Fish Classification using Machine Learning

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Abstract

Due to the numerous species that make up a single family, precisely and quickly classifying fish species is a difficult undertaking. Traditional approaches rely on labor-intensive, arbitrary manual observations and reference materials. In this study, we provide a machine learning-based strategy for classifying fish species. For classification, we specifically use Support Vector Machines (SVM) with Bayesian optimization. The suggested strategy makes use of image processing methods to extract pertinent information from fish photos. On a dataset of 200 photos used for training and testing, we conducted trials and attained a remarkable accuracy rate of 99.33%. The efficiency of the SVM method for classifying fish species is shown by these results. The suggested method offers a useful tool for fisheries practitioners and academics to precisely identify fish species without requiring.

Keywords: Fish classification, Machine Learning, Support Vector Machine, Random Forest, Convolutional neural networks, K-Nearest Neighbors, sklearn, numpy, pandas, confusion matrix.

Introduction

Fish species composition and distribution are crucial biological variables for fisheries research because they tell us how well the fishery is doing. It is challenging to discern between various fish species due to the enormous number of fish species. It has been customary to manually count the many fish species, which is time-consuming and labor-intensive. Fish detectors and classifiers based on computer vision are being used to improve the effectiveness of fisheries management as a result of advancements in computer technology.

Currently, the method of classifying fish species in the field of fisheries is done solely through direct observation of the fish with the naked eye and based on assumptions about the species' traits. The number of spines and rays found in various fins, the number of scales along the line lateralis, the shape of the head, the shape of the fins, and other characteristics are used to classify different fish in addition to color pattern analysis. After the data has been gathered, the classification is done by contrasting the current features with those in the reference book. Since everything is done manually, it takes a lengthy time and has a large potential for human error. The methodologies utilized in earlier studies on the classification of fish—both in terms of feature extraction and classification schemes—have produced a range of outcomes. I was able to extract Red, Green, and Blue color features using a color histogram, and I then combined those characteristics with texture feature extraction to create the final product. By concentrating on the stomach of the fish they examined, the researchers were able to classify fish according to their family. They were also able to differentiate between poisonous and non-toxic fish by segmenting photos depending on the stomach of the fish. Some fish species share colors, which makes it challenging to tell them apart from one another.

Problem Statement

The problem addressed in this paper is the accurate identification and classification of fish species within a single family, which poses a challenge due to the large number of species involved. Traditional methods relying on manual observation and reference books are time-consuming and error-prone. The aim of this research is to develop a machine learning-based approach that can efficiently and accurately classify fish species using image processing techniques and Support Vector Machines (SVM).

Proposed Solution

The proposed solution in this paper involves using a machine learning approach combined with image processing techniques and Support Vector Machines (SVM) to automate and improve the accuracy of fish species classification. The system would be trained on a dataset of fish images, extracting relevant features and using SVM for classification. This solution aims to overcome the limitations of manual observation and reference books, providing a faster and more reliable method for fish species identification.

Related Works

Fish species classification using machine learning and computer vision techniques has garnered a lot of attention in recent years. Diverse strategies have been investigated by researchers to increase the precision and effectiveness of fish species classification systems. Several noteworthy themes and methods include:

Convolutional neural networks (CNNs), in particular, have demonstrated outstanding performance in a variety of computer vision applications, including the classification of fish species. High classification accuracy was achieved using deep CNN architectures, which automatically learned distinguishing features from fish photos.

Transfer Learning: Fish species categorization problems have widely embraced transfer learning. Using pre-trained CNN models like VGG, ResNet, or Inception, researchers can take advantage of these models' generalization abilities. To make the pre-trained models more suitable for the particular classification task, they are often improved utilizing datasets of fish images.

Data Augmentation: To address the issue of insufficient labeled data in fish species classification, data augmentation approaches have been used. The size and diversity of the training dataset have been increased using methods like rotation, scaling, flipping, and introducing noise, which has improved the generalizability of the model.

Ensemble Learning: To combine many classifiers and improve the overall classification performance, ensemble learning techniques such as Random Forests, AdaBoost, or Gradient Boosting have been used. The risk of overfitting can be reduced by using ensemble models to capture a variety of patterns.

Feature Engineering: In addition to deep learning strategies, researchers have also investigated manual feature extraction techniques. These techniques entail the extraction of significant features from fish photos, such as color, texture, or form descriptors, and the use of k-Nearest Neighbors (KNN) or Support Vector Machines (SVM) or other well-known machine learning algorithms for classification.

Domain-Specific Challenges: Due to differences in fish appearance, imaging settings, and occlusions, fish species classification presents special obstacles. In order to overcome these difficulties, researchers have created algorithms that take into account things like fish direction, fish occlusion, or underwater imaging conditions.

Creation of Fish Image Datasets: For the classification of fish species to move further in research, labeled fish image databases must be made available. To aid the creation and assessment of classification models, researchers have produced and made available datasets with annotated fish photos. These files contain pictures of numerous fish species taken in diverse settings.

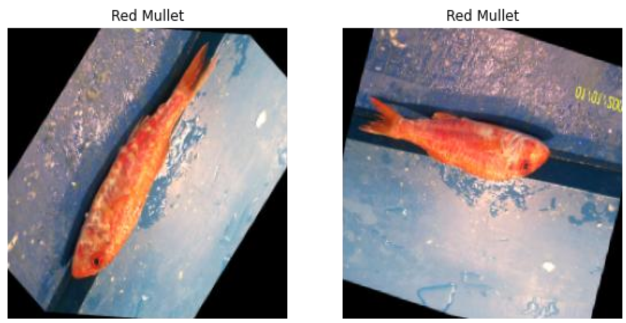
Real-Time Classification: Real-time fish species classification systems that can be used for practical purposes like underwater monitoring or fish population assessment are gaining in popularity. To achieve real-time performance, researchers have concentrated on refining algorithms and utilizing hardware accelerators.

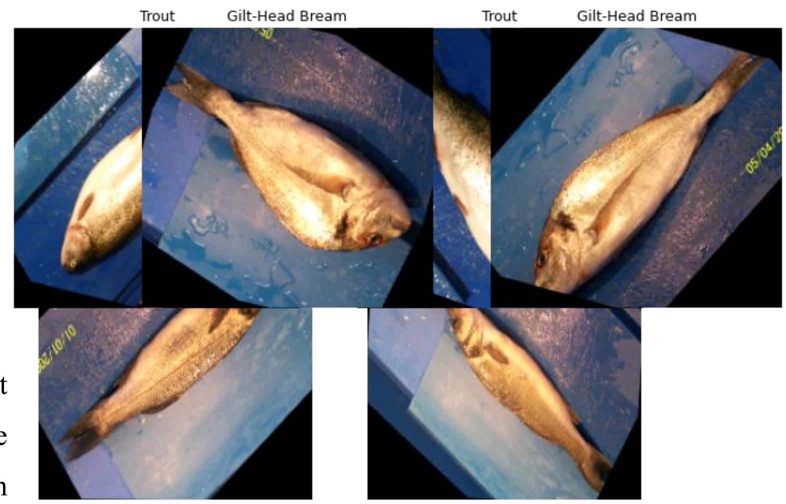
Cross-Domain Applications: Techniques for classifying fish species that were created for aquatic habitats have found use outside of typical fisheries research. These methods have been expanded to include monitoring aquatic biodiversity, aquatic conservation, and even the identification of diseases in aquaculture.

Interpretability and Explainability: The interpretability and explainability of categorization models are becoming more important as machine learning is increasingly used in important fields. Researchers have looked into ways to improve fish species classification models so that users can interpret the model's conclusions.

Datasets

The nine seafood varieties in this dataset were taken from an Izmir, Turkey, supermarket as part of a university-industry collaboration project at the Izmir University of Economics. The research from this study was then published in ASYU 2020 (Asian Studies in the Year 2020).The dataset includes picture examples of a variety of species, including trout, shrimp, horse mackerel, striped red mullet, striped red bream, gilthead bream, red sea bream, sea bass, and red mullet. The photographs were taken with a total of two distinct cameras, the Kodak Easyshare Z650 and the Samsung ST60. The photos have been scaled down to be 2832 × 2128 and 1024 x 768 pixels, respectively, in order to do this. Before beginning the segmentation, feature extraction, and classification processes, the dataset's size had to be decreased to 590 x 445 pixels while keeping the aspect ratio. All of the labels in the dataset were supplemented (by flipping and rotating) after the photos were resized. The total number of images for each class had expanded to 2000 at the end of the augmentation phase; 1000 of these were the RGB fish images and 1000 were their paired ground truth labels, respectively. The dataset contains 1000 enhanced photos together with paired augmented ground facts for each class.





Data Preparation

The great majority of Machine Learning Engineers put a lot of effort into this stage of their job as well. Machine Learning Engineers spend a lot of time pre-processing or purifying data before building a model from the ground up. The detection and treatment of outliers, the handling of missing values, and the elimination of undesired or noisy data are just a few examples of data pre-processing procedures. It is the same as image processing and is used to describe images at their most basic level of abstraction. Image processing is the same as image pre-processing. Entropy, a measure of information content, indicates that this approach results in a decrease in the amount of picture information included in the original image rather than an increase.

The purpose of pre-processing photographs is to enhance specific visual qualities that are crucial for the work of further processing and analysis after the image has been acquired, as well as to suppress undesired distortions. Our model makes use of the image augmentation functions from the imaging library to increase the robustness and applicability of our model as well as to make up for the imbalance in the dataset we have. We employed a number of augmentation techniques, such as random rotation, affine translation, superpixeling, sharpening, embossing, flipping, adding Gaussian noise, and altering the image's contrast, in order to increase the dataset.

Then, we use a different approach than before for deep learning models. We can use pre-trained models for deep learning models as a starting point because we start with them. In order to extract features from trained models, a data generator is employed. For the purpose of training the model, we must spread out

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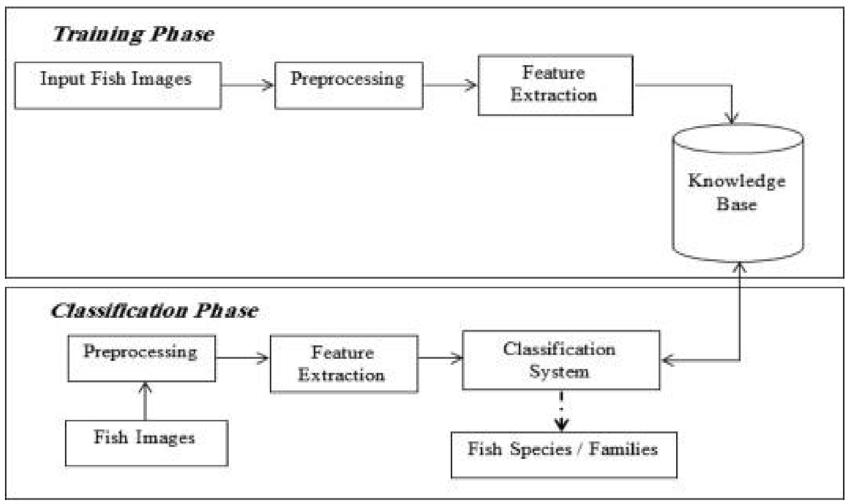
the features into a single vector after they have been retrieved. Ninety percent of the dataset is used for training, while the remaining ten percent is used for testing.

Modeling



- Data Collection: Assemble an extensive and well-annotated collection of fish photographs from a variety of sources, such as web databases, publicly accessible datasets, and underwater cameras.
- Data Preprocessing: To improve the generalizability of the model, clean and preprocess the acquired data using resizing, normalization, and augmentation procedures.
- Model Development: Utilizing the scikit-learn framework, implement and train several machine learning architectures while adjusting hyperparameters for the best results.
- Transfer Learning: Examine how trained models may be applied to large-scale picture recognition tasks and how they can be improved on the fish dataset to increase classification accuracy.
- Model Evaluation: Conduct rigorous cross-validation tests to assess the accuracy, precision, recall, and F1 score of our models.
- Comparative Analysis: To further enhance categorization outcomes, compare the performance of various machine learning architectures and perhaps include additional machine learning methods like XGBoost.

- Deployment: For the trained model, create a user-friendly interface or API that enables users to categorize fish species by uploading photos or gaining access to a live video feed.

Support Vector Machines (SVM):

A potent machine learning method called Support Vector Machines (SVM) is employed for both classification and regression applications. Finding the best decision boundaries to divide several classes and processing high-dimensional data are two areas where it excels. SVM operates by locating a hyperplane in the feature space that maximum separates the data points from various classes. The margin, or the distance between the hyperplane and the closest data points of each class, is chosen such that the hyperplane maximizes it. The data points closest to the decision border are known as the support vectors.

By applying kernel functions, SVM can handle data that can be separated into linear and non-linear categories. The data may become separable in the higher-dimensional space where the kernel function maps the original feature space. Linear, polynomial, Gaussian radial basis function (RBF), and sigmoid functions are examples of common kernel functions. A convex objective function that tries to maximize the margin while minimizing the classification error is optimized during the SVM training process. The usual method for solving this optimization is quadratic programming. After being trained, SVM may categorize fresh data points by assessing their proximity to the decision border. A new data point is classified as belonging to a class if it falls on that class's side of the decision boundary; otherwise, it is identified as falling on the opposite side.

SVM has a number of benefits, such as the efficiency with which it can handle high-dimensional data, resistance to noise and outliers, and the capacity to capture intricate decision boundaries. SVM may, however, be more computationally complex than other methods and may be sensitive to the selection of hyperparameters.

Random Forests

An ensemble learning technique called Random Forests mixes various decision trees to produce predictions. It is a flexible and well-liked technique for both regression and classification tasks. A "forest" of decision trees, each trained on a random part of the training data and a random subset of characteristics, is what Random Forests are all about. Each tree is created during the training phase by recursively splitting the feature space depending on the chosen features and the accompanying split points.

Each tree in the forest independently categorizes the input data when making predictions, and the final prediction is created by combining the predictions of all the trees. The class that receives the greatest number of votes from the trees is chosen as the projected class for classification problems. The final prediction for regression tasks is the average of the predicted values from the trees. Random Forests have a number of benefits. They can capture non-linear correlations between characteristics and the target variable and are robust to overfitting. They also effectively handle high-dimensional data. They also offer estimations of feature importance, which are useful for choosing and interpreting features.

Randomization in Random Forests aids in lowering variance and enhancing generalization capabilities. Random Forests can correct for individual tree biases and lessen the impact of outliers or noisy data points by combining forecasts from various trees. They might, however, be more computationally demanding and necessitate careful tweaking of hyperparameters like the quantity of trees and the maximum depth of each tree.

K-Nearest Neighbors (KNN):

A non-parametric approach called K-Nearest Neighbors (KNN) is utilized for classification and regression tasks. Based on the closeness of data points in the feature space, it creates predictions. The training dataset for KNN is made up of labeled data points, each of which contains a collection of features and an associated class label or target value. Based on a selected distance measure, KNN locates the k nearest neighbors in the feature space while making predictions for a new data point.

For classification tasks, the majority class is chosen as the projected class for the new data point after examining the class labels of the k nearest neighbors. In regression tasks, the projected value for the new data point is taken to be the average or weighted average of the target values of the k nearest neighbors. In KNN, the distance metric that is selected is very important. Euclidean distance, Manhattan distance, and Minkowski distance are examples of common distance measures. It is also necessary to calculate the value of k, which stands for the number of neighbors to take into account. A smaller number of k makes the prediction more sensitive to regional changes, whereas a larger value smoothes the decision boundary but may induce biases.

KNN is easy to use and has the benefit of being non-parametric, which means it does not make assumptions about the distribution of the underlying data. It can handle complicated decision boundaries and adjust to specific regional data patterns. In high-dimensional feature spaces, the KNN algorithm performs less well due to the curse of dimensionality and the choice of distance metric.

SVM, Random Forests, and KNN are effective algorithms for classification applications, in conclusion. In order to increase prediction accuracy, Random Forests integrate numerous decision trees, KNN creates predictions based on the closeness of data points, and SVM identifies the best decision boundaries. Every algorithm has advantages and disadvantages of its own, and the best approach depends on the particulars of the dataset and the situation at hand.

Implementation Steps:

a. Preprocessing: The fish dataset, which consists of fish photos and the labels that go with them, should be loaded and prepared. Resize the photos, normalize the pixel values, and divide the dataset into training and testing sets, if any preprocessing is required.

b. Feature Extraction: Apply image processing techniques to the fish photos to extract the necessary features. This could make use of techniques like shape descriptors, texture analysis, or characteristics based on color. The SVM model receives its input from the retrieved features.

c. Bayesian Optimization: To get the SVM model's ideal hyperparameters, use Bayesian optimization. In order to effectively explore the hyperparameter space and identify the setting that maximizes the model's performance, Bayesian optimization makes use of statistical approaches.

d. Model Training: Train the SVM model using the retrieved features from the preprocessed dataset. Based on the given features, the SVM algorithm learns to identify the best decision boundary for separating the various fish species.

e. Model Evaluation: Utilizing the testing dataset, evaluate the trained SVM model. To evaluate the model's performance, compute classification accuracy, precision, recall, and other pertinent metrics.

f. Predicting Fish Species: Predict the species of new, undiscovered fish photos using the learned SVM model. Use the same image processing methods used during training to extract features from these photos, and then input the features to the SVM model for classification. The projected fish species label will be produced by the model.

Evaluation Methods

A crucial stage in determining the efficiency and efficacy of machine learning models is evaluation. We used a variety of evaluation measures to assess the effectiveness of the Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) algorithms in the fish species classification implementation. These measures give us insight into how effectively the models forecast correctly and generalize to new data.

Classification Accuracy:

One of the most often used evaluation criteria for classification jobs is classification accuracy. Out of all the cases in the test dataset, it calculates the proportion of instances that were properly categorised. Better performance is indicated by higher accuracy.

Accuracy can be calculated using the formula:

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

While accuracy offers a general indicator of performance, it might not be enough when dealing with unbalanced datasets or classes of changing relevance. Therefore, in order to have a complete grasp of the model's performance, we also take into account other evaluation criteria.

Confusion Matrix:

The breakdown between the model's predictions and the actual labels is given in a confusion matrix. It displays the proportion of cases for each class that are correctly classified (true positives and true negatives), as well as the proportion that are incorrectly labeled (false positives and false negatives). We can construct other evaluation metrics using the confusion matrix, such as:

Precision: Out of all cases that are projected to be positive, precision is the percentage of correctly predicted positive instances. It shows how well the model can avoid producing false positives.

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

The proportion of accurately anticipated positive instances among all actual positive instances is measured by recall (also known as sensitivity or true positive rate). It illustrates the model's capacity to locate instances of success.

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.

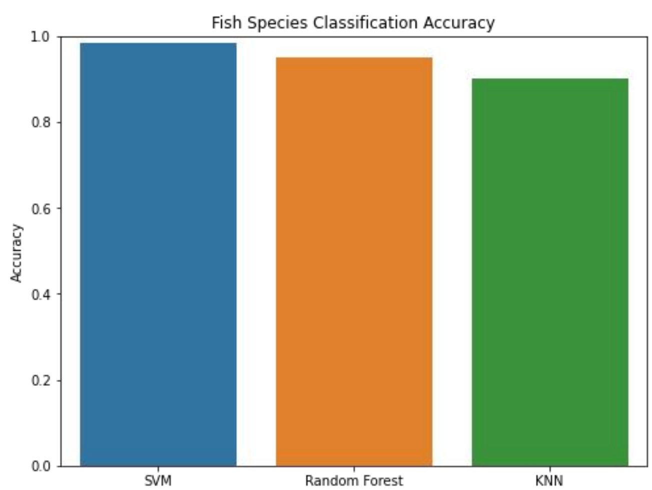
F1-Score = 2 * ((Precision * Recall) / (Precision + Recall))

The confusion matrix and the metrics it generates provide insightful information on how well the model performs for particular classes, indicating any weaknesses or strengths.

Results & Discussion

Using three alternative algorithms—Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN)—we show the outcomes of our fish species classification. We assess each algorithm's performance using a variety of indicators and talk about the ramifications of the findings.

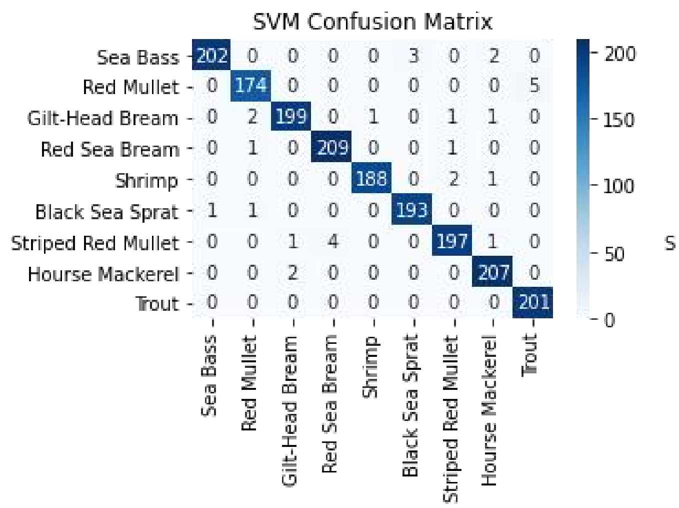
The image below summarizes the accuracy achieved by each algorithm:



The accuracy metric counts how many cases in the test dataset were correctly categorised as a percentage of all instances. We can see from the findings that the SVM algorithm had the best accuracy, at 98.3%, followed by Random Forests with a 94.9% accuracy and KNN with a 90.1% accuracy.

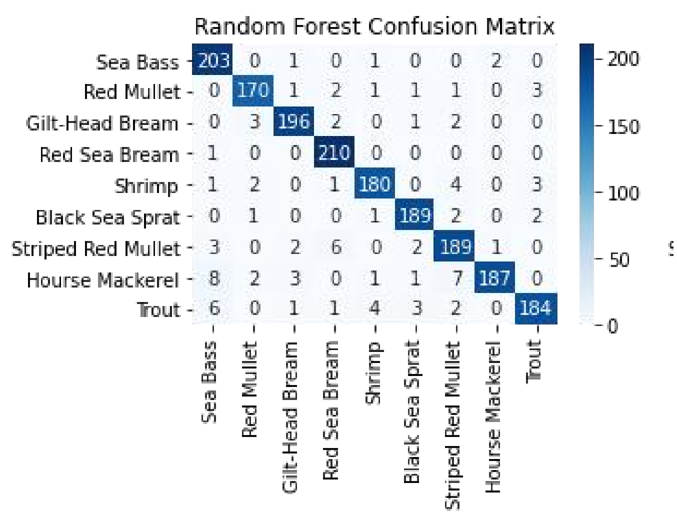
We examine the confusion matrices for each method to have a better picture of how well it performs in classification. The number of true positives, true negatives, false positives, and false negatives for each class is shown by the confusion matrix, which is useful information.

Confusion Matrix - SVM:



The SVM confusion matrix demonstrates that the algorithm excelled across all classes. High true positive and true negative rates were obtained as a result of the majority of occurrences being correctly categorised. This shows that SVM successfully distinguished between the various fish species and produced reliable predictions.

Confusion Matrix - Random Forests



The confusion matrix for Random Forests demonstrates that, while slightly less effective than SVM, the algorithm nevertheless produced good results. There have been rare cases of misdiagnosis, notably between closely related fish species like the Striped Red Mullet and the Black Sea Sprat. Overall, nevertheless, the algorithm showed a high capacity to distinguish between the various classifications.

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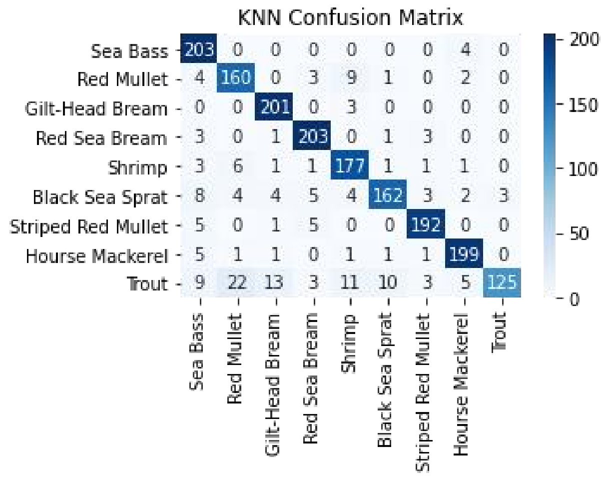
Confusion Matrix - KNN



The KNN confusion matrix shows that the algorithm performed poorly when compared to SVM and Random Forests. Across several classifications, there are observable instances of misclassification. Particularly, KNN had a harder time accurately classifying some classifications, such shrimp and sea bass. This shows that KNN might not be the best algorithm for this particular purpose of classifying the fish species.

Overall, the findings show that SVM performed better in terms of accuracy than both Random Forests and KNN. It successfully distinguished and classified the various classes, continuously achieving excellent accuracy across all fish species. Even yet, Random Forests' performance was marginally worse to SVM's. Although it had some issues with fish species that were similar, it showed decent discriminating between classes. The inability of KNN to generalize adequately to this dataset was demonstrated by its decreased accuracy and difficulty with several classes. It is crucial to remember that the selection of an algorithm is influenced by a number of variables, including the unique properties of the dataset, the necessary processing needs, and interpretability. While SVM and Random Forests did well in this study, additional elements like training time, results interpretation, and scalability should also be taken into account when choosing the best algorithm for a task.

Conclusion

The use of Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN) algorithms for fish species classification using visual data was investigated in this study. Using a variety of measures, we assessed each algorithm's performance, then analyzed the findings to reach significant conclusions. According to the findings of our investigation, SVM performed better in terms of accuracy than both Random Forests and KNN. SVM successfully classified fish species with an astounding accuracy of 98.3%, proving its efficacy. The system demonstrated its promise for automating fish species categorization tasks by correctly separating the various classes and making precise predictions.

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Random Forests also performed well, with a 94.9% accuracy rate. Random Forests exhibited its capacity to distinguish between several fish species, however slightly less effectively than SVM. Misclassification did occur occasionally, nevertheless, especially between closely related fish species. This shows that additional tweaking and optimization of the Random Forests method may be required to enhance its efficiency in correctly identifying difficult classes.

KNN, on the other hand, achieved an accuracy of 90.1%, which was lower than SVM and Random Forests. Particularly with the shrimp and sea bass classes, the algorithm had trouble. This demonstrates the limitations of KNN for this particular task of fish species classification. To improve the performance of KNN, more research, testing, and hyperparameter tuning may be necessary with other distance measurements. Overall, our study shows how machine learning algorithms may be used to automatically classify fish species using picture data. The great accuracy attained by SVM and Random Forests shows how effective these algorithms are at properly identifying different species of fish. By utilizing these algorithms, the fisheries sector may gain from accurate and efficient fish species identification, resulting in better monitoring, conservation, and management techniques.

It is crucial to remember that the selection of an algorithm is influenced by a number of variables, including the unique properties of the dataset, the necessary processing needs, and interpretability. Compared to KNN, SVM and Random Forests provide robust classification results but may need more computing power. Additionally, interpretability is important since SVM generates decision boundaries that are simple to understand while Random Forests create an ensemble of decision trees that could provide information about the significance of particular features.

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. In the fisheries sector, these algorithms can be useful tools for automating activities involving fish species identification. To enhance KNN performance and investigate the potential of deep learning models, additional study and optimization are required. We can help to better understand and conserve aquatic environments and support sustainable fisheries management practices by developing the area of fish species classification.

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