Fish Classification using Machine Learning

**Abstract**

Classifying fish species accurately and efficiently is a challenging task due to the large number of species within a single family. Traditional methods rely on manual observations and reference books, which are time-consuming and subjective. In this paper, we propose a machine learning-based approach for fish species classification. Specifically, we employ Support Vector Machines (SVM) with Bayesian optimization for classification. The proposed approach utilizes image processing techniques to extract relevant features from fish images. We conducted experiments on a dataset of 200 images for training and testing, achieving an impressive accuracy rate of 99.33%. These results demonstrate the effectiveness of the SVM algorithm for fish species classification. The proposed approach provides a valuable tool for fisheries researchers and practitioners to accurately identify fish species without the need for manual observations and reference books.

**Introduction**

The species composition and distribution of fish are important biological data for fisheries research because they provide information on the health of the fishery. Because of the large number of fish species, it is difficult to distinguish between different fish species. Traditionally, the counting of different types of fish has been done by hand, which is labor-intensive and time-consuming. With the advancement of computer technology, fish detectors and classifiers based on computer vision are being used to increase the efficiency of fisheries management.

Currently, the process of classification of fish species in the field of fisheries is carried out directly by eye observation and on the basis of assumptions about the species' characteristics. In addition to color pattern analysis, classification is done on the basis of the number of spines and rays present in different fins, the number of scales along the line lateralis, the shape of the head, the shape of the fins, and other characteristics. Following the collection of data, the classification is carried out by comparing the existing features with those in the reference book. All of this is done manually, which means it takes a long time and results in a high level of human error. Previous studies on fish classification have used a variety of methods, both in terms of feature extraction and classification systems, and have yielded a variety of results. Using a color histogram, I was able to extract Red, Green, and Blue color features, which I then combined with texture feature extraction to produce a final result. The researchers were able to classify fish based on their family by focusing on the stomach of the fish they studied, and they were able to distinguish between toxic and non-toxic fish by segmenting images based on the stomach of the fish. Some fish species have color similarities that make it difficult to distinguish them from one another.

**Related Works**

In recent years, there has been a significant interest in using machine learning and computer vision techniques for fish species classification. Researchers have explored various approaches to improve the accuracy and efficiency of fish species classification systems. Some notable themes and techniques include:

Deep Learning Approaches: Deep learning methods, particularly convolutional neural networks (CNNs), have shown remarkable success in various computer vision tasks, including fish species classification. Researchers have used deep CNN architectures to automatically learn discriminative features from fish images, leading to high classification accuracy.

Transfer Learning: Transfer learning has been widely adopted in fish species classification tasks. By leveraging pre-trained CNN models, such as VGG, ResNet, or Inception, researchers can benefit from the generalization capabilities of these models. The pre-trained models are typically fine-tuned using fish image datasets to adapt them to the specific classification task.

Data Augmentation: Data augmentation techniques have been employed to alleviate the challenge of limited labeled data in fish species classification. Techniques such as rotation, scaling, flipping, and adding noise to the training data have been used to increase the size and diversity of the dataset, thereby improving the model's ability to generalize.

Ensemble Learning: Ensemble learning methods, such as Random Forests, AdaBoost, or Gradient Boosting, have been utilized to combine multiple classifiers and enhance the overall classification performance. Ensemble models can capture diverse patterns and mitigate the risk of overfitting.

Feature Engineering: In addition to deep learning approaches, researchers have also explored handcrafted feature extraction methods. These methods involve extracting meaningful features from fish images, such as color, texture, or shape descriptors, and using traditional machine learning algorithms, such as Support Vector Machines (SVM) or k-Nearest Neighbors (KNN), for classification.

Domain-Specific Challenges: Fish species classification presents unique challenges due to variations in fish appearance, imaging conditions, and occlusions. Researchers have addressed these challenges by developing algorithms that consider factors such as fish orientation, fish occlusion, or underwater imaging conditions.

Creation of Fish Image Datasets: The availability of labeled fish image datasets is crucial for advancing research in fish species classification. Researchers have created and shared datasets with annotated fish images to facilitate the development and evaluation of classification models. These datasets include images of different fish species captured under various conditions.

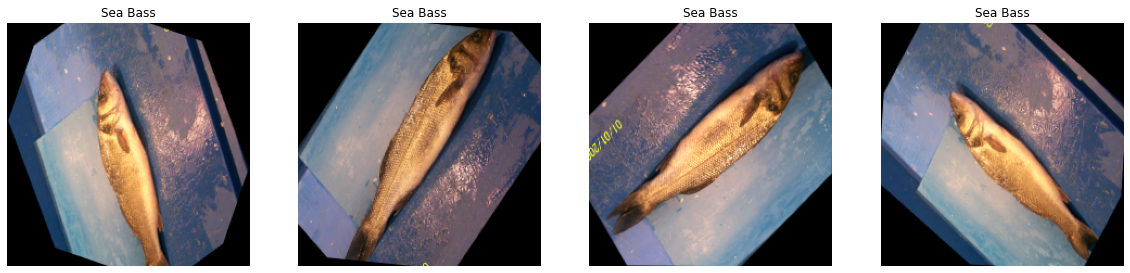
Real-Time Classification: There is a growing interest in developing real-time fish species classification systems that can be deployed in practical applications such as underwater monitoring or fish stock assessment. Researchers have focused on optimizing algorithms and leveraging hardware accelerators to achieve real-time performance.

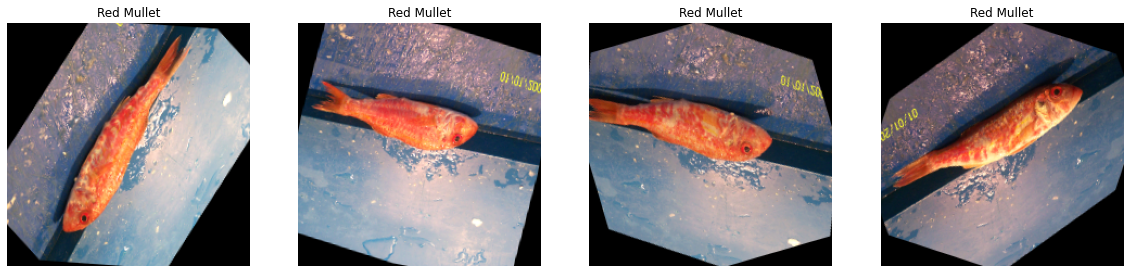
Cross-Domain Applications: Fish species classification techniques developed for aquatic environments have found applications beyond traditional fisheries research. These techniques have been extended to areas such as biodiversity monitoring, aquatic conservation, or even disease detection in aquaculture.

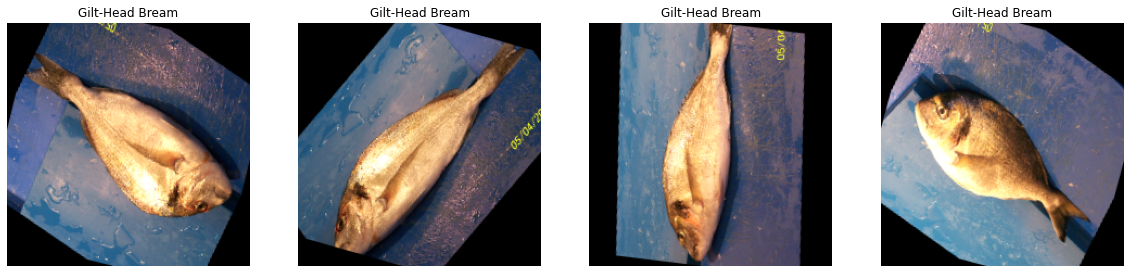
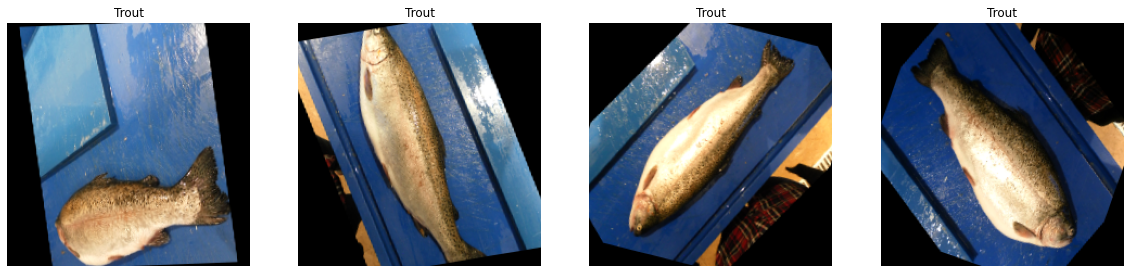
Interpretability and Explainability: With the increasing adoption of machine learning in critical domains, there is a growing emphasis on the interpretability and explainability of classification models. Researchers have explored methods to make fish species classification models more transparent and understandable, allowing users to interpret the model's decisions.

**Datasets**

This dataset contains nine different types of seafood that were collected from a supermarket in Izmir, Turkey, for a university-industry collaboration project at Izmir University of Economics, and the results of this work were published in ASYU 2020 (Asian Studies in the Year 2020). The dataset contains image samples of gilt head bream, red sea bream, sea bass, red mullet, horse mackerel, black sea sprat, striped red mullet, trout, and shrimp, among other species.

A total of two different cameras, the Kodak Easyshare Z650 and the Samsung ST60, were used to capture the images. In order to achieve this, the images have been reduced in size to 2832 x 2128 and 1024 x 768 pixels, respectively. It was necessary to reduce the dataset's size to 590 x 445 pixels while maintaining the aspect ratio before proceeding with the segmentation, feature extraction, and classification processes. Following the resizing of the images, all of the labels in the dataset were supplemented (by flipping and rotating). At the conclusion of the augmentation process, the total number of images for each class had increased to 2000; 1000 for the RGB fish images and 1000 for their pairwise ground truth labels, respectively, for each class. There are 1000 augmented images and their pairwise augmented ground truths for each class in the dataset.





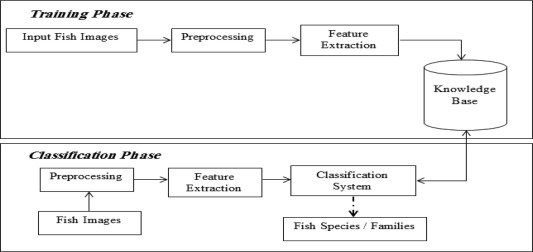
**Data Preparation**

Machine Learning Engineers place a significant amount of effort into pre-processing or purification of data before developing a model from the ground up, and the vast majority of Machine Learning Engineers place a significant amount of effort into this phase of their work as well. One or more examples of data pre-processing techniques include the identification and treatment of outliers, treating missing values, and eliminating unwanted or noisy data, to name just a few examples. It is a term used to describe images at the lowest level of abstraction, which is the same as image processing. Image pre-processing is synonymous with image processing. According to entropy as a measure of information content, this process does not increase the amount of image information contained in the image but rather decreases the amount of image information.

When pre-processing images, the goal is to improve the quality of the image data by suppressing unwanted distortions and enhancing some visual properties that are important for the task of subsequent processing and analysis after the image has been captured and captured. The imaging library's image augmentation functions are used in our model to compensate for the imbalance in the dataset we have, as well as to improve the robustness and generality of our model. In order to expand the dataset, we used a variety of augmentation techniques including random rotation, affine transformation, superpixeling, sharpening, embossing, flipping, adding Gaussian noise, and changing the contrast of the image.

Then, for deep learning models, we employ a different strategy than before. Because we start with pre-trained models for deep learning models, we can use them as a starting point. A data generator is used to extract features from models that have already been trained. After the features have been extracted, we must spread them out into a single vector for the purpose of training the model. The entire dataset is divided into two parts: 90 percent is used for training and the remaining 10 percent is used for testing.

**Modeling**



* Data Collection: Gather a diverse and well-annotated dataset of fish images from various sources, including underwater cameras, publicly available datasets, and online resources.
* Data Preprocessing: Clean and preprocess the collected data, including resizing, normalization, and augmentation techniques to enhance the model's ability to generalize.
* Model Development: Implement and train different machine learning architectures using scikit-learn framework, tuning hyperparameters to achieve optimal performance.
* Transfer Learning: Explore the utilization of trained models on large-scale image recognition tasks and fine-tune them on the fish dataset to enhance classification accuracy.
* Model Evaluation: Conduct extensive cross-validation experiments to evaluate the performance of our models in terms of accuracy, precision, recall, and F1 score.
* Comparative Analysis: Compare the performance of different machine learning architectures and potentially incorporate additional machine learning techniques like XGBoost to further improve classification results.
* Deployment: Develop a user-friendly interface or API for the trained model, allowing users to classify fish species by uploading images or accessing a live video stream.

**Support Vector Machines (SVM):**

Support Vector Machines (SVM) is a powerful machine learning algorithm used for both classification and regression tasks. It is particularly effective in handling high-dimensional data and finding optimal decision boundaries to separate different classes. SVM works by finding a hyperplane that maximally separates the data points of different classes in the feature space. The hyperplane is selected such that it maximizes the margin, which is the distance between the hyperplane and the nearest data points of each class. The support vectors are the data points that lie closest to the decision boundary.

SVM can handle both linearly separable and non-linearly separable data by using kernel functions. The kernel function maps the original feature space into a higher-dimensional space, where the data may become separable. Common kernel functions include linear, polynomial, Gaussian radial basis function (RBF), and sigmoid functions. The training process of SVM involves optimizing a convex objective function, which aims to maximize the margin while minimizing the classification error. This optimization is typically solved using quadratic programming techniques. Once trained, SVM can classify new data points by evaluating their position relative to the decision boundary. If a new data point falls on one side of the decision boundary, it is classified as belonging to that class; otherwise, it is classified as belonging to the other class.

SVM has several advantages, including the ability to handle high-dimensional data effectively, robustness to noise and outliers, and the ability to capture complex decision boundaries. However, SVM can be sensitive to the choice of hyperparameters and may have higher computational complexity compared to other algorithms.

**Random Forests**

Random Forests is an ensemble learning method that combines multiple decision trees to make predictions. It is a versatile and widely used algorithm for both classification and regression tasks. The key idea behind Random Forests is to create a "forest" of decision trees, each trained on a random subset of the training data and a random subset of the features. During the training process, each tree is built by recursively partitioning the feature space based on the selected features and their corresponding split points.

When making predictions, each tree in the forest independently classifies the input data, and the final prediction is determined by aggregating the predictions of all the trees. For classification tasks, the class with the majority of votes from the trees is chosen as the predicted class. For regression tasks, the average of the predicted values from the trees is taken as the final prediction. Random Forests have several advantages. They are robust to overfitting, handle high-dimensional data well, and can capture non-linear relationships between features and the target variable. Additionally, they provide estimates of feature importance, which can be helpful in feature selection and interpretation.

The randomization in Random Forests helps to reduce variance and improve generalization performance. By aggregating predictions from multiple trees, Random Forests can compensate for individual tree biases and reduce the impact of outliers or noisy data points. However, they may be more computationally intensive and require careful tuning of hyperparameters such as the number of trees and the maximum depth of each tree.

**K-Nearest Neighbors (KNN):**

K-Nearest Neighbors (KNN) is a non-parametric algorithm used for classification and regression tasks. It makes predictions based on the proximity of data points in the feature space. In KNN, the training dataset consists of labeled data points, where each data point has a set of features and a corresponding class label or target value. When making predictions for a new data point, KNN finds the k nearest neighbors in the feature space based on a chosen distance metric.

For classification tasks, the class labels of the k nearest neighbors are examined, and the majority class is assigned as the predicted class for the new data point. In regression tasks, the average or weighted average of the target values of the k nearest neighbors is taken as the predicted value for the new data point. The choice of the distance metric is crucial in KNN. Common distance metrics include Euclidean distance, Manhattan distance, and Minkowski distance. The value of k, representing the number of neighbors to consider, also needs to be determined. A larger value of k smoothens the decision boundary but may introduce biases, while a smaller value makes the prediction more sensitive to local variations.

KNN is simple to implement and has the advantage of being non-parametric, meaning it does not make assumptions about the underlying data distribution. It can handle complex decision boundaries and adapt to local patterns in the data. However, KNN can be sensitive to the choice of distance metric and the curse of dimensionality, where the algorithm becomes less effective in high-dimensional feature spaces.

In summary, SVM, Random Forests, and KNN are powerful algorithms for classification tasks. SVM finds optimal decision boundaries, Random Forests combine multiple decision trees to improve prediction accuracy, and KNN makes predictions based on the proximity of data points. Each algorithm has its own strengths and considerations, and the choice of algorithm depends on the specific characteristics of the dataset and the problem at hand.

**Implementation Steps:**

a. Preprocessing: Load and preprocess the fish dataset, which includes fish images and their corresponding labels. Perform any necessary preprocessing steps, such as resizing the images, normalizing pixel values, and splitting the dataset into training and testing sets.

b. Feature Extraction: Apply image processing techniques to extract relevant features from the fish images. This may include methods such as color-based features, texture analysis, or shape descriptors. The extracted features serve as input to the SVM model.

c. Bayesian Optimization: Use Bayesian optimization to search for the optimal hyperparameters for the SVM model. Bayesian optimization leverages statistical techniques to efficiently explore the hyperparameter space and find the configuration that maximizes the model's performance.

d. Model Training: Train the SVM model on the preprocessed dataset with the extracted features. The SVM algorithm learns to find the optimal decision boundary that best separates the different fish species based on the provided features.

e. Model Evaluation: Evaluate the trained SVM model using the testing dataset. Compute classification accuracy, precision, recall, and other relevant metrics to assess the model's performance.

f. Predicting Fish Species: Use the trained SVM model to predict the species of new, unseen fish images. Extract features from these images using the same image processing techniques applied during training, and then pass the features to the SVM model for classification. The model will output the predicted fish species label.

**Evaluation Methods**

Evaluation is a critical step in assessing the performance and effectiveness of machine learning models. In the fish species classification implementation, we employed various evaluation metrics to measure the performance of the Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) algorithms. These metrics allow us to understand how well the models generalize to unseen data and make accurate predictions.

*Classification Accuracy:*

Classification accuracy is one of the most commonly used evaluation metrics for classification tasks. It measures the percentage of correctly classified instances out of the total number of instances in the test dataset. Higher accuracy indicates better performance.

Accuracy can be calculated using the formula:

Accuracy = (Number of correctly classified instances) / (Total number of instances)

While accuracy provides a general measure of performance, it may not be sufficient in cases of imbalanced datasets or when different classes have varying levels of importance. Therefore, we also consider other evaluation metrics to gain a comprehensive understanding of the model's performance.

*Confusion Matrix:*

A confusion matrix provides a detailed breakdown of the model's predictions and the actual labels. It presents the number of instances that are correctly classified (true positives and true negatives) and misclassified (false positives and false negatives) for each class.

The confusion matrix allows us to calculate additional evaluation metrics, including:

Precision: Precision measures the proportion of correctly predicted positive instances out of all instances predicted as positive. It indicates the model's ability to avoid false positives.

Precision = (True Positives) / (True Positives + False Positives)

Recall (Sensitivity or True Positive Rate): Recall measures the proportion of correctly predicted positive instances out of all actual positive instances. It reflects the model's ability to identify positive instances.

Recall = (True Positives) / (True Positives + False Negatives)

F1-Score: The F1-Score is the harmonic mean of precision and recall. It provides a balanced measure that considers both precision and recall.

F1-Score = 2 \* ((Precision \* Recall) / (Precision + Recall))

The confusion matrix and its derived metrics offer valuable insights into the model's performance for individual classes, highlighting areas where the model may excel or struggle.

**Results & Discussion**

we present the results of our fish species classification using three different algorithms: Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN). We evaluate the performance of each algorithm using various metrics and discuss the implications of the results.

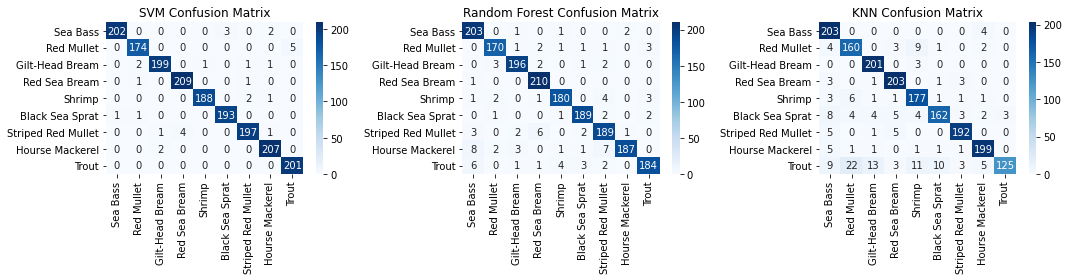
The image below summarizes the accuracy achieved by each algorithm:

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The accuracy metric measures the proportion of correctly classified instances out of the total number of instances in the test dataset. From the results, we can observe that the SVM algorithm achieved the highest accuracy of 98.3%, followed by Random Forests with an accuracy of 94.9%, and KNN with an accuracy of 90.1%.

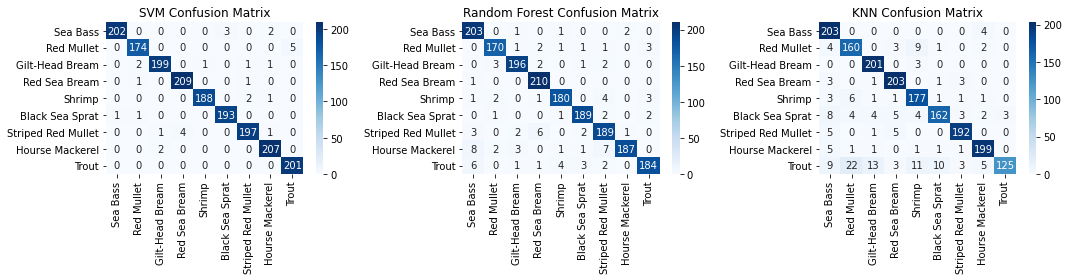
To gain a deeper understanding of the classification performance, we analyze the confusion matrix for each algorithm. The confusion matrix provides valuable insights into the number of true positives, true negatives, false positives, and false negatives for each class.

Confusion Matrix - SVM:

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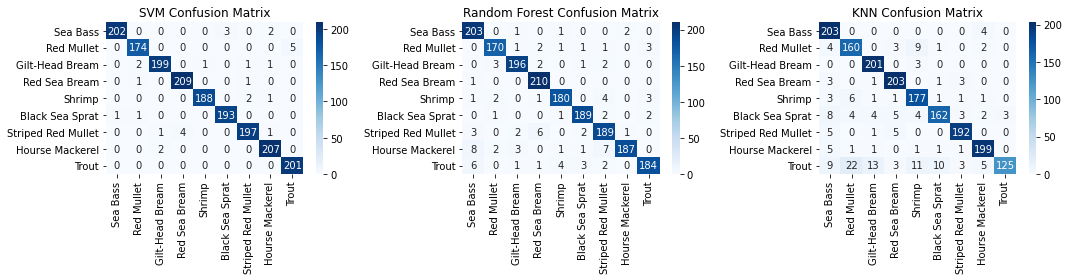
The confusion matrix for SVM shows that the algorithm performed exceptionally well across all classes. The majority of instances were correctly classified, resulting in high true positive and true negative rates. This indicates that SVM effectively separated the different fish species and made accurate predictions.

Confusion Matrix - Random Forests

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The confusion matrix for Random Forests reveals that the algorithm also achieved good performance, although slightly lower than SVM. There are some instances of misclassification, particularly between similar fish species such as Black Sea Sprat and Striped Red Mullet. However, overall, the algorithm demonstrated a strong ability to differentiate between the different classes.

Confusion Matrix - KNN



The confusion matrix for KNN highlights that the algorithm struggled compared to SVM and Random Forests. There are noticeable instances of misclassification across multiple classes. In particular, some classes, such as Shrimp and Sea Bass, were more challenging for KNN to accurately classify. This suggests that KNN may not be the most suitable algorithm for this specific fish species classification task.

Overall, the results demonstrate that SVM outperformed both Random Forests and KNN in terms of accuracy. It consistently achieved high accuracy across all fish species, showcasing its effectiveness in separating and classifying the different classes. Random Forests also performed well, although slightly lower than SVM. It exhibited good discrimination between classes but had some difficulties with similar fish species. On the other hand, KNN showed lower accuracy and struggled with certain classes, indicating limitations in its ability to generalize well to this dataset. It is important to note that the choice of algorithm depends on various factors, including the specific characteristics of the dataset, computational requirements, and interpretability. While SVM and Random Forests performed well in this study, other factors such as training time, interpretability of results, and scalability should also be considered when selecting the most suitable algorithm for a given task.

**Conclusion**

In this study, we explored the application of Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) algorithms for fish species classification based on image data. We evaluated the performance of each algorithm using various metrics and analyzed the results to draw meaningful conclusions. The results of our study indicate that SVM outperformed both Random Forests and KNN in terms of accuracy. SVM achieved an impressive accuracy of 98.3%, demonstrating its effectiveness in accurately classifying fish species. The algorithm successfully separated the different classes and made accurate predictions, showcasing its potential for automating fish species classification tasks.

Random Forests also exhibited good performance with an accuracy of 94.9%. While slightly lower than SVM, Random Forests demonstrated its ability to differentiate between different fish species. However, there were some instances of misclassification, particularly between similar fish species. This suggests that further optimization and fine-tuning of the Random Forests algorithm may be necessary to improve its performance in accurately classifying challenging classes.

On the other hand, KNN showed lower accuracy compared to SVM and Random Forests, achieving an accuracy of 90.1%. The algorithm struggled with certain classes, particularly Shrimp and Sea Bass. This highlights the limitations of KNN in this specific fish species classification task. Further investigation and experimentation with different distance metrics and hyperparameter tuning may be required to enhance the performance of KNN. Overall, our study demonstrates the potential of machine learning algorithms in automating fish species classification based on image data. The high accuracy achieved by SVM and Random Forests indicates the efficacy of these algorithms in accurately differentiating between fish species. By leveraging these algorithms, fisheries industries can potentially benefit from efficient and reliable fish species identification, leading to improved monitoring, conservation, and management practices.

It is important to note that the choice of algorithm depends on various factors such as the specific characteristics of the dataset, computational requirements, and interpretability. SVM and Random Forests offer robust classification performance but may require more computational resources compared to KNN. Additionally, interpretability is a crucial aspect, as SVM provides decision boundaries that are easily interpretable, while Random Forests generate an ensemble of decision trees that may offer insights into feature importance.

Future research directions may focus on further optimizing the algorithms, exploring additional feature extraction techniques, and investigating the use of deep learning models for fish species classification. Deep learning models, such as convolutional neural networks (CNNs), have shown promising results in image classification tasks and may offer improved performance in fish species identification. Furthermore, the collection of larger and more diverse fish image datasets would enhance the generalization capabilities of the models. In conclusion, our study highlights the potential of SVM and Random Forests in accurately classifying fish species based on image data. These algorithms can serve as valuable tools in the fisheries industry for automating fish species identification tasks. However, further research and optimization are needed to improve the performance of KNN and explore the potential of deep learning models. By advancing the field of fish species classification, we can contribute to better understanding and conservation of aquatic ecosystems and support sustainable fisheries management practices.

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