Artificial Neural Network Techniques for Differentiating Poisonous and Edible Fish Species

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***Abstract*—Oman is known for its diverse marine life, including many species of fish that can pose a risk to human health if eaten. In this study, we aim to develop an effective system that classifies between edible fish and poisonous fish based on the combination of CNN-MLP networks to identify poisonous fish. A hybrid architecture that incorporates convolutional neural networks (CNNs) will be utilized for feature extraction and multilayer perceptrons (MLPs) for additional descriptive features. The model will be trained with a combination of CNN-MLP architecture using backpropagation to improve prediction accuracy. Our model achieved a 92.4% accuracy rate. The results of this study will contribute to the understanding of toxic fishes in Oman and will provide a valuable tool to mitigate risks associated with marine life in the region and enhance safety.**

***Keywords:* CNN, Fish classification, Image processing, Poisonous fish.**

I. INTRODUCTION

Oman, with its diverse marine life, is also home to many fish species that can pose a significant health risk if consumed. The adverse effects of consuming poisonous fish can range from mild symptoms to severe and even fatal conditions. Tragically, many fishermen and other users may not be fully aware of the risks associated with certain types of fish, or they may struggle to distinguish between poisonous and non-poisonous species. This lack of awareness was starkly highlighted in 2018 when six individuals were hospitalized in the intensive care unit of a government hospital in Muscat after consuming poisonous puffer fish [1]. This incident underscores the urgent need for a reliable and efficient method to identify poisonous fish in Oman, a need that this research aims to address.

Machine learning techniques, particularly deep learning models such as convolutional neural networks (CNNs), have been widely used for image recognition tasks in recent years. These models have shown great promise in identifying and classifying objects in images, including in the fields of biology and marine science. In this study, we aim to leverage these techniques to develop a machine-learning model for the recognition of poisonous fish in Oman.

The problem statement for the proposed project on poisonous fish recognition in Oman is that there is currently no comprehensive and reliable tool for identifying poisonous fish species in the country. Oman is known for its diverse marine life, including many species of fish that can pose a danger to human health if consumed. However, there is currently no standardized system in place for identifying these species, which can lead to accidental poisoning and health risks. Fishermen and other users may rely on visual cues or traditional knowledge to identify potentially poisonous fish, which can be unreliable and put them at risk. Additionally, tourists and other non-experts may not be aware of the dangers associated with consuming certain fish species.

To address this problem, the proposed project aims to develop a machine-learning model for the recognition of poisonous fish in Oman. By creating a comprehensive digital dataset of fish images and training a machine learning model using convolutional neural networks (CNNs) and multilayer perceptrons (MLPs). The project seeks to provide a reliable and accurate real-time tool for identifying poisonous fish. This tool can promote aquatic safety in Oman and help mitigate the health risks associated with consuming potentially poisonous fish species. The results of this study will have implications for aquatic safety and public health in Oman and may also be useful for similar applications in other regions.

II. LITERATURE REVIEW

Image processing and identification systems face numerous problems, such as noise, overlap, distortion, segmentation errors, and object occlusion. Previous studies have attempted to address these issues through different techniques and Algorithms. To classify the object correctly, Feature extractions and combination theories have been instrumental in developing systems that recognize objects within images. For example (texture, anchor points, and statistical measurements) have been utilized for object recognition.

The following studies have been done in the fish image recognition domain.

In reference [2], they proposed a model that distinguishes between poisonous and edible fish species using three machine learning (ML) techniques. The dataset includes 300 fish photos from 20 species, representing various forms, sizes, and colours. Training strong machine learning models that can effectively generalise to fresh, untested data requires this diversity. From the photos, hybrid features are derived, capturing crucial attributes required for precise categorization. Then, three distinct machine learning algorithms are fed these features: neural networks (NN), support vector machines (SVM), and k-nearest neighbour (K-NN). The performance of the models is assessed by dividing the dataset into subsets for training 70% and testing 30%. They achieved accuracy rates for their proposed system of 91.1%, 92.2%, and 94.4% for KNN, SVM, and NNs, respectively.

In reference [3], Researchers have employed a combination of Genetic Algorithms and Simulated Annealing along with a back-propagation algorithm to classify different fish species accurately. They used these Algorithms to classify dangerous and non-dangerous fish. In addition, they classify dangerous fish into predatory or poisonous families and non-dangerous fish into garden or food families. The researcher evaluated their experiment using 250 images for training and 150 for testing, achieving 90% accuracy.

In reference [4], the researcher utilised the YOLO deep-learning fish recognition algorithm. Their study has four main stages: developing the YOLO algorithm, collecting and labelling fish images, training, and testing. The researcher evaluated their experiment using 120 images for training and 100 for testing, achieving 92% accuracy.

In reference [5], the authors utilised the MobileNetv3-large and VGG16 backbone networks for fish recognition. The researcher evaluated their experiment using 70 images for training and 30 for testing, achieving 79.7% accuracy.

In reference [6], the authors proposed a classification of Underwater Fish Species Using the Alexnet model. This study used the Kaggle dataset, which contained 400 images under the following species: Dasyatis Centroura, Epinephelus Caninus, and Tetrapturus Belone, achieving 90% accuracy.

Table 1 provides a clear comparison of different models, datasets, and accuracies achieved in previous studies related to fish classification. In summary, the primary weaknesses in previous studies are the limited dataset sizes, potential lack of generalization, specificity of features, limited scope of evaluation, and potential overfitting due to the size of the datasets. Our study aims to address these issues by using large and more diverse datasets to ensure more comprehensive evaluation methods and accurate results.

Table 1. Summary of the previous studies

Study	**Algorithm**	**Dataset Size**	**Dataset Split**	**Features**	**Accuracy**
[2]	KNN,& SVM	300 photos from 20 species	70% training, 30% testing	Hybrid features capturing various forms, sizes, and colours	KNN: 91.1%, SVM: 92.2%,
[3]	Genetic Algorithms + Simulated Annealing + Back-propagation	400 images (250 for training, 150 for testing)	250 training, 150 testing	Classification of dangerous (predatory or poisonous) and non-dangerous (garden or food) fish	90%
[4]	YOLO deep-learning algorithm	220 images	120 training, 100 testing	Fish recognition	92%
[5]	MobileNetv3-large, VGG16	100 images	70 training, 30 testing	Fish recognition	79.7%
[6]	AlexNet model	400 images (Kaggle dataset)	Not specified	Species: Dasyatis Centroura, Epinephelus Caninus, Tetrapturus Belone	90%

III. MATERIALS AND METHODS

This project aims to create an artificial neural network (ANN) method that properly categorises fish species as poisonous or edible. Our goal is to enhance the precision and dependability of fish species identification by utilising a hybrid model that combines CNN for image analysis and MLP for feature analysis. This section provides a comprehensive description of the materials and techniques employed for data collection and preprocessing, as well as the development of the neural network structure, model training, and performance evaluation. Figure 1 shows the general structure of the methods used in this study.

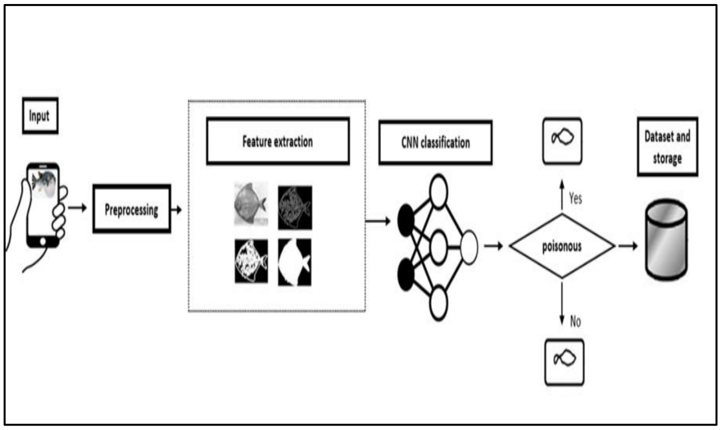

Fig. 1. Architecture of the proposed system.

A) Fish species datasets

Unfortunately, we did not find a ready database for fish in the Sultanate of Oman, but we took the names of the families of edible fish in Oman and poisonous fish from the Ministry of Agriculture and Fisheries in Oman. Then, we searched for it on the following reliable sources: **[7]** and **[8].** These datasets contain pictures of poisonous fish and known edible fish. This research focused on six families of poisonous fish: TETRAODONTIDAE, MOLIDAE, PASTINACHUS SEPHEN, DIODONTIDAE, and GEMPYLIDAE. See **Figure 2.** And 6 families of edible fish: Pampus argenteus, Dentex macrophthalmus, barbus, carps, Tenualosa Ilisha, and Caesio lunaris. See **Figure 3.** Furthermore, the images were chosen based on differences in size, colour, and controlled or uncontrolled illumination, whether in or out of the water or on plain or complex backgrounds. The total number of images was 966 (522 poisonous images and 444 edible images).

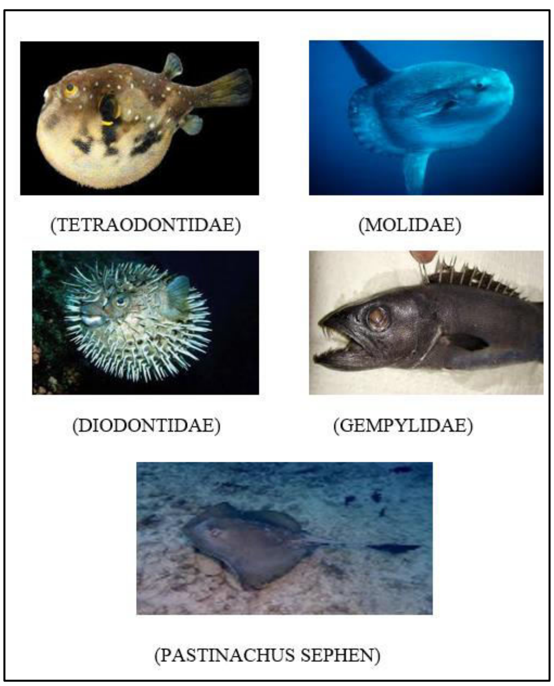

Fig. 3 Sample of the edible fish dataset

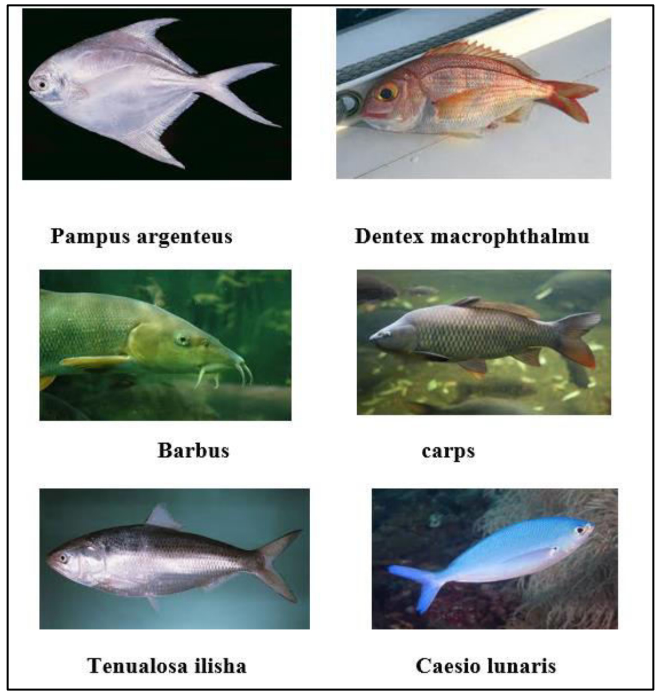

Fig. 2. Sample of the poisonous fish dataset.

B) Data preprocessing

Data processing is crucial in preparing datasets to train an artificial neural network (ANN) and produce more accurate results. After collecting the images, the following pre-processing steps were performed to ensure that the data is clean, uniform, and suitable for training the model:

- Resizing images: To ensure consistency, all images have been resized to a uniform size, 128 x 128 pixels.
- Normalization: Pixel values were resized to (rescale = 1.0/255.0). This helps with rapid convergence during training.
- Augmentation: To help prevent overfitting, the dataset has been made more diverse by applying the following techniques: rotate, flip, zoom, and transform. The setting has been used from [9].

C) The models

This study used artificial neural networks (ANNs) to extract and classify features efficiently. This study uses a hybrid architecture that incorporates convolutional neural networks (CNNs) for feature extraction and multilayer perceptrons (MLPs) for additional descriptive features.

CNN effectively extracts meaningful features from images **[10, 11& 12].** It contains multiple layers, such as convolutional layers, pooling layers, and activation functions.

These layers apply convolution operations to the input image using filters (kernels). Each filter extracts specific features (edges, textures, shapes) by convolving across the input image. Then, we will use Pooling layers to reduce the spatial and reducing computational complexity. In addition, activation functions(ReLU) were used to introduce non-linearity, enhancing the model's ability to learn complex patterns and relationships within the data. The setting of CNN has been used from **[13].** See **Table 2.**

The following tables provide a detailed outline of the CNN Architecture for Image Feature Extraction **Table 2** and the classifier Architecture **Table 3**.

MLP classifiers were used to integrate additional descriptive features beyond those extracted directly from images by CNN. These features include numerical data like weight and length and categorical data like species.

To connect the features extracted by the CNN with MLP, we flattened them into a vector and concatenated them with the additional descriptive features. This combined feature vector serves as input to the MLP.

Table 2. CNN Architecture.

Layer	Kernel Size	Output
Input Layer	(256, 256, 3)	(256, 256, 3)
Layer 1	3x3	(256, 256, 32)
Max Pooling 1	2x2	(128, 128, 32)
Layer 2	3x3	(128, 128, 32)
Max Pooling 2	2x2	(64, 64, 64)
Layer 3	3x3,	(64, 64, 128)
Max Pooling 3	2x2	(32, 32, 128)
Flatten Layer	-	131,072

Table 3. MLPs classifier Architecture

Layer	Kernel Size	Output
CNN Flatten Layer	The output of the final CNN layer	131072
MLP Input Layer	Input Layer	20
MLP Dense Layer 1	ReLU	64
MLP Dense Layer 2	ReLU	32
Concatenate Layer	CNN and MLP outputs	131,104
Dense Layer 1	ReLU	128
Dense Layer 2	ReLU	64
Output Layer	SoftMax	2

D) Training and Testing model

Training and testing: Our method used images of both poisonous fish and known edible fish to train the classifier for poisonous fish detection. This paper uses the 644 images dataset, 80% of which were used for training and 20% for testing. The combination CNN-MLP architecture was trained using backpropagation. The aim is to reduce a loss function, adjusting the model’s weights to improve prediction accuracy.

IV. RESULTS

The model was trained using Python programming language for a total of 30 epochs to distinguish between poisonous and edible fish. The result demonstrates strong performance on the training data with accuracy consistently above 92% and steadily decreasing loss. The training loss decreased from 0.2487 to 0.1880 over the final epochs, indicating effective learning. Nonetheless, the validation results showed more variability. See Figure 4 The validation accuracy ranged from approximately 71% to 77%, and the validation loss fluctuated. See Figure 5. This might suggest a potential overfitting or sensitivity to the validation data. Despite these fluctuations, the model achieved a respectable final validation accuracy of 71.28% with a corresponding loss of 0.7548. This indicates the model is generally effective but may benefit from further fine-tuning or additional data to enhance its generalization capability. More distal is shown in **Table 4**. In our study, the CNN-MLP model achieved the highest accuracy at 92.4%, indicating its superior performance compared to the other methods listed in **Table 5.**

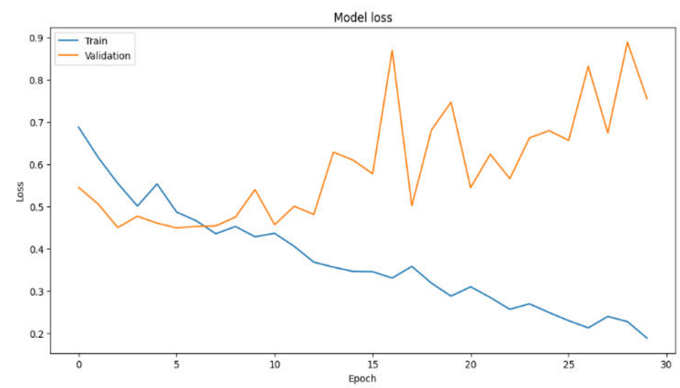

Fig. 4 Model loss

Fig. 5 Model accuracy

TABLE 4. PERFORMANCE METRICS OF CNN-MPL MODEL

Model	Optimizer	Total Params	Accuracy	Epoch
CNN-MPL	Adm	3314241	0.9244	30

Table 5. Comparison of previous study results with our study

Study	Algorithm	Accuracy
[2]	KNN & SVM	KNN: 91.1%, SVM: 92.2%,
[3]	Genetic Algorithms + Simulated Annealing + Back-propagation	90%
[4]	YOLO deep-learning algorithm	92%
[5]	MobileNetv3-large, VGG16	79.7%
[6]	AlexNet model	90%
Our study	**CNN-MLP**	**92.4%**

V.CONCLUSION

In conclusion, this study developed an effective system to classify edible and poisonous fish based on the combination of CNN-MLP networks. By utilizing convolutional neural networks (CNNs) for feature extraction and multilayer perceptrons (MLPs) for additional descriptive features, we aimed to improve prediction accuracy. Our CNN-MLP model achieved an impressive accuracy rate of 92.4%, outperforming other methods such as KNN, SVM, and YOLO. This demonstrates the potential of our hybrid architecture in identifying poisonous fish and contributing to marine safety. Future work will increase the dataset to include different fish families and images under different conditions to enhance the model's generalization ability.

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REFERENCES

[1] Bitwize. "After 6 cases of poisoning due to fish in Muscat... 10," Shabiba,3/6/2024, https://www.atheer.om/archives/486426/

[2] Jalal, A., Salman, A., Mian, A., Shortis, M. and Shafait, F., 2020. Fish detection and species classification in underwater environments using deep learning with temporal information. Ecological Informatics, 57, p.101088.

[3] Alsmadi, M.K., Tayfour, M., Alkhasawneh, R.A., Badawi, U., Almarashdeh, I. and Haddad, F., 2019. Robust feature extraction methods for general fish classification. International Journal of Electrical & Computer Engineering (2088-8708), 9(6), pp.5192-5204.

[4] Yusup, I. M., M. Iqbal, and I. Jaya. "Real-time reef fishes identification using deep learning." In IOP Conference Series: Earth and Environmental Science, vol. 429, no. 1, p. 012046. IOP Publishing, 2020.

[5] Alaba, Simegnew Yihunie, M. M. Nabi, Chiranjibi Shah, Jack Prior, Matthew D. Campbell, Farron Wallace, John E. Ball, and Robert Moorhead. "Class-aware fish species recognition using deep learning for an imbalanced dataset." Sensors 22, no. 21 (2022): 8268.

[6] Bhanumathi, M., Rithika, R., Roshni, R. and Selvaraj, S., 2022. Underwater Fish Species Classification Using Alexnet. In Advances in Parallel Computing Algorithms, Tools and Paradigms (pp. 400-405). IOS Press.

[7] https://www.freepik.com/

[8] https://www.fishbase.se/photos/BestPhotos.php?start=54

[9] Alkishri, W., Widyarto, S. and Yousif, J.H., 2024. Evaluating the Effectiveness of a Gan Fingerprint Removal Approach in Fooling Deepfake Face Detection. Journal of Internet Services and Information Security (JISIS), 14(1), pp.85-103.

[10] Al Husaini, M.A.S., Hadi Habaebi, M., Gunawan, T.S. and Islam, M.R., 2021. Self-detection of early breast cancer application with infrared camera and deep learning. electronics, 10(20), p.2538.

[11] Al Husaini, M.A.S., Habaebi, M.H., Gunawan, T.S., Islam, M.R., Elsheikh, E.A. and Suliman, F.M., 2022. Thermal-based early breast cancer detection using inception V3, inception V4 and modified inception MV4. Neural Computing and Applications, 34(1), pp.333-348.

[12] ALKISHRI, W. and AL-BAHRI, M.A.H.M.O.O.D., 2023. Deepfake Image Detection Methods Using Discrete Fourier Transform Analysis And Convolutional Neural Network. Journal of Jilin University (Engineering and Technology Edition), 42(2).

[13] Alkishri, W., Widyarto, S., Yousif, J.H. and Al-Bahri, M., 2023. Fake Face Detection Based on Colour Textual Analysis Using Deep Convolutional Neural Network. J Internet ServnInf Secur, 13(3), pp.143-155.