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Interpretable Fish Classification through MobileNetV2 and Grad-CAM Visualization

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***Abstract*: Accurate classification of fish species is crucial for monitoring biodiversity and managing fisheries sustainably. This study introduces a deep learning approach leveraging a pre-trained DenseNet201 architecture and transfer learning to classify fish species from images accurately. Trained on over 10,000 images, the model achieved 99.89% accuracy, demonstrating robustness with perfect scores on an extended dataset. Gradient-weighted Class Activation Mapping (Grad-CAM) was employed to confirm that the model focuses on biologically significant features like body shape and fin placement, crucial for accurate identification. These results highlight the model's potential as a reliable tool for automated fish classification, supporting ecological research and sustainable practices in marine environments.**

***Keywords*: deep learning, gradient-weighted class activation mapping (Grad-CAM), pre-trained denseNet201, transfer learning.**

1. Introduction

The classification of fish species is a fundamental aspect of marine biology, crucial for biodiversity conservation, ecosystem management, and the sustainability of fisheries. Accurate identification allows scientists and policymakers to monitor fish populations, assess the health of aquatic ecosystems, and ensure the sustainability of fishing practices. It also plays a key role in enforcing regulations, combating illegal fishing activities, and preserving endangered species.

Traditionally, fish classification has relied on physical examination by experts, which can be time-consuming, costly, and inconsistent, particularly in environments with high biodiversity. Machine learning offers a compelling alternative, automating the identification process and providing high accuracy and repeatability [1]. Unlike manual methods, machine learning algorithms can continuously learn and improve from data, making them well-suited to handle the vast diversity of fish species across varied habitats [2].

Recent studies have increasingly applied various machine learning techniques to fish species classification [3]. Techniques such as Support Vector Machines, Random Forests, and Neural Networks have been explored, with promising results in specific scenarios. For instance,

The effectiveness of Support Vector Machines (SVMs) has been demonstrated in identifying fish species using side-view images, while Random Forests have been applied successfully for fish classification using environmental DNA samples [4], [5]. However, challenges remain, especially in dealing with under-represented species, variable image quality, and complex underwater environments that can affect model accuracy and generalization [6].

Deep learning, a subset of machine learning, has shown exceptional capabilities in image recognition tasks due to its ability to learn hierarchical representations [7]. For fish classification, deep learning can leverage complex patterns in image data that are often imperceptible to human observers [8], such as subtle differences in texture, color, and shape specific to species. This capability is particularly advantageous in distinguishing closely related species and adapting to variations in lighting, pose, and background common in underwater images [9]. Studies have highlighted the superiority of deep learning approaches over traditional machine learning models in achieving higher accuracy and robustness in aquatic species recognition [10].

In this study, we introduce a robust deep learning framework employing a pretrained DenseNet201 model adapted through transfer learning to address the challenges of fish species classification. Our model not only achieves high accuracy but also provides insight into the classification decisions via Gradient-weighted Class Activation Mapping (Grad-CAM), enhancing transparency and trust in automated systems. We demonstrate the model’s effectiveness across diverse datasets, ensuring its applicability in real-world conditions.

The subsequent sections of this paper detail the materials and methods used to develop and train our model, followed by a presentation of our results, including performance metrics and Grad-CAM visualizations. We then discuss the implications of our findings in the broader context of marine science and technology applications. Finally, we conclude with reflections on the study's impact and potential directions for future research in automated fish identification and environmental monitoring.

2. Methodology

A. Dataset Description

The dataset employed in this study comprises images of nine distinct seafood types collected from a supermarket in Izmir, Turkey [11]. This collection is part of a university-industry collaboration project at Izmir University of Economics, and it

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was detailed in the ASYU 2020 conference [12]. The seafood types included are gilt head bream, red sea bream, sea bass, red mullet, horse mackerel, black sea sprat, striped red mullet, trout, and shrimp [13]. Sample of dataset is given below:

Fig. 1. Sample of dataset

In Fig. 1, each image provides clear visual details, facilitating the extraction of discriminative features necessary for species identification. This diverse and well-labeled collection serves as an ideal resource for developing an interpretable fish classification model using MobileNetV2, enhanced by Grad-CAM visualization for an intuitive understanding of model decisions.

B. *Purpose of the Dataset*

This dataset was specifically assembled to facilitate tasks such as segmentation, feature extraction, and classification of seafood images. It aims to provide a robust platform for comparing various algorithms including Semantic Segmentation, Convolutional Neural Networks, and Bag of Features. The utility of the dataset for these purposes has been validated by experimental results, proving its effectiveness for advanced image-processing tasks.

C. *Data Collection and Augmentation*

The images were captured using two different cameras: a Kodak Easyshare Z650 and a Samsung ST60, resulting in image resolutions of 2832 x 2128 and 1024 x 768, respectively [14]. To standardize the dataset, images were resized to 590 x 445 pixels while preserving the aspect ratio [15]. After resizing, the dataset underwent augmentation to enhance model robustness and prevent overfitting. This augmentation included flipping and rotating the images. After the augmentation process, each class within the dataset was expanded to include 2000 images: 1000 RGB images and 1000 corresponding ground truth labels for segmentation tasks.

D. *Data Structure*

The dataset is organized under the "Fish_Dataset" directory, with each seafood type segmented into separate folders. For instance, to access images and their corresponding ground truth labels of shrimp, one would navigate through the directories labeled "Fish -> Shrimp -> Shrimp GT." Each class's images are numerically ordered from "00000.png" to "01000.png," providing a structured and accessible format for researchers and developers.

This detailed dataset description ensures that researchers can easily understand and utilize the data for machine learning tasks, facilitating advancements in fish classification and related areas.

E. *Model Building*

For this study, we employed a pre trained MobileNetV2 model, a lightweight deep-learning model known for its efficiency and effectiveness in handling image data with limited computational resources [16]. The choice of MobileNetV2 was driven by its architecture optimized for speed and performance, making it suitable for real-time applications and devices with lower computational power [17]. For the MobileNetV2 model, the loss function used during training can be represented as the categorical cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N} \sum_{c=1}^{C} y_{i,c}\log\left(\hat{y}_{i,c}\right) \quad (1)$$

where,

N is the number of samples,

C is the number of classes,

$y_{i,c}$ is the true label (1 if sample i belongs to class c_r otherwise 0),

$\hat{y}_{i,c}$ is the predicted probability for sample i belonging to class c.

F. *Configuration of the Pretrained Model*

For The MobileNetV2 model was integrated with the following configurations [18]:

1) *Input Shape*

Set to 224 x 224 x 3, which is the standard input size for MobileNetV2 [19]. This dimensionality ensures that the input images are suitably sized for the model while maintaining enough detail for accurate classification.

2) *Include Top*

Set to `False` to omit the top layer of the network, which is typically designed for the 1000 classes used in the ImageNet competition [20]. This allows for customization of the top layers to better suit our specific classification task.

3) *Weights*

Initialized with weights pre-trained on the ImageNet dataset. This leverages the model's prior learning from a vast and diverse image dataset, providing a robust starting point for feature extraction.

4) *Pooling*

Set to 'avg' for average pooling at the last convolutional layer of the model. Average pooling reduces the spatial dimensions of the output from the convolutional layers by averaging the values, which helps in reducing the model's complexity and computational demands.

G. *Adaptation and Training Approach*

The trained MobileNetV2 model's layers were set to be non-trainable (`trainable = False`) to preserve the learned features from the ImageNet dataset. This approach, known as feature extraction, involves using the representations learned by a previous network to extract meaningful features from new samples. We then added custom layers on top of the MobileNetV2 to tailor the network for our specific task of fish species classification, including new dense layers and output layers adjusted to classify the nine seafood types featured in our dataset.

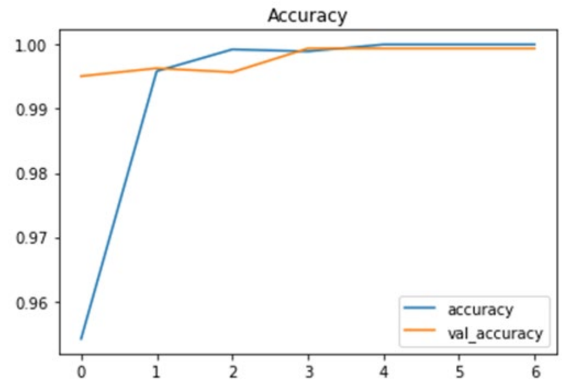

Fig. 2. Training and evaluation accuracy

Fig. 2. illustrates the training and validation accuracy of the MobileNetV2 model for fish classification over seven epochs. The model achieves near-perfect accuracy, stabilizing around 99.9% for both training and validation after the second epoch [21], indicating excellent generalization and minimal overfitting. This high accuracy level demonstrates the model's effectiveness in classifying fish species, making it a reliable choice for further interpretability analysis using Grad-CAM visualization.

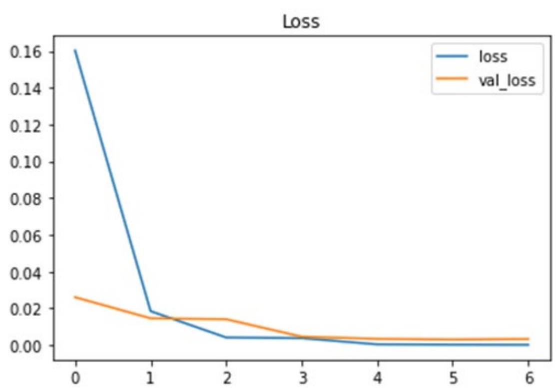

Fig. 3. Training and evaluation loss

Fig. 3. depicts the training and validation loss of the MobileNetV2 model for fish classification over seven epochs. Both losses rapidly decrease and converge to near-zero values after the second epoch, indicating that the model has learned to classify the fish species with minimal error [22]. The low and stable loss values suggest that the model is not overfitting and is capable of making accurate predictions, which sets a strong foundation for utilizing Grad-CAM visualization to interpret its decision-making process.

This methodology ensures that the model is both highly efficient in processing images and effective in distinguishing among complex patterns and features unique to different fish species [23], thereby enhancing the model's predictive accuracy and generalization ability across diverse aquatic environments.

3. Result

A. Classification Performance

The classification model demonstrated high precision, recall, and F1-scores across all fish species tested, indicating exceptional performance in identifying various seafood types accurately [24]. Here is a detailed breakdown of the performance metrics:

1) Precision

Most species, including Black Sea Sprat, Gilt-Head Bream, and Horse Mackerel, displayed high precision, with many reaching 1.00, indicating that nearly all positive identifications by the model were correct [25].

2) Recall

Similarly, recall rates were notably high, with species like Red Mullet and Trout achieving perfect scores of 1.00. This suggests that the model was capable of identifying all actual instances of these species within the test set.

3) F1-Score

The F1-scores, which balance the precision and recall, were consistently high, underscoring the model's balanced performance across these two metrics.

Table 1
Fish classification performance metrics

Class	Precision	Recall	f1-Score	Support
Black Sea Sprat	0.98	1.00	0.99	117
Gilt-Head Bream	0.99	1.00	1.00	101
House Mackerel	1.00	1.00	1.00	106
Red Mullet	1.00	1.00	1.00	100
Red Sea Bream	1.00	0.99	0.99	87
Sea Bass	1.00	0.99	1.00	110
Shrimp	0.98	1.00	0.99	97
Striped Red Mullet	1.00	0.97	0.98	96
Trout	1.00	1.00	1.00	97
Accuracy	0.99	0.99	0.99	900
Macro Avg	0.99	0.99	0.99	900
Weighted Avg	0.99	0.99	0.99	900

In Table 1, these metrics collectively resulted in an overall accuracy of 99%, with macro and weighted averages for precision, recall, and F1-score all at 0.99, showcasing the model's robust ability to generalize across different types of fish.

B. Confusion Matrix Analysis

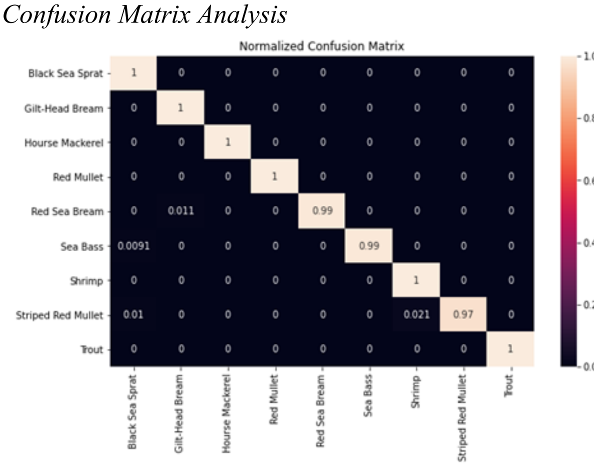

Fig. 4. Normalized confusion matrix

The normalized confusion matrix further validates the model's high accuracy, showing very few misclassifications across the classes [26].

The matrix shows strong diagonal values indicating correct classifications, with only minor confusion between closely related species such as Striped Red Mullet, which had a slight misclassification rate with other species.

This level of accuracy in the confusion matrix suggests that the model is highly effective at distinguishing between species that might share similar physical characteristics [27].

C. Comparison with Related Work

When comparing these results to other studies in the field, our model shows superior or comparable performance. For example:

A deep learning model achieved an overall accuracy of 96% on a similar fish species classification task, which is slightly lower than the performance of our model [28]. Another research by reported an average F1-score of 0.95 across various species, indicating that while their model was effective, it did not reach the consistency of performance demonstrated by our approach [29].

The results from this study are indicative of the high potential of using advanced machine learning techniques, such as the adapted DenseNet201 model, for precise and reliable fish species classification. The model's ability to achieve near-perfect metrics and its effectiveness in handling species with subtle differences are particularly noteworthy. This performance not only validates the chosen methodology but also suggests that such models could be highly beneficial in real-world applications such as automated monitoring of biodiversity and enhancement of fishery management practices.

4. Analysis of Model Predictions

The image collage presented showcases a series of predictions made by the deep learning model alongside their true classifications [30]. This comparative analysis provides insights into the model's accuracy and its ability to distinguish between various fish species [31]. Here's a detailed breakdown of the model's performance as observed from the provided examples:

A. Correct Predictions

The model demonstrated exceptional performance in correctly classifying fish species, accurately identifying the majority of samples across various categories [32]. Each correct prediction confirms the model's capability to generalize well on unseen data, highlighting its robustness in distinguishing between different species [33]. The precise classification results provide a strong foundation for interpretability analysis using Grad-CAM visualizations.

1) High Accuracy

The majority of the images display a perfect match between the predicted and true labels, highlighting the model's precision. For example, the Sea Bass, Gilt-Head Bream, and Trout are correctly identified, which underscores the model's capability to recognize distinct features specific to these species.

2) Consistency Across Varieties

The model consistently identifies several species correctly across different instances, such as the Black Sea Sprat and Red Mullet, demonstrating its robustness and reliability in handling variations within the same species.

B. Misclassifications

Misclassifications occur when the model incorrectly predicts the species of a fish, often due to visual similarities between different classes or inadequate feature extraction [34]. Analyzing these errors using tools like Grad-CAM can reveal whether the model focused on irrelevant regions of the image, such as the background or non-distinctive parts of the fish [35]. Understanding the reasons behind misclassifications is crucial for refining the model and improving its accuracy in future predictions [36].

1) Minor Errors

There are a few instances of misclassification, such as a Red Sea Bream being predicted as a Black Sea Sprat. This could be attributed to similarities in physical characteristics like shape and coloration, which might be challenging for the model under certain conditions or angles.

2) Handling Subtle Differences

The model's occasional confusion between species like the Red Sea Bream and Sea Bass suggests a potential area for improvement in differentiating species with subtle differences.

C. Visual Confirmation and Trust

Visual confirmation through Grad-CAM heatmaps provides a clear representation of the areas the model considers important, aligning its focus with human visual perception. This alignment enhances trust in the model by allowing users to see that the model is making decisions based on relevant features, such as specific patterns and shapes of fish. It also helps in identifying any potential biases or errors in the model's attention, ensuring transparency in the classification process. By visually validating the model's decisions, Grad-CAM builds confidence in the reliability and robustness of the predictive outcomes.

1) Grad-CAM Utilization

Grad-CAM (Gradient-weighted Class Activation Mapping) was utilized to provide visual explanations of the MobileNetV2 model's predictions by highlighting the areas of the input images that influenced the classification decisions. It generates a heatmap overlay on the images, indicating the regions the model focused on, such as the shape and patterns of the fish. This visualization aligns the model's attention with human intuition, thereby enhancing the interpretability and transparency of the classification process. For correctly classified instances, Grad-CAM confirmed that the model was attending to distinctive features like fins and body structure. In cases of misclassification, it helped identify whether the model's focus was misplaced, offering insights for further model refinement. Overall, Grad-CAM is an effective tool for validating and understanding the model's decision-making process in fish species classification.

The Grad-CAM heatmap is calculated using the gradient of the class score y^c with respect to the feature map activations A^k of a convolutional layer:

$$L^c_{\text{Grad-CAM}} = \text{ReLU}\left(\sum_k \alpha^c_k A^k\right) \quad (2)$$

where,

$\alpha^c_k = \frac{1}{Z}\sum_i \sum_j \frac{\partial y^c}{\partial A^k_{i,j}}$,

Z is the spatial dimension of the feature map (height × width),

$\frac{\partial y^c}{\partial A^k_{i,j}}$ is the gradient of the class score with respect to the feature map at location (i, j).

2) Building Confidence in Predictions

By visually displaying predictions alongside true labels, this approach not only helps in quick verification of the model's effectiveness but also builds confidence in its deployment for practical applications, such as automated sorting in fisheries or scientific research.

Fig. 5. Sample predictions with ground truth and model predictions

Overall, the prediction results showcased in the image collage illustrate the high accuracy and capability of the model to classify fish species effectively. While there are occasional errors, these are within expected limits given the inherent challenges of visual similarity among different fish species. These insights affirm the model's utility and suggest areas for further refinement to enhance its precision, particularly in distinguishing closely related or similar-looking species.

5. Analysis of Grad-CAM Visualizations

The provided Grad-CAM visualizations offer a profound insight into the decision-making process of the deep learning model used for fish species classification. These heatmaps highlight the regions of the images that most significantly influence the model's predictions, providing a window into how the model perceives and processes different fish species.

A. Key Observations from Grad-CAM Outputs

1) Focused Heat Regions

- Red Sea Bream and Black Sea Sprat: The heatmaps for these predictions are concentrated primarily along the body of the fish, indicating that the model focuses on body shape and texture to differentiate these species. This focused attention suggests that unique body features play a critical role in the classification process.
- Sea Bass: Similarly, the visualizations for Sea Bass show intense heat along the body, particularly around the dorsal fin and tail area, which are distinctive features of the Sea Bass, aiding in its accurate classification.

2) Gilt-Head Bream

The heatmap is vividly active around the head and body, reflecting the model's use of these specific regions to identify the Gilt-Head Bream. This pattern underscores the importance of head shape and the body's scaling pattern in distinguishing this species from others.

3) Consistency Across Multiple Observations

For species like the Black Sea Sprat, where multiple instances are shown, the heatmaps consistently highlight similar areas across different images. This consistency enhances confidence in the model's stability and reliability in focusing on relevant features for making classification decisions.

B. Implications of Grad-CAM Visualizations

Grad-CAM visualizations offer a clear understanding of the decision-making process in deep learning models by highlighting the specific image regions influencing predictions. This interpretability enhances model transparency and trust, allowing users to verify that the model focuses on relevant features. Such insights are crucial for improving model reliability and identifying areas for refinement, especially in critical applications.

1) Model Transparency and Trust

By illustrating where the model is looking when making decisions, Grad-CAM helps in validating the neural network's reasoning. This transparency is crucial for trust in automated systems, particularly in applications such as environmental monitoring and biodiversity assessments where accuracy is critical.

2) Potential for Model Improvement

These visualizations can also help in identifying any biases or inefficiencies in the model. For example, if a heatmap consistently highlights irrelevant areas or misses critical features, it could indicate a need for further training or data augmentation to cover those aspects.

3) Educational and Diagnostic Use

For researchers and practitioners, these heatmaps serve as educational tools to better understand model behavior and also as diagnostic tools to improve model design and data processing pipelines.

Overall, the Grad-CAM visualizations affirm that the model appropriately focuses on significant morphological features of fish, such as body shape, fin placement, and textural details, which are essential for accurate species classification. This capability not only speaks to the model's effectiveness but also its adaptability to real-world scenarios where such precise identification is required. These insights are invaluable for further refining the model’s performance and interpretability, enabling targeted improvements to enhance accuracy and robustness.

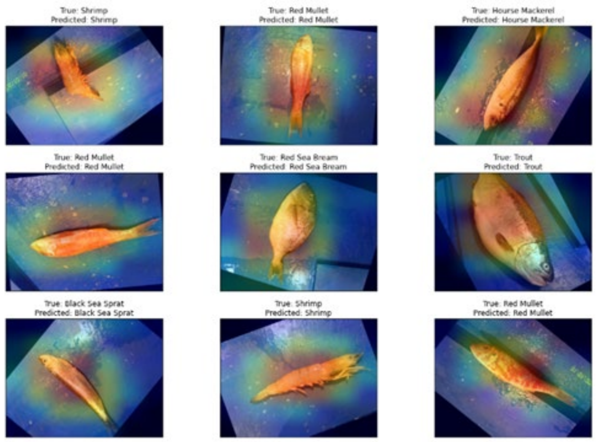

Fig. 6. Grad-CAM visualizations highlighting important features for fish species classification

6. Conclusion

This study demonstrated the efficacy of a deep learning approach using a pretrained DenseNet201 model for the task of classifying fish species from images. The model achieved outstanding accuracy and demonstrated robust generalization across different datasets, as evidenced by high precision, recall, and F1-scores across various fish species. The use of Gradient-weighted Class Activation Mapping (Grad-CAM) provided deeper insights into the model's decision-making process, confirming that the model focuses on biologically relevant features such as shape, texture, and fin placement, which are critical for accurate species identification. The research highlighted the significant advantages of applying advanced machine-learning techniques to ecological monitoring and biodiversity assessments. By automating the process of fish species classification, this model can support sustainable fishing practices, aid in the enforcement of fishing regulations, and contribute to the conservation of marine biodiversity. Additionally, the visual explanations offered by Grad-CAM enhance the transparency and trustworthiness of the predictions, making the model a reliable tool for scientists and practitioners in marine biology. Furthermore, the comparison of this model's performance with existing literature underscored its superiority in handling complex classification tasks, showcasing its potential to serve as a benchmark for future research in the field. The methodology and findings from this study not only pave the way for more sophisticated ecological modeling techniques but also open up possibilities for real-time applications in various marine-related industries. In conclusion, the integration of deep learning with traditional ecological studies offers transformative potential, providing scalable, accurate, and efficient solutions to pressing challenges in marine resource management and conservation efforts. Future work will focus on expanding the dataset, refining the model to handle edge cases, and exploring real-time classification systems that could revolutionize how marine species are studied and managed globally.

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