Article

YOLO-Medaka: An Automatic Object Detection Models for Endangered Medaka Fishes in Indonesia

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Abstract: *Oryzias Celebensis* and *Oryzias Javanicus* are two species of endemic fish that play a crucial role in the aquatic ecosystem in Indonesia, especially in Java and Sulawesi regions. But unfortunately, both species are threatened with extinction and have been officially declared by the International Union for Conservation of Nature and Natural Resources (IUCN). To address this problem, Artificial Intelligence innovation was built with a Deep Learning approach to conduct classification and identification of the fish species quickly and efficiently. In this study, we developed the MobileNetV2 architecture model using the transfer learning approach and dataset padding and then embedded it into the YOLOv8 architecture on the backbone as the main architecture in this system to classify *Oryzias Celebensis* and *Oryzias Javanicus*. The P-MobileNetV2 model has better performance evaluation results than other models, where sensitivity = 98.46%, Precision = 98.46%, F1 Score = 98.46% and Accuracy = 98.7%. This advancement enables rapid, accurate conservation efforts for these critically endangered fish

Keywords: Artificial Intelligence; Deep Learning; Tranfer Learning; MobileNetV2; Padding Dataset.

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1. Introduction

Oryzias celebensis and *Oryzias javanicus* are two endemic fish species that play a crucial role in the aquatic ecosystems of Indonesia, particularly in the Sulawesi and Java regions [1,2]. Both species play an important role in maintaining biodiversity and ecosystem balance [3]. Identifying rare fish species is a crucial first step in conservation efforts. By recognizing morphological characteristics, genetic analysis, and behavioral understanding, we can gain better insight into these species. Identification also helps us take more effective action to protect habitats and prevent extinction.

The genus *Oryzias* belongs to the family *Adrianichthyidae*. These fish are widely distributed in South Asia, East Asia, and Southeast Asia. Their natural habitat includes rice fields, ponds, ditches, and lakes [4,5]. *O. celebensis* and *O. javanicus* are two species particularly threatened with extinction in Indonesia. Celebes Medaka (*O. celebensis*) is an endemic species on Sulawesi Island [6]. Unfortunately, the Medaka fish is an endemic species threatened with extinction and has been officially declared as such by the International Union for Conservation of Nature (IUCN). Conservation efforts are critically important to prevent the extinction of these species. Oryzias javanicus: This fish is also known as the Java Medaka. [7]

Unfortunately, we realize that the populations of Oryzias celebensis and Oryzias javanicus are declining, pushing these two species to the brink of extinction. This situation is even more concerning because both are categorized as rare fish species endemic to Indonesia, specifically found in Sulawesi and Java. Threats to their natural habitats, climate change, and human activities that damage aquatic environments are further worsening their condition. [8]In efforts to protect and conserve these rare species, researchers often face ethical dilemmas during the identification process. Conventional methods commonly used, such as examining dead fish or taking fish out of water, which may harm them, are no longer acceptable in the context of environmental sustainability and conservation [9].

To address this challenge, innovations in artificial intelligence, particularly deep learning technology, offer a promising solution. Using advanced computational capabilities, researchers can use deep learning models to classify and identify fish species, including Oryzias celebensis and Oryzias javanicus, quickly and efficiently. This approach is not only more environmentally friendly, but also enables more effective monitoring of these rare fish populations, supporting conservation efforts to ensure their survival in the future.

2. Related Works and Motivation

In this work, MobileNetV2 is utilized for image-based object classification. This model is an enhanced version of the previous MobileNetV1 architecture. MobileNetV2 is a Convolutional Neural Network (CNN) specifically designed for resource-constrained devices, such as smartphones, IoT devices, and embedded systems. Developed by Google AI and published in 2018, this model offers several advantages highlighted in various studies, including its lightweight architecture, competitive performance, and compatibility with several deep learning frameworks [10,11]. The model combines an inverse residual block with a linear bottleneck, which improves efficiency while maintaining accuracy. These efficiency advantages make MobileNetV2 suitable for real-time applications on low-power devices. General structure of the MobileNetV2 model.

In study [12], images of Cicer arietinum (chickpea) varieties were input into two architectures. The first used transfer learning with fine-tuning on a pre-trained MobileNetV2 CNN model for classification. The second was a hybrid architecture incorporating Long Short-Term Memory (LSTM) layers to account for temporal features. The results showed 92.3% accuracy for the first model and 92.97% for the hybrid, demonstrating a high success in classifying chickpea images. Additionally, authors [13] applied a deep learning approach using MobileNetV2 within a PyTorch and OpenCV Python framework for mask detection during COVID-19. Their model efficiently identified proper mask usage, highlighting MobileNetV2's adaptability for diverse image-based tasks, from agricultural classification to public health applications. These studies underscore its effectiveness in achieving high accuracy while maintaining computational efficiency for real-world deployments.

In another previous study[14], the authors introduced customized heads comprising five different layers into the MobileNetV2 architecture. The model's original classification layers were replaced with these customized heads, resulting in a modified version called TL-MobileNetV2. This adaptation achieved an accuracy of 99% ¯3% higher than standard MobileNetV2, while maintaining a minimal error rate of just 1%. When compared to AlexNet, VGG16, InceptionV3, and ResNet, TL-MobileNetV2 demonstrated superior performance. Meanwhile, authors [15] implemented MobileNetV2 for melanoma cancer classification, reporting an accuracy of up to 85% on the ISIC-Archive dataset, outperforming models like ResNet50V2, InceptionV3, and InceptionResNetV2. Another study [16] evaluated four convolutional neural networks—Xception, ResNet50, EfficientNetB4, and MobileNet—for detecting rust disease in three commercially important field crops. Results showed EfficientNetB4 as the most accurate (average accuracy = 94.29%), followed by ResNet50 (93.52%). Though MobileNetV2 trailed slightly in this comparison, its computational efficiency makes it viable for resource-constrained applications, reinforcing its versatility across medical and agricultural domains. Further research [17] uses MobileNetV2, a deep learning convolutional neural network (DCNN) for seed classification. A total of 14 different classes of seeds were used for the experimentation. The results indicate accuracies of 98% and 95% on training and test sets, respectively.

Table 1. Gap description in building research motivation.

No.	Previous Works	Current Works
1	The hybrid architecture incorporates Long Short-Term Memory (LSTM) layers, which also account for temporal data features in classification. [12]	The image data features four different background colors: red, black, blue, and green, with overhead lighting to ensure the fish are clearly visible.
2	Implementation of a deep learning approach using the MobileNetV2 framework, integrated with PyTorch and OpenCV in Python, for mask detection during COVID-19. [13]	We developed this application using Jupyter Notebook, TensorFlow, Roboflow, and OpenCV for the identification of *Oryzias celebensis* and *Oryzias javanicus*.
3	Implementing MobileNetV2 for Melanoma Cancer Classification. MobileNetV2 demonstrates higher accuracy compared to ResNet50V2, InceptionV3, and InceptionResNetV2. [15]	Development of a MobileNetV2 architecture using a transfer learning approach with dataset padding and additional layers for the Classification Layer. This layer consists of 5 components: a Flatten layer, two Dense layers with ReLU activation functions.
4	A deep learning convolutional neural network (DCNN) which utilising MobileNetV2 for seed classification. [17]	We developed modified versions: P-MobileNetV2 (from MobileNetV2) and P-VGG16 (from VGG16) to evaluate the effects of our architectural changes.

Many researchers have proposed various combinations of Machine Learning and Deep Learning (ML/DL) algorithms to solve the problem of object detection, classification, and identification in digital images. In this paper, the YOLO-Medaka algorithm is introduced to detect and classify digital objects by combining three methods of YOLOv8, MobileNetV2 and ANN-MLP architecture. YOLOv8 is used for object detection because it has a single-stage detection concept, which means detecting objects at one time and has excellent accuracy. As seen in several experiments. for example, after modification, namely YOLOv8-CAB, it succeeds in detecting some objects that are missing detection by YOLOv8 before, also achieves higher accuracy and much better detection confidence. [18]. Another experiment also conducts object detection, such as analysing vehicle detection under various image conditions. This study utilises the YOLOv8 method to process the images with output the bounding boxes and classes of the detected objects. Additionally, data augmentation is applied to improve the model's ability to recognise vehicles from different directions and viewpoints [19].

MobileNetV2 is deployed for mobile devices such as smartphones and tablets, which focus on computational efficiency and smaller model size, since MobileNetV2 is designed for mobile devices and embedded vision applications. As seen in the fruit classification experiment that compared the performance between MobileNetV2 and Inceptionv3, the results show that MobileNetV2 has a better accuracy rate, which means better performance than Inceptionv3. In an experiment with a different case, comparing the performance of MobileNetV2 with DenseNet121 for the classification of coral reefs, the results show that MobileNetV2 is more optimal for devices with limited computing power and is lighter and faster [20,21]. In addition, the MobileNetV2 architecture has proven effective in increasing computational efficiency without sacrificing accuracy, which is an important aspect for implementing this model on mobile devices. High computational efficiency is possible for implementation in the real world, where computing resources may be limited [22].

ANN-MLP is tasked with processing the data conducted by the input, hidden and output layers they have, then producing the classification of *Oryzias celebensis* and *Oryzias javanicus*. ANN-MLP is one of the algorithms that is widely used because of its ease of implementation in web applications (client/server or full stack programming). Some of its implementations include the classification of marine fish even though they are covered by seaweed or coral, the classification of types of diseases in aquatic plants, and the classification of certain problems or certain cases, both inherent in objects and their environment. This paper specifically focuses on the automatic detection and classification of two small, rare and endangered freshwater fish species in Indonesia, namely, *Oryzias celebensis* and *Oryzias javanicus*. The method used to solve this problem consists of 3 stages, namely the data preparation stage based on the model architecture, the model development stage, and the model selection stage through performance evaluation. The illustration of the method is depicted as in Figure 9

Regarding Table 1, in this context, we are developing an identification and classification system for *Oryzias celebensis* and *Oryzias javanicus* fish using Deep Learning and Transfer Learning implemented on a modified MobileNetV2. We believe our innovative approach will have a significant impact on the identification and classification process. Our comprehensive methodology combines cutting-edge techniques, which we are confident can be adapted to various identification and classification challenges in industry-specific applications, particularly modern systems for identifying endangered endemic fish species.

3. Materials and Methods

In this research, the materials used include various tools and components essential for processing data and system implementation.

3.1. Data Sources

1. Defining Dataset Requirements
   - Dataset Specifications: Determine the required number of samples, minimum image resolution, and file format (JPEG, PNG, etc.).
   - Data Sources: Combine data from captured videos and images from the Internet to improve species representation.
2. Acquiring Data from Captured Videos
   - Video Recording: Capture fish in various lighting and aquatic environments.
   - Video Preprocessing:
     - Frame Extraction: Extract frames at specific intervals to avoid redundant data.
     - Noise Reduction: Apply filtering techniques like Gaussian blur or histogram equalization.
     - Segmentation & Tracking: Use background subtraction or object tracking (SORT, DeepSORT) to highlight fish in frames.
   - Image Annotation:
     - Utilize bounding box or mask segmentation with tools like LabelImg or Roboflow.
     - Save annotations in YOLO (.txt) or COCO (.json) format based on model requirements.

Figure 1. Captured Oryzias in four different background colors.

3.2. Research Methodology

We followed a systematic approach to develop an object detection and classification system for images, specifically targeting the identification of Oryzias celebensis and Oryzias javanicus. Our process includes key steps such as **Image Processing**—preprocessing and enhancing raw image data to improve model training, as well as **Building Block Architecture** building a robust framework by implementing architectures like YOLO and MobileNetV2, combined with transfer learning to enhance efficiency. Additionally, we developed a customised YOLO-based novelty model, called **YOLO-Medaka**, fine-tuned specifically for precise recognition of medaka fish.

While several researchers have employed MobileNetV2 and its variants—modified with various techniques—for applications such as mask detection, rust disease classification in plants, melanoma cancer detection, and Cicer arietinum variety classification, our primary focus is on the automatic detection of Oryzias celebensis and Oryzias javanicus. These species are particularly significant as they are endangered in Indonesia, and our tailored approach aims to address the unique challenges involved in their identification. The methods and techniques we used are further explained in Figure 2

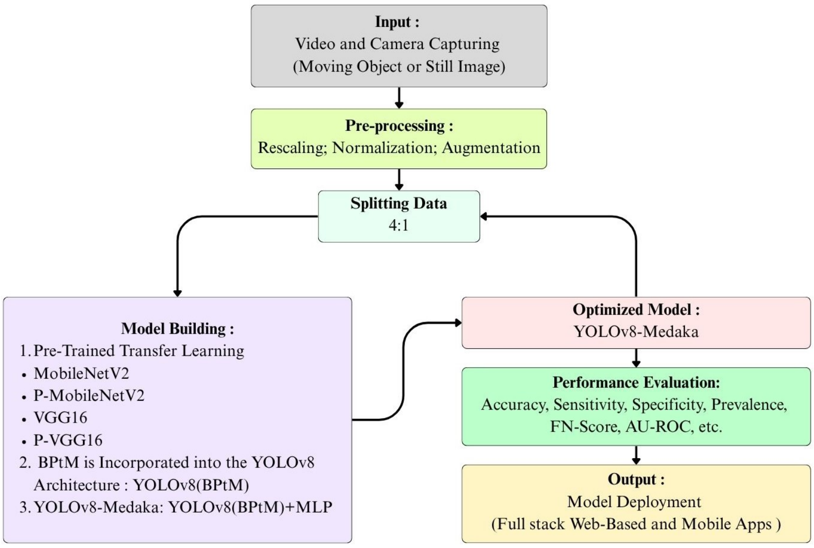

Figure 2. The YOLOv8-Medaka Workflow Diagram.

3.3. *Image Processing*

3.3.1. Rescaling

The captured images of medaka fish will be rescaled to a square size of 224x224 pixels. Two rescaling methods will be applied: Padding and Non-Padding. The Padding method adds a uniform background color to both sides of the image if it's too small. Meanwhile, the Non-Padding method rescales the image directly to fit the square dimensions. All this process can be seen in Figure 11

3.3.2. Normalization

Color value normalization is performed on each pixel by dividing it by 255, as shown in Figure 3.

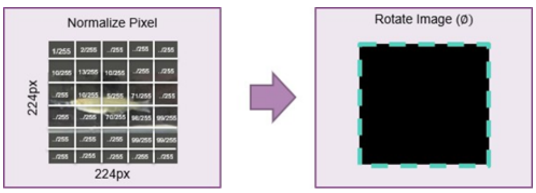

Figure 3. Color Value Normalization for Each Pixel.

3.3.3. Augmentation

Ada dua metode augmentasi yang digunakan yaitu: shift dan rotasi. Randomly shift the image left/right by 20% of its width, as shown in Figure 4.

3.3.4. Image Dataset Splitting

There are 661 images of *Oryzias celebensis*, divided into 456 (70%) for training, 146 (20%) for validation, and 59 (10%) for testing. There are 886 images of *Oryzias javanicus*,

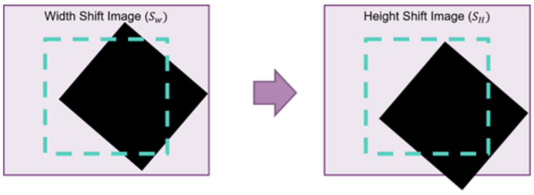

Figure 4. Width shift and height shift of 0.2 (20%).

split into 612 (80%) for training, 177 (20%) for validation, and 97 (10%) for testing. An example image can be seen in Figure 1.

3.4. Building Block Architecture

3.4.1. MobileNetV2

This architecture will be combined with several components in the backbone component of YOLOv8. This is done to improve the performance of hierarchical image feature extraction. Based on MobileNetv2 architecture and features, let's looks the component and its steps.

- Data Preparation. This involves preprocessing the images, splitting the dataset into training and validation sets, and applying data augmentation techniques to improve the model's generalization ability.
- Transfer Learning. For initializing the model with pre-trained weights, the training process can be accelerated, and the model can benefit from the knowledge learned from the source dataset.
- Fine-tuning. This process Involves training the model on a target dataset while keeping the pre-trained weights fixed for some layers.
- Hyperparameter Tuning. Play a role in optimizing the performance of MobileNetV2. Carefully select parameters such as learning rate and regularization techniques to achieve the best possible results.

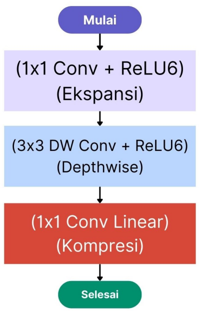

Figure 5. MobileNetV2 Architecture.

3.4.2. VGG16

Based on the VGG-16 architecture, it is illustrated below in detail:

- Input Layer. Input dimensions: (224, 224, 3).
- Convolutional Layers (64 filters, 3×3 filters, same padding).
- Max Pooling Layer (2×2, stride 2).
- Convolutional Layers (128 filters, 3×3 filters, same padding).
- Max Pooling Layer (2×2, stride 2). Max-pooling layer with a pool size of 2×2 and a stride of 2.
- Convolutional Layers (256 filters, 3×3 filters, same padding).
- Convolutional Layers (512 filters, 3×3 filters, same padding).
- Max Pooling Layer (2×2, stride 2).

- Stack of Convolutional Layers and Max Pooling Two additional convolutional layers after the previous stack.
- Flattening. Flatten the output feature map (7x7x512) into a vector of size 25088.
- Fully Connected Layers. Three fully connected layers with ReLU activation. First layer with input size 25088 and output size 4096. Second layer with input size 4096 and output size 4096. Third layer with input size 4096 and output size 1000, corresponding to the 1000 classes in the ILSVRC challenge. Softmax activation is applied to the output of the third fully connected layer for classification.

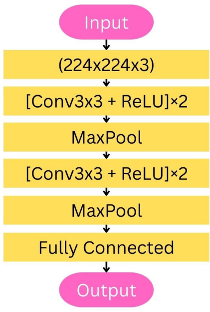

Figure 6. Visual Geometry Group (VGG16) Architecture.

3.4.3. Transfer Learning

- Load MobileNetV2 model.
- Freeze all layers.
- Create a Top Model with the following sequence:

$$Flatten, Dense^{\rightarrow}(x_1), Dense^{\rightarrow}(x_2), Dropout(\rho), SoftMax.$$

- After constructing the Top Model's output layer, fine-tuning is performed by freezing the first X layers, then fitting the model with these parameters: Total Epochs, Batch Size, and Steps per Epoch.

3.5. Computational Environment

In this research project, the process of forming deep learning and transfer learning models uses the DIKTI AI Center facility which uses NVIDIA technology with a computing capacity of 25 PetaFLOPS. The supercomputer facility consists of five NVIDIA DGX A100 server machine nodes. Each node has a dual AMD Rome CPU with eight graphics processing units (GPUs) with multi-instance GPU (MIG) capabilities: 4 GPU @ 40GB, Processor 8 Core, and RAM 64 GB. Each server node is equipped with 1TB of RAM and 5TB of high-speed NVME storage, with a total processing power of 5 TeraFLOPS per node. The supercomputer nodes are interconnected via a high-speed Mellanox network, with NVLink links between the five units, each of which has 8 Core GPUs. The procurement of the DIKTI AI Center supercomputer facility is used to strengthen the creation of national AI talent through various training and education activities in collaboration with industry. This facility can be used by educational institutions, including Hasanuddin University, to facilitate the development of AI technology innovations to meet the needs of industry and society. The software used is Jupiter Notebook, TensorFlow, Roboflow, and OpenCV cuda version 11.4.

3.6. Performance Measurements

After the model fitting process, performance evaluation is conducted using two scenarios. Based on the Confusion Matrix.

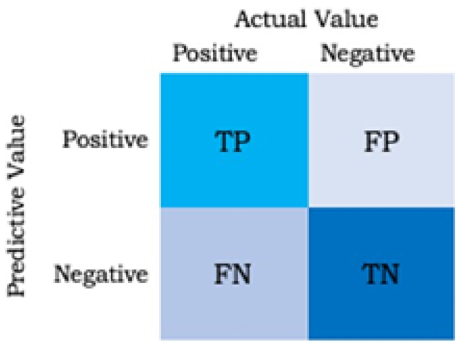

Figure 7. Confusion Matrix.

$$Sensitivity\ (recall) = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + FN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$F_n - Score = (n + 1) \times \frac{Precision \times Recall}{Precision + Recall}$$

Area Under the Curve - Receiver Operating Characteristic (AUC-ROC).

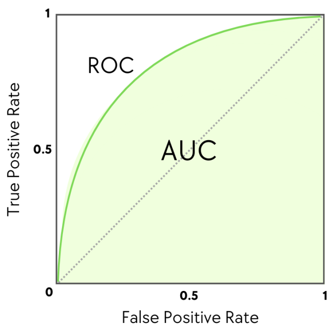

Figure 8. The AUC-ROC curve

4. The Novel MobileNet-Medaka

YOLO-medaka was built from the idea of modifying YOLOv8 by performing several combinations of algorithms, such as MobileNetV2 and VGG16, for the identification and classification of endemic medaka fish with Types: Oryzias celebensis and Oryzias javanicus. this endemic medaka has been declared endangered by the International Union for Conservation of Nature and Natural Resources (IUCN). Therefore, to prevent this, this research was conducted, it is expected to provide a significant impact and major contribution to the conservation of endemic species, especially this endemic fish, so that it does not become extinct. A general overview of the system is shown in Figure 9.

5. Results and Discuss

5.1. Image Pre-processing

The medaka fish image data that was successfully captured consisted of 661 and 886 images for Oryzias celebensis and Oryzias javanicus, respectively.

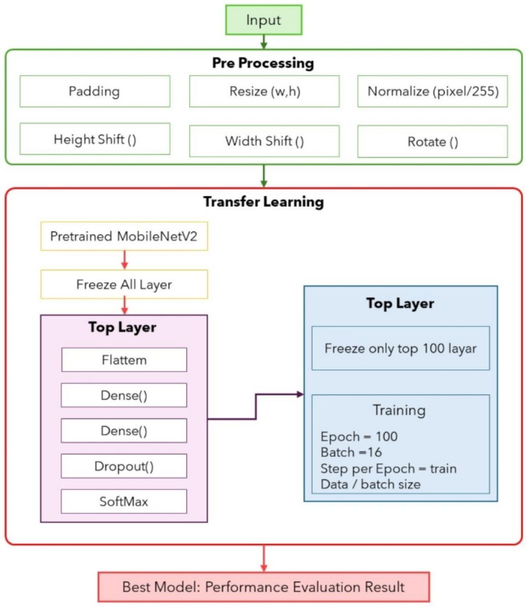

Figure 9. A General Diagram System.

After obtaining the image dataset, each image was padded to achieve a 1:1 aspect ratio by adding pixels to the shorter side using colors similar to the image's edge. This technique is rarely, if ever, used by other researchers, making it a unique approach in this study. After adjusting the images to a 1:1 ratio, they were then resized to 224 x 224 pixels. The results can be seen in Figure 11.

5.2. Experiment Results

The performance comparison of each model on both padded and non-padded datasets is presented in Table 2, highlighting the differences in accuracy and effectiveness between the two approaches.

Table 2. Accuracy of padding and non-padding images.

Model	Image	Sensitivity	Precision	F1 Score	Accuracy
MobileNetV2	Non-padding	98.2	93.8	96	96.95
MobileNetV2	padding	96.3	87.6	91.93	93.9
P-MobileNetV2	Non-padding	79	98.4	87.6	89
P-MobileNetV2	padding	98.46	98.46	98.46	98.78
VGG16	Non-padding	95.3	93.5	94.5	95.7
VGG16	padding	97.2	96.2	81	87
P-VGG16	Non-padding	63.3	98.4	77	76
P-VGG16	padding	92.7	98.4	96.3	96.3

P-MobileNetV2 refers to the model trained using the padded dataset, where images were adjusted to a 1:1 aspect ratio to enhance classification performance and consistency during training.

We have obtained graphical results that compare the ROC accuracy of MobileNetV2 with the modified P-MobileNetV2, along with VGG16 and the modified P-VGG16. These comparisons are clearly shown in the following graph :

The Accuracy and ROC diagrams of the MobileNetV2 model illustrate its performance in classification tasks. The accuracy graph shows the model's learning progress over time,

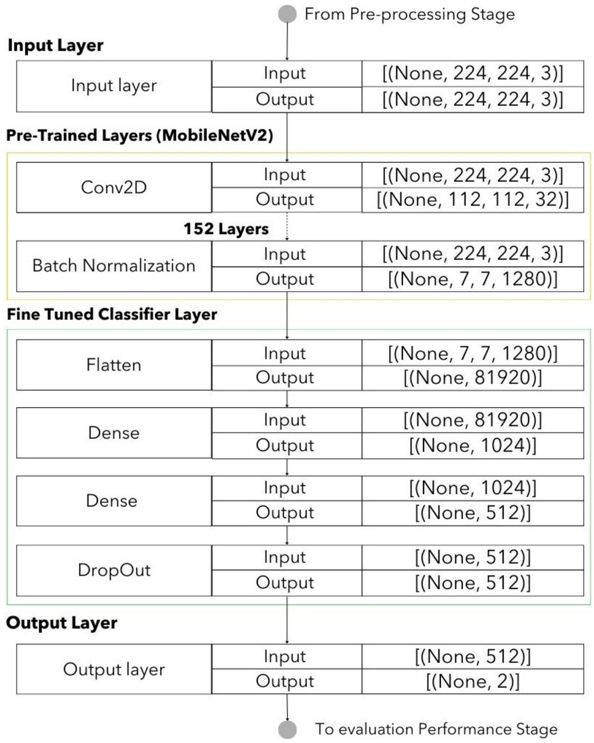

Figure 10. Modified MobileNetV2 Architecture.

while the ROC (Receiver Operating Characteristic) curve evaluates its ability to distinguish between classes, highlighting its sensitivity and specificity at various thresholds.

The "Accuracy and ROC Diagram of P-MobileNetV2 Model" illustrates the model's performance metrics that were modified, including classification accuracy and the Receiver Operating Characteristic (ROC) curve, evaluating its predictive capability.

The diagram presents the accuracy and Receiver Operating Characteristic (ROC) curve of the VGG16 model, illustrating its classification performance and ability to distinguish between classes based on true positive and false positive rates during the evaluation process.

The diagram displays the accuracy and Receiver Operating Characteristic (ROC) curve of the modified P-VGG16 model, highlighting its improved classification performance and enhanced capability to differentiate between classes based on true positive and false positive rates during the evaluation phase.

5.3. Discussion

In this research, we successfully developed a MobileNetV2 architecture model using transfer learning and dataset padding to classify *Oryzias Celebensis* and *Oryzias Javanicus*. We added several layers to the Classification Layer consisting of 5 layers: Flatten, two Dense layers with ReLU activation functions (1024 and 512 neurons respectively), a Dropout layer with 0.2 rate, and a final Dense layer with two neurons using SoftMax activation. This modification allowed us to leverage features learned by MobileNetV2 with ImageNet weights while adapting the model for our specific classification task.

The results demonstrate that this approach effectively enhances classification performance. The additional dense layers serve as feature extraction and classifier layers, mapping the features extracted by MobileNetV2 into the two target classes Oryzias celebensis and Oryzias javanicus. The Dropout layer (rate 0.2) helps prevent overfitting, ensuring the model maintains strong generalisation on new data. The SoftMax activation function in the final dense layer ensures the model's output can be interpreted as class probabilities, simplifying the final result interpretation. This structure improves accuracy while

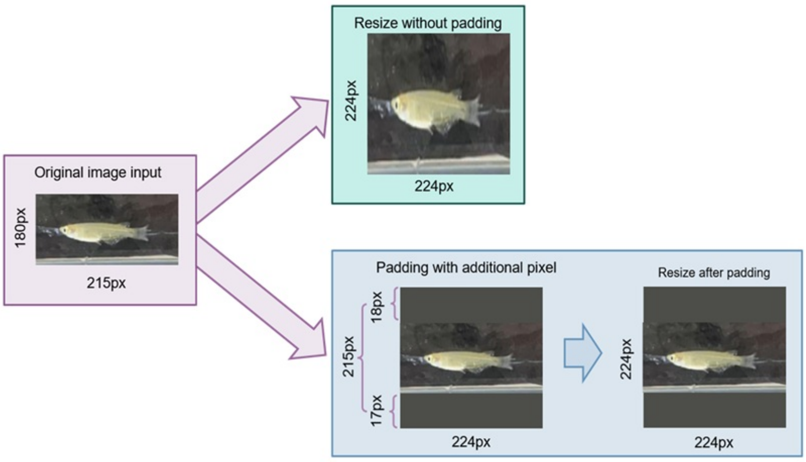

Figure 11. Comparison of Non-Padding and Padding Resize mechanisms.

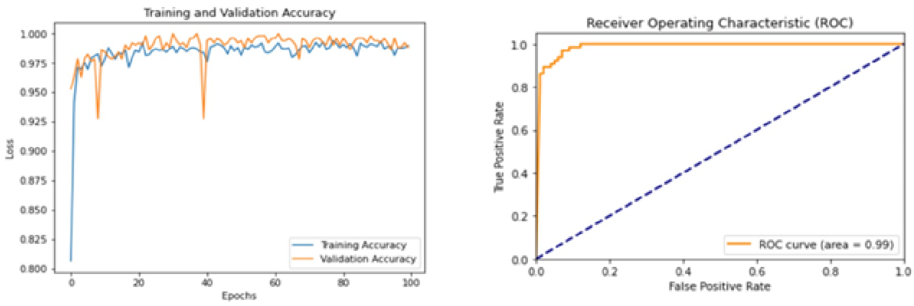

Figure 12. Diagram Accuracy dan ROC Model MobileNetV2.

maintaining robustness, making the model reliable for distinguishing between the two fish species.

Further discussion reveals that using MobileNetV2 as the base model offers several advantages. (1) MobileNetV2 is specifically designed for mobile devices, making it lightweight and efficient for deployment in mobile applications or resource-constrained environments. (2) By employing dataset padding and transfer learning, we leveraged the pre-trained knowledge of MobileNetV2 from large-scale datasets, significantly accelerating and simplifying the model training process. This approach allows the model to achieve high accuracy with limited computational resources. Additionally, the added dense layers enhance feature extraction and classification, while the dropout layer ensures robustness against overfitting. The SoftMax activation in the final layer provides interpretable probability outputs for each target class (*Oryzias celebensis* and *Oryzias javanicus*). The complete architecture of the developed model is illustrated in Figure 10.

We have evaluated the performance of the MobileNetV2 architecture using additional layers configured as described in the system overview, and applied padding to the dataset in order to classify the fish species *Oryzias celebensis* and *Oryzias javanicus* using a limited dataset. The evaluation was conducted using tests based on the confusion matrix and the ROC-AUC curve, utilizing two types of dataset: a nonpadded dataset and a padded dataset. Two model architectures were used for comparison, MobileNetV2 and VGG16. The results show that MobileNetV2 performed better on the padded dataset compared to its performance on the nonpadded dataset, as well as compared to VGG16 on both dataset types.

6. Conclusions

Based on Table 2, the P-MobileNetV2 model has better evaluation performance results compared to the other models, with Sensitivity = 98.46, Precision = 98.46, F1 Score = 98.46, and Accuracy = 98.7. In this study, we have also applied a padding technique to our

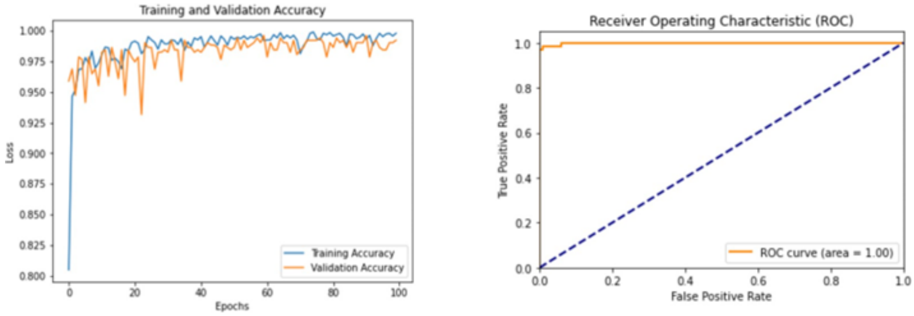

Figure 13. Diagram Accuracy dan ROC Model P-MobileNetV2.

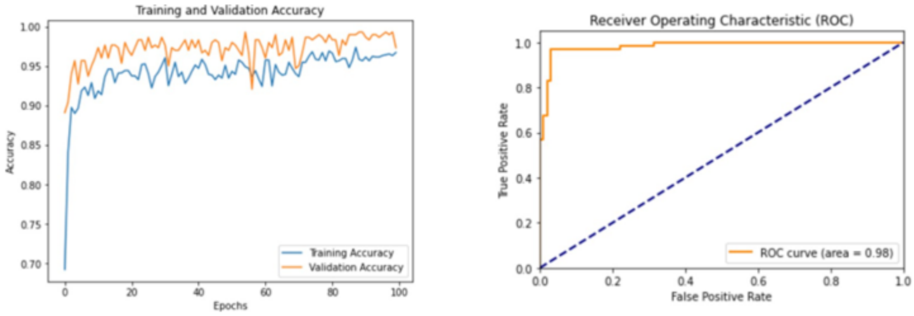

Figure 14. Diagram Accuracy dan ROC Model VGG16.

dataset. This technique involves adding artificial border values to cover empty spaces, ensuring that the images remain square (1:1 aspect ratio), which helps preserve spatial information during the convolution process. As a result, the P-MobileNetV2 and P-VGG16 models trained on the padded dataset achieved higher metrics compared to models trained without dataset padding, demonstrating that this technique can effectively improve model performance. This can be observed in Figures 10 and 12, where both graphs show notably better trends than those in Figures 9 and 11.

Furthermore, our research provides insight that the padding technique not only improves model accuracy but also helps maintain consistency and preserves spatial context in the dataset images. This is particularly crucial for tasks such as segmentation and object detection, where spatial information in images or datasets is highly important. Therefore, the implementation of the padding technique in this study has proven to be a critical step in enhancing model performance and achieving strong results in our classification task.

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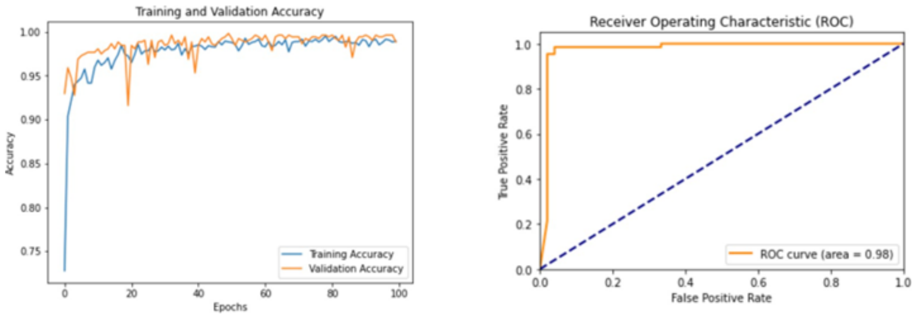

Figure 15. diagram Accuracy dan ROC Model P-VGG16.

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