Classifying different sea species using Deep Learning techniques

MSc Research Project

Master of Science in Data Analytics

Niranjan Pramod Desai
Student ID: x20181787

School of Computing
National College of Ireland

National College of Ireland
Project Submission Sheet
School of Computing

Student Name:	Niranjan Pramod Desai
Student ID:	x20181787
Programme:	Data Analytics
Year:	2022
Module:	MSc Research Project
Supervisor:	Professor Taimur Hafeez
Submission Due Date:	13/08/2022
Project Title:	Classifying different sea species using Deep Learning techniques
Word Count:	
Page Count:	21

I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.

ALL internet material must be referenced in the bibliography section. Students are required to use the Referencing Standard specified in the report template. To use other author's written or electronic work is illegal (plagiarism) and may result in disciplinary action.

Signature:	
Date:	14th August 2022

PLEASE READ THE FOLLOWING INSTRUCTIONS AND CHECKLIST:

Attach a completed copy of this sheet to each project (including multiple copies).	☐
Attach a Moodle submission receipt of the online project submission, to each project (including multiple copies).	☐
You must ensure that you retain a HARD COPY of the project, both for your own reference and in case a project is lost or mislaid. It is not sufficient to keep a copy on computer.	☐

Assignments that are submitted to the Programme Coordinator office must be placed into the assignment box located outside the office.

Office Use Only	
Signature:	
Date:	
Penalty Applied (if applicable):	

Classifying different sea species using Deep Learning techniques

Niranjan Pramod Desai
x20181787

Abstract

Due to all the nutrients and delicious flavors that seafood contains, seaside nations use it as the major component of their diet. To satisfy their demand, the seafood industry must produce and offer high-quality seafood. Each year, the globe produces 200 million tonnes of seafood and fish. The current level of fish collection is unsustainable due to the overfishing of fish populations. Four times as many fish and marine foods are produced now as there were fifty years ago. We have developed an innovative method for preventing overfishing that makes use of deep learning and machine learning techniques. It allows us to keep the fish we want while not killing and returning undesired unwanted fish to the water. In this study, we will classify nine distinct fish species utilizing 430 photographs in total. Two models were used in this study: MOBILENET_V2 and VGG16. MOBILENET_V2 provided a test loss of 0.12303 and an accuracy of 96.51 percent, while vgg16 provided a test loss of 0.39825 and an accuracy of 88.37 percent. To improve the accuracy of both models, we have used data augmentation and model tuning strategies. The purpose of this research is to preserve natural habitat and solve the problem of identifying the fishes, which has been always a challenge because of the scarcity of data sources and the quality of available images. This study has also demonstrated that MOBILENET_V2 can still provide good accuracy even with a less dataset.

Contents

1 Introduction

The three most basic requirements for survival are clothing, shelter, and food. The world's population is already reach more than 7 billion people in 2022Godfray et al. (2010), considering feeding everyone on the planet the biggest challenge. There are two categories of food: plant-based and animal-based. Vegetarians are persons who only consume plant-based foods, whereas non-vegetarians consume animal products. Non-vegetarians typically eat meat from cattle, lamb, pigs, poultry, and fish from bodies of water. Since it provides necessary elements including vitamin A,amino acids, omega 3 fatty acids,iron, calcium, which are the building blocks of protein, meat is an important source of nutrition. Because of all the nutrients, it provides and the incredible flavor it has, seafood is a staple in the diets of seaside countries. Additionally, about 17 percent of the animal protein eaten comes from marine fish. The United Nations Food and Agriculture Organization reports that the average individual consumed 20 kilograms more fish in 2016 than they did in 2015.Barik (2017) As a result, the seafood industry must produce and provide high-quality fish to meet consumer demand. Bennett and Basurto (2018)Ritchie and Roser (2021)Madichie (2020)

1.1 Research Question

The issue that the research is intended to address is referred to as a research question.

Our methodology's research topic is as follows:

1. How and which model can most accurately anticipate the picture of fishes and provide the single type of seafood we seek?

2. Which deep learning model performs better when less data is available for aquatic seafood prediction?

The set of activities that will be carried out to address the research question comprise the planned goal of the research.

1.2 Motivation for the research

Internationally, 59.5 million people worked as a fisherman in 2018, according to the UN FOOD AND AGRICULTURE ORGANIZATION (FAO)(hunting wild fish). Fishing provides a living and a source of income for over 59.9 million people worldwide.200 million tonnes of fish and seafood were produced worldwide in a single year. The existence of production and consumption is evident, yet the resource is sustainable. Numerous additional concerns are brought forth by overfishing. The nutrition and flavor of the seafood/creatures decline as a result of their progressive demise after being taken out of the water since they have very little life left in them. By a certain time, they start to deteriorate inside and their lives are squandered if they are not devoured or eaten. Some people work hard to preserve the fish to stop the decaying process to prevent such problems. But the preservation process must be carried out as soon as feasible so that it may be consumed after a long time. Ritchie and Roser (2021)

With a supply of 340 million tonnes in 2018, which is more than three times the production of around 50 years ago, approximately 80 million animals were killed on land worldwide. In comparison to land, fish production during the past 50 years was 4 times higher.Nicholas K. Dulvy (2021) Similar to how they were fifty years ago, overfishing of stocks, which accounts for the present number of fish caught, is unsustainable. This is a result of both fishing for wild fish and fish aquaculture. 37 percent of the world's sharks and rays are currently driven to extinction, according to the red list's 2020 update. Worldwide, 109 million of tons of fish were caught. Of this, 84 percent was used for straight human consumption. For animal feed, fish meal and oils were created from the remaining 16 percent. Land-based livestock including cows, pigs, and chickens received 5 percent of the total. Aquaculture fish farms received 11% of the total as feed. 34 percent of the world's fish stocks were overfished in 2017. Physiologically, two-thirds were sustainably fished, with only 6% overfished and 60% overfished. According to the statement, by the year 2048, the oceans "will be almost empty if present fishing trends continue." If you Google "empty oceans by 2048," you'll get hundreds of thousands of hits, thus piracy at sea is by no means the only source to make this claim. By 2050, there won't be any fish left for fishing, according to some reports..Worm et al. (2006)Ritchie and Roser (2021)ROACH (2006)Agnew et al. (2009)

The second most common fishing technique, purse seine, accounts for 20% of the whole haul. Major fishing techniques like trawling, which capture 35 percent of the fish caught, account for 25 percent of bottom trawling and 10 percent of mid-water trawling. This strategy accounts for the bulk of bottom trawling catch methods, which are popular in China and India. One-fifth, or around 21%, of the total catch is rejected. Particularly, a million tons of fish are thrown away annually due to the waste of 54.9 percent of shrimp trawls and 43.5 percent of otter twin trawls.A lesser portion of the global harvest is produced by other small-scale fishing techniques including gillnets and longlines. Accidental fish kills result in no one gaining extra money or food since the fish are not sold or consumed Ritchie and Roser (2021)

There is a need to avoid overfishing, due to the fact that large-scale fishing techniques catch a lot of fish that are hard to catch and are then preserved by being placed in deep freezers, where many of the fish die without ever having the chance to feed someone.

We have proposed a method that makes use of deep learning techniques to combat over-fishing. We suggest a concept where, as soon as the fish is caught, it is sent to a moving belt where it is identified as the desired variety and conserved, while the other is swiftly returned to the ocean. By doing this, we can keep the fish we want while returning unwanted fish to the water without harming them. Previously, this type of separation required physical labour. We will need a highly accurate, real-time image classification technique that can categorize fish based on the digital image for such classification and identification. And this is how we protect the ecosystem and the natural habitat at the same time.

2 Literature Review

2.1 Classification of fishes based on machine learning techniques

The fishes classified in Hu et al. (2012) research are based on texture and color. The images shot with the use of a smartphone are included in the data. In this paper, a new method was used with the help of a multiclass support vector machine (MSVM). Six groupings of vectors were produced utilizing texture, color, statistical, and wavelet qualities, as well as sub-images, were brought out. The LIBSVM program was used to analyze using leave-one-out cross-validation to find the best group of classification in the features selection phase. A one vs one algorithm-based DAGMSV classifier with a wavelet domain feature extractor employing a boir 4.4 wavelet filter in HSV color space was determined to be the best classification model for fish species detection.

The old methods such as throwing nets or under water monitoring to determine the presence and quantity of certain fish species were done by aquatic professionals. Fouad et al. (2013) used a low cost technique to perform a large number of underwater species observations utilizing digital cams and memory. The SVM technique was used once more, this time in conjunction with feature extraction methodologies based on the SURF and SIFT algorithms (Speeded Up Robust Features (SURF) and Scale Invariant Feature Transform (SIFT)). The main motivation for employing an extraction approach was to explain local features extracted from fish photographs. This research revealed that fish species may be categorized using support vector machines and digital cams pictures of fishes. The SVM model outperformed K-mean Clustering then the Neural Network and K-Nearest Neighbor (KNN) in this study.

Due to differences in undiscovered emerging species and their environmental circumstances, and other factors such as size and posture, detecting classifying sea creatures has always been a challenge. Due to which, there is a scarcity of research. Length of fin and body shape can also be used to categorize fish. One of many, is the research conducted and studied by Ogunlana et al. (2015) , which used compact data from 150 fishes to calculate dorsal fin length, body length, pelvic fin length, pectorial fin length and anal fin length. A total of 150 photographs were gathered, which were then divided into two halves: 76 images of fishes for the training the model and 74 images of fishes for testing the model. The SVM model was utilized, which claimed to be more accurate than Neural Network, K-mean Clustering and K-Nearest Neighbor (KNN). Because, data was little, the model was unable to provide greater accuracy, resulting in a score of 78.59, indicating that there is still room for improvement. Which tells us that more data should be verified, and accuracy should be improved.

Due to the requirement of assessing freshwater bodies and marine conversation status, the sampling of fish and monitoring the total inhabitants of fishes in lakes and seas is inevitable. Before the triumph of computer vision for classifying and identifying, fishes were manually sampled and labeled. It was seen that from the two test data sets, lcf-14 and lcf-15, the CNN was employed for classifying. Deep architectures like SVM and KNN, on the other hand, perform poorly or over-fit to a specific environment of the dataset, whereas PCA KNN and PCA SVM fared badly, according to them. All other models were outperformed by CNN Architect, which produced exceptional results. Salman et al. (2016)

A useful study was conducted by Ulucan et al. (2020) in 2020 by a combination of industry and university research, and the dataset was acquired from a shop in Izmir, Turkey, which featured 18000 photos of 9 different varieties of seafood. The dataset was partitioned into a 70:30 ratio in this case. The training set received 70% of images, whereas the test set received 30% of images. To categorize the fishes, particularly SVM-based classifier models were utilized. For each individual species categorization, the accuracy was greater than 90%.

SVM has indeed been applied in disease classification to determine the origin of a disease. Ahmed et al. (2021) conducted a study in May 2021 to determine the illness spread by infectious fishes in aquaculture, notably salmon. With the use of image recognition and machine learning, researchers were able to identify diseased fish caused by numerous pathogens. The photos were subjected to image segmentation to minimize noise and emphasize the image. Then, using the SVM kernel, processed pictures were sent through it. In this manner, a unique dataset both with and without image augmentation was created. The accuracy of the SVMs used was 91.42 and 94.12 percent, respectively.

2.2 Classification of fishes based on deep learning techniques

Pornpanomchai et al. (2013) developed a texture-based and shaped-based fish image detection and recognition that covers image capturing, processing, extraction of features, image classification, and ultimately the result. 30 fish species were used in this study, including 600 fish photos in the training data and 300 images in the testing dataset. Euclidean distance and ANN were the two methods chosen. With an accuracy of 99.0 percent, Ann outperformed Euclidean distance. And, for EDM and ANN, the average load time per photo was 24.4 seconds and 154.3 seconds, respectively. Hernandez-Serna and Jimenez-Segura (2014) developed a photographic-based approach for categorizing fish, butterfly, and plant species starting from Europe to South America. To extract the texture of the images, their anatomy, and geometry, the classification system employs a variety of image processing techniques. Ann was well-versed in pattern recognition. Fish identifications achieved 91.65% true positives, 92.87 percent true positives for plant identifications, and 93.25 percent true positives for butterfly identifications using a dataset of 740 species and 11198 individuals.

Chen et al. (2017) published a study in 2017 that included 3777 photos acquired with the use of cameras mounted on various fishing boats. Dolphinfish, Opah, Shark, Yellowfin tuna, Albacore tuna, Bigeye tuna, and other fish were among the many species. Deep learning techniques including CNN, as well as Inception V3 and resnet50, were utilized to identify the photos. The model was created in such a manner that it could categorize fish based on texture and size in both the terrestrial and underwater environments. It was demonstrated that the system was functional, but it ran into many issues since it was caught using a camera mounted on a fishing boat, and as a consequence, there were several disturbances such as employees strolling, fishing gear, fish nets, and containers are strewn about. There were only 3777 photos in this data collection, and there was a lot of undesirable image interference. We may state that the procedure described above is useful, however, the data is tiny and confined to eight species.

The dataset utilized in this study was Fish4knowledge, which was released by Rathi et al. (2017). The first thing they did was reduce noise from the dataset. They've been shown to help remove underwater impediments, silt, and non-fish bodies from photographs. Then, using a deep learning approach, CNN was implemented, and they claimed that a new technique based on CNN, deep learning, and image classification was used to reach a 96.29 percent accuracy. In terms of classification accuracy, these solutions beat the previously stated alternatives.

A categorization method was created by Chhabra et al. (2019) to identify nutritive and medicinal value from fishes existing in their original underwater environment. People working in marine biology, doctors, and the fishing industry are said to benefit from this information. Chhabra et al. (2019) utilized a hybrid deep learning approach in which a pre-trained model such as VGG16 has been used for extracting features and a layering ensemble model was used to identify and classify fishes from photographs. As there was no dataset obtainable for free sourcing, they created their own. With a classification result of 93.8 percent, their proposed approach surpassed models like KNN, RF, SVM, and TREE. On a dataset of photographs taken by a single cam at a poolside in Punjab, Pakistan, categorization was done. There were six different fish species captured. The resulting dataset was useful for comparing classification features including momentum, learning rate, and overall performance. CNN was used to categorize the architecture of six different fish using varying quantities of pictures in the dataset: grass crap, common crap, mori, rohu, silver crap, and thala. Every one of the fish was captured using a single camera so the dataset can be more balanced. The internal representation of the future map was obtained from the 2nd convolutional layer utilizing the initial 64 maps using Vggnet. The experiment used a 3 x 3 kernel with a pad of (1, 1) and a stride of 128. It has been shown that as the layer depth increases, the image becomes unreadable to human sight. Shah et al. (2019)

For a food categorization, Yadav et al. (2021) used squeeze net and VGG-16 and Convolutional Neural Networks. These networks are done much better after data augmentation and finetuning the parameters of the model, indicating that they are suitable for real-time applications in the medical and health sectors. Because Squeezenet is a lightweight model, it is simpler to set up and maintain, as well as more interesting. Squeezenet achieved an outstanding 77.20 percent accuracy despite having seven fewer parameters. They claim that the VGG-16 network significantly increases the accuracy of automatic food image classification. Due to improved network depth, VGG-16 obtained a significantly better accuracy of 85.07 percent.

2.3 Segmentation technique used on fishes photo

On the photo of fishes, a segmentation method was employed. The act of setting distinct borders inside an image to improve the accuracy of object recognition by bringing the emphasis to the region of interest is known as picture segmentation. Artificial Neural Network-Based Segmentation, Edge-Based Segmentation, Threshold-Based Segmentation, Clustering-Based Segmentation, and Region-Based Segmentation are the five types of segmentation techniques. Threshold-based segmentation is the most often used segmentation technique. Ibrahim et al. (2018) created a fish picture segmentation model based on the Salp Swarm Algorithm. The Simple Linear Iterative Clustering (SLIC) approach is used to produce the segmentation, with the Salp Swarm Algorithm optimizing the beginning parameters. The SLIC approach was used to cluster image pixels in order to create compact and somewhat homogeneous superpixels. Finally, we used threshold-based segmentation, which generated good results on extracted fishes from the source photographs in a variety of conditions.

2.4 Feature extraction technique used on images

The crucial facts are taken out of raw data via feature extraction. Shape, motion, localization, face, text, and color may all be used as inputs for feature extraction. A study by Yan et al. (2021) developed a genetic method to sort low-quality photos by extracting useful features using genetic programming. Along with the creation of the new software, a new function was established. The results of this strategy revealed that it performed better than the 11 benchmark techniques and the state-of-the-art GP approach. The generated GP trees' excellent interpretability and the effectiveness of the picture filtering or restoration operators applied are both shown in a later study. The study has revealed that obtaining useful global and/or local information from the fish picture requires choosing informative locations. The research has proven that the suggested GP approach can readily handle picking useful areas from the fish picture and extracting effective global and/or local features from the fish photos. Another study by Ghapar et al. (2021) has identified wood using distinctive characteristics seen on the cross-sectional surface of each tree species. A qualified expert can instantly recognize the differences in patterns and features, however, it is exceedingly difficult for non-experts to discern various patterns. The method was created using machine vision to achieve remarkable accuracy comparable to a skilled professional.KenalKayu was the system's name.Accuracy fell off when additional trees were added. A custom feature extractor for statistical features of pores distribution (SPPD) was then included in the system, and this later proved to boost accuracy. As the wood surface has both pores and lines, the further study offered a method based on statistical characteristics of line distribution (SPLD).This aids in capturing the distinctive traits of each species. When applied, the statistical characteristics of the line distribution had an accuracy of 88 percent.

2.5 Classification of different species rather than fishes

A machine learning method for identifying the birds, Islam et al. (2019) employed the VGG-16 network model to extract features from bird pictures. They took data collection including photos of different Bangladeshi bird species which are used as is to accomplish the classification. Then they used a variety of types of classification techniques, each one yielded a different set of results. Support Vector Machine (SVM), Random Forest, and K-Nearest Neighbor (KNN), SVM achieved the greatest accuracy of all, with 89 percent.

A machine learning approach for enhancing plant species detection was described in a study report. CNN has been used for feature extraction from deep learning methods like MOBILENET_V2, Resnet50, VGG16, and Inception V3, in this research. After a comparison of these deep learning methods, the k-nearest neighbor (KNN) and Support Vector Machine (SVM) was used for categorization. MOBILENET_V2 surpassed all these other models, with a 95.6 % accuracy rate. In the accuracy of the models, the Classification algorithm outperformed the classification algorithm in the plant image identification system. Le Huy Hien and V.H. (2020)

Rajabizadeh and Rezghi (2021) conducted research that examined the performance of many cutting-edge machine learning methodologies, including holistic and neural network methods. Six snake varieties from Iran's Lar National Park were included in the study. Various machine learning techniques such as SVM, k-nearest neighbor, and logistic regression, also with the inclusion of PCA, were used in this research, although none of them produced accuracy greater than 50%.lda was then used to collect the features. The combined accuracy of LDA and the SVM kernel reached 84 percent. In comparison to CNN's comprehensive approaches, w With VGG16, the color pattern and form of the snake help to distinguish between snake species. MOBILENET_V2, on the other hand, performed best, with 93.16%.

On February 25th, 2022, a paper was published. For industrial applications utilizing picture-based fruit categorization, Shahi et al. (2022) proposed a novel feature selection technique based on these two modules: CNN combining and attention-based feature extraction. Three distinct kinds of datasets were selected for this purpose, as the aim of the study was to produce light in weight module. MOBILENET_V2 was the only architecture used in this research. MOBILENET_V2 delivered the best accuracy in comparison to the other methods employed on the datasets, with the accuracy of 95.75 %, 96.74 %, and 96.23 % on the three different datasets.

Figure 1 represents the Literature review table for all the research related to the fish classification which were studied prior writing this report. In the papers Shahi et al. (2022)Le Huy Hien and V.H. (2020)Islam et al. (2019)Rajabizadeh and Rezghi (2021)MOBILENET2 surpassed VGG16 in terms of accuracy. We'll utilize MOBILENET_V2 by comparing its accuracy against VGG16, which has been used extensively in previous deep learning fish classification research. We will be utilizing the dataset used by Ulucan et al. (2020) in its study.

Literature and year	Database	Approach	Best performing model	Performance
Hu et al. (2012)	Self-created	Machine learning	DAGMSVM	ACC 97.96%
Fouad et al. (2013)	Article photos of Tilapia	Machine learning	SVM	ACC 94.4%
Ogunlana et al. (2015)	Fishery Departments of the Federal University of Technology	Machine learning	SVM	ACC 78.59%
Salman et al. (2016)	LifeCLEF14 and LifeCLEF15	CNN	CNN SVM	ACC 90%
Ulucan et al. (2020)	A large scale fish dataset	CNN	CNN SVM	ACC 88.69%
. Ahmed et al. (2021)	salmon fish image dataset	Machine learning	SVM	ACC 93.75%
Pornpanomchai et al. (2013)	KAGGLE	ANN	ANN EDM	ACC 81.67%
Hernandez-Serna and Jimenez-Segura (2014)	MIXED SPECIES DATASET	ANN	ANN	ACC 90% +
Chen et al. (2017)	The Nature Conservancy Fisheries Monitoring Competition	DEEP LEARNING - CNN	INCEPTION_V3	LOSS 0.64%
by Rathi et al. (2017).	Fish4Knowledge	DEEP LEARNING with CNN	Relu as an activation function	ACC 96.29%
Chhabra et al. (2019	Created own dataset	Hybrid deep learning	VGG16	ACC 93.8%
. Shah et al. (2019)	Fish-Pak	CNN	CNN	ACC
Yadav et al. (2021)	Food-101 dataset	Deep learning with CNN	VGG16	ACC 85.07 %
. Ibrahim et al. (2018)	real-world images	Segmentation	Simple Linear Iterative Clustering	
Islam et al. (2019)	Bangladeshi bird species	Deep learning	VGG16 Svm	ACC 89%
m. Le Huy Hien and V.H. (2020)	Vietnamese plant image dataset	Deep learning	MobilenetV2	ACC 83.9%
Rajabizadeh and Rezghi (2021)	Self-created (six snake species)	Deep learning	MobilenetV2	ACC 93.16%
Shahi et al. (2022)	public fruit-related benchmark dataset	Deep learning	MobilenetV2	ACC 95.75%

Figure 1: Literature review comparison Table

3 Research Methodology

This part outlines the recommended procedures to follow, to carry out our research to answer our question for the research effectively. Figure 2 represents the research methodology which we are following to implement this research.

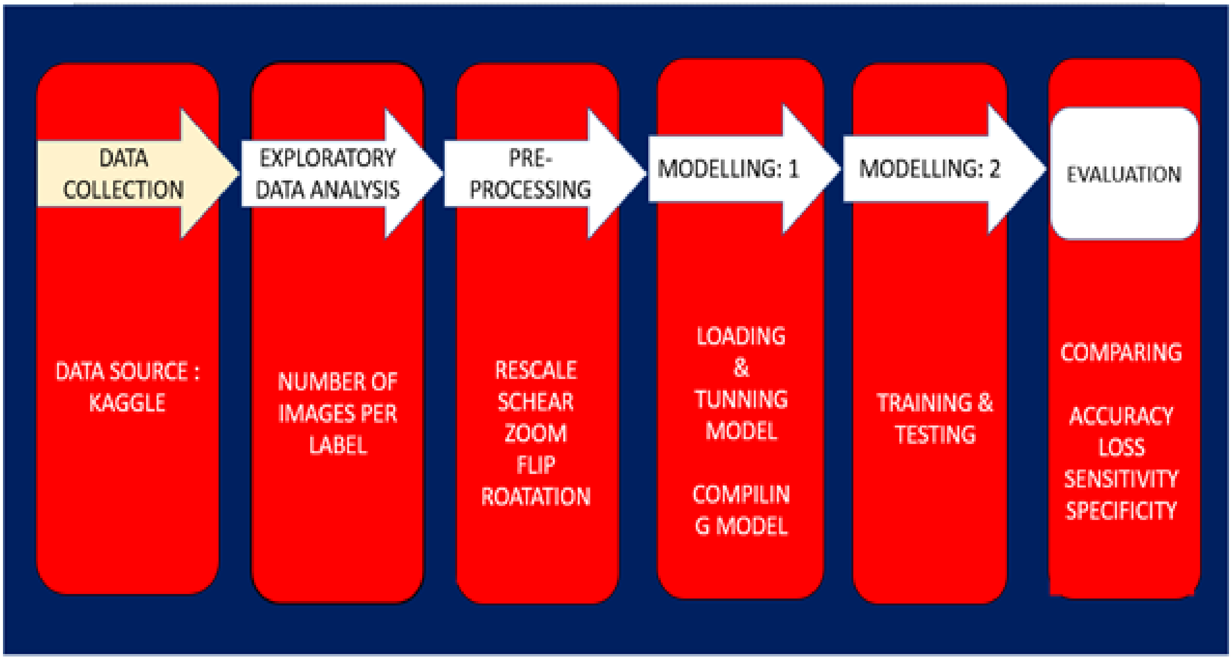


Figure 2: METHODOLOGY

3.1 Dataset description and Collection

The dataset we have use here is "A LARGE-SCALE FISH DATASET" Ulucan et al. (2020) from Kaggle, which comprises 9 different sea food species gathered from a supermarket in Turkey as part of a university-industry partnership study at Izmir University of Economics. The collection includes image samples from trout, horse mackerel, gilt head bream, sea bass, red mullet,black sea sprat, striped red mullet,red sea bream, and shrimp. The dataset includes nine distinct varieties of seafood.

3.2 Exploratory Data Analysis

After doing the exploratory data analysis we came to know that (Figure 3) there are total of 430 images for 9 different species out of which 50 each belong to the 8 classes such as Black Sea Sprat, Gilt Head Bream , Horse Mackerel, Red Mullet, Red Sea Bream, Sea Bass, Shrimp, Striped Red Mullet and last 30 images belongs to Trout.

3.3 Pre-Processing

Before the photographs are put via data modeling, the photos that will be using in our study are taken by a digital camera in a fish-market, where there is a lot of background and random noise in the photos. To increase the effectiveness of the classification model

Total images belonging to 9 classes	Training data split 80%	Validation data spilt 20%
430 images	344 images	86 images

Figure 3: Total images Train/Validate data split

that will be developed, these images could also need to be modified using a number of techniques. By applying changes like rescaling, shearing , zooming , rotation and flipping to our source photographs, image augmentation is a technique for artificially expanding datasets. In the next phases of deployment, the freshly developed improved photographs will serve as the source data. In order to expand the amount of images in our dataset, we will employ image augmentation techniques. Because the data set is low we cannot train it properly , due to the same background it starts learning the background .

3.4 Modelling

We are loading and tuning models like mobilenetv2 and vgg16 in this stage. Following tuning, compilation is completed, and the model's training and testing are then carried out.

3.5 Evaluation

When evaluating the model, accuracy, precision, recall, and F1 score are employed. One of the metrics used to evaluate a model's performance is model accuracy. MOBILENET_V2 and VGG16, depending on the results of numerous parameter tests both the models will be properly evaluated as we compare them, and the model with the best results will be chosen.

4 Implementation and Evaluation

4.1 Setting up the environment

The training of hthe models are done on a system of Intel Corei5, 8th gen with 8 gigabytes of ram. Python version 3.8.3 over Jupyter Notebook is the language utilized for the programming.

4.2 Importing the libraries

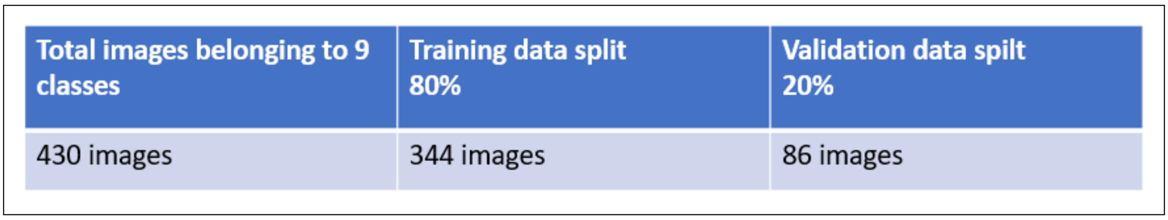
Operating system along with cv2 was imported. Similarly numpy ,seaborn , from matplotlib cm and pyplot were imported . from tensorflow keras models ,layers ; application such as VGG16 , MobileNetV2 were imported.

4.3 Importing the dataset

By importing the dataset and setting its height along with width as 224 by 224 , the models are implemented on 10 epochs and the batch size is set to 32 so that we can have least error rate.

4.4 Augmentation

As the dataset is less we are augmenting the images for artificially expanding dataset by applying changes like rescaling, shearing , zooming , rotation and flipping to our source photographs. Then splitting the dataset in the ratio of 80:20 for training and validation as shown in Figure 4.



Total images belonging to 9 classes	Training data split 80%	Validation data spilt 20%
430 images	344 images	86 images

Figure 4: Total images Train/Validate data split

4.5 Loading and tunning the model

4.5.1 For Mobilenet_V2

Loading the pretrained MOBILENET _V2 by keeping pooling layer as an average. And finally freezing all the trainable parameters by keeping the value as false, so that when the tunning is done , the old parameters does not get updated. For tunning we are adding 3 layers of 128 nodes in 1 2 layer by keeping activation function as relu and adding a 3rd final sigmoid layer for classification for 9 classes by keeping activation function as SoftMax. Figure 5 shows the total parameters before loading,after freezing and after tunning the models architecture of MOBILENET_V2.

Mobile net_v2 architecture			
	Loading model	After Freezing layer	After Fine Tune added layer
Total params	2,257,984	2,257,984	2,439,625
Trainable params	2,223,872	0	181,641
Non-trainable params:	34,112	2,257,984	2,257,984

Figure 5: Mobilenet_V2 architecture

4.5.2 For VGG16

Vgg16 architecture			
	Loading model	After Freezing layer	After Fine Tune added layer
Total parameters	14,714,688	14,714,688	27,564,873
Trainable parameters	14,714,688	0	12,850,185
Non-trainable parameters	0	14,714,688	14,714,688

Figure 6: VGG16 architecture

Loading the pretrained vgg16 by keeping pooling layer as an average. And finally freezing all the trainable parameters by keeping the value as false, so that when the tunning is done , the old parameters does not get updated. For tunning we are adding a fully connected layer with 512 hidden units and activation function as relu , setting dropout as 50% so that the model does not get overfit and adding a final sigmoid layer for classification for 9 classes by keeping activation function as SoftMax.

Figure 6 shows the total parameters before loading,after freezing and after tunning the models architecture of VGG16.

4.6 Compiling the model

Both models are built using the Adam optimizer, and the loss function for both is categorical cross-entropy.

4.7 Training both the models

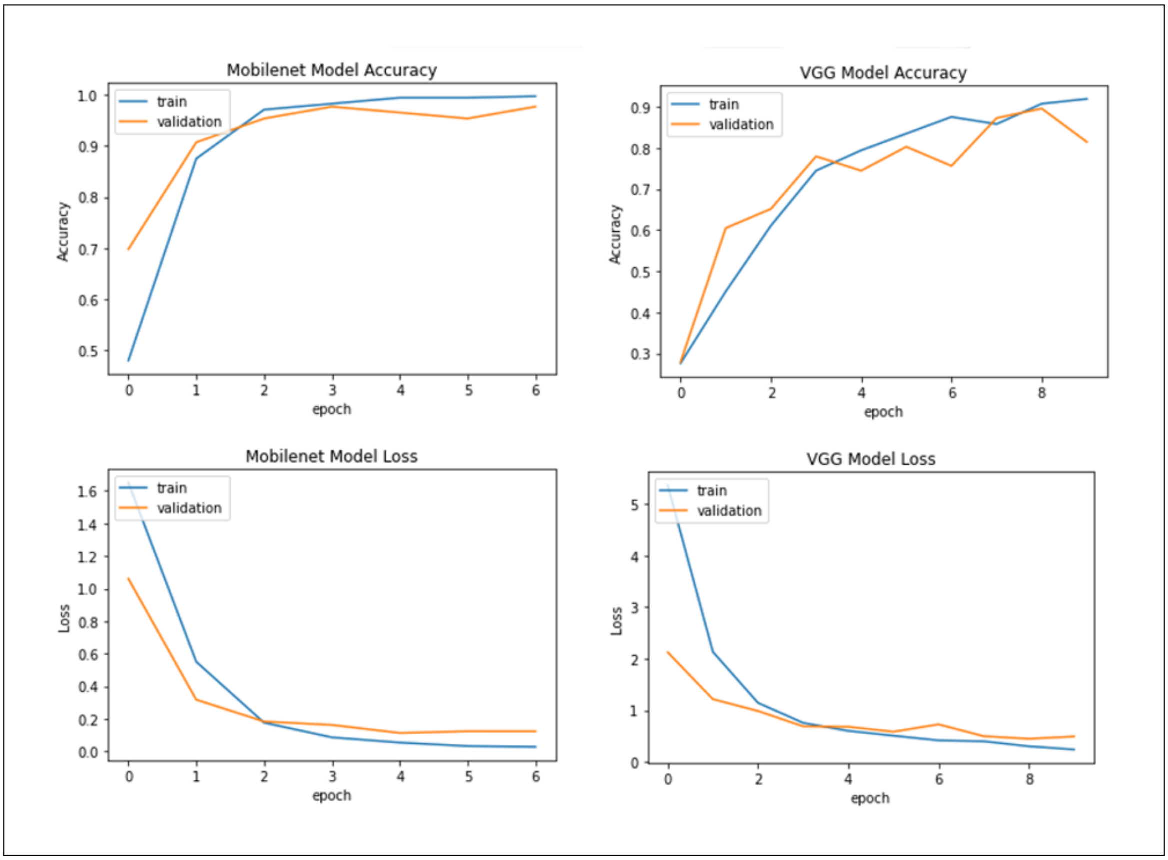


Figure 7: Training MOBILENET _V2 and VGG16 (Accuracy and loss)

In this step both the model are trained .As shown in the Figure 7 MOBILENET_V2 for 9th epoch has given a loss of 0.0173 accuracy of 0.9971 , along with the validation loss of 0.0742 and validation accuracy of 0.9767. Here VGG16 for 11th epoch has given a loss of 0.3524 accuracy of 0.8837 , along with the validation loss of 0.4862 and validation accuracy of 0.8605

4.8 Testing the model/ Model selection

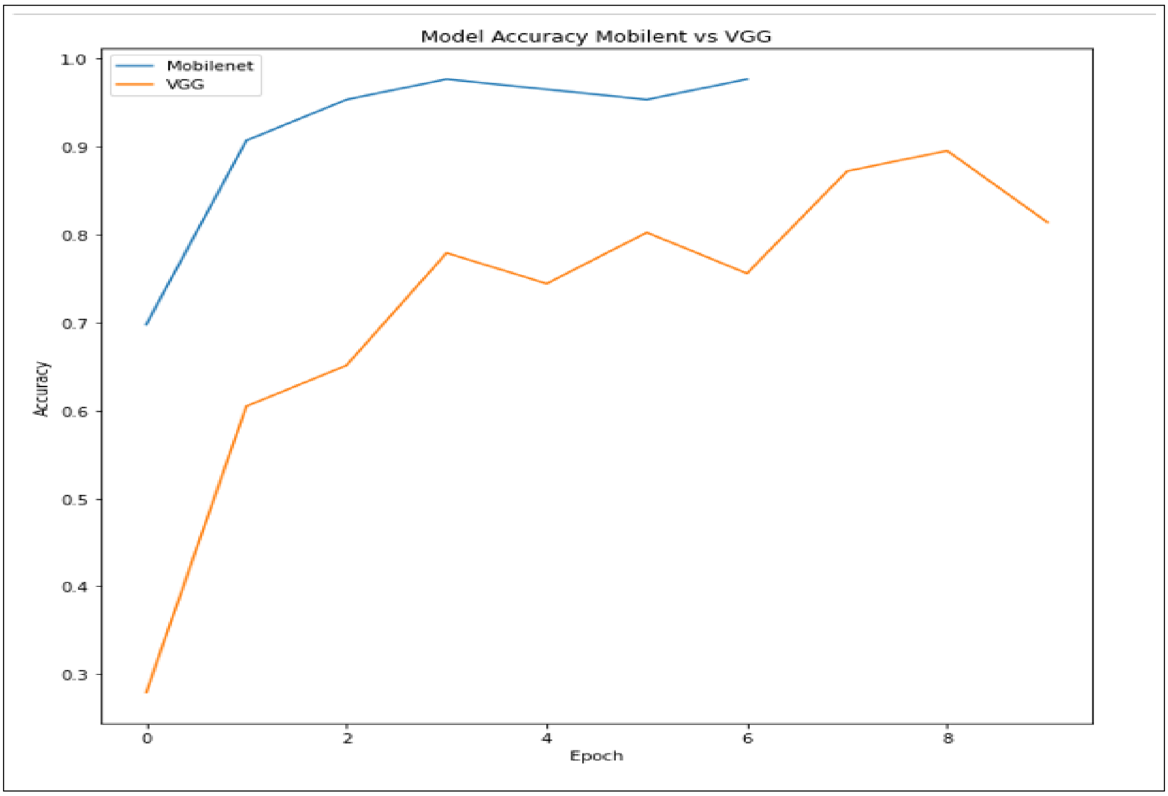


Figure 8: Testing MOBILENET _V2 and VGG16 (Accuracy)

We have successfully created and train MOBILENET_V2 and VGG16 models. We will select only that technique that performs better in order to deploy the model. The evaluation criteria will be best on the accuracy score. To classify the data fishes , we will use the best method with the best test accuracy score. This will be the selection standard. In the above Figure 8 we can clearly see that MOBILENET_V2 has outperformed in our case , thus we will use it construct a model .This is the outcome of the test accuracy and test validity for MOBILENET_V2 and VGG16.

4.9 Model deployment

In this stage, we'll show 25 images of the dataset's expected images together with their labels. To implement, we will generate figures and axis of the pictures that will be called by plt.subplots with the parameters like number of rows will be 5, number of columns will be 5, and figure size would be (25,25). We will use both model just to know how MOBILENET_V2 predicts better than VGG16 model.

This is the outcome of model deployment (Figure 9),

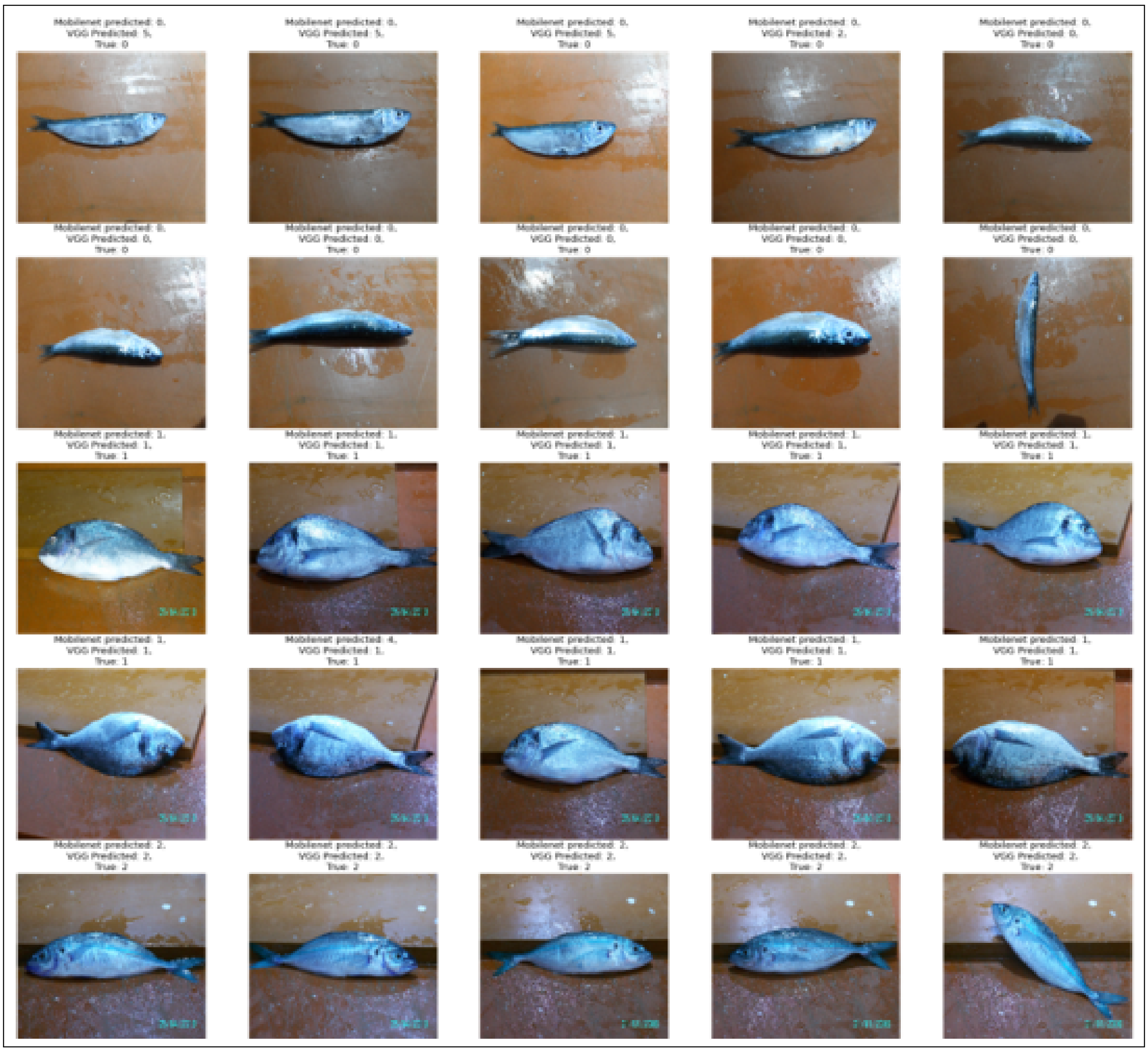


Figure 9: output

5 Comparison and Results

Model Comparison	Training		Validation		Testing	
	Loss	Accuracy	Loss	Accuracy	Loss	Accuracy
Mobilenet_v2	0.0173	0.9971	0.0742	0.9767	0.07362	98.84%
vgg16	0.3524	0.8837	0.4862	0.8605	0.41876	87.21%

Figure 10: Model Comparison (Training/Validation/Testing)

In this research we have used MOBILENET_V2 and VGG16 models for neural networks for photos classification. We have also employed a more effective classification method in order to increase the accuracy of our model by tunnig the model and putting more layers. We have set the test accuracy score as the evaluation criteria to evaluate the model performance .Here,(Figure 10) we have got MOBILENET_V2 for 9th epoch has given training loss of 0.0173 and training accuracy of 0.9971 , along with the validation loss of 0.0742 and validation accuracy of 0.9767. Here VGG16 for 11th epoch has given a loss of 0.3524 accuracy of 0.8837 , along with the validation loss of 0.4862 and validation accuracy of 0.8605. For testing, mobile net has shown loss of 0.07362 and accuracy of 98.84% while VGG16 has shown loss of 0.41876 and accuracy of 87.21%. We have deploy both the models just to show how good one model performs better than others .We here, are not only dependent on accuracy but also on the precision , recall and f1 score of the model . Here, it is undeniable that the MOBILENET_V2 has performed better than the VGG16 in terms of accuracy, not only in training and validation but also in testing.

The average time for MOBILENET_V2 for to complete training for one epoch was around 27 sec while for vgg16 to complete training for one epoch was around 79 sec, which is more than the double time. We can say that not only MOBILENET_V2 is light weight model but also the faster model.

Mobilenet Report	precision	recall	f1-score	support
Black Sea Sprat	0.09	0.10	0.10	10
Gilt Head Bream	0.40	0.40	0.40	10
Horse Mackerel	0.00	0.00	0.00	10
Red Mullet	0.20	0.20	0.20	10
Red Sea Bream	0.30	0.30	0.30	10
Sea Bass	0.00	0.00	0.00	10
Shrimp	0.30	0.30	0.30	10
Striped Red Mullet	0.10	0.10	0.10	10
Trout	0.17	0.17	0.17	6
accuracy			0.17	86
macro avg	0.17	0.17	0.17	86
weighted avg	0.17	0.17	0.17	86

Figure 11: Confusion matrix for Mobilenet_V2

VGG Report	precision	recall	f1-score	support
Black Sea Sprat	0.11	0.10	0.11	10
Gilt Head Bream	0.20	0.20	0.20	10
Horse Mackerel	0.00	0.00	0.00	10
Red Mullet	0.07	0.10	0.08	10
Red Sea Bream	0.18	0.20	0.19	10
Sea Bass	0.00	0.00	0.00	10
Shrimp	0.18	0.20	0.19	10
Striped Red Mullet	0.40	0.20	0.27	10
Trout	0.00	0.00	0.00	6
accuracy			0.12	86
macro avg	0.13	0.11	0.11	86
weighted avg	0.13	0.12	0.12	86

Figure 12: Confusion matrix for VGG16

6 Future-work and Conclusion

The research's ultimate objective is to identify seafood from various seafood species. This will enable us to classify the fish as soon as they are caught and transport them through the moving belt, where they will be identified based on the desired kind and kept, while the other will be immediately released back into the sea or water bodies. This enables us to release undesired fish back into the sea without injuring them while keeping the fish we intend to keep. MOBILENET_V2 and VGG16, both the models have performed great but MOBILENET_V2 has shown better test accuracy of 98.84% with a loss of 0.07 than VGG16 which has a test accuracy of 87.21% and a loss of 0.41% . In the future, the more vibrant and larger dataset can be used for the training MOBILENET_V2, so that model can be trained and reached a higher accuracy with real-time picture classification. Real fish, rather than photos, can be used to classify the fish utilizing a moving belt that is attached to the ships. This will help us to preserve the ecosystem's natural habitat.

7 Acknowledgement

Without Prof. Taimur Hafeez's guidance, this research endeavor would not have been able to be finished. I want to thank Prof. Taimur Hafeez for constantly guiding me in the correct route and giving me advice on how to structure this research.

References

Agnew, D. J., Pearce, J., Pramod, G., Peatman, T., Watson, R., Beddington, J. R. and Pitcher, T. J. (2009). Estimating the worldwide extent of illegal fishing.
URL: *https://doi.org/10.1371/journal.pone.0004570*

Ahmed, M. S., Aurpa, T. T. and Azad, M. A. K. (2021). Fish disease detection using image based machine learning technique in aquaculture, *Journal of King Saud University - Computer and Information Sciences* .
URL: *https://www.sciencedirect.com/science/article/pii/S1319157821001063*

Barik, N. K. (2017). Freshwater fish for nutrition security in india: Evidence from fao data, *Aquaculture Reports* **7**: 1–6.
URL: *https://www.sciencedirect.com/science/article/pii/S2352513416301351*

Bennett, Abigail, P. P. K. K. D. R. J. V. and Basurto, X. (2018). Contribution of fisheries to food and nutrition security.

Chen, G., Sun, P. and Shang, Y. (2017). Automatic fish classification system using deep learning, *2017 IEEE 29th International Conference on Tools with Artificial Intelligence (ICTAI)*, pp. 24–29.

Chhabra, H., Srivastava, A. and Nijhawan, R. (2019). *A Hybrid Deep Learning Approach for Automatic Fish Classification*, pp. 427–436.

Fouad, M. M. M., Zawbaa, H. M., El-Bendary, N. and Hassanien, A. E. (2013). Automatic nile tilapia fish classification approach using machine learning techniques, *13th International Conference on Hybrid Intelligent Systems (HIS 2013)*, pp. 173–178.

Ghapar, H. A., Khairuddin, U., Yusof, R., Khairuddin, A. S. M. and Ahmad, A. (2021). New feature extraction for wood species recognition system via statistical properties of line distribution, *2021 International Conference on Electrical, Communication, and Computer Engineering (ICECCE)*, pp. 1–5.

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M. and Toulmin, C. (2010). Food security: The challenge of feeding 9 billion people, *Science* **327**(5967): 812–818.
URL: *https://www.science.org/doi/abs/10.1126/science.1185383*

Hernandez-Serna, A. and Jimenez-Segura, L. (2014). Automatic identification of species with neural networks, *PeerJ* **2**: e563.

Hu, J., Li, D., Duan, Q., Han, Y., Chen, G. and Si, X. (2012). Fish species classification by color, texture and multi-class support vector machine using computer vision, *Computers and Electronics in Agriculture* **88**: 133–140.
URL: *https://www.sciencedirect.com/science/article/pii/S0168169912001937*

Ibrahim, A., Ahmed, A., Hussein, S. and Hassanien, A. E. (2018). Fish image segmentation using salp swarm algorithm, *in* A. E. Hassanien, M. F. Tolba, M. Elhoseny and M. Mostafa (eds), *The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2018)*, Springer International Publishing, Cham, pp. 42–51.

Islam, S., Khan, S. I. A., Abedin, M. M., Habibullah, K. M. and Das, A. K. (2019). Bird species classification from an image using vgg-16 network, *Proceedings of the 2019 7th International Conference on Computer and Communications Management*, ICCCM 2019, Association for Computing Machinery, New York, NY, USA, p. 38–42.
URL: *https://doi.org/10.1145/3348445.3348480*

Le Huy Hien, N. and V.H., N. (2020). Recognition of plant species using deep convolutional feature extraction, **11**: 904–910.

Madichie, N. (2020). The big issues – food, clothing and shelter: An introduction, **5**: 6–12.

Nicholas K. Dulvy, Nathan Pacoureau, C. L. R. R. A. P. R. W. J. (2021). Overfishing drives over one-third of all sharks and rays toward a global extinction crisis. https://www.cell.com/current-biology/fulltext/S0960-9822(21)01198-2?$_{r}eturnURL =$ *https*

Ogunlana, S. O., Olabode, O., Oluwadare, S. A. and Iwasokun, G. B. (2015). Fish classification using support vector machine.

Pornpanomchai, C., Lurstwut, B., Leerasakultham, P. and Kitiyanan, W. (2013). Shape- and texture-based fish image recognition system, *Kasetsart Journal - Natural Science* **47**: 624–634.

Rajabizadeh, M. and Rezghi, M. (2021). A comparative study on image-based snake identification using machine learning, *Scientific Reports* **11**: 19142.

Rathi, D., Jain, S. and Indu, S. (2017). Underwater fish species classification using convolutional neural network and deep learning, *2017 Ninth International Conference on Advances in Pattern Recognition (ICAPR)*, pp. 1–6.

Ritchie, H. and Roser, M. (2021). Biodiversity, *Our World in Data* . https://ourworldindata.org/biodiversity.

ROACH, J. (2006). Seafood may be gone by 2048, study says. https://www.nationalgeographic.com/animals/article/seafood-biodiversity.

Salman, A., Jalal, A., Shafait, F., Mian, A., Shortis, M., Seager, J. and Harvey, E. (2016). Fish species classification in unconstrained underwater environments based on deep learning, *Limnology and Oceanography: Methods* **14**(9): 570–585.
URL: *https://aslopubs.onlinelibrary.wiley.com/doi/abs/10.1002/lom3.10113*

Shah, S. Z. H., Rauf, H. T., IkramUllah, M., Khalid, M. S., Farooq, M., Fatima, M. and Bukhari, S. A. C. (2019). Fish-pak: Fish species dataset from pakistan for visual features based classification, *Data in Brief* **27**: 104565.
URL: *https://www.sciencedirect.com/science/article/pii/S2352340919309205*

Shahi, T. B., Sitaula, C., Neupane, A. and Guo, W. (2022). Fruit classification using attention-based mobilenetv2 for industrial applications, *PLOS ONE* **17**(2): e0264586. https://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0264586type=printable.
URL: *https://app.dimensions.ai/details/publication/pub.1145856465*

Ulucan, O., Karakaya, D. and Turkan, M. (2020). A large-scale dataset for fish segmentation and classification, *2020 Innovations in Intelligent Systems and Applications Conference (ASYU)*, pp. 1–5.

Worm, B., Barbier, E. B., Beaumont, N., Duffy, J. E., Folke, C., Halpern, B. S., Jackson, J. B. C., Lotze, H. K., Micheli, F., Palumbi, S. R., Sala, E., Selkoe, K. A., Stachowicz, J. J. and Watson, R. (2006). Impacts of biodiversity loss on ocean ecosystem services, *Science* **314**(5800): 787–790.

Yadav, S., Alpana and Chand, S. (2021). Automated food image classification using deep learning approach, *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Vol. 1, pp. 542–545.

Yan, Z., Bi, Y., Xue, B. and Zhang, M. (2021). Automatically extracting features using genetic programming for low-quality fish image classification, *2021 IEEE Congress on Evolutionary Computation (CEC)*, pp. 2015–2022.