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Design of Shark Detection and Decoy Buoys

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***Abstract*—Humans and wildlife negatively interact when there is a loss of property, livelihood, or even life; this interaction is referred to as a human-wildlife conflict. Defensive and retaliatory killing may lead to the eventual extinction of these species. One such conflict occasionally occurs near coastal areas between cold-blooded saline water creatures like sharks and people. This work presents a proof of concept for developing a buoy that can detect cold-blooded predators and serve as a decoy system to deter human attacks. The decoy system is based on numerous biological facts and information about shark species. The model can detect up to 14 species of sharks and saline crocodiles using pattern recognition with a collective accuracy of 92%. The designed buoy is a novel approach to prevent human attacks near the coast with its decoy system based on the factual behavior of the predatory shark species and crocodiles.**

Keywords— Shark Species Detection, Deep Learning, Decoy System, Predator alert.

I. Introduction

In coastal regions, human-wildlife conflicts are considered a significant threat. The likelihood of getting bitten by a shark is 1 in 3,748,067. In 2021 alone, there were 73 unprovoked shark bites on people. In surf zones where sharks are known to swim, board sports are typically played produce a lot of splashing and disturb the water in a way that can draw sharks. Sharks are good indicators of the health of the ocean ecosystem. However, due to a lack of data, inadequate taxonomic knowledge, and undeveloped monitoring techniques, they are continually threatened by increasing fishing demands and poor management and conservation [1]. Sharks congregate in specific regions worldwide due to water pollution, habitat disruption, and a change in prey distribution brought on by global warming, which raises the possibility of encounters between humans and sharks.

Sharks do not always bite in order to kill. The three most frequent encounters with humans are as follows:

1)"Hit-and-run," which frequently occur in surf zones and are brought on by low visibility. During these assaults, sharks often merely bite their victim before swimming away since they find it repulsive.
2)"Bump and bite," a feeding technique in which sharks bump into their victim before repeatedly biting it.
3) Attacks that are "sneak" in nature result in biting that, unlike "bump and bite," occurs suddenly and without warning.[13]

In culmination, this paper contributes to the following.

- Designed a novel buoy capable of detecting predatory shark species and saline crocodiles using pattern recognition.
- The buoy can classify shark species and saline crocodiles and determine their predatory level using a deep learning algorithm (YOLOv5).
- Designed an alert and a decoy system for predatory shark species.

To provide a chance for the swimmers to reach the shore before a possible shark attack, a novel decoy system has been proposed based on the factual behavior of predatory shark species.

II. RELATED WORKS

Shark observation data through surveying and fisheries monitoring is frequently very expensive or challenging to gather, which is worse when species with greater home ranges are considered [2]. Sharks continue to be a marine animal group for which there is a severe lack of data, and these data gaps are a factor in the lack of abundance and distribution indices as well as the taxonomic precision required to assess population statistics accurately [3]. Importantly, remote monitoring techniques produce visual content that can assist close knowledge gaps about sharks. These techniques help to reduce the number of samples required and are non-intrusive. However, they create much material that must be post-processed for species identification and studies, which may involve eliminating pointless photographs [10]. Deep learning algorithms are very adaptable and suitable for taking on many of these tasks [11]. Rarely are sharks captured on camera or video during commercial fisheries. These photos come from visitors, social media, and underwater photographers more trustworthy [12]. Shark classification is a challenging task for machine learning due to the large number of morphologically diverse and data-poor shark species. Here, we tackle this problem by building the most extensive training dataset of shark pictures. Second, in order to make it easier to create biologically pertinent data on sharks, we combine object detection and hierarchical classification approaches for photos and videos. A new strategy involves assembling and annotating massive amounts of user-uploaded and data-mined media for conservation purposes [14]. In the past two

decades, machine learning algorithms have only recently started to be used for fish species classification. The most extensive and varied database of shark pictures has been produced due to our collaboration with big data and citizen scientists. Object detection and categorization have rarely been coupled in research to improve shark taxonomy accuracy [15].
When it comes to shark deterrents, there are many available in the commercial markets, Kempster et al. [19], in their investigative study, claim that the commercially present electric anklet shark deterrent "Electronic Shark Deterrent System" (ESDS) is unreliable in reducing the risk of a negative interaction with C. Carcharias. Blount et al. [20] mentioned that when an electric deterrent was active, the probability of a shark attack was reduced from (0.75 to 0.25), which is a 66% reduction; it was also mentioned that electric deterrents do not altogether remove the risk of the shark attack. Clever Buoy ™ is a sonar-based system that detects the presence of predatory shark species using their sonar fingerprints [21] DeNezzo et al. have mentioned that there were instances of Clever Buoy ™ trials at Hawks Nest Beach, NSW, in 2016 and City beach in Perth, Australia in 2017, both the trials were concluded unsuccessfully due to inability of independently verifying reports of shark detections and occurrence of very high false-positives.
The current developments in this field are promising but require lots of testing and validation.
Even though with timely detection of sharks near the coast, sharks move at a speed of 40 Kms/Hour [23], without a good decoy system possibility of a shark attack is still very prominent.

III. PROPOSED WORK

A. Working

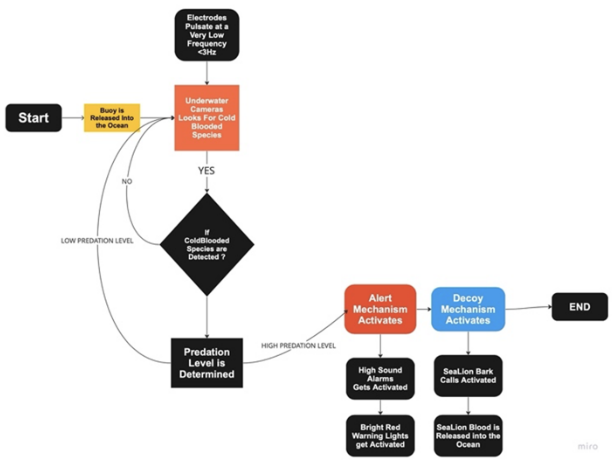

Fig:1 Working methodology of shark detection and decoy buoy

The above image explains the use case of the designed buoy.

- Buoy is released into the ocean, prone to shark attacks.
- To improve the probability of detecting sharks, a low-frequency electric pulse is released into the water; meanwhile, the underwater cameras look out for cold-blooded species in all directions.
- If cold-blooded species are detected, the predating level is determined according to the species.
- Based on the predating level, the alert and decoy mechanisms start their operation.

B. *Predatory Shark Species / Saline Crocodile Determination.*

- The predation level of the shark species is determined by its previous attacks on human [16].

Table I – Predation Level of Different Shark Species

S. No	Shark Species	Predation Level (1-10)
1	Great White Shark	10
2	Tiger Shark	9
3	Bull Shark	8
4	Blue Shark	7
5	White Tip Shark	7
6	Mako Shark	7
7	Sand Tiger Shark	6
8	Black Tip Shark	6
9	Saline Crocodiles	6

The above table determines the predation level of eight different shark species and saline crocodiles, from numbers 1-10, with "10" being the highest level of predation. The predation level of this shark species has been determined from previous shark fatal and not fatal attacks worldwide.

C. *Importance of Pulsating Electrodes*

Every living being releases milli-amperes of electricity during respiration [17]. Sharks have a specific sensory organ called "Ampullae of Lorenzini" [9]. This specific sensory organ can detect tiny amounts of electricity from very far proximity. Sharks tend to investigate these tiny impulses of electricity, judging them as prey.
This behavior of sharks can be considered highly helpful in detecting their presence by the cameras on board due to their close vicinity.

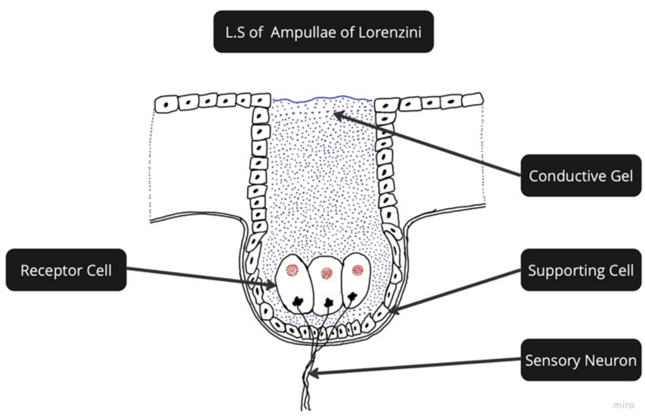

Fig:2 Ampullae of Lorenzini

The above image is the Longitudinal section of Ampullae of Lorenzini, a Sensory organ found in sharks.

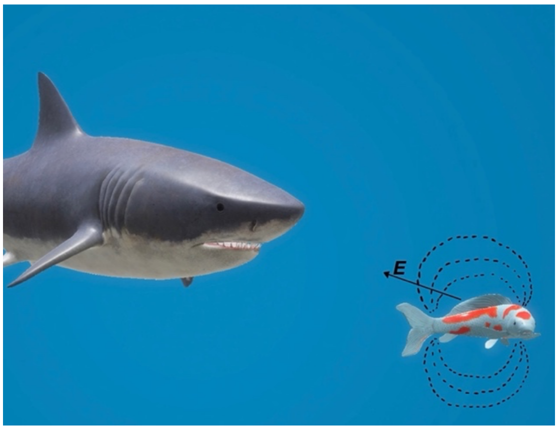

Fig:3 Shark detecting prey using "Ampullae of Lorenzini"

The above image is a visual representation of how the shark uses its "Ampullae of Lorenzini" to detect the electric field caused due to respiration of the fish(prey).

D. Alert Mechanism

- The alert mechanism consists of warning lights and 100W generic speakers.
- The alert mechanism gets activated in case of a possible predatory species detection.

E. Decoy Mechanism

The decoy mechanism mainly consists of two essential parts:

1)*Sea Lion Blood Tank:*
Sea lion blood tanks consist of fresh sea lion blood, which can be used to lure sharks in case of an attack.
Sealion blood consists of fresh RBCs, which have considerable electrical activity, that can be detected by sharks [7].

2)*Sea Lion Barking Speakers:*
Sea lion barking speakers are activated in case of an attack to lure sharks back to the buoy; the sound played will be below 1000Hz. Because the hearing capacity of sharks lies well below 1Khz [8,18].

IV. Design Aspects

A multipurpose buoy is the proposed solution. It has non-corrosive steel frames and features, including a caution light, anchor, air-filled base, and antennas like any other primary type of buoy. In order to collect the most power possible, solar panels are positioned vertically below the warning lights to provide the power source.

Due to two factors, speakers have been added as the next layer (above solar panels):

1. Sharks frequently hunt sea lions.
2. Sharks can see, but their sense of hearing is superior.

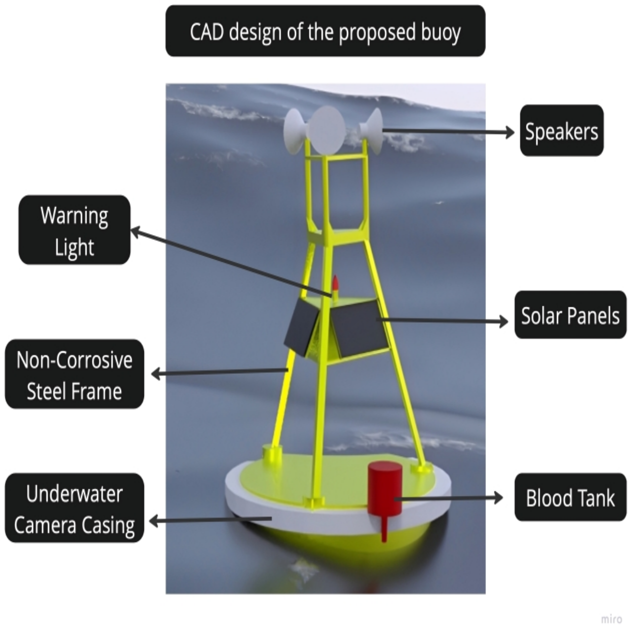

Fig:4 3D CAD design of the buoy

The above image is the 3D CAD design of the buoy designed using Solidworks ™ and visualized using Blender ™ software.

The purpose of a sea lion blood-filled tank is to attract the predatory shark species from humans towards the buoy. It coordinates with the decoy speakers, creating a visualization of a sea lion to the shark (in case of detecting a shark), which will change its direction away from the humans. The four Cameras are placed above the air-filled sacs in a clear polycarbonate casing. The clear polycarbonate casing also houses the electrical components of the buoy.

A. Hardware Design

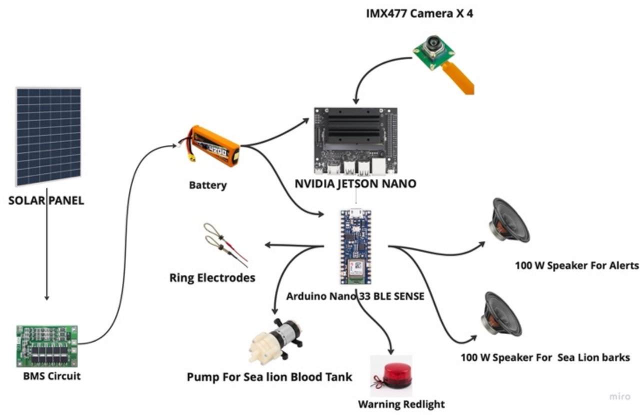

Fig 5. Hardware Connections

The above image explains the interconnections between different hardware used.

NVIDIA® Jetson Nano ™: The NVIDIA® Jetson Nano ™ Developer Kit is a compact, powerful computer that enables the parallel operation of multiple neural networks for tasks like speech processing, object detection, segmentation, and image classification. All this on a simple platform that consumes as low as 5 watts of power [4].The latter acts as the main CPU of the buoy. It obtains the camera feed from all four cameras, processes it, and deploys the trained model to predict the presence of any shark species or saline crocodiles present.

Fig 6. NVIDIA® Jetson Nano ™ Developer Board

The above image is of a NVIDIA® Jetson Nano ™ developer board.

The NVIDIA® Jetson Nano TM developer board is connected to 4 IMX477 Cameras to provide multidirectional coverage. The high-definition camera module IMX477 is outstanding, professional, and has a square pixel rate. It has a 1/2.3-inch CMOS active imaging pixel array sensor, which is great for low-light performance. The IMX477 supports 12-megapixel digital still images measuring 4056 (H) X 3040 (V) in size and video.

Fig 7. IMX477 Camera Connected to Nvidia Jetson Nano

The above image is of a IMX477 Camera Connected to Nvidia Jetson Nano.

In case of a predatory species is detected, the Jetson Nano ™ sends a digital control signal to the secondary CPU (Arduino Nano BLE 33 Sense) to perform the necessary actions.The Arduino Nano 33 BLE Sense is based on the Arm® Mbed ™ OS and the nRF52840 microcontroller [5]. The Arduino Nano 33 BLE Sense acts as the second CPU of the buoy, which performs the alert and decoy mechanisms. The **decoy system** consists of R385 diaphragm-based pump and Loudspeakers. The decoy mechanism gets activated when a digital control signal from the primary computer (Jetson Nano) is sent to the secondary computer (Arduino Nano). A non-submersible pump, such as the R385 6-12V DC Diaphragm-Based Mini Aquarium Water Pump, has sufficient pressure to create a spray system when used with a nozzle. It can handle heated liquids up to an 80°C temperature. The electric pump used in the buoy pumps out the Sealion blood from the blood-filled tanks at the base of the buoy. Speakers play the recorded sea lion barks at 1KHz, to create a perception of a real live sea lion. Multiple speakers are placed in the buoy's top section for sounding alarms and playing sea lion barks. Alert system also includes bright red-colour warning lights on the buoy's top section.

Power Supply:

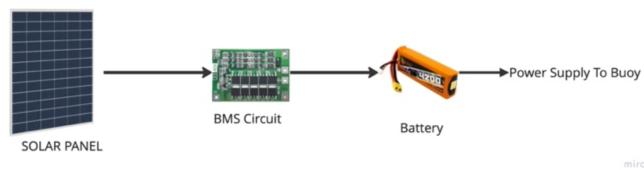

Fig 8. Power flow of the Buoy

The above image is of the power flow of the buoy.

- Solar Panel recharges the battery using the battery management system (BMS) circuit when there is adequate sunlight.
- The battery management system (BMS) manages the re-charging of the battery.
- The Battery powers the primary CPU, secondary CPU, and other mechanisms in the buoy.

B. Software Design

Data Collection:

Pictures of 14 different species of sharks and saline crocodiles have been collected from various online sources.
Total Pictures Collected:2725
Shark Species Collected: Basking Shark – 151 Pictures, Blacktip Shark -151 Pictures, Blue Shark -147 Pictures, Bull Shark - 151 Pictures, Hammerhead Shark -149 Pictures, Lemon Shark - 146 Pictures, Mako Shark – 155 Pictures, Nurse Shark – 149 Pictures, Sand tiger Shark-151 Pictures, Thresher Shark-151 Pictures, Tiger Shark-151 Pictures, Whale Shark -146 Pictures, Whitetip Shark - 151 Pictures, White Shark- 162 Pictures and Saline Crocodiles - 614 Pictures.

The collected pictures were resized to 416X416 for uniformity during model training.

Preprocessing Steps include labelling of dataset, contrast adjustment, grayscale conversion and noise addition.

a) Labeling of Dataset:
In this preprocessing technique, the area of interest is marked and labeled.

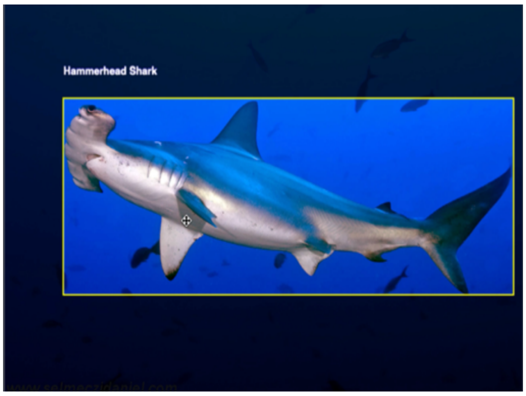

Fig 9. Labeled image excerpt of a hammerhead shark

The above image is of a labeled image excerpt of a hammerhead shark.

b) Contrast Adjustment:
In this process, the Histogram Equalization technique is used. Adjusting Contrast makes the model detect edges better.

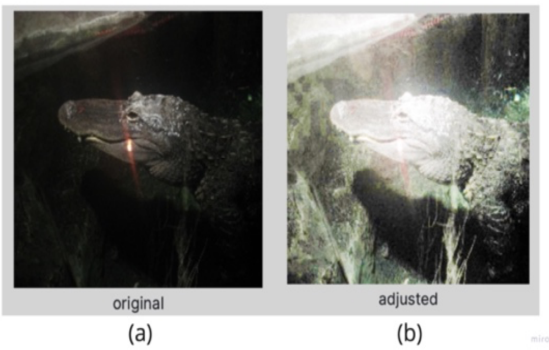

Fig 10. Contrast Adjustment – Original Image (a) and Adjusted Image (b)

The above image is of a contrast adjusted photo variation from the data set.

c)Grayscale conversion:
Color Channels are merged in this process to make the model detection faster and insensitive to the subject color.

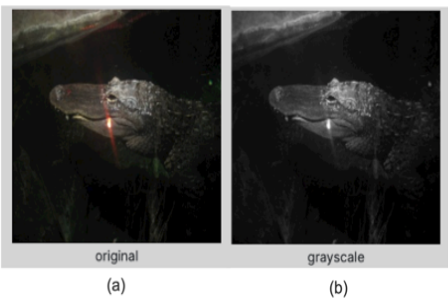

Fig11.Grayscale– Original Image (a) and Grayscale Image (b)

The above image is of a Grayscale converted photo variation from the data set.

d) *Noise Addition*:
Adding Noise to the dataset will help the model to become more resilient to camera artifacts and prevent overfitting of the model.

Fig12. Noise added Images – Original Image (a) Vs Noise added (b)

The above image is of a Noise added photo variation from the data set.

By performing the above-mentioned Pre-processing steps, the dataset is prepared for model training.

Training, Validation and Testing Spilt Ratio:

Training Set Consists of 2200 Images, Validation set consists of 273 Images, and Testing Set consists of 272 Images. The Ratio is Split as 80:10:10 for training, validation, and testing, respectively.

V. MODEL TRAINING

YOLOv5:
A family of compound-scaled object identification models called YOLOv5 developed using the COCO dataset has basic capabilities for Test Time Augmentation (TTA), model ensembling, hyperparameter evolution, and export to ONNX, CoreML, and TFLite.

Model Training:
The Model has been Trained with the YOLOV5x variant for 100 Epochs with Learning Rate set as 0.001 and SGD as its Optimizer.

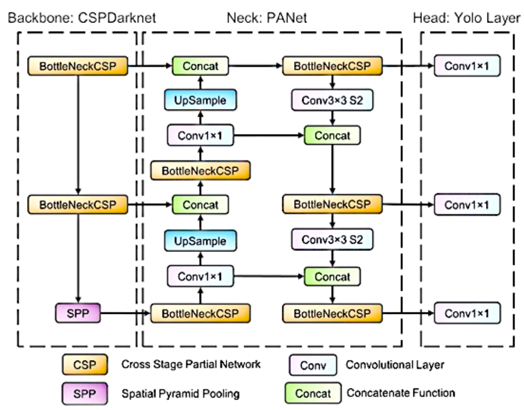

Fig13. Overview of the trained YOLOv5x model

The above image provides an architectural overview of the YOLOv5x model.

Yolov5's network architecture. It consists of three parts: CSPDarknet for the backbone, PANet for the neck, and Yolo Layer for the head. Before being sent to PANet for feature fusion, the data are first supplied to CSPDarknet for feature extraction. Yolo Layer then outputs the results of the detection (class, score, location, size) [22].

VI. MODEL TESTING

Precision-Confidence Curve:

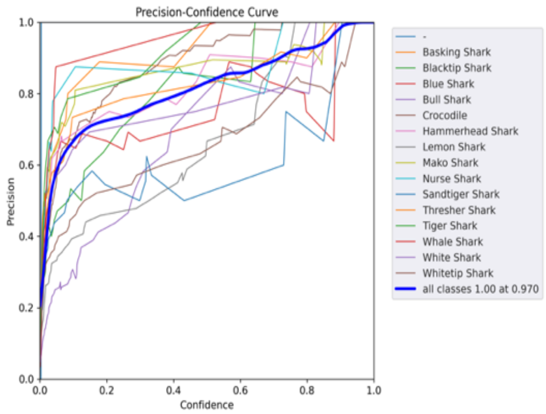

Fig14. Precision-Confidence Curve

From the above figure, it can be inferred that the confidence value that optimizes the precision is 0.970.

Recall-Confidence Curve:

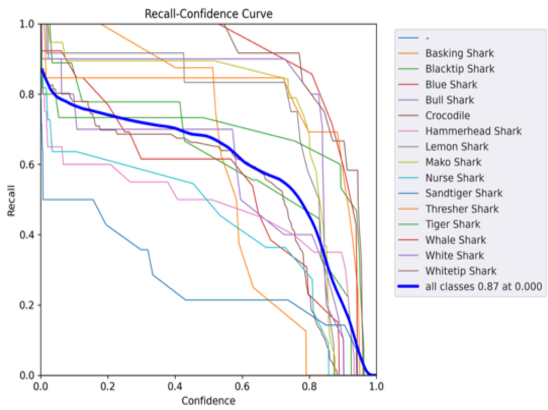

Fig15: Recall-Confidence Curve

From the above figure, it can be inferred that the Confidence value that optimizes the Recall is 0.870.

F1- Confidence Curve:

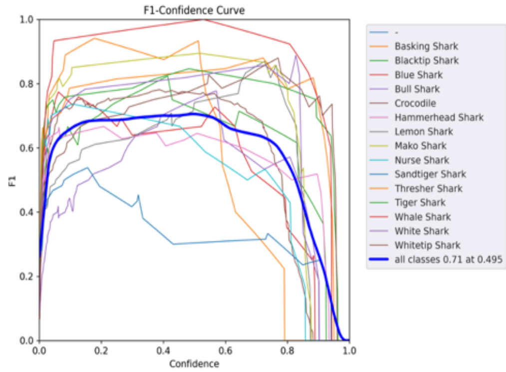

Fig16. F1-Confidence Curve

From the above figure, it can be inferred that the confidence value that optimizes the precision and recall is 0.495.

Fig.14, Fig.15, Fig.16 provides a visual representation on the performance of the trained model. The threshold value for detection has to be set at 0.495 for the best performance of the trained model.

Confusion matrix:

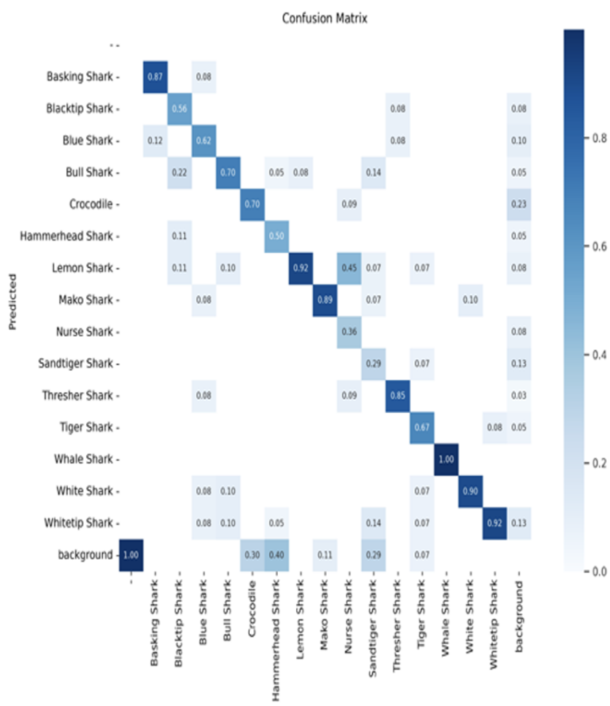

Fig17. Confusion Matrix

From the above confusion matrix, it can be inferred that the classification of whale sharks has the highest accuracy of 100% while testing and Sand tiger Sharks have the least accuracy of 29%. Multiple factors can affect the accuracy due to the similar skin patterns of the species.
The overall collective accuracy of the model is 76.785% with respect to testing dataset.

VII. Result Analysis

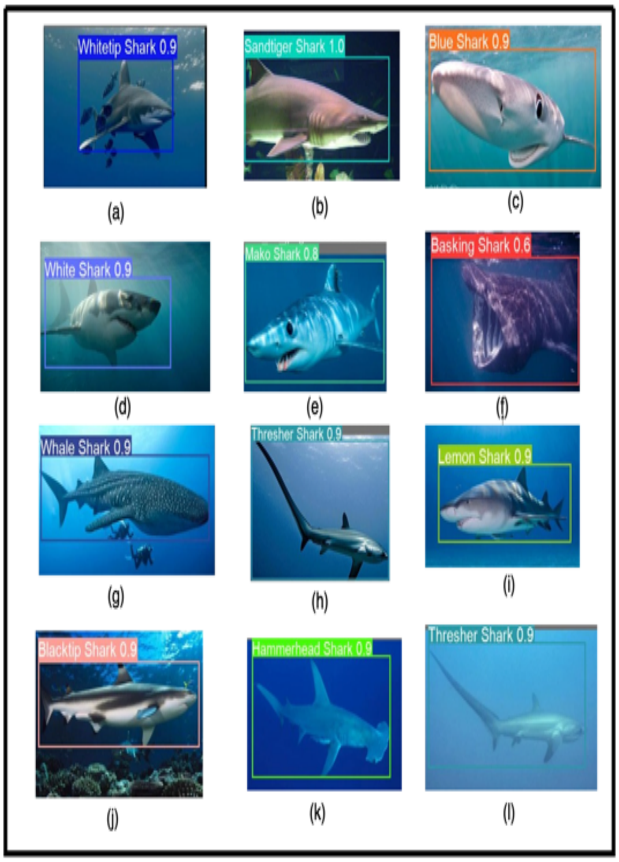

Fig18. Prediction Results

From the above image, we can infer the prediction results of the trained model.

In Fig.18(a), a White tip shark is predicted with 90% confidence; In Fig.18(b), a Sand tiger shark is predicted with 100% confidence; In Fig.18(c), a Blue shark is predicted with 100% confidence; In Fig.18(d), a White shark is predicted with 90% confidence; In Fig.18(e), a Mako shark is predicted with 90% confidence; In Fig.18(f), a Basking shark is predicted with 60% confidence; In Fig.18(g), a Whale shark is predicted with 90% confidence; In Fig.18(h), a Thresher shark is predicted with 90% confidence; In Fig.18(i) , a Lemon shark is predicted with 90% confidence; In Fig.18(j), a Blacktip shark is predicted with 90% confidence; In Fig.18(k), a Hammerhead shark is predicted with 90% confidence; and In Fig.18(l), a Thresher shark is predicted with 90% confidence.

The following images used in the prediction are from the testing set of the dataset.

Testing of the System:

The different systems used in the buoy was tested in a controlled environment, due to unavailability of real sharks.

a) Setup of the controlled environment:

- The control environment consists of LCD color displays that play recorded videos of different species of sharks.
- Multiple Videos of different Shark species, that were recorded in different lighting conditions were played on the LCD color screens.
- The cameras were pointed toward the LCD color displays to perform predictions.
- In place of Sea-lion blood, fresh water is filled in the tank to validate the pump's performance.
- Performance of alert and decoy systems were evaluated.

Results from the controlled environment test can be discussed as follows:

- The System **performed satisfactorily well**; it identified all species of shark in its training database along with the saline crocodiles.
- The alert and decoy mechanisms got **activated** for appropriate predator shark species.
- The functioning of the Pump, Speakers, and warning light were **satisfactory**.
- The system **struggled** to classify species in videos with deplorable light conditions.

Out of the 25 different videos played during the testing, 23 videos had correct/satisfactory responses from the system. It was concluded that the test results had validated the system to be **92% accurate**. A system that can detect cold-blooded species through pattern recognition and a decoy system that can deter shark attacks is designed successfully as a product of this paper.

TABLE II – COMPARATIVE ANALYSIS OF DIFFERENT MODELS

S. No	Subject	Accuracy
1	Proposed model	92%
2	[10]	76%
3	[24]	81%

The above table compares the accuracy rate of the proposed model with other models [10,24]. The accuracy of the proposed model is validated highest.

VIII. CONCLUSION

Moving on to the ecological implications of the designed buoy, the ecological relationship between shark species and humans can be improved qualitatively, with lesser deadly attacks between them and even more positive interactions. Future works can include multiple pattern recognition techniques using IR-UWB (Impulse Radio - Ultra Wide Band) technology through radar detection techniques for robust detections since cameras cannot perform well in low light conditions. The two different classification systems can act independently to validate the classifications mutually.

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