

**REAL-TIME MILKFISH FINGERLINGS COUNTER
USING DEEP LEARNING APPROACH**

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*This piece of work
is wholeheartedly dedicated to
our Almighty God, loving parents,
relatives, friends,
faculty and staff of the CCS.*

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ABSTRACT

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The manual counting of milkfish fingerlings in the fish industry can be a time-consuming and labor-intensive process that is prone to errors. Thus, this study proposed a real-time counting of milkfish fingerlings for faster and more accurate fingerling counts. This study specifically performed image preprocessing; trained a deep convolutional neural network with image segmentation; and assessed the model's classification performance. The dataset was manually collected on a milkfish fingerlings farm. The gathered videos were converted into image frames before doing polygon annotation. These images underwent various augmentation techniques before feeding into a deep neural network for training. Using the YOLOv7 object detector with segmentation, the SGD optimizer reached as high as 91.54% accuracy.

Keywords: milkfish fingerlings, image preprocessing, segmentation, YOLOv7

Chapter 1

INTRODUCTION

Situation Analysis

Aquaculture provides a high-quality protein source for humans and has become one of the fastest-growing food production industries in the world. In fact, the Philippines is reliant on aquaculture for food sources. As an essential part of aquaculture, fish play a crucial role in fishery production safety and nutrition strategy. However, with the traditional way of counting fish, fish aquaculture faces some challenges. Fast-tracking of fish is unachievable, and using large quantities of manpower often causes fish growers to fail to acquire a sustainable income. If it fails to fast-track and compensate for the large amounts of manpower, it will seriously restrict the sustainable development of aquaculture. Thus, in real-time, a deep neural network is proposed to detect and count milkfish fingerlings in aquaculture.

The primary aquaculture product of the Philippines is milkfish, often known as “Bangus,” which is occasionally pronounced “Bangos.” Among Filipinos, it is the most widely consumed seafood dish. Its capacity to adapt to its surroundings is one of its most vital traits. It may live in marine cages and restricted freshwater or brackish fish enclosures. Scientific methods are used to examine their growth and behavior, which also aids in reducing the harm caused by stress and other variables. Traditional methods take much time, require much work, and are prone to accidents. Various industries, including aquaculture, are quickly embracing deep learning (DL) technology. Identifying fish populations must be exact and accurate for smart fish farming. Improving feeding decisions

requires real-time observation of fish behavior (Iqbal et al., 2022). Due to the current challenges that all aquaculture farmers are facing as a result of the Philippines' economic growth faltering in 2020 and moving into negative territory (Mendoza, 2022), developing a milkfish fingerling counter using deep learning approach is a top choice that can be accessed by the local milkfish fingerling farmers that can significantly aid in reducing the impact of the current economic crisis that the country is experiencing.

One of fish farmers' most expensive and challenging responsibilities is monitoring the fish farms, such as managing fishponds. Fish farmers typically perform these tasks manually, costing them time and money. Mohamed et al. (2020) proposed a system that automates the monitoring of the fish farm. This study describes a method to improve the identification of fish and their motions in difficult water quality. The research team's experimental setup was used for all experiments. When applied, the technique produced encouraging outcomes regarding detection and tracking precision.

To address the issues of color cast, poor contrast, and fuzz in the original underwater image, Chen et al. (2020) proposed an underwater image enhancement algorithm based on Retinex and wavelet fusion. The multi-scale Retinex algorithm was first used in this research to color-correct underwater picture processing. The image is then subjected to gamma modification and sharpening to enhance contrast and sharpness. Their work used the wavelet fusion process to produce underwater photos with distinct textures and details. The technique improves the color cast and fuzz, as well as the contrast and clarity of the image, through subjective and objective comparison with previous algorithms.

In addition, Singh & Kaur (2016) proposed a multiple fish tracking system for low-contrast and low-frame-rate stereo videos using a trawl-based underwater camera system. The results show that the proposed method outperforms other state-of-the-art methods in terms of contrast, details, and noise reduction. Ordinary histogram equalization uses the same transformation derived from the image histogram to transform all pixels. In their work, the Gaussian mixture model and filter are used to enhance the frames, detect the fish, and achieve 80% accuracy.

Several works that have previously been done on object detection using convolutional neural network (CNN) by various authors have been carried out. Within the last few decades, underwater image processing has attracted much interest and made significant advancements.

YOLOv3 and MobileNetv1 have combined in Cai et al. (2020), a new method for fish detection in actual breeding farms. MobileNet's feature maps are reselected according to their receptive fields to improve fish detection rather than the fixed chosen technique used in the original YOLOv3 framework. The suggested strategy is assessed using fish picture data collected on a breeding farm. The proposed method's usefulness is supported by the high accuracy of the detection results. Additionally, "ImageNet" is replaced with a smaller dataset that includes fish photos from 16 different species for the pretraining of the backbone network to extract fish features. As a result, the model's effect of detection is further enhanced because the features that were extracted are closer to fish items. Therefore, it has been demonstrated that the suggested method can produce the required and precise quantity of fish, which will subsequently be utilized to identify the appropriate

breeding measures. Future research can employ the suggested method to recognize numerous classes of fish, which are more challenging and useful.

The study of Prasetyo et al. (2020) evaluated several pre-trained CNN models to classify milkfish eye freshness. The dataset consists of 234 milkfish eye images and three freshness classes. The experiments and analysis results show that NasNet Mobile and Densenet outperform state-of-the-art with the best performance on training, validation, and testing data. However, CNN with low performance requires further investigation to discover the problem.

Khai et al. (2022) used robotic eye cameras to capture shrimp photos on a shrimp farm to train the model. The image data were classified into three categories based on the density of shrimps: low density, medium density, and high density. The researchers used the parameter calibration strategy to discover the appropriate parameters and provided an improved Mask Regional Convolutional Neural Network (Mask R-CNN) model. As a result, the enhanced Mask R-CNN model can reach an accuracy rate of up to 97.48%.

Iqbal et al. (2022) proposed an efficient end-to-end CNN that categorizes normal fish behavior and famine in fish behavior. The performance of CNN is assessed by changing the number of fully connected (FC) layers and using or not using the max-pooling procedure. Adding three FC layers and a max pooling operation raises the detection algorithm's accuracy by 10%. The results demonstrated that the shallow architecture of the CNN model, which employs a max-pooling function with more FC layers, exhibits promising performance and achieves 98% accuracy.

Zhao et al. (2018) used a modified motion influence map and recurrent neural network (RNN) to systematically detect, localize, and recognize unusual local behaviors.

The results show that the proposed method performed better than many other state-of-the-art methods in tests on a dataset comprising three generally local atypical behaviors (accuracy: 98.91%, 91.67%, and 89.89% of detection, localization, and recognition, respectively).

The study proposed by Wang et al. (2022) combined an end-to-end neural network to detect and track the abnormal behavior of porphyry seabream. YOLOV5s is enhanced in the target detection section by introducing feature mapping and multi-level features. Compared with the original network, the detection precision AP (Average Precision) 50:95 has increased by 8.8% while AP50 reaches 99.4%.

The significant contribution of Yu et al. (2020) is the introduction of SSD-MobileNet V3, a novel architecture combining hardware Network Architecture Search (NAS) and NetAdapt, along with a real-time object detection algorithm. This combination of network design and autonomous search algorithm in SSD-MobileNet V3 results in improved performance and raises the technical level overall. The authors demonstrate the effectiveness of SSD-MobileNet V3 through theoretical and practical research.

Zhao et al. (2022) proposed a paper with a high-precision and portable end-to-end target detection model based on enhanced YOLOv4 and deformable convolution. The proposed model has an accuracy of 95.47% compared to the YOLO series, but the parameter amount is decreased by ten times, and the FPS is doubled. In systems with real-circulating fish, deceased fish can be quickly detected.

Based on the conducted interviews, the researchers gathered information regarding milkfish fingerlings farming. It was observed that milkfish fingerlings farming is seasonal, occurring only between April and October. The farmers use basins and strainers for

manually counting fingerlings, which can be time-consuming. The farm owner mentioned that they call in a maximum of 40 people and start counting from 5:00 AM to 10:00 PM to count 30,000 pieces of ordered fingerlings. Payment for fingerling counters is calculated as 10% of the total sale, divided among the counting personnel. Typically, 100,000 fingerlings are stocked in a pond per farming cycle. The farm owner expressed that automating the counting process would reduce expenses and improve efficiency in the farming operation.

Due to the above-stated scenarios, the researchers of this study have inferred to supplement the traditional methods of monitoring the amount of milkfish fingerlings into a scientific procedure using a deep learning approach which will make the process faster, reduce the required amount of work, and avoid mistakes. This will help aquaculture farmers know the amount of their harvest and not just rely on their guesses. Milkfish fingerling farmers can use this information to fast track to reduce the time consumed in the traditional counting and lessen manpower, leading to increased income for the milkfish fingerling growers. The amount of milkfish fingerlings can also be used as a sign that they will have the knowledge of their next target milkfish fingerling product. This information will give the community time to take the necessary actions to keep milkfish fingerling farming abundant. This study will be expected to help the production of milkfish fingerlings. In many cases, the more marketable fish are being sold to provide income that is used to purchase other more affordable food items. Thus, aquaculture and fishing reduce poverty, positively impacting the government's economy and securing wholesome food for coastal and rural communities.

Statement of Objectives

The study mainly focused on developing a real-time milkfish fingerlings counter using deep learning for aquaculture farmers to have a more efficient and accurate tool for managing their fish populations and improving their overall productivity.

Specifically, it sought to achieve the following objectives:

1. To perform image preprocessing to manually acquired videos of milkfish fingerlings;
2. To train a deep convolutional neural network with image segmentation; and
3. To assess the model's classification performance in terms of accuracy.

Time and Place of Study

The study was conducted at the College of Computer Science, DMMMSU-SLUC, Agoo, La Union, from August 2022 to April 2023. In addition, the researchers collected data at a milkfish fingerling pond located in Sta. Rita Central, Agoo, La Union.

Definition of Terms

For a better understanding of this research report, the following terms are operationally defined:

Accuracy refers to the metric for evaluating classification models. It measures how many forecasts are correctly predicted by the model that was developed. This was calculated using the number of classifications a model correctly predicts divided by the total number of fingerlings. The researchers used this evaluation metric to assess the model's performance.

Aquaculture is a method used to produce food and other commercial products in water. It is the aquatic equivalent of agriculture or farming on land. The researchers applied the scientific method by developing a real-time milkfish fingerlings counter using a deep learning approach.

Convolutional Neural Network (CNN) draws inspiration from the structure of the human brain. Artificial neurons, or nodes in CNN, collect inputs, analyze them, and deliver the result as output, much like a neuron in the brain does when it distributes information throughout the body. This subset of machine learning is a type of neural that the researchers used to analyze the visual inputs.

Deep Learning is the machine learning technique that the researchers of this study chose to use for training the model using YOLOv7 on detecting and counting milkfish fingerling in the bucket or basin.

Image Preprocessing is the process by which the researchers apply algorithms to improve the image data that suppresses unwilling distortions or enhances some image feature important for better object detection and classification performance.

Image Segmentation refers to the digital image processing that this study used to partition a digital image into multiple image segments to represent images into something more meaningful and easier to analyze. This process was used to locate the object and boundaries of the milkfish fingerling and to assign a label to every pixel of the milkfish fingerling in an image such that pixels with the same label share certain characteristics.

Milkfish or *Chanos chanos* is the selected subject for this study, given that it is the national fish of the Philippines. It is frequently raised in fish farms because it is an adaptive, strong, and durable fish that can live in small places, which explains why it is readily

accessible across the Philippines. This fish's color and shiny exterior characteristics helped the model easily identify and detect milkfish fingerling, even in challenging scenarios.

Milkfish Farmers or Milkfish Growers are the ones who breed, raise, and harvest milkfish. They culture milkfish in confined spaces to efficiently turn milkfish into milkfish flesh that used to be directly for human consumption. They will benefit from this study to supplement their traditional methods of monitoring the amount of milkfish fingerling with a scientific procedure using a deep learning approach.

Milkfish Fingerlings Counter is the main functionality of the model that the researchers developed. It refers to the counting of milkfish fingerlings that the model detected within the manually acquired video footage in a bucket or basin.

Object Detection is a computer vision technique for locating instances of objects in images or videos. The researchers used this technique to leverage deep learning to produce the milkfish fingerling detection.

Real-Time is the actual time in which milkfish fingerlings were detected and counted in the bucket or basin by the YOLOv7.

YOLOv7 uses convolutional neural networks to identify and count milkfish fingerling in real-time quickly.

Chapter 2

METHODOLOGY

Research Design

Experimental and quantitative research designs were the methods of investigation utilized in this study. According to Kamiri & Mariga (2021), the experimental method involves the design of an experiment and conducting experiments to obtain results. The type of experiments that were performed is called controlled experiments. These were experiments where all known independent variables were held constant and modified one at a time to determine their impact on the dependent variable. The results were compared to a baseline or no-treatment called a “control.” This could result from a baseline method like persistence, the Zero Rule algorithm, or the method’s default configuration. In each experiment, one must measure some aspect of the system’s behavior for comparison across the different conditions.

In this study, using image preprocessing techniques on datasets, such as resizing and augmenting, helped model the deep learning model to the desired level of accuracy and performance. Afterward, the deep convolutional neural network was trained to generate a model to make predictions on detecting milkfish fingerling. There were various experiments, as training the model requires more than a single learning run. It required several runs to be carried out under different conditions.

Another research design that was best suited to the study was the quantitative method. According to Bloomfield & Fisher (2019), the quantitative research method is concerned with collecting and analyzing structured data that can be represented

numerically. One of the central goals was to build accurate and reliable measurements for statistical analysis. To assess the performance of the trained model, an accuracy evaluation metric was used.

Materials and Procedures

This section discusses the data acquisition, data preparation, different image preprocessing techniques, dataset distribution, the deep convolutional neural network, and the model's performance evaluation (see Figure 1).

Data Acquisition

The videos were all acquired from a milkfish farm situated in Sta. Rita Central, Agoo, La Union. The fish grower collected fingerlings in his pond that were ready for selling (see Plate 1). These fingerlings were placed in a bucket for counting. During this procedure, the researchers captured videos of these fingerlings using a Realme 7 Pro smartphone.

Proposed Milkfish Fingerlings Counter Pipeline

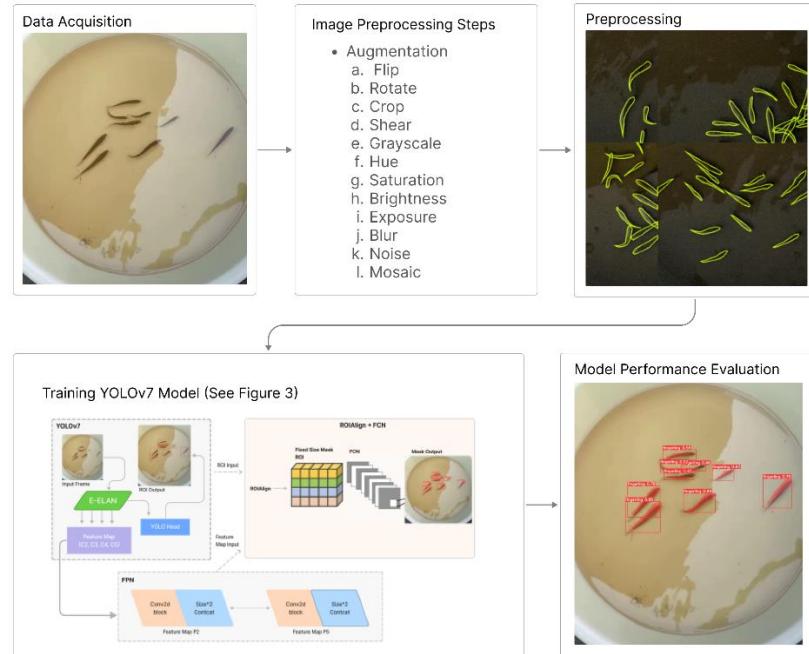


Fig.1. Proposed Milkfish Fingerlings Detection and Counting Pipeline



Plate 1. Pictures of Milkfish Fingerlings Pond at Sta. Rita Central, Agoo, La Union

Data Preparation

After data collection, the video clips were prepared by converting them to a series of images or in frames. The number of frames and the size must be uniform in all inputs. Unfortunately, the video clips have different numbers of frames and sizes. Therefore, frame conversion and resizing are necessary. Frame conversion is a process of extracting frames or series of images in a video, whereas resizing is altering the size of your image without cutting anything out. The researchers manually selected only the frames with possible milkfish fingerling.

These frames underwent an annotation process, where they were presented to the one milkfish fingerling grower. The grower identified the milkfish fingerling in frames or images. After the grower had inspected all images, the researchers used the Roboflow computer vision platform for polygon annotation. This tool is open-source and free to use.

Image Preprocessing

The image frames had to undergo image preprocessing before being used for model training and inference. This was intended to improve the picture data by enhancing some crucial visual characteristics or suppressing unintentional distortions of the images in the dataset. The techniques that were applied for the image preprocessing were as follows:

Resizing. This is a critical step in image preprocessing. According to Nelson (2020), machine learning models train faster in smaller images. There is no magic set for the dimension, a good strategy that the researchers employed was progressive resizing. This was applied by starting with smaller image inputs to save time. The aspect ratio was consistent. This was by checking which raw image dimension is greater, then scaling that

dimension to be equivalent to the output's max dimension, and modifying the second dimension to scale proportionally.

Bilinear interpolation is a commonly used technique for resizing images, including frames extracted from videos, and it involves using weighted averages of neighboring pixels to estimate the color value of new pixels. The formula for bilinear interpolation can be expressed as follows:

Suppose there is an input image of size $M \times N$, and it needs to resize to a new size $P \times Q$. Let $I(x, y)$ be the color value of the pixel at coordinates (x, y) in the input image, where $0 \leq x < M$ and $0 \leq y < N$. The color value of the pixel at coordinates (u, v) in the resized image is computed, where $0 \leq u < P$ and $0 \leq v < Q$.

To compute the color value of the pixel at coordinates (u, v) , the four nearest neighbors of the pixel in the input image are found. Let these neighbors be (x_1, y_1) , (x_1, y_2) , (x_2, y_1) , and (x_2, y_2) , where $x_1 \leq u < x_2$ and $y_1 \leq v < y_2$.

Then, the weighted average of these four neighbors is computed based on their distance from the target pixel (u, v) . The formula for calculating the color value of the pixel at coordinates (u, v) is:

$$I(u, v) = (1 - d_x) * (1 - d_y) * I(x_1, y_1) + d_x * (1 - d_y) * I(x_2, y_1) + (1 - d_x) * d_y * I(x_1, y_2) + d_x * d_y * I(x_2, y_2)$$

where, $d_x = u - x_1$ and $d_y = v - y_1$

This formula computes the weighted average of the four nearest neighbors, where the weights are proportional to the distance of each neighbor from the target pixel (u, v) . The closer a neighbor is to the target pixel, the higher its weight. This results in a smooth

interpolation of the color values between neighboring pixels and helps to minimize artifacts and distortion that can occur during resizing.

Data Augmentation. Due to the limited time and resources, the researchers applied the image augmentation technique in this study. It is a method for artificially expanding the data collection in a dataset. Zoom, shear, rotation, and other image augmentation parameters were employed to enhance the number of milkfish fingerlings images. In general, picture samples produced by image augmentation led to an approximately 3x to 4x increase in the sample size of the current data (Sudhakar, 2017).

Dataset Distribution

The dataset was distributed into training, validation, and testing sets. The training set was the data from which the deep neural network learned. The majority of the total samples in the dataset were put in a training set. In contrast, a validation set was a data set used for training to find and optimize the best model to identify milkfish fingerlings. On the other hand, a test set was secondary data used to test the model after it was trained. This study divided the dataset into 60% training, 20% validation, and 20% test sets.

Training a Deep Convolutional Neural Network

You Only Look Once (YOLO) is a new approach to object detection. This algorithm detects and recognizes various objects in a picture (in real-time). Object detection in YOLO is done as a regression problem and provides the class probabilities of the detected images. Direct prediction of bounding boxes and class probabilities by a single neural network complete photo in a single assessment. Since the detection pipeline consists of a single network, detection performance may be improved end-to-end (Lee & Kim, 2020).

The base YOLO model processes images at 45 frames per second in real time. Fast YOLO, a scaled-down version of the network, processes an astounding 155 frames per second while outperforming other real-time detectors in mean average precision (mAP) by a factor of two. Compared to state-of-the-art detection systems, YOLO has a higher localization error rate but has a lower likelihood of predicting false positives against a backdrop. Finally, YOLO learns very general representations of objects. When applied to other domains like artwork, it performs better than detection techniques like deformable parts model (DPM) and R-CNN when generalizing from natural pictures (Redmon et al., 2016).

This study proposed a detection algorithm based on computer vision for object detection and milkfish fingerlings population statistics using the latest version of YOLO. YOLOv7 is the newest version of the YOLO, it is faster and more accurate than any other known object detector in the range of 5 to 160 frames per second, and on GPU V100, it has the greatest accuracy of 56.8% AP of all real-time object detectors with 30 frames per second or more.

In Figure 2, the SEG-YOLO model can be separated into three parts. The first part is YOLOv7, which proposes the region of interest (ROI) and regresses the classes and confidence scores. In this thesis, YOLOv7 will be implemented, which outputs the feature maps from every last layer of the residual blocks. The second part is ROIAlign which takes different YOLO bounding box outputs and feature maps as inputs and generates the fixed-size ROI feature maps. The last part is the Fully Convolution Network (FCN), which transforms the ROI inputs into semantic mask outputs.

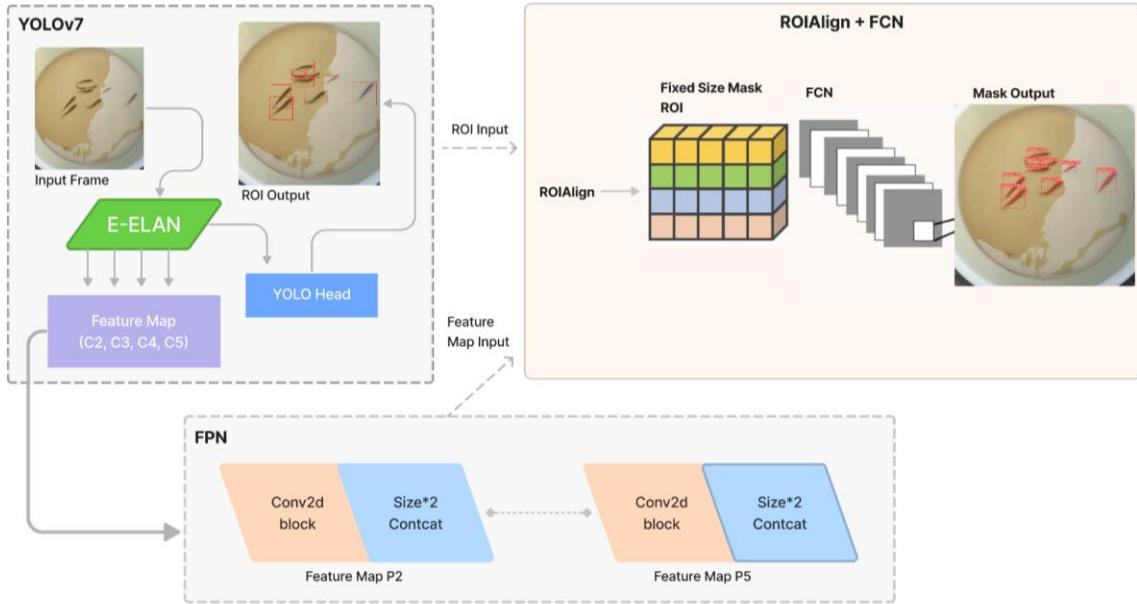


Fig. 2. YOLOv7 Architecture for Milkfish Fingerlings Counter

The YOLO v7 model is the latest in the family of YOLO models. YOLO models are single-stage object detectors. Image frames in a YOLO model are enhanced by a backbone. The head of the network receives these properties after they have been integrated and blended in the neck of the network, which then predicts the positions and types of objects around which bounding boxes should be created. To reach its final forecast, YOLO uses non-maximum suppression post-processing (Solawetz, 2022).

There are three key components to the YOLO detector. First is the YOLO Backbone, second is the YOLO Neck, and Third is the YOLO Head (Solawetz & Nelson, 2020). The Backbone primarily pulls out the most important aspects of a picture and transmits them through the Neck to the Head. The Neck compiles feature maps that the Backbone has retrieved and builds feature pyramids. The head's output layers with final detections make up the head in the end (Kukil & Rath, 2022).

Backbone. A convolutional neural network serves as the YOLO backbone, pooling picture pixels to create features at various granularities. Usually, a classification dataset is used to pretrain the backbone (Solawetz & Nelson, 2020).

As shown in Figure 3, the proposed extended efficient layer aggregation networks based on ELAN (E-ELAN) utilize group convolution to raise the cardinality of the new features and mix the features of several groups in a shuffle and merge cardinality manner. However, it does not alter the gradient transmission path of the original design in any way. This method of action can improve the capabilities learned by many feature maps and enhance the application of calculations and parameters. The proposed E-ELAN employs expand, shuffle, and merge cardinality to constantly improve the network's capacity for learning while preserving the original gradient path (Wang et al., 2022).

Neck. Before sending the representations from the ConvNet layer to the prediction head, the YOLO neck combines and mixes them (Solawetz & Nelson, 2020).

Head. This area of the network is responsible for the class and bounding box predictions. The three YOLO loss functions for class, box, and objectness serve as its guidelines (Solawetz & Nelson, 2020).

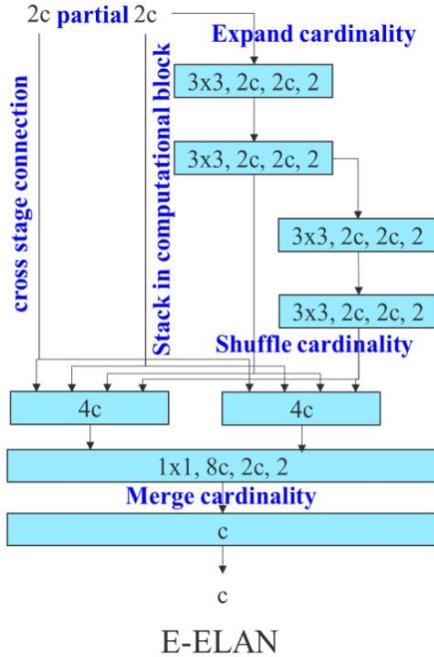


Fig.3. Extended efficient layer aggregation networks based on ELAN (E-ELAN)
(Wang et al., 2022).

On the other hand, feature maps are generated by applying Filters or Feature detectors to the input image or the feature map output of the prior layers. The underlying representations for particular input for each of the Convolutional layers in the model will be revealed through feature map visualization (Khandelwal, 2020).

Further, a unified structure that may be utilized for feature augmentation and multi-scale object recognition is the Feature Pyramid Network (FPN) (see Figure 2). According to Lin et al. (as cited in Wang, 2019), the top-level feature map was the sole one used for prediction in most object identification and segmentation tasks. The position data, which was lost during the pooling, is more precise at the lower level. FPN predicts utilizing each scale in addition to employing different scale feature fusion. FPN merges the lower-level

feature map with the higher-level feature map using a 3x3 convolutional layer for anti-aliasing.

ROIAlign takes different YOLO bounding box outputs and feature maps as inputs generates the fixed-size ROI feature maps and combines them with the FCN, which transforms the ROI inputs into the semantic mask outputs.

Fixed-size picture input is necessary for the mask generation network FCN. The ROI's size needs to be unified since YOLOv7 generates bounding boxes for objects of various sizes. To rescale all of the ROI areas on the feature map to the same size more quickly, faster R-CNN (Ren et al., 2015) advocated ROI pooling.

Mask R-ROIAlign CNN (He et al., 2017) is a method for extracting ROIs from feature maps and scaling them to the same size. The scaled size output is not in the same location as the original ROI's position, which is a misalignment issue that the ROIAlign is intended to address. Instead of directly sampling the pixels, ROIAlign employed bilinear interpolation to anticipate the value of the pixels. By avoiding two integer operations and maintaining the float point number, ROIAlign increases accuracy (Wang, 2019).

Major Improvement in YOLOV7

Among all currently known object detectors, YOLOv7 is the newest state-of-the-art detector. The model has undergone several architectural changes that considerably increase speed and accuracy. This model makes use of the COCO dataset, just like scaled YOLOv4. E-ELAN and model scaling for concatenation-based models are included in the architectural improvements to improve learning capacity. In addition, planned re-parameterized convolution, coarse for auxiliary, and fine for lead loss are referred to as the

“bag of freebies” that complement the model for improved learning without raising the training cost (Wang et al., 2022).

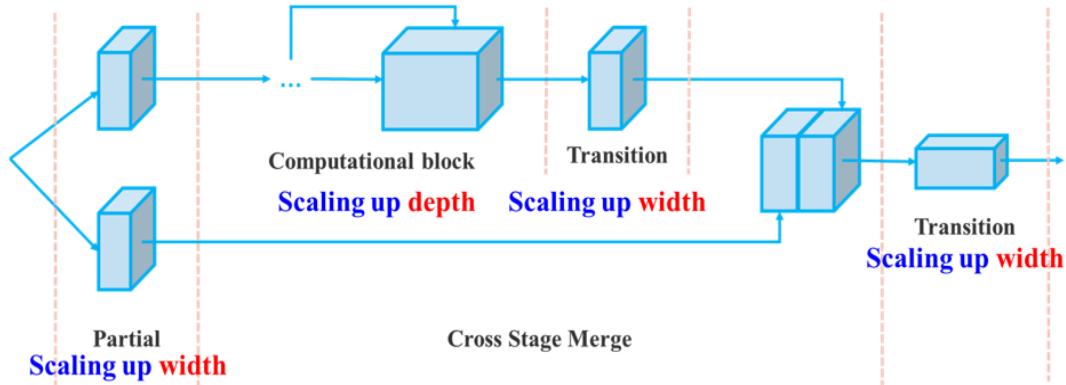
The suggested E-ELAN employs expand, shuffle, and merge cardinality to constantly enhance the network’s capacity for learning while maintaining the initial gradient route. Based on the previously created ELAN computational block, this block is in YOLOv7.

Another factor contributing to YOLOv7’s better performance is compound model scaling. The accuracy and speed criteria were determined using the model scaling to make it more computer-friendly.

Due to parameter-specific scaling, NAS is typically utilized for model scaling. However, YOLOv7 uses a compound model scaling strategy to refine the model further. For concatenation-based models, this method coherently scales with depth (Gillani et al., 2022), as seen in Figure 4.

Additionally, this model proposed the intended re-parameterization convolution, which substantially impacts accuracy. After training, one may improve the model using re-parameterization approaches. Although the training procedure takes longer, the inference results are superior. The two methods of ensemble re-parametrization utilized to finish these models are model level and module level.

The outputs are often acquired at the head of the YOLO architecture, which typically has a neck, head, and backbone. YOLOv7 has also made a few adjustments in this area. It is not held back by just one head. It has several heads, so it can do whatever it wants. Prior to now, this methodology was also employed in the Deep Supervision technique, which deep learning models use to take advantage of many heads.



(c) compound scaling up depth and width for concatenation-based model

Fig.4. Compound Model Scaling in YOLOv7 (Wang et al., 2022)

There are two heads in YOLOv7. The lead head is known as the final output head, while the Auxiliary Head is the head that aids in middle-layer training. The weights of the auxiliary heads are changed with the help of an assistant loss, enabling Deep Supervision and improving the model's capacity for learning. The Lead Head and the Label Assigner are both intimately tied to this strategy. The approach known as Label Assigner assigns soft labels after considering the results of the ground truth and the network prediction. Important to note is that the label assigner produces soft and coarse labels rather than hard labels (see Figure 5).

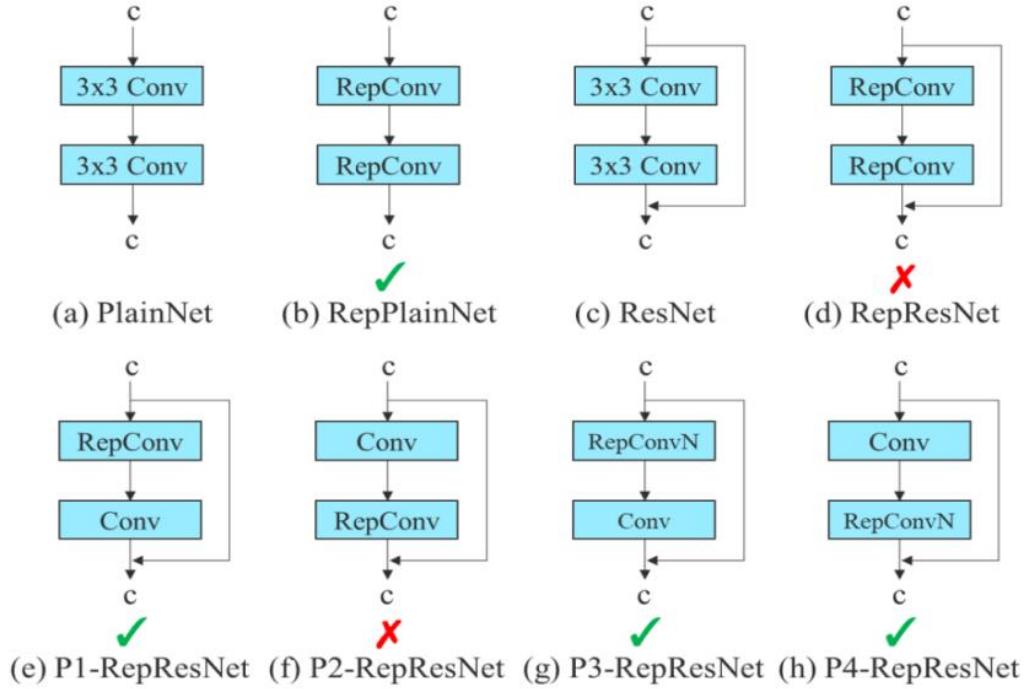
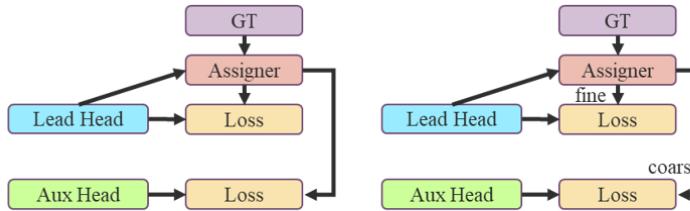


Fig. 5. Best ways to perform module-level ensemble (Wang et al., 2022).

The Lead Head of the YOLOv7 network predicts the result. Soft labels are created using these results in the end. The most important component is that the loss for both the lead head and the auxiliary head is calculated using the same soft labels that are created. In the end, both heads are trained using soft labels. This is because the lead head has a relatively strong learning capacity, which suggests that the soft label that emerges from it should be more accurate in capturing the distribution and correlation between the source and target data. By allowing the shallower auxiliary head to study the information that the lead head has learned quickly, the lead head will be better able to focus on learning residual information that has not yet been taught.



(d) Lead guided assigner (e) Coarse-to-fine lead guided assigner

Fig. 6. Lead guided Assigner and Coarse to fine Lead Guided Assigner (Wang et al., 2022).

Approaching the labels that range from coarse to fine (see Figure 6). The method described above really yields two separate soft label sets. The first is a set of fine labels to train the lead head and a set of coarse labels to train the auxiliary head. The instantly produced soft labels and the fine labels are the same. However, more grids are treated as affirmative targets to create coarse labels. To do this, the restrictions of the positive sample assignment technique are loosened (Gillani et al., 2022).

After setting up the YOLOv7, the researchers now started training. They manually searched for the best parameters (i.e., model's configuration) and hyperparameters (i.e., explicitly specified parameters that control the training process). Also, the researchers explored whether or not image preprocessing can affect the performance of the model. Therefore, various experiments were conducted. The significant results were recorded and discussed.

Experimental Environment. In Table 1, the experimental environment information was declared, where the researchers used Tensorflow version 2.10.0 and Keras version

Table 1. Experimental Environmental Information

Attribute Name	Attribute Value
Tensorflow Version	2.10.0
Keras Version	2.0.8
RAM	16 GB
Processor	11 th Gen Intel ® Core i7 – 11800H Processor CPU 8 Cores/ 16 Threads up to 4.6 GHz
Graphics	GeForce RTX 3060
Operating System Version	Windows 10 Pro, 64 bit
Google Colaboratory	Pro Plus

2.11.0 to extract important YOLOv7 libraries for the software part. The researchers ran the code on a computer with 16 GB RAM, an i7 Processor with a CPU clock speed of 4.6 GHz, and a GPU GeForce RTX 3060 running Windows 10, 64-bit.

Model Performance Evaluation

Model evaluation is an integral part of the model development process. This helped find the best model representing the milkfish fingerlings data. The researchers used the Hold-Out method of evaluating models. This method used a test set to assess model performance. The test set or unseen image samples are a subset of the dataset. If a model fits the training set much better than the test set, overfitting is probably the cause. Accuracy was used as an evaluation metric.

Data Gathered

The video data were manually acquired from a milkfish farm in Agoo, La Union, using a smartphone and were annotated by the researchers with the guidance of the milkfish growers for the online polygon annotation using the Roboflow computer vision platform. The manually selected frames underwent image preprocessing techniques such as filtering and augmentations to solve the issue of poor-quality images caused by the lack of light and limited resources, respectively.

Data Analysis

To calculate the accuracy of the milkfish fingerling model counter, the following Python code was used:

```
# Ten actual count numbers
true_count = [9, 20, 30, 42, 50, 60, 70, 80, 90, 100]

# Ten prediction count numbers
prediction_count = [9, 21, 28, 40, 48, 57, 67, 80, 82, 54]

# Calculate the accuracy percentage for each prediction
accuracies = []
for i in range(len(true_count)):
    if prediction_count[i] <= true_count[i]:
        accuracy = prediction_count[i] / true_count[i] * 100
    else:
        accuracy = 100 - (abs(true_count[i] - prediction_count[i])) / true_count[i] * 100
    accuracies.append(accuracy)
```

```

# Calculate average accuracy percentage

avg_accuracy = sum(accuracies) / len(accuracies)

# Print results
print("Accuracy percentages:")
for i in range(len(accuracies)):
    print(f"Prediction {i+1}: {accuracies[i]:.2f}%")
print(f"Average accuracy: {avg_accuracy:.2f}%")

```

The formula used is the percent error formula, which is commonly used in scientific experiments and research to evaluate the accuracy of results. This formula determines the difference between an *prediction_count* and *true_count*, expressed as a percentage of the *true_count*. By subtracting the percent error from 100, the researchers can determine the accuracy of the *prediction_count* (CK-12, 2014).

This code consists of two lists: *true_count* and *prediction_count*. The *true_count* contains ten true count numbers, whereas *prediction_count* contains ten predicted count numbers. The code then calculates the accuracy percentage for each prediction and stores them in a list called accuracies. The accuracy percentage is calculated using the following formula (Don Mariano Marcos Memorial State University, 2018):

- If the predicted count is less than or equal to the true count, then

$$\text{accuracy} = (\text{predicted_count} / \text{true_count}) * 100$$

- If the predicted count is greater than the true count, then

$$\text{accuracy} = 100 - (\text{abs}(\text{true_count}[i] - \text{predicted_count}[i])) / \text{true_count}[i] * 100$$

The formula determines the percentage of correct predictions from the total number of predictions made. The code then calculates the average accuracy percentage by summing up all the accuracy percentages and dividing by the number of predictions. Finally, the code prints the accuracy percentage for each prediction and the average accuracy percentage. Overall, this code measures the accuracy of the predicted counts compared to the true counts, and it outputs the results in a clear and organized manner.

Barkved (2022) states that anything greater than 70% is a great model performance. In fact, an accuracy percentage of anything between 70%-90% is not only ideal but also realistic. This is also consistent with industry standards.

Ethical Consideration

The protection of human subjects through the application of appropriate ethical principles is important in this study. As seen in Appendix C, this study has been granted clearance by the Research Ethics Committee, ensuring that it meets the highest ethical standards and upholds all participants' dignity, rights, and welfare. The rigorous review process has deemed this study safe, responsible, and ethical, highlighting our commitment to conducting research that prioritizes the protection of human subjects.

The researchers obtained consent from the selected milkfish owners/growers. The process of acquiring informed consent consists of the following: consent should be given freely (voluntary), respondents should understand what is being asked of them, and the researchers must be competent to consent. This means that to participate in this study; participants must be adequately informed about the research, comprehend the information, and have the freedom to decide whether to participate or decline.

All selected respondents were approached individually and were given an explanation of the purpose of the study and the data collection process. They were given appropriate time to ask questions and address any concerns. It was explained that as their participation is voluntary, refusing to participate or withdraw from the study while it is in progress would not affect their job. Participants' agreement to participate was obtained after thoroughly explaining the research process by the researchers. They were required to sign the informed consent form before the interview to indicate their permission to be part of the study. An explanation was clearly given to participants that they have a right to withdraw from the study at any time, even after the informed consent has been signed. Consent to record the interview was also asked of them.

Moreover, the confidentiality of the participants was preserved by not revealing their names and identity in the data collection, analysis, and reporting of the study results. Privacy and confidentiality of the interview environment were managed carefully while disseminating findings.

Chapter 3

RESULTS AND DISCUSSION

Preprocessing the Manually Acquired Video of Milkfish Fingerlings

To preprocess the manually acquired video of milkfish fingerlings, the researchers gathered data using Realme 7 pro smartphone in a cream-colored basin filled with milkfish fingerlings taken from the milkfish fingerling pond. The gathered video data was 20 minutes long. While gathering the video data, the researchers added ten milkfish fingerlings in the basin with each passing minute up to a maximum of 200 milkfish fingerlings.

The data collection was conducted at 9 o'clock in the morning under slightly cloudy weather conditions. The camera was positioned above a cream-colored basin at the height of approximately 4 feet, using a tripod, as set up by the researchers (see Plate 2).



Plate 2. Camera Setup for Milkfish Fingerlings Manual Video Acquisition

Frame Extraction of the Manually Acquired Video of Milkfish Fingerling

After gathering the required videos, the researchers cleaned the video data by removing unnecessary parts of the video. A 3-minute video data was utilized for the dataset of the model. The researchers extracted a frame every multiple of 12 frame intervals from the 3-minute video to produce a dataset composed of 360 frames for annotation.

For evaluation of count accuracy, ten individual 20-second videos were extracted from the 20-minute video data (see Plate 3). Each individual video contains a count of milkfish fingerlings of 9, 20, 30, 42, 50, 60, 70, 80, 90, and 100, which are confirmed and examined by the milkfish fingerling farmer. Ten frames were extracted for every individual video by selecting a frame every multiple of 50 frame intervals.



Plate 3. 20-Minute Video

Resizing of Extracted Frames

Resizing extracted frames from a collected video is a common technique used in computer vision tasks to prepare input data for deep learning models. In this study, the researchers used bilinear interpolation to resize the frames to 416x416, which is a standard size used by the YoloV7 model. Resizing frames to a uniform size can be beneficial for several reasons. Firstly, it can help reduce the computational complexity of the deep learning model, improving training and inference time. Secondly, it can help ensure that all input data is the same size, which is essential for some deep learning models to work correctly.

As an illustration in Plate 4, the 1920 pixels width became 416, and the 1080 pixels height became 332.8 when a 1000x800 photo of milkfish fingerling was resized to 416x416. The researchers then filled the gap between 332.8 and 416 via padding.



(a) Original Image

(b) Resized Image

(c) Padded Image

Plate 4. Images Resized to 416x416

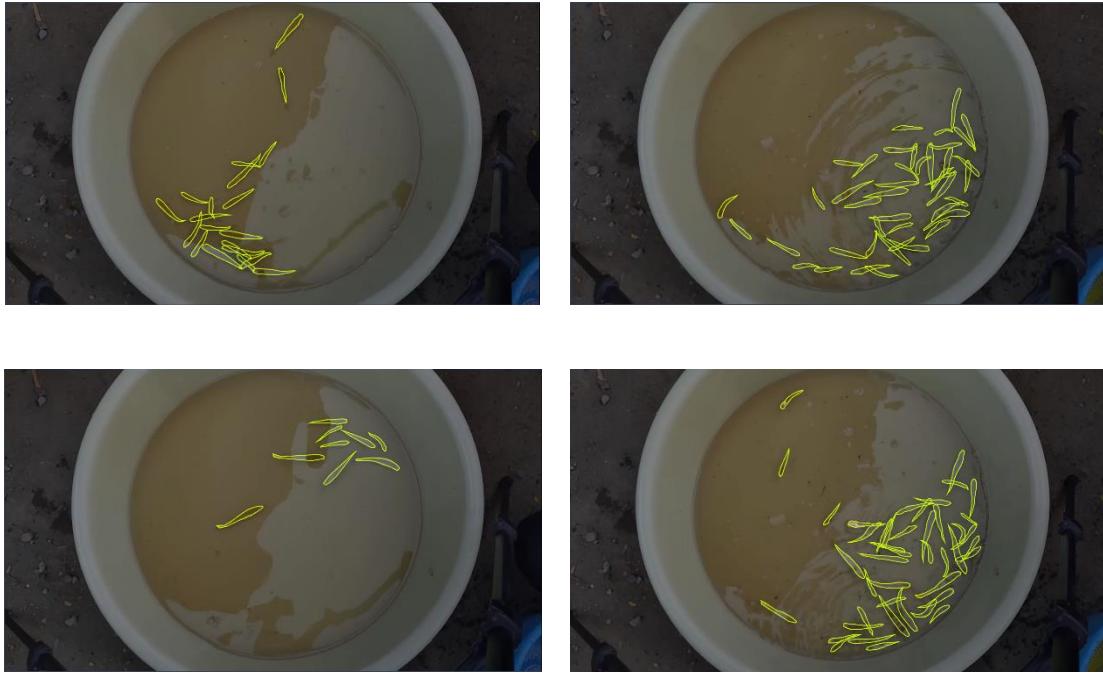


Plate 5. Sample Images of the Annotated Milkfish Fingerlings Using Roboflow

Annotation of Extracted Frames Using Roboflow Computer Vision Platform

The researchers annotated the extracted frames of milkfish fingerlings using the Roboflow Computer Vision Platform. Plate 5 shows a sample image of milkfish fingerlings. The highlighted parts are the annotated milkfish fingerlings.

Dataset Distribution

After annotating all of the extracted frames of milkfish fingerlings, the dataset was divided into three groups for training, validation, and testing: 60%, 20%, and 20% of the dataset were used for each group, respectively. The augmentation techniques were applied exclusively to the training dataset. Prior to augmentation, the training set consisted of 216 images. After the augmentation process, the number of images in the training set increased to 648, resulting in a 300% increment. However, the validation and testing sets were left

Table 2. Division of Dataset to Training, Validation, and Testing

	Class Label	Train Set Size	Valid Set Size	Test Set Size	Total
Before Augmentation	fingerling	216	72	72	360
After Augmentation	fingerling	648	72	72	792

unchanged, each containing 72 images (see Table 2). The overall total of annotated milkfish fingerlings, including the dataset used on augmentation methods, is 10,728.

Data Augmentation

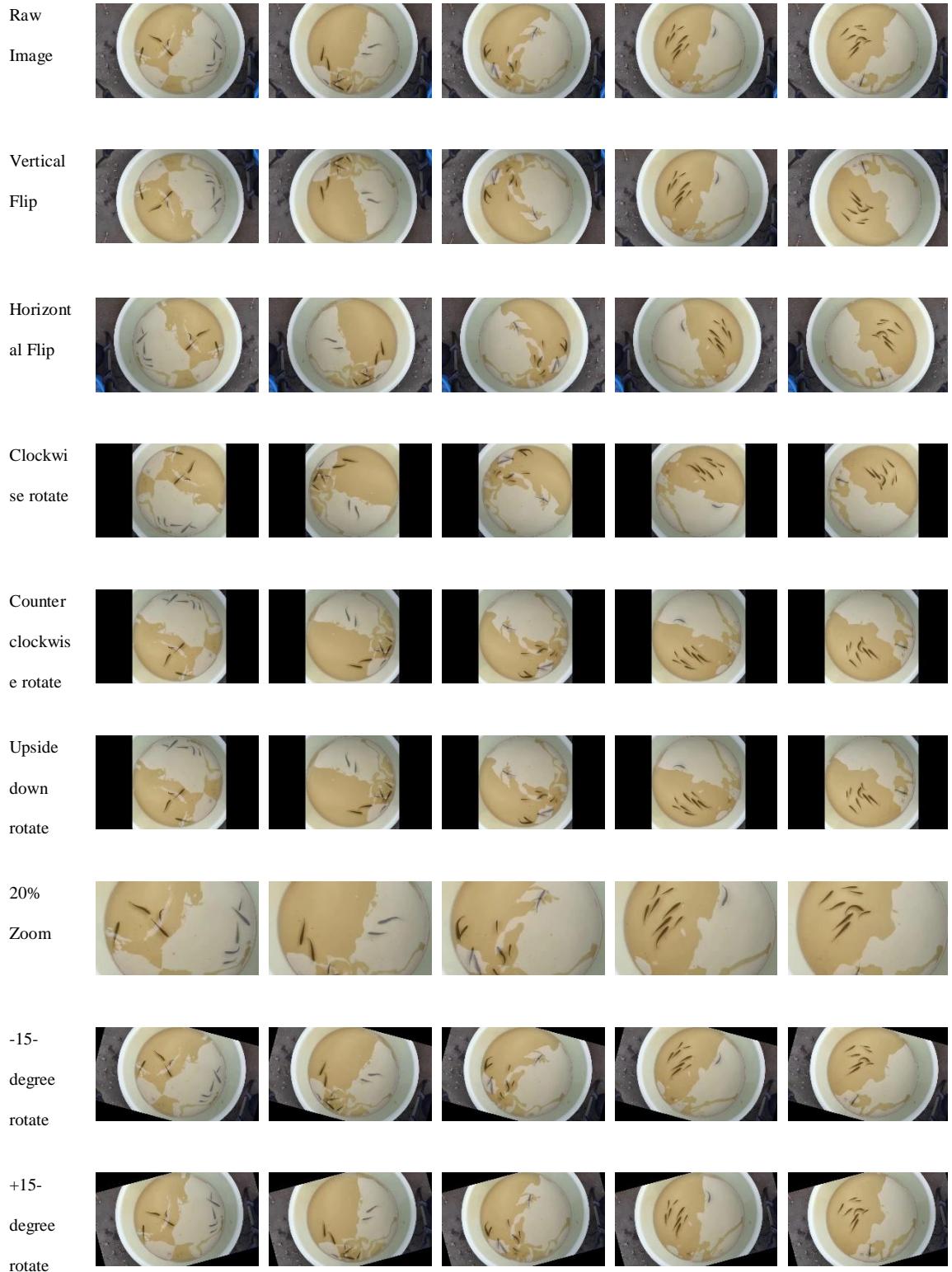
The researchers used data augmentation because it has been shown in numerous studies to be an essential technique for improving the performance and generalization of deep learning models. For example, in their work on object recognition in images, Krizhevsky et al. (2012) found that data augmentation techniques such as random cropping, flipping, and color distortion were critical for improving the robustness of their model.

Similarly, in their work on medical image classification, Gao et al. (2021) found that applying various data augmentation techniques, such as rotation, scaling, and translation, significantly improved the model's accuracy and robustness.

Moreover, recent studies have shown that data augmentation can also help to mitigate the issue of class imbalance in datasets, which can be particularly problematic for deep learning models. For example, in their work on skin lesion classification, Kwon et al. (2020) found that augmenting the minority class with rotation and flipping significantly improved the model's ability to classify the minority class accurately.

Overall, the use of data augmentation techniques in deep learning is widely recognized as a crucial step in improving the performance and generalization of the model and has been validated in numerous studies across various domains.

The researchers applied 13 types of augmentation methods (see Plate 6) to the training set which included adding horizontal or vertical flips to help the model be insensitive to subject orientation, rotated 90-degrees in all three directions: clockwise, counter-clockwise and upside down to allow the model be insensitive to camera orientation, adding variability to positioning and size which are 0% minimum zoom and 20% maximum zoom to help the model be more resilient to subject translations and camera position, adding variability to rotations between -15-degree and +15-degree to support the model be more resilient to camera roll, adding variability to perspective which are ± 15 -degree horizontal and ± 15 -degree vertical to help the model be more resilient to camera and subject pitch and yaw, grayscale are also applied to the 25% of the training set, randomly adjust the colors in the images between -25% and +25%, randomly adjust the vibrancy of the colors in the images between -25% and +25%, adding variability to image brightness and exposure between -25% and +25% to help the model be more resilient to lighting and camera setting changes, adding random Gaussian blur up to 10% to help the model be more resilient to camera focus, adding noise up to 5% of pixels to help the model be more resilient to camera artifact, and adding mosaic to help the model better on small objects. Plate 5 shows the augmentation samples that are applied to the dataset.



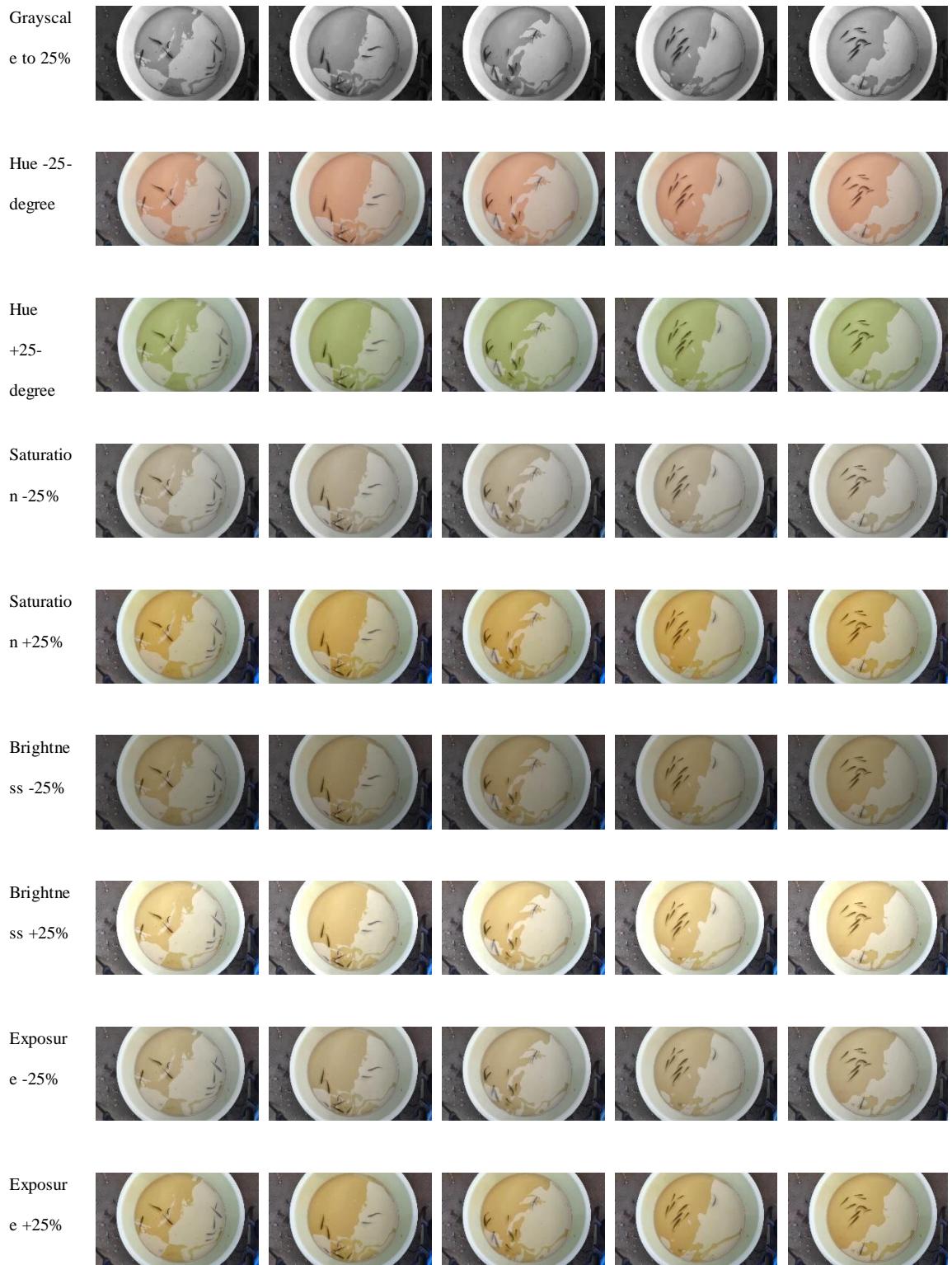




Plate 6. Sample Images of Augmentation Methods

The researchers annotated the 360 raw images before applying data augmentation to improve the size and diversity of the dataset. When using data augmentation tools like Roboflow, the augmented images can be automatically annotated, saving time and effort in the annotation process.

After applying data augmentation techniques, the dataset increased from 360 to 792 images, totaling 10,728 annotations. This increase in data size and diversity can be critical for training robust and generalizable deep learning models, as it can help the model learn features and patterns invariant to variations in the data.

The presented annotation heatmap in this research is useful for visualizing the distribution of fingerlings annotations within the dataset. This heatmap provides insights into the density of annotations across the image and can be used to identify any patterns or trends within the dataset. With a total of 10,728 annotations, the dataset is sufficiently large to provide a diverse range of annotated images for training and evaluation.

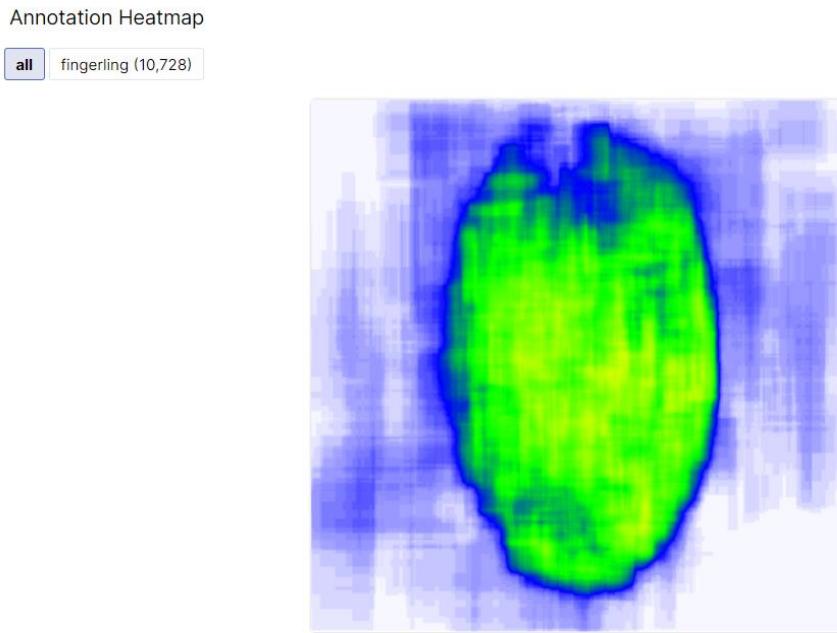


Fig. 7. Annotation Heatmap

As shown in Figure 7, the heatmap can be used to identify areas where the annotation is more concentrated, which can be useful in identifying specific characteristics or features of the more commonly annotated fingerlings. Furthermore, it can help evaluate the quality of the annotations in the dataset by identifying any missing or inaccurate annotations. This information can then be used to improve the accuracy of the deep learning model, ultimately enhancing the performance of the system.

Training a Deep Convolutional Neural Network-Based Milkfish Fingerling Counter Using YOLOv7

To meet the computational requirements and runtime for training the real-time milkfish fingerlings counter model, the researchers employed Google Colaboratory Pro Plus, taking into account the size of the dataset used in the study. They opted to use the

YOLOv7 Instance Segmentation architecture to train the model, by using Colaboratory Pro Plus, the researchers were able to access powerful GPUs and work collaboratively, allowing them to conduct research effectively. Table 2 shows the model summary of the SGD model. It can be observed that there are 417 convolutional layers, 37,866,092 parameters, 37,866,092 gradients, and 142.6 GigaFLOPS (GFLOPS), indicating its complexity and computational intensity.

Table 3. Model Summary of YOLOv7 using SGD Optimizer

	from	n	params	Module	arguments
0	-1	1	928	models.common.Conv	[3, 32, 3, 1]
1	-1	1	18560	models.common.Conv	[32, 64, 3, 2]
2	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
3	-1	1	73984	models.common.Conv	[64, 128, 3, 2]
4	-1	1	8320	models.common.Conv	[128, 64, 1, 1]
5	-2	1	8320	models.common.Conv	[128, 64, 1, 1]
6	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
7	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
8	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
9	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
10	[-1, -3, -5, -6]	1	0	models.common.Concat	[1]
11	-1	1	66048	models.common.Conv	[256, 256, 1, 1]
12	-1	1	0	models.common.MP	[]
13	-1	1	33024	models.common.Conv	[256, 256, 1, 1]
14	-3	1	33024	models.common.Conv	[256, 256, 1, 1]
15	-1	1	147712	models.common.Conv	[128, 128, 3, 2]
16	[-1, -3]	1	0	models.common.Concat	[1]
17	-1	1	33024	models.common.Conv	[256, 128, 1, 1]
18	-2	1	33024	models.common.Conv	[256, 128, 1, 1]
19	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
20	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
21	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
22	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
23	[-1, -3, -5, -6]	1	0	models.common.Concat	[1]
24	-1	1	263168	models.common.Conv	[512, 512, 1, 1]
25	-1	1	0	models.common.MP	[]
26	-1	1	131584	models.common.Conv	[512, 256, 1, 1]

	from	n	params	Module	arguments
27	-3	1	131584	models.common.Conv	[512, 256, 1, 1]
28	-1	1	590336	models.common.Conv	[256, 256, 3, 2]
29	[-1, -3]	1	0	models.common.Concat	[1]
30	-1	1	131584	models.common.Conv	[512, 256, 1, 1]
31	-2	1	131584	models.common.Conv	[512, 256, 1, 1]
32	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
33	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
34	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
35	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
36	[-1, -3, -5, -6]	1	0	models.common.Concat	[1]
37	-1	1	1050624	models.common.Conv	[1024, 1024, 1, 1]
38	-1	1	0	models.common.MP	[]
39	-1	1	525312	models.common.Conv	[1024, 512, 1, 1]
40	-3	1	525312	models.common.Conv	[1024, 512, 1, 1]
41	-1	1	2360320	models.common.Conv	[512, 512, 3, 2]
42	[-1, -3]	1	0	models.common.Concat	[1]
43	-1	1	262656	models.common.Conv	[1024, 256, 1, 1]
44	-2	1	262656	models.common.Conv	[1024, 256, 1, 1]
45	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
46	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
47	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
48	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
49	[-1, -3, -5, -6]	1	0	models.common.Concat	[1]
50	-1	1	1050624	models.common.Conv	[1024, 1024, 1, 1]
51	-1	1	7609344	models.common.SPPCSPC	[1024, 512, 1]
52	-1	1	131584	models.common.Conv	[512, 256, 1, 1]
53	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, ‘nearest’]
54	37	1	262656	models.common.Conv	[1024, 256, 1, 1]
55	[-1, -2]	1	0	models.common.Concat	[1]
56	-1	1	131584	models.common.Conv	[512, 256, 1, 1]
57	-2	1	131584	models.common.Conv	[512, 256, 1, 1]
58	-1	1	295168	models.common.Conv	[256, 128, 3, 1]
59	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
60	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
61	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
62	[-1, -2, -3, -4, -5, -6]	1	0	models.common.Concat	[1]
63	-1	1	262656	models.common.Conv	[1024, 256, 1, 1]
64	-1	1	33024	models.common.Conv	[256, 128, 1, 1]
65	-1	1	0	torch.nn.modules.upsampling.Upsample	[None, 2, ‘nearest’]

	from	n	params	Module	arguments
66	24	1	65792	models.common.Conv	[512, 128, 1, 1]
67	[-1, -2]	1	0	models.common.Concat	[1]
68	-1	1	33024	models.common.Conv	[256, 128, 1, 1]
69	-2	1	33024	models.common.Conv	[256, 128, 1, 1]
70	-1	1	73856	models.common.Conv	[128, 64, 3, 1]
71	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
72	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
73	-1	1	36992	models.common.Conv	[64, 64, 3, 1]
74	[-1, -2, -3, -4, -5, -6]	1	0	models.common.Concat	[1]
75	-1	1	65792	models.common.Conv	[512, 128, 1, 1]
76	-1	1	0	models.common.MP	[]
77	-1	1	16640	models.common.Conv	[128, 128, 1, 1]
78	-3	1	16640	models.common.Conv	[128, 128, 1, 1]
79	-1	1	147712	models.common.Conv	[128, 128, 3, 2]
80	[-1, -3, 63]	1	0	models.common.Concat	[1]
81	-1	1	131584	models.common.Conv	[512, 256, 1, 1]
82	-2	1	131584	models.common.Conv	[512, 256, 1, 1]
83	-1	1	295168	models.common.Conv	[256, 128, 3, 1]
84	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
85	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
86	-1	1	147712	models.common.Conv	[128, 128, 3, 1]
87	[-1, -2, -3, -4, -5, -6]	1	0	models.common.Concat	[1]
88	-1	1	262656	models.common.Conv	[1024, 256, 1, 1]
89	-1	1	0	models.common.MP	[]
90	-1	1	66048	models.common.Conv	[256, 256, 1, 1]
91	-3	1	66048	models.common.Conv	[256, 256, 1, 1]
92	-1	1	590336	models.common.Conv	[256, 256, 3, 2]
93	[-1, -3, 51]	1	0	models.common.Concat	[1]
94	-1	1	525312	models.common.Conv	[1024, 512, 1, 1]
95	-2	1	525312	models.common.Conv	[1024, 512, 1, 1]
96	-1	1	1180160	models.common.Conv	[512, 256, 3, 1]
97	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
98	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
99	-1	1	590336	models.common.Conv	[256, 256, 3, 1]
100	[-1, -2, -3, -4, -5, -6]	1	0	models.common.Concat	[1]
101	-1	1	1049600	models.common.Conv	[2048, 512, 1, 1]
102	75	1	295424	models.common.Conv	[128, 256, 3, 1]

	from	n	params	Module	arguments
103	88	1	1180672	models.common.Conv	[256, 512, 3, 1]
104	101	1	4720640	models.common.Conv	[512, 1024, 3, 1]
105	[102, 103, 104]	1	1395404	models.yolo.ISegment	[1, [[12, 16, 19, 36, 40, 28], [36, 75, 76, 55, 72, 146], [142, 110, 192, 243, 459, 401]], 32, 256, [256, 512, 1024]]]
<hr/>					
Total Layers 417					
Total Parameters 37866092					
Total Gradients 37866092					
GFLOPES 142.6					
<hr/>					

In this study, the researchers aimed to find the best combination of hyperparameters to train a deep learning model for object detection. They specifically considered the number of epochs and batch size, which are key parameters that determine how many times the model is trained on the dataset and how many samples are processed in each iteration. They also experimented with different optimizers, including SGD, Adam, and AdamW, to find the most effective optimization algorithm. Table 3 shows the summary of SGD model hyperparameters that are used.

Table 4. Summary of Best Combination of Hyperparameters

Hyperparameters	Values
Epoch	120
Batch Size	11
Initial learning rate	0.01
Final learning rate	0.01
Momentum	0.937
Weight decay	0.0005
Number of epochs for warmup	3.0

Warmup momentum	0.8
Warmup bias learning rate	0.1
Loss weight for bounding box	0.05
Loss weight for class prediction	0.5
Class prediction loss weight power	1.0
Objectness loss weight	1.0
Objectness loss weight power	1.0
IoU threshold	0.2
Anchor threshold	4.0
Focal loss gamma	0.0
Hue shift range	0.015
Saturation range	0.7
Value range	0.4
Rotation degree range	0.0
Translation range	0.1
Scaling range	0.5
Shear range	0.0
Perspective range	0.0
Probability of flipping image vertically	0.0
Probability of flipping image horizontally	0.5
Probability of using mosaic augmentation	1.0
Probability of using mixup augmentation	0.0
Probability of using copy-paste augmentation	0.0

In the specific case of milkfish fingerlings detection, the YOLOv7 algorithm takes an input image and processes it using a series of convolutional layers to extract features. These features are then used to predict the locations and classes of objects in the image, including the milkfish fingerlings.

The images in Figure 8 are the final stage of the YOLOv7 algorithm, which provides pixel-level segmentation masks for each instance of the detected objects. The algorithm not only detects the presence of milkfish fingerlings in the image but also accurately outlines the contours of each fingerling using a binary mask that assigns a value of 1 to the pixels belonging to the fish and 0 to the background. In the context of the feature map, the brightness of the color used in the visualization represents the likelihood of the pixels being part of the detected objects, with lighter colors indicating higher likelihood (fingerlings) and darker colors indicating lower likelihood (background).

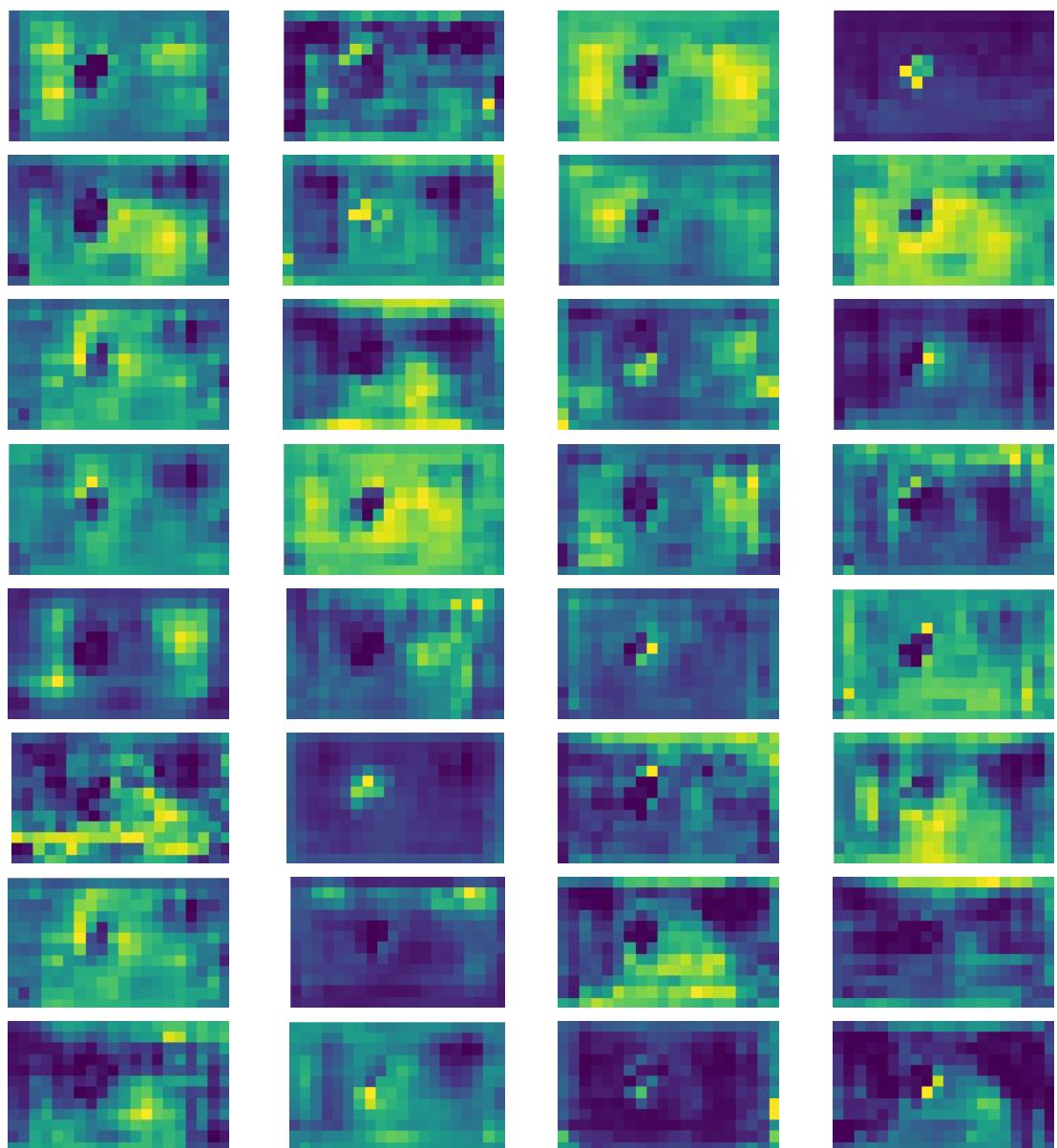


Fig. 8. Feature Map

In this study, various experiments were conducted on YOLOv7 namely, tuning the batch size and epochs, optimization techniques, and freezing layers.

Deep learning has revolutionized computer vision by enabling accurate object recognition and classification. However, a significant challenge in deep learning is preventing overfitting, which occurs when a model becomes too tailored to the training data and performs poorly on new, unseen data.

To address this challenge, experiments were conducted to determine the optimal combination of epoch and batch size that would yield the highest accuracy while also considering the efficiency in terms of GPU memory usage. The experiments involved training the model with batch sizes ranging from 11 to 16 and epoch sizes ranging from 60 to 140, as detailed in Appendix F.

Experiments on Different Batch Sizes. In the experiments conducted to determine the optimal batch size, a batch size of 16 was initially used. However, if an error occurred due to excessive usage of the allocated GPU memory during training, the batch size was decremented by 1 and the training was restarted until a batch size was found that could be accommodated by the available GPU memory. The process was repeated until a batch size of 11 was reached, which is the maximum size that can be used without exceeding the GPU memory limit. This iterative approach allowed for the optimal use of available resources and ensured that the model was trained using the maximum amount of data that could be accommodated by the GPU memory without compromising accuracy.

Experiments on Different Epochs. The researchers tested the model's accuracy with different numbers of epochs, starting with 60 epochs, then 120 epochs, and finally, 140 epochs. The model's accuracy at each epoch were monitored which leads to a finding

that the accuracy increased up to a certain point, and then started to decline. When comparing the accuracy of the model at 60 epochs and 120 epochs, the accuracy increased significantly at 120 epochs. Therefore 120 epochs were the optimal number required to achieve the best possible accuracy for this model. However, when the model is tested with 140 epochs, the accuracy was lower than that of the 120-epoch model. Based on this observation, it is decided to stop at 120 epochs, even though more epochs were tested, because the accuracy stopped improving beyond that point.

Experiments on Different Optimization Techniques. After identifying the best performing combination of batch and epoch size, the researchers explored various optimization algorithms (see Appendix F), including SGD, Adam, and AdamW, in conjunction with the YOLOv7 Instance Segmentation architecture. SGD (Stochastic Gradient Descent), Adam, and AdamW are popular optimization algorithms used in training deep neural networks. SGD performs a simple update based on the gradient of the loss function. Adam is an extension of SGD that uses adaptive learning rates for each parameter and incorporates momentum, allowing for faster convergence and better performance on ill-conditioned or noisy datasets. On the other hand, AdamW is a variant of Adam that includes weight decay as a regularization technique to prevent overfitting. It modifies the weight decay computation in Adam to address potential biases during optimization. By experimenting with different optimizers, the researchers aimed to improve the accuracy and speed of the model. This approach is common in machine learning research as it allows researchers to compare and contrast the performance of different optimization algorithms and select the best one for a specific task. The exploration of different optimization algorithms highlights the importance of fine-tuning.

Base on the results, between the three optimization techniques that have been applied, the SGD achieved the highest accuracy. This finding suggests that SGD is better suited to this model than Adam or AdamW, possibly due to its ability to converge quickly and handle large datasets. The researchers find that when comparing the SGD, Adam, and AdamW optimizers, the SGD performed the best (see Appendix F), it is because SGD performed 5.88% better between 98.9%(SGD) and 93.4%(Adam), and 11.12% better between 98.9%(SGD) and 89%(AdamW). The choice of optimization algorithm can have a significant impact on the performance of deep learning models, and it is important to carefully evaluate different methods to choose the most suitable one.

Experiments on Different Freezing Layers. Additionally, the researchers explored the effect of freezing different layers (1, 2 and 3) of the model during training which will fix the weights of certain layers in the model so that they are not updated during training, which can help prevent overfitting by keeping the model's early layers from being too specialized to the training data.

"Freeze 1" involves freezing the initial layers responsible for low-level feature extraction, "Freeze 2" refers to freezing intermediate layers capturing higher-level features, and "Freeze 3" involves freezing a different set of intermediate layers or a combination of layers based on task-specific requirements.

To evaluate the performance of the trained models, the researchers plotted the train and validation losses for the box, segmentation, and object detection tasks over the course of training. These plots provide a visual representation of how well the model is learning from the training data and how well it generalizes to new, unseen data.

The results of the experiments conducted in this study suggest that the best configuration for training YOLOv7 instance segmentation deep learning model involves using 120 epochs, a batch size of 11, the SGD optimizer, and Freeze 2. These hyperparameters were carefully balanced to optimize the model's performance and minimize the risk of overfitting.

The following layers have been frozen during training:
`model.0.conv.weight`(weights of the convolutional layer in the first block of the model), `model.0.bn.weight`(batch normalization layer in the first block of the model), `model.0.bn.bias`(biases of the batch normalization layer in the first block of the model), `model.1.conv.weight`(the weights of the convolutional layer in the second block of the model), `model.1.bn.weight`(weights of the batch normalization layer in the second block of the model), and `model.1.bn.bias`(biases of the batch normalization layer in the second block of the model). These layers correspond to the backbone network of the YOLOv7 instance segmentation model, which consists of multiple convolutional and batch normalization layers responsible for feature extraction.

According to Yosinski et al. (2014), Freezing layers during training means that the weights of those layers are not updated during backpropagation, it improved the performance of the model, especially that the model that is being developed is being fine-tuned for a specific task. The frozen layers correspond to the backbone network responsible for feature extraction, which can be leveraged to accelerate convergence and improve generalization. By freezing these layers, the model is less likely to overfit the training data

and can better generalize to new examples. Additionally, freezing certain layers can help reduce the computational load during training, improving overall efficiency.

This study focuses on optimizing the YOLOv7 instance segmentation deep learning model by tuning hyperparameters such as batch size, epochs, optimization techniques, and freezing layers. The researchers experimented with different batch sizes and epochs and identified the optimal combination of 11 batch size and 120 epochs. They also explored different optimization techniques such as SGD, Adam, and AdamW and found that SGD outperformed the other two. The researchers froze layers in the model to prevent overfitting and found that freezing intermediate layers (Freeze 2) produced the best results. The study's findings suggest that the optimal configuration for training the YOLOv7 model is 120 epochs, a batch size of 11, the SGD optimizer, and Freeze 2.

Performance Evaluation of the Classification in Terms of Accuracy

Performance evaluation is a critical step in the development and application of machine learning models, as it provides an objective measure of their effectiveness in solving real-world problems. In the field of classification, accuracy is a commonly used metric to assess the performance of the model in correctly predicting the class label and its count.

In this study, the focus is on the evaluation of classification models in terms of its accuracy. Specifically, we aim to investigate the performance of the best performing model in different optimizer as well as freezing specific layers of the architecture, and compare their accuracy under varying conditions such as different number of fingerlings which consists of 9, 20, 30, 42, 50, 60, 70, 80, 90, and 100. The researchers employed a confidence

threshold of 0.55 as a criterion during the evaluation process. This means that only results or findings that had a confidence score equal to or higher than 0.55 were considered valid or reliable. The utilization of this specific threshold helped the researchers ensure that the results they obtained were statistically significant and met the predetermined level of confidence for their study.

The results of this study will provide insights into the strengths and limitations of different combinations of hyperparameters, and help guide the selection of appropriate methods for specific classification tasks. Additionally, the findings of this research can be applied to improve the accuracy of existing models, and inform the development of new machine learning techniques for instance segmentation tasks. In Table 5 (see next page), a comparison of test performance is presented for different models, along with their respective freeze numbers.

Table 5. Test Performance Comparison

Optimizer	Freeze No.	9	20	30	42	50	60	70	80	90	100	Average Accuracy	
SGD	No freeze	9/9 100.00%	20/20 100.00%	30/30 100.00%	40/42 95.24%	43/50 86.00%	62/60 96.67%	69/70 98.57%	82/80 97.50%	75/90 83.33%	57/100 57.00%	91.43%	
	1	9/9 100.00%	20/20 100.00%	28/30 93.33%	40/42 95.24%	45/50 90.00%	53/60 88.33%	62/70 88.57%	78/80 97.50%	76/90 84.44%	58/100 58.00%	89.54%	
	2	9/9 100.00%	21/20 95.00%	28/30 93.33%	40/42 95.24%	48/50 96.00%	57/60 95.00%	67/70 95.71%	80/80 100.00%	82/90 91.11%	54/100 54.00%	91.54%	
	3	9/9 100.00%	19/20 95.00%	26/30 86.67%	37/42 88.10%	42/50 84.00%	55/60 91.67%	66/70 94.29%	77/80 96.25%	76/90 84.44%	57/100 57.00%	87.74%	
	Adam	No freeze	9/9 100.00%	22/20 90.00%	25/30 83.33%	40/42 95.24%	47/50 94.00%	49/60 81.67%	67/70 95.71%	78/80 97.50%	73/90 81.11%	50/100 50.00%	86.86%
		1	10/9 88.89%	21/20 95.00%	23/30 76.67%	43/42 97.62%	42/50 84.00%	52/60 86.67%	66/70 94.29%	76/80 95.00%	73/90 81.11%	50/100 50.00%	84.92%
		2	10/9 88.89%	22/20 90.00%	28/30 93.33%	40/42 95.24%	48/50 96.00%	53/60 88.33%	66/70 94.29%	76/80 95.00%	76/90 84.44%	52/100 52.00%	87.75%
	3	9/9 100.00%	20/20 100.00%	27/30 90.00%	42/42 100.00%	49/50 98.00%	53/60 88.33%	61/70 87.14%	79/80 98.75%	66/90 73.33%	48/100 48.00%	88.36%	
AdamW	No freeze	10/9 88.89%	24/20 80.00%	27/30 90.00%	47/42 88.10%	49/50 98.00%	57/60 95.00%	67/70 95.71%	82/80 97.50%	80/90 88.89%	52/100 52.00%	87.41%	
	1	9/9 100.00%	23/20 85.00%	25/30 83.33%	42/42 95.24%	45/50 90.00%	53/60 88.33%	62/70 88.57%	78/80 97.50%	72/90 80.00%	51/100 51.00%	85.90%	
	2	9/9 88.89%	22/20 90.00%	25/30 93.33%	38/42 95.24%	44/50 96.00%	51/60 88.33%	58/70 94.29%	75/80 95.00%	69/90 84.44%	46/100 52.00%	87.75%	
	3	10/9 88.89%	20/20 100.00%	26/30 86.67%	39/42 92.86%	46/50 92.00%	51/60 85.00%	57/70 81.43%	80/80 100.00%	73/90 81.11%	55/100 55.00%	86.30%	

Discussion of the Different Optimization Results. It can be noted that the application of optimization techniques and freezing layers had a significant impact on the performance of the three different optimizers, namely SGD, Adam, and AdamW. The results obtained showed that SGD achieved the highest accuracy range of 87.74% to 91.54%, followed by Adam with a range of 84.92% to 88.36%, and AdamW with a range of 85.90% to 87.75%.

Furthermore, in the case of SGD optimizer, it is interesting to note that freezing two layers resulted in the highest accuracy of 91.54%. However, this improvement in accuracy is not very significant when compared to the second-highest accuracy of 91.43% achieved by using the SGD optimizer with no freeze. This suggests that in some cases, the benefits of freezing layers may be limited and other optimization techniques may need to be explored to achieve significant improvements in accuracy. Overall, these results demonstrate the importance of carefully selecting and applying optimization techniques to improve the performance of deep learning models.

Discussion of the Results with Lowest Accuracy. Taking into consideration the optimization techniques and freezing layers applied in the experiment have a varying impact on the accuracy of the model. The results show that the lowest accuracy was achieved by SGD using freeze 3 with a percentage of 87.74%. Similarly, Adam using freeze 1 and AdamW using freeze 1 had the lowest accuracies with 84.92% and 85.90%, respectively. These results suggest that the combination of certain optimization techniques and freezing layers may not always result in improved accuracy. It is important to carefully consider which techniques to use and how to apply them based on the specific task and data at hand. It is also worth noting that although these models had lower accuracy

compared to other experiments, they may still have practical applications depending on the required level of accuracy for the given task.

The researchers observed that the accuracy of the system varied across different image inputs, with some images accurately counting the number of fingerlings while others had lower accuracy. The over-detection of milkfish fingerlings by the YOLOv7 model can be attributed to the fact that the model is designed to maximize the detection of fingerlings while minimizing the number of false negatives. This can result in the detection of multiple instances of the same fingerlings or detection of objects that are not actually present in the image.

Additionally, the model may be sensitive to certain features or patterns in the image that are not related to the presence of the fingerlings. It is worth noting that object counting can be a challenging task, especially when objects are densely packed or partially occluded. This can lead to difficulties in accurately counting the number of objects in the image, and may result in a higher number of false positives.

The study showed that the accuracy of the system decreased considerably when processing images with 90 and 100 fingerlings. The reason for this decrease in accuracy was due to the overlapping fingerlings and an over-crowded basin, which made it more challenging for the trained model to detect and count each individual fingerling accurately.

Overall, our results suggest that the accuracy of fingerling counting systems can be affected by environmental factors such as crowding and overlapping, and that these factors should be taken into consideration when developing and using such algorithms. Further research is needed to explore strategies for improving the accuracy of fingerling counting systems under such challenging conditions.

Fingerlings True Count	Sample Image	Resulting Image	Accuracy
9			100%
20			100%
30			100%
42			100%
50			100%
60			100%

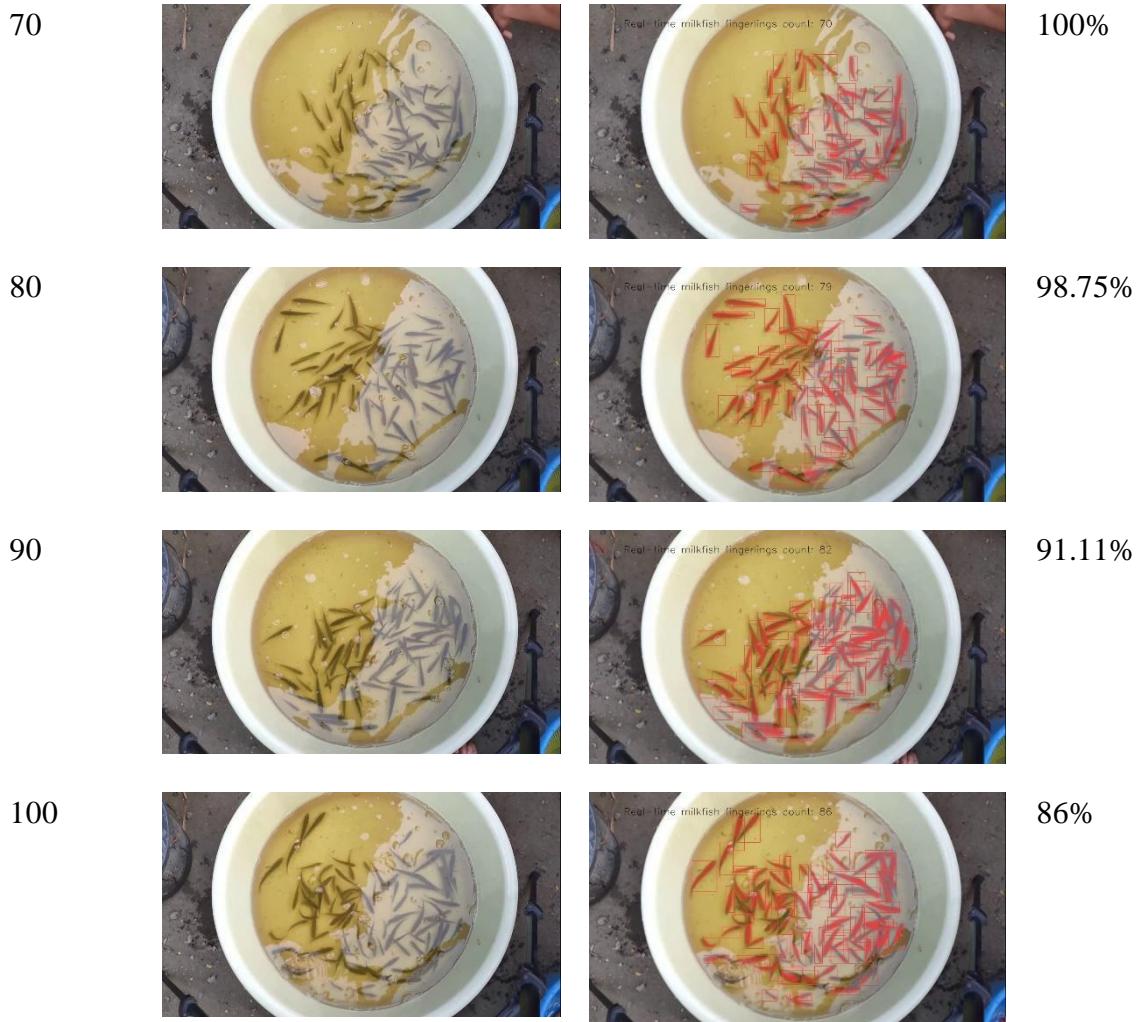


Plate 7. Sample Images with Prediction.

The research demonstrated that the YOLOv7 instance segmentation achieved a range accuracy between 86% to 100%, indicating a high level of accuracy for object detection and recognition tasks (see Plate 7). These results are in contrast to the findings reported by Feng et al. (2022) in their where they reported a range accuracy between 74.23% to 95.76% for their models. The accuracy range observed in our study was higher

than that reported by Feng et al., indicating that the YOLOv7 instance segmentation used in our research was more effective in detecting and recognizing milkfish fingerlings.

The difference in the range accuracy between the two studies is attributed to various factors, such as differences in the dataset used, the number of training iterations, and differences in the model architecture. Nonetheless, the results of our study suggest that YOLOv7 instance segmentation is an effective tool for object detection and recognition tasks.

In summary, the range accuracy of YOLOv7 instance segmentation in our study was higher than the range accuracy reported in the study ‘‘Fry Counting Models Based on Attention Mechanism and YOLOv4-Tiny’’.

Chapter 4

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

Summary

The objective of this study was to develop a real time deep learning-based milkfish fingerling counter model with the following objectives: 1) To perform image preprocessing to manually acquired videos of milkfish fingerlings; 2) To train a deep convolutional neural network with image segmentation; and 3) To assess the model's classification performance in terms of accuracy.

The study used experimental and quantitative research designs. The Real-Time Milkfish Fingerlings Counter Using Deep Learning Approach utilized the YOLOv7 instance segmentation model implemented in a custom dataset consisting of 792 images with a total of 10,728 fingerling annotations.

The following are the salient findings of the study:

1. To improve the performance of the model, the datasets were preprocessed using 13 augmentation techniques, including flips, rotations, crops, shearing, and adjustments to hue, saturation, brightness, and exposure. The researchers also applied blur, noise, and the mosaic technique to increase the diversity of the dataset.
2. The real-time milkfish fingerlings counter model was created by employing the YOLOv7 Instance Segmentation architecture and refining the hyperparameters to achieve the best possible performance. Specifically, the researchers set the epoch at 120 and the batch size at 11. They utilized the SGD optimizer to improve the accuracy of the model, and they set the number of layers to freeze at 2. By fine-

tuning these hyperparameters, the researchers were able to develop a more efficient and accurate model for counting milkfish fingerlings in real-time.

3. After evaluating the results using average accuracy, a total of 12 models with varied hyperparameter combinations were trained and compared in the study to identify the best performing model, which achieved an average accuracy of 91.54%.

Conclusion

Based on the findings of the study, the following conclusion were drawn:

1. The implementation of 13 different types of augmentation techniques during preprocessing has proven to be beneficial in enhancing the detection of milkfish fingerlings.
2. Based on the results obtained, it can be concluded that the YOLOv7 Instance Segmentation Architecture-based deep learning model developed for real-time counting of milkfish fingerlings is a practical and effective detection model, demonstrating satisfactory performance.
3. The developed model performed well with 120 epochs, batch size of 11, and SGD optimizer and freeze 2 in terms of accuracy.

Recommendations

Based on the conclusion of the study, the following recommendations are offered:

1. Additional investigations into the efficacy of alternative implementations of the preprocessing techniques could be conducted to ascertain their impact on the performance of the developed model in the thesis.

2. Given the utility and functionality of YOLOv7 instance segmentation, further state-of-the-art versions of YOLO Architecture could be undertaken to enhance its performance in detecting milkfish fingerlings in the study.
3. Future research could explore the integration of the developed milkfish fingerlings counting model into the construction of a software or application for practical use in counting milkfish fingerlings in aquaculture or fisheries management settings.

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APPENDICES

APPENDIX A**Interview Guide**

Name: _____

Address: _____

Contact Number: _____

1. When do you usually start farming milkfish fingerling?
2. What mechanism are you using to determine the number of milkfish fingerlings?
3. How much time is spent in counting fingerlings?
4. How many people are needed to count fingerlings?
5. How much will it cost you to hire people to count fingerlings?
6. Based on your experiences, what is the estimated number of milkfish fingerlings in your pond every farming?
7. How does the proposed automatic milkfish fingerlings counter help you?

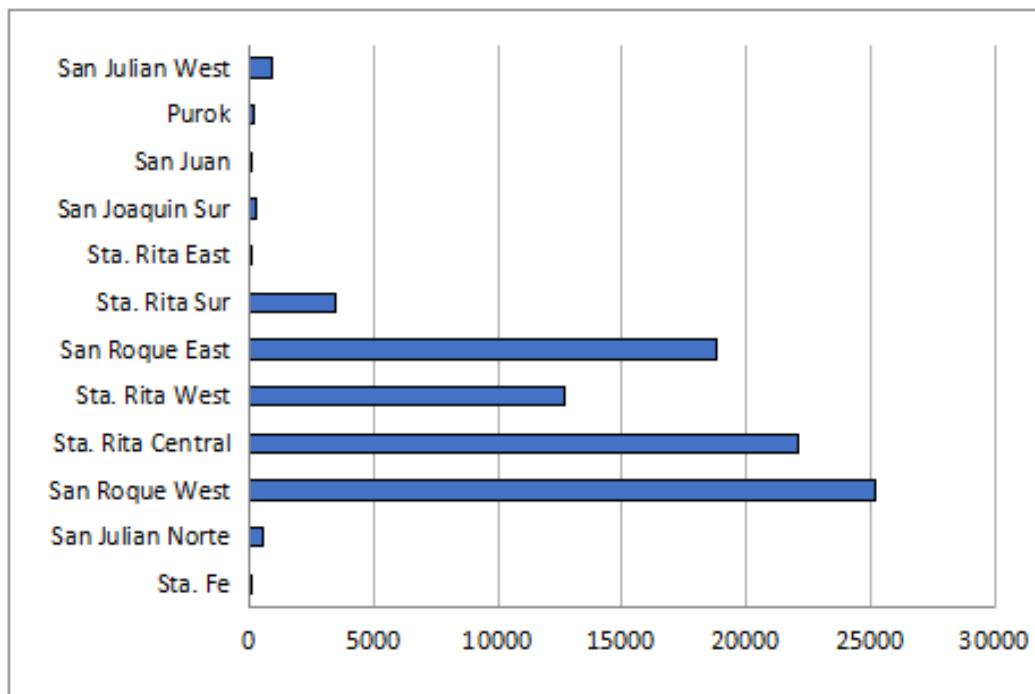
Respondent's Signature

Date: _____

APPENDIX B

Production List & Graph of Milkfish Farms in Agoo, La Union

Barangay	Production(kg)	No. of farms
San Julian West	864	7
Purok	170	5
San Juan	20	1
San Joaquin Sur	225	2
Sta. Rita East	20	1
Sta. Rita Sur	3496	14
San Roque East	18811	23
Sta. Rita West	12650	10
Sta. Rita Central	22096	33
San Roque West	25149	62
San Julian Norte	506	7
Sta. Fe	120	2



APPENDIX C

Ethical Clearance



**Don Mariano Marcos Memorial State University
Research Ethics**
Bacnotan, La Union, Philippines
Email: rec@dmmmsu.edu.ph
Level I Accredited by the Philippine Health Research Ethics Board (PHREB)

DECISION LETTER

March 13, 2023



MR. CHRISTIAN JOSE SIBAYAN
BS Information Technology Student, CCS
DMMMSU - SLUC, Agoo, La Union

RE: Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach

RETC code: 2023-235-Dead Milkfish Counter-Sibayan

Subject: Evaluation results, findings, and recommendations

Dear *Mr. Sibayan*:

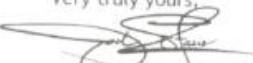
This is to acknowledge receipt of your request and the following supporting documents dated February 22, 2023.

- Request Letter for Review
- Application for Ethics Review of a New Protocol Form
- Full proposal / Study protocol
- Questionnaire
- Informed Consent Form
- Curriculum Vitae
- Technical Review Approval/Compliance Matrix

After review of your initial submission documents, the REC decides to APPROVE your protocol. Attached with this letter is your Ethical Clearance.

Please note the responsibilities of the researchers/Investigators after protocol approval. Note that failure to comply with the conditions and responsibilities may result in the withdrawal of approval of your protocol.

Very truly yours,


JOEL C. ESTACIO

Chair, Research Ethics



**Don Mariano Marcos Memorial State University
Research Ethics**

Bacnotan, La Union, Philippines

Email: reco@dmmsu.edu.ph

Level I Accredited by the Philippine Health Research Ethics Board (PHREB)

**Research Ethics
Committee**

Prof. Joel C. Estacio
(Health)
Chair

Engr. Luis A. Tattao
(Engineering and Technology)
Vice-Chair

Prof. Sherille A. Orejudos
(Health)
Member Secretary

Members:

Dr. Jomar L. Aban
(Teacher Education)

Dr. Arvelia M. Albay
(Psychology)

Dr. Amy P. Balcita
(ICT)

Prof. Claudia Denise P.
Barbadillo
(Social and Behavioral Sciences)

Prof. Janina M. Boado
(Health)

Dr. CF Omar D. Domingo
(Animal Science and Veterinary
Medicine)

Dr. Tjaart Jan B. Estrada
(Math and Sciences)

Dr. Joyencio M. Milan Jr.
(Health)

Dr. Genaro D. Omo
(Agriculture, Aquaculture and
Natural Resources)

Prof. Led Karen R. Zamudio
(Health)

External Members:

Ptr. Epifanio D. Aduan
(Humanities and Spirituality)

Mr. Enrico S. Del Rosario
(Health)

Atty. Leenard S. Dulay
(Governance and Management)

Mr. Alex P. Sarmiento
(Criminal Justice Education)

Secretariat:

Engr. Rhodora S. Mortela
Staff Secretary

ETHICAL CLEARANCE

March 13, 2023

This is to certify that DMMMSU Research Ethics Committee has
APPROVED the following study protocol.

Name of Principal Investigator:
Christian Jose Sibayan

Title of Study / Protocol: **Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach**

RETC Code: **2023-235-Dead Milkfish Counter-Sibayan**

The following are the responsibilities of the investigators / researchers after protocol approval:

1. Seek approval from DMMMSU Research Ethics for any protocol amendment after this date.
2. Submit SAE and SUSAR Reports to RETC when deemed necessary.
3. Submit progress report.
4. Notify DMMMSU RETC of any Protocol deviation/violation.
5. Abide by the principles of good clinical practice and ethical research
6. Comply with relevant international and national guidelines and regulations
7. Submit the **final report** after study completion using the Final Report Form (DMMMSU-RETC-F022).

This Ethical Clearance is valid until March 13, 2024.

JOEL C. ESTACIO
Chair
DMMMSU Research Ethics Committee



APPENDIX D

Informed Consent Form



Don Mariano Marcos Memorial State University
South La Union Campus
COLLEGE OF COMPUTER SCIENCE
Agoo, La Union



This informed consent form is for the selected Milkfish growers/owners in various barangays in the Municipality of Agoo whom we are inviting to participate in this research study titled “Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach”.

Principal Investigator: Sibayan, Christian Jose

Name of Organization: Don Mariano Marcos Memorial State University
South La Union Campus

Other Investigators: Abando, Benjie

Acosta, Justine P.

Madreljos, Johnico D.

Part I: Information Sheet

Introduction

I am Christian Jose Sibayan, with my co-researchers Benjie Abando, Justine Acosta, and Johnico Madreljos. We are 4th year BS Computer Science students in the College of Computer Science at Don Mariano Marcos Memorial State University - South La Union Campus, and presently conducting a research study on real-time dead milkfish counter for underwater images using a deep learning approach.

In line with this, we are humbly informing you and extending an invitation for you to participate in this study. As I explain, this consent form may include words or phrases you may not understand. In such instances, kindly ask me or one of my co-researchers to pause, and we will explain clearly what the words/ phrases mean. If you have any questions regarding our study, you are free to ask any of us.

Purpose of Research

The main purpose of this study is to develop an artificial intelligence-based model that will automatically count dead milkfish. This will help aquaculture farmers know the amount of their harvest and not just rely on their guesses. Milkfish farmers can use this information to adjust the amount of fish feed to prevent overfeeding and water contamination that will lead to fish death. The death of some milkfish can also be a sign of disease or bacteria. This information will give the community time to take the necessary actions to prevent diseases or bacteria from spreading further. This study will be expected to help the production of milkfish. In many cases, the more marketable



Don Mariano Marcos Memorial State University
South La Union Campus
COLLEGE OF COMPUTER SCIENCE
Agoo, La Union



fish are being sold to provide income that is used to purchase other more affordable food items.

Type of Research Intervention

This research will involve your participation in an interview that will take about 30 minutes.

Participant Selection

You are being invited to take part in this research because your experience as a milkfish farm grower can contribute much to our understanding and knowledge of managing milkfish in farms. Aside from this, you also qualify as our study's participant because you are an already adult (i.e., at least 18 years of age).

Voluntary Participation

Your participation in this study is completely voluntary. It is your choice whether to participate or not. The choice that you make will have no bearing on any study matter. You may change your mind later and stop participating even if you agreed earlier. It is assured that your data will be used for academic purposes only, and none of the answers will affect your personal or professional life as everything will be kept confidential.

Procedures

Beforehand, you will be asked if you are a farm grower or farm owner through a yes-or-no question that will determine your eligibility to proceed with the study. We will explain the study "Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach." Afterward, we can start asking questions to you. Your answers will be recorded using an audio recorder. You may inquire about the questions and the study any time especially for the clarifications and potential terms that difficult to understand. It is within your right and freedom to revoke your participation at any given amount if you feel the need to.

Duration

The research will last a total of 10 months (August 2022 - May 2023). During that time, we will visit or meet you once. The purpose of the first meeting is for the interview, which will last 30 minutes.

DMMMSU-RETC-F039
Rev.00 (12.15.2021)



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COLLEGE OF COMPUTER SCIENCE
Agoo, La Union



Risks

There is an anticipated risk for you in participating in this research study. If the interview questions are on sensitive and personal issues and you may feel uncomfortable answering them, you do not have to answer any questions.

Benefits

This study will be beneficial to both the participants and the researchers. The developed system will be helpful to farm growers/owners to count the dead milkfish automatically. By conducting this study, we will be able to develop an AI-based model that will address the problems encountered by farm growers.

Reimbursements

You will be given a free snack for participating in the study.

Confidentiality

We promise and assure you that the data to be gathered will be kept private, confidential, and used only for this research study. Your name will be optional on the survey questionnaire and interview; it's your choice if you will provide your name or not. Suppose there are hard copies throughout the process containing the respondent's personal information. In that case, the researchers will see that they are stored in protected spaces, and they will be incinerated after the study.

Sharing the Results

Rest assured, the information you shared with us will remain only within our research team and not be shared outside our knowledge.

Right to Refuse or Withdraw

The decision to take part in this study is totally up to you. Even if you are chosen to participate, you have the freedom to stop at any time if you so choose. Different respondents will be chosen if it is rejected. If you decide to quit taking part, please let the researcher know as soon as you can so that your responses can be separated at that time.



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 South La Union Campus
COLLEGE OF COMPUTER SCIENCE
 Agoo, La Union



Who to Contact

This proposal has been reviewed and approved by DMMMSU Research Ethics Committee, which is a committee whose task it is to make sure that research participants are protected from harm. If you wish to find about more about the Committee, contact:

Joel C. Estacio
 Chair, DMMMSU REC
rec@dmmmsu.edu.ph

Do you know that you do not have to take part in this study if you do not wish to? You can say No if you wish to? Do you know that you can ask me questions later, if you wish to? Do you know that I have given the contact details of the person who can give you more information about the study?

You can ask me any more questions about any part of the research study, if you wish to. Do you have any questions? You can contact me through the following:

Christian Jose Sibayan
 Research Leader, DMMMSU-SLUC
 09501147756 / cjsibayan@student.dmmmsu.edu.ph

Part II: Certificate of Consent

I have read the foregoing information, or it has been read to me. I have had the opportunity to ask questions about it and any questions I have been asked have been answered to my satisfaction. I consent voluntarily to be a participant in this study

Name of Participant:

Amado Alost

Signature of Participant:

Date:

April 19, 2023

Day/month/year



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 South La Union Campus
COLLEGE OF COMPUTER SCIENCE
 Agoo, La Union



If illiterate¹

I have witnessed the accurate reading of the consent form to the potential participant, and the individual has had the opportunity to ask questions. I confirm that the individual has given consent freely.

Name of witness _____

Thumb print of participant

Signature of witness _____

Date _____

Day/month/year

Statement by the researcher/person taking consent

I have accurately read out the information sheet to the potential participant, and to the best of my ability made sure that the participant understands that the following will be done:

1. _____
2. _____
3. _____

I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

A copy of this ICF has been provided to the participant.

Name of Researcher/person taking the consent _____

Signature of Researcher /person taking the consent _____

Date _____

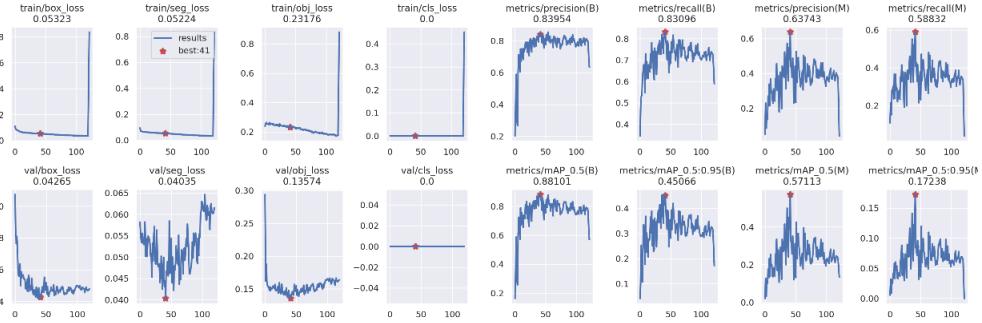
Day/month/year

¹ A literate witness must sign (if possible, this person should be selected by the participant and should have no connection to the research team). Participants who are illiterate should include their thumb print as well.

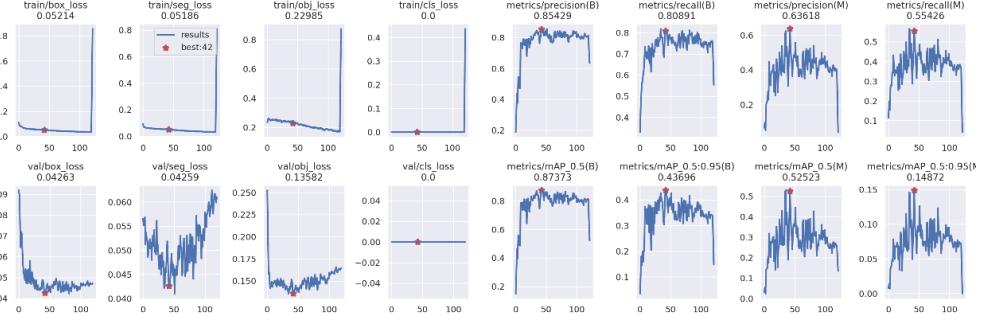
APPENDIX E

Results of Training Loss and Accuracy Using SGD, Adam, and AdamW

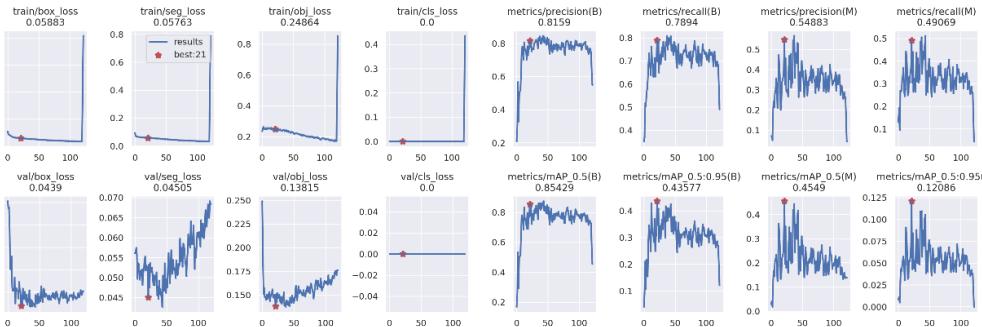
SGD No Freeze



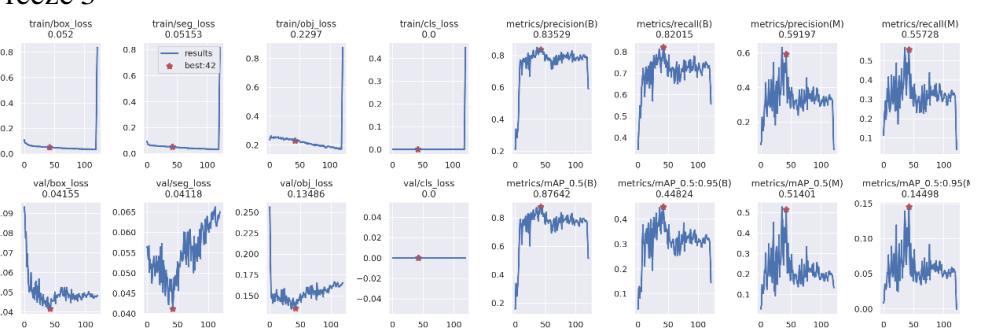
SGD Freeze 1



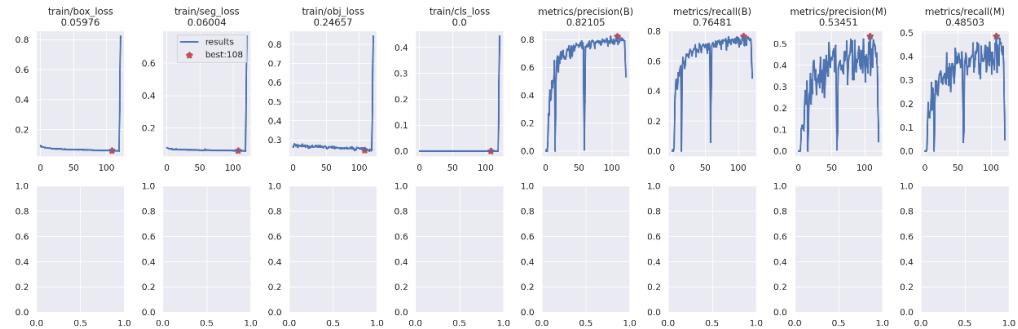
SGD Freeze 2



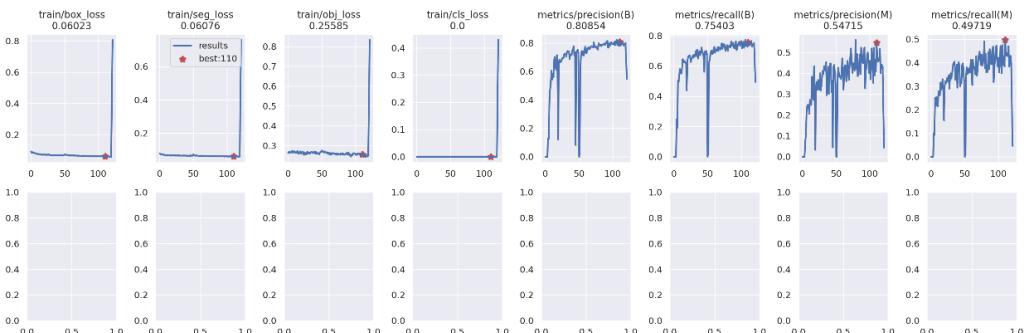
SGD Freeze 3



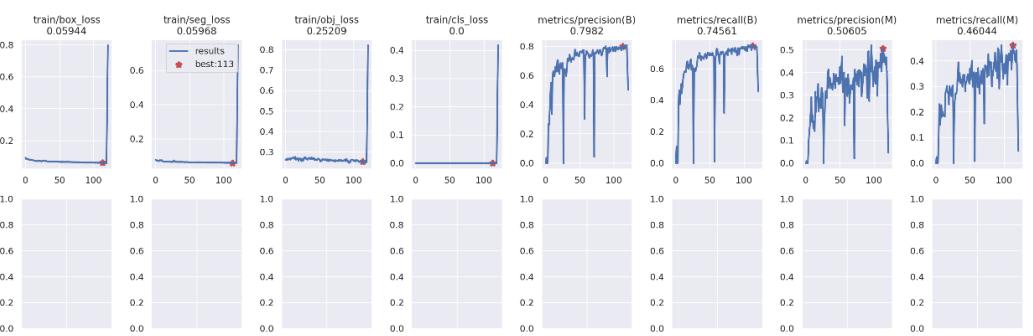
Adam No Freeze



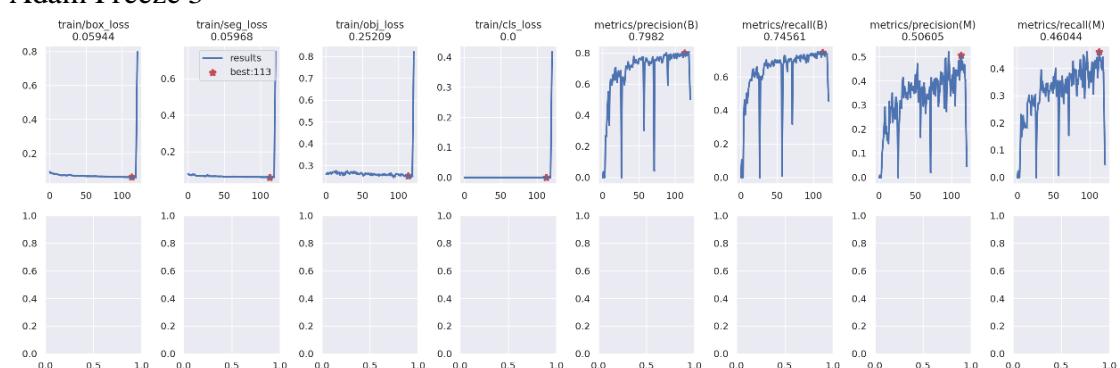
Adam Freeze 1



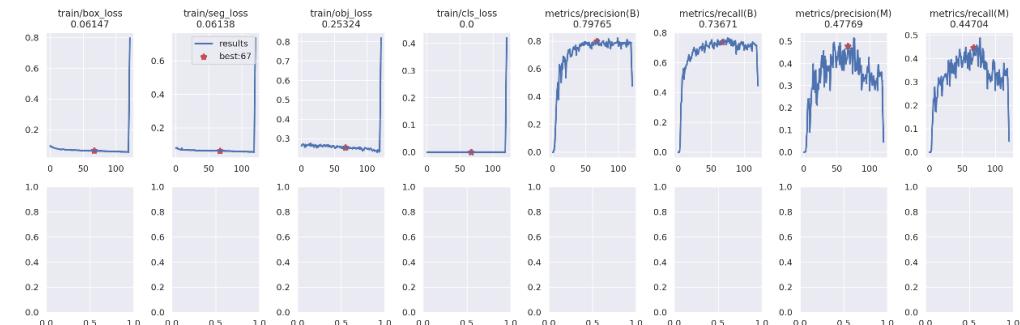
Adam Freeze 2



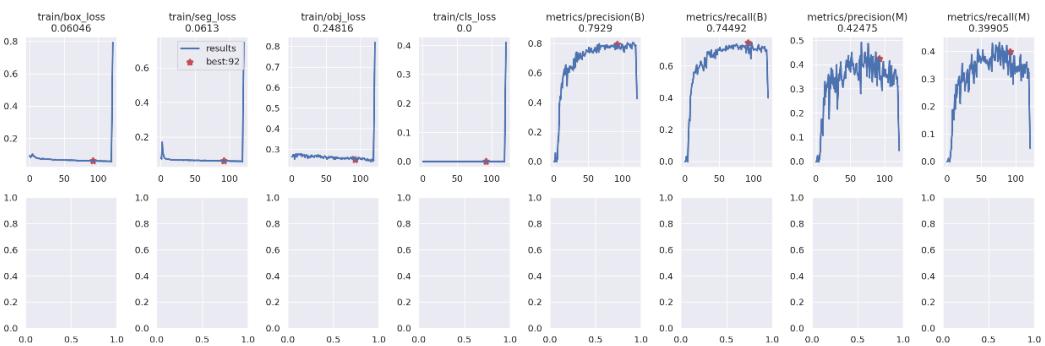
Adam Freeze 3



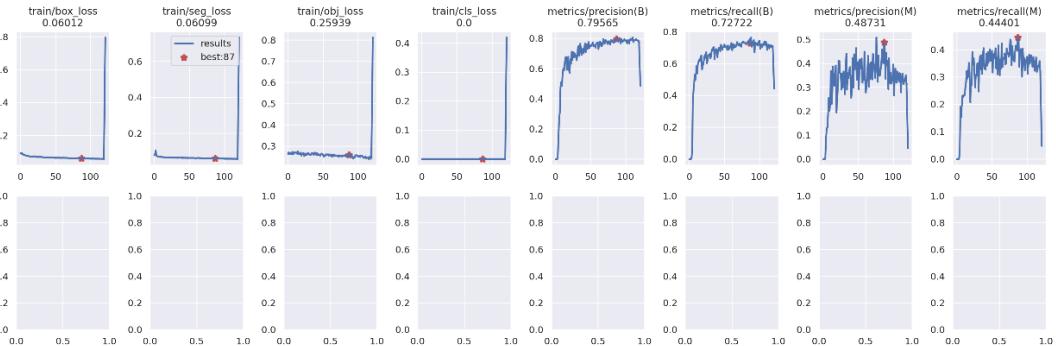
AdamW No Freeze



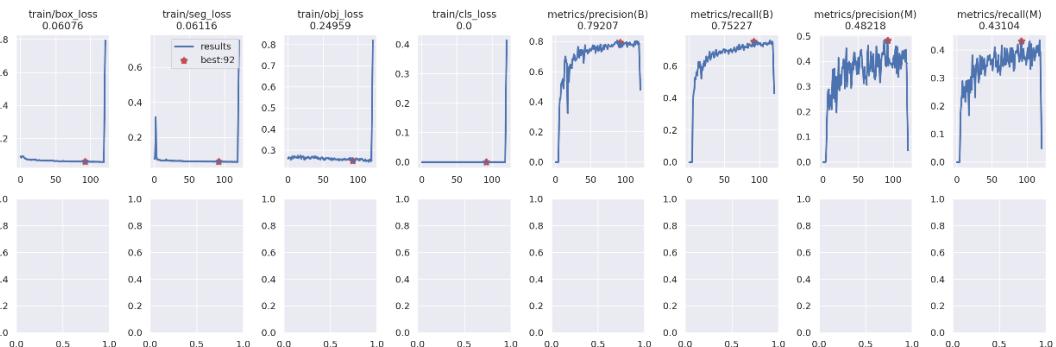
AdamW Freeze 1



AdamW Freeze 2



AdamW Freeze 3



APPENDIX F

List of Conducted Experiments

		Experiment Results									
		Fingerlings Count Confirmed By The Milkfish Farmers									
		9 Fingerlings	20 Fingerlings	30 Fingerlings	42 Fingerlings	50 Fingerlings	60 Fingerlings	70 Fingerlings	80 Fingerlings	90 Fingerlings	100 Fingerlings
Model 1 60epochs-11batch-with-overlap-sqd	Confidence Threshold	Count Accuracy: 81.3%	Count Accuracy: 77%	Count Accuracy: 90%	Count Accuracy: 92%	Count Accuracy: 86%	Count Accuracy: 88%	Count Accuracy: 69.54%	Count Accuracy: 87.50%	Count Accuracy: 85.00%	Count Accuracy: 84.10%
	0.15	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.25	Count Accuracy: 94.5%	Count Accuracy: 92%	Count Accuracy: 86%	Count Accuracy: 90%	Count Accuracy: 95%	Count Accuracy: 86%	Count Accuracy: 60.57%	Count Accuracy: 86%	Count Accuracy: 74%	Count Accuracy: 70%
	0.35	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.45	Count Accuracy: 95.6%	Count Accuracy: 84%	Count Accuracy: 74%	Count Accuracy: 80%	Count Accuracy: 82%	Count Accuracy: 75%	Count Accuracy: 50.86%	Count Accuracy: 74.12%	Count Accuracy: 61.67%	Count Accuracy: 59.60%
	0.55	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.65	Count Accuracy: 94.5%	Count Accuracy: 86.5%	Count Accuracy: 62%	Count Accuracy: 64%	Count Accuracy: 70%	Count Accuracy: 65%	Count Accuracy: 40.71%	Count Accuracy: 63.25%	Count Accuracy: 48.44%	Count Accuracy: 59.60%
	0.75	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.85	Count Accuracy: 87.9%	Count Accuracy: 77%	Count Accuracy: 46%	Count Accuracy: 47%	Count Accuracy: 56%	Count Accuracy: 50%	Count Accuracy: 30.43%	Count Accuracy: 49.00%	Count Accuracy: 33.89%	Count Accuracy: 35.40%
	Confidence Threshold	Count Accuracy: 71.3%	Count Accuracy: 59%	Count Accuracy: 22%	Count Accuracy: 25%	Count Accuracy: 33%	Count Accuracy: 29%	Count Accuracy: 18.43%	Count Accuracy: 30.62%	Count Accuracy: 33.89%	Count Accuracy: 20.90%
Model 2 120epochs-11batch-with-overlap-sqd	Confidence Threshold	Count Accuracy: 98.9%	Count Accuracy: 96%	Count Accuracy: 89%	Count Accuracy: 92%	Count Accuracy: 92%	Count Accuracy: 88%	Count Accuracy: 61.29%	Count Accuracy: 84%	Count Accuracy: 68%	Count Accuracy: 74%
	0.15	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.25	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.35	Count Accuracy: 97.8%	Count Accuracy: 91.5%	Count Accuracy: 78%	Count Accuracy: 78%	Count Accuracy: 80%	Count Accuracy: 76%	Count Accuracy: 50.71%	Count Accuracy: 73.88%	Count Accuracy: 56.56%	Count Accuracy: 62.40%
	0.45	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.55	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.65	Count Accuracy: 51.3%	Count Accuracy: 57.5%	Count Accuracy: 23%	Count Accuracy: 22%	Count Accuracy: 35%	Count Accuracy: 32%	Count Accuracy: 15.71%	Count Accuracy: 30.75%	Count Accuracy: 16.44%	Count Accuracy: 19.90%
	0.75	Experiment Link: https://c	Experiment Link: https://l	Experiment Link: https://dri	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri	Experiment Link: https://dr	Experiment Link: https://d	Experiment Link: https://dr	Experiment Link: https://dri
	0.85	Count Accuracy: 0%	Count Accuracy: 1%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0.25%	Count Accuracy: 0%

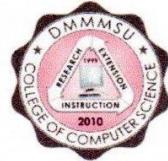
Experiment Results											
		Fingerlings Count Confirmed By The Milkfish Farmers									
Model	Confidence Threshold	9 Fingerlings	20 Fingerlings	30 Fingerlings	42 Fingerlings	50 Fingerlings	60 Fingerlings	70 Fingerlings	80 Fingerlings	90 Fingerlings	100 Fingerlings
		Count Accuracy: 84.6% Count Accuracy: 76%	Count Accuracy: 86%	Count Accuracy: 92%	Count Accuracy: 92.2%	Count Accuracy: 93%	Count Accuracy: 61.71%	Count Accuracy: 88.12%	Count Accuracy: 80.56%	Count Accuracy: 84.10%	
120epochs-11batch-with-overlap-sgd-freeze1	0.15	Experiment Link: https://k	Experiment Link: https://d								
	0.25	Count Accuracy: 94.6% Count Accuracy: 95%	Count Accuracy: 88%	Count Accuracy: 86%	Count Accuracy: 91%	Count Accuracy: 81%	Count Accuracy: 55.00%	Count Accuracy: 80%	Count Accuracy: 67%	Count Accuracy: 71%	
	0.35	Count Accuracy: 94.5% Correct Count: 95%	Count Accuracy: 74%	Count Accuracy: 76.19%	Count Accuracy: 81.2	Count Accuracy: 69.50%	Count Accuracy: 48.43%	Count Accuracy: 72.50%	Count Accuracy: 56.89%	Count Accuracy: 60.50%	
	0.45	Count Accuracy: 94.5% Count Accuracy: 82%	Count Accuracy: 58%	Count Accuracy: 63.57%	Count Accuracy: 70.4	Count Accuracy: 59.17%	Count Accuracy: 40.57%	Count Accuracy: 63.00%	Count Accuracy: 45.89%	Count Accuracy: 49.90%	
	0.55	Count Accuracy: 85.7% Count Accuracy: 78.5%	Count Accuracy: 44%	Count Accuracy: 46.67%	Count Accuracy: 57.0	Count Accuracy: 46.83%	Count Accuracy: 29.22%	Count Accuracy: 50.50%	Count Accuracy: 35.22%	Count Accuracy: 38.90%	
	0.65	Count Accuracy: 73.6% Count Accuracy: 62.5%	Count Accuracy: 22%	Count Accuracy: 24.76%	Count Accuracy: 38.0	Count Accuracy: 25.67%	Count Accuracy: 15.57%	Count Accuracy: 33.88%	Count Accuracy: 20.33%	Count Accuracy: 24.00%	
	0.75	Count Accuracy: 33.3% Count Accuracy: 30.5%	Count Accuracy: 7%	Count Accuracy: 4.76%	Count Accuracy: 12.4	Count Accuracy: 5.33%	Count Accuracy: 3.71%	Count Accuracy: 14.00%	Count Accuracy: 6.89%	Count Accuracy: 8.60%	
	0.85	Count Accuracy: 1.1% Count Accuracy: 2%	Count Accuracy: 0%	Count Accuracy: 0.62%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%				
	Fingerlings Count Confirmed By The Milkfish Farmers										
	Count Accuracy: 87.9% Count Accuracy: 86%	Count Accuracy: 89%	Count Accuracy: 88%	Count Accuracy: 86%	Count Accuracy: 87%	Count Accuracy: 62.14%	Count Accuracy: 85.25%	Count Accuracy: 83.78%	Count Accuracy: 88.70%		
120epochs-11batch-with-overlap-sgd-freeze2	0.15	Experiment Link: https://k	Experiment Link: https://d								
	0.25	Count Accuracy: 93.4% Count Accuracy: 93%	Count Accuracy: 79%	Count Accuracy: 86%	Count Accuracy: 93%	Count Accuracy: 85%	Count Accuracy: 56.29%	Count Accuracy: 84%	Count Accuracy: 69%	Count Accuracy: 70%	
	0.35	Count Accuracy: 93.4% Count Accuracy: 80.5%	Count Accuracy: 68%	Count Accuracy: 72.38%	Count Accuracy: 76.8	Count Accuracy: 67.33%	Count Accuracy: 42.86%	Count Accuracy: 67.12%	Count Accuracy: 52.00%	Count Accuracy: 53.50%	
	0.45	Count Accuracy: 84.6% Count Accuracy: 80.5%	Count Accuracy: 50%	Count Accuracy: 52.62%	Count Accuracy: 62.0	Count Accuracy: 52.17%	Count Accuracy: 30.57%	Count Accuracy: 53.12%	Count Accuracy: 36.44%	Count Accuracy: 40.50%	
	0.55	Count Accuracy: 62.3% Count Accuracy: 60.5%	Count Accuracy: 30%	Count Accuracy: 33.10%	Count Accuracy: 41.6	Count Accuracy: 34.50%	Count Accuracy: 19.14%	Count Accuracy: 35.62%	Count Accuracy: 21.67%	Count Accuracy: 24.40%	
	0.65	Count Accuracy: 40.9% Count Accuracy: 35%	Count Accuracy: 11%	Count Accuracy: 12.38%	Count Accuracy: 17.2	Count Accuracy: 16.50%	Count Accuracy: 7.86%	Count Accuracy: 18.12%	Count Accuracy: 8.00%	Count Accuracy: 10.90%	
	0.75	Count Accuracy: 10% Count Accuracy: 9.5%	Count Accuracy: 3%	Count Accuracy: 2.38%	Count Accuracy: 2.20%	Count Accuracy: 2.00%	Count Accuracy: 0.86%	Count Accuracy: 2.75%	Count Accuracy: 1.1.11%	Count Accuracy: 2.60%	
	0.85	Count Accuracy: 0% Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%	Count Accuracy: 0%
	Fingerlings Count Confirmed By The Milkfish Farmers										
	Count Accuracy: 87.9% Count Accuracy: 86%	Count Accuracy: 89%	Count Accuracy: 88%	Count Accuracy: 86%	Count Accuracy: 87%	Count Accuracy: 62.14%	Count Accuracy: 85.25%	Count Accuracy: 83.78%	Count Accuracy: 88.70%		

APPENDIX G

Letter to the Adviser



Don Mariano Marcos Memorial State University
South La Union Campus
COLLEGE OF COMPUTER SCIENCE
Agoo, La Union



September 19, 2022

CHARLIE S. MARZAN, MIT

Faculty Member

Don Mariano Marcos Memorial State University
Agoo La Union

Sir:

We, the undersigned BS Computer Science students are enrolled in the subject Thesis Writing 1 and one of the requirements of the subject is for us to conduct a research.

In this connection, may we request you to be our Thesis Adviser on our study entitled "*Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach*". We anticipate for your consideration to this humble request.

Thank you.

Very truly yours,

Chrisitan Jose Sibayan
CHRISITAN JOSE SIBAYAN
Thesis Writer

Johnico D. Madrelijos
JOHNICO D. MADRELIJOS
Thesis Writer

Benjie Abando
BENJIE ABANDO
Thesis Writer

Justin P. Acosta
JUSTIN P. ACOSTA
Thesis Writer

Approved:

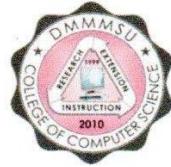
Charlie S. Marzan
CHARLIE S. MARZAN, MIT
Thesis Adviser

APPENDIX H

Letter to the Technical Panel Members



Don Mariano Marcos Memorial State University
South La Union Campus
COLLEGE OF COMPUTER SCIENCE
Agooo, La Union



November 11, 2022

BELINDA D. CELESTIAL, PhDCS

Faculty Member

Don Mariano Marcos Memorial State University
Agooo La Union

Sir:

We, the undersigned BS Computer Science students are enrolled in the subject Thesis Writing 1 and one of the requirements of the subject is for us to conduct a research.

In this connection, may we request you to be our Thesis Panel Member on our study entitled "*Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach*". We anticipate for your consideration to this humble request.

Thank you.

Very truly yours,

C. Sibayan
CHRISITAN JOSE SIBAYAN
Thesis Writer

P. Madrelijos
JOHNICO D. MADRELIJOS
Thesis Writer

B. Abando
BENJIE ABANDO
Thesis Writer

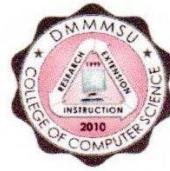
J. Acosta
JUSTIN P. ACOSTA
Thesis Writer

Approved:

B. Celestial
BELINDA D. CELESTIAL, PhDCS
Thesis Panel Member



Don Mariano Marcos Memorial State University
South La Union Campus
COLLEGE OF COMPUTER SCIENCE
Agoo, La Union



November 11, 2022

JOE ANTHONY M. MILAN, PhDCS
Faculty Member
Don Mariano Marcos Memorial State University
Agoo La Union

Sir:

We, the undersigned BS Computer Science students are enrolled in the subject Thesis Writing 1 and one of the requirements of the subject is for us to conduct a research.

In this connection, may we request you to be our Thesis Panel Member on our study entitled "*Real-Time Dead Milkfish Counter for Underwater Images Using Deep Learning Approach*". We anticipate for your consideration to this humble request.

Thank you.

Very truly yours,

Chrisitan Jose Sibayan
CHRISITAN JOSE SIBAYAN
Thesis Writer

Johnico D. Madrelijos
JOHNICO D. MADRELIJOS
Thesis Writer

Benjie Abando
BENJIE ABANDO
Thesis Writer

Justin P. Acosta
JUSTIN P. ACOSTA
Thesis Writer

Approved:

Joe Anthony M. Milan, PhDCS
JOE ANTHONY M. MILAN, PhDCS
Thesis Panel Member

CURRICULUM VITAE

CHRISTIAN JOSE SIBAYAN

Poblacion East, Rosario, La Union
 2506 Philippines
 Contact No: 0950-114-7756
 E-mail: cjsibayan@student.dmmmsu.edu.ph
 josentrating@gmail.com



Educational Background

<i>2019 - present</i>	Bachelor of Science in Computer Science Don Mariano Marcos Memorial State University Consolacion, Agoo, La Union <i>Thesis: "Real-Time Milkfish Fingerling Counter Using Deep Learning Approach"</i>
<i>2017 - 2018</i>	Alternative Learning System Poblacion East, Rosario, La Union
<i>2005 - 2009</i>	Mabini Elementary School Salud Mitra, Baguio City, Benguet
<i>2004 - 2005</i>	Rosario Integrated School Subusub, Rosario, La Union
<i>2003 - 2004</i>	Union Institute of Rosario MacArthur Hwy, Rosario, La Union

Work Experiences

<i>2017 - present</i>	Warehouse Crew & Utility Value Chain Solutions, Inc. - P&G Division Rosario, La Union
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Seminars and Trainings Attended

<i>October 2022</i>	Data Analytics Intermediate Session DICT - Trainee Consolacion, Agoo, La Union
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July - August 2022 On-the-Job Training
Office of the Program Chair
College of Computer Science, DMMMSU-SLUC
Agoo, La Union

July 2022 Webinar on On-Job-Training Orientation
College of Computer Science
DMMMSU-SLUC

Special Skills and Talents

- Web Development
- Database Management
- Programming Languages: HTML, CSS, JavaScript, PHP, Python, Java, C, and SQL
- Video Editing using DaVinci Resolve
- Document preparation and presentation using Microsoft Office, Google Workspace and WPS Applications
- Knowledge in Software Engineering and System Development
- Knowledgeable in Machine Learning and Artificial Intelligence

Certified true and correct.


CHRISTIAN JOSE SIBAYAN

Signature over printed name

BENJIE RAMOS ABANDO

Sta. Maria, Agoo, La Union
 2504 Philippines
 Contact No: 0926-0088-209
 E-mail: babando@student.dmmmsu.edu.ph



Educational Background

<i>2018 - present</i>	Bachelor of Science in Computer Science Don Mariano Marcos Memorial State University Consolacion, Agoo, La Union Thesis: " <i>Real-Time Milkfish Fingerling Counter Using Deep Learning Approach</i> "
<i>2012 - 2018</i>	President Elpidio Quirino National High School San Agustin East, Agoo, La Union
<i>2006 - 2012</i>	Ambitacay Elementary School Ambitacay, Agoo, La Union

Work Experiences

<i>2018-2019</i>	Promodizer (National Book Store, SM branch) Baguio City
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Seminars and Trainings Attended

<i>July - August 2022</i>	On-Job-Training Barangay Hall Sta. Maria Agoo, La Union
<i>July 2022</i>	Webinar on On-Job-Training Orientation College of Computer Science DMMMSU-SLUC

Special Skills and Talents

- Document preparation and presentation using Microsoft Office Applications
- Computer Software and Application Knowledge
- Programming Language/s: Php, SQL, JavaScript, C, CSS, and HTML5
- Web Development
- Database Management
- Video Editing using CapCut
- Knowledge in Layouting and Photo Editing

Certified true and correct.



BENJIE R. ABANDO
Signature over printed name

JUSTIN PERALTA ACOSTA

Bail Sto. Tomas La Union
 2505 Philippines
 Contact No: 0950-838-0513
 E-mail: jacosta@student.dmmmsu.edu.ph



Educational Background

<i>2019 – present</i>	Bachelor of Science in Computer Science Don Mariano Marcos Memorial State University Consolacion, Agoo, La Union Thesis: “Real-Time Milkfish Fingerling Counter Using Deep Learning Approach”
<i>2013 – 2019</i>	Bail National High School Bail Sto. Tomas La Union
<i>2007 – 2013</i>	Bail Elementary School Bail Sto. Tomas, La Union

Awards/Honors Received

<i>March 2019</i>	Certificate of Accomplishment Participation on the following seminars: How to Collect, My Business, Basic Skin Care & Make up. Bail Senior High School (GAS STRAND)
<i>November 2018</i>	Certificate of Accomplishment Sales and Marketing on the Job Training during the AVON the Academe Programs. Bail Senior High School (GAS STRAND)

Work Experiences

<i>Oct 2018 - Nov 2018</i>	Salesperson AVON Agoo, La Union
----------------------------	---------------------------------------

Seminars and Trainings Attended

October 2022 Data Analytics Intermediate Session
 DICT - Trainee
 Consolacion, Agoo, La Union

July - August 2022 On-Job-Training
 Barangay Hall
 Sta. Maria, Agoo, La Union

July 2022 Webinar on On-Job-Training Orientation
 College of Computer Science
 DMMMSU SLUC

November 2018 Sales and Marketing on the Job training during the AVON
 At the Academe Programs.
 Agoo, La Union

Special Skills and Talents

- Graphics editing using PicsArt and Adobe Photoshop
- Programming Language/s: Php, SQL, JavaScript, C, CSS, and HTML5
- Computer Software and Application Knowledge
- Web Development
- Database Management
- Computer Software and Application Knowledge
- Knowledge in Developing Mobile Application using Android Studio

Certified true and correct.


JUSTIN P. ACOSTA
 Signature over printed name

JOHNICO DULAY MADRELIJOS

Sta. Barbara, Agoo, La Union
 2504 Philippines
 Contact No: 0915-373-0103
 E-mail: jmadrelijos@student.dmmmsu.edu.ph
 johnicomadrelijos@gmail.com



Educational Background

<i>2019 – present</i>	Bachelor of Science in Computer Science Don Mariano Marcos Memorial State University Consolacion, Agoo, La Union Thesis: “ <i>Real-Time Milkfish Fingerling Counter Using Deep Learning Approach</i> ”
<i>2012 - 2019</i>	Agoo Kiddie Special School Consolacion, Agoo, La Union
<i>2005 - 2012</i>	Agoo East Central School Consolacion, Agoo, La Union

Work Experiences

<i>Nov - Dec 2018</i>	Technical Support Local Government Unit, BAC Office Agoo, La Union
<i>July - Aug 2022</i>	Apprentice Programmer DILG Central Office, ISTMS Quezon City, Metro Manila, Philippines

Seminars and Trainings Attended

<i>October 2022</i>	Webinar on Data Analytics (Intermediate Session) Department of Information and Communication Technology Agoo, La Union
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Jul - Aug 2022 On-the-Job Training
 DILG Central Office, ISTMS
 Quezon City, Metro Manila, Philippines

August 2022 Webinar on On-Job-Training Orientation
 DMMMSU SLUC BSCS
 Agoo, La Union

Special Skills and Talents

- Microsoft Office Literate (e.g Ms Word, Ms Excel, Ms PowerPoint)
- Programming Language/s: Php, SQL, JavaScript, C, CSS, and HTML5
- PC Troubleshooting
- Good communication skills
- Web Development
- Database Management
- Video Editing using CapCut
- Knowledgeable in using Microsoft Office such as Ms Word, Ms Excel, and Ms PowerPoint
- Knowledge in Software Engineering and System Development
- Good communication skills
- Knowledgeable in Yii2 Framework

Certified true and correct.


JOHNICO D. MADRELIJOS
 Signature over printed name