ISSN 2278-3091
Volume 9, No.1.1, 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse4691.12020.pdf
https://doi.org/10.30534/ijatcse/2020/4691.12020

Feeding Behavior Classification of Nile Tilapia (*Oreochromis niloticus*) using Convolutional Neural Network

Ben Saminiano[1,2], Arnel Fajardo[3], Ruji Medina[4]
[1]Technological Institute of the Philippines, Quezon City, Philippines, ben.saminiano@gmail.com
[2]Bicol University Polangui Campus, Polangui, Albay, Philippines, ben.saminiano@bicol-u.edu.ph
[3]School of Engineering and Information Technology, Manuel L. Quezon University, Quezon City, Philippines, acfajardo2011@gmail.com
[4]Technological Institute of the Philippines, Quezon City, Philippines, ruji_p_medina@yahoo.com

ABSTRACT

Feeding management in aquaculture is very important and has a big impact to the farmers and environment. A good feeding management optimizes growth and feeding efficiency. It also decreases the amount of excess nutrients entering the environment. Several existing systems aimed to provide an efficient and effective feeding management using image processing and deep learning. This study developed a model that will be part of a fish feeding management system that used fish feeding behavior to know the feeding state of the fish. The methodology used was image generation, image processing, classification and testing. Convolutional Neural Network (CNN) was utilized to classify fish feeding behavior into two states; to feed or not to feed. The CNN model was tested for accuracy, precision, recall, and specificity and the results were 96.4%, 97.87%, 94.867% and 97.93%, respectively. The result of the study will be used and integrated to a feeding management system.

Key words: CNN, Fish Behavior, Computer Vision, Image Processing

1. INTRODUCTION

Aquaculture [1] in Southeast Asia from 2010-2030 is estimated to have shares about 97% from the total fish production which make Southeast Asia play a strong role in contributing to global fish supply. With this strong demand, aquaculture needs to intensify its production. Improvements in feed and disease management are needed to increase yield in productions.

Tilapia production in the Philippines has increased for the last five years [2]. Commercial tilapia aquaculture has improved because farmers are now aware of the importance of adopting innovative husbandry technologies. These include the use of intensive culture, novel feed ingredients, improved quality of industrial aquafeeds, having a cost-effective feeding management, efficient pond fertilization and improved genetic strains.

One of the main determinants of the amount of excess nutrients entering the environment is the use of poor feeding strategy that leads to overfeeding [3]. Poor feeding strategy have major environmental impact. Excess nutrients not utilized by the fish are released into the environment. Feed management strategies control how farmer feeds fish with primary aim to deliver the ration size that optimizes both growth and feeding efficiency. In addition, farmers need to understand the appetite variability of fish in order to prevent underfeeding and overfeeding.

Computer vision technologies application [4] in aquaculture is very challenging. The fish are can be easily stressed and sensitive Further, they are free to move in an environment where there are parameters that are uncontrollable like visibility, lighting and stability. The sensors must also operate underwater and in a wet environment. Counting, size and mass estimation and species identification are some of the applications of computer vision. Computer vision can be used in counting, size measurement and mass estimation, gender identification and quality assessment, species and stock identification as well as monitoring welfare.

This paper developed a model that will be applied in feeding management systems in aquaculture. It used fish feeding behavior to determine the feeding state of the fish using Convolutional Neural Network.

The paper is presented as follows: Section 1 introduces the area of concentration and motivation of the research. Related works concentrated on image processing and CNN are discussed in Section 2. Section 3 presents the methodology of the research. Test and results are presented in Section 4. Finally, conclusion and future work are discussed in Section 5.

2. RELATED WORKS

Image Processing was used in the different computer application like in aquaculture. Image processing techniques, average background method and background subtraction method are used to obtain background [5]. Image contrast enhancement was also used after background subtraction. Further, Delaunay Triangulation (DT) was utilized to extract the quantitative index of feeding behavior. Automatic background extraction also captures consecutive images of the feeding area at short delay [6]. Every image is compared to the previous one and if the difference is not substantial then the image is rejected as it will cause biased background toward one of the images. Fish counting was performed by image subtraction from the background and blob analysis was performed. Gaussian filter was used to smoothen the preprocess video frames to detect body fish [7]. The objects are then detected by adaptive background approaches which are based on frame difference and background difference. Contrast limited adaptive histogram equalization and wavelength transform enhanced image quality of sea cucumber [8]. It is used to process the underwater image for increasing contrast based on the Rayleigh distribution. Their method performed well compared to other enhancing methodology.

Convolutional Neural Network was used to identify fish that are behind corals or overlapped other fish [9]. It is found that the identification of smaller and blurry images of fish using CNN is much effective than humans. In addition, CNN performs identification efficiently in underwater water images. An implementation of CNN with adaptation of a regional proposal network accelerates underwater object detection and recognition [10]. Detection acceleration was implemented using convolutional networks to generate high quality object candidates and by sharing networks with original detection networks. In addition, result showed that by sharing convolutional features with following fish detection and recognition network, proposal generation is nearly cost-free in the whole fish detection and recognition process.

Deep learning was also applied for automatic fish identification system to help marine biologist estimate fish existence and quantity [11]. The results demonstrate the performance of their detection system with a higher mean Average Precision (mAP) relative to Deformable Batch Model (DPM) and detects faster than previous R-CNN on a single fish image. Visual Fish Tracking [12] investigated approached for tracking of fish in their unrestricted natural environment. They used two-stage graph as activations of CNN model which resulted to a higher tracking accuracy and faster than other systems.

Texture features of the fish image was also used with deep CNN to detect the group behavior of the fish [13]. An underwater camera was used to avoid the effects of water surface movement. With this methodology, improved accuracy of the state of classification detection was observed. A fish detection and recognition system [14] also introduced an end-to-end deep learning architecture compared to the current methods on fish assessment task. A Region Proposal Network was combined with R-CNN for detection and recognition of fish species obtained from Remote Underwater Video Stations (RUVs). CNN was also used for splash detection which outperformed all existing algorithm based on local descriptors [15]. The proposed approach obtained an accuracy of 99.9% in splash detection.

3. METHODOLOGY

This paper used different techniques in order to classify the feeding behavior of the tilapia. Block diagram of the methodology is shown in Figure 1.

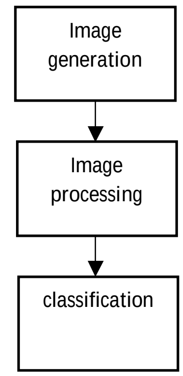


Figure 1: Block diagram of the proposed fish feeding behavior classification

3.1. Image generation

Images that were classified were extracted from a video sequence. The generated images were used for training, and validating the classification algorithm. The images for training were divided equally into two classes, to feed and not to feed. Fish is considered ready to be fed if its mouth is on the surface of the water [16]. The remaining images were used to validate the trained CNN model.

3.2. Image Processing

The extracted images had a resolution of 1920x1080. The images were resized to 64x64 image before it was fed to the classification algorithm.

3.3. Classification

Convolutional Neural Network is a multi-layer feed-forward artificial neural network which is proposed for two-dimensional image processing. The convolutional layers convolve with raw input data using multiple local kernel filters and generate invariant local features. After multi-layer feature learning, fully connected layers converts a two-dimensional map into a one dimensional vector and then feed it into a softmax function for model construction [17]. A typical CNN is constructed as shown in Figure 2.

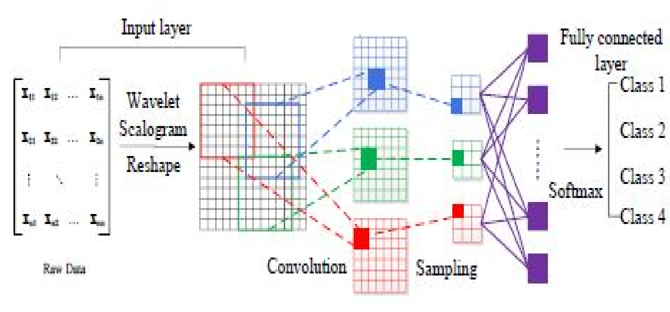


Figure 2: CNN Architecture

3.4. Evaluation

Confusion matrix was used to group the results according to the following conditions:

- **True positives (TP):** The model predicted to feed, and the fish do really need to be fed.
- **True negatives (TN):** The cases are predicted not to feed, and the fish need not to be fed.
- **False positive (FP):** The predictions are to feed but don't actually need to be fed.
- **False negative (FN):** The prediction is not to feed, but the fish needs to be fed.

The CNN model was evaluated in terms of the following metrics: recall, precision, specificity and accuracy.

Recall is the quotient of the true positives and the summation of the true positives and false negatives [18]. It is used to know how many relevant items are correctly classified. Recall is calculated using (1).

$$Recall = \frac{TP}{TP+FN} \quad (1)$$

Precision is the number of true positives divided by the sum of true positives and false positives. It is the ability to calculate the relevant instances of data. It is calculated using (2).

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Specificity is calculated by dividing the true negative by the sum of the true negative and false positive [19]. The formula is presented in (3).

$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

Accuracy is defined as the sum of true positives and true negatives divided by the total number of data. The calculation is done using (4).

$$Accuracy = \frac{TP+TN}{n} \quad (4)$$

4. TESTS AND RESULTS

4.1. CNN model architecture

The flowchart of the classification model of the system is presented in Figure 3. It is comprised of training and classification subsystems. There were 7000 original images used for training the model. The training images were divided into two classes, to feed and not to feed, where each class has 3500 images.

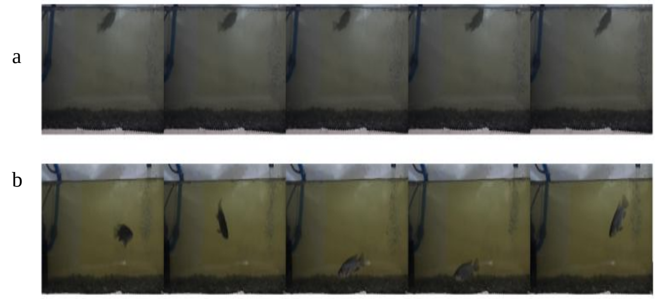
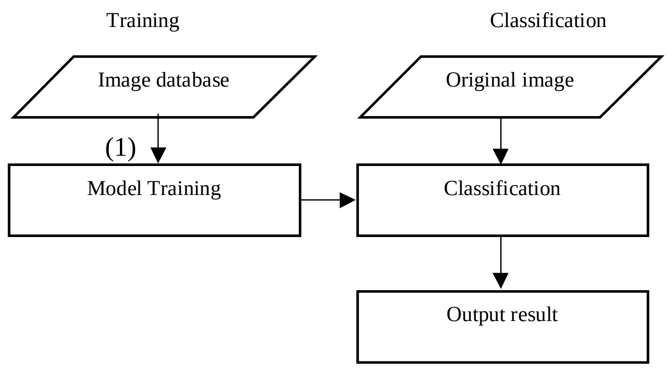


Figure 3: Fish images for classification. (a) to feed (b) not to feed

Aside from the training images, there were 3000 generated images used for validation. The 1500 images were grouped as to feed and the other 1500 for not to feed.



(2)

Figure 4: Flowchart of the classification model

During the training of the model after 10 epochs, an accuracy level of 99.61% for training and 96.40% for validation was reached. Variation of training and validation is presented in Table 1.

(3)

Table 1: Variation of training and validation

Epoch	Training		Validation	
	Loss	Accuracy	Loss	Accuracy
0	0.4374	0.7414	0.1619	0.9620
1	0.0942	0.9674	0.3516	0.8607
2	0.0498	0.9829	0.7915	0.7943
3	0.0309	0.9891	0.1891	0.9417
4	0.0297	0.9899	0.4778	0.9067
5	0.0227	0.9929	0.3120	0.9483
6	0.0195	0.9949	0.2465	0.9800
7	0.0203	0.9946	0.5215	0.8600
8	0.0097	0.9969	0.3478	0.8857
9	0.0136	0.9961	0.1755	0.9640

Figure 5 and Figure 6 show the change diagram for accuracy and loss of the training (orange line) and validation (blue line). This shows that the training reached an accuracy level of 99.61% and loss level of 1.36% after 10 epochs. Furthermore, the validation gained 96.40% and 17.55% for accuracy and loss, respectively.

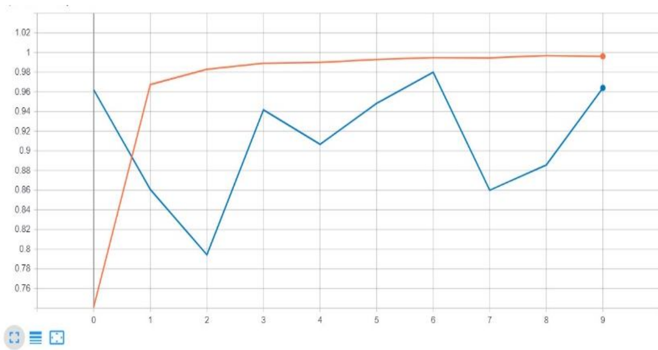


Figure 5: Accuracy change diagram of the CNN model.

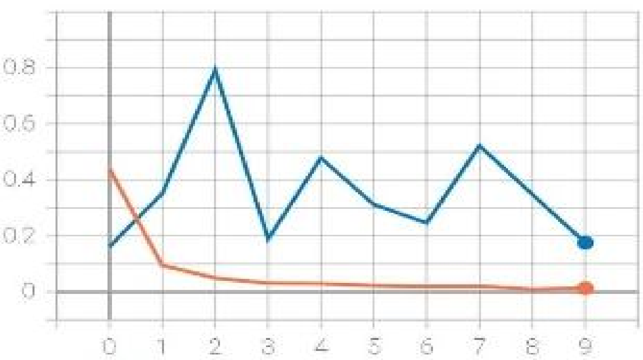


Figure 6: Loss change diagram of the CNN model

4.2. Evaluation of CNN Model

Confusion matrix is one of the most intuitive and easiest metrics used for finding the correctness and accuracy of the model [20]. The performance of the CNN model was presented in confusion matrix in Table 2.

Table 2: Confusion matrix of the fish behavior classification

		Predicted	
Actual		Positive	Negative
	Positive	1423	77
	Negative	31	1469

Generated images for validation is 3000. It was divided into two classifications, to feed or not to feed. The results of the validation were True Negative with 1469 images, False Positive (FP) with 31 images, False Negative (FN) with 77 images and True Positive (TP) with 1423 images.

The CNN model was evaluated using recall, precision, specificity and accuracy metrics. The result for recall gained 94.87%. Next, the precision garnered a rating of 94.87%. Then, the specificity rating was 97.93%. Lastly, the accuracy of the model gained a rating of 96.40%.

5. CONCLUSION

This work presented the effectiveness of the Convolutional Neural Network in classifying the fish behavior whether to feed or not to feed. Based from the result of the evaluation, the proposed CNN model has a high level of detection and accuracy. This shows that the model can be integrated to a system for fish feeding management. To further enhance the study, it is suggested to integrate counting, tracking and density prediction of fish.

REFERENCES

1. S. Msangi and M. Batka, **“The rise of aquaculture: The role of fish in global food security.,”** *In 2014-2015 Global food policy report*, Washington, D.C., pp. 61–71, 2015.
2. M. R. R. Romana-Eguia, M. A. Larona, and M. R. Catacutan, **“On-farm feed management practices for Nile tilapia (Oreochromis niloticus) in the Philippines,”** 2013.
3. P. G. White, **“Environmental consequences of poor feed quality and feed management,”** *On-farm Feed. Feed Manag. Aquac.*, no. C, pp. 553–564, 2013.
4. B. Zion, **“The use of computer vision technologies in aquaculture - A review,”** *Comput. Electron. Agric.*, vol. 88, pp. 125–132, 2012. https://doi.org/10.1016/j.compag.2012.07.010
5. C. Zhou *et al.*, **“Near infrared computer vision and neuro-fuzzy model-based feeding decision system for fish in aquaculture,”** *Comput. Electron. Agric.*, vol. 146, no. October 2017, pp. 114–124, 2018.
6. H. S. Alzubi, W. Al-Nuaimy, J. Buckley, and I. Young, **“An intelligent behavior-based fish feeding system,”** *13th Int. Multi-Conference Syst. Signals Devices, SSD 2016*, pp. 22–29, 2016. https://doi.org/10.1109/SSD.2016.7473754
7. G. Xiao, W. Zhang, Y. Zhang, J. Chen, S. Huang, and L. Zhu, **“Online Monitoring System of Fish Behavior,”** *11th Int. Conf. Control. Autom. Syst.*, pp. 1309–1312, 2011.
8. X. Qiao, J. Bao, H. Zhang, L. Zeng, and D. Li, **“Underwater image quality enhancement of sea cucumbers based on improved histogram equalization and wavelet transform,”** *Inf. Process. Agric.*, vol. 4, no. 3, pp. 206–213, 2017.
9. S. Villon *et al.*, **“A Deep learning method for accurate and fast identification of coral reef fishes in underwater images,”** *Ecol. Inform.*, 2018.
10. X. Li, M. Shang, J. Hao, and Z. Yang, **“Accelerating Fish Detection and Recognition by Sharing CNNs with Objectness Learning,”** 2016.
11. X. Li, M. Shang, H. Qin, and L. Chen, **“Fast Accurate Fish Detection and Recognition of Underwater Images with Fast R-CNN,”** pp. 1–5, 2015.
12. J. Jonas, V. Wolff, K. Fricke-neuderth, and O. Mothes, **“Visual Fish Tracking : Combining a Two-Stage Graph Approach with CNN-Features,”** pp. 1–6, 2017.
13. B. Zhang and F. Xie, **“Fish Population Status Detection Based on Deep Learning System,”** *2019 IEEE Int. Conf. Mechatronics Autom.*, pp. 81–85, 2019.
14. R. Mandal, R. M. Connolly, T. A. Schlacher, and B. Stantic, **“Assessing fish abundance from underwater video using deep neural networks,”** *2018 Int. Jt. Conf. Neural Networks*, pp. 1–6, 2018.

https://doi.org/10.1109/IJCNN.2018.8489482

15. V. Jovanovi, S. Member, E. Svendsen, V. Risojevi, and Z. Babi, **"Splash Detection in Fish Plants Surveillance Videos Using Deep Learning,"** *2018 14th Symp. Neural Networks Appl.*, pp. 1–5, 2018.
16. A. Addiction, **"How Do You Know When A Fish Is Hungry? | Aquascape Addiction."** [Online]. Available: https://www.aquascapeaddiction.com/articles/how-do-you-know-when-a-fish-is-hungry.
17. J. Wang, Y. Ma, L. Zhang, R. X. Gao, and D. Wu, **"Deep learning for smart manufacturing: Methods and applications,"** *J. Manuf. Syst.*, pp. 1–13, 2018.
18. W. Koehrsen, **"Beyond Accuracy: Precision and Recall – Towards Data Science,"** 2018. [Online]. Available: https://towardsdatascience.com/beyond-accuracy-precision-and-recall-3da06bea9f6c.
19. D. N. Carvajal and P. C. Rowe, **"Research and Statistics: Sensitivity, Specificity, Predictive Values, and Likelihood Ratios,"** *Pediatr. Rev.*, vol. 31, no. 12, pp. 511–513, 2010. https://doi.org/10.1542/pir.31-12-511
20. M. Sunasra, **"Performance Metrics for Classification problems in Machine Learning,"** 2017. [Online]. Available: https://medium.com/greyatom/performance-metrics-for-classification-problems-in-machine-learning-part-i-b085d432082b.