



Separation of Commercially Important Tuna from Other Fishes Using Feature Descriptor and Pre-trained CNN Models

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Aims / Objectives: Identification of fish species is essential in export industries. Among the different fish species exported, tuna forms a significant portion and hence the separation of tuna from other fishes is necessary. The work aims to develop automated systems for the separation of commercially important tuna from other fishes.

Methodology: The work proposes two models for the classification of commercial fishes. The first model uses conventional feature descriptors, which extract features from both spatial and frequency domain. These features are combined and are reduced by an ensemble dimension reduction method. The combined and reduced feature sets are evaluated using different classifiers. The second proposed model uses four pre-trained convolutional neural networks, VGG16, VGG19, Xception, and MobileNet, for the classification. The models are fine-tuned for the classification process.

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Results: Results show that for the first model, extreme learning machine classifier with Mercer wavelet kernel gives high accuracy on combined feature set while the polynomial kernel ELM provides better performance with the reduced set. For the second model, a comparison of the performance of four CNN models is done, and results indicate that VGG19 outperforms other networks in the classification task.

Conclusion: Among the two proposed models, pre-trained CNN based model shows better performance than the conventional method in the separation task. Different performance measures, accuracy, precision, recall, F-score, and misclassification error are used to evaluate the system. A comparison of performance of the proposed models with the state-of-the-art systems is also reported.

Keywords: Colour histogram; fuzzy local binary pattern; histogram of oriented gradients; dual tree complex wavelet transform; ensemble dimension reduction; CNN.

1 INTRODUCTION

Fish is a vital source of protein and other nutrients and is consumed as food globally because of its health benefits. In export industries, fishes are sorted into their types for packing and exporting. Among the various fishes, tuna has excellent economic importance compared to other fishes [1]. The most relevant tuna species from the commercial point of view are the Bigeye tuna, Yellowfin tuna, and Skipjack tuna [2]. Therefore separation of these fishes from others is essential.

Recently different image processing and machine learning algorithms are used for the classification of fishes into different species. Ogunlana et al. [3] used shape features obtained by finding distance between different points on the fish body for the classification of two species of fishes. A support vector machine (SVM) is used here which gives an accuracy of 78.59%. Classification of three species of tuna using shape and textural features is proposed by Khotimah et al. [4]. A decision tree classifier showed an average classification accuracy of 88.00% in the process. A graph embedding discriminant analysis method [5] is used for fish classification, where the species are identified by matching the image sets. Different feature descriptors such as scale-invariant feature transform (SIFT), speeded up robust features (SURF), local binary pattern (LBP), and the histogram of oriented gradients (HOG) are also used for fish classification [6, 7].

With the advancement in deep learning techniques, different convolutional neural networks (CNN) are used for fish classification [8, 9]. Li et al. [10] proposed a system for fish detection and recognition from underwater images. A fast region with CNN (R-CNN) is used for the detection and identification of fish species. Classification of fishes from low-resolution images using CNN is proposed by Rachmatullah et al. [11]. A network with two convolution layers is trained using augmented images and the system shows an accuracy of 99.73%. Rauf et al. [12] proposed a 32 layer CNN architecture for the classification of six species of fishes. Three different image views are used for the classification and the receiver operating characteristics (ROC) of the system show an area under the curve (AUC) of 0.969.

Two models are proposed in this work for the classification of fishes into two classes. Since Bigeye tuna, Skipjack tuna, and Yellowfin tuna have greater economic importance when compared to others, we have considered these three species as class 1 and other species belonging to the same and different families as class 2. The first model uses the conventional feature descriptors with classifiers, while the second model uses pre-trained CNN models for the classification. Details of the dataset and the proposed models are given in section 2. Section 3 discusses the performance of the proposed models in classifying fishes. The conclusion of the work is given in section 4.

2 MATERIALS AND METHODS

2.1 Fish Image Dataset

The work uses a dataset with 1157 images. Bigeye tuna (*Thunnus obesus*), Skipjack tuna (*Katsuwonus pelamis*), and Yellowfin tuna (*Thunnus albacares*) form class 1 which consists of 612 images. These fishes belong to the family *Scombridae*. Class 2 is formed by Frigate tuna (*Auxis thazard*), Kawa kawa (*Euthynnus affinis*), Bullet tuna (*Auxis rocheri*), Bonito (*Sarda sarda*), Indian mackerel (*Rastrelliger kanagurta*), Seer fish (*Scomberomorus commerson*), and fishes belonging to other families such as Moontail

bullseye (*Priacanthus hamrur*) and Milk fish (*Chanos chanos*). Class 2 consists of a total of 545 images. Fig. 1 shows the sample images of class 1 and Fig. 2 shows the sample images of fishes in the class 2 belonging to the family *Scombridae*. Sample image of fishes belonging to different families which are included in class 2 is shown in Fig. 3.

Images were collected from various harbours, Vizhinjam, Cochin, and Thengapattanam harbours. A Nikon DSLR camera is used to capture the images and all the images were labelled by the third author of the paper, who is a professional at Fisheries University.

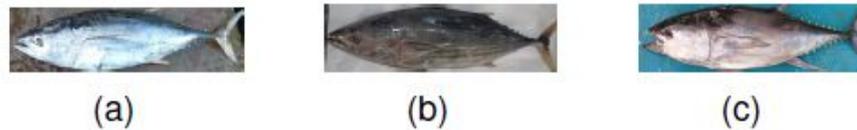


Fig. 1. Sample images of class 1: (a) Bigeye (b) Skipjack (c) Yellowfin

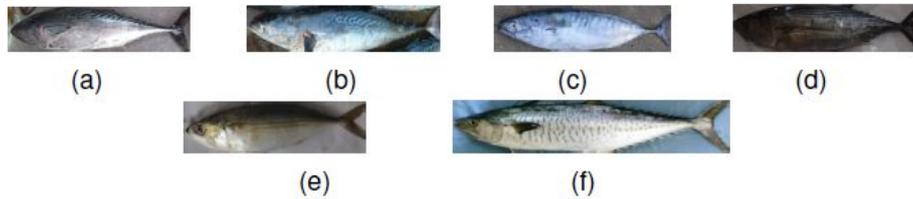


Fig. 2. Sample images of fishes in class 2 which belongs to the family *Scombridae*: (a) Frigate (b) Kawa kawa (c) Bullet (d) Bonito (e) Indian Mackerel (f) Seer fish



Fig. 3. Sample images of fishes in class 2 which belongs to other families: (a) Moontail bullseye (b) Milk fish

2.2 Image Preprocessing

The images are enhanced by using an adaptive histogram equalisation technique [13]. This technique helps to enhance the contrast of the image, thereby boosting the structures in the images. Images are applied to different augmentation techniques so as to increase their number. Augmentation is a well-known process used to improve a machine learning system's performance by training the system with more diverse data [14]. The different augmentation techniques applied to the images are rotation, translation, shearing, brightness adjustment, and zooming.

2.3 Proposed Models

Two models are proposed for the classification of the fishes into two classes. The first model uses

a multi-domain feature set for the classification, while the other model classifies using pre-trained CNN models.

2.3.1 Model 1: Multidomain feature-based system

Fig. 4 shows the block diagram of the proposed model for fish classification using multi-domain features.

Preprocessed images are applied to different feature descriptors for extracting features. Features from both spatial and frequency domains are used for the classification. Spatial domain feature descriptors used are colour histogram, fuzzy LBP, and HOG. Dual tree complex wavelet transform (DTCWT) [15] is used for extracting frequency domain features.

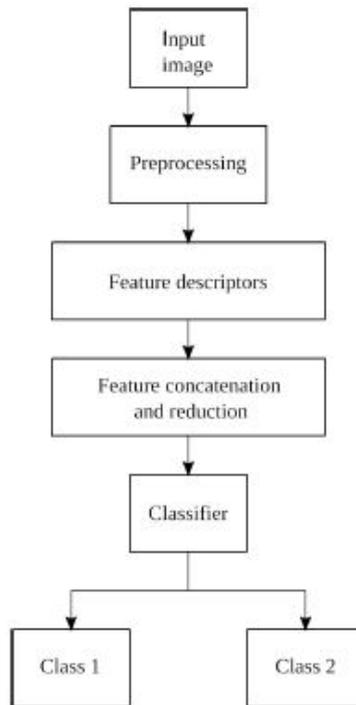


Fig. 4. Block diagram of the model using multi domain features for fish classification

Spatial domain features: Colour histogram features are extracted by finding the pixel intensity distribution of the R, G, and B planes of the raw images. Mean and variance of each plane histogram forms the colour histogram features [16]. A fuzzy-based LBP descriptor [17] is used to extract spatial textural features. FLBP incorporates fuzzy logic into the standard LBP descriptor. In standard LBP [18], the neighbouring pixels and the central pixel of a neighbourhood are compared to generate an LBP code. The comparison results in assigning the neighbouring pixels to any of the two sets: set '0' or set '1'. While in FLBP, each neighbouring pixel can belong to both sets with some degree of membership. The membership value is obtained using different membership functions. The resulting sets will generate two different LBP codes, and the total contribution of these codes to the LBP histogram will always be equal to one. Histogram of FLBP images form the spatial textural features in the system. HOG descriptor [19] is used to get the structural characteristics of an image. Each image is divided into smaller blocks, and the gradient of each region image is obtained. A region-wise histogram using gradient magnitude and angle is generated and are concatenated to get the final histogram.

Frequency domain features: Wavelet transforms are used to analyse the signals in both time and frequency domain and can effectively extract transient features from a signal. A dual-tree complex wavelet transform is used in this work to extract frequency-domain features. DTCWT has a dual-tree architecture where one tree gives the wavelet's real components and the other provides the imaginary components. DTCWT with five scales and six orientations are used here for feature extraction. The real and imaginary subbands of a scale and an orientation are combined, and the magnitude of the combined subband is determined. Hence, for a scale, six subbands are obtained for feature extraction. A coefficient co-occurrence matrix is generated from these subbands [20]. The co-occurrence matrix of all the subbands is added together to get a combined matrix. Four

features, energy, correlation, homogeneity, and contrast, are extracted from the combined co-occurrence matrix which forms the frequency domain features.

The features from the spatial and frequency domain are concatenated to form the combined feature set. An ensemble of dimension reduction techniques [21] are used to generate a reduced feature set. Different dimension reduction techniques viz., principal component analysis (PCA), linear discriminant analysis (LDA), multidimensional scaling (MDS), factor analysis (FA), probabilistic PCA (ProbPCA), and large margin nearest neighbour (LMNN), are used to reduce the combined feature set. Each method is applied separately on the feature set to reduce its dimension to a size of 75. The reduced feature set from each technique is evaluated using a classifier, and the methods that show better performance are identified. The best dimension reduction methods are then ensemble to generate the final reduced feature set.

In the final stage, the input images are separated into two classes by a classifier. The effectiveness of both combined and reduced feature sets is evaluated using different classifiers, SVM, ANN, LDA, bagged tree, and kernel ELM. Each classifier's performance is assessed using different metrics, accuracy, precision, recall, F-score, and misclassification error (MCE).

2.3.2 Model 2: Pre-trained CNN based system

Four pre-trained models, such as VGG16, VGG19, Xception, and MobileNet, are used in this work. These networks are pre-trained on the ImageNet dataset, and the fully connected layers are modified according to the application. Fig. 5 shows the block diagram of the proposed system with VGG19 pre-trained model. Preprocessed images are applied as input to each of the CNN, and their performance is evaluated. All the layers of the CNN models are kept trainable during the training process.

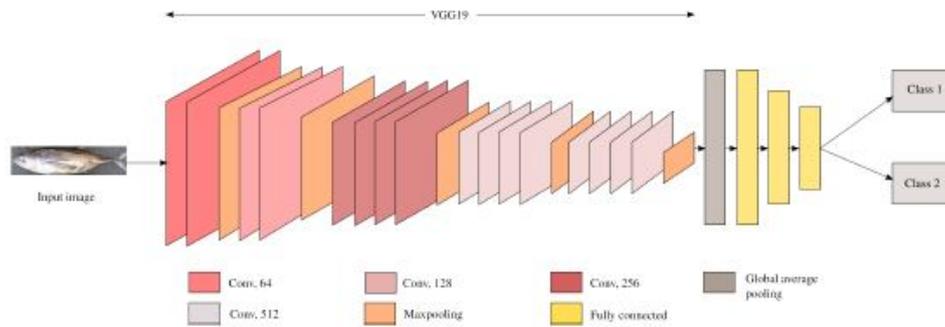


Fig. 5. Block diagram of the model using pre-trained CNN for fish classification

VGG16 is a network that has 16 layers which uses convolution layers with filters of size three and activation function ReLU [22]. Convolution layers with 64, 128, 256, and 512 filters are used in the network. Max pooling layers are provided between the convolution layers to reduce the size of the feature maps. A stride of two is used in the pooling layers. VGG19 is similar to VGG16 but with 19 convolution layers with filter size three [23]. It has convolution layers with 64, 128, 256, and 512 filters. Feature map size is reduced by using max-pooling layers with a stride of two.

Xception [24] is a network architecture inspired by the Inception model. The network uses depthwise separable convolutions, which involves a depthwise convolution followed by a pointwise convolution. A batch normalisation layer follows all depthwise separable convolution layers. MobileNet also uses depthwise separable convolutions and has a streamlined architecture [25]. In this convolution, the filter kernels are split into two: one for filtering and the other for combining. Filtering is done by depthwise convolution, whereas combining is done by spatial convolution.

The fully connected layers follow a global average pooling layer in the network. Three dense layers with 512, 256, and 2 neurons form the fully connected layers. A drop out layer with a value of 0.5 is provided in between the dense layers. A batch normalisation layer follows each drop out layer. Dense layers are provided with ReLU activation and l_2 regulariser. Values from uniform distribution initialise its kernels. A softmax

classifier with a categorical cross-entropy error function is used for the training of the networks.

3 RESULTS AND DISCUSSION

Two models are proposed to classify fishes into two classes using image processing and machine learning techniques. The adaptive histogram equalisation technique enhances the raw images, and these preprocessed images are applied to different augmentation techniques. These augmented images are given to the two models for classification. Images of pixel size 128×256 are used in this work.

Model 1: The images are split into R, G, and B planes for extracting the colour histogram features. Colour features obtained from an image is of size six. After getting the colour features, images are converted to grayscale for further processing. Gray images are applied to the FLBP, HOG, and DTCWT to generate the textural and structural features. FLBP descriptor uses the Gaussian membership function in this work. FLBP histogram of length 100 is used as the spatial textural features. HOG descriptor provides a feature vector of size 81 while four features are obtained from the frequency domain. A feature vector of size 191 is obtained by combining the features from both the domains. The feature set's effectiveness is analysed using various classifiers, and the performance of the classifiers is evaluated. Table 1 shows the performance measure values of different

classifiers using the combined feature set. Results show that the ELM classifier with Mercer wavelet kernel gives a higher performance in the classification process.

Different dimension reduction techniques are applied to reduce the combined feature set. The reduced predictors from each method are evaluated using ELM with Mercer wavelet kernel since it shows the highest performance with combined features. Table 2 shows the classification accuracy of KELM with reduced features obtained from different techniques. Results show that the highest accuracy is given by the predictors obtained from PCA, FA, and

MDS. Hence, an ensemble of these methods is used to generate the final reduced feature set.

The first fifteen predictors from the feature set reduced by PCA, FA, and MDS are combined to get a reduced feature vector of length 45. The reduced attribute is evaluated with the classifiers that showed the best performance with the combined feature set. Fig. 6 shows the performance measure values of different classifiers on the reduced feature set. Results show that the images are separated into the two classes with an accuracy of 96.78% by ELM classifier using a polynomial kernel of degree 2 with the reduced feature set.

Table 1. Performance of different classifiers using non reduced feature set

Performance measure	Classifiers							
	SVM	LDA	KELM d=2	KELM Morlet	KELM Mercer	Bagged	ANN tree	QSVM
Accuracy	96.72	95.15	97.40	97.92	97.98	96.07	97.93	97.72
Precision	97.00	96.00	97.54	98.08	98.12	96.50	98.06	98.00
Recall	96.01	94.07	96.89	97.46	97.54	95.22	97.50	97.13
F-score	96.46	94.84	97.20	97.75	97.82	95.79	97.77	97.54
MCE	3.28	4.85	2.60	2.08	2.02	3.93	2.07	2.28

Table 2. Classification accuracy of Mercer KELM with features reduced by different dimension reduction methods

Method	PCA	LDA	MDS	LMNN	ProbPCA	FA
Accuracy	97.79	56.90	97.78	88.29	82.34	95.49

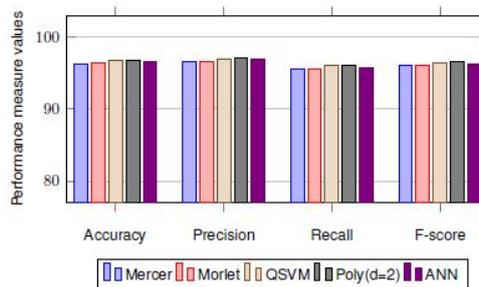


Fig. 6. Performance measure values of different classifiers with features reduced by ensemble dimension reduction method.

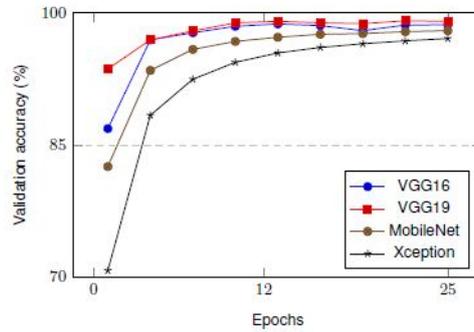


Fig. 7. Variation of validation classification accuracy of pre-trained models with epochs

Model 2: This system uses pre-trained CNN models to separate fishes into two classes. The fully connected layers of the pre-trained models are modified for binary classification. Each model is trained using a stochastic gradient descend (SGD) optimiser with a learning rate of 0.0001 and momentum of 0.9. Networks use a batch size of 64. Fig. 7 shows the variation of each model's validation classification accuracy with epochs.

Accuracy, precision, recall, and F-score of each pre-trained model is evaluated and is shown in Table 3. Results show that VGG19 offers the best performance with 99.05% accuracy in classifying fishes into class 1 and class 2. The proposed models are also compared with state-of-the-art systems and the performance comparison is shown in Table 4.

Table 3. Performance measures of different pre-trained models

Model	Accuracy	Precision	Recall	F-score
VGG16	98.66	98.50	98.50	99.00
VGG19	99.05	99.00	99.50	99.00
MobileNet	97.98	98.00	98.00	98.00
Xception	97.09	97.00	97.00	97.00

Table 4. Performance comparison of the proposed models with the state-of-the-art systems

Method	Technique used	Accuracy	Precision	Recall	F-score
Hu et al. [26]	Wavelet norm features and LIBSVM classifier	89.79	89.18	88.74	88.94
Andayani et al. [27]	Colour, structure features PNN classifier	90.93	90.46	89.97	90.20
Jose et al. [28]	Saptial and wavelet based feature with KELM classifier	96.54	96.95	95.76	96.29
Iqbal et al. [29]	Reduced AlexNet model	97.06	97.00	97.00	97.00
Proposed model 1	Multidomain features with KELM classifier	96.78	97.16	96.03	96.54
Proposed model 2	VGG19 model	99.05	99.00	99.50	99.00

4 CONCLUSION

Separation of Bigeye, Skipjack, and Yellowfin tuna from other fishes is essential to fasten the process at tuna export industries. Two models for commercial fish classification are proposed in this work. The first model is a multidomain feature-based system that uses spatial and frequency domain features for classification. Features from the spatial and frequency domain are combined and are evaluated using several classifiers. An ensemble dimension reduction technique is applied to the combined feature set to get a reduced feature set. The efficacy of the reduced feature set is also evaluated using different classifiers. Results show that KELM with Mercer wavelet kernel offers the highest accuracy with the combined feature set and polynomial kernel of degree 2 outperforms others on the reduced feature set.

A second model for fish classification is proposed using pre-trained CNN. Four pre-trained models, VGG16, VGG19, MobileNet, and Xception, are used, with the fully connected layers modified. SGD optimiser is used for training the layers, and the best network for the classification task is identified. Results indicate that VGG19 has the highest value for accuracy, precision, recall, and F-score compared to the others. Results indicate that among the two models proposed, the pre-trained CNN model using VGG19 shows an accuracy of 99.05% in classifying commercially important tuna from the other fishes.

DISCLAIMER

The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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