Grading Quality of Tuna Loin Using Computer Vision and Deep Learning

1st Mochamad Reyhand Landrenzy Zulfikar
Faculty of Electrical Engineering
Telkom University
Bandung, Indonesia
mochreyland@student.telkomuniversity.ac.id

2nd Ledya Novamizanti
Faculty of Electrical Engineering
Telkom University
Bandung, Indonesia
ledyaldn@telkomuniversity.ac.id

3nd Gelar Budiman
Faculty of Electrical Engineering
Telkom University
Bandung, Indonesia
gelarbudiman@telkomuniversity.ac.id

Abstract— Assessing the quality of tuna loin remains a pivotal aspect of the global seafood industry, necessitating precise, consistent, and efficient grading methods that can be broadly implemented. This study addresses these challenges by developing a robust, cloud-native system for automated tuna loin quality classification. Utilizing a tailored image dataset, the system's core processing is handled by a scalable cloud-based backend on Google Cloud Platform, specifically employing Cloud Run for serverless inference. The deep learning model, EfficientNetV2M, is optimized into the ONNX format and executed efficiently by ONNX Runtime within this cloud environment, achieving a classification accuracy of 96% with rapid prediction times. An intuitive Flutter frontend application serves as the user interface, facilitating the transmission of image data to the cloud service and displaying real-time grading results. This architectural design ensures dynamic resource allocation, high availability, and cost-effectiveness through a pay-per-use model. Data integrity and security are maintained via HTTPS for secure communication between the frontend and the cloud-deployed backend. The integration of Docker for containerization, Google Cloud Run for serverless deployment, and Flask for API management collectively yields a highly scalable, reliable, and efficient system. This research presents a robust, cloud-centric solution for automated tuna loin quality classification, offering real-time predictions, secure data handling, and a user-friendly interface suitable for industrial quality control and research applications.

Keywords — cloud computing, serverless, Google Cloud Run, Docker, ONNX, deep learning, computer vision, real-time prediction.

I. INTRODUCTION

The global tuna market, projected at $43.14 billion in 2024, highlights the significant economic importance of tuna worldwide, valued for its nutritional benefits and adaptability [1]. Despite its market prominence, a persistent challenge within the seafood industry, particularly concerning tuna loin, stems from traditional grading practices. These methods largely depend on manual, sensory evaluations, which are inherently labor-intensive, time-consuming, and highly susceptible to inconsistencies [2]. Variables such as fluctuating environmental lighting during inspection and the subjective judgment of human graders introduce substantial variability into the assessment process. This lack of standardization directly impacts product quality control, market value, and ultimately, consumer confidence and satisfaction [3].

To overcome these limitations, innovative solutions capable of providing objective, accurate, and scalable quality assessment are essential. Cloud computing emerges as an ideal paradigm for such a solution, providing on-demand access to computing services—including powerful processing, scalable storage, and advanced software—over the Internet [4]. This approach liberates organizations from the burden of owning and maintaining physical infrastructure, thereby reducing operational overhead and capital expenditure. For demanding tasks like real-time image-based quality grading, cloud infrastructure offers the elasticity and reliability that traditional on-premises solutions often lack. Our research capitalizes on these advantages by implementing a robust, cloud-native system for automated tuna loin quality grading. The core intelligence is powered by a deep learning model, specifically EfficientNetV2M, selected for its optimal balance of high accuracy and rapid inference capabilities, which are crucial for high-throughput processing [5].

This model is optimized into the ONNX format for efficient execution across various cloud environments. The entire inference pipeline, from initial image preprocessing to final model prediction, is deployed within a serverless architecture on Google Cloud Platform, primarily leveraging Google Cloud Run. This serverless approach ensures dynamic resource allocation, enabling the system to scale instantly from zero instances to meet fluctuating demand, and to scale back down when idle, thereby optimizing cost-efficiency [6]. User interaction with this powerful cloud backend is facilitated by an intuitive Flutter frontend application. This mobile application serves as the primary user interface, allowing for seamless image capture or upload, and securely transmitting this data to the cloud service for analysis. The real-time prediction results, including the assigned grade and confidence score, are then delivered back to the user's device, providing immediate feedback for quality control decisions [7]. This integrated system exemplifies how cloud computing can form the foundation for complex machine learning applications, delivering a scalable, reliable, and efficient solution for critical industrial processes.

II. THEORY REVIEW

A. Deep Learning Models & Optimization

Deep learning is a subfield of machine learning that utilizes artificial neural networks with multiple layers to learn complex patterns and features from large amounts of data [8]. Architectures like **EfficientNetV2** are designed for high accuracy and computational efficiency, making them suitable for various applications [9]. These models classify inputs by outputting raw scores, known as logits, which are then transformed by a **Softmax** activation function into probabilities, indicating the likelihood of an input belonging to a specific class [10]. For deployment, models are often converted to optimized, open formats like **ONNX (Open Neural Network Exchange)**, which standardizes model representation for interoperability [11]. The **ONNX Runtime** is a high-performance inference engine that efficiently executes ONNX models across various platforms, ensuring rapid predictions [12].

B. Frontend Application Development (Flutter)

Frontend application development is centered on crafting the user interface and overall user experience, enabling direct interaction with the software [13]. Contemporary development frequently utilizes cross-platform UI toolkits, such as Flutter, which empower developers to construct natively compiled applications for diverse platforms (e.g., mobile, web, desktop) from a unified codebase [14]. The fundamental aim of a frontend application is to deliver an intuitive, responsive, and visually appealing interface. This interface facilitates user input, clearly presents information, and manages user interactions seamlessly, often by establishing communication with backend services to retrieve or transmit data [15].

C. Cloud Computing Fundamentals

Cloud computing is defined as the on-demand provision of shared computing resources—encompassing servers, storage, databases, networking, software, analytics, and intelligence—accessible over the Internet [16]. This paradigm represents a fundamental shift in responsibility, transferring the burden of owning, operating, and maintaining physical computing infrastructure from the end-user to a third-party cloud provider. Key attributes of cloud computing include self-service provisioning, broad network accessibility, resource pooling, rapid elasticity, and measurable service usage. This model offers substantial benefits in terms of scalability, cost-effectiveness, and operational efficiency, thereby serving as a foundational element for modern application deployment and data processing [17].

D. Serverless Computing & Gooogle Cloud Run

A prominent operational model within cloud computing is serverless computing, which effectively abstracts away the complexities of server management from the developer [18]. Within a serverless environment, developers deploy their application code or containers, and the cloud provider automatically manages all aspects of infrastructure provisioning, scaling, and maintenance. Computing resources are dynamically allocated only when actively required for execution, and can scale down to zero instances during periods of inactivity. This "pay-per-use" or "pay-per-execution" model optimizes costs by eliminating charges for idle capacity [19]. Google Cloud Run is a prime example of a fully managed serverless platform that enables the deployment of containerized applications without the need for explicit server management. It automatically adjusts application scaling based on incoming traffic, thereby providing inherent high availability and resilience [20].

E. Containerization & Cloud Model Deployment

Containerization, primarily facilitated by technologies like Docker, involves packaging an application and all its dependencies (including code, runtime, system tools, libraries, and configuration settings) into a single, portable, and isolated unit known as a container [21]. This methodology ensures consistent execution across disparate environments, ranging from local development machines to various cloud platforms, by establishing a standardized and isolated runtime. For deploying machine learning models in the cloud, containerization is vital as it bundles the model, its inference engine (such as ONNX Runtime), and any required preprocessing libraries into a self-contained package. This facilitates seamless and reliable deployment to serverless platforms like Cloud Run, where the container can be rapidly instantiated to process inference requests [22].

III. RESEARCH METHODS

The research methodology for developing the automated tuna loin grading system adopted a structured approach, beginning with the meticulous collection and preprocessing of the image dataset. This prepared data was subsequently used for training and optimizing the deep learning model. Following model development, the system underwent a rigorous deployment phase to a cloud-based infrastructure, succeeded by comprehensive testing to validate its performance and reliability in real-world scenarios, with a particular emphasis on the cloud integration.

A. Data Collection & Preprocessing

TABLE 1
Tuna Loin Image Dataset Distribution After Augmentation

Grades	Original	Augmented	Original + Augmented
Grade A	418	3762	4180
Grade B	602	3612	4214
Grade C	247	3952	4199
Total	1,267	11,326	12,593

The foundation of this investigation is a custom dataset of tuna loin images, categorized into three distinct quality grades: Grade A, Grade B, and Grade C [23]. The dataset initially comprised original images captured under varied lighting conditions, which were then substantially augmented to mitigate class imbalances and enhance the model's generalization capabilities [24]. Prior to model training, a series of image preprocessing techniques were systematically applied to ensure consistent illumination and to accentuate the visibility of crucial visual features like color and texture across the entire dataset. These techniques included Shades

of Gray (SOG) for white balance correction, Self-Adaptive Illumination Correction (SAIC) for brightness normalization, and Contrast Limited Adaptive Histogram Equalization (CLAHE)for localized contrast enhancement [25]. Furthermore, image augmentation techniques, such as rotation, flipping, shearing, and zooming, were utilized to further expand the dataset size and bolster model robustness, thereby preparing the data for effective deep learning [26].

B. Model Training & Optimization

The central component of the tuna loin quality grading system is built upon the **EfficientNetV2M architecture**, a convolutional neural network (CNN) specifically optimized for both training efficiency and high accuracy in image classification tasks [27]. The model was implemented using the PyTorch framework. Training experiments were systematically conducted to identify the optimal combination of hyperparameters and preprocessing methods, a crucial step for a model designated for cloud deployment. This involved evaluating various optimizers, including Stochastic Gradient Descent (SGD), Adam, and AdamW, paired with different learning rate schedulers (LRS), such as Cosine Annealing and Cyclic LRS [28]. The training process spanned a set number of epochs with a defined batch size, leveraging GPU acceleration for efficient computation. The model's performance was continuously monitored using metrics like training accuracy, validation accuracy, and their corresponding losses, to track learning behavior and prevent overfitting, ultimately ensuring the selection of a robust model for subsequent deployment [29].

C. Model Deployment and Integration

FIGURE 1
System Workflow Diagram

Upon finalizing the optimal model configuration, the trained deep learning model was meticulously prepared for cloud deployment, forming the foundational element of our scalable solution. This preparation involved converting the model to the **ONNX (Open Neural Network Exchange) format**, which optimizes it for high-performance inference in diverse production environments by providing a standardized, interoperable representation [30]. The entire application, comprising the ONNX model and its associated dependencies, was then **containerized using Docker**. This process consolidates all necessary components into a single, portable image, guaranteeing consistent execution across different environments and streamlining deployment to cloud platforms [31].

The Docker image was subsequently deployed to Google Cloud Run, a fully managed serverless platform. This serverless approach is fundamental to our system's design, as it ensures that compute resources are dynamically allocated only when actively needed, scaling instantly from zero instances to handle concurrent requests and scaling back down when idle, thereby optimizing cost-effectiveness [32]. The deployed service exposes a Flask-based API endpoint, which serves as the interface for the mobile application. Within the Cloud Run container, the ONNX Runtime is utilized to efficiently execute the ONNX-formatted model, perform necessary image preprocessing, and generate real-time predictions. This integrated cloud pipeline enables highly scalable and responsive image processing, allowing the system to handle concurrent user requests and perform updates with minimal disruption, thereby guaranteeing the system's high scalability and reliability for real-time grading tasks [33].

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D. System Testing and Evaluation

System testing was executed in two primary phases: offline and online. The offline stage concentrated on the rigorous evaluation of the deep learning model's inherent performance, assessing its accuracy, precision, recall, F1-score, and analyzing its confusion matrix on previously unseen test data [34]. The online stage involved comprehensive testing of the integrated mobile application and the cloud-deployed model in real-world scenarios, with a strong emphasis on the cloud service's performance. This included functionality testing to verify correct image upload, secure transmission to the Cloud Run API, reception of predictions, and accurate display of results. Response time testing measured the end-to-end latency from image submission from the mobile application to prediction receipt from the Cloud Run service, confirming real-time capabilities. Accuracy testing was performed using actual tuna loin images captured under diverse lighting and background conditions to assess the system's robustness in varied field conditions. Furthermore, error handling was verified to ensure graceful responses to network connection issues, corrupted image files, or unforeseen server errors, particularly those originating from the cloud backend.

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IV. RESULT AND ANALYSIS

The evaluation of the automated tuna loin grading system encompassed both offline assessment of the deep learning model's intrinsic performance and online testing of the integrated cloud-based application. This comprehensive analysis aimed to validate the system's accuracy, efficiency, robustness, and user experience in real-world scenarios. Performance metrics were meticulously collected during various testing phases, including model training, inference, and end-to-end system interactions. The obtained data was then analyzed to ascertain the effectiveness of the deep learning model, the efficiency of the cloud deployment, and the overall usability of the mobile application.

A. Deep Learning Model Performance (Offline Evaluation)

The deep learning model, based on the EfficientNetV2M architecture, underwent rigorous offline evaluation using a dedicated test dataset. This dataset comprised 10% of the total augmented image collection, ensuring that the model was assessed on unseen data. The model achieved a classification accuracy of 96% on this test set, demonstrating its strong capability in correctly identifying the quality grades of tuna loin images. Beyond overall accuracy, the model's performance was further analyzed using a Confusion Matrix, which provided detailed insights into its ability to correctly classify each grade (Grade A, Grade B, Grade C) and identify instances of misclassification. Metrics such as Precision, Recall, and F1-Score were also computed for each class, offering a more nuanced understanding of the model's performance, particularly in distinguishing between similar grades. The effectiveness of the integrated preprocessing pipeline, including SAIC and CLAHE, was evident in the high accuracy achieved, indicating that these steps successfully normalized image conditions and enhanced critical features for the model's recognition.

B. Cloud Service Performance (Online Evaluation)

The performance of the cloud-deployed service was a critical aspect of the online evaluation. This involved measuring the end-to-end response time from the moment an image was submitted from the mobile application to the reception of the prediction result from the Cloud Run backend. The serverless nature of Google Cloud Run proved highly effective in delivering rapid inference times. While initial 'cold starts' for new instances might introduce a slight delay for the very first request after a period of inactivity, subsequent 'warm' requests demonstrated consistently low latency, ensuring a smooth user experience for continuous operation. The dynamic scaling capabilities of Cloud Run allowed the service to handle concurrent requests efficiently, maintaining low response times even under increased load, without requiring manual intervention or pre-provisioning of resources.

B. System Robustness and Reliability

The system's robustness was assessed through various tests designed to simulate real-world conditions. Accuracy testing was performed using actual tuna loin images captured under diverse lighting and background conditions, confirming the system's ability to maintain high performance outside of the controlled training environment. Error handling mechanisms were thoroughly verified to ensure the application gracefully managed scenarios such as network connection issues, corrupted image file uploads, or unexpected responses from the cloud backend, providing informative feedback to the user. Furthermore, inference tests were conducted under varying network conditions, specifically 4G and WiFi, to evaluate the application's responsiveness and consistency across different connectivity environments. These tests confirmed that the cloud-based inference pipeline remained reliable, with network latency being the primary variable affecting overall response time, rather than backend processing.

D. User Experience Evaluation

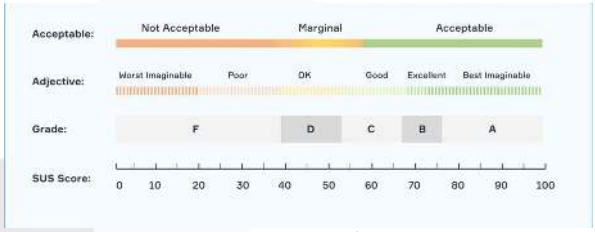

FIGURE 2
System Usability Scale (SUS) Score Interpretation

Beyond technical performance, the user experience of the mobile application was evaluated using the System Usability Scale (SUS). The SUS is a widely accepted, simple, 10-item questionnaire that provides a quick and reliable measure of usability. The results from the SUS questionnaire provided quantitative insights into the application's ease of use, learnability, and user satisfaction. A high SUS score indicates that the cloud-powered solution is not only technically sound but also provides a user-friendly interface suitable for its intended users in industrial quality control settings.

V. CONCLUSION

Based on the comprehensive evaluation, it is concluded that the automated tuna loin grading system effectively leverages deep learning and cloud computing to provide an accurate, efficient, and scalable solution. The EfficientNetV2M model achieved a high classification accuracy of 96% on unseen

data, demonstrating its robust capability in distinguishing between different tuna loin quality grades. The deployment on Google Cloud Run proved highly effective in delivering rapid, real-time inference, benefiting from serverless auto-scaling and cost-optimization. The system's reliability was confirmed across various network conditions, and its user-friendliness was validated through the System Usability Scale, indicating a positive user experience. This project successfully presents a robust, cloud-centric solution for automated tuna loin quality assessment, addressing the limitations of traditional manual methods and offering significant potential for industrial quality control.

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