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Inspiring Excellence

Monitoring of Endangered Fish Using Image Processing and AI Tools

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We would like to dedicate this thesis to our loving parents …

Declaration

It is hereby declared that this thesis /project report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

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Abstract

Marine life constitutes half of earth's total biodiversity. But preservation and monitoring of them efficiently face setbacks largely due to technological limitations and economic reasons. Technological challenges include lack of effective image processing methods curtailed to underwater environment. Underwater image processing, object detection and classification have always been a challenge to accomplish through traditional methods. The methods including sonar radiation produces results, but they are nowhere near economical or accurate as intended. Alternatively, research has been conducted in solid and stationary object detection. Combining the knowledge of the already existing researches done in object detection, in this thesis, we compare performances of various classification algorithms using the data extracted from images of fishes taken in various luminous conditions. For this paper we will only consider large to medium sized fishes but exclude other non-chordate bio-life. The first step is to prepare the images for suitable feature extraction.The next step is to extract suitable features from the available images of the dataset.The next step is to classify the fishes through four different classifiers (SVM, KNN, NB and Random forest classifier) on the basis of the features we have extracted. Lastly we compare the relative performances of these classifiers.

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List of Abbreviations

Acronyms / Abbreviations

ANN Artificial Neural Network

ISV Intersession Variability

KNET Deep Neural Network

KNN K-Nearest Neighbor

LDA Linear Discriminant Analysis

NB Naive Bayes

PCA Principle Component Analysis

RF Random Forset

SVM Support Vector Machine

Chapter 1

INTRODUCTION

1.1 Motivation

Loss of marine lives is a huge loss to a country's biotic community as well as economy. Although in recent years governments are adapting pro-environment policies, the unintended consequences of past actions have already caused irreparable damages. Without fast technological intervention the recovery will prove to be elusive for a long time. For this reason, through this thesis we wish to contribute to the marine live preservation research community, so that in future scopes of further research in this field increase and attain visibility creating awareness [12]. Through studying already existing research papers, we came to realize feature extraction and filtering is of utmost importance for an object detection method to function to its fullest [26]. Thus, we acquired both underwater and above ground fish images and extracted features to use in the aforementioned classifiers to compare their relative performances. In the future, we would like to use different sets of combination of features to increase the classification accuracy[22].

1.2 Thesis overview

The primary purpose of fish species behavior observation is to gain practical knowledge about the ecological system. Distribution of fishes is a valuable indicator of the change in biotic environment [31] at any given time. It also enriches the knowledge the current researches are providing. The source of these reliable data can be obtained either through videos or through still images[16]. A Large amount of data increases the probability of more accurate pattern recognition. Although a large dataset is a necessary parameter in successfully classification of fishes, there are other factors that largely affect fish species classification; for example, noise, segmentation error, distortion etc. [8].Inconsistent lighting and sediments also degrades the color of the water, as such simple background subtraction approach becomes toilsome. In the end, machine learning and state of the art algorithms rely heavily on shape and texture feature extraction matching [25]. For our Classification we used the same dataset that a WACV 2014 paper used[32] and required feature vectors were obtained through image pre-processing. Features were extracted using Harris corner detection method. Through the use of Euclidean geometry the descriptive feature vectors such as length of the fish, width of the fish, angles of mouth position, angles between tail,mouth and fins etc. were calculated to be fed into the four classifiers. Before the pre-processing, the images' sizes were adjusted to be of the same size.The images,originally in RGB format, were converted to grayscale image.

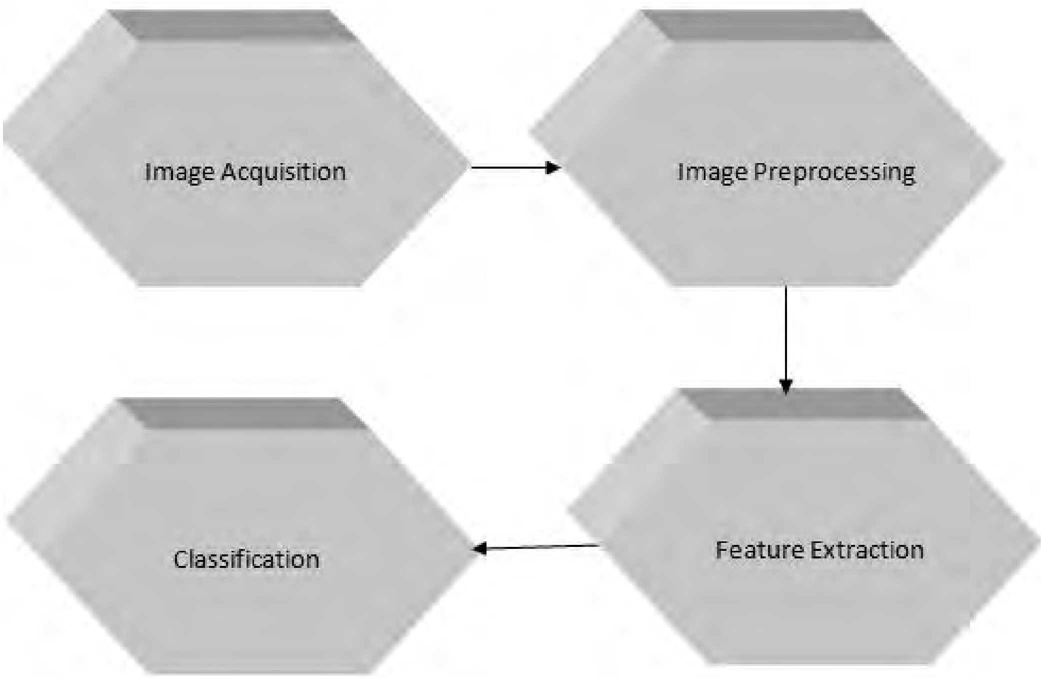

Fig. 1.1 The Block Diagram of Fish Classification system

In figure 1.1 it is shown that through image pre-processing we extract the desired features. We used OpenCV platform and Python programming language for feature extraction. The four classifiers namely SVM, KNN, NB and Random Forest classifier all will work on the same features, in a supervised manner and produce outputs for us to compare.The process of feature extraction and image pre-processing in this thesis will be discussed broadly in chapter 4.

1.3 Thesis Orientation

The following sections of this thesis paper have been organized as follows. Chapter 2 reviews current research done in this field. Chapter 3 provides an overall analysis of the core foundation of this research. Chapter 4 introduces the proposed method for identifying and classifying fishes. Chapter 5 elaborates on the experimental results. Finally, Chapter 6 concludes and summarizes the report.

Chapter 2

LITERATURE REVIEW

Although in recent years object detection and facial recognition technology is gaining rapid momentum, there are still challenges to overcome. The primary obstacle in object detection is redundancy of a large volume of data [1]. We can get data through two medium:

1. Static.
2. Dynamic.

Still images are static and needs no motion correction, which in case of processing dynamic images, that is images acquired from video sources, is an absolute necessity to maintain temporal coherence of the images [17], [24].To reduce data the idea of image pre-processing is used. Images can be pre-processed in various ways, which includes data compression, image enhancement, segmentation, morphological processing, wavelets and multiresolution processing etc.

We have come upon researches that enhance underwater images by the correction of white-balance and saturated colors.[3] Here the cause attributed to the degradation of color is scattering of lights under water. From the degraded images, two processed image is selected and fused together, a process that is termed as multiscale fusion strategy, to form an input in the neural classifier. The benefit of this method is that it does not require the algorithm to consider the background medium. Also this algorithm is independent of any light intensity; during nighttime it has no added disadvantage.

In another method [8], static object detection in underwater environment is developed, which uses color compensation strategy to enhance the images before the pixels go into an artificial neural network system. The AI system classifies real time pixels into different categories that include different objects present in the scene. Finally, intuitional shape reasoning is used to discriminate the false objects and to promote accuracy.

Since methods for object detection are vast, there are some non-conventional methods that do not use supervised learning for object detection [32]

Such a method performs the detection task by background modeling and on the basis of motion information [34]. In this method motion segmentation is of utmost importance [23]. The frames of the videos are vectorized and represented through a low-rank matrix. The framework used here is unified Detecting Contiguous Outliers in the Low-rank Representation (DECOLOR) which simultaneously detects object and estimates motion.

In terms of fish detection and classification research, there has been a lot of trial and error approach. No single approach has guaranteed definite success. With the advent of deep neural network and similar classifying algorithm pattern detection has been easier than before. For instance in S.O Ogunlana et. al [20] Support vector machine algorithm was used to classify a total of 76 fishes with 78.59% accuracy. The features used in this paper were shape of the fish. Using the same shape feature and adding a texture feature and feeding the data-set through ANN on a training set of 600 images and test set of 300 images 99% accuracy was obtained [21].Also, 91.65% accuracy was achieved using Artificial Neural Networks for the automatic identification of species on a data-set of 697 images[10]. Although these experiments achieved high accuracy through the use of ANN, ANN sometimes may not cater to human specification.

In another paper [19] Takakazu Ishimatsu et al. used two identification features: speckle patterns and scale forms of fish. For classification morphological algorithms and filters were used. The accuracy of detecting three species namely Pilchard Sardine, and Common Mackerel and Japanese Horse Mackerel were 90%, 90% and 88% respectively.

Using SIFT feature extraction [7], Gabor filter extraction [13] the classification achieved 92% accuracy for the first case and 80.3% and 70.6% accuracy for the second. For the first experiment only a 6 species with a total of 162 images were considered to use in PCA. The second experiment made use of 200 images of two species of fish in a non-uniform colored background. Proposing to use shape analysis for filtering out the redundant edge points, D. J. Lee et al.[**?**] used 22 images of nine fish species in curvature function analysis algorithm.

Invariant points, points which do not change with respect to the orientation of the image, were selected through this method to determine the features for classification.

There has been studies showing deep neural network can achieve better result than conventional classifiers like SVM [14]. One of the reasons for this could lie in the internal architecture of both classifiers. While deep neural network builds its feature through its in built optimal feature extractors, SVM is more susceptible to human errors. In the following table 2.1 we can see and compare the results of few studies done on fish recognition and classification.

Table 2.1 Studies on Fish Classification through Different Methods

Study	Method used	Data set	Percentage
[15]	Shape feature, SVM classifier	76 Fish images	78.59%
[16]	Shape and texture feature, EDM, KNN classifier	600 training image,300test image	81.67%,99% respectively
[17]	Speckle pattern, scale form feature Morphological algorithm and filter	3 Species	90%,88% and 90% respectively
[18]	Automatic identification, ANN	697 images	91.65%
[19]	SIFT feature,PCA (Principal component analysis)	6 species, 162 images	92%
[20]	Gabor filter	2 species,200 images	70.6%

In the following chapter, the basics of feature extraction used in this research will be discussed.

Chapter 3

BACKGROUND ANALYSIS

3.1 Image Pre-processing

Before using images for object detection, in order to be able to manipulate data more efficiently, redundant data need to be curtailed. Generally it is known as image pre-processing. Few of the reason that may necessitate image pre-processing include inclusion of noise in images resulting in suppression of attributes necessary for machine learning algorithms. There are many pixel position dependent and independent operations [28] such as grayscale transformation, brightness correction and gamma correction. Histogram equalization, the process through which contrast of the image is improved to obtain a uniform histogram, is also a very important part of image processing.Moreover,there are different kinds of filtering process which convert the image brightness to another set of brightness for specific purposes of the intended experiments. For this thesis paper we do grayscale conversion to reduce the set of pixel points of the fish in the image through corner detection method . The pre-processing of the images can be divided into four stages.They are:

1. Size adjustment.
2. Dimensionality reduction.
3. Corner detection.

3.1.1 Size Adjustment

We have 100 images from which we need to extract features for classification. It is seen that in a lot of image the fish is not placed centrally. In fig 3.1 a fish is placed perfectly horizontally with uniform brightness. Generally in a database, there may be rotational image of fish bodies which create more difficulties for successful detection. Furthermore there is a possibility of noises being present in the background in the form of coral reefs, plants and dirt. To ease our experiment we used a data-set which contains images in controlled environment, having a constant uniform background with controlled illumination. Machine learning algorithms respond best to images having the same attributes and sizes. The images are readjusted through the method of compression. Although few pixels are lost and relapsed, all the images become the same size thus increases the probability of successful classification.

Fig. 3.1 Readjusted fish image from the training dataset

3.1.2 Dimensionality Reduction

Currently there are abundant researches going on in dimensionality reduction. Two of them are Principal component analysis (PCA) [18] and Linear Discriminant analysis (LDA) [11], [27].Gradient oriented dimension reduction for object detection from image has also been proposed [30]. For our problem at hand, it is seen that features cannot be efficiently extracted from the images of current data-set through few trials. The solution to this is to filter out the unnecessary background pixels as shown in figure 3.2 .For this reason, the RGB images is converted into a gray-scale images.The formula used for conversion is as following :

$GR = .0.299 * R + 0.587 * G + 0.114 * B$..........(i)

Where,

- GR = Gray
- R = Red
- G = Green
- B = Blue

Fig. 3.2 Gray-scale image of fish converted from RGB

Corner Detection

Although the dataset we are using have been curtailed to our specification as much as possible, to ensure that the features we extract is optimal for the machine learning algorithms, we chose to use a feature extraction method that is rotation, scale and illumination variation independent. Harris corner point detector is such an extracting method. The equation that is used to detect the corners is given by-

$E(x,y) =_{(} x,y)w(x,y)[I(x+u,y+v)-I(x,y)]^2$..........(ii)

Where,

- E =the difference between the original and the moved picture.
- U= the picture's displacement in the x direction.
- V= the picture's displacement in the y direction
- w(x, y) = the picture at position (x, y).

- I = the intensity of the image at a position (x, y).
- I(x+u, y+v) = the intensity of the moved picture.
- I(x, y) = the intensity of the original picture.

3.2 Fish Classification with Various Algorithms

Machine learning is the study that aims to solve specific problems that arise when manipulating a large amount of data in order to make prediction or perform a task without being programmed for it. It builds a set of training data to perform analytic task on a large amount of information.The training process can be done in two ways:

1. Supervised.
2. Unsupervised.

Supervised algorithm is used when the output is already known. Unsupervised algorithm uses method of clustering to output a result that has desired output attributes. For this paper we are considering both supervised and unsupervised learning method.Table 3.1 provides a list of such algorithms.

Table 3.1 List of supervised and unsupervised algorithms

Supervised	Unsupervised
KNN	ANN
Random Forest	
SVM	
NB	

3.2.1 Fish Classification using SVM

Fig. 3.3 Training Thumbnails from the MARBEC database

On a database of 8 species SVM were used. The database is shown below in Table 3.2.

Table 3.2 Fish species in the learning database

Species	No. of images
Acanthuruslineatus	493
Acanthurusnigrifuscus	1455
Chromisternarensis	951
Chromis/viridis	523
Ctenochatusstriatus	1400
Pomacentrussulphureus	766
Pseudantthiassquamipinnis	1180
Zebrasoma scopas	488

The Support Vector Machine (SVM) [9] is a supervised method to classify feature vectors. SVM method represents each vector in a high dimensional space, mapped separated by a hyperplane representing class separation boundary. Support vector machines is a very reliable classifier that has shown good result in many problems [6], [33]. In the research [29], the thumbnail features were used as an input of the SVM. The SVM separates the classes, which can be represented by the following figure3.4.The principle of the SVM algorithm is to find the optimal distance from the hyperplane separating the the two classes that needs to be classified.

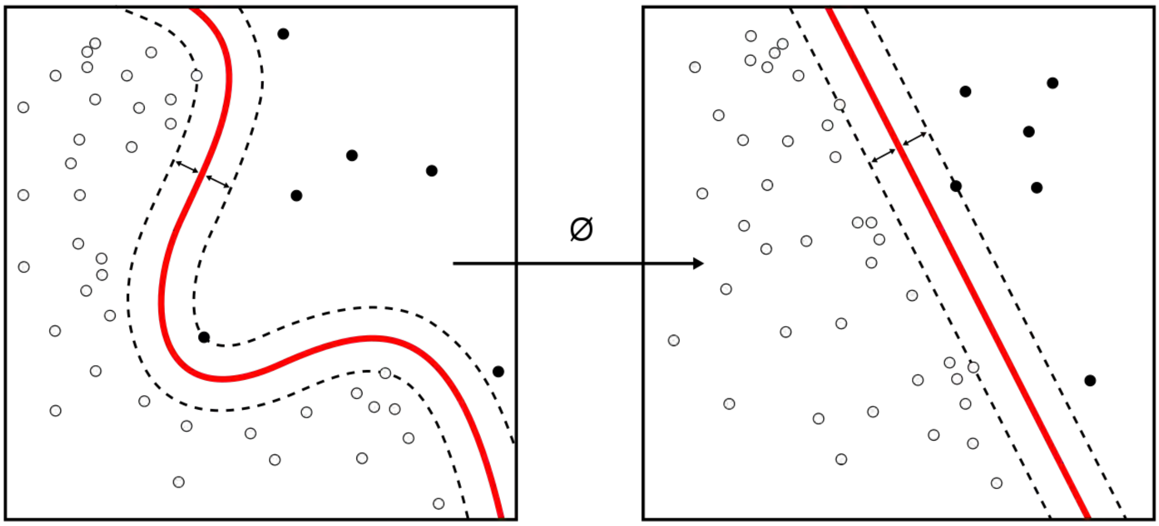

Fig. 3.4 Input spaces and feature extraction using SVM

3.2.2 Fish Classification using Deep Neural Network

Deep neural network is able to both built feature vector and classify them, DNN or CNN. It functions like mimicking human brains [15], [29]. A neural network is composed of interconnected nodes called neurons and each neuron of each layer receives a signal from the neurons of the previous layer. This signal is modified according to an activation function and transferred to the neurons of the next layer. The first layer and the last layer which receives input are hidden and are called hidden layer. Since it is an optimization process, the parameters keep changing and may not produce the same result to the same input in every instance. GoogLeNet architecture [29] is used to reduce the dimensionality and perform classification. The result of the classification of fishes of MARCBEC database was shown to reveal that deep neural network performs significantly better at fish recognition and classification than SVM [9].

Chapter 4

PROPOSED MODEL

For data-sets we are considering a controlled set of data. The data set contains images of fishes with background having both constant and varying luminous state and also underwater images of various species for fish recognition training. We obtained the data-sets from [2]. This data are used for WACV 2014 paper "Local Inter-Session Variability Modelling for Object Classification". Baseline classification results can also be found in this paper [4].Although there are also other data-sets available containing more images, these are more catered to our needs because:

1. It doesn't contain other species such as octopuses or mollusks.
2. It contains fish in both in and out of the water state.

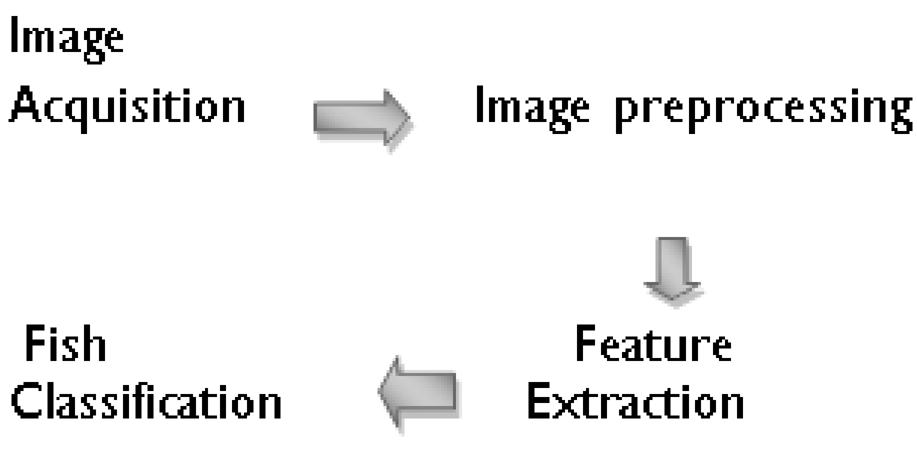

Fig. 4.1 Workflow of the Proposed Model

Since we are only considering chordates, this data-set is appropriate for this paper.

4.1 Data Description

In this research, the Robotic@QUT Dataset [2] is used as the source of fish images. This dataset was used for a WACV 2014 paper [5]. The experiment was carried out underwater and had a total fish image of 3960. There are a total of 468 species.

Fig. 4.2 Acanthaluteres Vittiger, Achoerodus Gouldii and Acanthopagrus Berda Respectively

Fig 4.2 and table 4.1 represents 3 of the species included in the Robotic-QUT dataset. The fish images were taken in three conditions-

1. Out of the water in varying lights with objects in the background.

2. Out of the water in varying lights with constant background.

3. Underwater.

Table 4.1 Few Species name of the used dataset

Species name	No. of images
Acanthaluteres Vittiger	10
Achoerodus Gouldii	40
Acanthopagrus Berda	35

If the fish images contained rotational images, we would have needed to pre-process the data. Since this dataset already contained fish out of water and underwater with varying lighting, we decided to work with the already pre-processed data file.During feature extraction, the selected images were fed into the batch feature extractor, and the output was a matrix of invariant corner pixels on the fish. The corner pixels were then used to determine the angles and length required to build descriptive features.

4.2 Feature Extraction

We extract six total features from the points detected by the Harris Corner Detection method. The points are named as P1, P2, P3 and P4.These points are used to calculate descriptive features of the fishes.

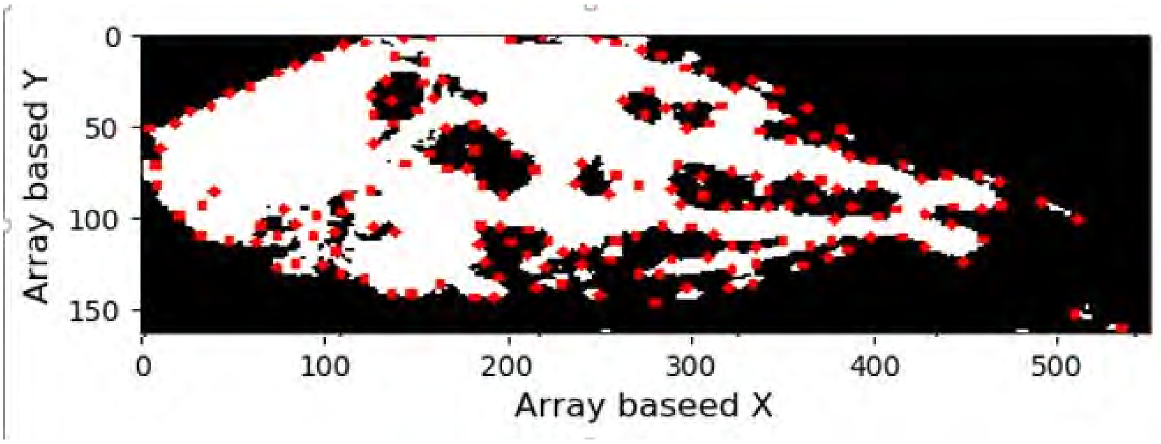

Fig. 4.3 Data points acquired through Harris Corner Detection method

In the figure 4.3 the points along the corners of the fish body is plotted in color red. From these points the rightmost, leftmost, topmost and the bottommost points are extracted. Let the uppermost point be P1, bottommost P3, rightmost P2 and the leftmost P1.For P5,P6,P7 and P8,the points are taken as being between two points. It is observed that to the rightmost corners two isolated points are located. For this paper, we will discard any seemingly isolated discontinuous point and also no two points will be the same. The unique points are necessary to formulate a definitive feature of the fish which will be discussed shortly.

Table 4.2 List of features extracted

Points Selected	Features Extracted
P1	Length
P2	Width
P3	Deg1(angle between upperfin,mouth,lowerfin)
P4	Deg2 (angle between upperfin,tail,lowerfin)
P5	Deg3 (angle between,(Mouth,upperfin,tail)
P6	Deg4(angle between upperfin,Mouth,lowerfin)
P7	D1,D2,D3,.......D8[D=distance between any two points]
P8	

Table 4.2 shows us the features that is needed for the fish classification. These features are a function of the points P1, P2, P3, P4, P5, P6, P7 and P8.

Length and width is calculated using the formula –

$((x2-x1)^2+(y2-y1)^2)$.........(iii)

The method used: defcalculateDistance(x1,y1,x2,y2): dist = math.sqrt((x2 - x1)**2 + (y2 - y1)**2) return dist

Degree is calculated using the formula –

$cos = ((a^2+b^2-c^2))/(2ab)$..........(iv)

The method used: def angle (a, b, c): return math.acos(((a**2) + (b**2) - (c**2)) / (2 * a * b))

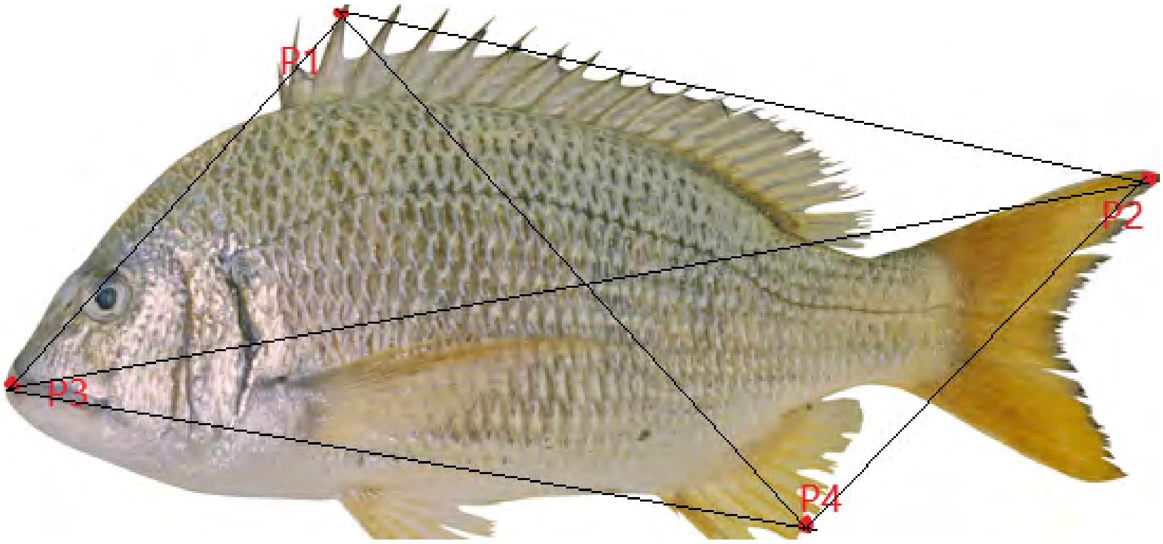

Fig. 4.4 Length, width and angle derivation through data points

From Figure 4.4, the calculations are done by measuring distances and angles between four points detected by the Harris Corner detection method.

4.3 Fish Classification

The features are saved in a .csv file as shown in fig 4.4 and used as an input to the four algorithms.In the result section we compare the results of the fish classification. We used 80% of the images as training set and the remaining 20% was used as a test set.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	F:/thesis/	1.2E+101	209.6115	425.4421	133	436.0975	388.0116	120.2414	118.7939	217.0092	564.1454	169.2395	2.121441	0.937791	0.394684	2.829269	1
2	F:/thesis/	1.1E+101	162.6407	291.0017	385.1883	50	292.0154	166.3881	133.8432	255.002	429.9419	253.9016	2.463493	0.493306	0.675149	2.651238	2
3	F:/thesis/	1.2E+101	146.1677	500.029	276.5249	289.1712	291.0069	208.4322	90.19978	473.0042	559.7517	258.2576	1.861715	1.175436	0.394708	2.851327	3
4	F:/thesis/	1.1E+101	196.6367	316.8359	376.4492	162.41	394.0114	85.90693	86.64872	402.0012	481.0873	268.5442	2.406109	0.750601	1.011035	2.11544	4
5	F:/thesis/	1.1E+101	296.4928	345.323	415.9243	174.1063	360	203.4945	91.08787	537.0037	584.77	224.1093	2.289347	0.546797	0.598631	2.84841	4
6	F:/thesis/	1.1E+101	128.6546	173.9684	126.7636	195.4942	226.0088	59.64059	75.28612	202.0025	297.0606	90.42677	2.753105	0.723618	0.480861	2.325602	4
7	F:/thesis/	1.2E+101	189.3911	427.7873	172.7223	517.3973	584.1036	217.4626	209.2964	196	599.9208	219.5313	2.626759	1.299887	0.429272	1.927267	5
8	F:/thesis/	1.2E+101	179.2345	315.1016	208.7774	321.9938	63	230.8528	184.8946	473.6771	483.9876	154.3794	2.714972	0.804863	0.489039	2.274311	5
9	F:/thesis/	1.2E+101	147.136	239.7749	259.6786	89.44272	270.3516	86.37129	94.62558	398.6477	341.4923	183.3576	2.13073	0.758616	0.733148	2.660692	5
10	F:/thesis/	1.2E+101	171.9767	40.1995	38.01316	140.0321	50.01	42.80187	41.10961	111.162	174.5623	142.6359	1.5187	0.615413	1.492553	2.65652	5
11	F:/thesis/	1.2E+101	333.2642	145.1654	309.0906	149	174.0115	152.7416	215.7267	269.9037	437.6528	151.4199	2.231827	0.470051	1.081135	2.500172	5
12	F:/thesis/	1.2E+101	293.2883	275.9438	406.8538	141.3542	346.0361	217.3131	91.92388	111.1126	532.8199	201.3753	2.422015	0.486189	0.777911	2.59707	5
13	F:/thesis/	1.2E+101	14.31782	578.5171	618.0655	103.1213	130.0038	196.7587	271.68	506.08	589.6041	608.6214	2.448694	0.841761	1.782782	1.209949	6
14	F:/thesis/	1.2E+101	293.8469	344.0233	394.8721	220.6581	190.0105	216.4902	153.7693	386.0117	543.5899	328.8921	2.036514	0.954695	1.172588	2.119388	6
15	F:/thesis/	1.2E+101	348.2829	305.0148	542.2638	261.6123	158.0506	146.4923	284.1848	391.0051	612.0694	381.2414	2.425622	0.77442	1.469553	1.61359	6
16	F:/thesis/	1.2E+101	244.7611	365.4217	523.1157	137.7135	161.0031	140.0893	126.0635	160.5273	542.5173	404.8135	2.169981	0.846472	1.684067	1.582665	6
17	F:/thesis/	1.2E+101	298.4125	341.0015	379.269	156.2082	150.2132	205.4556	242.8003	480	499.0271	321.5603	1.787184	0.961759	1.213276	2.320966	6
18	F:/thesis/	9.7E+100	346.0303	221.199	274.1751	312.8226	29	228.1776	270.712	476.0263	538.4069	221.199	2.484598	0.692981	0.785398	2.320208	7
19	F:/thesis/	9.7E+100	210.6799	381.4826	326.974	172.6297	93.00538	149.0939	130.9809	182.0027	471.0679	310.2032	1.771149	1.159576	0.926557	2.425903	7
20	F:/thesis/	9.7E+100	302.5359	260.7144	191.1282	305.3948	253.002	134.8332	136.5284	109.0046	474.1519	238.4659	1.997718	0.907648	0.856043	2.521777	7
21	F:/thesis/	9.7E+100	213.1783	345.475	201.0995	300.641	247.2023	178.5077	102.5914	97	479.702	211.0261	2.030224	1.067497	0.651294	2.53417	7
22	F:/thesis/	9.7E+100	357.5486	217.7544	365.0452	189.4888	136.0037	188.5206	181.1574	411	508.2519	234.2328	2.133436	0.659924	1.218723	2.271102	7

Fig. 4.5 Aportion of the extracted features in dataset

The images are read into the feature point extractor algorithm and after detecting corners, the points are used to find out the angle between fins, tails and mouth of the fish. The distances between the points are termed as D1, D2, D3, D4,D5,D6,D7 and D8,length and width of the fish.The angles are stored as deg1, deg2, deg3 and deg4. Based on these features the four classifiers will classify the fishes into groups.

Chapter 5

RESULT AND DISCUSSION

We know,

Accuracy =(TP+TN)/(TP+TN+FP+FN) . . . . (v)

Precision = TP/(TP+FN) . . . . (vi)

Where,

- TP = no. of times correct recognition occurs
- TN = no. of times incorrect recognition occurs
- FP = no. of false positive
- TN = no. of false negative

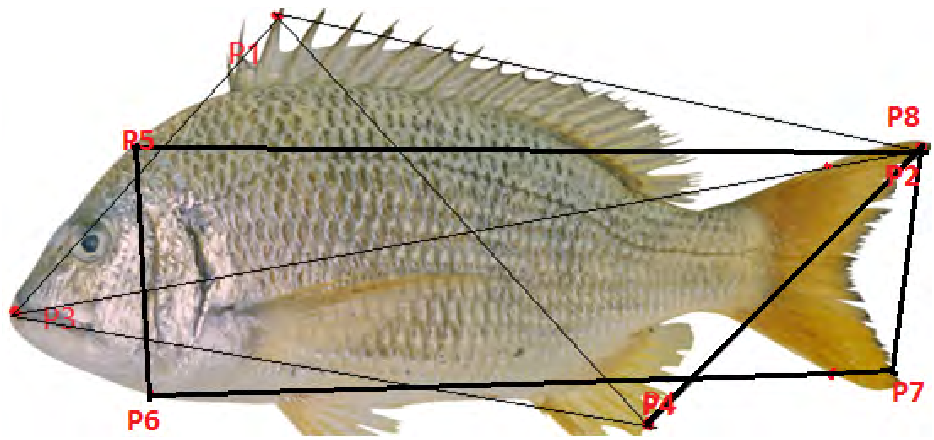

Fig. 5.1 Adding new points

We conduct the experiment twice. In the first instance we consider 10 features and the in the following one 14 features are considered to determine the efficacy of the features that we have chosen.

In Fig 5.1 we use the points P1,P2, P3 and P4 we construct 10 features named length,width,D1, D2, D3, D4, Deg1, Deg2, Deg3 and Deg4.The performance of the algorithms based on these features are shown in Table 4.2.

In an effort to increase accuracy, we extract 4 more points named P5, P6, P7 and P8 shown in Fig 4.5.We derive four more distance vectors called D5, D6, D7 and D8.

5.1 Performance comparison

It is observed from Fig 5.2 that while KNN and SVM performance remain relatively constant,the random forest classifier and naive bayes show a decrement in performance.Specially naive Bayes performs poorly when additional features are used. This shows that the additional features affect the classification negatively. For this reason, we consider the original 10 feature approach as more being effective for the classification of the considered dataset.

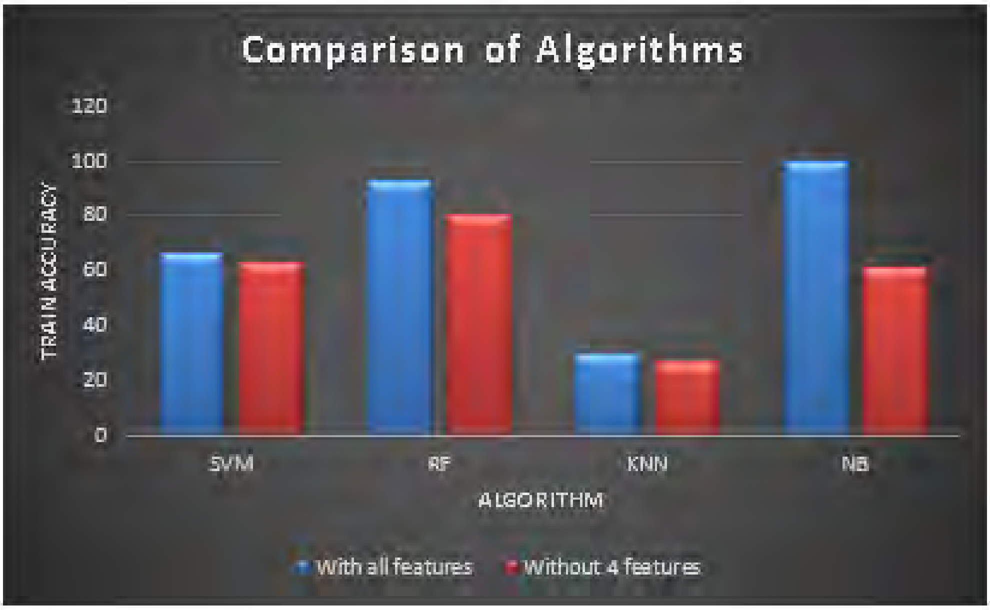

Fig. 5.2 Performance comparison with different sets of features

5.2 KNN Algorithm Accuracy

We know KNN uses training datasets directly to make future assumptions. It uses a value of 'K' to establish class boundaries to group the observations into. Here the choice of K-is critical.A small value of k means that noise will have a higher influence on the result. On the other hand, a large value makes it computationally expensive defeating the basic philosophy behind KNN which is points that are near generally belong to the same classes. In figure 5.1, we observe that the accuracy came to be 29.4% which is not a satisfactory number. Here, along x-axis the cross validation iteration starts from 0.Along y-axis the accuracy is plotted.

From the figure 5.3 it can be seen that at iteration 0, the accuracy rate is the lowest, while at iteration 5 the accuracy is the highest.

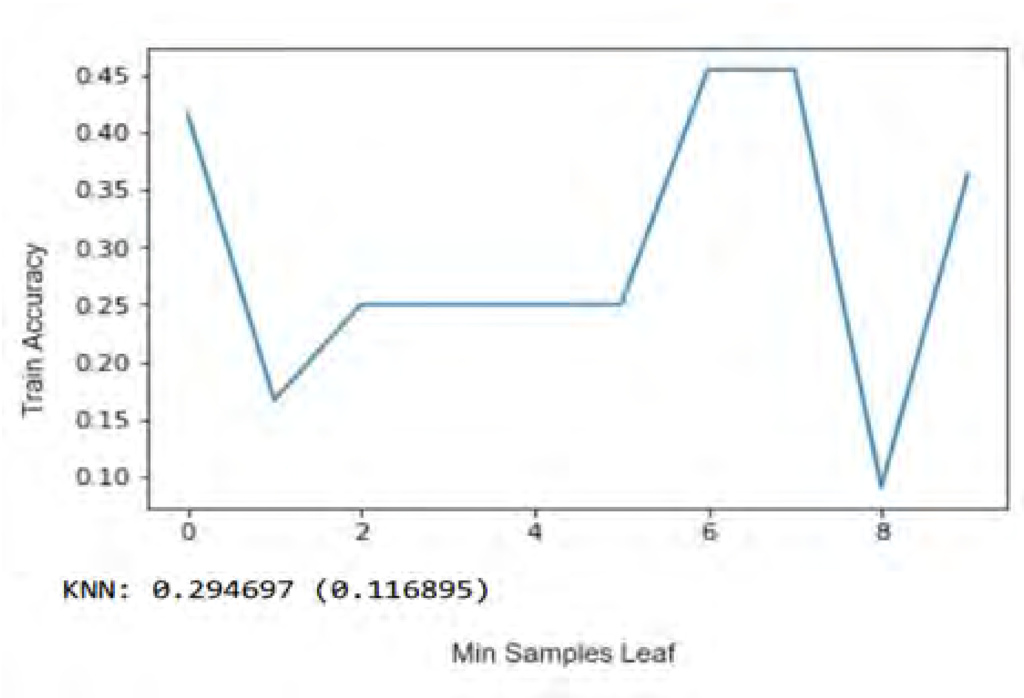

Fig. 5.3 Diagram accuracy of KNN

5.3 SVM Algorithm Accuracy

From figure 5.4 it is seen that for SVM algorithm the accuracy is 66.5%.It is quite satisfactory but there is a high fluctuation in the graph. We know SVM creates a boundary plane between two classes calculating the optimal greatest distance from both of them. Because the algorithm is distance dependent, it is also highly dependent on kernel[30]. Kernels are generally distance based. To improve the SVM's performance the choice of kernel is of utmost importance. In this graph too steep fluctuations are observed.One of the possible reason is it is caused by the high variance of our considered dataset. Because there are not many instances of fish images of the same species, the dataset considered for training is not the perfect representative of the whole dataset. We assume if the instances of images are increased, the shifts and fluctuations will lessen.

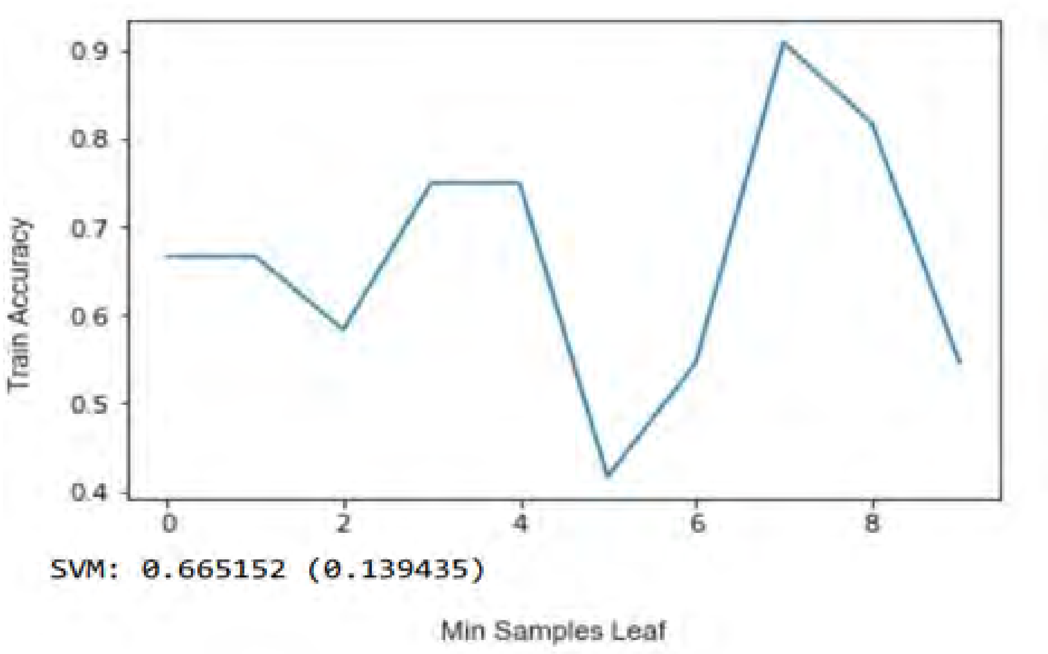

Fig. 5.4 Diagram accuracy of SVM

5.4 Random Forest Algorithm Accuracy

A combination of tree classifiers combine together to form the random forest algorithm. The induction of a tree begins when the trees randomly select a feature from the input feature vector. To classify a class, all the trees randomly chooses one class. For Random Forest our training accuracy is 92.3%.Random Forest can also be used for both classification and regression like SVM.

Figure 5.5 illustrates high fluctuation of the accuracy but still overfitting is not a problem for random forest as the number of trees keeps growing generating a big of observation pool. Although steep fluctuations are observed in this graph,it is an advantage that random forest classifier is not affected greatly by the variance of the data.

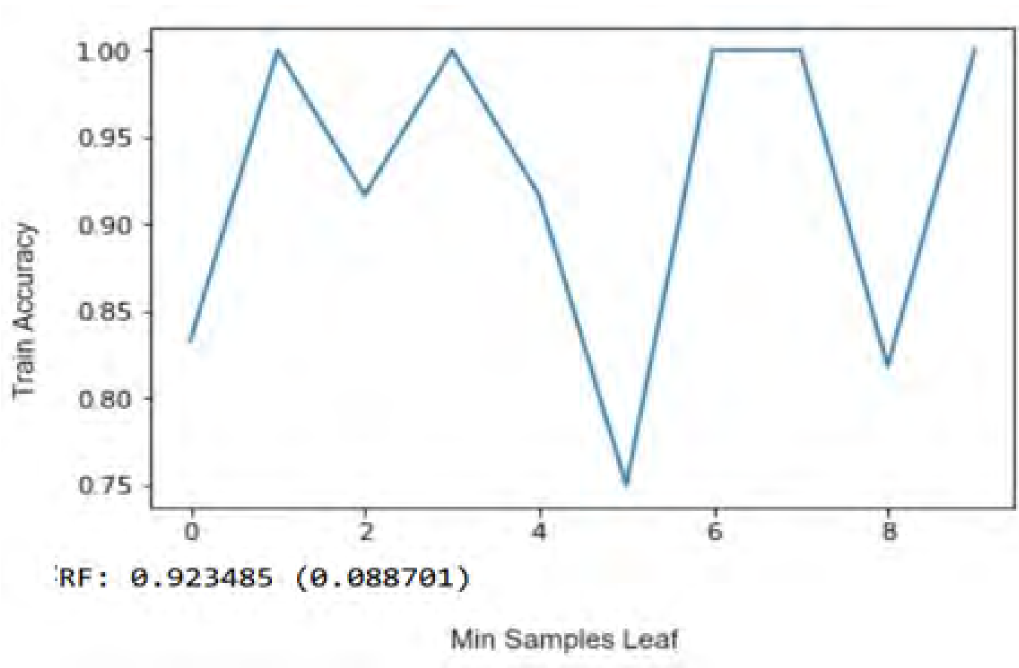

Fig. 5.5 Diagram accuracy of Random Forest

5.5 Naive Bayes

Naive Bayes algorithm is a relatively fast and simple algorithm which uses Bayes theorem of probability to predict the class of unknown data set. We got 100% accuracy as shown in Fig 5.6 which is the best among the four algorithm we have used.

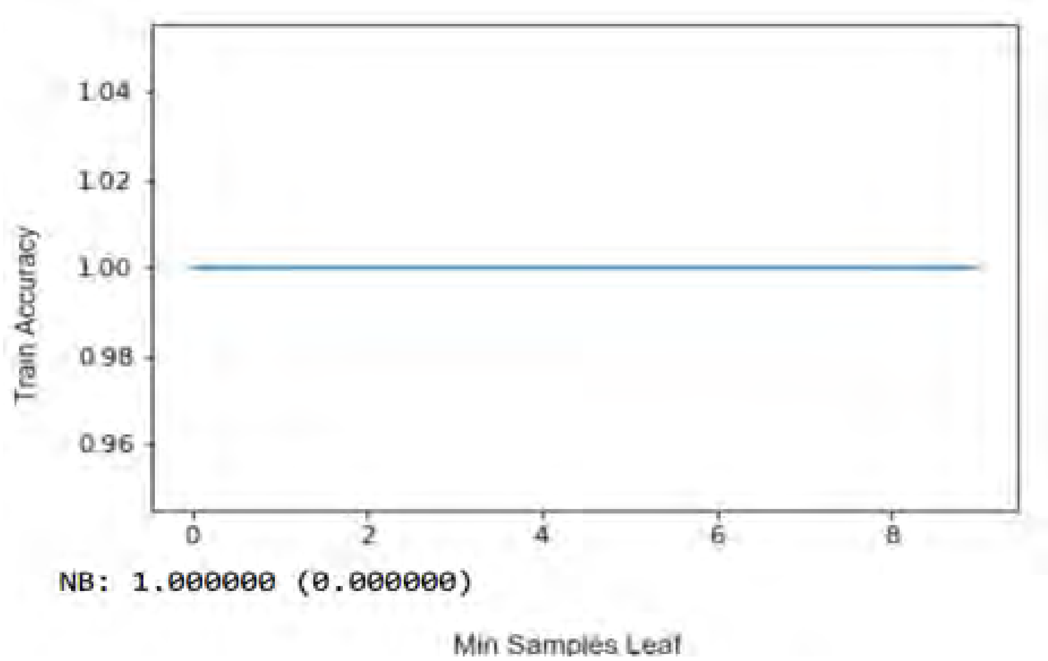

Fig. 5.6 Diagram accuracy of Naive Bayes

5.6 Algorithm's Comparison

In table 5.1 we determined the accuracy of the classifier models we used. Based on the values we have calculated we can say Naive Bayes classifier gives us the best Accuracy and precision in our method of detecting fish using our selected features.In order to obtain a satisfactory accuracy, before giving the data as input, accuracy on each of the training set and test set should be done,which will determine if the dataset is prone to overfitting or underfitting.. If the accuracy of the training set is greater than that of the test set then the model has an overfitting problem. Overfitting problem is characterized by a model not being able to infer from the already existing knowledge it has built.

Table 5.1 Comparison of relative performances of the algorithm

Algorithm	Accuracy(with 10 feature)	Accuracy (with 14 feature)
KNN	29.4%	26.9%
Random Forest	92.3%	80.3%
SVM	66.5%	66.5%
NB	100%	61.2%

Figure 5.7 shows a box plot which represents the mean, standard deviation of the algorithms we used. This is a graphical comparison that helps us to compare the classifiers we used, enabling us to choose the best classifier among them which is the Naive Bayes classifier.

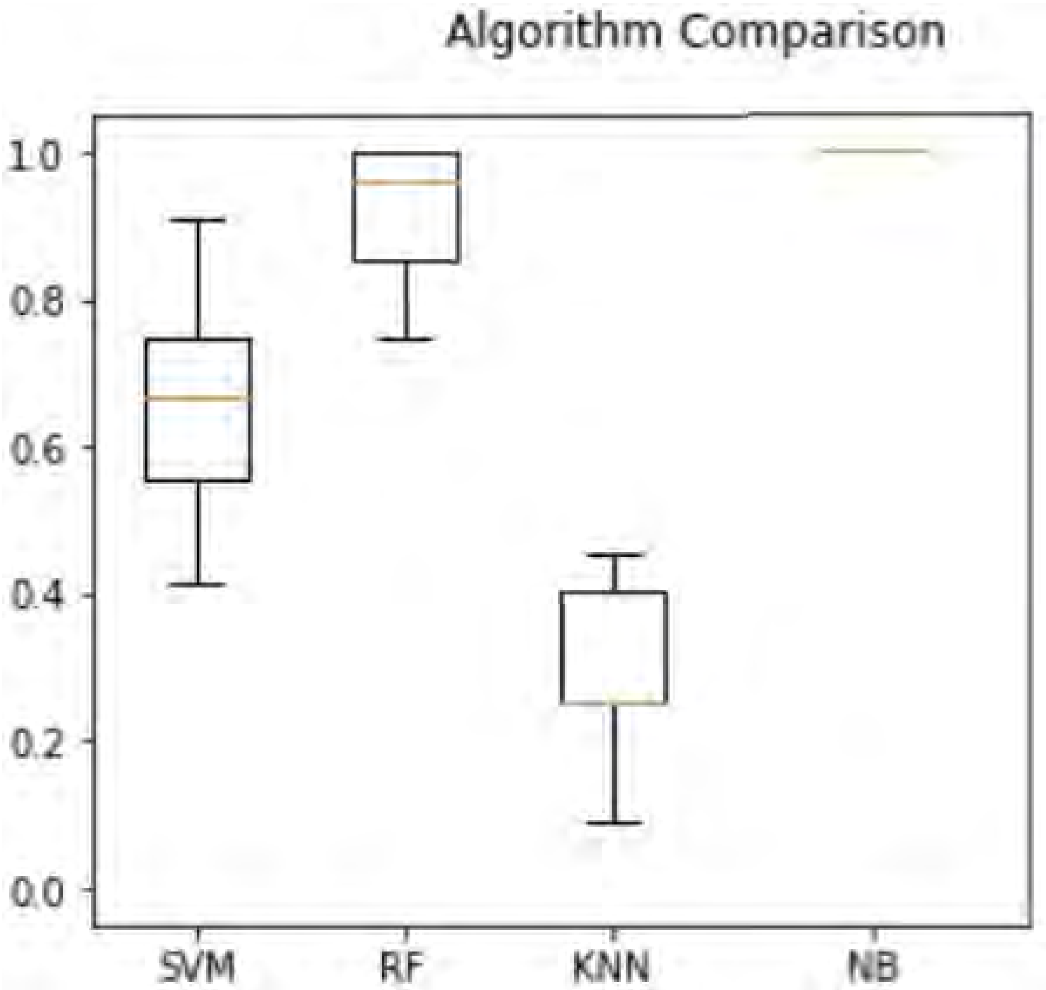

Fig. 5.7 Diagram of Algorithms comparison

From fig 5.7, Naive bayes classifier shows the perfect result in classifying the fishes, while KNN performs poorly. As mentioned in section, the high variance in our dataset may have reduced the efficiency of KNN. The performance of both SVM and random forest are satisfactory.

In the original paper a local region based intersession variability (ISV) modelling approach method is used for object classification. This method depends on surface illumination variation to create a generalized image which is detectable in computer vision from different poses. This paper shows a relative performance improvement of 35% on the acquired fish image dataset. Our proposed method uses the technique of image processing and machine learning and table 5.2 shows that it provides comparatively better result in detection of the fishes and in addition classifying the fishes.

Table 5.2 Comparison between local ISV method and machine learning technique for this dataset.

System	Protocol 1a Dev	Protocol 1a Eval	Protocol 1b Dev	Protocol 1b Eval	Accuracy	Precision
Local ISV	43.1%	49.3%	40.8%	46.7%		
Random Forest					92.3%	87%
SVM					66.5%	62.4%
NB					100%	92.6%
KNN					29.4%	26.2%

Our proposed method uses the technique of image processing and machine learning and table 5.2 shows that it provides comparatively better result in detection of the fishes and in addition classifying the fishes.

Chapter 6

CONCLUSION

In the recent years, environmental awareness and climate change debate is gaining spotlight day by day. The environment is consists of both air-space and water bodies. We are already facing a huge setback in ozone protection Endeavour because of the recklessness of the consumer industry of our world. The coral reefs are endangered along with many other exotic fishes and animals. To protect the marine lives, there are scientists who are contributing as much as they can for preservation of our diverse animal community. With the accessible technology, both in object detection and AI prediction, it has become quite economical to conduct researches. Although a tested and perfect dataset is difficult to come upon, the dataset we used contained enough images for us to gather our own dataset selected by us. Finally, we extracted features on those dataset through a corner pixel detecting algorithm and used that to build feature to be used in our classifiers. The accuracy of the algorithms although is not perfect but awaits further improvement through selecting different feature vectors. In the future, we would like to be more precise in fish classification accuracy by opting various other mathematical pixel detecting operators such as Sobel, Canny edge detection method, SUSAN detector etc.

References

[1] Alsmadi, M. K., Omar, K. B., Noah, S. A., and Almarashdeh, I. (2010). Fish recognition based on robust features extraction from size and shape measurements using neural network. *Journal of Computer Science*, 6(10):1088.

[2] Anantharajah, K., Ge, Z., McCool, C., Denman, S., Fookes, C. B., Corke, P., Tjondronegoro, D. W., and Sridharan, S. (2014). Local inter-session variability modelling for object classification.

[3] Ancuti, C. O., Ancuti, C., De Vleeschouwer, C., and Bekaert, P. (2018). Color balance and fusion for underwater image enhancement. *IEEE Transactions on Image Processing*, 27(1):379–393.

[4] Boom, B. J., Huang, P. X., Beyan, C., Spampinato, C., Palazzo, S., He, J., Beauxis-Aussalet, E., Lin, S.-I., Chou, H.-M., Nadarajan, G., et al. (2012a). Long-term underwater camera surveillance for monitoring and analysis of fish populations. *VAIB12*.

[5] Boom, B. J., Huang, P. X., He, J., and Fisher, R. B. (2012b). Supporting ground-truth annotation of image datasets using clustering. In *ICPR*, pages 1542–1545.

[6] Das, S., Mirnalinee, T., and Varghese, K. (2011). Use of salient features for the design of a multistage framework to extract roads from high-resolution multispectral satellite images. *IEEE transactions on Geoscience and Remote sensing*, 49(10):3906–3931.

[7] Davis, T. A. (2004). A column pre-ordering strategy for the unsymmetric-pattern multifrontal method. *ACM Transactions on Mathematical Software (TOMS)*, 30(2):165–195.

[8] Foresti, G. L. and Gentili, S. (2000). A vision based system for object detection in underwater images. *International journal of pattern recognition and artificial intelligence*, 14(02):167–188.

[9] Hearst, M. A., Dumais, S. T., Osuna, E., Platt, J., and Scholkopf, B. (1998). Support vector machines. *IEEE Intelligent Systems and their applications*, 13(4):18–28.

[10] Hernández-Serna, A. and Jiménez-Segura, L. F. (2014). Automatic identification of species with neural networks. *PeerJ*, 2:e563.

[11] Iester, M., Oddone, F., Prato, M., Centofanti, M., Fogagnolo, P., Rossetti, L., Vaccarezza, V., Manni, G., and Ferreras, A. (2013). Linear discriminant functions to improve the glaucoma probability score analysis to detect glaucomatous optic nerve heads: a multicenter study. *Journal of glaucoma*, 22(2):73–79.

[12] Jabr, F. (2010). The evolution of emotion; charles darwin's little known psychology experiment. *Scientific American. May*, 24.

[13] Joginipelly, A., Charalampidis, D., Ioup, G., Ioup, J., and Thompson, C. (2013). Species-specific fish feature extraction using gabor filters. In *Proceedings of 66-th Annual Conference Gulf and Carribean Fisheries Institute, Corpus Cristi*, volume 66, pages 283–291.

[14] Joly, A., Goëau, H., Glotin, H., Spampinato, C., Bonnet, P., Vellinga, W.-P., Champ, J., Planqué, R., Palazzo, S., and Müller, H. (2016). Lifeclef 2016: multimedia life species identification challenges. In *International Conference of the Cross-Language Evaluation Forum for European Languages*, pages 286–310. Springer.

[15] Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105.

[16] Lee, C. M. and Narayanan, S. S. (2005). Toward detecting emotions in spoken dialogs. *IEEE transactions on speech and audio processing*, 13(2):293–303.

[17] Matthies, L., Kanade, T., and Szeliski, R. (1989). Kalman filter-based algorithms for estimating depth from image sequences. *International Journal of Computer Vision*, 3(3):209–238.

[18] Mirgolbabaei, H. and Echekki, T. (2013). A novel principal component analysis-based acceleration scheme for les–odt: An a priori study. *Combustion and Flame*, 160(5):898–908.

[19] Nagashima, Y. and Ishimatsu, T. (1998). A morphological approach to fish discrimination. In *MVA*, pages 306–309.

[20] Ogunlana, S., Olabode, O., Oluwadare, S., and Iwasokun, G. (2015). Fish classification using support vector machine. *African Journal of Computing & ICT*, 8(2):75–82.

[21] Pornpanomchai, C., Lurstwut, B., Leerasakultham, P., Kitiyanan, W., et al. (2013). Shape-and texture-based fish image recognition system. *Kasetsart Journal-Natural Science*, 47(4):624–634.

[22] Rached, T. S. and Perkusich, A. (2013). Emotion recognition based on brain-computer interface systems. In *Brain-computer interface systems-Recent progress and future prospects*. InTech.

[23] Recht, B., Fazel, M., and Parrilo, P. A. (2010). Guaranteed minimum-rank solutions of linear matrix equations via nuclear norm minimization. *SIAM review*, 52(3):471–501.

[24] Shapiro, L. S., Wang, H., and Brady, J. M. (1992). A matching and tracking strategy for independently moving objects. In *BMVC92*, pages 306–315. Springer.

[25] Spampinato, C., Giordano, D., Di Salvo, R., Chen-Burger, Y.-H. J., Fisher, R. B., and Nadarajan, G. (2010). Automatic fish classification for underwater species behavior understanding. In *Proceedings of the first ACM international workshop on Analysis and retrieval of tracked events and motion in imagery streams*, pages 45–50. ACM.

[26] Suslick, K. S. (1998). Kirk-othmer encyclopedia of chemical technology. *John Wiley&Sons: New York, NY, USA*, 26:517–541.

[27] Tzimiropoulos, G., Zafeiriou, S., and Pantic, M. (2012). Subspace learning from image gradient orientations. *IEEE transactions on pattern analysis and machine intelligence*, 34(12):2454–2466.

[28] Umbaugh, S. E. (1997). *Computer vision and image processing: a practical approach using cviptools with cdrom*. Prentice Hall PTR.

[29] Villon, S., Chaumont, M., Subsol, G., Villéger, S., Claverie, T., and Mouillot, D. (2016). Coral reef fish detection and recognition in underwater videos by supervised machine learning: Comparison between deep learning and hog+ svm methods. In *International Conference on Advanced Concepts for Intelligent Vision Systems*, pages 160–171. Springer.

[30] Wang, J., Li, Y., Bai, X., Zhang, Y., Wang, C., and Tang, N. (2011). Learning context-sensitive similarity by shortest path propagation. *Pattern Recognition*, 44(10-11):2367–2374.

[31] Webster, J. G. (2009). *Medical instrumentation application and design*. John Wiley & Sons.

[32] Yilmaz, A., Javed, O., and Shah, M. (2006). Object tracking: A survey. *Acm computing surveys (CSUR)*, 38(4):13.

[33] Zhang, W., Sun, X., Fu, K., Wang, C., and Wang, H. (2014). Object detection in high-resolution remote sensing images using rotation invariant parts based model. *IEEE Geoscience and Remote Sensing Letters*, 11(1):74–78.

[34] Zhou, X., Yang, C., and Yu, W. (2013). Moving object detection by detecting contiguous outliers in the low-rank representation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(3):597–610.