

The classification of hunger behaviour of *Lates Calcarifer* through the integration of image processing technique and *k*-Nearest Neighbour learning algorithm

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Abstract. Fish Hunger behaviour is essential in determining the fish feeding routine, particularly for fish farmers. The inability to provide accurate feeding routines (under-feeding or over-feeding) may lead the death of the fish and consequently inhibits the quantity of the fish produced. Moreover, the excessive food that is not consumed by the fish will be dissolved in the water and accordingly reduce the water quality through the reduction of oxygen quantity. This problem also leads the death of the fish or even spur fish diseases. In the present study, a correlation of Barramundi fish-school behaviour with hunger condition through the hybrid data integration of image processing technique is established. The behaviour is clustered with respect to the position of the school size as well as the school density of the fish before feeding, during feeding and after feeding. The clustered fish behaviour is then classified through *k*-Nearest Neighbour (*k*-NN) learning algorithm. Three different variations of the algorithm namely cosine, cubic and weighted are assessed on its ability to classify the aforementioned fish hunger behaviour. It was found from the study that the weighted *k*-NN variation provides the best classification with an accuracy of 86.5%. Therefore, it could be concluded that the proposed integration technique may assist fish farmers in ascertaining fish feeding routine.

1. Introduction

In understanding fish characteristics, one should consider the various factors that lead to its behaviour such as the movement activity, sensory cues, and the circadian rhythm. The locomotor activity of the fish either individually or in groups has been reported to increase in the event when it is anticipating food [1]. The hunger demand that affects the fish movement has caught the attention of researchers throughout the years. It was inferred that fish scatters in a larger area when they are hungry, and they move away from the walls of confinement [2]. A behavioural pattern or in general term the circadian rhythm is an endogenous type which is a biological conduct that the fish encounter. It emulates similar patterns with sleeping representation and mostly associated with feeding rhythms [3]. Researchers have labeled this pattern as free running when the routine preserve for a period of 24 hours.

Modelling the hunger behaviour requires an essential form of evidence on the necessary amount of food and the timing gaps between each meal for the feeding time to be assessed. The locomotor activity of



the fish usually decreases after it has repleted [4]. It has been reported that data gathered from a school of fish replicates the individual fish movement as the movement does not vary significantly [5]. Moreover, it has also been demonstrated in a study that fish also are sensitive towards ultradian rhythm when they are hungry [6]. An automated feeder was used in the aforementioned study, to serve food based on the demand of the fish. In the present study, a similar concept is applied will be discussed in great length in the subsequent section. To gather the adequate amount of food during the experiment, the usage of a self-demand feeder is necessary, as suggested in [7]. Due to the myriad number of variables such as social interactions, species and environmental shifts that have been discovered to influence the fish hunger behaviour, there is a need for a standardised experimental setup. Different type of fish species was investigated on the circadian rhythm throughout the years with respect to the Asian sea bass or commonly known as Barramundi. For instance, the growth rate of the fish in correlation to light sensitivity was investigated [8]. The resting time, as well as the active motion between genders of zebrafish or *Danio rerio* and razor fish or *Xyriichthys novacula* with relation to feeding state, has also been investigated [9-10].

Several classification techniques have been employed due to its superiority against conventional statistical concept [11-12]. For instance, SVM classification was performed on rainbow trout or *Oncorhynchus mykiss* in observing the muscle activity either in the satiated or hungry state [13]. *k*-Nearest Neighbour (*k*-NN) algorithm has also been demonstrated to be able to detect abnormal fish trajectories [11]. This study aims at evaluating the classification ability of *k*-NN in identifying the hunger behaviour based on two distinct parameters namely the location of the centre of gravity and of the school size of *Lates Calcarifer*.

2. Materials and Methods

This section describes the experimental setup that includes the fish species, the quantity of the fish, laboratory condition and the classification method.

2.1 Fish

The Asian sea bass species was selected in the present study as it depicts the typical circadian rhythm on food demand of day and night cycle. The fish was acquired from Fisheries Research Institute, Gelang Patah Johor, Malaysia, with a quantity of 20 juveniles sea bass that is stationed at the International Islamic University Malaysia laboratory.

2.2 Experiment Setup

The amount of water filled into the tank is 130 L where the fish is being placed, and the dimension of the tank is 92cm x 46cm x 46cm. The fish then triggered the suspended infrared sensor that is installed on the self-demand feeder when the school reaches slightly below the water surface. Each time the sensor is prompted, approximately 0.5g of pellets will drop with a size of 3 mm in diameter, and this continues until the sensor was not triggered from any of the fish. Data for generated feeding moments and timestamp will be sent via microcontroller to the computer and recorded for clustering purposes with the tags of Before Feeding (BF), During Feeding (DF) and After feeding (AF). The location of parameters above if the centre of gravity (COG) and the box size is captured using a webcam modeled Logitech, C270h. The video is then converted into .avi file and evaluated to Roborealm software for evaluation as in figure 1. Hence, each parameter had (x, y) coordinates in pixels which then indicates the position of the fish at the given period. The clustering was made from the evaluated parameters of BF, DF, and AF and is then classified via the *k*-NN models.

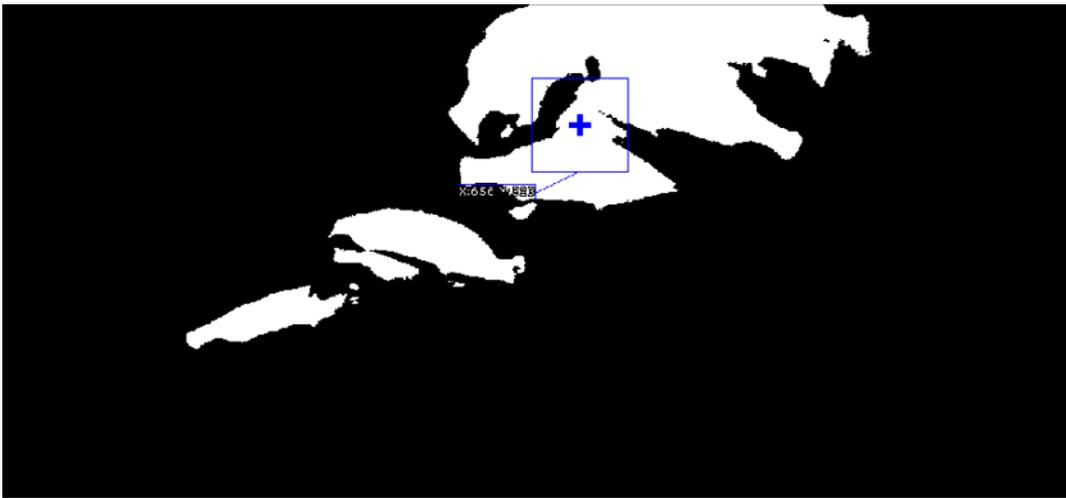


Figure 1. COG of the box which gives x and y coordinates for the school from Roborealm.

2.3 Classification method

In this study, three different k -NN variations viz. cosine, cubic and weighted are investigated. The number of neighbours, k employed for all variations is 10, whilst the distance metrics used are cubic, cosine, and Euclidean, respectively. The equal distance (no weight assigned) are used for all the evaluated variations except for the weighted variation, in which an inverse squared distance weight is imposed. In addition, a fivefold cross-validation procedure was used for model training and testing [14]. The performance of the models were assessed and evaluated through its classification accuracy (CA) via MATLAB 2016a (Mathworks Inc., Natick, USA).

3. Results and Discussion

Table 1. k -NN classification results.

k -NN variation	CA (%)
Cubic	68.8
Cosine	78.5
Weighted	86.5

It is apparent from table 1 that the weighted k -NN variation is able to provide reasonably accurate classification with a classification accuracy of 86.5 %. Furthermore, it could also be seen that the cubic variation performs the worst amongst all variation tested. Nevertheless, it is worth to mention that the ability of the weighted k -NN is dependent of the parameters selected i.e. the centre of gravity as well as the school density, suggesting that the selected parameters are nontrivial or vital in describing the feeding behaviour of *Lates Calcarifer*. The importance of the aforementioned parameters i.e. COG and box size density has been reported in a previous study for understanding fish feeding behaviour [10]. Figure 2 depicts the confusion matrix of the tested models.

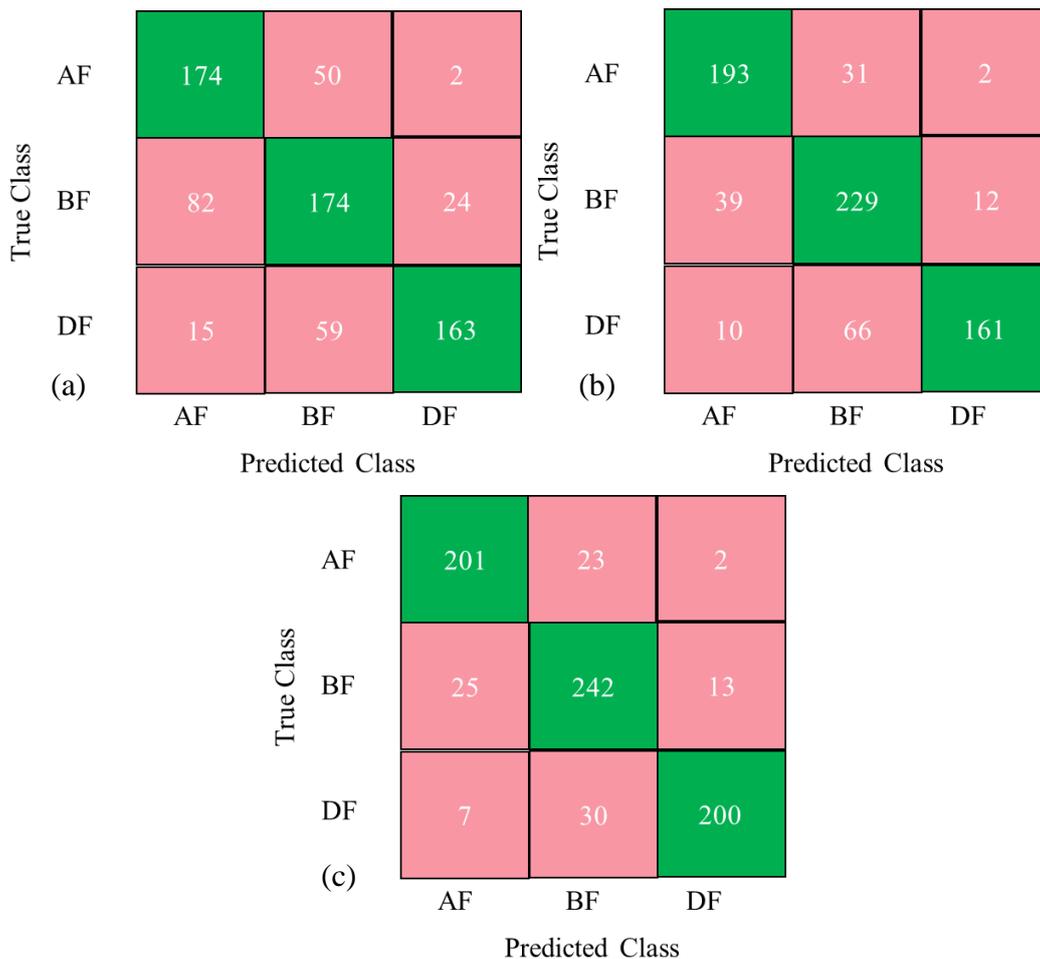


Figure 2. Confusion matrix for the k-NN variations (a) Cubic; (b) Cosine; (c) Weighted.

4. Conclusion

It could be concluded from the present investigation that weighted k -NN variation is able to provide a reasonably accurate classification of fish feeding behaviour with regards to the abovementioned parameters examined viz. centre of gravity and school fish density. Further study could be carried out by considering other relevant parameters that may explain the hunger behaviour of *Lates Calcarifer* as well as the effectiveness of other forms of classification techniques.

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