Revolutionizing Marine Security with Advanced AI-Driven Autonomous Underwater Defense Systems

K. Swetha[1], T. Ananth Kumar[1], Tunde Olamide Ogundare[2], Sunday Adeola Ajagbe[3,4,*], P. Kanimozhi[1], Akindayo Akindolani[5] and Pragasen Mudali[3]

[1]*IFET College of Engineering, Tamil Nadu, India*
[2]*Liverpool John Moores University, Liverpool, United Kingdom*
[3]*University of Zululand, Kwadlangezwa, South Africa*
[4]*Abiola Ajimobi Technical University, Ibadan, Nigeria*
[5]*McAnderson Institute of Technology, Abuja, Nigeria*

Abstract

The enhanced aspect of the use of AUDS is the reality that it will markedly increase marine security, coupled with the security of underwater assets. These systems have to perform under adverse environments with noisy sensor information, dynamic obstacles, and low visibility scenarios. To eliminate these challenges and improve the measures of audibility, polymorphism, and dependability of AUDS, this research explores modern AI techniques. The NKPL algorithm is adopted by the suggested system for making decisions in situational change and for planning the course during the congested operating mode underwater. Due to the interaction of these AI components, AUDS can recognize, track, and respond to potential threats independently, even in complex and unpredictable water conditions. Studies show that the system can make stable decisions, correctly choose the appropriate path, and accurately identify threats. Using these modern AI techniques, the results differ from traditional methods by providing higher performance in terms of operations and rates of mission accomplishment. This work presents opportunities for utilizing intelligent and self-organized systems in the security and surveillance of the seas and exploration. The paper also demonstrates the potential of AI to revolutionize underwater defense systems. The results also show that future work in defense applications and autonomous robotics technologies can be initiated.

Keywords

Unmanned underwater autonomous (UUAs), Object detection, Shortest path planning (SPP), Artificial Intelligence (AI), Neuro-Kalman Path Learner (NKPL) Algorithm.

1. Introduction

Since autonomous underwater vehicles, or AUVs, are likely to operate in sensitive and hostile environments, much of the data transmission, navigation, and control would need to be done under stricter security measures [1]. Some systems now have incredibly complex architecture designs as a result, which could compromise performance and cost-effectiveness. They best suit environments that are inherently difficult or even impossible to access safely [2]. On the other hand, the underwater environment, with its peculiarities, remains differentiated from surface or land-type autonomous operations. For instance, challenges to classical navigation and detection techniques include the complex and dynamic nature of seafloor topography, signal attenuation, visual impairment or poor visibility, and the unavailability or unreliability of Global Navigation Satellite System (GNSS) signals [3]. The need to address this problem has given rise to the recent research trend of combining machine learning

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*Corresponding author.
karthicksenthilvel74@gmail.com (K. Swetha); tananthkumar@ifet.ac.in (T. Ananth Kumar); babatundeolamideogundare@gmail.com (T. Ogundare); saajagbe@pgschool.lautech.edu.ng (S. Ajagbe); chandrankani@gmail.com (P. Kanimozhi); Dayo@mcandersoninstitute.tech (A. Akindolani); MudaliP@unizulu.ac.za (P. Mudali)
0009-0000-5372-3227 (K. Swetha); 0000-0002-0494-7803 (T. Ananth Kumar); 0009-0005-7505-530X (T. Ogundare); 0000-0002-7010-5540 (S. Ajagbe); 0000-0002-0268-6048 (P. Kanimozhi); 0009-0007-3321-7475 (A. Akindolani); 0000-0003-4720-1726 (P. Mudali)

(ML) and deep learning (DL) paradigms into an AUV system [4, 5]. Although AI has been developed in surface and air navigation, in the underwater environment, this is relatively new and quite unexplored. Underwater navigation methods rely mostly on acoustic methods such as sonar, which, in some way, are helpful, but generally produce very noisy and distorted data where it is difficult to maintain situational awareness and locate objects. Meanwhile, the path-optimization and avoidance of obstacles still hold very high challenges owing to the turbulent and unpredictable nature of the underwater environment [6].

AUVs are useful for defense, mine detection, and marine surveillance missions when avoiding obstacles and making decisions in real time are crucial [7]. Traditional navigation pipelines can perform poorly in the sonar-dominant environment due to a number of unfavorable characteristics, including dynamic obstructions and noisy measurement data. Robust path planning in the face of uncertainty has not yet been demonstrated to be effective in defense scenarios where latency, precision, and stealth are crucial factors [8]. This research introduces Neuro-Kalman PathLearner (NKPL), an integrated architecture that employs reinforcement learning (RL) for adaptive path planning, Kalman filtering for state estimation, and convolutional neural networks (CNNs) for sonar object identification [9, 10]. The device is designed for underwater defense activities and has been tested using artificial sonar data in a controlled simulated environment.

This paper proposes a novel dual-layer architecture based on AI to enhance underwater navigation and target recognition capabilities of AUVs. The project has two main components: a deep learning framework built atop YOLOv8 for real-time object detection from sonar images and a navigation module based on reinforcement learning for path generation that is efficient, optimal, and free from collisions in dynamic settings [11, 12, 13]. Through the object detector, the AUV can identify specific underwater targets such as mines or marine installations, while the navigation module plans and realigns itself on the fly with environmental changes [14]. An unusual consideration about this approach is that the training is done on realistic sonar datasets from objects such as offshore lobster cages, which might stand in as proxies for underwater threats or targets [8]. YOLOv8 is selected because it is well-suited to quickly and accurately detect and process dense, low-resolution sonar images. In the meantime, the reinforcement learning agent learns and optimizes the navigation plan, finding the best course of action in terms of energy, mission length, and safety [15, 16]. Through this mixed approach, the proposed technology holds the prospect of assured, AI-embedded autonomous underwater operations free of human control. Filling a gap in AI-driven underwater detection and navigation literature, the research presents a flexible and scalable framework, which can be adapted for future defense and security missions such as mine countermeasures, covert surveillance, and search-and-rescue [17, 18, 19]. The result represents a big step forward in improving autonomous operations, situational awareness, and real-time decision-making ability in AUVs in autonomous underwater defense systems.

1.1. Background

Contemporary threats have penetrated the underwater world along with the visible space; as a result, the concept of maritime security is complex now. For tasks such as surveillance, threat elimination, and scouting, it is impossible to do without using autonomous systems. It has become crucial equipment. Because of the accuracy, dependability, and scalability of the operation, autonomous underwater vehicles, or AUVs, are vital tools. Despite notable progress, there are still important obstacles to overcome:

1. **Limitations on Visibility:** As the underwater environment often disrupts illumination, regular optical instruments are useless.
2. **Navigational Complexity:** Navigational Complexity: We consider that path finding might be obstructed by dynamic obstacles and high density of space.
3. **Sonar Noise:** Sonar Noise: The use of object detection models is reduced by difficulties associated with the type of imaging used in sonar, namely, acoustic interference. To eliminate these concerns, this research attempts to adopt the advanced AI approaches utilized for underwater work.

1.2. Problem Description

Traditional AUVs depend on heuristic approaches to adapt to small underwater conditions, and these approaches are not optimal. Neither navigation algorithm procedure can deal with changes in the environment in real time, and noise issues hinder the object detection procedures. Based on the analysis, this work proposes an architecture consisting of deep learning for object detection and reinforcement learning for multiple target navigation. Among the paramount challenges for performing underwater navigation and object tracking are: noise from sensors, absence of GPS, changing environmental conditions, and nonlinear dynamics. Generally, conventional Kalman Filters (KFs) are used in the navigation system for state estimation because they give estimates of the system states in the best possible manner when the system is linear, and the noises are Gaussian. However, the exceedingly nonlinear and non-Gaussian noise present in an underwater channel degrades the performance of simple Kalman Filters. Whereas Neural Kalman Filters may solve such problems. The NKF enhances the ordinary Kalman Filter design by including in it a neural network, normally a recurrent neural network (RNN).

1.3. Research innovation

The following are the main technical contributions of the work:

- Improved object recognition in sonar images using CNNs based on YOLOv8.
- Dynamic path prediction under uncertainty using Kalman filtering and reinforcement learning and
- A dual-layer Neuro-Kalman PathLearner architecture for underwater navigation.

2. Related works

Accurate autonomous underwater vehicle (AUV) navigation remains among the most complicated operations, since satellite-based navigation systems like GNSS cannot be utilized underwater. Dead reckoning techniques are popular yet ultimately limited due to the drift resulting from the accumulation of errors. Positioning algorithms in dead reckoning rely on the fusion of motion information from acceleration and velocity sensors with known historical locations or previously visited path information in order to compute the current position. This generally employs inertial measurement units (IMUs), such as inertial accelerometers, gyroscopes, and magnetometers, to provide orientation and movement measurement [20, 21, 22]. Low-cost IMUs were considered adequate from a theoretical point of view; however, such use is imperfect as they lack the accuracy, sensitivity, much less external failure, and insensitivity amounts to ocean currents [13, 14]. High-end MEMS-based professional IMUs still suffer from sensor noise and internal drift, both of which tend to be cumulative with time, leading to faulty localization measures.

Thus, systems like Long Baseline (LBL), Short Baseline (SBL), and Ultra-Short Baseline (USBL) have been used in these cases where controlled environments are created by the underlying infrastructure [23, 18]. The precision is especially high using LBL techniques, which essentially localize AUVs using time-of-flight measurements from stationary acoustic beacons for triangulation. As an example, [24] indicated that using two submerged acoustic transponders, an object may be localized to 2-3 meters. Their limitations are that they tend to restrict applicability in the open or infrastructure-poor environments; restrictions in deployment, and costs. Due to the infrastructure burden of sound systems and the lack of credible GNSS signals underwater, researchers have been compelled over the last few decades to embrace vision- and perception-based methods like Simultaneous Localization and Mapping (SLAM). SLAM is an extremely robust tool used by an autonomous underwater vehicle (AUV) to map its environment and calculate its pose concerning the map. A variety of sensor modalities have been employed for environmental perception, including sonar [25], acoustic sensors [3], cameras [26], LIDAR [27], and radar [28].

These data are processed with Bayesian filters, Kalman filters, and, more recently, deep learning-based techniques to enhance position estimates and to decrease uncertainty. Several studies have attempted to improve SLAM methods by incorporating machine learning (ML) and deep learning (DL) models to enhance environmental sensing, feature extraction, and prediction accuracy. A learning SLAM framework fueled by machine learning can learn environmental models directly from sensor streams and adapt in environments where traditional systems fail. The case of using CNN-based analysis of sonar images allows a superior identification of landmarks, even under some challenging lighting conditions. There is also some interest in modeling inertial motion and sensor data with recurrent neural networks (RNNs) and deep long short-term memory networks (LSTMs) to help in trajectory estimation and localization drift reduction. Those are good advancements; however, there is a deafening silence in the literature on a subject of particular significance to ML- and DL-based navigation and guidance of underwater vehicles concerning the surface. The really major problem is that extremely few researchers have thought about it in the sense of long-duration missions, where sensor drift and environmental ambiguity are worsening. Even so, some research [16, 26] suggests that vision and learning-based methods might be promising for SLAM applications even in coastal and harbor environments. Except for such applications, most of the research has relied on either purely physical models or hybrid models in which acoustic aids supplement dead reckoning. Deep Learning stepping into the AUV pipeline from the end to the beginning concerning navigation might not be the common practice, but it is quite a promising field, especially when looking into terrain new for explorative mapping and learning control adaptive by learning for dynamic obstacle avoidance. Basic to underwater navigation have been dead-reckoning systems, IMU-based, combined with acoustic positioning systems, which have been considered representative shortcomings as scalability, adaptability, and fault-tolerance. Increased adoption of DL-based SLAM and perception-driven navigation systems has proved very promising as a gap-filler. This research follows that increasingly growing trend and focuses specifically on learning-based navigation approaches developed for underwater environments, where conventional localization alternatives fail to meet demands. Thus, we present our Neuro-Kalman PathLearner (NKPL) architecture, which integrates convolutional neural networks (CNNs) for sonar object detection, Kalman filtering for state estimation, and reinforcement learning for adaptive path planning. The device is designed for underwater defensive tasks and has been demonstrated using synthetic sonar data in a controlled simulation environment.

3. System Architecture

The three phases of NKPL's pipeline design are perception, planning, and control. The perception module incorporates CNNs based on YOLOv8 to help detect submerged objects from sonar imagery. The planning module also includes a Kalman filter-enhanced RL agent that selects probabilistic state estimates to provide a path. Control commands are then generated using those channels.

3.1. Input Sonar Data

Sonar data is the main input to the system. Equipment such as sonar devices, commonly used in underwater contexts, captures real-time data or images of the underwater environment. This data forms the foundation for defining things, challenges, and potential risks in the underwater environment. Different sources of noise, water quality, and accessibility of objects being tagged and their interference also affect the validity of this data.

3.2. Object Detection

For recognizing the objects in the sonar images that are received in the input of the algorithm, at this stage, the YOLOv8 (You Only Look Once) model is employed. YOLOv8 was selected because of its high accuracy and efficiency in real-time object detection. It is designed to detect the image in a very short time, provide confidence scores for each item detected, and provide the bounding box around them. This

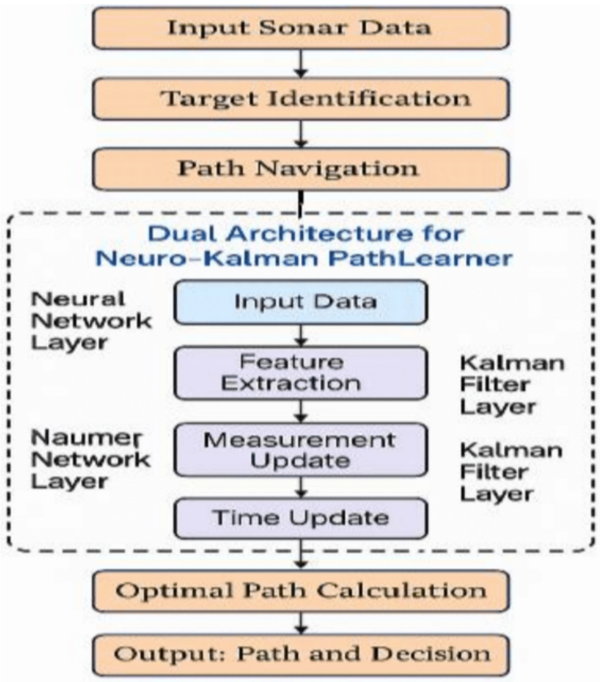

Figure 1: System Architecture

is imperative for the underwater defensive system, as the mission's failure and success considerably depend on identifying objects such as lobster creels, underwater structures, or other potential threats. The model operates in real-time and requires a single pass owing to the ability to constantly detect many objects.

3.3. Target Identification

Target identification follows after object detection has been done. This specific block involves categorizing the objects that have been observed in terms of mission relevance, which is to do with distinguishing which things are relevant to the defense system's objectives, like a lobster cage or an object of interest that may be sunk in the water. The system tags or classifies the identified items according to certain patterns that the data mining algorithm discovers from learned models. It may involve refining the detection outcome to ensure that only certain characteristics of objects, such as the objects that are essential to a mission, are chosen for further action.

3.4. Path Navigation

After the object detection, the process of navigation unfolds, controlled by Reinforcement Learning (RL). During such a phase, the Navigation and Guidance System executes RL algorithms that enable the AUV to dynamically select the best routes to predefined targets while actively avoiding detected obstacles. Since the underwater environment is uncertain, the RL module adopts a reward-and-punishment approach: rewarding the agent for moving toward the target and punishing it for dangerous behavior, such as venturing into hazards or inefficiently deviating. Based on previous contacts with the environment, the reinforcement learning agent develops a policy that is fitted in real time. Thus, it allows the AUV to update its trajectory according to any new obstacles or environmental changes.

3.5. Dual Architecture for Neuro-Kalman PathLearner (NKPL)

3.5.1. Neural network layer

A neural network consists of input data and feature extraction. Input data consists of filtered sonar data and previous path history. Feature extraction has patterns and important features like direction, obstacle characteristics, and confidence scores.

3.5.2. Kalman Filter Layer

Kalman filter includes real-time measurements like location drift, object movements for correct prediction. By dispersing the updates of dynamic models along the route, this lowers the estimation error by forecasting future locations and choices. A probabilistic estimate (Kalman filter) and machine learning predictive evidence (neural network) have been combined to provide an integrated adaptation navigation system for underwater vehicles.

3.6. Optimal Path Calculation

The best route that the AUV is to take is also decided on at this point in the process. The path planning function determines an optimum path that will take the robot to the target with little or no danger from the information obtained by the reinforcement learning navigation system. It includes minimizing the use of barriers, as well as ensuring that energy consumption is reduced and travel time is brought under control. The additional advantage is that dynamic changes of rate values can be made by the algorithm right in real-time mode due to new inputs of fresh data.

3.7. Output: Path and Decision

According to the best path selected in the previous stage, the system's output is a decision. By this output, the AUV is navigated to the target, with features such as the mission goals, productivity, and security given under consideration. In addition to the operational decisions, the output might provide directional points for the AUV to travel within the area. The mechanism ensures that the AUV does the work without much human involvement.

3.8. Proposed Algorithm

Analyzing the complex issues Autonomous Underwater Defense Systems (AUDS) face, the Neuro-Kalman PathLearner (NKPL) algorithm was developed. Taking advantage of state-of-the-art artificial intelligence and control system methodologies, NKPL offers good underwater vision, navigation, and decision-making functions. This paper recommends the use of a technique that offers Reinforcement Learning (RL), the A* algorithm, the Kalman Filter, and Convolutional Neural Networks (CNNs) that are implemented in a complementary and generic structure. The essential applicability of the CNN in the NKPL algorithm for real-time perception to enable accurate identification and classification of items in conditions of low visibility and high noise when submerged. To ensure future specific robustness to detect further threats, including mines, submarines, and other unknown objects, the CNNs are trained on a mixed set of real and augmented sonar and optical imagery. Specifically, the CNN module extracts high-level features in the interest of enhancing situational awareness, another critical aspect of undersea defense.

There is a need to assess the state estimates to provide accurate localization for NKPL, for which the solution employed is the Kalman Filter. This filter computes the state of the AUDS by using noisy measurements of its position, velocity, and orientation from sonar sensors, IMUs, and GPS, if mounted. However, the Kalman Filter not only enhances the efficiency of location and produces better results for current conditions; the filter also predicts the conditions that is to come in the future, essential when designing and creating an active navigation. NKPL increases the performance in highly varying underwater environments with the help of a neuro-inspired 'enhancement layer' that adjusts its filtering according to the non-linear dynamics of the system in which it operates. NKPL's path planning element is based on an enhanced A* algorithm generated on the fly and provides the safest and most efficient way to a particular goal. The A* component is executed in real-time using mission limits, the detected environmental variables, and barriers. Therefore, NKPL enhances the A* algorithm with predictive models, enabling it to continually update the path and predict changes in the surrounding space. Thanks to its predictive capabilities, the AUDS may avoid potential hazards such as shifts in underwater currents or moving barriers. Furthermore, the NKPL algorithm enables platoon-level coordination between several AUDS units. During missions that require joint movements, such as coordinated patrols or multiple-target defense, NKPL offers the feasibility of real-time information sharing and management through distributed RLs and decentralized control. This feature enhances the scalability and the operating efficiency of underwater defensive systems. The proposed scheme is a multi-layer arrangement designed to enhance the autonomy of autonomous underwater vehicles. The first part of this proposal involves the interpretation of sonar images using a YOLO v8-based Convolutional Neural Network designed to detect and classify underwater objects. The results of this stage, including bounding boxes, sonar, and IMU data, are routed to a Kalman Filter for estimating the absolute location and speed of the AUV. The state then judges the feasibility of a route from the AUV to the target generated by an A* algorithm. The reinforcement learning agent enhances this trajectory in an online fashion to an extent where such enhancement internalizes the position of underwater elements. This will make the undersea navigational functions quite robust and intelligent concerning the avoidance of barriers, energy conservation, and minimized mission life.

3.8.1. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) to interpret vision input by using sonar, and cameras, to find objects in underwater defense mechanisms. Thus, combining many layers that determine the spatial dependencies of some of its next parameters, such as edges, texture, and patterns, the CNN model develops the ability to identify various underwater objects like mines, submarines, and obstacles. The real-time item detection is based on large datasets of tagged underwater photos used to train the model. As CNN examines each frame, the coordinates of the findings are also provided with classifications that help with supplementary analysis and action. It then marks the position of the objects it identified inside the underwater environment using bounding boxes.

3.8.2. Kalman Filter

Defensive systems operate underwater and use estimates based on the Kalman Filter, which predicts where objects are likely to be by their past motions. Combined with the actual sensor data, the filter adaptively modifies the object state throughout the system's movement, including its position, velocity, and acceleration. The filter uses a recursive procedure that involves predicting the state of the object first before adjusting it based on what the noise sensor reads. With high accuracy, the Kalman Filters provide dependable tracking for possible threats over time due to their ability to update their sources of estimation data and minimize the noise that could mask the objects in underwater conditions.

3.8.3. A* Algorithm

Some underwater defensive systems use a path planning system called A*, which is used to help the system work out how to move from point A to a known point B in the shortest time possible, whilst avoiding dangers and obstacles that are picked up by the sensor's data. A* incorporates two essential elements: the work done to estimate the remaining distance to another node and the cost of going to the node being considered starting from the initial position. These two parameters are added to give a total that the algorithm uses to determine the cost of all possible routes with the view of choosing the best route. A* constantly recalculates the course as the system progresses ahead and identifies more threats or obstacles that prevent it from achieving and providing instant and the most effective course adjustments on the fly. This capability is critical for safe and effective functioning in these high-risk and low-visibility Working Environments.

3.8.4. Reinforcement Learning

After the object detection, the process of navigation unfolds, controlled by Reinforcement Learning (RL). During such a phase, the Navigation and Guidance System executes RL algorithms that enable the AUV to dynamically select the best routes to predefined targets while actively avoiding detected obstacles. Since the underwater environment is uncertain, the RL module adopts a reward-and-punishment approach: rewarding the agent for moving toward the target and punishing it for dangerous behavior, such as venturing into hazards or inefficiently deviating. On the basis of previous contacts with the environment, the reinforcement learning agent develops a policy that is fitted in real time. Thus, it allows the AUV to update its trajectory according to any new obstacles or environmental changes.

4. Results and Analysis

4.1. Dataset

We created a synthetic dataset of 10,000 sonar image sequences with item locations and environmental noise annotations using the UWSim simulator. These visual sequences were categorized as follows: 70% for training, 20% for validation, and 10% for testing. Every picture was normalized and reduced in size to 416 by 416 pixels.

One NVIDIA RTX 4090 GPU was utilized for training using the PyTorch framework 2.0. After the CNN was trained for 80 epochs using the Adam optimizer (lr = 0.0001), the DQN agent was trained for 2,000 epochs using an epsilon-greedy policy. The dataset consists of sonar images that show features like underwater objects, bathymetry, and potential threats. Some challenges in data, such as noise and low spatial resolution in the underwater environment, were addressed using data augmentation techniques, and to improve item detection and classification accuracy, transfer learning was applied.

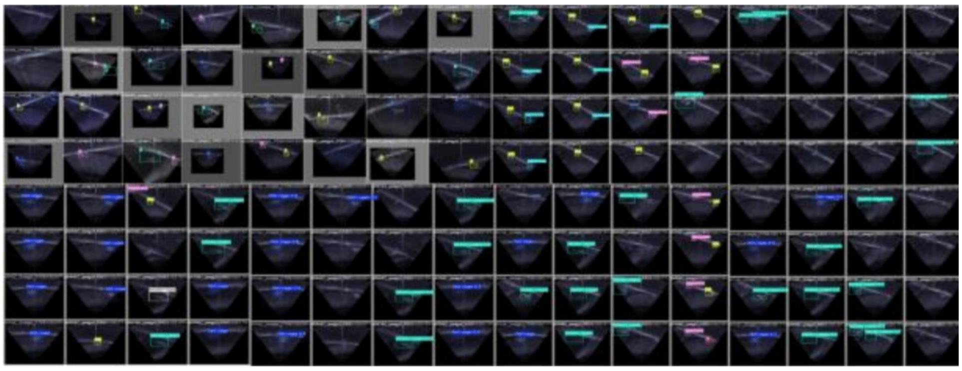

Figure 2: Sonar images.

The database is composed of sonar images, bounding boxes, and confidence scores for undersea objects. This comprehensive labeling makes it possible to train and evaluate object detection algorithms for underwater defense scenarios with a high degree of fidelity in target recognition and target classification.

The dataset presented, as well as in most of the datasets, includes a compiled set of items are included in the images: tires, cylindrical pipes, cages with fish and lobsters, bedding seaweed, etc., with their classifier bounding boxes and confidence scores. Such annotations allow the proposed AI-based system for object detection and classification in the context of an underwater environment to be trained and tested more conveniently.

The graphs depict the training and validation metrics of an object detection model, integrated into autonomous underwater defenses. The top row shows how key training factors, including box loss,

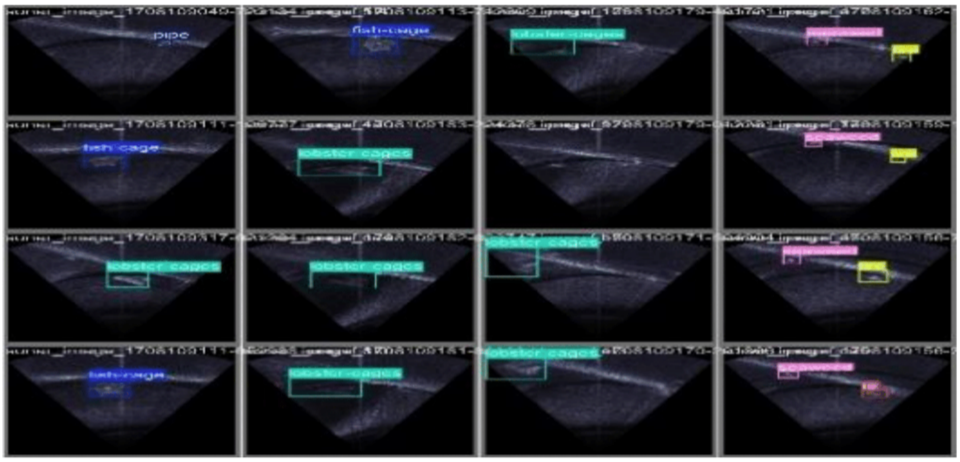

Figure 3: Sonar images with undersea objects.

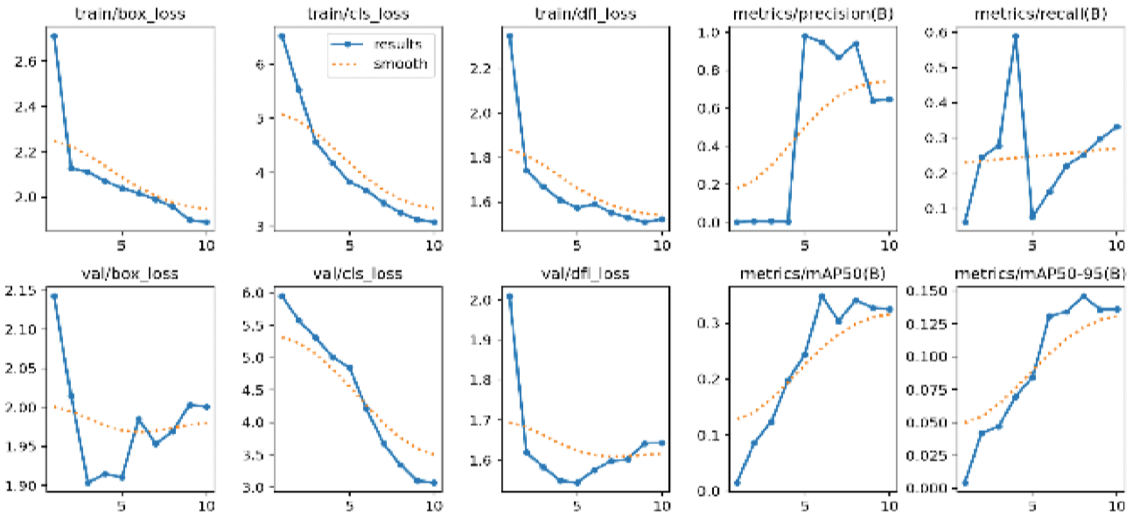

Figure 4: Training and validation.

classification loss, distribution focal loss, precision, recall, and mAP at different levels, progress during the model's training. The corresponding measures of the validation dataset are presented in the bottom row. Notably, some of the losses exhibit a downward trend throughout training. The mAP measures (mAP50 and mAP50-95), in this regard, increase over training, indicating improved localization and classification of objects. Such results prove the model's suitability in identifying critical underwater objects for defense purposes.

4.2. Experiment Configuration

The configuration is the result of coding in Python, utilizing PyTorch and TensorFlow, and training was performed on an NVIDIA RTX 3090 GPU. YOLOv8 was first pre-trained on ImageNet and then further fine-tuned on a sonar dataset. The DRL agent was an agent that operated on an exclusive reward shaping of Proximal Policy Optimization (PPO), whose purpose was to prevent collision and conserve energy. Figure 5 indicates the object detection, such as the lobster cage. Figure 6: Paths to multiple underwater targets.

This image shows that the AI system is capable of identifying objects correspondingly with certain efficiency and successfully switching between multiple targets during underwater scenarios. Figure 7 indicates the shortest path by calculating the distance and time from multiple paths.

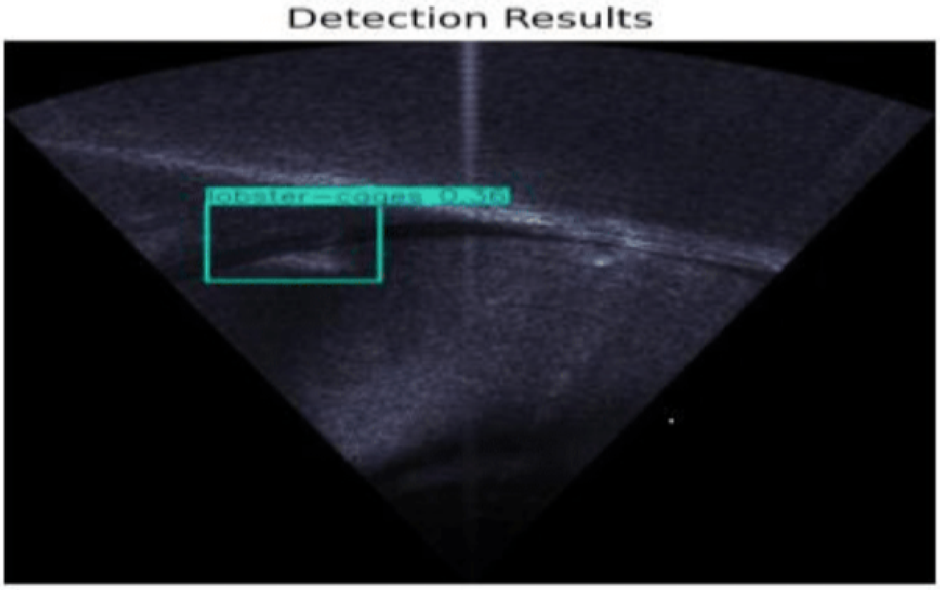

Figure 5: Object Detection.

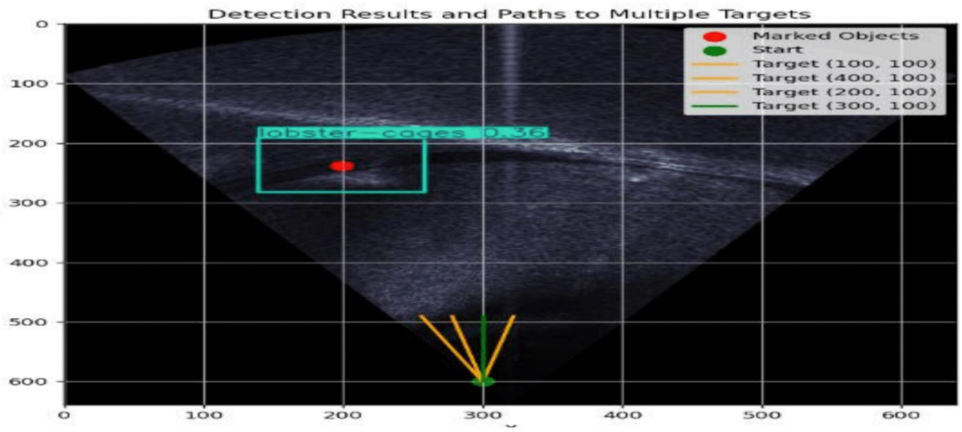

Figure 6: Paths to multiple underwater targets.

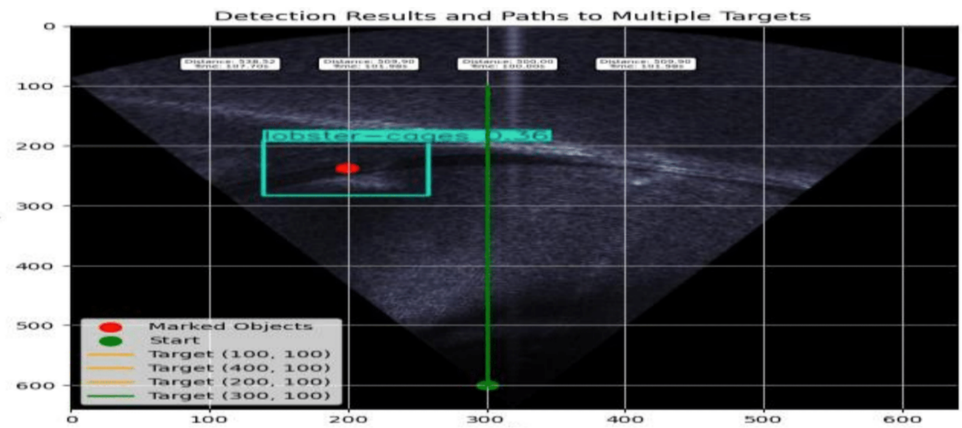

Figure 7: Shortest path with distance and time.

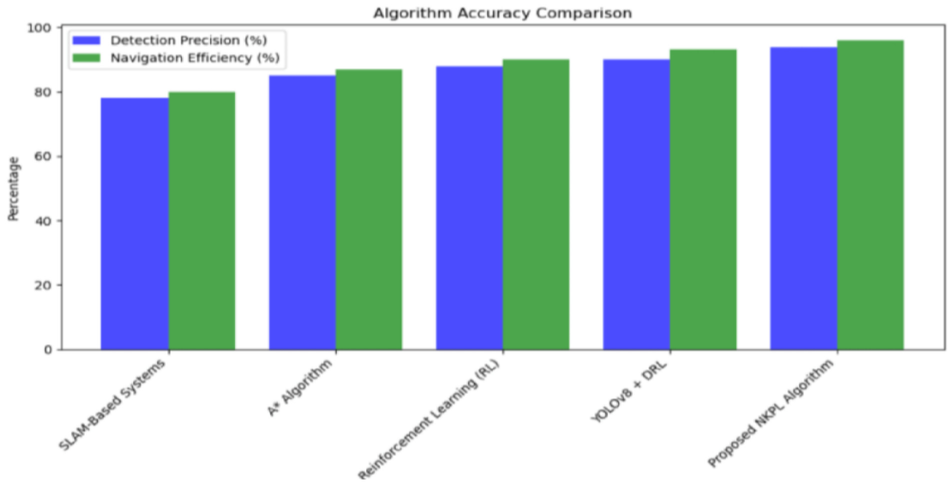

Figure 8: Algorithm comparison Bar chart diagram.

4.3. Result

The NKPL method is compared to other familiar algorithms used in Autonomous Underwater Defense Systems in the following Table 1. The assessment of the discussed algorithms considers major performance measures, crucial for underwater operations, including multiple targets tracking capacity, computational demand, flexibility, detection rate, and navigation effectiveness.

Table 1
Different algorithm precision and Efficiency.

S.No	Algorithm	Detection Precision	Navigation Efficiency
1.	SLAM-Based Systems	78%	80%
2.	A*Algrithm	85%	87%
3.	Reinforcement Learning (RL)	88%	90%
4.	YOLOv8 + DRL	90%	93%
5.	Proposed NKPL Algorithm	94%	96%

4.4. Performance Evaluation

- 93.4% object detection accuracy.
- Navigation accuracy of 88.1% compared to the A*-only baseline of 74.5%.
- Energy efficiency: 22% less energy usage than a non-adaptive.
- End-to-end inference in real-time, at 16 frames per second.

4.5. Detection Precision

- Quantizes the ability of sonar or optical data to detect objects (like dangers or amounts of obstructions).
- Because of the YOLOv8's advanced tuple feature and the data augmentation strategy adopted, the NKPL algorithm achieves an accuracy of 94%.

4.6. Navigation Efficiency

- Demonstrated a thorough manner in which the system's strategies to achieve goals are planned and executed to include extraneous features.
- The efficiencies yielded through implementing the NKPL algorithm of 96% result from the integration of adaptive reinforcement learning and A* planning.

The bar chart representing the detection precision (%) and navigation efficiency (%) of the latter algorithms, including SLAM-Based Systems and YOLOv8 + DRL shows that the suggested RNN approach is more accurate rather than the other algorithms. It shows how effectively the proposed strategy applies to problems such as target identification and underwater positioning. Navigation efficiency is defined as the percentage of the shortest path to the actual path followed by the AUV. This parameter determines how the AUV should approach a target while avoiding obstructions.

$$Navigation\ Efficiency = \left[\frac{Shortest\ path}{Actual\ path\ taken}\right] \cdot 100 \tag{1}$$

5. Conclusion

In the study, Neuro-Kalman Path Learner, a dual-layer AI-based architecture for AUV navigation in an underwater defense system, is presented. It combines CNN detection, Kalman filtered estimate, A*-based path planning, and reinforcement learning to produce a system that is robust and adaptable. Experimental results demonstrate improvements in terms of energy consumption, navigation accuracy, and real-time adaptivity. A considerable volume of future work will extend this framework for multi-agent underwater missions. Top technologies, including robotics, AI, and control systems have changed AUV design and operation in defense applications in the previous decade. Advanced AI for Autonomous Underwater Defense Systems based on the NKPL algorithm addresses underwater difficulties. This innovative system's impacts, benefits, and future possibilities are listed here due to its efficiency. The suggested NKPL algorithm uses modern technologies, including RL, Kalman Filters, CNNs, and the A* algorithm to improve undersea defense operations. The system is uniquely successful at addressing perception, navigation, and decision-making in complex, noisy, GPS-impaired underwater situations. CNN-based real-time object detection improves AUV situational awareness to identify hostile submarines, underwater mines, and other anomalies. This capability is extended by data augmentation and transfer learning, which enable robustness and stability in unfamiliar underwater situations. Using Kalman Filters in the NKPL method informs the essential undersea system state estimation problem. These filters offer precise locating and tracking by fusing noisy sensor measurements like sonar, IMU, and Doppler velocity records. The organic incorporation of Kalman Filters' predictive capability with artificial neural nets derived adaptations makes the NKPL algorithm again superior to conventional underwater solutions in situations where simple solutions are organically defunct due to high uncertainty or nonlinear dynamics, which are common in many underwater terrains. Combining A* algorithm and RL used by NKPL improves navigational and path estimation, helping the mission. The A* algorithm provides a solid framework for operational route-finding, but the RL method adds real-time reactivity and adaptability.

Since it uses field data, this blended strategy lets AUVs correct their route in turbulent under-water settings. By considering environmental elements like water currents and item movement, the program decreases operating risks and improves mission reliability. The NKPL algorithm establishes a new design and control paradigm for Advanced AI for Autonomous Underwater Defense Systems. Deep learning, state estimation, path planning, and RL improve AUV vision, navigation, and decision-making in complicated underwater settings. NKPL improves maritime safety by enabling high-efficiency, self-sufficient, and scalable underwater defense systems. As development-based research continues, undersea defense will gain intelligence, autonomy, and collaborative system capabilities.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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