Exploring the Combined use of Deep Learning and LiDAR Bathymetry Point-Clouds to Enhance Safe Navigability for Maritime Transportation: A Systematic Literature Review

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***Abstract*—Maritime transport significantly contributes to global economic growth. The majority of global commerce is transported via sea. Ensuring navigable conditions for maritime transportation is essential to keep ships moving safely and efficiently. Remote sensing technologies, particularly Aerial Laser Scanning (ALS) technology, can be adapted to monitor sub-sea conditions. Based on point clouds from LiDAR Bathymetry, the ALS supports practitioners in classifying submerged objects. However, this technology provides an extensive amount of Big Data which needs to be processed by practitioners. With recent advancements in Deep Learning (DL), multiple researchers have begun exploring DL algorithms to classify Airborne Bathymetry LiDAR point cloud data. This paper employs a Systematic Literature Review (SLR) methodology to examine the applicability of DL in the classification of airborne Bathymetry LiDAR point cloud data. Through the SLR process, we identified nineteen hundred relevant articles from the ScienceDirect and Google Scholar databases over the last decade. A comprehensive analysis of identified articles revealed that the majority employed deep learning models are for classification, detection, and semantic segmentation. The most commonly used algorithms are Convolutional Neural Networks (CNNs), Multi-Layer Perceptrons (MLPs), Random Forest, and Support Vector Machines. In addition, in the identified articles, it was observed that these algorithms were applied to both waveform data and image data.**

***Index Terms*—Maritime Transportation, Aerial Laser Scanning, LiDAR, Point-Cloud, deep learning algorithms**

I. Introduction

The transport of goods and people via seas is recognized as an efficient transport solution around the globe [1] [2] [3]. To maintain the movements of goods and people at expected levels, it is fundamental to ensure safe navigable conditions. Monitoring underwater conditions is an important activity to keep safe navigability. Remote sensing technologies may support the monitoring activities [4]–[7]. These technologies can reproduce a surface of interest without being in contact with it [8]. Among the remote sensing technologies, there is the Aerial Laser Scanning (ALS) based on the Light Detection and Ranging (LiDAR) [9]. Mounted on airplanes or drones, the LiDAR technology is capable of reproducing in the form of a 3D point cloud the platform's surrounding environment [10], [11]. Due to their promising potentialities, LiDAR scanners are adopted in a wide variety of sectors [5], [12]–[17]. Today exist two types of LiDAR: topographic and bathymetric. The former detects elevation above sea level, the latter detects surfaces and objects underwater. Bathymetric LiDAR offers the opportunity to monitor, at high resolution, sea levels, and sub-sea objects until sea beds [18].

Despite the promising potentialities, LiDAR technology is challenged by the handling of the big data retrieved during the scanning phase. Currently, data handling is human-based [19]. Therefore, to explore the information obtained from ALS LiDAR-based, it is necessary to pre-process the big data obtained from the monitoring activities through manual intervention. This manual task is time and resource-consuming discouraging the usage of this technology. Deep Learning methods may facilitate this limitation [20]. By utilizing deep learning methods, the need for human-based data handling can be reduced, thereby minimizing human errors while efficiently identifying and classifying sub-sea objects of interest.

This study explores how "*deep learning algorithms*" may improve the handling of big data retrieved from bathymetric LiDAR aerial-based. "*Which deep learning (DL) algorithms are adopted to classify Airborne Bathymetry LiDAR point cloud data?*"(RQ). To answer this RQ, this study conducted a Systematic Literature Review (SLR) to investigate how DL was adapted to classify Airborne Bathymetry LiDAR point cloud data over the past decade (2014- 2024).

This paper is organized as follows. In Section II, we explain the methodology that has been used for a systematic literature review analysis on the role of using artificial intelligence to classify Airborne Bathymetry LiDAR point cloud data. Section III presents and discusses the results of our analysis. Finally,

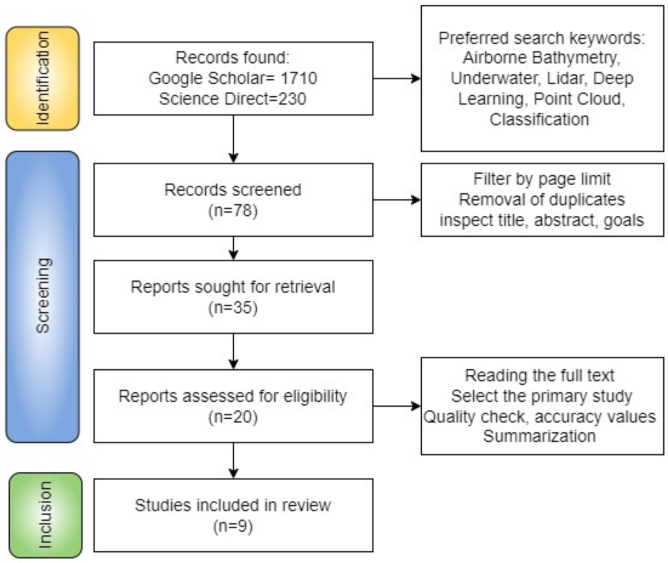

Fig. 1. PRISMA

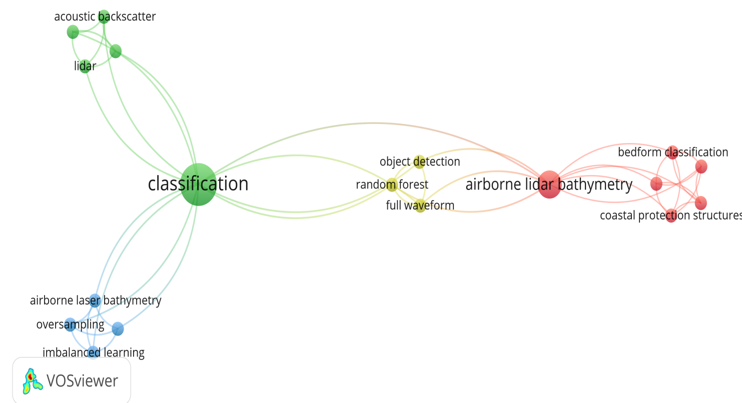

Fig. 2. Keyword Density

Fig. 3. Word cloud of the keywords from the selected articles

section IV concludes our findings with future directions.

II. Research Methodology

A. Data Collection

According to the standard procedure for systematic literature review explained by author [21], a systematic literature review method called "Preferred Reporting Items for Systematic Review and Meta-Analyse" (PRISMA) was utilized in this study as well to answer the research question outlined in Section I. It includes three stages. The first stage is identification, the second stage is screening and the third and final stage is the inclusion of the relevant articles. All these steps can be seen in Figure 1.

In the first stage, we conducted an extensive search in ScienceDirect and Google Scholar databases in the title and abstract filed with the following combination of search terms and their variants. All the used combinations and the identified number of articles can be seen in Table I. This systematic review resulted in an initial pool of over 1940 scientific articles.

In the second stage, screening criteria were applied to the retrieved article. Specifically, no duplicate English-written articles within the topic of interest were selected. In the third and final stage, the results were filtered and that led to the inclusion of merely nine articles in this study. These nine articles have worked with Airborne Bathymetry and classified the point cloud data using various machine learning or deep learning techniques. The summary of these selected nine articles is shown in Table II and a detailed analogy is presented in the following sections.

III. Results and Discussion

This section presents the results based on keyword analysis, deep learning algorithms, test areas, and datasets.

A. Test Areas and Datasets

From the identified articles, the most frequently occurring keywords are Airborne", ”Bathymetry", and ”Classification". Additionally, words such as ”deep", ”learning", ”Lidar", and ”Laser" are noted. Other words, such as ”waveform", ”underwater", ”ocean-land", ”coastal", and ”nearshore" indicate the surrounding environment of the LiDAR system. Finally, the words ”neural", ”networks", ”2D", ”CNN", and ”multichannel" describe the commonly used technique CNN for the classification process and these occurred words can be seen in the Figure 3.

Previous studies are scattered into different parts of the world, creating a variation in the used datasets, as shown in Figure 4. The authors of [4], [22], [30] chose to work with the same location, that is, the Rosenort artificial reef, located in the Baltic Sea, which is approximately 25 km north of the city of Rostock (Germany). Another study [31] was done in Europe using the location of Corsica (France).

Authors in [24], [27] set their location in the Asian territory selecting their test area in Japan and China. Another author

TABLE I
KEYWORDS

Keyword Combinations	Database	Identified Papers
”Underwater” AND ”Lidar” AND ”Deep Learning” AND ”Point Cloud”	Google Scolar	1,710
”Seabed” AND ”Lidar” AND ”Deep Learning” AND ”Point Cloud” AND ”Classification”		343
”Airborne Bathymetry” AND ”Underwater” AND ”Deep Learning” AND ”Classification” AND ”Point Cloud”		10
”Airborne Bathymetry” AND ”Seabed” AND ”Deep Learning” AND ”Classification” AND ”Point Cloud”		11
”Underwater” AND ”Classification” AND ”Bathymetry” ”Lidar”	Science Direct	230
”Underwater” AND ”Lidar” AND ”Deep Learning” AND ”Point Cloud”		84
”Underwater” AND ”Classification” AND ”Bathymetry” AND ”Lidar” AND ”Deep learning”		21

TABLE II
DATASET

Previous Work	**Goal**	**Dataset**	**Classification with Waveform data / Images**
[22]	Classification and detection of seabed objects	The artificial reef Rosenort on the Baltic Sea	Waveform
[4]	seabed modeling and object detection	The artificial reef Rosenort on the Baltic Sea	Waveform
[23]	the semantic segmentation of water surface and seabed on the large-scale ALB point cloud	The coastal-urban scenes of Tampa Bay, Florida, USA	Images
[24]	classification of Ocean–land waveform	Qinshan Island of Lianyungang City, Jiangsu Province, China	Waveform
[25]	Classification of nearshore bathymetry	Appalachian Bay (AB), Virgin Islands (VI), and Cat Island (CI) of the United States.	Images
[26]	Multi-class classification of airborne laser bathymetry data.	The artificial reef Rosenort on the Baltic Sea.	Waveform
[27]	classify riverine land cover using orthophoto with the aid of the ALB dataset	Asahi River in Japan	Images
[28]	Automatic classification and mapping of the seafloor	Polish coast of the Southern Baltic	Images
[29]	Classification of returned waveform	The western Gulf of Maine, USA	Waveform

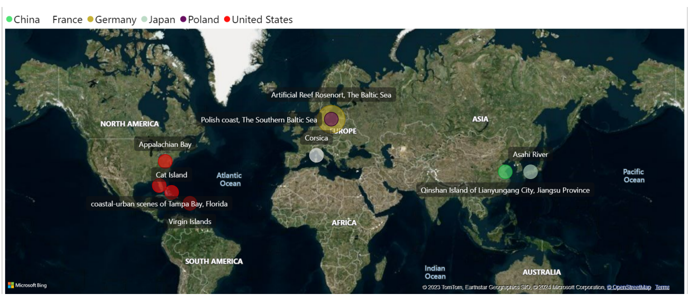

Fig. 4. Identified test areas from previous studies

[25] used four different locations, but all of them were located in the United States which were Appalachian Bay, Virgin Islands, and Cat Island. In the identified literature, many different datasets were used which are tabulated in table II. From this table, it can be seen that most of the works mentioned that collected dataset and used test area was at Baltic Sea. Other researchers collected data from the USA. The used test areas are depicted in Figure 4.

B. Deep Learning Algorithms

From our analysis, we have found that deep learning algorithms have been employed on various types of data and this is presented below.

1) Classification using Lidar Point Cloud data: From Table III, it can be seen that for the classification of airborne bathymetry point cloud waveform data, various deep learning (DL) algorithms such as Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNNs), and machine learning algorithms like SVM, and Random Forest are commonly used.

A multichannel green laser waveform was adopted by [24] to present a technique named Multichannel Voting Convolutional Neural Network (MVCNN). The combination of a supervised classification technique with SVM was investigated by [29] to perform a bottom return residual analysis for the characterization of seabed surfaces. [26] using the Random Forest classifier, divided the classification tasks into two groups: the classification of the entire point cloud and the classification of the points that were not part of the water's surface. A few years later, [22] reported the use of multilayer perceptron neural networks with softmax activation for classifying and detecting objects on seabed surfaces. In a later study, to ameliorate the accuracy of seabed modeling, [4] adopted 53 Synthetic Minority Oversampling Technique (SMOTE) methods in addition to MLP.

2) Classification using Images: In recent years, many approaches have been adopted in the field of image-based classification for bathymetric studies. For instance, to investigate the nearshore bathymetric inversion, [25] adopted a deep learning architecture based on 2D Convolutional Neural Networks (CNN). [28] was able to identify nine types of natural seabed surfaces and three classes of anthropogenic structures using the Geographic Object-Based Image Analysis (GEOBIA) coupled with machine learning-supervised classifiers. Combining orthophotos and ALB dataset, [27] investigated the categorization of riverine land cover. A semantic segmentation approach was adopted by [23] in combination with a large-

TABLE III
ALGORITHMS

Previous Work	Algorithm	Feature Extraction Methods	Performance Evaluation Metrics
[22]	MLP	Gaussian decomposition	Confusion Matrix Manual Comparison
[4]	MLP	53 oversampling algorithms	Confusion matrix, precision, recall, and F1-score
[23]	Superpoint graph (SPG) + VSP	Voxel-Sampling Pre-Processing (VSP) Geometric Separation	Comparison between PointNet, PointNet++, Dynamic Graph CNN (DGCNN), RandLA-Net, SPG
[24]	Multichannel Voting Convolutional Neural Network (MVCNN)	Batch normalization, Max Pooling, Global max pooling	Overall accuracy (OA), and kappa coefficient (Kappa)
[25]	2D CNN	Pooling	Comparison with other models (LR, MLP, RF)
[26]	RF	Gaussian function	Comparison with other models (SVM)
[27]	Transfer Learning Method	RGB and RGBnl	confusion matrix
[28]	K-Nearest Neighbour (KNN), Support Vector Machines (SVM), Classification and Regression Trees and Random Forest	Geographic Object-Based Image Analysis	Error matrix
[29]	SVM	A total of eleven waveform parameters are extracted	Overall accuracy and Kappa coefficient

scale airborne Lidar bathymetry (ALB) point cloud. In their work, the authors applied the voxel sampling pre-processing (VSP) technique to effectively divide the point cloud into two classes: bottom surface and water surface.

IV. CONCLUSIONS AND FUTURE WORK

This study aims to perform a Systematic Literature Review (SLR) to address the research question: "*Which deep learning (DL) are adopted to classify Airborne Bathymetry LiDAR point cloud data?*". This exploration investigates the use of deep learning algorithms for handling the big data retrieved from bathymetric LiDAR, ultimately improving the navigability of maritime transportation. Deep-learning algorithms offer a promising solution for the automation of the data handling process, thereby reducing the need for manual intervention and minimizing human errors in identifying and classifying subsea environments. Through the systematic literature review, we identified nine relevant papers that address our research question. The findings of this review highlight multiple DL methods, particularly Convolutional Neural Networks (CNNs) and multi-layer Perceptrons (MLPs), alongside a few machine learning algorithms like Random Forest, and Support Vector Machines, which significantly enhance the efficiency and accuracy of bathymetric LiDAR data processing. These models facilitate automated feature extraction and classification, enabling real-time data analysis and reducing the dependency on human-based processing.

As a future work, we would like to explore the use of transformer-based deep learning models to improve the classification of features of interest obtained from LiDAR bathymetry point-cloud in the subsea environment. While these models are widely adopted in different sectors, their application in combination with LiDAR Bathymetry point clouds remains unexplored.

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