Journal of Environmental Management 362 (2024) 121275

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Review

Environmental impact assessment of ocean energy converters using quantum machine learning

Taha Rezaei [*], Akbar Javadi

Department of Engineering, University of Exeter, EX4 4QJ, United Kingdom

ARTICLE INFO

Handling editor: Dr. Lixiao Zhang

Keywords:
Ocean energy converters
Marine Environment
Marine ecosystem
Environmental impacts
Machine learning
Quantum machine learning

ABSTRACT

The depletion of fossil energy reserves and the environmental pollution caused by these sources highlight the need to harness renewable energy sources from the oceans, such as waves and tides, due to their high potential. On the other hand, the large-scale deployment of ocean energy converters to meet future energy needs requires the use of large farms of these converters, which may have negative environmental impacts on the ocean ecosystem. In the meantime, a very important point is the volume of data produced by different methods of collecting data from the ocean for their analysis, which makes the use of advanced tools such as different machine learning algorithms even more colorful. In this article, some environmental impacts of ocean energy devices have been analyzed using machine learning and quantum machine learning. The results show that quantum machine learning performs better than its classical counterpart in terms of calculation accuracy. This approach offers a promising new method for environmental impact assessment, especially in a complex environment such as the ocean.

1. Introduction

With the increasing developments in technology and technological infrastructure, there is a rising demand, globally, for electricity. Given the promonent role of fossil fuels in electricity generation and supply, there is an increasing concern over the environmental impacts of burning fossil fuels. Meanwhile, the role of renewable energy is relatively small and needs more research and development (Farrok et al., 2020). With the global movement to reduce greenhouse gas emissions by 2050, countries are expected to ramp up their efforts towards developing renewable energy resources. This is one of the most important areas discussed by the United Nations with the introduction of “carbon neutrality by 2050". To achieve this goal, many countries are committed to greatly reducing greenhouse gas emissions (Guo and Ringwood, 2021). For example, European countries plan to replace 32% of their energy demand with energy from renewable sources by 2030 (Galparsoro et al., 2021). There has been a significant increase in the production of renewable energy, which promises to accelerate the commercial production of this energy, especially in North America, the United Kingdom, Europe, and China. Among the different types of renewable energy systems, ocean energy, especially tidal energy, has received significant financial support for research and development (‘REN21’ and 2021, 2021). One of the main goals of the development of renewable energy is to decarbonize and help reduce climate change. In addition, the development of renewable energy infrastructure to generate electricity for remote areas and places with limited access to energy requires the use of high-efficiency and reliable source of energy, and ocean energy meets this requirement (Galparsoro et al., 2021). In this regard, the use of machine learning methods, which are powerful tools for environmental assessments, especially in oceanic environments, is suggested. One of the key applications of machine learning algorithms is in the initial data analysis stage, where they manage and analyze large volumes of collected data and prepare it for further evaluation. It is another important application in continuous monitoring of natural environments. Here, machine learning is useful in continuously analyzing data to detect sudden changes in environmental models. Additionally, these algorithms help predict potential impacts by using historical data and making accurate predictions that can be compared to EIA standards. This comprehensive approach allows for a more effective and efficient environmental impact assessment process (Pourzangbar et al., 2023), (Hsieh, 2022).

2. Overview of types of ocean power converters

According to the National Oceanic and Atmospheric Administration

* Corresponding author.
E-mail address: tr445@exeter.ac.uk (T. Rezaei).

https://doi.org/10.1016/j.jenvman.2024.121275
Received 23 November 2023; Received in revised form 7 May 2024; Accepted 27 May 2024
Available online 4 June 2024

Abbreviations

NOAA	The National Oceanic and Atmospheric Administration
SVM	Support Vector Machine
QSVM	Quantum Support Vector Machine
$\|\psi$	Qubite state
$\|0\rangle$	0 in quantum state
$\|1\rangle$	1 in quantum state
OES	Ocean Energy Systems
OAT	one-at-a-time technique

Table 1
Potential installable capacity and energy production from three types of marine energy sources (Curto et al., 2021).

Ocean Energy	Capacity (GW)	Potential Generation (TWh/y)
Tide	90	800
Marine currents	5000	50,000
Sea wave	1000–9000	8000–80,000

(NOAA), 71% of the Earth's surface is covered by oceans (National Oceanic and Atmospheric Administration). Ocean energy has the potential to generate 45,000 to 130,000 TWh of energy (I. Renewable Energy Agency, 2021), which can meet the earth's need for electrical energy, which according to the statistics presented in 2021, was 25,300 TW h and exceed it (Statista, 2023). Table 1 shows the potentials of various methods for generating energy from the ocean. The data presented shows the significant impact that these technologies could have on global energy production (Curto et al., 2021).

Another factor that has enabled these emerging energy sources to rank highly among other renewable energies is that, according to statistics, 40% of the world's population lives within 100 km from the coast. This factor can reduce the cost of transferring ocean energy and make it very effective and efficient. This, together with the reliability of these resources, makes ocean energy an attractive choice among other renewable energy sources (I. Renewable Energy Agency, 2021).

2.1. Wave energy technologies

Wave Energy is a function of several factors, such as wave height, wave velocity, wavelength, and wave density. These factors have the highest efficiency at latitudes between 30° and 60° and in deep waters. Wave energy is one of the safest marine energies, accounting for nearly 80% of ocean energy. The sun's rays create winds on the surface of the oceans which in turn create ocean waves that contain a large amount of energy with little loss. Therefore, wave energy has a high-power density. Waves can have an energy potential of 30 kW/m, which is 10 times more than solar energy and 5 times more than wind (Sang et al., 2018). Also, one of the main advantages of this type of energy is that it is predictable from several hours to several days (OES, 2017).

In general, methods of generating energy from waves are divided into three categories: oscillating water columns, oscillating bodies, and overtopping devices (Fig. 1) (I. Renewable Energy Agency, 2021).

Wave energy converters are used onshore, nearshore, or offshore (Farrok et al., 2020) and they can be floating, semi-submerged or fully submerged. Distance from the shore is an important factor in the efficiency of energy converters. 40 m is an optimal depth for efficient use of these converters, which is generally about 1 km from the shore. However, at this distance from the shore many problems are faced by these converters such as: increased cost of transmission, exposure to high and severe waves that sometimes cause damage and breakdown of devices, and increased cost of maintenance (Burhanudin et al., 2022).

2.2. Tidal energy technologies

Tides are generated by the rising and falling of the sea due to the gravitational pull of the moon and the sun and the rotation of the earth. Tidal converters use this potential to generate electricity. The structure of these converters has two main types: tidal range energy and tidal current energy. Tidal range energy exists in the form of gravitational potential energy at higher sea levels, and tidal current energy is the kinetic energy of tidal induction currents (Sang et al., 2018), (OES, 2017)

Tidal range energy systems consist of several main parts, which are: embankment, sluice gates, turbines. The function of this type of converter is that after the ocean water rises, the water is trapped behind the embankments and when the ocean water goes down, the difference in height is used to produce electrical energy by the turbines installed in the embankment body. These models of tidal converters are divided into

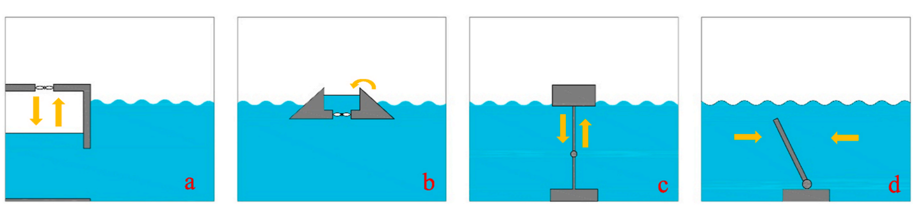

Fig. 1. Different main types of wave energy generation methods. Oscillating Water Column (OWC) (a), overtopping device (b), Point absorber (c), Oscillating Water Surge Converter (OWSC) (d).

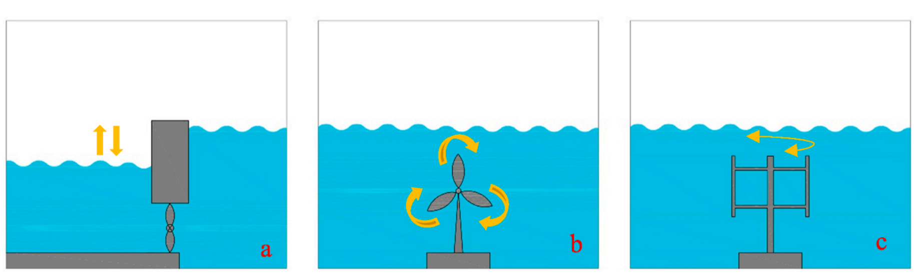

Fig. 2. Different main types of tidal energy generating methods. Barrage (a), Horizontal-axis turbine (b), Vertical-axis turbine (c).

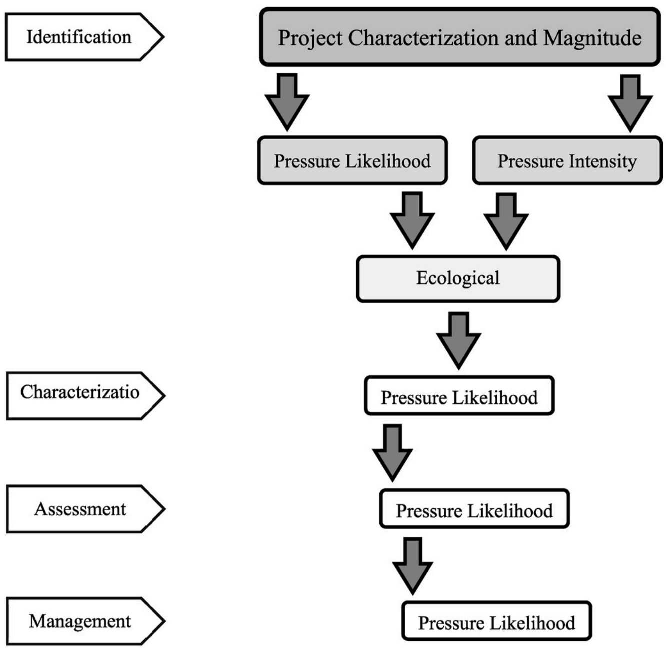

Fig. 3. General framework implemented for ecological risk assessment of wave energy projects (Galparsoro et al., 2021).

two categories: single basin and double basin (Sang et al., 2018).

Tidal current energy is derived from the kinetic energy of continuous ocean currents resulting from salinity gradients, tides, ocean floor topography, and temperature. These currents can move in different directions, which increases the system efficiency and improves the design of converters. In addition, due to the density of water, which is about 800 times the density of air, the energy density of this converter is much higher than wind exchangers (Sang et al., 2018). Tidal current energy devices consist of three main types, which are axial flow turbines, crossflow turbines and reciprocating devices (Fig. 2) (I. Renewable Energy Agency, 2021).

3. Environmental impacts of ocean power converters

Transitioning from fossil fuel-based energy to renewable ocean energies is a complex task and involves various challenges. One of the major obstacles is the established dominance of fossil fuels in the market, which has been built over a long period of time and is deeply entrenched in industrial societies. To successfully replace fossil fuels with renewable ocean energies, certain factors must be in place that can effectively challenge the dominance of the fossil fuels market. These factors include economic viability and mass production of renewable ocean energy systems for all countries, which require large investments from both the government and private sectors. The mass industrial production and installation of energy converters on a large scale may have great impact on the environment and ecosystem of the areas where they are installed. In this research, the impacts of these ocean converters were investigated using the principles of the Ecological Risk Assessment (ERA) framework (Galparsoro et al., 2021).

3.1. Ecological risk assessment framework has 4 main stages which are

1 Risk identification: specifies the human pressure(s) of concern, which result in impacts on the environment and human health. The amount and probability of occurrence of pressure and its impact on the ecosystem depend on the sensitivity of each element to pressure (Gitinavard et al., 2020).
2 Risk characterisation: highlights the likely impacts on ecosystem elements (Solgi et al., 2022).
3 Risk assessment: requires the interpretation of the results, the identification of the most relevant pressures and the most critical ecosystem elements that could be affected, and the evaluation of the total risk (Solgi et al., 2019).
4 Risk hazard identification: which would lead to the adoption of alternative management measures for hazard reduction or mitigation (Fig. 3) (Galparsoro et al., 2021).

3.2. The environmental impacts of ocean energy converters can be divided into five general categories (Mendoza et al., 2019)

3.2.1. Hydrodynamic impacts on water flow

One of the important environmental factors in ocean environments is ocean currents. These currents, which follow certain patterns, are disrupted by contact with foreign objects such as energy generators, and the structure of the water column changes due to the immersion of some converters. These changes in the flow patterns can have serious environmental impacts on plants and aquatic organisms in the ocean (Mendoza et al., 2019). The deployment of these devices can alter physical processes in the ocean, including tidal circulation, waves, and ocean currents. This in turn can affect the habitats and water quality that support marine life. These converters can affect oceanographic systems by extracting energy from water currents, which may alter natural flow patterns around the devices and can also reduce wave height. These changes occur both in the vicinity of the devices (near-field effects) and in wider regional contexts (far-field effects) (Copping and Hemery, 2020).

3.2.2. Negative impacts on the ocean floor

The ocean floor, a vast and vital component of the ocean ecosystem, is significantly affected by the installation of ocean energy converters such as tidal turbines and wave energy devices. These structures disrupt the existing ocean regime by changing water flow patterns and local currents. This disorder can lead to a change in the amount of sediment and an increase in scouring around the installation site. Such changes in the ocean floor environment can have profound effects on deep sea organisms, especially corals, which are very sensitive to changes in their sedimentary habitat. This can lead to reduced coral cover and reduced biodiversity in affected areas (Mendoza et al., 2019), (Copping and Hemery, 2020) On the other hand, the establishment of these converters can have a significant impact on the ocean ecosystem because a major part of this ecosystem includes aquatic animals that are very sensitive to changes in temperature, oxygen and other parameters. This sensitivity causes changes in temperature, oxygen and other environmental parameters to disrupt the ocean ecosystem. Since the widespread use of these oceanic energy converters in the depths of different waves changes the environmental factors, it is necessary to consider them in the environmental assessment (Morris et al., 2022), (Kroeker et al., 2020)

3.2.3. Chemical impacts

Due to their mechanical structure, ocean energy converters use special chemicals such as hydraulic oils and lubricants necessary to move or improve their performance. These chemicals are essential for maintaining moving parts and efficient energy transfer. With these conditions, they are a significant threat in case of leakage into the ocean environment, and such leakage can occur due to damage or breakdown of transducers over time (Mendoza et al., 2019). When these substances enter the ocean ecosystem, they can cause severe pollution with devastating effects. For example, spills of these chemicals into the oceans can cover marine plants such as seaweed and phytoplankton, blocking their ability to photosynthesize by blocking sunlight. This not only damages the plants themselves, but also affects the entire food web that depends on them. In addition, these pollutants can be toxic to marine animals, especially those living on the edge of this device (Copping and Hemery, 2020)

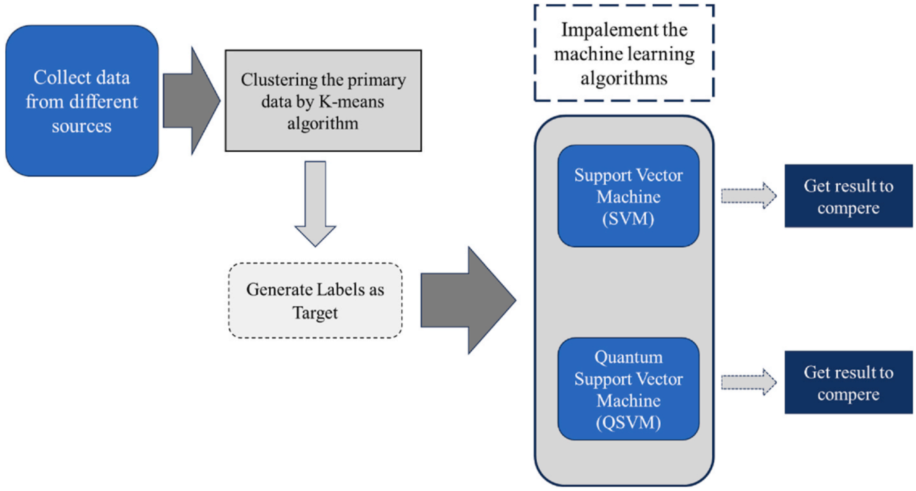

Fig. 4. Methodology implementation process.

3.2.4. *Physical impacts (noise and magnetic field)*

Noise produced by marine renewable energy devices as well as electromagnetic fields emitted by electric cables are a major part of their environmental concern (Mendoza et al., 2019). Underwater noise from these devices can lead to physical and psychological stress in marine species, potentially causing hearing loss, changes in communication patterns, and disruption of normal behaviors. This effect varies among species, with cetaceans and pinnipeds being particularly sensitive due to their reliance on sound for navigation and communication. In the case of electromagnetic fields, there are concerns about potential interference with the sensory and navigational systems of marine species such as sharks and rays that use electroreception. There is evidence to suggest behavioral changes and disruption of movement patterns due to electromagnetic exposure. Actual risk levels from both noise and electromagnetic fields depend on the proximity of the animal to the source, the nature of the energy device, and the duration of exposure. Both sections highlight the need for further research to accurately assess environmental impacts and develop mitigation strategies that minimize harm to marine life (Copping and Hemery, 2020).

3.2.5. *Impact on the flow regime in the ocean (collision risk)*

Migration is an essential aspect of the life cycle of many oceanic animals, especially mammals such as whales and dolphins, whose survival depends heavily on their ability to travel long distances across oceans. This migratory behavior is critical not only for finding food and breeding, but also for maintaining genetic diversity among populations. Large-scale installation of energy converters, such as wind turbines or tidal generators, in marine environments poses significant risks to these migration routes. By blocking these pathways, these structures can disrupt the natural movement patterns of aquatic animals and significantly increase the likelihood of collisions. Such encounters not only result in direct mortality among these animals, but also contribute to wider ecological disturbances. For example, blocking migration routes can lead to reduced reproductive success, as animals may not be able to reach their breeding grounds. converters may suffer structural damage from collisions with large marine mammals, leading to costly repairs and maintenance (Mendoza et al., 2019), (Copping and Hemery, 2020).

4. Novelty and motivation of research

In general, the use of advanced machine learning algorithms is one of the most suitable options for improving environmental assessment, especially the assessment of ocean environments, due to the increase in the huge volume of data extraction from the ocean. In this regard, in this research, it has been tried to use this methodology in the environmental assessment of ocean energy converters. Accordingly, in this study, for the first time, machine learning algorithms and quantum machine learning algorithms have been implemented on data from ocean energy converters. The obtained results showed that the quantum machine learning algorithm has the best performance in terms of accuracy compared to its classical counterpart.

5. Methodology

In this research, different machine learning algorithms are used for environmental assessment, which are presented below. In the first stage, the data collected from different sources are clustered by one of the most popular and widely used unsupervised learning algorithms, namely K-means. This clustering categorizes the raw data into three default clusters. In the second step, the label determined in the clustering step is considered as a target in the supervised learning algorithm. In the third step, the output of the support vector machine algorithm is evaluated using the accuracy criterion. The quantum support vector machine is implemented on the data in the second and third stages, and finally the results are compared (Fig. 4).

5.1. *Machine learning*

Machine learning is one of the important applications of artificial intelligence in various fields of science and engineering. Its primary function is to capture and learn the complex relationships between various parameters of a complex system without requiring direct human intervention. One of the key advantages of machine learning is its ability to predict future events and states in various fields, offering potential for practical applications (Korkmaz and Correia, 2019). The main purpose of machine learning algorithms is to process data so that it can learn different patterns and use them in other processes (Sarker, 2021). Machine learning is a very powerful tool in the process of learning the behavior of a system or structure in a large amount of data. In many cases it is very difficult (or sometimes impossible) to identify the appropriate patterns of data, and this is when machine learning can be used to extract these patterns (Mahesh, 2018). Machine learning can generally be done unsupervised or supervised (Sarker, 2021). In unsupervised learning, the machine evaluates the data without direct human input and predicts their trends, while in supervised learning, the machine can capture the patterns from a set of input and output data and use them to predict future patterns in different data. Due to the rapid growth of data production, the assessment and analysis of big data require powerful and fast tools (Niranjan et al., 2016)

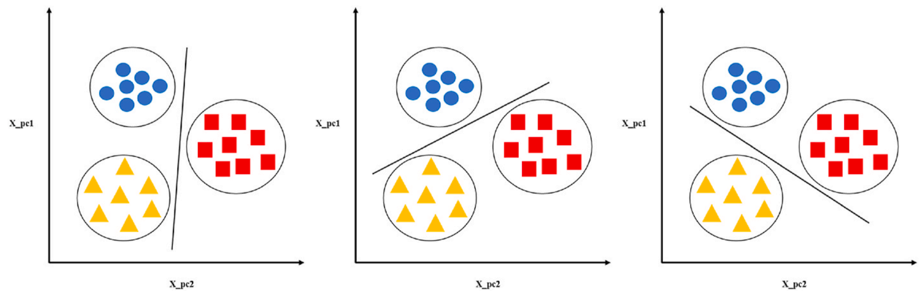

Fig. 5. All-pair method (Kumar et al.b).

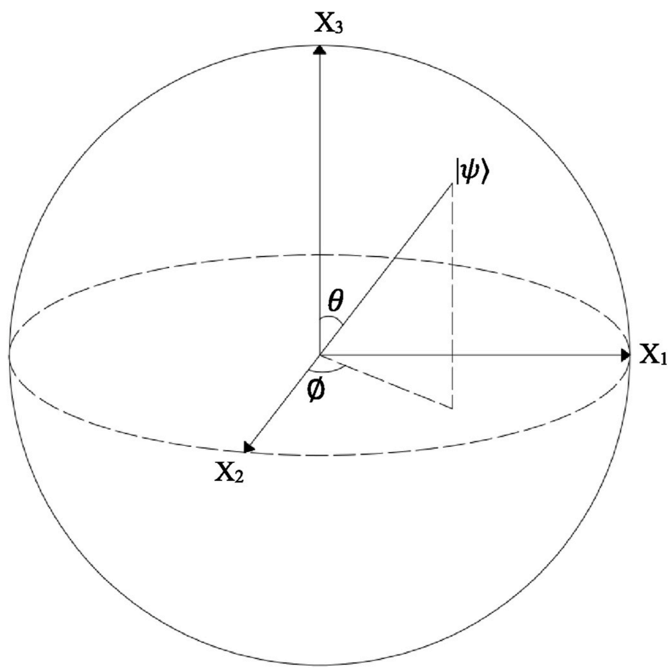

Fig. 6. The Bloch sphere representation of a qubit.

5.1.1. Unsupervised machine learning

Unsupervised learning is a machine learning technique that enables the discovery of patterns and relationships within data without the need for explicit labeling or classification by humans. This approach involves the analysis of unlabeled data, with the aim of identifying meaningful structures and groupings within it. In this process, relationships, featues and patterns are identified that might not be immediately apparent to human observers, providing valuable insight to the problem. One of the approaches to examine these relationships is measuring the distances of samples and placing them in specific clusters. The similarity of these clusters is checked by the distance of the samples from each other in the feature space (Károly et al., 2018). Applications of unsupervised learning include clustering, density estimation, feature learning, dimensionality reduction, finding association rules, and anomaly detection. In this research, unsupervised learning is used to cluster the data. The K-Means algorithm, which is one of the simplest and most widely used unsupervised algorithms, is used for data clustering in this research (Sarker, 2021)

5.1.1.1. K-means clustering. In unsupervised clustering, one of the simplest methods used is K-Means. In this method, K centers are defined for clustering. The selection of these cluster centers is very important because the change in the position of these centers can change the results. In the next step, all points related to each cluster are connected to the center of the cluster and this continues until all members are connected. This completes the first stage. In the next stage the center of the new cluster is determined, and this process continues until the best center of the cluster is found (Mahesh, 2018). The Euclidean distance between the points and the cluster centers can be calculated using the vector that connects the two points (Károly et al., 2018), using the following equation:

$$\|x\| = \sqrt{x_1^2 + \ldots + x_n^2} \tag{1}$$

After finding the Euclidean distance between the cluster center and the samples, the steps of changing the clustering continue to find the best center (Károly et al., 2018).

5.1.2. Supervised machine learning

Supervised learning is the most widely used machine learning technique. In supervised learning, the database used is divided into training and testing datasets. The input and output data in the training dataset are used to derive a function that can describe the relationship between these data, and it is then tested on the unseen testing dataset. Once the accuracy of the model in describing the training and testing datasets is considered satisfactory, the model is considered sufficiently trained and can then be used to make predictions on other unseen data (Sarker, 2021).

5.1.2.1. Support vector machine classification. Support Vector Machine (SVM) is a widely used machine learning technique. In SVM learning algorithms are used to analyze the data for classification and regression analysis. In SVM, in addition to linear classification, non-linear classification can also be used, which considers the existing features in a higher space. The function of the support vector is to create a protected space between the classes and the margin, such that the maximum confidence space is created, and less error occurs in learning data as well as new data (Mahesh, 2018).

In general, SVM is a binary classifier, but in recent years, it has been studied in the field of multi-class structures. In the binary structure, the separation of different classes in the SVM is done by a hyperplane. This hyperplane divides the incoming data into two parts that are in a higher space. In a multi-class structure, the same process is used for classification, in which a group of data is scaled relative to the rest of the data, which can be referred to as an all-pair method (Fig. 5) (Bishwas et al., 2018).

5.2. Quantum machine learning

Quantum machine learning emerged in the early part of this century. It employs the quantum structure to improve the efficiency of machine learning. With the remarkable progress in data mining and the very high speed of data production in various scientific and engineering fields, there is a growing demand for high-speed calculations and more sophisticated data structures (Park et al., 2020). Quantum calculations differ from classical calculations in that they rely on qubits instead of bits as the primary unit of information. Qubit $|\psi\rangle$ consists of two fundamental states $|0\rangle$ and $|1\rangle$, which serve as the basis for more

Fig. 7. Location of ocean power converters (Google, 2023).

Table 2
Summary of the status of wave and tidal converters (The Portal and Repository for Information on Marine Renewable Energy (PRIMRE)).

Type of resource	The number of projects	Capacity (MW)	status
Wave	55	418	Active
Tidal	94	15,833	Active

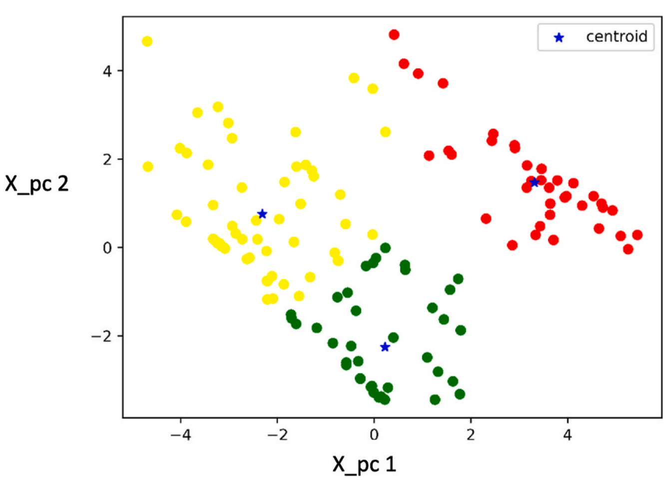

Fig. 8. Classical K-Means clustering.

complex quantum operations.

This state of $|\psi\rangle$ in quantum computing enables a superposition of $|0\rangle$ and $|1\rangle$, allowing for powerful and complex quantum computations (Martín-Guerrero and Lamata, 2022).

$$0 \longrightarrow |0\rangle$$

$$1 \longrightarrow |1\rangle$$

The vectors $|0\rangle$ and $|1\rangle$ form an orthonormal basis of a two-dimensional Hilbert space which is also called the computational basis

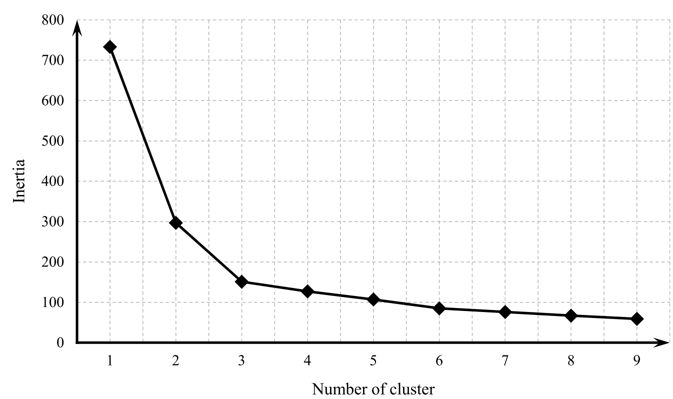

Fig. 9. Elbow plot to select K value in cluster.

(Fig. 6) (Schuld and Petruccione, 2021).

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

In this equation $\alpha, \beta \in \mathrm{C}$ and due to vector normalization $|\alpha|^2 + |\beta|^2 = 1$. In general, each qubit can be displayed parametrically, and in this regard, geometric representation can be very helpful (Schuld and Petruccione, 2021). Due to the need for high-speed data processing as well as high accuracy in calculations, quantum computing can be a more suitable and faster option for information processing compared to classical machine learning, especially in processing of big data. In recent years, there has been an increase in the use of quantum machine learning to create a transformation in the speed of exponential learning (Kerenidis et al., 2018). It has been proven that quantum computing can outperform its classical counterpart (Kerenidis et al., 2018). From a technical point of view, quantum computing is faster in dealing with complex problems and data and can provide better learning in data analysis compared to classical machine learning. Quantum machine learning can be used in quantum clustering, quantum automatic encryptions, quantum reinforcement learning, quantum nonlinear modeling, improving the active learning process, as well as different types of machine learning methods to work more efficiently

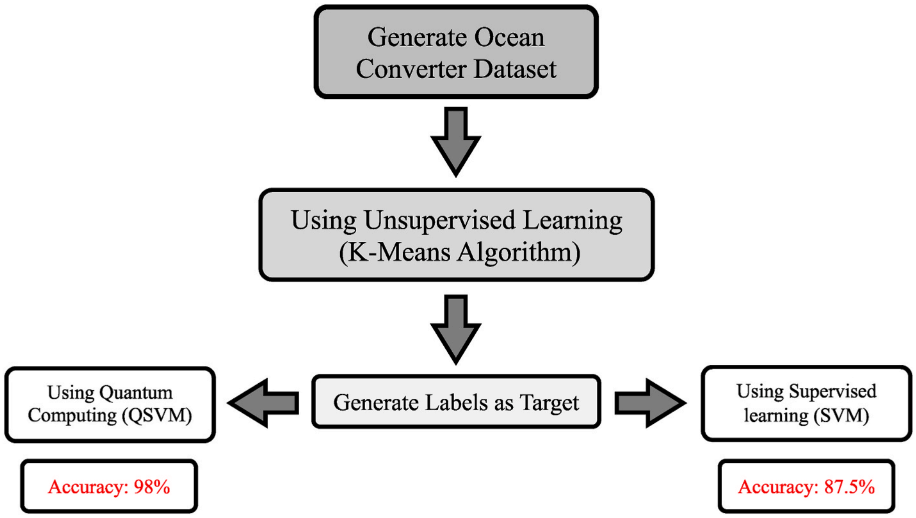

Fig. 10. The process of running SVM and QSVM algorithms.

(Martín-Guerrero and Lamata, 2022). One of the important factors in quantum computing is the understanding of quantum environments and the provision of quantum algorithms that can improve the correlation between the learning agent and its environment. Quantum machine learning strives to increase the speed of calculations and reduce the complexity for more accurate analysis and more robust learning of relationships and structures in databases. This increase in speed in quantum environments, which can be easily done by increasing the number of qubits, can sometimes lead to the creation of new solutions with better performance (Martín-Guerrero and Lamata, 2022). Other uses for quantum machine learning include very complex statistical patterns that are very difficult to detect and even generate new data in the classical machine learning. Quantum machine learning holds the potential to generate data with significantly more complex statistical patterns than what is currently available (Park et al., 2020).

5.2.1. Quantum support vector machine (QSVM)

Support vector machine (SVM) is an efficient and widely used algorithm for classification. However, as the complexity and volume of data increases, it becomes exceedingly difficult, and sometimes impossible, for SVM to analyze and assess the data. In quantum support vector machines (QSVM), using quantum mapping, a feature map is prepared to improve the performance of the algorithm for complex data analysis (Kavitha and Kaulgud, 2022). The feature map transforms the data into a set of multi-qubit states. This allows the data to be classified by the algorithm (Suzuki et al., 2020). QSVM, like its classical counterpart, SVM, attempts to create the maximum distance between data with high-precision classification. But in complex and large data, QSVM outperforms SVM (Park et al., 2020). In QSVM, by using the principle of superposition, it is possible to classify the data using a super-plane or a non-linear function for mapping. The feature map can be transferred in a space called Hilbert space in which the separation is done (Kavitha and Kaulgud, 2022). The classification methods have a binary structure, which can be used to classify data into several classes in a one-against-all manner. QSVM follows the same process to find the maximum margin between each class (Kavitha and Kaulgud, 2022). In the quantum multi-class classification used in this research, one-versus-others and one-versus-one strategies are used to build a multi-class QSVM that uses pre-designed quantum annealing to find the separating hyperplane between classes. The goal of this approach is to find the maximum margin between each class (Dema et al., 2020).

It has been shown that using a quantum environment for data processing can lead to better results (Kavitha and Kaulgud, 2022). Also, as the number of data points and the calculation time increase, quantum computation results can be much better than their classical counterpart due to the significant reduction in processing time. After running quantum codes on several standard datasets, it was found that the processing time for quantum computing can be as low as 0.01%–1% compared to the classical methods (Kavitha and Kaulgud, 2022).

5.2.2. Application of quantum computing to assess impacts of wave and tidal devices

UK is one of the leading countries in the production of energy from the ocean due to its geographical conditions and the existence of wide beaches (Farrok et al., 2020).The dataset used in this research includes 149 devices of wave and tidal energy converters located in England (longitude: 350.5, latitude: 49.5) (Fig. 7). In general, 55 wave energy devices with a total capacity of 418 MW and 94 tidal energy devices with a total capacity of more than 15,800 MW have been analyzed in this data (Table 2). This dataset consists of 21 parameters. These parameters include temperature, water salinity, oxygen concentration, as well as related ocean parameters collected from the NOAA website of the National Oceanic and Atmospheric Administration (National Oceanic and Atmospheric Administration). Also, some information about the physical characteristics of converters such as single device or array, the number of devices and the area occupied by the device has been collected from papers and documents related to the converters. But some important features such as the extent of the devices' impact on the ecosystem and water quality, the impact on aquatic life and aquatic organisms, and the impact on the ocean floor regime are taken from the OES-Environmental 2020 State of the Science Report (Copping and Hemery, 2020). This report presents a dashboard to classify the impacts of ocean devices between very low impact to very high impact. This categorization is used in the current research to evaluate the qualitative data available in the dataset. This classification helps to score converters more accurately for each feature (Copping and Hemery, 2020). Generally, Information about converters has been collected from various sources, including websites of designers or manufacturers and related scientific articles. In addition to the technical details of the converters, oceanic data were also collected for the same geographic coordinates (The Portal and Repository for Information on Marine Renewable Energy (PRIMRE)). In this paper, a new approach involving the use of quantum computing to investigate the environmental impacts of wave and tidal devices on the ocean is introduced. This paper uses two different (classical and quantum) structures for data analysis and compare the results of these two structures.

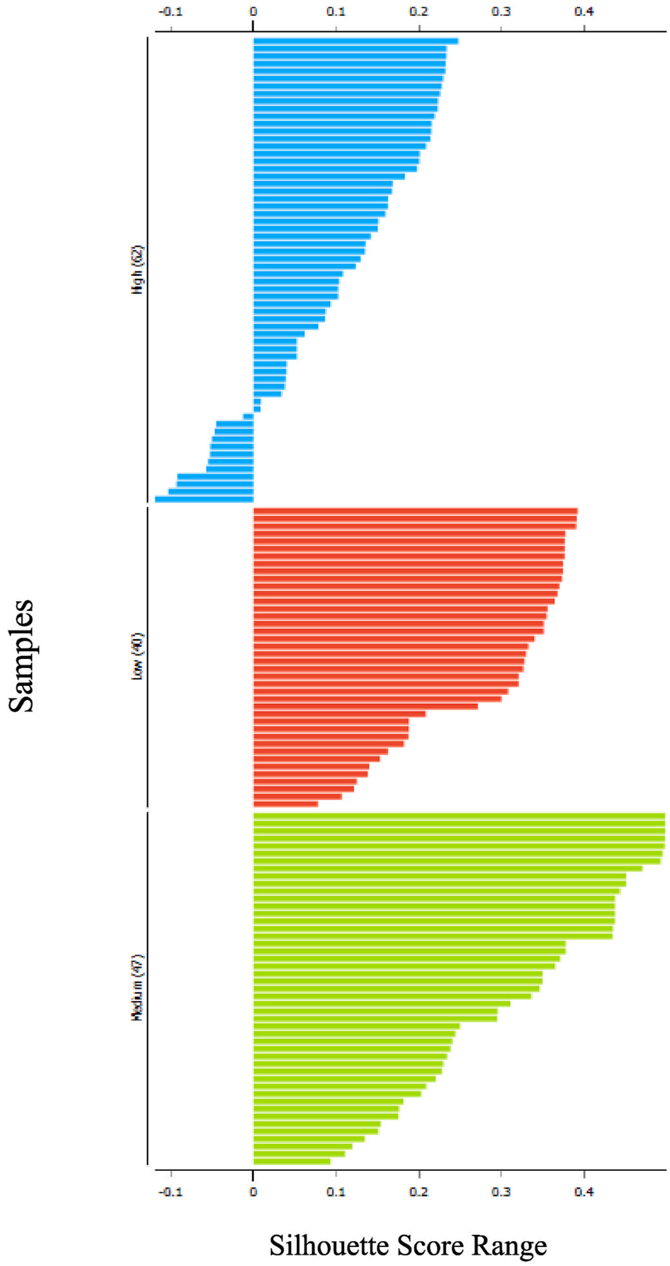

Fig. 11. Silhouette plot.

6. Results

In the first step, the K-Means algorithm is implemented on the existing dataset and then the proposed clustering is determined by the model (Fig. 8).

After running this algorithm and finding the inertia value for each cluster (which is calculated from the sum of squares of the distance of each data point to the center of the cluster and drawing the knee chart), it was found that the 3 selected clusters are the correct choice for data analysis and prediction. are. In general, in most cases, increasing the number of clusters does not help to improve the performance of the algorithm. It may even complicate the calculations unnecessarily. Therefore, choosing more than 3 clusters will not have a noticeable change in performance improvement (Fig. 9).

In the next step, the clustering obtained from the K-Means model is considered as the final class in the classical SVM model. Then, with the investigations carried out on the clustered data, these three clusters were classified with the labels of low impact, medium impact, and high impact. After analyzing the dataset in the three classes by the classical SVM, this research was able to obtain an accuracy score of 87.5%. Accuracy is a common performance measure that is a measure of the proportion of observations that are correctly predicted. This score indicates the accuracy of model in making predictions by SVM and its ability to predict the environmental impacts of new devices. In the final stage, the labeled data (which were produced by the K-Means model), were implemented in the quantum support vector machine (QSVM) model. The results show the accuracy of the QSVM was significantly higher (98%) than its classical counterpart (87.5%) (Fig. 10). The higher accuracy of the quantum vector machine compared to the supporting vector machine shows the superior ability of this model to predict the state of new data. This means that if new converters are proposed, this model can accurately predict which category these converters would fall into. With a highly accurate prediction of the influence of new converters on the marine environment, it is possible to reduce the possible impacts or revise the design to reduce the environmental impacts.

6.1. Silhouette score

Determining the number of clusters is one of the important factors in data clustering. One of the common measures to determine the number of clusters for the *K-Means* algorithm is the silhouette score. This index, which ranges from −1 to 1, uses the average intra-cluster distance *a*, and the average distance of the nearest cluster for each data point b (Shahapure and Nicholas, 2020).

Silhouette score = (b-a) / max(a, b)

The highest silhouette score for the dataset considered in this research was 0.465 for three clusters. According to Fig. 11, the placement of the data in the selected clusters has been appropriate; except for

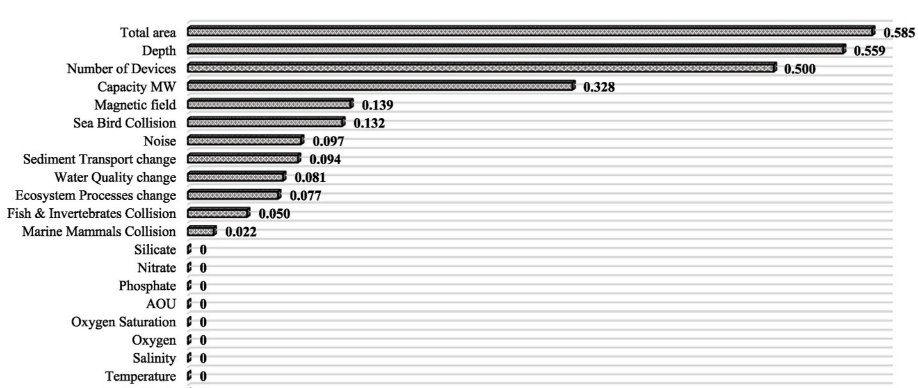

Fig. 12. One-at-a-time (OAT) sensitivity analysis bar chart.

a few data points, the rest of the data correspond to the cluster to which they were allocated.

6.2. Features analysis

An approach for determining the relative weights of various input variables in a model is called one-at-a-time (OAT) sensitivity analysis. This type of local sensitivity analysis only considers the impacts of altering one input variable at a time while holding the others constant. The OAT method entails repeatedly running the model while methodically altering the value of one input variable at a time. The output from each run is then used to assess the model's sensitivity to each individual input variable. The output from the model is compared between the various runs to determine the sensitivity of the model to each input variable. The range of possible values for each output variable is determined, and for each unit change in the input variable, the percentage change in the output is determined. This provides indicators of the model's sensitivity to a specific input variable. There are some drawbacks to the OAT method as it only considers the impacts of altering one input variable at a time and ignores interactions between variables. As it calls for running the model multiple times, it is also a computationally intensive method. However, it can be a useful tool for determining the relative significance of various input variables and directing further investigations (Borgonovo) (Fig. 12).

Based on the study of several aquatic species in the waters of southwest England, the most populous species of this region live in the epipelagic zone (Devon wildlife trust, n.d.). This area forms the upper part of the ocean and its depth is 200 m. Due to the penetration of sunlight, this part of the ocean hosts many marine species that use sunlight for photosynthesis. It should be noted that this area is shallower in the coastal strip and many aquatic animals live near the shore (Sutton et al., 2017). According to the evaluation results, two important factors are important in the way they move: the depth and the specific range of horizontal movement of aquatic animals on the water surface. In these geographical coordinates where the converters have been studied, it is known that a large percentage of aquatic and marine mammals dive at a depth of 30–50 m and most large mammals generally swim in this area. Another important point in the behavior of some aquatic animals, especially marine mammals such as dolphins and whales, is the degree of breathlessness. This causes the mammals to surface and dive back into the water at regular intervals. This group of aquatic animals needs airing at the water surface for 10–30 min (Kooyman and Ponganis, 1998). This allows the mammals to move between the 30 m depth and the surface in constant motion. This traffic greatly increases the risk of aquatic animals' collision. As a result, the obtained results about the sensitivity of the depth feature are consistent with the real data (Devon wildlife trust, n.d.).

7. Conclusion

Environmental impact assessment in all aspects of engineering is a complex task. This assessment increases the complexity in large environments such as oceans where various factors are involved and interact. Because of their vastness, the oceans are the habitat of many species of living organisms on this planet. In recent years, with the advancement of technology, the extraction of data from the oceans has greatly increased (Brett et al., 2020). Therefore, examining and analyzing these data for environmental assessments, focusing on marine renewable energy generation converters, requires powerful data analysis tools that can provide us with more accurate answers in a shorter period of time. Therefore, due to the high accuracy and learning ability of quantum machine learning compared to classical machine learning for various databases, especially big data, quantum machine learning is expected to perform better in the analysis of marine environment data.

In this paper, the application of quantum machine learning in evaluating the environmental impacts of wave and tidal energy devices was investigated. Quantum machine learning was used to analyze and evaluate ocean energy generation converters at a specific location off the coast of England. In this research, it has been determined that QSVM algorithm of quantum machine learning provides better accuracy for data analysis with 98% accuracy compared to 87.5% accuracy of classical machine learning SVM algorithm. QML provides a new approach to marine environmental impact assessment. This approach provides a powerful bridge between ocean environmental assessment and the use of emerging technologies in artificial intelligence and quantum mechanics. It can be confirmed that researchers can achieve much better and more accurate results using a larger and more complete data set in the future.

On the other hand, the analysis of ocean data by quantum machine learning provides a new window to increase speed and accuracy. This will increase the accuracy of engineers and especially designers in important areas such as the design of ocean energy converters with better capabilities and lower costs. Another important point in big data calculations is time. And also one of the important points is that quantum machine learning algorithms will decrease the costs and increase the flexibility of decisions by reducing the calculation time.

CRediT authorship contribution statement

Taha Rezaei: Writing – original draft. **Akbar Javadi:** Writing – review & editing.

Declaration of Competing Interest

I clearly declare that I do not have any financial or personal relationship with anyone, any group, or any specific organization.

Data availability

No data was used for the research described in the article.

References

E. Borgonovo,.'International Series in Operations Research & Management Science'. [Online]. Available: http://www.springer.com/series/6161.

Burhanudin, J., Hasim, A.S.A., Ishak, A.M., Burhanudin, J., Dardin, S.M.F.B.S.M., 2022. A review of power Electronics for nearshore wave energy converter applications. IEEE Access 10, 16670–16680. https://doi.org/10.1109/ACCESS.2022.3148319. Institute of Electrical and Electronics Engineers Inc.

Copping, A., Hemery, L., 2020. OES-environmental 2020 State of the Science Report: Environmental Effects of Marine Renewable Energy Development Around the World. Report for Ocean Energy Systems (OES)' https://doi.org/10.2172/1632878. Richland, WA (United States).

Curto, D., Franzitta, V., Guercio, A., 2021. Sea wave energy. A review of the current technologies and perspectives. Energies 14 (20). https://doi.org/10.3390/en14206604.

Brett, Annie, Jim Leape, Mark Abbott, Hide Sakaguchi, Ling Cao, Kevin Chand, Yimnang Golbuu, Tara J. Martin, Juan Mayorga, and Mari S. Myksvoll. "Ocean data need a sea change to help navigate the warming world." *Nature* 582, no. 7811 (2020): 181-183.

Dema, B., Junya Arai, Keitarou, Horikawa., 2020. Support vector machine for multiclass classification using quantum annealers. Proc. DEIM Forum.

Farrok, O., Ahmed, K., Tahlil, A.D., Farah, M.M., Kiran, M.R., Islam, M.R., 2020. Electrical power generation from the oceanic wave for sustainable advancement in renewable energy technologies. Sustainability 12 (6). https://doi.org/10.3390/su12062178. MDPI.

Galparsoro, I., et al., 2021. A new framework and tool for ecological risk assessment of wave energy converters projects. Renew. Sustain. Energy Rev. 151 https://doi.org/10.1016/j.rser.2021.111539.

Gitinavard, H., Shirazi, M.A., Fazel Zarandi, M.H., 2020. Sustainable feedstocks selection and renewable products allocation: a new hybrid adaptive utility-based consensus model. J Environ Manage 264 (Jun). https://doi.org/10.1016/j.jenvman.2020.110428.

Guo, B., Ringwood, J.V., 2021. A review of wave energy technology from a research and commercial perspective. IET Renew. Power Gener. 15 (14), 3065–3090. https://doi.org/10.1049/rpg2.12302. John Wiley and Sons Inc.

Hsieh, W.W., 2022. Evolution of machine learning in environmental science—a perspective. Environmental Data Science 1. https://doi.org/10.1017/eds.2022.2.

I. Renewable Energy Agency, 2021. Offshore renewables: An action agenda for deployment (A contribution to the G20 Presidency) [Online]. Available: www.irena.org.

Károly, A.I., Fullér, R., Galambos, P., 2018. Unsupervised Clustering for Deep Learning: A Tutorial Survey.
Kavitha, S.S., Kaulgud, N., 2022. Quantum machine learning for support vector machine classification. Evol Intell. https://doi.org/10.1007/s12065-022-00756-5.
Kerenidis, I., Landman, J., Luongo, A., Prakash, A., 2018. q-means: A quantum algorithm for unsupervised machine learning [Online]. Available: http://arxiv.org/abs/1812.03584.
Kooyman, G.L., Ponganis, P.J., 1998. The physiological basis of diving to depth: Birds and mammals. Annu. Rev. Physiol. 60, 19–32. https://doi.org/10.1146/annurev.physiol.60.1.19.
Korkmaz, C., Correia, A.P., 2019. A review of research on machine learning in educational technology. EMI Educ Media Int 56 (3), 250–267. https://doi.org/10.1080/09523987.2019.1669875.
Kroeker, K.J., et al., 2020. Ecological change in dynamic environments: accounting for temporal environmental variability in studies of ocean change biology. Global Change Biol. 26 (1), 54–67. https://doi.org/10.1111/gcb.14868. Blackwell Publishing Ltd.
Google. 2023 "Map of [Southwest of England]." Google Maps, Google, 2023, https://www.google.com/maps/@50.8458116,-5.4809926,234875m/data=!3m1!1e3.
Bishwas, Arit Kumar, Mani, Ashish, Palade, Vasile, 2018. An all-pair quantum SVM approach for big data multiclass classification. Quantum information processing 17, 1–16.
Mahesh, B., 2018. Machine learning algorithms-A review machine learning algorithms-A review view project Six Stroke engine view project Batta Mahesh Independent researcher machine learning algorithms-A review. Int. J. Sci. Res. https://doi.org/10.21275/ART20203995.
Martín-Guerrero, J.D., Lamata, L., 2022. Quantum machine learning: a tutorial. Neurocomputing 470, 457–461. https://doi.org/10.1016/j.neucom.2021.02.102.
Mendoza, E., Lithgow, D., Flores, P., Felix, A., Simas, T., Silva, R., 2019. A framework to evaluate the environmental impact of OCEAN energy devices. Renew. Sustain. Energy Rev. 112, 440–449. https://doi.org/10.1016/j.rser.2019.05.060.
Morris, J.J., Rose, A.L., Lu, Z., 2022. Reactive oxygen species in the world ocean and their impacts on marine ecosystems. Redox Biol. 52 https://doi.org/10.1016/j.redox.2022.102285. Elsevier B.V., Jun. 01,.
National Oceanic and Atmospheric Administration,.'NOAA'.
Niranjan, S.K., Aradhya, V.N.M., University, Amity, 2016. IEEE-USA, Institute of electrical and Electronics engineers. Uttar Pradesh section, and Institute of electrical and Electronics engineers. Proceedings of the 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I). Noida, India.
OES, 2017. An International Vision of. Energy'.
Park, J.-E., Quanz, B., Wood, S., Higgins, H., Harishankar, R., 2020. Practical application improvement to Quantum SVM: theory to practice [Online]. Available: http://arxiv.org/abs/2012.07725.
Pourzangbar, A., Jalali, M., Brocchini, M., 2023. Machine learning application in modelling marine and coastal phenomena: a critical review. Frontiers in Environmental Engineering 2. https://doi.org/10.3389/fenve.2023.1235557.
Sang, Y., Karayaka, H.B., Yan, Y., Yilmaz, N., Souders, D., 2018. Ocean (marine) energy. Comprehensive Energy Systems 1–5, 733–769. https://doi.org/10.1016/B978-0-12-809597-3.00120-6. Elsevier Inc.
Sarker, I.H., 2021. Machine learning: algorithms, real-world applications and research directions. SN Computer Science 2 (3). https://doi.org/10.1007/s42979-021-00592-x. Springer.
Schuld, Maria, Petruccione, Francesco, 2021. *Machine learning with quantum computers*. Springer, Cham.
Shahapure, K.R., Nicholas, C., 2020. Cluster quality analysis using silhouette score. In: Proceedings - 2020 IEEE 7th International Conference on Data Science and Advanced Analytics, DSAA 2020. Institute of Electrical and Electronics Engineers Inc., pp. 747–748. https://doi.org/10.1109/DSAA49011.2020.00096
Solgi, E., Moattar Husseini, S.M., Ahmadi, A., Gitinavard, H., 2019. A hybrid hierarchical soft computing approach for the technology selection problem in brick industry considering environmental competencies: a case study. J Environ Manage 248 (Oct). https://doi.org/10.1016/j.jenvman.2019.06.120.
Solgi, E., Gitinavard, H., Tavakkoli-Moghaddam, R., 2022. Sustainable high-Tech brick production with energy-Oriented Consumption: an Integrated Possibilistic approach based on Criteria Interdependencies. Sustainability 14 (1). https://doi.org/10.3390/su14010202.
Statista, 2023. Global Electricity Consumption 1980-2021. Statista Research Department.
Sutton, T.T., et al., 2017. A global biogeographic classification of the mesopelagic zone. Deep-Sea Res. Part I Oceanogr. Res. Pap. 126, 85–102. https://doi.org/10.1016/j.dsr.2017.05.006. Elsevier Ltd.
Suzuki, Y., et al., 2020. Analysis and synthesis of feature map for kernel-based quantum classifier. Quantum Mach Intell 2 (1). https://doi.org/10.1007/s42484-020-00020-y.
Devon Wildlife Trust. (n.d.). Retrieved [2023], from https://www.devonwildlifetrust.org/.
'REN21' and 2021, 2021 'REN21',.2021.
The Portal and Repository for Information on Marine Renewable Energy (PRIMRE)'. [Online]. Available: https://openei.org.