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IsVoNet8: A Proposed Deep Learning Model for Classification of Some Fish Species

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ABSTRACT

In the classification of fish, both knowledge and great effort are required to determine the characteristics of fish. Traditionally, however, manual classification of extrinsic characteristics of different fish species has been a difficult and time-consuming process due to their close resemblance to each other. Recently, deep learning methods used in the light of developments in the field of computer vision have facilitated the training of fish image classification models and the recognition of various fish species. In this study, a new convolutional neural network model classifying 8 different belonging to 6 families (Mullidae, Sparidae, Carangidae, Serranidae, Clupeidae, Salmonidae) fish species using deep learning methods was proposed. The species include *Clupeonella cultriventris* N., *Sparus aurata* L., *Trachurus trachurus* L., *Mullus barbatus* L., *Pagrus major* T & S., *Dicentrarchus labrax* L., *Mullus surmuletus* L. and *Oncorhynchus mykiss* W. The proposed model (IsVoNet8) is compared with the ResNet50, ResNet101 and VGG16 models. The success accuracies obtained as a result of the comparison are respectively; 98.62% in the IsVoNet8, 91.37% in the ResNet50 model, 86.12% in the ResNet101 model and 97.75% in the VGG16 model. However, it was obtained that the loss rates of ResNet50 0.3646, ResNet101 0.5811, VGG16 0.0696 and with the IsVoNet 0.0568. As a result, it has been observed that the IsVoNet classifies marine fish, which is widely consumed in Türkiye.

Keywords: Artificial intelligence, Deep learning, Convolutional neural network, CNN, Fish taxonomy

1. Introduction

Fish are very diverse animals of all the vertebrate groups of animals with more than 33000 species in the world. There are different types of fish in the four major geographical regions of Turkey. Classification of different fish species is very important for aquaculture, stock management of water bodies, monitoring of aquatic organisms and conservation of marine biology. The fish species numbers of Türkiye's four major geographic regions is as follows: Aegean Sea coasts 389 species, Mediterranean Sea coasts 388 species, Sea of Marmara coasts 249 species and Black Sea coasts 151 species (Bilecenoglu et al. 2002). The classification of different fish species is very important for the preservation and protection of aquaculture and marine biology. Global warming and climate change have a negative impact on the amount of fish species, their habitats and stock distribution. Traditionally, manual classification of different species fish is quite difficult and time-consuming. Species identification in morphometric studies of fish species creates a database for biologists, scientists and aquaculture. However, these studies took a long time, which led to the emergence of new techniques. Today, with the use of automatic identification systems, systems that analyse and classify fish species are developed without any human intervention. In the light of the developments in computer technologies, computerized fish classifiers have been widely used for the classification of fish. Advanced technology equipped with artificial intelligence using deep learning methods facilitates the recognition of a diverse range of fish species. Deep learning is a branch of machine learning which uses multiple layered neural network topology to represent high-level abstractions of data (Sarigül & Avci 2017). The deep learning structure is based on the learning of more than one feature level of data. It is based on learning from the representation of the main data (Lecun et al. 2015). The representation of an image can be considered to comprise a vector of density values per pixel or features such as clusters of edges and custom shapes, with some representing the data better (Song & Lee 2013). Convolutional neural network (CNN) is one of the most popular deep learning methods used currently (Hridayami et al. 2019). Among the most accepted and used CNN models in the literature are Resnet50, Resnet101, VGG16 models.

CNN used as basic deep learning tools have obtained significant success in classifying fish species. In the literature, there are many studies based on CNN on the classification of fish species. Montalbo & Hernandez (2019) proposed a methodology to recognize fish species using VGG16 Deep CNN (DCNN). Hridayami et al. (2019) applied VGG16 DCNN, which is pre-trained on ImageNet via transfer learning method to recognize fish images. In this approach, 50 species of fishes are recognized with different accuracies on four different datasets. Zhang et al. (2019) studied the classification of fish and realized the rapid and accurate identification of common freshwater fish species by machine vision technology. Rauf et al. (2019) have carried out the experimental comparison with other deep learning frameworks involving VGG16 for transfer learning, one block VGG, two block VGG, three block VGG, LeNet-5, AlexNet, GoogleNet, and ResNet50 on the Fish-Pak data set. Simonyan & Zisserman (2014) VGGNet is one of the top CNN models used for classification as it integrates better learning capabilities compared with AlexNet. Shah et al. (2019) a dataset containing six different fish types (grass carp, common carp, mori, rohu, silver carp, thala) is collected in Pakistan. Each class in the dataset contains three dominant features of fish types (body, scale and head) with different number of images. CNNs are utilized to classify fish from their body images. There are several examples of this model being used in other fields of research. Ranzato et al. (2007) combined hierarchical tree with Gaussian mixture model to recognize 15 species of fish in underwater videos. Marini et al. (2018) estimated the abundance of the fish using an autonomous imaging device and genetic-programming-based classifier. Vabø et al. (2021) applied CNNs with transfer learning on a novel dataset of 9056 images of Atlantic salmon scales for four different prediction tasks.

In this study, a new model has been proposed by using deep learning methods in order to avoid the difficulty of species identification and loss of time in classifying fish species with traditional methods. The use of 8 fish species is limited, the use of more fish specimens might increase the applicability of the model to field studies. One of the disadvantages of this model is that the success of model classification may decrease if the number of fish species is hundreds. Model success may vary in real-time applications. In summary, some studies have been carried out in the literature using machine learning and image processing techniques to classify fish (İşçimen et al. 2014; Kutlu et al. 2017). However, there are few studies on the use of deep learning methods in the classification of fish species in Türkiye increases the importance of the study (Sarigül & Avci 2017; Kayaalp & Metlek 2021). For this reason, the proposed model provides superiority in classifying fish species due to the lowest error rate and high success accuracy. In addition, the proposed model to determine the success accuracy of this model; compared with Resnet50, Resnet101 and VGG16 models. Firstly, the aim of this study is to determine the CNN model performance that can be achieved for fish species classification. Therefore, this model will offer a new approach to the identification of marine fish that are widely consumed.

2. Material and Methods

2.1. Acquisition of image

In this study, a Large-Scale Fish Dataset was used (except for shrimp). This dataset consists 8 species belonging to 6 families (Mullidae, Sparidae, Carangidae, Serranidae, Clupeidae, Salmonidae). There are; black sea sprat (*Clupeonella cultriventris* N.), gilt head bream (*Sparus aurata* L.), horse mackerel (*Trachurus trachurus* L.), red mullet (*Mullus barbatus* L.), red sea bream (*Pagrus major* T & S.), sea bass (*Dicentrarchus labrax* L.), striped red mullet (*Mullus surmuletus* L.) and trout (*Oncorhynchus mykiss* W.) (Ulucan et al. 2020).

2.2. Image data preprocessing

This dataset contains 9 different seafood types collected from a supermarket in Izmir, Turkey for a university-industry collaboration project at Izmir University of Economics (Ulucan et al. 2020). In this study, there are 1000 fish images of 590x445 pixels from each class belonging to 8 fish species and a total of 8000 fish images in RGB format. The fish images in the original dataset were converted to 224x224 pixel gray color format by pre-processing and labelled under the same class. The sample images of fish images obtained as a result of pre-processing are given in Figure 1.

2.3. Convolutional neural networks model

In this study, along with the classification models Resnet50, Resnet101, VGG16 an alternative model (IsVoNet8) has also been proposed. ResNet50, classical neural network model and frequently used in the training of deep learning networks, and shows superior

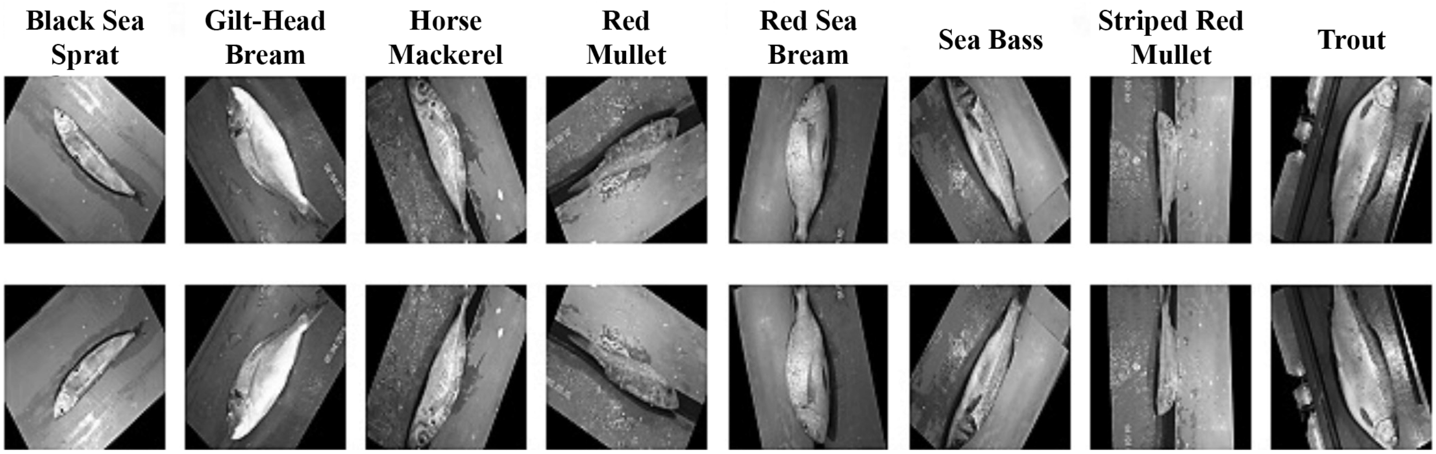

Figure 1- Image examples from the dataset

success among ResNet (He et al. 2016) architectures, consisting of 50 layers and 23M parameters, and ResNet101 models consisting of 101 layers and 42M parameters were preferred. However, the VGG16 model, one of the VGGNet architectures that forms the basis of object recognition models, consisting of 41 layers and 134M parameters, was preferred.

The proposed model in Figure 2 consists of 18 layers (convolution, maximum pooling, dropout, ReLU, flattening, fully connected and classification layers) and a total of 6.813.064 parameters.

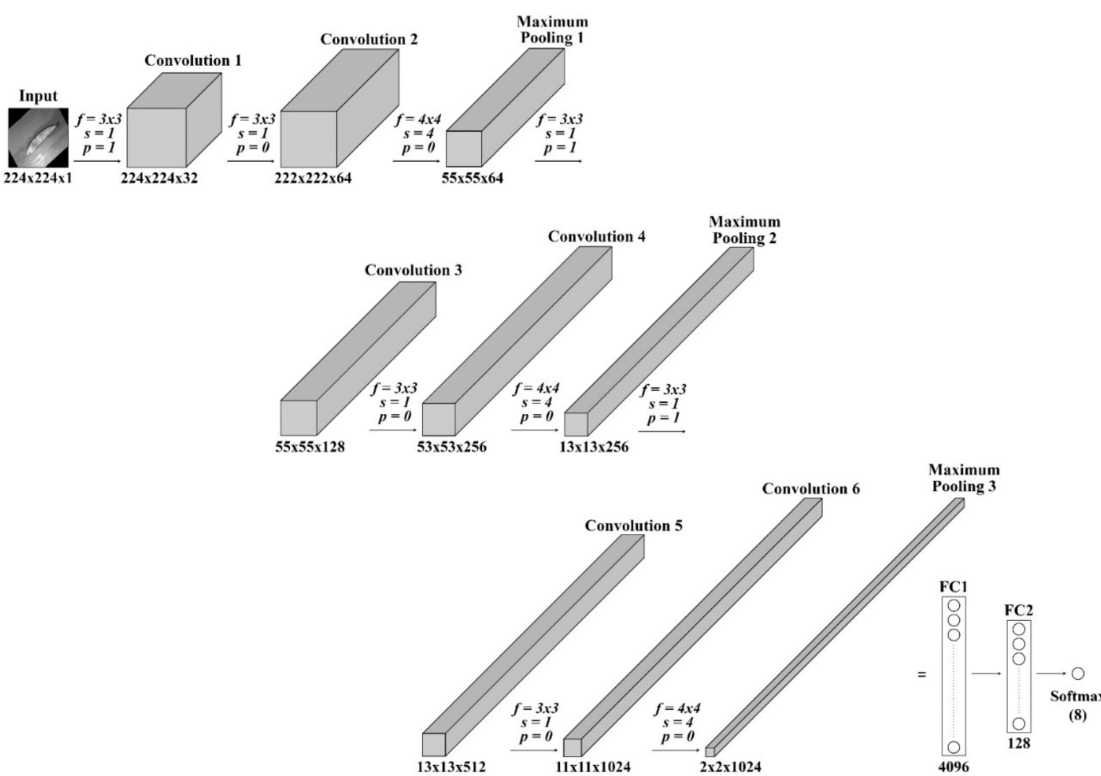

Figure 2- Proposed CNN model (IsVoNet8) (f: filter size, s: stride, p: padding, FC: fully connected)

In Figure 2, an image of a fish in a gray color format with a size of 224x224 pixels is given to the input of the proposed model. Initially, the first convolution of the input image (convolution) filter size 3x3 convolution layer 32, the second convolution layer convolution filter size 3x3, 64 applying the filter size 4x4 with a maximum dry docking has been obtained by applying 55x55x64 feature map pixels. Then, the image obtained by applying 128 and 256 two convolution layers, respectively, in 3x3 filter size and maximum pooling in 4x4 filter size, with the size of 13x13x256 pixels, the feature map was given as input to next block. As a result of this process, the image obtained by applying 512 and 1024 two convolution layers, respectively, in 3x3 filter size and maximum pooling in 4x4 filter size, with the size of 2x2x1024 pixels, the feature map was given as input to the full connection layer (FC1), and 4096 neurons were obtained. Then, 128 neurons were obtained using the full connection layer (FC2) and 8 output fish classes were obtained by applying the Softmax activation function to the neurons. In addition, the ReLu activation function, which regulates non-zero input values to zero in each convolution operation, and a 15% dropout layer are used to prevent the network from over-memorizing after each maximum pooling and FC2.

The low number of layers used in the proposed model reduces the computational complexity of the neural network. In this way, the proposed model takes less time in classifying fish species, making its use in real-time applications superior.

2.4. Training and testing

The models used in the study were coded using the Python programming language and the proposed model codes were published as open access on a website for other researchers to use (GitHub 2022). All models used in the study were run in Google Colaboratory (Colab 2021) environment with a high-performance NVIDIA Tesla K80 graphics processor. In addition, a dataset of 8 different fish species; divided into three groups as training, testing and validation. The number of fish images belonging to each group is given in detail in Table 1. The dataset consisting of fish images was randomly divided into three as 80% training, 10% testing and 10% validation data group. As a result of this process, a total of 8000 fish images were used, of which 6400 in the training data group, 800 in the test data group and 800 in the validation data group.

Table 1- Dataset of 8 different fish species

	Training (80%)	*Test (10%)*	*Validation (10%)*	*Total (100%)*
Dataset	6400	800	800	8000

Epoch (20), Mini Batch Size (32) and Optimization Algorithm (Adamax) training parameters were used for each model training in the study. However, in the proposed model, dropout (15%) and ReLU were used as activation functions.

2.5. Performance metrics

As a result of the model training process, the mathematical expressions of the precision, recall, f1-score and accuracy performance criteria were given between Equations 1 and 4. In the formulas given below, TP represents the true positive, TN represents the true negative, FP represents the false positive and FN represents the false negative.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

$$f1-score = \frac{2*Precision*Recall}{Precision+Recall} \tag{3}$$

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{4}$$

3. Results and Discussion

The traditionally defined methods are those that require professional skill and take a long time. Therefore, feature extraction methods based on image processing technologies are used in order to eliminate human-induced errors in fish images efficiently, in a short time. In this study, a new evolutionary neural network model recognizing and classifying 8 different fish species using deep learning methods was proposed. The species include *Clupeonella cultriventris* N., *Sparus aurata* L., *Trachurus trachurus* L., *Mullus barbatus* L., *Pagrus major*

T & S., *Dicentrarchus labrax* L., *Mullus surmuletus* L. and *Oncorhynchus mykiss* W. from Mullidae, Sparidae, Carangidae, Serranidae, Clupeidae, Salmonidae family.

According to the experimental results obtained using the training and test data groups, the precision, recall, f1-score and accuracy performances criteria of the models as a result of the training process are given in Table 2. In addition, the accuracy and loss graphs of each model are shown in Figure 3.

Table 2- Performance criteria for each model using training and test data groups

Model	*Class*	*Precision*	*Recall*	*F1-Score*	*Model*	*Class*	*Precision*	*Recall*	*F1-Score*
ResNet50	Black Sea Sprat	0.84	1.00	0.91	ResNet101	Black Sea Sprat	0.78	1.00	0.88
	Gilt-Head Bream	0.98	0.80	0.88		Gilt-Head Bream	0.89	0.85	0.87
	Horse Mackerel	0.97	0.92	0.94		Horse Mackerel	0.98	0.94	0.96
	Red Mullet	0.94	1.00	0.97		Red Mullet	0.77	0.96	0.85
	Red Sea Bream	0.74	0.99	0.85		Red Sea Bream	0.99	0.87	0.93
	Sea Bass	1.00	0.75	0.86		Sea Bass	0.74	0.99	0.85
	Striped Red Mullet	0.99	0.86	0.92		Striped Red Mullet	1.00	0.40	0.57
	Trout	0.97	0.99	0.98		Trout	0.94	0.88	0.91
	Accuracy			0.91		Accuracy			0.86
	Macro avg	0.93	0.91	0.91		Macro avg	0.89	0.86	0.85
	Weighted avg	0.93	0.91	0.91		Weighted avg	0.89	0.86	0.85
Model	*Class*	*Precision*	*Recall*	*F1-Score*	*Model*	*Class*	*Precision*	*Recall*	*F1-Score*
VGG16	Black Sea Sprat	0.97	0.98	0.98	IsVoNet8	Black Sea Sprat	0.98	0.99	0.99
	Gilt-Head Bream	0.99	0.97	0.98		Gilt-Head Bream	0.99	1.00	1.00
	Horse Mackerel	0.97	0.98	0.98		Horse Mackerel	1.00	0.98	0.99
	Red Mullet	1.00	0.99	0.99		Red Mullet	1.00	0.97	0.98
	Red Sea Bream	0.95	0.97	0.96		Red Sea Bream	0.98	0.99	0.99
	Sea Bass	0.98	0.97	0.97		Sea Bass	0.97	1.00	0.99
	Striped Red Mullet	0.97	0.96	0.96		Striped Red Mullet	0.99	0.97	0.98
	Trout	0.99	1.00	1.00		Trout	0.98	0.99	0.99
	Accuracy			0.98		Accuracy			0.99
	Macro avg	0.98	0.98	0.98		Macro avg	0.99	0.99	0.99
	Weighted avg	0.98	0.98	0.98		Weighted avg	0.99	0.99	0.99

When the graphs in Figure 3 are examined, the training process of the CNN in ResNet50 and ResNet101 models is realized with higher learning, however, as a result of the last epoch, the training rate in the ResNet50 model is 99.34% and the test rate is 92.37%; In the ResNet101 model, the training rate reached 98.50% and the test rate reached 88.13%. Since the training and testing rates are inconsistent in these two models, it seems that the testing process is not successful enough. However, the same situation is observed in the loss rate of these two models. In the VGG16 model, it seems that the training and testing process takes place well and the network learns properly. As a result of the last epoch of the VGG16 model, it was seen that the reached training rate 1.00% and the test rate 97.37%. Thus, it is seen that the training and testing ratio in the VGG16 model is more consistent than in the ResNet50 and ResNet101 models. This consistent situation is also seen in the loss graph of the VGG16 model (Figure 3c). In the proposed IsVoNet8 model, it is seen that the training rate is 98.89% and the test rate is 98.37% as a result of the last epoch. In the proposed model, it has achieved superior results due to the lower number of layers and parameters used and the cost lower compared to other models. Successful results were obtained in the loss graph of the proposed model compared to other models (Figure 3d).

After the training and testing process of each of the four models discussed in the study, the accuracy of the models was tested using a validation data group consisting of a total of 800 fish images never seen by the model nets (Table 3). In addition, a confusion matrix for 8 different fish classes obtained for each model using the same validation data group is given in Figure 4.

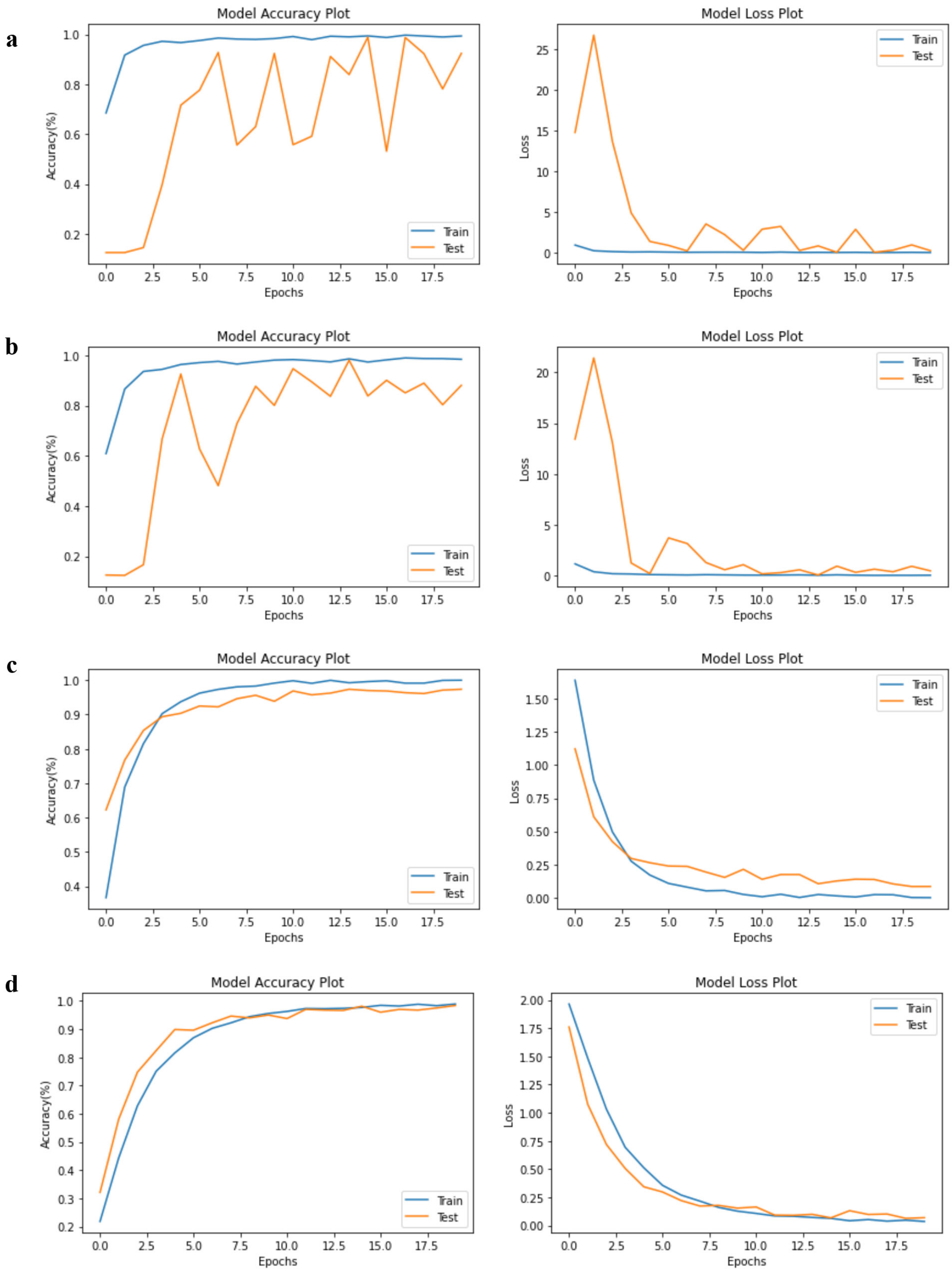

Figure 3- Accuracy and loss graphs for each model using training and test data groups: (a) ResNet50, (b) ResNet101, (c) VGG16, (d) IsVoNet8

Table 3- Accuracy and loss values for each model using the validation data group

Model	*Accuracy*	*Loss*
ResNet50	91.37%	0.3646
ResNet101	86.12%	0.5811
VGG16	97.75%	0.0696
IsVoNet8	98.62%	0.0568

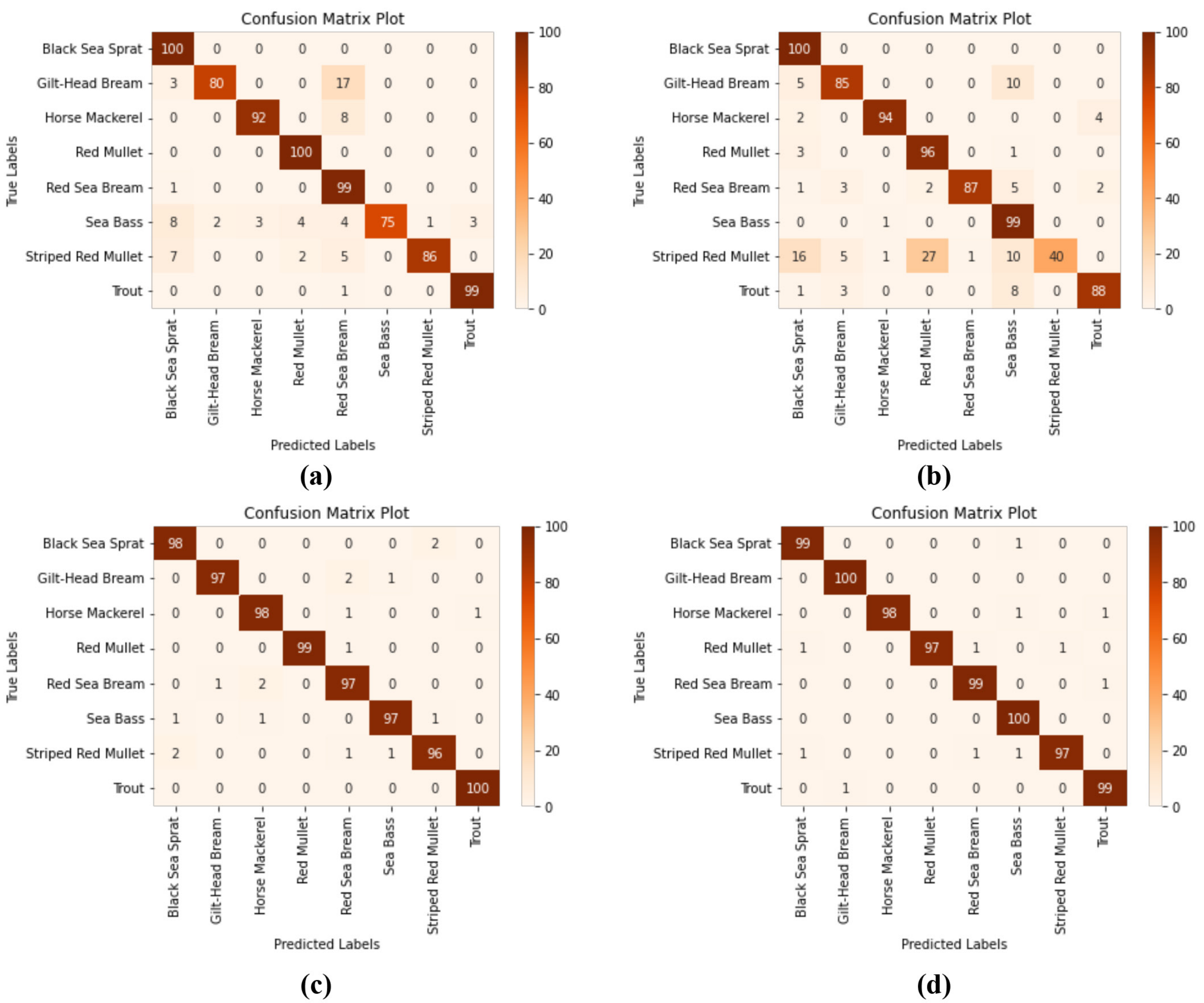

Figure 4- Confusion matrix for each model using the validation data group: (a) ResNet50, (b) ResNet101, (c) VGG16, (d) IsVoNet8

When the accuracy values given in Table 3 were examined, it was seen that the highest success accuracy rate was obtained from the IsVoNet8 model proposed with 98.62%. Rathi et al. (2017) developed a novel method based on CNN to classify 21 species of fishes and achieving an accuracy of 96.29 percent. In another study Khalifa et al. (2018) used a simplified AlexNet to identify multiple species of fishes. The data used was composed of eight species, with 191 sub-species trained. The results achieved 85.59 percent accuracy and 85.41 percent using AlexNet.

In addition, 91.37%, 86.12% and 97.75% success accuracy rates were obtained in ResNet50, ResNet101 and VGG16 models, respectively. The authors obtained the highest accuracy of 98.81% to recognize the Bangladesh freshwater fish for InceptionResnetV2 and Xception On the other hand, ResNet152V2 achieved 90.24% accuracy which is the lowest among all the working approaches (Majumder et al. 2021). When the loss rates of each model were examined, it was found that the ResNet50 model had 0.3646, the ResNet101 model was 0.5811, the VGG16 model was 0.0696, and the loss ratio of the proposed IsVoNet8 model was 0.0568. Kratzert & Mader (2018) proposed that an enhanced version of VGG16 model for the automated classification of the underwater fish species. The authors proposed a technique based on the monitoring system of FishCam for the observation of underwater objects. They classified 10 fish species and obtained 93.3% accuracy. Santos & Gonçalves (2019) compared results of VGG16 and VGG19 in classifying fish images and had VGG19 with 83%, which is 2% higher than VGG16 of 81%. Montalbo & Hernandez (2019) proposed a methodology to recognize fish species using VGG16 Deep Convolutional Neural Network (DCNN). Though this approach gets 98.67% accuracy, they have used synthetic augmented data for training and testing the proposed model for three different fish species. It has been seen that the model we proposed provides a better performance than the studies in the other literature due to both the low learning time of the neural network and the high accuracy of success.

In addition, in the confusion matrixes given in Figure 4, the results of estimating the fish class according to the validation data group of each model are seen. It seems that the best classification is in the proposed IsVoNet8 model. Therefore, according to the results given in Table 3 and Figure 4, it is seen that the IsVoNet8 model classifies the fish classes considered in the study with higher success accuracy. According to the results obtained; Selecting the layer and hyperparameter values used in the proposed model in accordance with the model network provided a superior performance compared to other studies used in the classification of fish species (Rathi et al. 2017; Khalifa et al. 2018; Kratzert & Mader 2018; Montalbo & Hernandez 2019; Santos & Gonçalves 2019; Majumder et al. 2021).

4. Conclusions

In this study, the common species of fish, which have an important role in the nutrition of human beings, have been predicted through the images of deep learning algorithms, which is one of today's popular machine learning methods. In this context, 8 different fish species were classified using deep learning architectures. A new model was developed in the classification process, and the proposed model was compared with the ResNet50, ResNet101 and VGG16 models accepted in the literature to prove the success accuracy of the model. While comparing, 8000 fish images in the data set; analyses were made by using 6400 of them in the model training, 800 in the model testing part and 800 in the validation data group.

As a result of the model training, according to the validation data group, 91.37% success accuracy in the ResNet50 model, 86.12% in the ResNet101 model, 97.75% in the VGG16 model and 98.62% in the proposed IsVoNet8 model were obtained. It has been observed that the proposed IsVoNet8 model has achieved high success accuracy compared to other models, despite the fact that both the number of parameters is little and the cost is low. The higher success of the proposed model compared to the other models discussed in the study highlights the superiority of the model. When the study was compared with other similar studies (Sarıgül & Avcı 2017; Iqbal et al. 2021; Ju & Xue 2020; Mathur & Goe 2021; Guo et al. 2020 and Kayaalp K & Metlek S 2021), although the number of classes was small, the high number of images in the data set led to a better success rate.

As a result, it was seen that the IsVoNet8 model proposed in the study classified fish images with a superior success rate compared to other models. The fact that the IsVoNet8 model is also applicable to classify different fish species increases the original value of the study. In further studies, the IsVoNet8 model is possible to be studied and subsequently evaluated with images of other fish species. Furthermore, the model is also possible to be developed to estimate fish biodiversity, species richness and size, weight, and age essential for stock assessment and management. Moreover, the study results could be used to develop mobile determination and classification applications depending upon deep learning in order to identify fish species.

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