

Underwater Object Prediction Using Sonar Waves

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Abstract

The detection and differentiation of potentially hazardous objects, such as mines and rocks, in underwater environments are crucial for the safe navigation of submarines during warfare scenarios. This study compares and contrasts different machine learning algorithms to determine whether an object detected by a submarine's sonar system is a mine or a rock. From the comparative analysis, we have proposed the Logistic Regression Model (LRM), which is used to train and test the models. To extract pertinent features like signal intensity, frequency content, and time-domain characteristics, sonar signals are essential to the labeled dataset. This dataset is made up of sonar signals and corresponding object classifications (mine or rock) based on the frequency range. These features served as inputs to the machine learning algorithms and enabled the features to learn the underlying patterns and make accurate predictions. In this paper, we have contributed a novel approach to underwater object detection using LRM, which is applied to sonar data. In summary, this research presents an innovative solution to the challenge of underwater object detection using sonar signals and machine learning algorithms. The developed model exhibits promising results, opening up new possibilities for advancing our understanding of underwater environments and enhancing underwater exploration and security capabilities.

Keywords: Sonar Signals, Logistic Regression Model (LRM), Underwater Exploration, Warfare Scenarios, Mine or Rock

1. Introduction

S, identify the objects concealed within. Our research is dedicated to unraveling the complexities of underwater object prediction, a task that has garnered significant attention due to its wide range of applications, including maritime safety, military operations, fisheries management, and archaeological exploration. [1-4] Among the multitude of machine learning techniques available, we have chosen the logistic regression model as our primary tool for this endeavor. As we delve deeper into this study, we aim to showcase the remarkable potential of the logistic regression model in the context of underwater object prediction. By combining the power of sonar technology with the precision of machine learning, we aspire to contribute to the growing body of knowledge that

enhances our understanding of underwater environments and, in doing so, advances the safety, efficiency, and [5] sustainability of our interactions with the underwater world.

2. Experimental Methodology

The machine learning process begins with training models on selected features, which may involve techniques such as logistic regression. Next, the dataset is divided into training and testing sets for model evaluation. Following training, the algorithms are tested, and their classification accuracy is compared. The methodology is shown in Figure 1. This framework consists of multiple modules, and machine learning empowers computer systems to learn automatically without explicit programming.

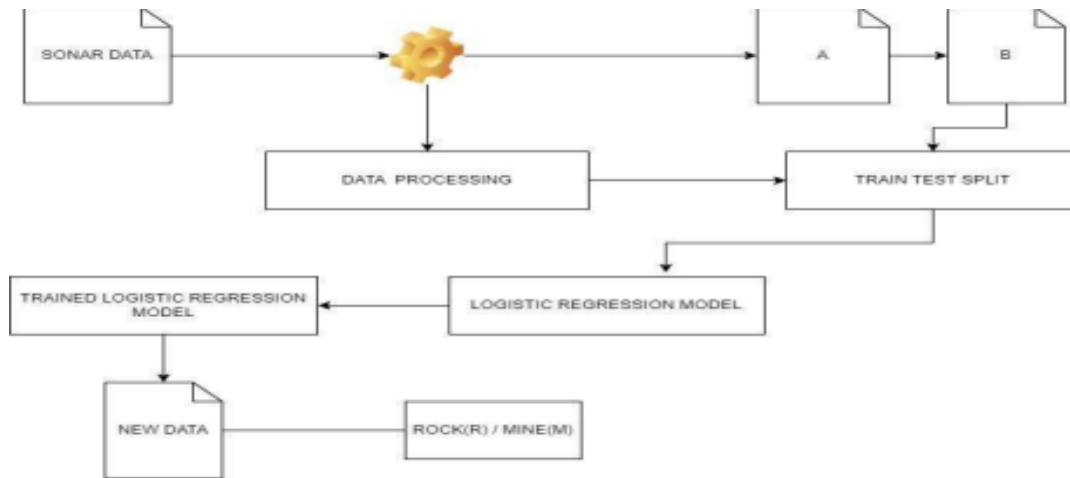


Figure 1 Methodology

Finally, the trained machine learning model is utilized to predict whether an input represents a rock or a mine, [7, 8] generating either a binary classification outcome or a probability score. The author employs three machine learning algorithms, including Support Vector Machine, [9-11] and the architecture diagram offers a high-level overview of key system components and their interactions. The sonar data is then subjected to machine learning algorithms, and the resulting model's classification accuracy is assessed [6].

3. Results and Discussion

A machine learning dataset is a collection of data that is used to train the model. A dataset acts as an example to teach the machine learning algorithm how to make predictions. [12] The common types of data include text data Figure 2.

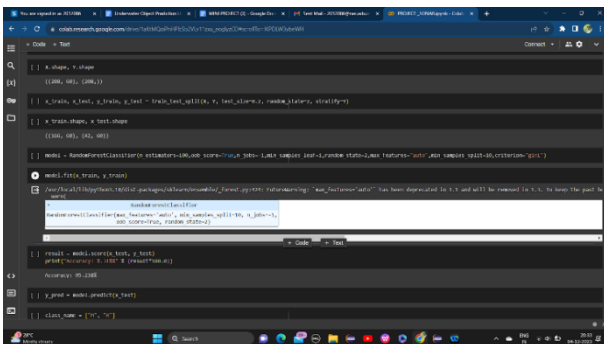


Figure 2 Common Types of Data

A confusion matrix is a tabular summary of the number of correct and incorrect predictions made by

a classifier. [13] It is used to measure the performance of a classification model. It can be used to evaluate the performance of a classification model [14, 15] through the calculation of performance metrics like accuracy, precision, recall, and F1-score Figure 3.

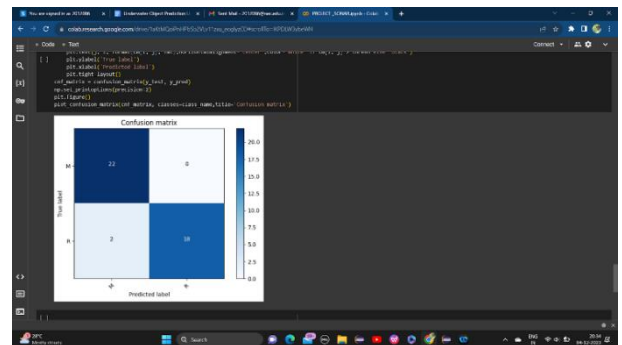


Figure 3 Classification Model

Conclusion

In conclusion, our study focused on the critical task of underwater object prediction using sonar waves, with a specific emphasis on distinguishing between mines and rocks in submarine warfare scenarios. Through a comprehensive comparative analysis of machine learning algorithms, we identified the logistic regression model as the most effective choice for this task. Our approach involved the utilization of a labeled dataset containing sonar signals and corresponding object classifications. These sonar signals were subjected to feature extraction, encompassing important characteristics

such as signal intensity, frequency content, and time-domain attributes. These features were instrumental in providing valuable inputs to our machine learning models, facilitating the learning of intricate patterns and thereby ensuring accurate predictions. The significance of our work extends beyond the realm of submarine warfare; it carries implications for enhancing safety and navigational efficiency in underwater environments across various domains. By harnessing the power of machine learning and sonar technology, we have taken a significant step toward addressing the challenges posed by potentially hazardous underwater objects, ultimately contributing to the safety and success of submarine operations. Our research underscores the potential of cutting-edge technology to mitigate risks and advance the capabilities of underwater exploration and defense. Among the three machine learning algorithms, the Logistic Regression Model demonstrates superior performance, achieving an accuracy of 95.238%. Our system, tailored for predicting underwater objects utilizing sonar waves, is designed to leverage these results effectively.

References

- [1]. V. Myers and J. Fawcett, "A template matching procedure for automatic target recognition in synthetic aperture sonar imagery," *IEEE Signal Processing Letters*, vol. 17, no. 7, pp. 683–686, 2010.
- [2]. J. Groen, E. Coiras, and D. Williams, "Detection rate statistics in synthetic aperture sonar images," in *Proceedings of the 3rd International Conference and Exhibition on Underwater Acoustic Measurements: Technologies and Results*, Nafplion, Greece, 2009.
- [3]. R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 580–587, 2014.
- [4]. X. Long, K. Deng, G. Wang, et al., "Polo: an effective and efficient implementation of object detector," 2020, <https://arxiv.org/abs/2007.12099>.
- [5]. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: unified, real-time object detection," in *Proceedings of the Ieee Conference on Computer Vision and Pattern Recognition*, pp. 779–788, 2016.
- [6]. S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: towards real-time object detection with region proposal networks," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 6, pp. 1137–1149, 2017.
- [7]. Z. Cai and N. Vasconcelos, "Cascade RCNN: delving into high-quality object detection," in *Proceedings of the Ieee Conference on Computer Vision and Pattern Recognition*, pp. 6154–6162, Salt Lake City, USA, 2018.
- [8]. J. Redmon and A. Farhadi, "YOLOV3: An incremental improvement," 2018, <https://arxiv.org/abs/1804.02767>.
- [9]. X. Huang, X. Wang, W. Lv et al., "PPYOLOV2: a practical object detector," 2021, <https://arxiv.org/abs/2104.10419>.
- [10]. S. Yun, D. Han, S. J. Oh, S. Chun, J. Choe, and Y. Y. Cut Mix, "Regularization strategy to train strong classifiers with localizable features," in *Proceedings of the IEEE/CVF international conference on computer vision*, pp. 6023–6032, 2019.
- [11]. E. Dura, Y. Zhang, X. Liao, G. J. Dobeck, and L. Carin, "Active learning for detection of mine-like objects in side-scan sonar imagery," *IEEE Journal of Oceanic Engineering*, vol. 30, no. 2, pp. 360–371, 2005.
- [12]. D. P. Williams and E. Fakiris, "Exploiting environmental information for improved underwater target classification in sonar imagery," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 52, no. 10, pp. 6284–6297, 2014.
- [13]. D. Neupane and J. Seok, "A review on deep learning-based approaches for automatic sonar target recognition," *Electronics*, vol. 9, no. 11, p. 1972, 2020.

- [14]. H. T. Nguyen, E.-H. Lee, C. H. Bae, and S. Lee, "Multiple object detection based on clustering and deep learning methods," *Sensors*, vol. 20, no. 16, p. 4424, 2020.
- [15]. M. Valdenegro-Toro, "End-to-end object detection and recognition in forward-looking sonar images with convolutional neural networks," in *2016 IEEE/OES Autonomous under Water Vehicles (AUV)*, pp. 144–150, 2016.