SuperFish: A Mobile Application for Fish Species Recognition using Image Processing Techniques and Deep Learning

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Abstract
People from all around the world face problems in the identification of fish species and users need to have access to scientific expertise to do so and, the situation is not different for Mauritians. An automated means to identify fish species would prove to be a real advantage to different stakeholders namely the government, marine managers, fish farmers, fisherman, fish mongers, boat owners, seafood industrialists, marine biologists, oceanographers, tourists, students and to the public at large. Thus, in this project, an innovative smartphone application has been developed for the identification of fish species that are commonly found in the lagoons and coastal areas, including estuaries and the outer reef zones of Mauritius. Our dataset consists of 1520 images with 40 images for each of the 38 fish species that was studied. Eighty-percent of the data was used for training, ten percent was used for validation and the remaining ten percent was used for testing. All the images were first converted to the grayscale format before the application of a Gaussian blur to remove noise. A thresholding operation is then performed on the images in order to subtract the fish from the background. This enabled us to draw a contour around the fish from which several features were extracted. These include: width of the fish, height of the fish, ratio of height to width, minimum height at the start of the tail, ratio of this minimum height to the height of the fish, distance of this minimum height from the mouth, ratio of this distance to the width of the fish, area of the fish, ratio of this area to the area of the bounding rectangle, perimeter of the fish contour, ratio of this perimeter to the perimeter of the bounding rectangle, ratio of area to perimeter, mean RGB values for each channel (extracted from the original images) and the proportion of pixels in which the red colour (blue and green) is highest. A number of classifiers such as kNN, Support Vector Machines, neural networks, decision trees and random forest were used to find the best performing one. In our case, we found that the kNN algorithm achieved the highest accuracy of 96%. Another model for the recognition was created using the TensorFlow framework which produced an accuracy of 98%. Thus, the results demonstrate the effectiveness of the software in fish identification and in the future, we intend to increase the number of fish species in our dataset and to tackle challenging issues such as partial occlusions and pose variations through techniques such as data augmentation.

Keywords:
fish recognition, computer vision, deep learning, mobile application

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1. Introduction

The term 'fish' refers to a group of aquatic organisms belonging to the Phylum Chordata and including a diversity of groups from Agnatha to Actinopterygii (Keat-Chuan, 2017). Fish have been studied worldwide because of their importance as food, as ornamental, as an important component of diversity, for recreational purposes and also for scientific studies. In all studies, the correct identification of the fish species is of crucial importance. Correct identification is essential for assessment of fish catch and stocks (Llonart et al., 2006) and seafood labelling (Kochzius et al., 2010). Fish identification or fish taxonomy is not an easy task and requires expert knowledge on morphological characters of fish and classification systems. The tools used for fish identification include, body characters and line drawings illustrations. Costa and Carvalho (2007) highlight the difficulties encountered in using phenotypic characters and the peculiarities of taxonomic protocols which constraint species diagnosis. Nowadays, an array of molecular techniques is also used for fish identification such as DNA barcoding (Costa and Carvalho, 2007; Kochzius et al., 2010; Xu, 2019). However, all these methods require expertise, specialized laboratories, are time consuming and costly.

In Mauritius, few people are familiar with identification of fish species. Some of the resources used for fish identification for Western Indian Ocean include information on the Pisces (Essen and Richmond, 2011). In the local context, information on fish species have been reported by Michel (1996). Moreover, there have been several posters produced by the Albion Fisheries Resource Centre and also one field guide edited (Terashima et al., 2001). However, knowledge on fish identification is sparse. Fish taxonomy requires scientific knowledge and ability to recognize the morphological characters of fish to be able to identify fish species. For Mauritian waters some of the scientific guides include the FAO reports (section 51) and also some information can be retrieved from FishBase (Froese and Pauly, 2017). However, there is no automated quick recognition system for fish species that are commonly found in Mauritian waters.

Eventually, having an automated means to identify fish species would prove to be a real advantage to different stakeholders namely the government, marine managers, fish farmers, fisherman, fish mongers, boat owners, seafood industrialists, marine biologists, oceanographers, tourists, students and to the public at large. Tourism is one of the pillars of our economy and marine ecotourism a growing sector (Ragoonaden, 2016), with sustainable ecotourism a new trend to be adopted. Such knowledge on fish species will be useful to tourists in the context of promoting marine ecotourism. Further development and scientific research in the field of automated fish identification can lead to development of tools which can be applied to study fish in their natural environment (Zhuang et al., 2017; Villon et al., 2018).

This paper proceeds as follows. In the next section, we provide an overview of recent works that have been done on fish recognition using computer vision and machine learning techniques. The methodology is described in section 3 while the implementation details are provided in section 4. Section 5 describes the results and their evaluation and section 6 concludes the paper with some ideas for future works.

2. Literature Review

One of the earliest works in the field of automatic fish species recognition was done by Strachan et al. (1990) who primary relied on geometric shape descriptors to identify the fish species. The outline of the fish was manually traced using a digitiser after having photographed them on a white surface. The procedure to create the fish templates was highly manual. Using this approach, there were able to reach an accuracy of 90% on seven different fish species. Storbeck and Daan (2001) have used a neural network to classify six different fish species with an accuracy of 98%. Fish contours were the primary information about the fish that were fed to the neural network, which consisted of two hidden layers.

Alsmadi and Bin Omar (2010) developed a feed-forward neural network classifier for fish recognition by performing image segmentation based on colour and texture information. The database consisted of 610 fish images from 20 distinct fish species. The training set consisted of 500 images while the testing set has 110 images. The best accuracy of their system was 90%. Benson et al. (2009) created an automated fish identification system based on a 16-stage Haar classifier with 83 features. Their dataset had 1077 positive images and 2470 negative images. The recognition accuracy was found to be 92%.

Colour and texture information were used by Hu et al. (2012) to categorise 540 fish images into six different fish species. The images were captured by a smartphone and sent to a remote processing lab via MMS. All the processing was done on a desktop computer running the Matlab software. The skins of the fish were manually extracted from each image from which colour and texture information were extracted. The researchers found that a wavelet-based feature extractor had the best performance compared to a statistical texture extractor and a colour extractor. Three different variations of support vector machines (SVM) were used as classifiers. An accuracy of 98% was achieved with the voting-based one-against-all multi-class SVM.

Singh and Pandey (2014) proposed a framework for image retrieval using artificial neural networks. Their aim was to identify the D. Macrophthalmus fish species from other fish species. The dataset consisted of 175 images (856 x 804 pixels) of which 100 were used for training and 75 for testing. Only seven fish species were considered in this study. An accuracy of 97.4% were obtained. Pornpanomchai et al. (2013) conducted their experiments on 30 fish species with 30 images for each fish species. 600 images were used for training and remaining 300 as testing. The k-Nearest neighbour algorithm produced an accuracy of 81.7% while the ANN was 99.0% accurate.

Li et al. (2015) have used a fast R-CNN in order to recognise fishes from underwater images. The images were obtained from the ImageClef 2014 database. An average recognition accuracy of 81.4% was obtained for 12 species. Their approach was also considerably faster than existing ones. Nasreddine and Benzinou (2015) have used shape outlines only for fish recognition. Experiments were conducted on the SQUID database (Abbasi et al., 2002). This is a database which consists of 1100 shapes of marine species. They showed that their approach performed better than traditional shape matching procedures. The proposed method is also independent of translation, scale, rotation and initial point selection.

Salimi et al. (2016) described a fully automated fish species recognition based on otolith contours using the Fourier transform and discriminant analysis. The proposed system was tested on 14 different fish species from three families and the overall classification accuracy was found to be 90%. The dataset consisted of 392 fish images with 252 of them being used for training and the rest for testing.

Using shape, colour and texture information and a random forest classifier, Saitoh et al. (2016) performed fish recognition on 11 different orders of fish. The average order-level accuracy was 62.9%. This shows that fish recognition from live images in uncontrolled underwater scenes is still a very challenging problem. Their dataset consisted of 129 different species. The authors also report a recognition accuracy of at least 80% for 55 species. Even fish from the same species differ in terms of appearance and shape based on the development stage (i.e. young, adult and senility) and gender. They also found that in underwater images, geometric features are more important than colour and texture features.

In an attempt to recognise invasive fish species, Zhang et al. (2016) modified a general object recognition framework known as Evolution-Constructed (ECO) features to classify eight different fish species from a dataset of 1049 images. The images were captured using a professional camera on a uniform background. An average classification accuracy of 98.9% was obtained using an Adaboost classifier. The strength of their work resides in the fact that their algorithm extracts the relevant features automatically from the fish and no manual intervention is required for any pre-processing tasks.

While most existing works have focussed on the analysis of dead fish from static images, Shafait et al. (2016) have developed a new procedure with can be used to identify fishes from uncontrolled underwater videos, using state-of-the-art computer vision and machine learning approaches. Previous approaches have used only single frames to identify a fish ignoring the fact that the same fish will be present in several continuous frames in a video sequence. Shafait et al. (2016) exploits this information and uses an image set-based approach based on the principles of the k-nearest neighbour algorithm for fish identification. They tested their algorithm on images obtained from the ImageClef 2014 database. Despite the challenges of underwater conditions, they obtained an overall accuracy of 95% on 10 fish species. Without doubt, this is one of the most promising works in this field and has huge potential for fish identification for video data.

A deep learning approach based on a convolutional neural network was used by Qin et al. (2016) to classify images from the Fish Recognition Ground-Truth (FRGT) dataset produced as part of the Fish4-Knowledge (F4K) project (Boom et al., 2012). This dataset consists of 27,370 fish images classified into 23 fish species. However, the dataset is a highly imbalanced one as one fish species had 12112 images while another one had only 16 images. Several deep learning architectures based on convolutional neural networks were implemented using the Caffe framework. An accuracy of 98.64% was obtained with their best model. This was achieved by replacing the softmax layer by a linear SVM classifier, although the improvement over softmax was minimal. Working on the same dataset, Ben Tamou et al. (2018) achieved a near perfect accuracy of 99.45% through transfer learning based on the pre-trained AlexNet CNN. They confirmed the superiority of SVM over softmax in the last layer, especially where the number of training instances is very small.

Ding et al. (2017) have proposed three CNN models based on convolutional neural networks to classify four different species of fish. Their dataset consists of 22437 images out of which 16800 were used for training and 5637 were used for testing the models. The images were obtained from underwater videos and is a subset of the FRGT dataset. However, they have used images only for the four most common fish species. Their best model delivered an accuracy of 96.55%. All their experiments were performed on the Matlab platform.

Deep learning methods have been used for the recognition of coral reef fishes from underwater videos and images (Villon et al., 2018). They created their own dataset of 44,625 images in the training set and 4405 images in the testing set by using fixed underwater cameras. Twenty different fish species were present in this dataset. The mean identification success rate was about 87% for each variation of the dataset. Augmenting the dataset with segments of fish slightly improved the accuracy. The performance of the convolutional neural network model was also compared with that of humans. On a sample of the images, it was found that the accuracy of the CNN was about 6% better than that of humans. Also, on average the humans took 5s to classify one fish whereas their CNN model took only 0.06s.

Because of the difficulties to collect image data on species such as the blue whiting, Atlantic herring and Atlantic mackerel, Allken et al. (2018) have augmented their dataset with synthetic data of fish images. These were generated by randomly selecting a cropped image of a fish and placing them on empty background, i.e., images in which there are no fish or other objects. To further augment the dataset, the images were rotated, translated, sheared, flipped and zoomed. Using synthetic data, the accuracy of the best CNN model reached up to 94.1% while the best CNN model trained on real images produced an accuracy of only 71.1%. Thus, the authors demonstrate that it is possible to overcome the challenge of the lack of data by generating synthetic data from real images.

Khalifa et al. (2019) have used four different deep learning models to identify eight different fish species. One thousand two hundred and forty-four images from the QUT dataset (Anantharajah et al., 2014) were used for training and validation. These fish images were captured underwater with no control on the illumination or background. This dataset is an imbalanced one as the fish with the least number of training images was *Bodianus* with 64 images while the fish with the largest number of training images was *Lutjanus* with 204 images. Testing was done on 277 images from the LifeClef2015 dataset (Joly et al., 2015). The deep convolutional neural network proposed by the authors achieved an accuracy of 85.6% while AlexNet, VGG-16 and VGG-19 had an accuracy of 85.4%, 87.9% and 89.9%, respectively.

3. Methodology

The aim of this study was to develop a mobile application for the identification of fish species which are found in Mauritian waters. Since such a dataset is not available, we had to create our own dataset of fish images. Thus, we collected images for 38 different fish species. Images were mostly taken from open fish markets that are available around the island in coastal regions. For each fish species, 40 images were taken with a smartphone whose resolution was 2048 x 1152. Thus, our dataset consists of 1520 fish images. As far as possible, the fish were placed on a white or uniform background before the images were taken. The list of fish is provided in the Appendix.

Two different approaches were used for the automatic recognition of the fish species. The first one relied heavily on a traditional image processing pipeline, involving a number of pre-processing steps which were performed automatically with no human intervention. A number of features are extracted from the images which are then fed to a traditional machine learning classifier. The second approach involved the use of a deep learning algorithm in which no pre-processing steps are required except for a resizing operation. The images are then simply fed to the classifier.

In the traditional image processing approach, an image (Fig 1.) is first converted to the grayscale format (Fig 2.) followed by a Gaussian blur operation in order to remove image noise and to smoothen the image by reducing image details. A binary thresholding operation is the applied on the grayscale image to obtain a binary (black and white) image (Fig 3.) from which the fish contours can be extracted. The contours are then overlaid onto the original fish image (Fig 1.) and pixels outside the contours are made transparent. The result is shown in Fig 4. Next, the image is cropped to remove any extra background. In other words, the fish is fitted to the smallest rectangle that can contain it.

Fig 1. Original fish image

Fig 2. Fish image in grayscale

Fig 3. Fish image after thresholding

Fig 4. Extraction of contours

The following features are extracted from this cropped image: width of the fish (same size as the width of the bounding rectangle) as shown in Fig 5., height (same size as the height of the bounding rectangle) as shown in Fig 5., ratio of height to width, minimum height at the start of the tail as shown in Fig 5., ratio of this minimum height to the height of the fish, distance of this minimum height from the mouth as shown in Fig 5., ratio of this distance to the width of the fish, area of the fish (number of pixels within the fish), ratio of this area to the area of the bounding rectangle, perimeter of the fish contour (number of pixels on the contour), ratio of this perimeter to the perimeter of the bounding rectangle, ratio of area to perimeter, mean RGB values for each channel (extracted from the original images) as shown in Fig 6., proportion of pixels in which the red colour is highest, proportion of pixels in the blue colour is highest and the proportion of pixels in which the green colour is highest.

Fig 5. Height and width of a fish

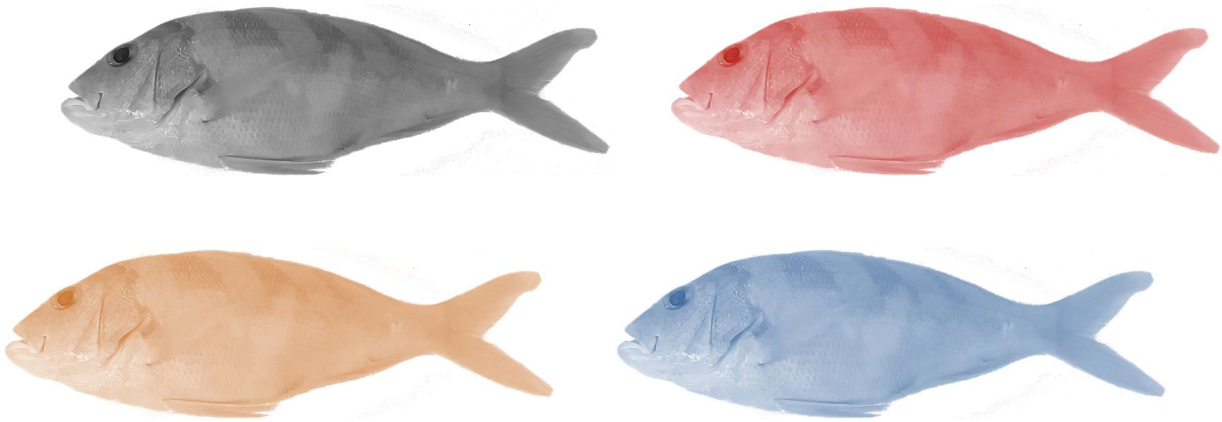

Fig 6. Fish image in grayscale, red, green and blue channels

4. Experiments, Results and Evaluation

All the programming to build the fish recognition system was done using Java running on the Android Studio platform. The image processing steps were carried out using the OpenCV library for Android while the Weka library was used for the traditional machine learning algorithms. The TensorFlow library was used for running the deep learning algorithms. It an open-source library for creating AI applications. It makes use of data flow graphs in order to build its models.

Experiments were conducted with five machine learning algorithms and the results are shown in Table 1. The default parameters were used for each classifier. Seventy-five percent of the images were used for training while the remaining twenty-five percent were used for testing. In other words, 30 images from each class were used for training while the remaining 10 images from each class were used for testing. The results show that kNN had the highest accuracy of 96%. Random Forest and MLP (a type of artificial neural network) which are respectively at the second and third places, but very close to kNN. The accuracy for Naïve Bayes was above 90% while SVM showed the worst performance. On average, the classifiers took about 1 second to return a prediction.

Table 1. Experiments with traditional machine learning classifiers

#	**Classifier**	**Accuracy (%)**
1	k-Nearest Neighbour (kNN)	96
2	Random Forest (RF)	95
3	Multilayer Perceptron (MLP)	94
4	Naïve Bayes (NB)	91
5	Support Vector Machines (SVM)	85

Another prediction model was built using a deep learning network (DNN). For this purpose, we have used a pre-trained Inception-v3 deep learning model which has been developed at Google (Szegedy, 2015). The Inception-v3 model consists of 42 layers which were trained on 1 million images from the ImageSet dataset. A new layer was added to recognise fishes. The concept of using information obtained from training on one dataset and applying it to another dataset is known as transfer learning. All the images were resized to 299x299 pixels because the computing requirements are remarkably high for such a deep network. Similar to the first approach, 75% of the dataset was used for training and 25% was used for testing. In other words, a total 1140 images were used for training and 380 images were used for testing. 372 out of these 380 images were correctly identified by the deep learning model which converts into an accuracy of 98%. Thus, we can see that the deep learning algorithm gave a slightly better performance than all the traditional machine learning classifiers, but it took about 10 seconds to return a prediction. We found that the deep learning algorithm is more robust with respect to changes in lighting conditions. Moreover, the deep learning algorithm has the potential to recognise a fish even when part of the fish is visible while the first approach is tied-up the shape of the fish. If the shape is not correctly extracted due to shadows, poor lighting conditions or multiple overlapping fishes, all the dimensions and the ratios will not be corrected calculated and the classifier will perform very poorly.

Since the deep learning model had the highest classification accuracy and it is also more robust, it was integrated into the SuperFish mobile app so that there no access to the cloud (internet) is required once the app is downloaded/installed on a smartphone running the Android operating system. The app has three main functionalities. Firstly, it enables a user to take a picture of a fish and then launch the recognition module. Once the fish is identified, a pre-stored image of the fish is displayed in an overlaid window together with details such as its Mauritian name, its English name and its scientific name as shown in Fig. 7. Other information such as its feeding habits and usual habitats are also mentioned. Secondly, instead of using the phone camera to take fish images in real-time, a user can also select a pre-captured fish image from his phone's gallery and then make a prediction. And finally, the user can search the list of fish that are available in the dataset.

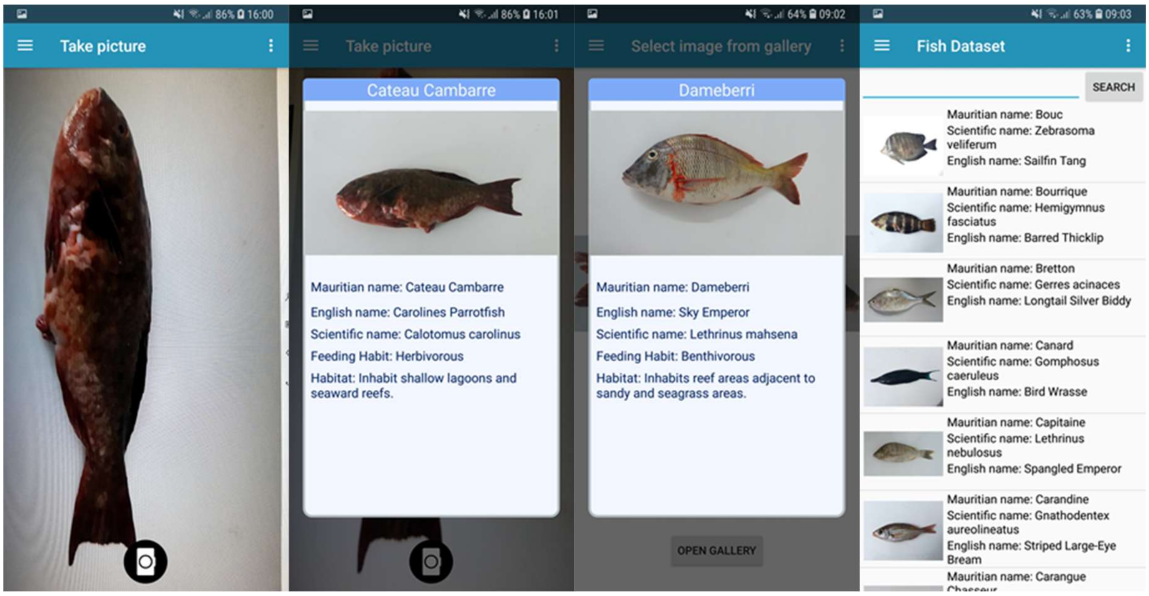

Fig 7. The SuperFish Mobile App

It is difficult to offer a fair comparison with other works that have been done in this field because the datasets are different in most of these works. There are different types and species of fish in different parts of the world and therefore the datasets are significant different from each other. Furthermore, the datasets also differ in the number of species being considered and the number of images taken for each species. In the last few years, there has also been a switch from static over-water images to dynamic under-water images and videos which makes the recognition an order of magnitude more difficult. Nevertheless, we provide a comparison of our work with some of the existing works. To our knowledge, our dataset is the biggest one in terms of the number of species that is being recognised. From the literature we saw that most research have been done on a dataset of 20 species or less (Alsmadi et al., 2010; Mushfieldt et al., 2012, Siddiqui et al, 2018). It is a well-known fact that the higher the number of classes in a computer vision task, the identification becomes more challenging. Even with 38 different species, we report the highest classification accuracy on static over-water images. Alsmadi et al. (2010) obtained an accuracy of 97.4% on a dataset of 20 species using a shape-based computer vision approach. Using an image set-based approach, Shafait et al. (2016) achieved an accuracy of 95% on a dataset of 10 different fish species in uncontrolled underwater environments. Using and state-of-the-art deep learning architectures, Siddiqui et al. (2018) achieved an accuracy of 94% on a dataset of 16 different fish species in underwater videos.

5. Conclusion

In the last decade, various attempts have been made to develop a fish identification system by using computer vision methods based on shape, texture and/or colour information and machine learning techniques. However, each of these proposed methods have their own shortcomings. Most of them have difficulties with changes in lighting conditions and they are not able to recognize the object when part of it is missing or occluded. The novelty of our approach lies in the fact that we are using a smart-phone app to identify fishes in real-time and without the need for an internet connection. Once the species is identified, the user is provided with additional information on that fish. Using a deep learning neural network allows the recognition of a fish even when part of it is hidden. The DNN is also very robust with regards to changes in brightness. Since the original images were augmented during the training phase, the DNN can also deal with rotated images. Furthermore, the DNN can even recognize fishes even from printed fish images or from computer screens. We have been able to achieve an impressive recognition accuracy of 98% on our dataset of 1520 images from 38 different fish species. In the future, we intend to increase the dataset by increasing the number of fish species and the number of training images in order to further increase the accuracy. Other deep learning architectures may also be investigated to find a better one either in terms of accuracy or shorter prediction time.

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