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Classification of Fresh Salmon Fish Based on Ensemble Learning Using ResNet50 and EfficientNetV2

Arko Dwiantoro[1], Abas Setiawan[2]
[1,2] Computer Science Department, Faculty of Mathematics and Natural Sciences,
Universitas Negeri Semarang, Indonesia

Abstract. The increasing demand for fresh salmon in Indonesia, despite it not being a producing country, poses challenges in maintaining product quality during distribution. Freshness is a critical factor due to the fish's high susceptibility to spoilage, which can lead to health risks and economic losses.
Purpose: Traditional inspection methods are inefficient for large-scale operations. Therefore, this study aims to develop an efficient and accurate classification model for fresh and infected salmon using ensemble learning based on Convolutional Neural Networks (CNN), particularly ResNet50 and EfficientNetV2 architectures.
Methods/Study design/approach: This research employs a quantitative approach using the SalmonScan dataset, consisting of 1,208 images divided into two classes: fresh and infected salmon. The data underwent preprocessing, including resizing and normalization. Two deep learning architectures, ResNet50 and EfficientNetV2, were applied using the transfer learning method. These models were then combined using ensemble learning with a concatenation strategy to enhance performance. Model evaluation was conducted using accuracy, precision, recall, and F1-score, based on the confusion matrix.
Results/Findings: Individual testing of ResNet50 and EfficientNetV2 models achieved high performance, but the ensemble of both architectures yielded the best results. The combined model achieved an accuracy of 98.33%, outperforming other models used in the experiment. These results indicate that the ensemble approach successfully improves the model's capability to classify salmon freshness and infection conditions.
Novelty/Originality/Value: This study presents a novel ensemble approach that integrates ResNet50 and EfficientNetV2 for classifying salmon freshness. Unlike previous works that utilized either single models or more computationally expensive ensemble methods with multiple architectures, this study provides a balanced, computationally efficient solution with high accuracy. The proposed method demonstrates potential for scalable applications in fish quality assessment systems, supporting food safety and sustainability in the fisheries industry.

Keywords: Salmon, Classification, CNN, Ensemble Learning, ResNet50, EfficientNetV2
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INTRODUCTION

Salmon is a high-value fishery commodity that thrives in cold-water habitats with temperatures ranging from 5–15°C, such as the Atlantic and Pacific Oceans [1]. The world's largest salmon producers include Norway, Chile, Canada, the United States (Alaska), and Scotland [2]. Due to the warmer tropical waters averaging 28–30°C, countries like Indonesia cannot cultivate salmon locally [3]. Nonetheless, domestic demand continues to rise due to the growing popularity of healthy food trends, particularly in Japanese restaurants and premium supermarkets. From January to November 2024, Indonesia imported approximately 8.55 thousand tons of salmon and trout, valued at USD 66.63 million [4].

Freshness is a critical factor for salmon, which is highly perishable [5]. The transportation process from production countries to Indonesia typically takes 7–14 days and requires a strict cold chain between 0–4°C. Deteriorated freshness can result in nutritional losses, poor texture, and off-flavors, potentially leading to product rejection or reduced market value [6]. Moreover, consuming spoiled or infected salmon poses serious health risks. Contaminated salmon may harbor pathogens like Salmonella and Listeria, causing foodborne illnesses, while heavy metal contamination such as mercury can result in chronic

[1]*Corresponding author.
Email addresses: dwiantoroarko@students.unnes.ac.id (dwiantoro)
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neurological damage [7].Traditionally, freshness evaluation relies on expert visual inspection or lab testing, which is time-consuming and expensive, making it less viable for large-scale industrial use [8].

As a faster and more cost-effective alternative, Artificial Intelligence (AI), particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool for visual analysis tasks in the fisheries sector. CNNs can effectively detect subtle visual indicators of salmon fresh or infection [9]. However, not all CNN architectures are equally effective. For example, VGG16, though simple and widely used, struggles with capturing complex features [10], while MobileNetV2, although lightweight and efficient, often sacrifices accuracy [11].

In contrast, ResNet50 and EfficientNetV2 offer more robust performance. ResNet50 utilizes residual learning with skip connections to address vanishing gradient issues in deeper networks [12], while EfficientNetV2 incorporates Fused MBConv layers for faster training with fewer parameters [13]. Previous studies have shown the promise of ensemble learning using these models. For instance, [14] achieved 97.53% accuracy using ensemble techniques involving ResNet50, while [15] reported 92.58% accuracy using a VGG16-ResNet50 combination. To address the limitations of single-model approaches, this study proposes an ensemble method combining ResNet50 and EfficientNetV2. This approach leverages feature diversity with ResNet50 extracting macro-level features (e.g., body deformation) and EfficientNetV2 focusing on micro-level cues (e.g., color changes or mucus texture) to build a richer representation of salmon conditions [16]. A concatenation of features followed by bagging on different data subsets is expected to improve accuracy and robustness.

METHODS

This study employed a quantitative research design utilizing a deep learning-based classification approach. The primary objective was to develop an ensemble learning model using Convolutional Neural Network (CNN) architectures ResNet50 and EfficientNetV2 for the classification of fresh and infected salmon. The methodology consisted of five main stages: data acquisition, preprocessing, model development, model training, and performance evaluation. Figure 1 below presents a comprehensive representation of the research flowchart.

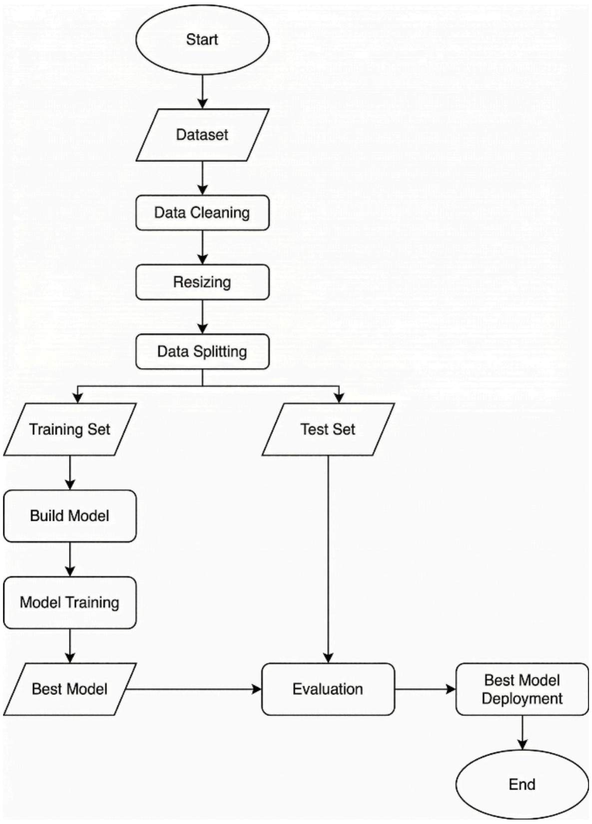

Figure 1. Flowchart Method

Dataset
The dataset used in this study was the SalmonScan dataset introduced by Ahmed et al. [17], which contains 1,208 labeled images of salmon divided into two classes: fresh and infected. The images vary in resolution and condition, requiring preprocessing prior to training. The dataset can be seen in the figure 2.

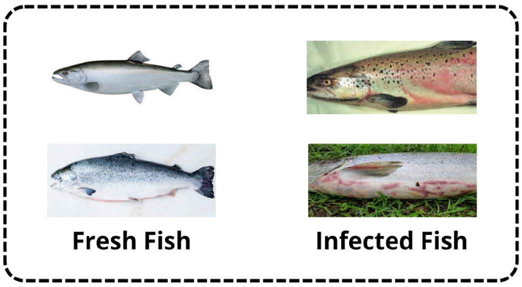

Figure 2. Dataset SalmonScan

Preprocessing
Preprocessing steps included resizing all images to a fixed resolution of 224×224 pixels to standardize the input dimensions compatible with the CNN architectures used [18]. Normalization was also applied to scale pixel values between 0 and 1, which improves training stability and convergence speed. Data splitting was performed using an 90:10 ratio for training and testing.

Model Architecture and Transfer Learning
Two pre-trained models, ResNet50 and EfficientNetV2, were utilized through transfer learning. The convolutional base of each model was retained, and the top classification layers were replaced with a custom fully connected layer structure: Global Average Pooling → Dense Layer (128 units, ReLU) → Dropout (rate = 0.3) → Output Layer (Sigmoid for binary classification). The transfer learning strategy allowed leveraging knowledge from ImageNet training while fine-tuning on the specific task of salmon classification.

Ensemble Learning Technique
To improve prediction performance, ensemble learning was implemented using a feature-level concatenation strategy [16]. Feature vectors from the penultimate layers of ResNet50 and EfficientNetV2 were merged into a single vector, followed by a fully connected classifier to make the final prediction. ResNet50 is chosen because of its ability to solve the vanishing gradient problem through the skip connection mechanism [19]. Meanwhile, EfficientNetV2 is integrated because of its efficiency in balancing model scalability, training speed, and computational resource usage thanks to compound scaling optimization [20]. These two models are combined hierarchically by utilizing feature maps from the final convolutional layers of each architecture, then combining them through a fusion technique based on weighted averaging or concatenation. The architecture of the ensemble model can be seen in Figure 3.

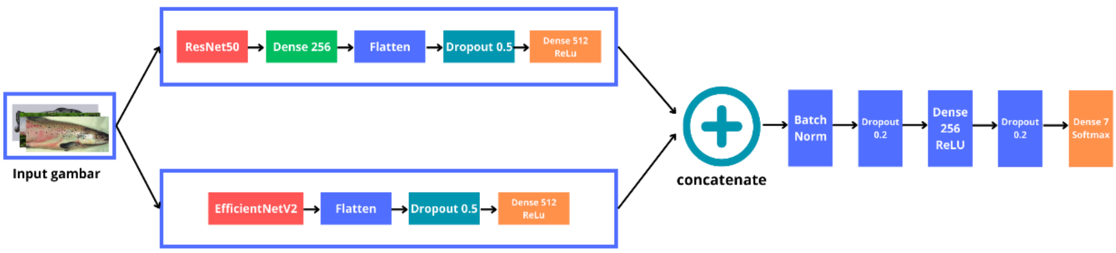

Figure 3. Ensemble Model Architecture

Model Training
Training was conducted using the TensorFlow framework with the Adam optimizer, a learning rate of 0.00005, and a batch size of 32 for 100 epochs. Early stopping and model checkpointing were applied to prevent overfitting and save the best-performing model. In the training model, there are four experimental scenario models used, that is ResNet50, EfficientNetV2, VGG16, and IncpetionV3.

Evaluation Metrics

The performance of the proposed salmon freshness classification system was rigorously evaluated using a comprehensive set of metrics to assess various aspects of classification effectiveness. Model performance was evaluated using several classification metrics: accuracy, precision, recall, and F1-score. These metrics were derived from the confusion matrix, which provides a detailed breakdown of true positives, false positives, true negatives, and false negatives. These measures are commonly used in medical image classification and food safety studies to assess the reliability of detection systems [21]. The confusion matrix consists of four cells, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), which can be seen in Table 1.

Table 1. Confusion Matrix

Confusion Matrix		Predicted Class	
		Positive	Negative
Actual Class	Positive	TP	FN
	Negative	FP	TN

RESULT AND DISCUSSION

Training Result

This study aims to get the optimum accuracy value for Convolutional Neural Network (CNN) ResNet50 and EfficientNetv2 using ensemble learning. The scenarios of this study are using ResNet50 and EfficientNetV2 for single model, then for ensemble model using ResNet50 + VGG16, EfficientNetV2 + InceptionV3, and ResNet50 + EfficientNetV2. Training results are shown in Figure 4.

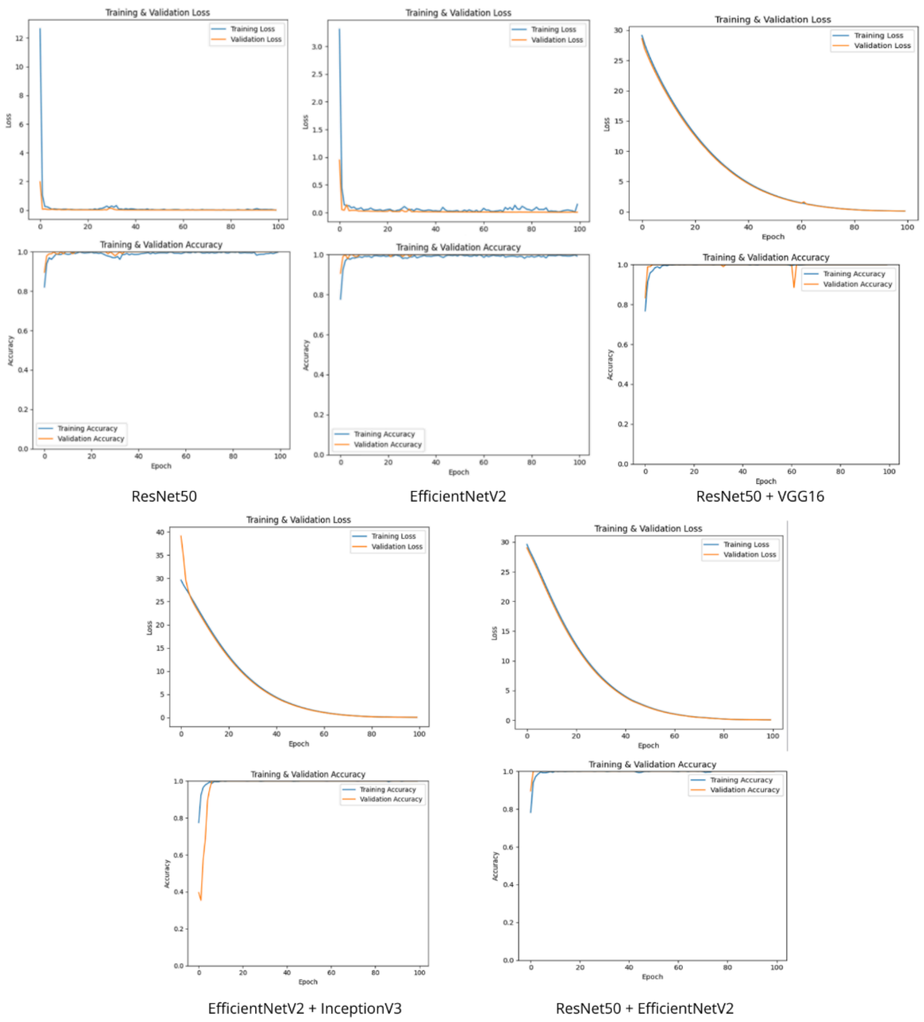

Figure 4. Training Result Each Scenarios

Based on Figure 4, the training results show the performance of each model. The quantitative results reveal significant improvements across scenarios are shown in Table 2. Initial evaluation using a single ResNet50 model yielded an accuracy of 89.16%, indicating a foundational yet limited performance in feature extraction. A modest improvement was observed with EfficientNetV2, reaching 91.66% accuracy, which reflects its enhanced capacity to capture image representations. The ensemble of ResNet50 with VGG16 significantly elevated the performance to 97.50%, highlighting the synergy achieved through combining diverse architectural strengths. Further integration of EfficientNetV2 with InceptionV3 maintained high performance at 95.83%, suggesting the complementary nature of their feature hierarchies. The highest classification accuracy was achieved by combining ResNet50 and EfficientNetV2, peaking at 98.33%. This result underscores the effectiveness of ensemble learning in leveraging the strengths of multiple deep learning models, leading to superior generalization and reduced error rates.

Table 2. The Training Result Each Scenarios

No	Scenarios	Accuracy	Precision	Recall	F1-Score
1	ResNet50	89,16%	88%	89%	88%
2	EfficientNetV2	91,66%	91%	90%	90%
3	ResNet50 + VGG16	97,50%	97%	96%	97%
4	EfficientNetV2 + InceptionV3	95,83%	95%	95%	96%
5	ResNet50 + EfficientV2	**98,33%**	**98%**	**97%**	**98%**

Additionally, the model's performance is evaluated using a confusion matrix. The results of this evaluation are illustrated in Figure 5 for each scenario.

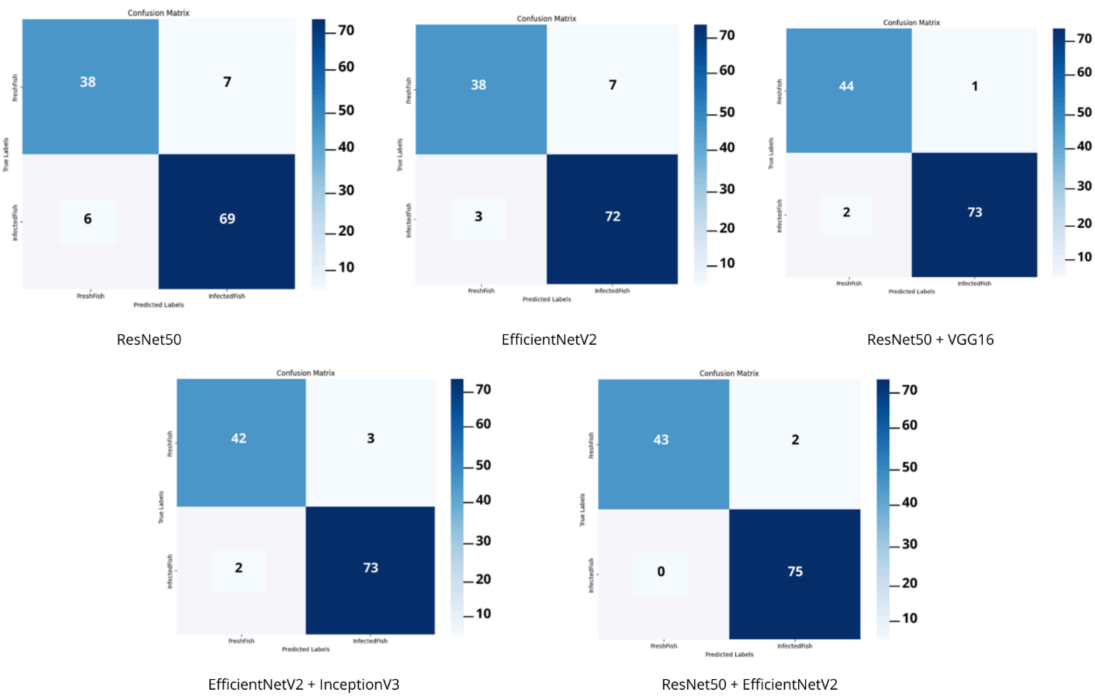

Figure 5. Confusion Matrix Each Scenarios

Model performance is evaluated using a confusion matrix along with key metrics such as accuracy (overall correctness), precision (correct positive predictions), recall (actual positive detections), and F1 score (balance of precision and recall). The optimal scenario in this study is an ensemble technique using the ResNet50 + EfficientNetV2 model, achieving an accuracy of 98.33%, indicating near-perfect class discrimination.

Performance Comparison Analysis on Previous Studies

This study conducted a comparison with several previous studies that used the SalmonScan dataset with a focus on salmon freshness but applied different algorithms and approaches. The comparison of accuracy results between this study and previous studies is shown in Table 3.

Table 3. Comparison on Previous Studies

No	Author	Method	Dataset	Result
1	Ahmed [22]	Support Vector Machine (SVM)	SalmonScan	94,12%
2	Biswas [23]	Ensemble VGG-16 + MobileNetV2 + InceptionV3 + SVM	SalmonScan	98%
3	Afridiansyah [24]	EfficientNetB1	SalmonScan	98,14%
4	Purpose Method	ResNet50 + EfficientNetV2	SalmonScan	98,33%

The selection of the right ensemble model can get good accuracy compared to previous studies. A big challenge to classify the freshness of salmon because it affects health and also the economy. This approach still has potential for further improvement by exploring alternative filtering techniques, architectures or classification algorithms.

CONCLUSION

This study has demonstrated that the integration of ResNet50 and EfficientNetV2 through ensemble learning significantly enhances the performance of deep learning models in classifying fresh and infected salmon images. The ensemble model achieved the highest accuracy of 98.33%, outperforming both single models and other combinations, indicating the effectiveness of feature-level fusion in capturing both macro and micro characteristics of fish conditions. By utilizing a computationally efficient yet accurate approach, this method provides a practical solution for rapid freshness detection in the fishery industry. The impact of this research lies in its potential application in real-time fish quality monitoring systems, contributing to improved food safety, reduced health risks, and enhanced sustainability in the global seafood supply chain.

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