CHAPTER I
IDEA PROPOSAL

1.1 General Problem Description

Tuna is a highly valued saltwater fish, consumed globally for its nutritional value and versatility, whether eaten raw, cooked, or canned. In 2023, the global market for tuna was valued at USD 41.94 billion and is expected to grow further [1]. This growth is largely driven by consumers' awareness of tuna's health benefits such as its high protein content and omega-3 fatty acids, which are vital for brain and heart health [2]. The tuna industry plays a significant role in the economy of the Asia-Pacific region where it is home to the largest producers of tuna, including Indonesia [3]. In 2022, Indonesia's exports reached USD 920.27 million, contributing to 19% of the global tuna supply [4].

As the industry continues to grow, it demands more efficient, scalable, and reliable techniques for grading tuna loin. Similar to other fish products, the freshness and quality of tuna is graded using sensory evaluation such as appearance and feel of texture [5]. However, this process is not only labor-intensive but also highly subjective, leading to inconsistencies in assessments across different samples [5]. Moreover, tuna products can degrade rapidly due to factors such as high water content, microbial activity, improper handling techniques, prolonged storage, and inadequate temperature control. Additionally, pre-mortem stress in the tuna can affect its quality, making accurate, real-time inspections essential for ensuring product standards [6].

As the industry grapples with challenges such as quality degradation and inefficiencies in grading processes, innovative solutions have become imperative to ensure product standards and market competitiveness. One such Indonesian company that can make use of innovative solutions for tuna loin grading is PT. Aruna Jaya Nuswantara. PT. Aruna strives to connect local fishermen to the global market through advanced technology, thus, streamlining the supply of fish products [7]. Their reach has spread across all major islands of Indonesia, empowering more than 40,000 fishers across 177 locations [7]. Figure 1.1 shows the logo of the PT. Aruna company.

Figure 1.1 PT. Aruna Jaya Nuswantara Logo

1.1.1 Objective

This project proposes the integration of computer vision and deep learning into a mobile application to automate the grading process into three standardized categories: A, B, and C with an accuracy of 90%. This solution can analyze visual attributes such as color and texture with high accuracy and consistency, minimizing subjective judgment and improving both speed and reliability. Automation not only reduces grading errors but also ensures fair pricing, better quality control, and increased productivity throughout the supply chain.

The proposed system is designed with adaptability in mind. It can be deployed on portable devices such as smartphones, allowing the classification to be performed in various environments, from centralized processing facilities to remote fishing locations. This flexibility is especially beneficial for regions like Indonesia, where small-scale fisheries contribute significantly to global tuna exports. By ensuring consistent performance under different lighting and environmental conditions, the system supports scalable, real-time quality assessments. This technology-driven solution improves transparency, reduces operational costs, and strengthens the industry's ability to meet the growing global demand with reliable, high-quality tuna products.

1.2 Problem Analysis

1.2.1 Technical Aspect

The use of computer vision and deep learning presents opportunities and challenges for efficient tuna loin grading. Tuna loins naturally exhibit variability in color and texture, which could possibly make accurate deep learning models complex. The system needs to be able to grade tuna loin in diverse environments such as in different lighting conditions [8]. Furthermore, computer vision and deep learning models rely on heavy hardware to ensure higher processing power and efficient training [9].

1.2.2 Economical Aspect

Traditional methods of tuna loin quality inspection rely on manual, sensory evaluations. These processes are labor intensive as they require trained inspectors and time-consuming inspections which leads to increased operational costs [10]. Furthermore, human assessments can result in misgraded products, causing financial losses through undervaluing premium products or overvaluing non-premium products [10].

1.2.3 Social Aspect

The implementation of computer vision and deep learning models brings opportunities and challenges from a social perspective. Automation may enhance job quality by reducing labor-intensive, repetitive tasks, allowing workers to focus on other important roles [10]. Moreover, with increased accuracy and consistency in automated grading, consumers will benefit from more reliable product quality [10]. Markets will receive tuna loin that is fresher and safer, improving public health. On the other hand, the automation of tuna loin grading may reduce the number of manual graders, which may lead to loss of job positions.

1.2.4 Manufacturability Aspect

Implementing computer vision and deep learning models into devices such as smartphones bring opportunities and challenges from the manufacturability aspect. Smartphones are portable devices that have cameras that can be used for computer vision. This can serve advantages such as having the ability to perform tuna loin grading in locations other than the grading facilities. The system can be implemented on any smartphone device, as long as it has the appropriate hardware specifications [11]. On the other hand, smartphones usually have limited hardware capabilities compared to computers [11]. Therefore, the computer vision and deep learning models need to be optimized so that it can run on smartphones with limited hardware capabilities [11].

1.3 Analysis of Existing Solutions

Traditional tuna grading relies on human sensory evaluation of appearance and texture. However, this approach suffers from high inter-rater variability, subjectivity, and inconsistent quality control across different batches [5]. These limitations can pose significant challenges in maintaining grading reliability, especially in large-scale processing environments.

1.4 Constraints & Tradeoffs of Proposed Solution

1.4.1 Dataset Quality and Quantity Constraints

The dataset quantity used to develop a model should be significant in number in order to achieve a high accuracy while also being balanced depending on how many grades the model is trained to. This means that if more grades are to be considered, a larger dataset may need to be achieved [12]. This dataset should also have varying characteristics in terms of visual quality such as color and lighting to ensure that the final model can generalize well to images outside the dataset used for its development [12]. Having a significant number of dataset with varying characteristics can prevent overfitting, a condition where a model is only able to generalize a dataset it is trained with but not able to accurately analyze new data. The dataset should also be properly annotated to ensure that the model can accurately predict the target, especially to consider factors such as its color and shape [13].

1.4.2 Model Quality and Performance Tradeoffs

A more complex computer vision and deep learning model can offer a higher overall accuracy at the cost of longer processing times [14]. On the other hand, a simpler model can have faster processing times at the cost of accuracy [14]. Additionally, computer vision and deep learning models often demand high specification hardware in order to train or run efficiently [14]. A great number of models exist, therefore, the appropriate model should be selected in order to fulfill the objective of classifying tuna loin grade accurately.

1.4.3 Mobile Application Performance

Deploying computer vision and deep learning models on mobile applications to run on smart phones poses certain challenges. Smart phones have limited processing power and memory constraints, therefore, model optimization techniques will be explored to ensure real-time processing on smart phones [13]. The mobile application must also be able to perform robustly across different smart phones with varying camera specifications, image resolutions, and environmental conditions [15]. To ensure consistency, the system must be designed to handle varying conditions with lighting, camera angles, and resolutions [15].

1.5 Conclusion

The grading of tuna loin using traditional methods has been a labor-intensive process, often prone to human subjectivity, which introduces inefficiencies. These inefficiencies can lead to inconsistencies in product quality and operational delays. As the tuna industry continues to expand, there is a growing demand for scalable, reliable, and efficient grading systems to meet the increasing market needs. The adoption of advanced technologies such as computer vision and deep learning presents a promising solution by automating the grading process. This shift to automation offers significant benefits, including consistent and real-time results, which are essential for maintaining high standards in the fast-paced tuna market.