-max, x-min. The data will then be held in one variable to determine if it matches the class_names that contain the configuration of Yolo classes that been setup. By default, it looks for the.name file and then crops the image for each detection and saves it as a new image.

3.6 Process Flow

The first stage involves conducting research on the automatic fish counting system. This is due to the fact that phase 1 entails obtaining input data or information for the process as well as initializing the process or system by configuring any required resources or variables and preparing for the subsequent phases. As a result, system settings must be modified, such as adjusting camera angles or setting detection parameters. This stage guarantees that the system is ready for accurate fish counting. Furthermore, the data input source for the system may be setup in phase 1. Connecting cameras or sensors to record video or image data of the Goldfish in a specific area could be part of this.

The second stage is the main procedure of detecting and counting fish. As a result, it begins by gathering information from the input source, such as video feeds or images taken by cameras. This data is used to identify and count fish. After that, include preprocessing procedures to increase the quality and applicability of the acquired data. This could include image enhancement or backdrop removal to isolate the fish from its surroundings.

Aside from that, fish detection techniques are being implemented. These algorithms examine preprocessed data to determine the presence and location of fish within collected frames or photos. Object recognition, pattern matching, and machine learning methods can all be used for this. Additionally, the tracking of individual fish across consecutive frames of photos. This is done to ensure consistency and avoid counting the same fish more than once. Motion analysis, feature matching, and other techniques can be used by tracking algorithms to connect fish across frames and follow their movement. Furthermore, the size of each discovered fish is estimated. This can be accomplished by using known reference objects or by calculating fish length-to-pixel ratios based on camera calibration data. Furthermore, actual fish counts based on recognized and monitored individuals. The flowchart could contain mechanisms for incrementing a counter for each successfully detected fish and recording the count for subsequent analysis or reporting.

Finally, in Phase 3, the fish counting data from Phase 2 will be analyzed. Various statistical or computational techniques may be used in this study to get insights and analyze patterns or trends in the fish population. The result will then display the data of the fish grading, which will be separated into several grades, which are grade A for bigger size, grade B for medium size, and grade C for smaller fish.

3.7 Parameter

An automatic fish counting system could be broken down into several parameters. A fixed parameter was a system attribute or property that remained constant regardless of the quantity or size of fish counted. As a result, there were set parameters that included the characteristics of the camera utilized in the system, such as resolution, frame rate, lens type, and field of view. Following that was the selection of image processing algorithms utilized in the system, such as object detection, tracking, and classification procedures, which were normally determined during system development and remained consistent during fish counting activities. Aside from that, the lighting system used to illuminate the underwater habitat where the fish were being viewed was noteworthy. It could include things like the type of lighting used, its intensity, angle, and color temperature

Furthermore, the variable parameter represents anything that may be altered or varies depending on a variety of conditions. These parameters can be tweaked to improve system performance and adapt to different fish counting conditions. The system first tracks fish movement over time, and there are tracking algorithm settings that can be changed. These parameters can be tweaked to improve the accuracy of fish tracking and counting. The system may then use various thresholds and filters to differentiate fish from the background or other objects. The intensity thresholds, size filters, and colour filters can all be modified depending on the fish type, water conditions, and imaging equipment.

3.8 Selecting and Evaluating Tools

The setup of an automatic fish counting system addresses multiple Sustainable creation Goals. First, Goal 2, 'Zero Hunger,' can be supported since this technology can contribute to sustainable fisheries management, assuring an adequate and consistent supply of fish for both local consumption and global food security. Second, Goal 9, 'Industry, Innovation, and Infrastructure,' is essential since the implementation of such a system necessitates breakthroughs in technology and infrastructure to properly and efficiently count fish populations. Third, Goal 12, 'Responsible Consumption and Production,' is relevant because the automatic fish counting system encourages responsible fishing practices by enabling more precise monitoring and assessment of fish stocks, decreasing overfishing, and assuring sustainable fisheries practices. Finally, Goal 14, 'Life Below Water,' is immediately addressed because the system contributes to the conservation and protection of marine ecosystems by giving reliable data on fish populations, helping in the preservation of biodiversity, and maintaining healthy aquatic conditions.

3.9 Equipment

The equipment for an automatic fish counting system typically requires a hardware to accurately count fish in a given environment.

A. Cameras

The device often employs a camera designed specifically to capture crisp and detailed photographs or movies of the fish. These cameras will capture images or movies from a well-lit top-view or the side-view and are equipped with features like as high-resolution imaging, low-light capabilities, and wide-angle lenses.

B. Computer/Laptop

To manage the high number of data generated by the cameras, the system requires a strong data storage and processing unit. This unit is frequently made up of powerful computers or servers with plenty of storage and processing capability. These gadgets use complex image processing software to analyze the collected photos or videos. To reliably recognize and count fish, the programmed employs algorithms and techniques such as computer vision and machine learning.

C. Fish tank

The fish tank housed the fish being monitored. It provided a limited space in which the fish could be studied without requiring direct access to natural bodies of water or open habitats. This regulated habitat kept the fish in the camera's frame of view and allowed for consistent monitoring circumstances.

D. Goldfish

Within the automatic fish counting method, the Goldfish were the subjects of study and observation. They were critical in providing data and insights on Goldfish populations, behavior, and ecology. The automatic fish counting system counted and tracked fish populations correctly. The system could collect data on Goldfish abundance, , size distribution, and population trends by monitoring the fish in the tank or the surrounding environment. This data was useful for a variety of applications, including fishery management, conservation activities, and scientific study.

3.10 Summary

To summarize this chapter, the quantitative research design and experimental design are the primary focus of this project. As a result, the quantitative technique is used to gather and interpret numerical data, while experimental design focuses on the structure of experiments to test hypotheses and evaluate the effectiveness. Furthermore, process flow includes a flowchart and a block diagram that depict the hardware and software flow. From the first phase, which highlights carrying out some research on the method of fish counting, to the second phase, which shows the process of fish counting, and finally to the third phase, which is the data result for fish counting, which can be separated into many fish grades.

CHAPTER 4

Result

4.1 Introduction

In this chapter, we will delve into thorough analyses conducted using a range of custom functions to designed for YOLOv3 in TensorFlow. The analyses aimed to determine suitable for Accuracy and illumination.When training a YOLOv4 model for object identification, pre-trained weights on a large datasets are commonly used. Also, the model is fine-tuned on a given datasets during training, which may contain different classes or objects of focus. Thus, to detect a goldfish that uses TensorFlow and YOLOv3 for object identification on images, a fully customized solution is required custom.weight file that inside of that file have every image of goldfish that share a similar look.

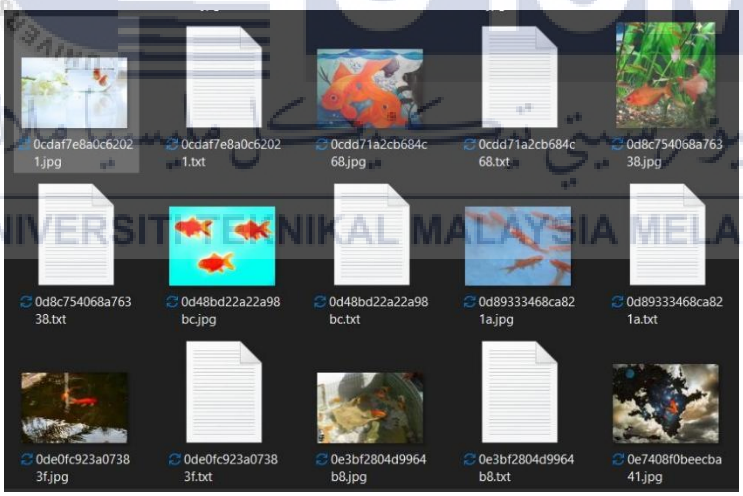


Figure 4.1: A image file have image.jpg of different goldfish and it txt.file that have it coordinate of the goldfish.

4.2 Hardware

This the hardware circuit that refer to the figure 3.3 from the methodology. Some of those wire cable or jumper need to be short this is because of when wire that connected to CLK is long the data output will be lost when transfer some data from the camera. Thus, figure 4.2 as it can see wire need to to be short so it can run the camera or else the camera doesn't work.

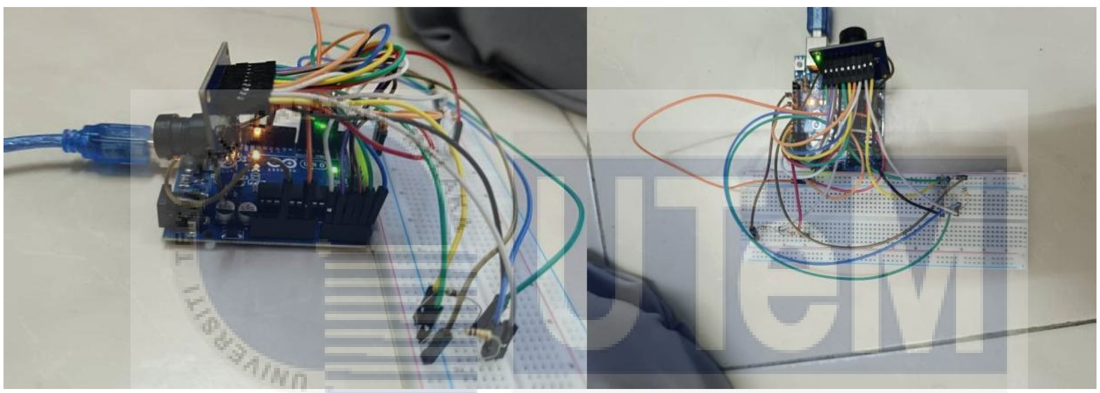


Figure 4.2: The circuit connection of the Arduino Uno to camera

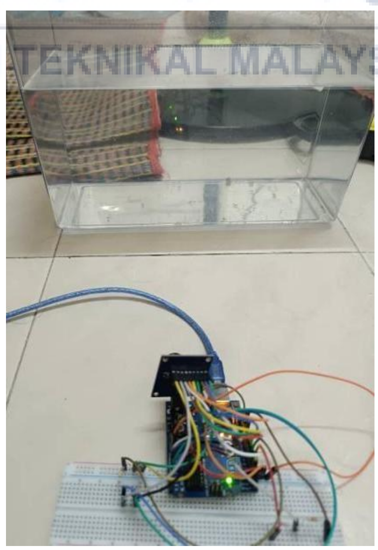
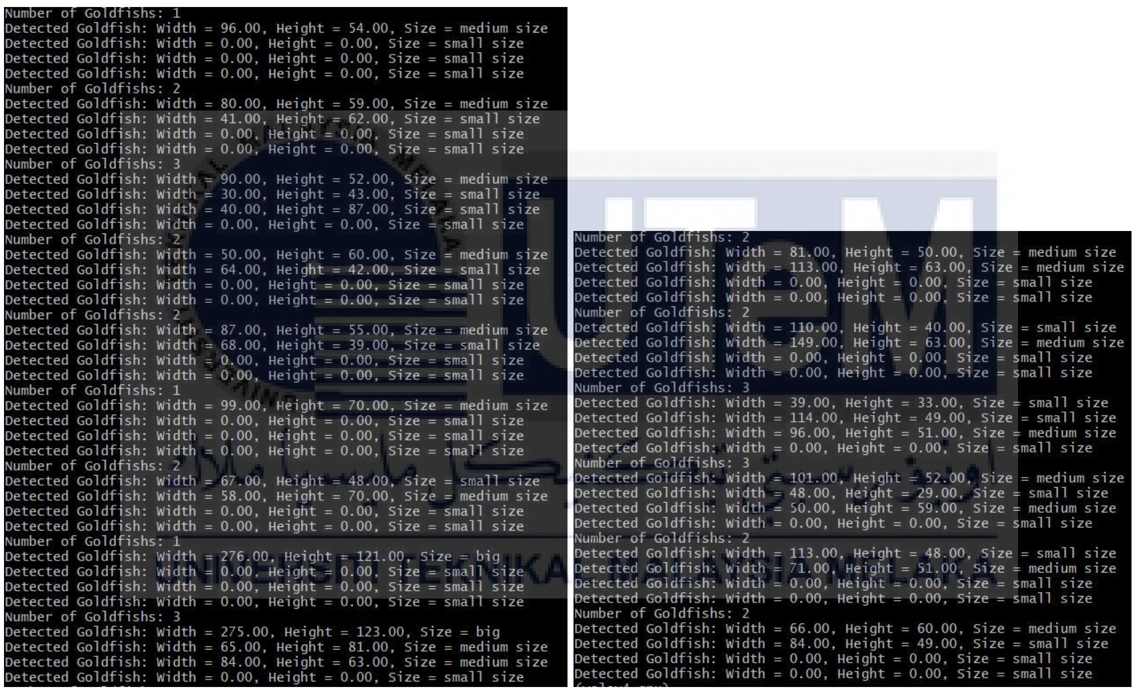


Figure 4.3: Another angle to take capture the tank

4.3 Results

Figure 4.4: The output result for counting and detection system



```
Number of Goldfishs: 1
Detected Goldfish: Width = 96.00, Height = 54.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 80.00, Height = 59.00, Size = medium size
Detected Goldfish: Width = 41.00, Height = 62.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 3
Detected Goldfish: Width = 90.00, Height = 52.00, Size = medium size
Detected Goldfish: Width = 30.00, Height = 43.00, Size = small size
Detected Goldfish: Width = 40.00, Height = 87.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 50.00, Height = 60.00, Size = medium size
Detected Goldfish: Width = 64.00, Height = 42.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 87.00, Height = 55.00, Size = medium size
Detected Goldfish: Width = 68.00, Height = 39.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 1
Detected Goldfish: Width = 99.00, Height = 70.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 67.00, Height = 48.00, Size = small size
Detected Goldfish: Width = 58.00, Height = 70.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 1
Detected Goldfish: Width = 276.00, Height = 121.00, Size = big
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 3
Detected Goldfish: Width = 275.00, Height = 123.00, Size = big
Detected Goldfish: Width = 65.00, Height = 81.00, Size = medium size
Detected Goldfish: Width = 84.00, Height = 63.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
```

```
Number of Goldfishs: 2
Detected Goldfish: Width = 81.00, Height = 50.00, Size = medium size
Detected Goldfish: Width = 113.00, Height = 63.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 110.00, Height = 40.00, Size = small size
Detected Goldfish: Width = 149.00, Height = 63.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 3
Detected Goldfish: Width = 39.00, Height = 33.00, Size = small size
Detected Goldfish: Width = 114.00, Height = 49.00, Size = small size
Detected Goldfish: Width = 96.00, Height = 51.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 3
Detected Goldfish: Width = 101.00, Height = 52.00, Size = medium size
Detected Goldfish: Width = 48.00, Height = 29.00, Size = small size
Detected Goldfish: Width = 50.00, Height = 59.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 113.00, Height = 48.00, Size = small size
Detected Goldfish: Width = 71.00, Height = 51.00, Size = medium size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Number of Goldfishs: 2
Detected Goldfish: Width = 66.00, Height = 60.00, Size = medium size
Detected Goldfish: Width = 84.00, Height = 49.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
Detected Goldfish: Width = 0.00, Height = 0.00, Size = small size
```

Figure 4.5: Output result for identify grading size

In these results, after executing our code, as depicted in Figure 4.4, a multitude of images will be generated, each showcasing the detection and counting of the goldfish. Figure 4.4 illustrates the number of goldfish detected and counted in each respective image, along with the confidence or percentage of the detection. Subsequently, following the production of all the image outputs responsible for counting and detecting goldfish, the fish grading size output will be generated, as illustrated in Figure 4.5.

4.4 Discussion

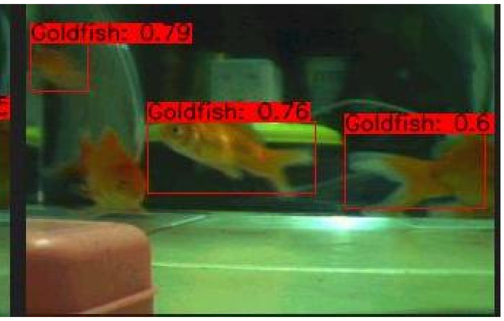
In this discussion, there a few challenges that were faced to be overcame. First problem also is the main problem that occurs is the Arduino camera. This is because while in process to verify the working of the Arduino camera, the output display at the Arduino capture will always turn red . This is due to the wire jumper cable is long or the connection is wrong. Next is, image when capture is blurring or can not see anything. One major reason is the OV7670 sensor's low resolution and sensitivity. The sensor has a poor resolution, which might cause a loss of information in the collected photographs, resulting in a perceived blurriness. Furthermore, the OV7670 camera module may struggle to handle quick changes in lighting conditions. Sharp and clear visuals can be harmed by sudden changes in light intensity or variations in ambient illumination. This might lead to blurring or distortion in the final image.

There some problem when trying to setup the Arduino camera to the Aquarium tank. Because when the Arduino camera is on top of the tank to have a top-view to detect the goldfish the light will deflect to surface of the tank and reflect back into the camera. Thus, the camera cannot able to detect the goldfish but also if there are no light the camera will not be able to detect the fish because is to dark. Next is, there are also a lot of error when working on the coding to detect and to identify the fish grading.

4.5 Data Analysis

Figure 4.6: Graph shows average loss rate during training

Figure 4.6 shows that I built a model using 500 images of goldfish from the internet. Then, as shown in figure 4.6, I train the data set using the YOLOv3 custom weights and then stop training whenever you like. This datasets are generated when I write a text file with the coordinates of the boxes for each image in the datasets, as shown in figure 4.1. The hundreds of blue dots show that my loss value is decreasing to form a curve. It starts at three thousand and gradually decreases until it reaches a point where the loss value is less than two, at which time the model is reasonably accurate and the detection works effectively.



Frame 1

Frame 2

Frame 3

Frame 4

Frame 5

Frame 6

Figure 4.7: Each frame of detect goldfish

Table 4.1 : The Accuracy for each frame

Frame	Number of detection	Accuracy
1	2	50%, 61%
2	3	60%, 76%, 79%
3	2	91%, 99%
4	3	74%, 96%, 99%
5	3	60%, 65%, 90%
6	2	74%, 80%

In Table 4.1, it is evident that Frame 4 exhibits the highest accuracy, recording values of 74%, 96%, and 99%. This notable accuracy is attributed to the camera being zoomed in on the goldfish, facilitating a more precise detection of the aquatic subjects. However, in certain frames pose a challenges in goldfish detection, such as Frame 6, where it fails to identify all instances accurately. For instance, although it is expected to detect 5 goldfish in Frame 6, the system only recognizes 2. This due to the predicted bounding boxes do not closely match the ground truth bounding boxes, thus the algorithm is unable to identify the object properly, resulting in a failure to classify the goldfish. The frame with the lowest accuracy in goldfish detection is Frame 1, registering values of 50% and 61%. This lower accuracy may be indicative of challenges in the detection algorithm or other factors affecting the model's performance.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In conclusion, the automated fish counting method, with further refinement and incorporation into existing fisheries management practices, has the potential to revolutionize fish population estimations, contributing to more effective and sustainable fisheries management strategies. Therefore, with the main objective that creating a fish counting system based on a computer vision platform that determines fish grading and quality.

Fish tracking and counting are vital for conservation, ecosystem health, scientific research, economic and social reasons, and informing policy and decision making about fish populations and habitats. Other that, the advantages of automated fish grading in fisheries management and seafood processing. Highlight the increased productivity, precision, and consistency gained by automation. Highlight the possible uses of automated fish grading, such as stock assessment, selective harvesting, product quality control, and traceability throughout the seafood supply chain.

5.2 Recommendations

There are several things might possibly impact the project's outcomes. Enhancements can be made by improving the system's accuracy and capability. This system's potential upgrades include the following:

- Use high-resolution cameras to obtain clear and detailed photographs of the aquatic environment. This permits precise tracking and detection of fish.
- Examine how it impacts of image capture distance or the angle on the image goldfish.
- Adjust or try a different approach in the algorithms can learn and adapt to diverse fish appearances, enhancing accuracy in identification.

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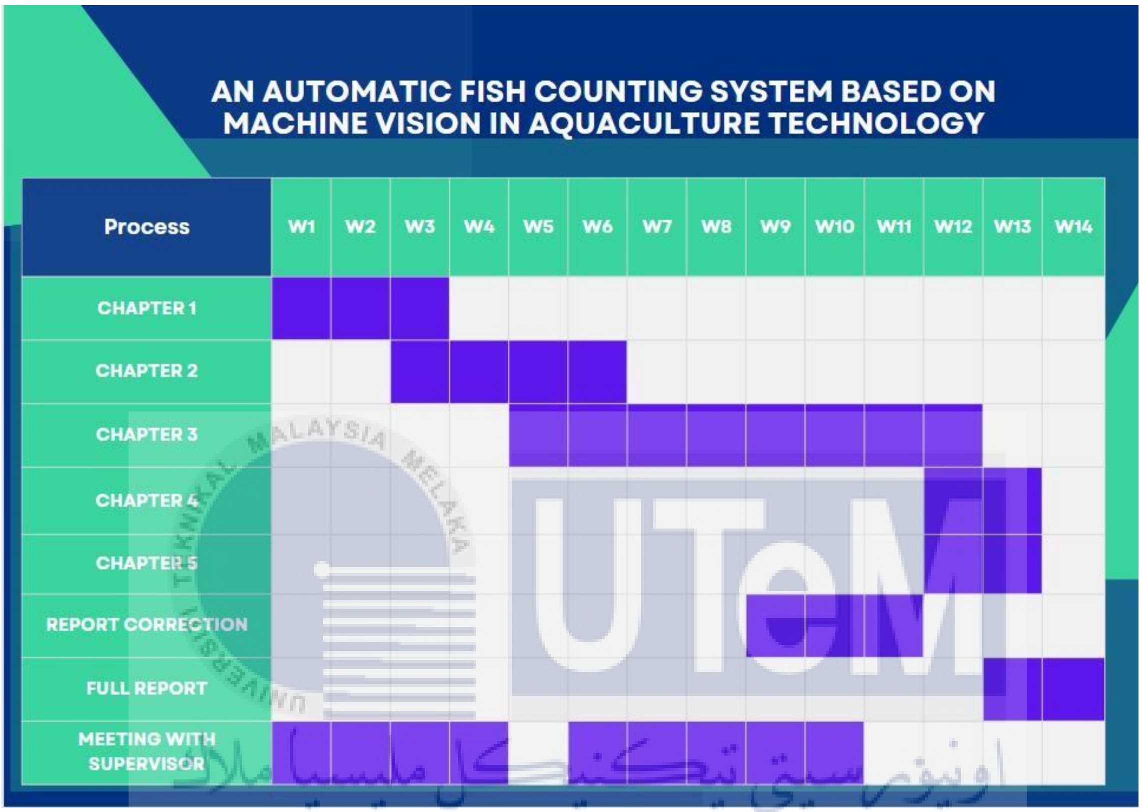
APPENDICES

APPENDIX A GANT CHART



APPENDIX B TURNITIN

Adam Harris

ORIGINALITY REPORT

13%	2%	11%	2%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Yuanyang Zhao, Weiran Li, Yiming Li, Yanyu Qi, Zhenbo Li, Jun Yue. "LFCNet: A lightweight fish counting model based on density map regression", Computers and Electronics in Agriculture, 2022 Publication	7%
2	Lu Zhang, Xinhui Zhou, Beibei Li, Hongxu Zhang, Qingling Duan. "Automatic shrimp counting method using local images and	2%