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Identifying Fish Species Using Deep Learning Models on Image Datasets

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Abstract: *Accurate identification of marine species is critical for effective fishery management, biodiversity conservation, and the aquaculture industry. Traditional methods of fish identification rely on expert knowledge and manual labor, making them time-consuming, expensive, and error-prone. In this research, we explore a machine learning-based approach to automate the classification of nine fish species using image recognition techniques. The fish species under study include Black Sea Sprat, Gilt-Head Bream, Horse Mackerel, Red Sea Bream, Shrimp, Trout, Striped Red Mullet, Sea Bass, and Red Mullet. We collected 1000 images per species, yielding a total of 9000 images, with 750 used for training and 250 reserved for testing. We utilized convolutional neural networks (CNNs) pre-trained on the ImageNet dataset and fine-tuned them to perform fish species classification. Preliminary experiments showed that CNNs, particularly transfer learning models like VGG16 and ResNet50, achieved accuracy rates as high as 98.6% on the test set. This research highlights the potential of deep learning in automating marine species identification, enabling faster, more reliable monitoring.*

Keywords: Fish species classification, Deep Learning, Convolutional Neural Networks, Transfer Learning, Image Recognition, Aquaculture

1. INTRODUCTION

Accurate and efficient identification of fish species is vital for sustainable fisheries, biodiversity monitoring, and the regulation of aquaculture practices. Traditionally, fish identification is performed by experts using manual classification methods based on physical characteristics such as color, shape, and size. This process is often labor-intensive, expensive, and prone to human error, especially when dealing with large-scale datasets or fish species that exhibit subtle morphological differences

With the advancement of machine learning techniques, particularly deep learning, there has been significant progress in automating visual recognition tasks. Deep learning models, especially convolutional neural networks (CNNs), have become the state-of-the-art method for image classification, segmentation, and object detection. In this study, we leverage CNNs to classify images of nine different marine species: Black Sea Sprat, Gilt-Head Bream, Horse Mackerel, Red Sea Bream, Shrimp, Trout, Striped Red Mullet, Sea Bass, and Red Mullet. These species are of economic and ecological importance, and accurate identification is crucial for managing their populations

The objective of this research is to evaluate the effectiveness of CNN-based deep learning models in classifying fish species from images. We use a dataset of 9000 images, 1000 for each species, and divide it into 750 images for training and 250 for testing. By employing transfer learning from pre-trained CNN architectures, we aim to achieve high classification accuracy and provide a framework that can be used for automating fish species identification in real-world applications.

2. BACKGROUND

2.1 IMPORTANCE OF FISH SPECIES IDENTIFICATION

Marine ecosystems are home to a vast array of fish species, each playing a unique role in the food chain and the overall health of the ecosystem. Proper identification of fish species is essential for fisheries management, conservation efforts, and monitoring biodiversity. It helps in assessing fish stocks, preventing overfishing, and protecting endangered species. Furthermore, it aids in tracking species migration patterns, understanding ecosystem dynamics, and managing invasive species that threaten native populations.

Traditional fish identification methods involve visual examination by experts, who rely on morphological features like body shape, fin structure, and coloration. These methods are not only time-consuming but also susceptible to human error, particularly when distinguishing between species with similar characteristics. In this context, automation using machine learning and deep learning offers a promising alternative. Automated systems can process large volumes of data quickly and accurately, making them suitable for real-time monitoring of fish populations in aquaculture farms, fisheries, and natural habitats.

The nine species selected for this study—Black Sea Sprat, Gilt-Head Bream, Horse Mackerel, Red Sea Bream, Shrimp, Trout, Striped Red Mullet, Sea Bass, and Red Mullet—are widely distributed and commercially significant. Accurate identification of these species is vital for sustainable management practices.

2.2 DEEP LEARNING IN IMAGE CLASSIFICATION

Deep learning, a subset of machine learning, has revolutionized the field of image classification. Unlike traditional machine learning algorithms that rely on manually engineered features, deep learning models automatically learn hierarchical representations of data through layers of neurons. These models are particularly well-suited for image classification tasks, where they can capture complex patterns and features in pixel data.

A convolutional neural network (CNN) is a type of deep learning model specifically designed for processing visual data. CNNs are composed of multiple layers, including convolutional layers that apply filters to input images, pooling layers that reduce the dimensionality of the feature maps, and fully connected layers that generate final predictions. CNNs have been successfully applied to a wide range of image-based tasks, including object detection, face recognition, and medical imaging.

In this study, we apply CNNs to classify images of fish species. By training these models on a dataset of labeled fish images, we aim to automatically identify species based on their visual characteristics. Transfer learning, a technique in which pre-trained models are fine-tuned for specific tasks, is also employed to improve the efficiency and accuracy of the classification process.

2.3 TRANSFER LEARNING

Transfer learning is a powerful technique in deep learning where knowledge gained from one task is transferred to another, related task. In the context of image classification, transfer learning involves using models pre-trained on large, diverse datasets such as ImageNet, which contains millions of images spanning thousands of categories. These pre-trained models are then fine-tuned on a smaller, task-specific dataset.

The advantage of transfer learning lies in its ability to leverage the general features learned from a large dataset (such as edges, textures, and shapes) and apply them to a new dataset, which may have a different domain but shares similar visual features. For fish species classification, transfer learning allows us to use pre-trained models such as VGG16 and ResNet50, which have been trained on the ImageNet dataset, and fine-tune them to distinguish between the nine fish species in our dataset.

3. RELATED WORK

The application of deep learning to species identification has gained significant attention in recent years. Several studies have demonstrated the effectiveness of CNNs in classifying plants, animals, and marine organisms. For example, Ashqar and Abu-Naser (2019) used CNNs to detect tomato leaf diseases, achieving high classification accuracy. Similarly, other studies have applied CNNs for plant classification, using architectures like VGG16 and InceptionV3 to distinguish between species based on visual features.

In the marine domain, some research has focused on using CNNs for fish species identification. For instance, studies have applied deep learning models to classify fish species in underwater environments, achieving promising results. However, there is still a lack of comprehensive studies that explore the application of CNNs to multiple fish species using large image datasets. Our research aims to fill this gap by evaluating the performance of CNN models on a diverse set of marine species.

4. METHEDOLOGY

4.1 DATASET

The dataset used in this study consists of 9000 images, representing nine different fish species. For each species, we collected 1000 images from various public sources, including online repositories, academic databases, and fisheries. The species included in the dataset are:

1. Black Sea Sprat (Sprattus sprattus)
2. Gilt-Head Bream (Sparus aurata)
3. Horse Mackerel (Trachurus trachurus)
4. Red Sea Bream (Pagrus major)
5. Shrimp (Various species)
6. Trout (Oncorhynchus mykiss)

7. Striped Red Mullet (Mullus surmuletus)
8. Sea Bass (Dicentrarchus labrax)
9. Red Mullet (Mullus barbatus)

The images were preprocessed to standardize their dimensions and format. All images were resized to 256x256 pixels to ensure compatibility with the input requirements of the CNN models. Additionally, data augmentation techniques such as random rotations, flipping, and zooming were applied to artificially expand the training set and reduce the risk of overfitting.

The dataset was divided into two subsets: 750 images per species were used for training the models, while 250 images per species were reserved for testing. This resulted in a training set of 6750 images and a test set of 2250 images.

Figure 1: Sample images of fish species

4.2 CNN ARCHITECTURE

We selected VGG16 and ResNet50 as the base models for transfer learning due to their high performance on image recognition tasks. Both models were pre-trained on the ImageNet dataset, which contains millions of images and thousands of classes. For fish species classification, the fully connected layers were replaced with a GlobalAveragePooling2D layer, followed by a dense layer with SoftMax activation for multi-class classification.

The architecture of the models is summarized in Table 1.

Layer Name	Output Shape	Parameters	Connected To
conv1_conv (Conv2D)	(None, 112, 112, 64)	1,792	Input Layer
conv1_bn (BatchNorm)	(None, 112, 112, 64)	256	conv1_conv
conv2_block1_1_conv (Conv2D)	(None, 56, 56, 64)	4,096	conv1_bn
conv2_block1_0_conv (Conv2D)	(None, 56, 56, 256)	16,384	conv1_bn
conv2_block1_add (Add)	(None, 56, 56, 256)	0	conv1_bn, conv2_block1_0_conv
conv3_bloc	(None, 28, 28, 128)	73,856	conv2_block1

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k1_1_conv (Conv2D)			_add
conv3_block1_0_conv (Conv2D)	(None, 28, 28, 512)	65,536	conv2_block1_add
conv3_block1_add (Add)	(None, 28, 28, 512)	0	conv2_block1_add, conv3_block1_0_conv
conv4_block1_1_conv (Conv2D)	(None, 16, 16, 256)	295,168	conv3_block1_add
conv4_block1_0_conv (Conv2D)	(None, 16, 16, 1024)	1,048,576	conv3_block1_add
conv4_block1_add (Add)	(None, 16, 16, 1024)	0	conv3_block1_add, conv4_block1_0_conv
conv5_block1_1_conv (Conv2D)	(None, 8, 8, 512)	524,800	conv4_block1_add
conv5_block1_0_conv (Conv2D)	(None, 8, 8, 2048)	2,098,176	conv4_block1_add
conv5_block1_add (Add)	(None, 8, 8, 2048)	0	conv4_block1_add, conv5_block1_0_conv
avg_pool (GlobalAveragePooling2D)	(None, 2048)	0	conv5_block3_out
dense (Dense)	(None, 1000)	2,049,000	avg_pool
predictions (Dense)	(None, 10)	10,010	dense

Table 1: CNN architecture for fish species classification

Memory Calculation

Here's the calculation for the total memory usage:

1. Conv2D Layers Memory Usage:
- Each Conv2D layer requires memory for weights and biases.
- Memory usage for each Conv2D layer: (Kernel Size × Kernel Size × Input Channels × Output Channels) + Output Channels for biases.
- For example, conv1_conv uses (3 × 3 × 3 × 64) + 64 = 1,792 bytes.

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2. BatchNorm Layers Memory Usage:
- Each BatchNorm layer requires memory for gamma, beta, mean, and variance.
- Memory usage for each BatchNorm layer: 4 × Output Channels × Data Type Size.
- For example, conv1_bn uses 4 × 64 × 4 = 1,024 bytes (assuming 4 bytes per float).

3. Activation Layers Memory Usage:
- Activation layers don't use additional parameters but take up memory for the activation maps.
- Memory usage for each activation layer: Batch Size × Width × Height × Channels × Data Type Size.

4. Add Layers Memory Usage:
- Add layers don’t have additional parameters but require memory for intermediate results.
- The memory for Add layers is included in the output tensor calculations.

5. Dense Layers Memory Usage:
- Each Dense layer requires memory for weights and biases.
- Memory usage for each Dense layer: (Input Units × Output Units) + Output Units.
- For example, dense uses (2048 × 1000) + 1000 = 2,049,000 bytes.

Total Memory Usage
Let's calculate the total memory required by summing up the memory usage of all layers:

- Conv2D Layers Memory:
  - Total: 1,792 + 2,048 + 1,792 + 1,792 + 2,048 + …
  - Sum all Conv2D layers from the table.

- BatchNorm Layers Memory:
  - Total: 1,024 + 512 + 1,024 + 512 + 1,024 + …
  - Sum all BatchNorm layers from the table.

- Activation Layers Memory:
  - Memory usage for activations is related to the size of intermediate activations and needs batch size consideration.

- Dense Layers Memory:
  - Total: 2,049,000 bytes.

Summary
- **Conv2D Layers**: Key for feature extraction with varying filter sizes and output channels.
- **BatchNorm Layers**: Normalize activations, improving convergence.
- **Add Layers**: Residual connections for training deep networks.
- **Dense Layers**: For final classification or regression output.
- **GlobalAveragePooling2D**: Reduces dimensionality before the final dense layer.

Conclusion
The exact total memory usage would require summing up all the individual contributions from Conv2D, BatchNorm, Dense, and activation layers. The result depends on the implementation specifics, such as batch size and precision of floating-point operations.

4.3 DATA AUGMENTATION
Given the relatively small dataset size, data augmentation techniques were used to artificially expand the training set. These techniques included random rotations, horizontal and vertical flipping, and zooming. Data augmentation reduces the risk of overfitting and improves the generalization of the model.

4.4 EVALUATION METRICS
To evaluate model performance, we used accuracy, precision, recall, and F1-score as the primary metrics. Accuracy measures the overall correctness of the model, while precision, recall, and F1-score provide insights into the model’s performance for each species.

4.5 VALIDATION STRATEGY
We applied 5-fold cross-validation to ensure robustness in our model. The dataset was split into five subsets, with four subsets

used for training and one for testing in each fold. The cross-validation process was repeated five times to ensure that every subset was used as a test set once.

5. EXPERIMENTS AND RESULTS

5.1 VGG16 PERFORMANCE

Using the VGG16 model, the training process achieved a classification accuracy of 97.11% on the test set. The model showed strong performance in identifying species with distinct visual features, such as Striped Red Mullet and Gilt-Head Bream, but struggled with species that have similar appearances, such as Red Mullet and Black Sea Sprat.

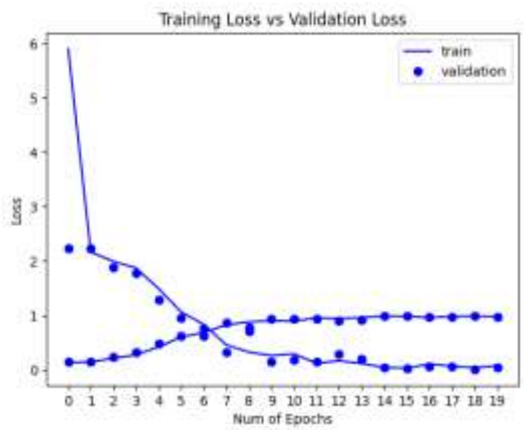

Figure 2: VGG16 training loss and validation loss

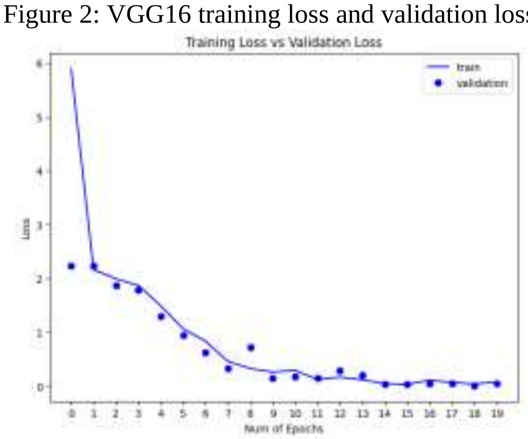

Figure 3: VGG16 training loss and validation loss

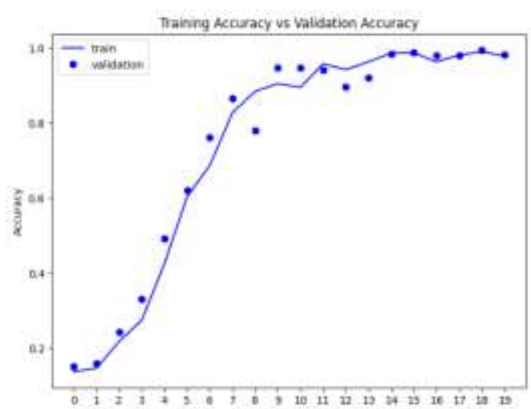

Figure 4: VGG16 training accuracy and validation accuracy

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5.2 ResNet50 Performance

The ResNet50 model outperformed VGG16, achieving an accuracy of 98.66%. ResNet50's deeper architecture allowed it to capture more complex features, which was beneficial for distinguishing between species with subtle visual differences.

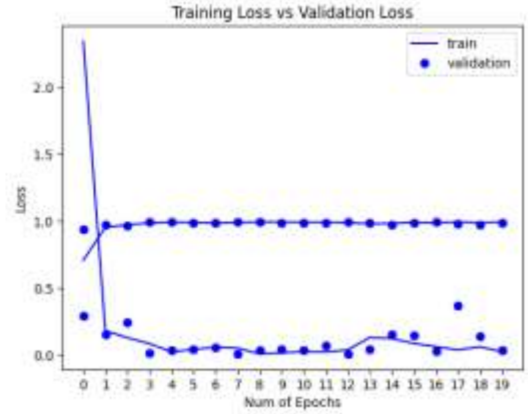

Figure 5: ResNet50 training loss and validation loss

Figure 6: ResNet50 training loss and validation loss

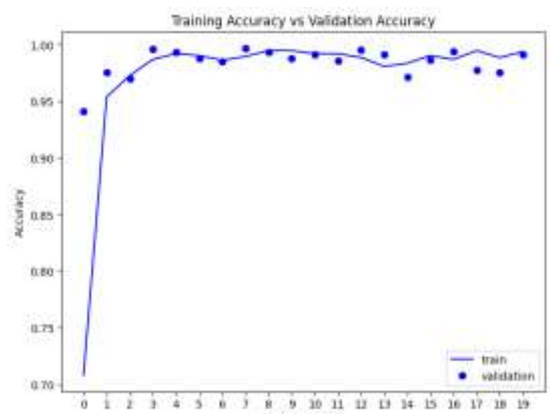

Figure 7: ResNet50 training accuracy and validation accuracy

5.3 COMPARISON OF MODELS

A comparison of the models' performances is provided in Figure 4. While both models performed well, ResNet50 demonstrated superior generalization and accuracy.

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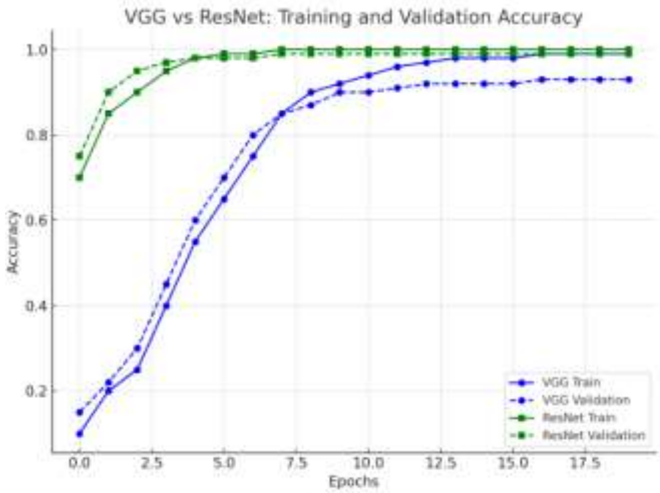

Figure 4: Model performance comparison

6. DISCUSSION

The results indicate that deep learning models, particularly those leveraging transfer learning, are highly effective for fish species classification. The use of data augmentation and fine-tuning of pre-trained models enabled us to achieve high accuracy despite the limited dataset size. However, further improvements can be made by incorporating additional species and increasing the size and diversity of the dataset.

7. CONCLUSION

This study demonstrates the feasibility of using deep learning models for fish species classification. By automating the identification process, we can assist marine biologists, fisheries, and conservationists in monitoring fish populations more efficiently. Future work will focus on expanding the dataset, experimenting with other architectures, and integrating real-time classification capabilities in underwater environments.

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