WikiFish: Mobile App for Fish Species Recognition Using Deep Convolutional Neural Networks

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ABSTRACT

Consumers of the fish market around the world face problems in the identification of fish species and people need to obtain expert assistance to do so. This situation is typically the same in Gaza Strip, the local fish market lacks such an application that exposes people to fraud by some sellers. On the other hand, many poisonous and exposed fishes were caught and sold in the fish market in Gaza Strip. Thus, in this work, an innovative mobile application is proposed for identifying fish species that are commonly available in the Mediterranean Sea and therefore in the local fish market. A considerable number of fish images as a dataset were obtained from El-Hesba and auction markets located next to Gaza Fishing Harbor of Gaza as well as aquaculture farms. The AlexNet was chosen for the proposed model. Moreover, RELU SOFTMAX was chosen for the main network the model exhibit accuracy of 80 %, 0.788 precision and recall of 0.631.

CCS CONCEPTS

• **Computing methodologies** → Machine learning; Machine learning algorithms; Artificial intelligence; Computer vision; Computer vision problems; Object recognition; • **Applied computing** → Computers in other domains; Agriculture.

KEYWORDS

Fish Species, Fish Recognition, CNN, Artificial Intelligence

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1 INTRODUCTION

Recently more attention is being paid to Fish studies because of their importance as food, which constitutes a capital source of protein worldwide and for scientific studies. The marine fishes caught in the Gaza Strip have never been scientifically studied. Unfortunately, with the lack of promising techniques for the identification of fishes many poisonous and dangerous fishes were caught and sold in the fish market in Gaza Strip. In this specific context, it appears of considerable importance to dispose of analytical methods able to perform an accurate and fast identification of fish species, guaranteeing to end consumers the origin and safety of edible fish.

Fish identification or fish classification is not a straightforward task and requires specialized knowledge of fish Biological features and taxonomy systems. Tools employed to identify fish include body figures, shapes and illustrations.

Costa and Carvalho (2007) highlighted the difficulties encountered in the diagnosis of species [1]. Currently, a range of molecular techniques is also used for fish identification like DNA barcoding [1], [2], [3]. However, all of these standard methods require specialized expertise and laboratories. They are also very time consuming and expensive processes. With the exploitation of Artificial Intelligence (AI) and Machine Learning (ML) techniques and especially Deep Learning (DL), most of the methodologies proposed to solve fish data collection and analysis issues are based on the Convolutional Neural Networks (CNN).

CNN is a type of Artificial Neural Network (ANN), which has deep feed-forward architecture and has the amazing generalizing ability as compared to other networks with FC layers; it can learn highly abstracted features of objects especially spatial data and can identify them more efficiently. A deep CNN model consists of a finite set of processing layers that can learn various features of input data (e.g. images) with multiple levels of abstraction. The initiatory layers learn and extract the high-level features (with lower abstraction), and the deeper layers learn and extract the low-level features (with higher abstraction) [4]. Important features of CNN such as reduce the number of trainable parameters, the output more dependent on the extracted features, and the implementation make CNN the most important prominent deep learning method to extract information. AlexNet, VGGNet, ResNet are examples of CNN used for the identification and classification of the fish species.

In the proposed work, authors use AlexNet based CNN to identify fish and provide information through a mobile application. The rest of the paper is organized as follow: the next section talks about previous related work, the third section presents the methodology, and finally the results and discussion.

2 RELATED WORK

Nowadays, most research projects focus on integrating AI and machine learning techniques in other fields to enhance productivity, extract better information, make decisions, and to identify problems. Therefore, many studies, related to fish classification and identification, have previously been presented with various algorithms and models. Most of the proposed work is based on CNN, some of them used a modified version of the VGG-16 model [5], [6], [7] while other researchers used AlexNet based models [8]. In

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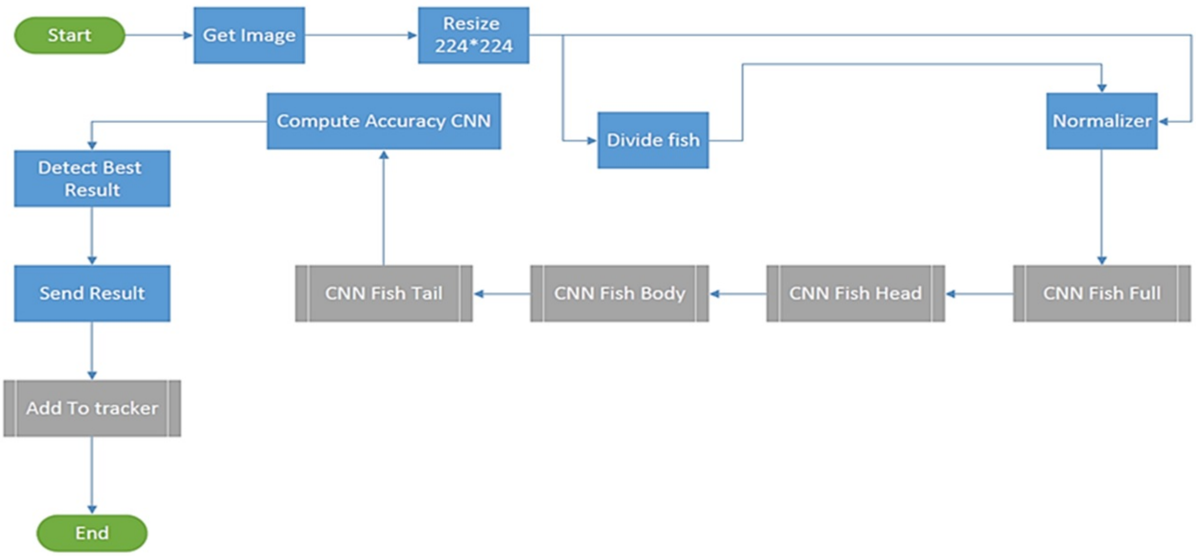

Figure 1: The general structure of the proposed system

addition, newly proposed methods were examined and compared to the known algorithms [8], [10], [11], [12] to demonstrate better results.

Some authors developed fish identification and classification methods for the underwater environment [5] where videos are captured for data collection and monitoring, these videos suffer challenges as underwater images have various noise issues in the background [11]. On the other side, mobile applications were developed to identify fish species from images and provide information such as FishAPP [13] and SuperFish [12].

A modified version of VGG achieve better accuracy results as the number of classes is smaller and the dataset is bigger where it ranges between 93% - 99% and the fish species between 3 and 50 classes [5], [6], [14]. While the AlexNet model achieves an accuracy of 90.48% with 6 classes of fish species in [8].

The above-mentioned methods process the fish image without any focus on the different parts of the fish that vary from a type of species to another. In our proposed algorithm, we have divided the fish body into three parts: the tail, the body, and the head then train the complete fish image, in similar work [7] author worked on the head and body region to compare different algorithms with their proposed one. Table 1 demonstrates the conclusion of some related work.

3 METHODOLOGY

This work is a part of SAMAKA Fish market management system (FMMS) which is designed to manage all fish market-related data and administered in Gaza Strip. The main aim of this paper is to develop an innovative mobile application for the identification of fish species that are commonly available in Gaza local fish market. Figure 1 illustrates the general structure of the proposed system.

Unfortunately, the Dataset required for the project property is not available, therefore; our dataset needs to be created. A total of 128 fish species belonging to 56 families were identified and recorded. During this study, the fish species were reduced from 128 to 89, which are the most common fish types that can be found in Gaza during different seasons. Thirty (30) images for each of the Eighty-nine (89) different fish species were collected from El-Hesba, auction markets located next to Gaza Fishing Harbor and aquaculture farms. The 2670 pictures were taken by different smartphones the image resolution was kept the same for all the devices used.

Several preprocessing steps were performed; initially, the images were scaled to 224 x 224-pixels size which is the CNN standard of deep learning specifications then followed by image noise and outliers remover to smooth the images and to mitigate the unwanted image objectives. Then the image segmentation is taking place in the pre-processing to partitioning the image into three parts (head, body, and tail). Subsequently, the images are normalized to convert the images to a set of numbers between zero and one [9]. The output of the previous operations is stored in a comma-separated values (CSV) file once the (CSV) file is produced then the dataset can be feed to the neural network. In the last step of pre-processing, the created data were then divided into three parts, where 80% of the dataset was randomly chosen as the training and validation datasets, and the remaining 20% was used as the testing dataset.

Deep Convolutional Neural Network (CNN) AlexNet [5] has been used in this study for image classification. Figure 2 shows the general structure of the proposed CNN. AlexNet was chosen as it provides a minimum number of layers and accepted accuracy for training and validation over 90%. AlexNet structure consists of 11x11, 5x5, 3x3, convolutions, max pooling, dropout, data augmentation, ReLU activations, SGD with momentum. It attached ReLU

Table 1: Conclusion of some related work

Ref	Algorithm/Model	Image size and No of classes	Dataset	%Accuracy results
[5]	Scaled-down VGG-16	Resized to 64x64 pixel / 23 classes	Fish4Knowledge dataset 27370 images: 75% for training 25% for testing	98.25%
[6]	VGG16 pre-trained on ImageNet via transfer learning method	Resized to 100×250 pixels/ 50 classes	QUT FISH dataset 750 images 66.6% for training 33.3% for testing	Blending image mixed with RGB image trained model exhibited the best genuine acceptance rate (GAR) value of 96.4%, RGB color space image trained model with a GAR value of 92.4% canny filter image trained model with a GAR value of 80.4%. Blending image showed the least GAR value of 75.6%.
[7]	32 deep layers that The deep supervision is inflicted on the VGGNet architecture	Images were taken with camera resolutions of 5202×3465 pixels converted into the size of 200×200./ 6 classes	Fish-Pak contains 915 images	96.94%.
[8]	reduced version of AlexNet model comprises of four convolutional layers and two fully connected layers	Resized to 227 × 227 /6 classes	The QUT fish dataset contain 3960 images LifeClef2015 Fish dataset of 20,000 images, 20% for testing 15% for validation	90.48%
[9]	TensorFlow deep learning framework implementation of CNN model Inception 3 classifier pretrained on the ImageNet classification dataset.	resized to (299, 299) for 10 epochs resized to (512, 512) for 50 epochs / 3 classes	15000 images of 133 sets. 3000 images obtained from the Deep Vision survey 80% for testing 20% for validating.	94.1% on test dataset 50.8% to 71.1% classifier on real images from
[10]	Probabilistic Neural Network	Acquired using smartphone camera 4608 × 2592 pixels (16:9 ratio). Rescalling to 1296 × 2304 pixels. Region of Interest 560 × 200 pixels /3 classes	141 images 80% for training 20% for testing	89.65%
[11]	mask regional-based CNN (mask R-CNN)	1280 x 720 pixel video. resized to 1024 x 576 pixels /4 classes	700 videos, 4000 images from 500 training videos, 80% for training, 20% for validating	98.06%
[12]	kNN algorithm Deep learning Neural Network (DNN). For this purpose, we have used a pre-trained Inception-v3 deep learning model which has been developed at Google	Images were taken with a smartphone resolution 2048 x 1152 then resized to 299 x 299 / 38 classes	1520 images: 80% for training, 10% for validation, 10% for testing 1140 images: 75% for training, 25% for testing.	KNN 96%. DNN using the TensorFlow framework 98%
[15]	A new CNN composed of three branches that classify the fish species, family and order.	Resized to 224×224 or 299×299 pixels during experiments./ 68 classes	75,806 images	recognition 87.3%. family recognition 93.8%. order recognition, 96%
[16]	Modified VGG16 Deep Convolutional Neural Network (DCNN)	3 classes	Fishbase dataset 530 images, 455 for training, and 75 for testing	99%

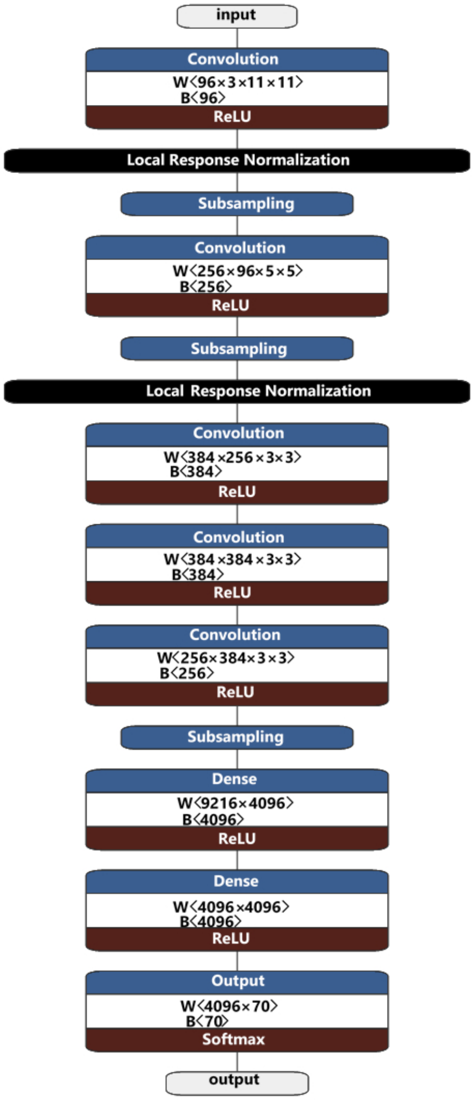

Figure 2: Detailed structure component of CNN

activations after every convolutional and fully connected layer. Java programming was used to develop the system under the Android Studio platform while working in the XML interfaces.

4 RESULT AND DISSECTIONS

In neural networks, many activation functions were evaluated but RELU SOFTMAX was chosen for the main network as RELU to train all layers of the main network and SOFTMAX were selected for the output layer.

The performance evaluation of the deep learning CNN model for the identification of fish species was done based on accuracy, precision, recall and F1 score. The confusion matrix of four possible results values: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) as shown in Table 2 were used.

The CNN model was developed and evaluated on a high-specification MSI device with an 8-core CPU with 3.60 GHz, 32GB of RAM and GPU of 21.9GB.

4.1 Accuracy

Please the model accuracy is the most intuitive performance measure and it describes the ratio of correctly identified fish images to total observations, as shown in Equation (1).

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

For our model, the 0.803 of accuracy was achieved which means the proposed model is approx. is 80% accurate.

4.2 Precision

Precision is the ratio of how many of the positive predictions made are correct to the total positive observations predicted by the classifier as shown in Equation (2). The model obtained a 0.788, which indicate good precision.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

4.3 Recall

Similarly, recall can be defined as the ratio of correctly predicted positive observations to all observations in actual class as formulated in Equation (3). We attain a recall of 0.631, which is considered a good result since it is above 0.5.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

4.4 F1-Score

Lastly, F1-Score is a measure combining both precision and recall. F1-Score is required to seek a balance between Precision and Recall as depicted in Equation (4). Usually, F1 is more useful than accuracy, especially when there is an uneven class distribution. In our case, the F1 score is 0.701.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{recision + Recall} \tag{4}$$

Table 2: A confusion matrix of class classification problem

Actual **Class**	Predictive/Classified		
		Positive	Negative
	Positive Negative	TP	FP
	Negative	FN	TN

Figure 3: The Scan fish interface of the Application

The app was run and tested on different mobile phones, under a variety of Android versions and no issues were encountered. The app enables a user to capture an image of a fish (Figure 3) and then launch the recognition module. The main screen of the application contains a side menu icon which contains a set of buttons, namely; (Profile, Add Fish, Notifications, Settings, Help, Exit), Fish info icon provide fish details that contains all the information about the recognized fish as shown in Figure 4.

5 CONCLUSION

In our methodology, we focused on the Image Processing and deep learning network which allows the recognition of a fish even when part of the fish is missing depending on the three parts (head, body, and tail). The mobile application is developed and achieved good recognition accuracy of 80%. Also during the app implementation, a huge data set were collected which helps other researchers and scientist to benefits from it. The dataset and the recognition considered the fish species that are available in the Mediterranean Sea and local fish market. Therefore, in the future, it is recommended to include more datasets of other fish families rather than the Mediterranean Sea fish family, which enables the app to be used worldwide. Another path for future work is to implement deep learning techniques that can help the customers recognizing the freshness of the fish in the same mobile app.

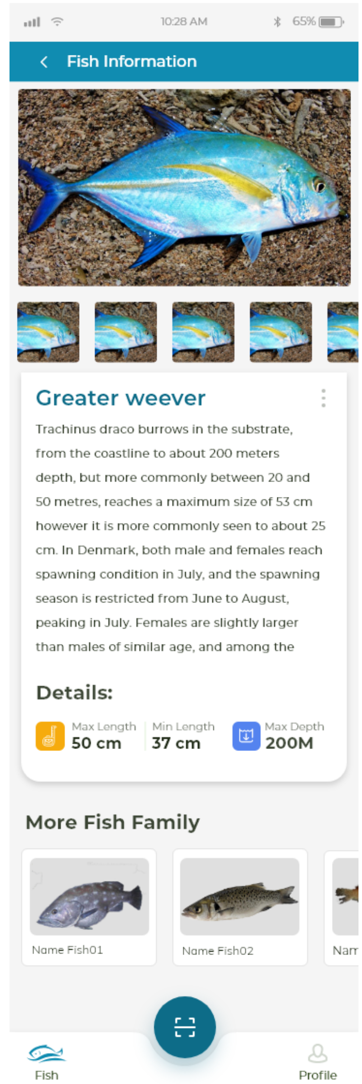

Figure 4: Fish information interface of the App

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