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RESEARCH ARTICLE

PERFORMANCE ENHANCEMENT OF UNDERWATER ACOUSTIC COMMUNICATION USING DEEP LEARNING APPROACH

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Abstract

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This research aims to improve underwater acoustic communication using deep learning. Due to an increase in undersea operations, dependable communication systems have become more important. The undersea environment's complexity reduces the efficacy of underwater audio communication, despite its widespread use. Using mathematical equations and approximations, the underwater sound pathway has been modeled. These projects aim to enhance underwater communication systems by better understanding the underwater audio channel. In this study, we investigate the abilities of device learning and deep studying to investigate and accurately replicate the underwater acoustic channel by making use of real-world underwater data. This is done by analyzing the results of the study. The information has been compiled with the aid of using a combination of strategies, which include machine learning and in-depth reading. In particular, the Deep Neural Community (DNN) and long quick term memory (LSTM) modeling strategies are used in order to achieve the goal of simulating the underwater audio channel. The results of the trials demonstrate that these models are capable of accurately modeling the underwater acoustic communication channel. Furthermore, the findings suggest that deep learning models, particularly LSTM, are better models in terms of mean absolute percentage error. The vast majority of the currently available UWSN routing protocols use a classical routing strategy.

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Introduction:-

Civil and military organizations have shown more interest in underwater wireless communication in recent years growing interest and this is due to a rise in undersea operations, such as military surveillance, underwater mining, pipeline and fibre optic cable construction, aquatic and biological research, and documentary filmmaking. Because water covers about 71 percent of the earth, marine biologists, engineers, and other researchers who are worried about the ocean's ecology desire instruments that will enable them to examine the underwater environment in greater depth [01]. As undersea operations increase, efficient underwater communication systems are needed. It is well acknowledged that the undersea environment is one of the most challenging communication mediums due to its complexity. When compared to terrestrial radio systems, the underwater acoustic (UWA) communication medium places restrictions on powerful communication [02].

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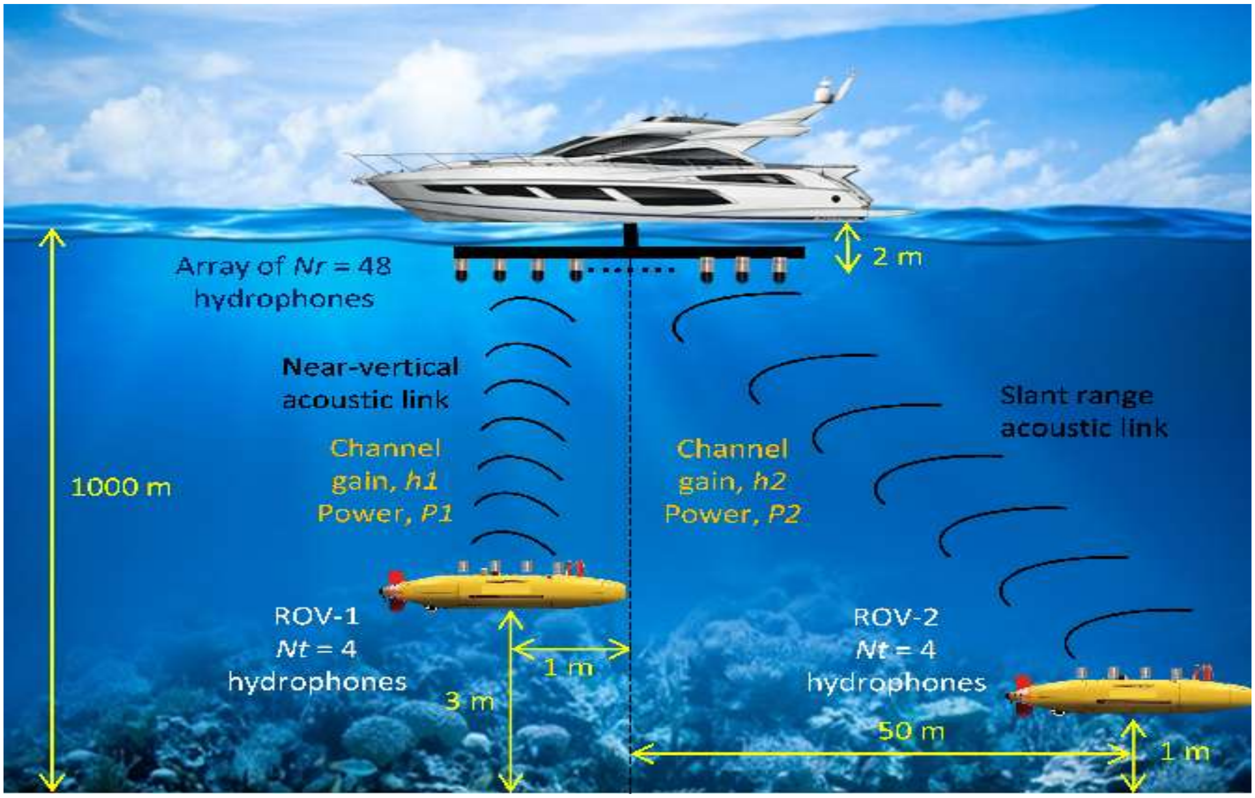

Fig no 1:- An overview on underwater acoustic system.

These restrictions are brought about by the medium's extremely sluggish propagation, restricted accessible bandwidth, extensive multipath delay spread, and other factors. As a result, modeling the underwater acoustic channel is quite difficult. When it comes to transmission, there are two basic proven technologies that are used for wireless communication underwater. These techniques include the transfer of information via auditory and electromagnetic mediums, respectively. An electromagnetic media requires electromagnetic waves, whereas an acoustic medium requires acoustic waves. Particle vibrations cause acoustic waves. Electric and magnetic fields interact to produce electromagnetic waves **(See Fig no 1)**. Both modes allow submerged communication. Acoustic waves are more effective in an underwater environment due to their physical properties. Electromagnetic waves have high power consumption, large antenna size, and can't go far underwater unless the frequencies are low [03]. Using electromagnetic waves at low frequencies needs a powerful and expensive transmitter, limiting its utility.

(1) The purpose of this research is to provide a data-driven method for modeling underwater audio channels in order to restrict the number of mathematical model assumptions and make use of an increasing number of experimental recordings. The goal of this work is to model underwater acoustic channels in a way that is more accurate. Because of this, the modeling of underwater acoustic channels may be able to achieve a higher level of precision. This work is one of the contributions to this paper.

(2) Work has been done to simulate underwater audio channels using both conventional machine learning strategies and more advanced forms of deep learning. The findings of the different models are compared, and then observations and insights are presented based on the comparison of those results [04].

Literature Survey:-

Wang et al. created a concept for a power-efficient and environmentally friendly statistics broadcasting machine, which they called power-performance Grid Routing on the notion of three-dimensional cubes (EGRCs) in UASNs. The name of this machine derives from the fact that it processes statistics in the form of three-dimensional cubes. The problematic characteristics of the underwater media, which include its changing topology in three dimensions, its high propagation latency, its node mobility and density, and its rotation method for CH nodes, are taken into account by this machine.

The complete network architecture is shown to be in the form of a three-dimensional cube in the beginning, while still being visible from the perspective of the grid. In addition to that, this three-dimensional cube has been cut up into many smaller cubes, and each of those smaller cubes has been given the name of a cluster. The true three-dimensional dice are formed by reassembling a number of smaller cubes into their original configuration. Muhammad and his associates were the ones who first created the environmentally friendly Hybrid Routing Protocol for the use of power (EEHR). The EEHR is a hybrid model in the sense that it incorporates both a multi-hop transmission model and a direct transmission model [05].

This allows for the linking of records among locales in an efficient manner. Acoustic communication was presented as a method of facilitating region-based collaboration between sensor nodes by **Hafeez et al.** The capacity of individual nodes in a network to work together to solve problems and share information is one of the most important but also one of the most energy-intensive strategies available. In this method, the data is resent from another node known as a cooperative node in the event that it is unable to reach its destination under any circumstances. **TAhmad et al.** came up with the idea for the UWSNs to use the Energy Efficient Reliable Transport (EERT) protocol. The EERT protocol is built on a foundation of Single-Path communication and incorporates hybrid aspects of FEC and ARQ into its operation. The Hadamard code is used by EERT for error detection as well as correction. This gives a dynamic feedback system that may adjust the data block size as well as the data transmission rate based on BER. According to the findings of their investigation, Single Path communication with hybrid FEC/ARQ is superior than the end-to-end FEC technique that is currently being recommended for UASNs in terms of both energy efficiency and the percentage of data that is successfully delivered [06].

When determining the ideal forwarding node, the authors took into account the leftover energy of each node. In addition to this, REEP makes use of ToA (Time of Arrival), which measures the distance between a node and the sink to which it is connected, in order to determine the best possible routing route. The energy balancing and interference avoidance strategy was suggested by **Maqsood et al.,** and it is thanks to this technique that the network lifespan and through put have increased.

They first presented the idea of energy balancing in the EB-IAEEDBR report. The authors Li et al. used a technique called Low-Energy Adaptive Clustering Hierarchy (LEACH) to determine how to achieve energy efficient routing. A novel M-FEC that is based on Hamming Coding was suggested by Xu et al. in order to improve the reliability of USNs as well as their energy efficiency. A Markovian model is developed in order to create the probability of MFEC. For the proposed verdict and feedback system, on the whole PER was calculated. This is able to reduce the number of the many paths and achieve the enviable on the whole PER in M-FEC [07].

A novel Quality of Service aware Evolutionary cluster based Routing Protocol (QERP) was proposed by **Faheem et al.** for use in UWSN. The researchers concentrated on developing a routing protocol while simultaneously lowering noise components, long propagation delays, high BER, low bandwidth capacity, multipath effects, and interference. The new protocol increases the Packet Delivery Ratio (PDR), while simultaneously decreasing the average end-to-end latency and the total energy use of the network.

Research Methodology:-

Dataset Description

This investigation employed three datasets to compare conventional and deep researching models' underwater audio channel simulations the datasets 1 is a test record. The test mattress was created without interruption using a water tank. Transmitter and receiver were submerged horizontally and perpendicularly determine 2 complete records 1 technique. QPSK modulated digital messages before becoming continuous. Non-stop signs have a greater cosine transmission clean out. The acoustic transmitter sent QPSK-filtered signals across the underwater channel. Sonar detected up continuous waves after the channel. Information objects have 60-second duration and 1,000,000 sampling charge [08].

Information 2 came from a lake surrounded by land and without artificial disruptions. This lake was chosen because it lacked human traces. Symbols were sent across a natural water body utilising the same signal levels as record 1. This was done to create an actual underwater dataset with the same sonar frequency, sampling rate, transfer speed, horizontal distance between the transmitter and receiver, and perpendicular distance into the sea (see parent 3). During the test, the horizontal distance between the transmitter and receiver was kept constant. The device learning models incorporated the transmitters and receiver's post-channel data 3 uses the same setup and settings. To simulate a chaotic environment, add a disturbance. Each group got 61 million samples [09].

Models And Approach Used

In the recent decade, machine learning models have been used for sentiment analysis, time series forecasting, and photo recognition. The undersea acoustic data is a continuous time-series and is one-dimensional. The underwater audio channel is modeled using regression. The undersea channel receives a data sequence and outputs the same size sequence **(See Fig no 2, 3)**. The data characteristics prevent using any regression models. Models must accept and predict data sequences. We analyzed many time series machine learning techniques. The research described machine learning models that could be applied to time series data and showed that preprocessing affected model performance. We compared the Long Short Term Memory (LSTM), a kind of RNN, with the Deep Neural Network (DNN). Deep learning uses buried neural network layers. By adding layers and nonlinear neurons, it reflects increasingly sophisticated functions. It can also read high-level data representations.

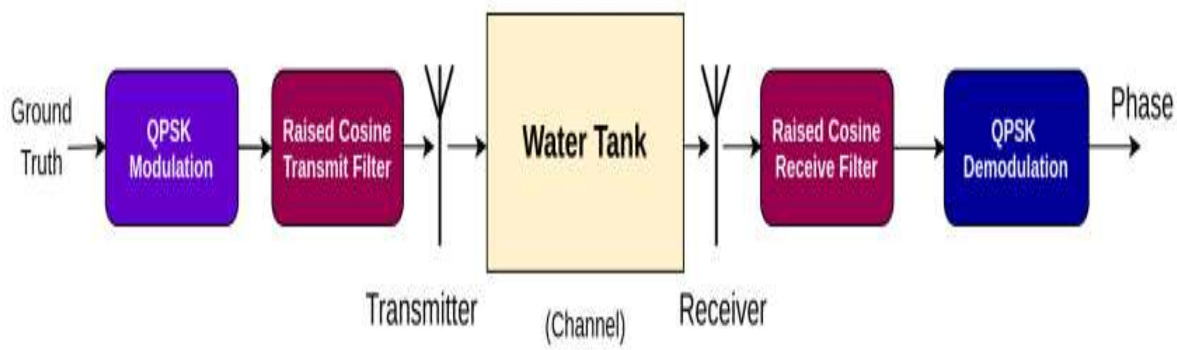

Fig no 2:- An overview on underwater Communication Channel.

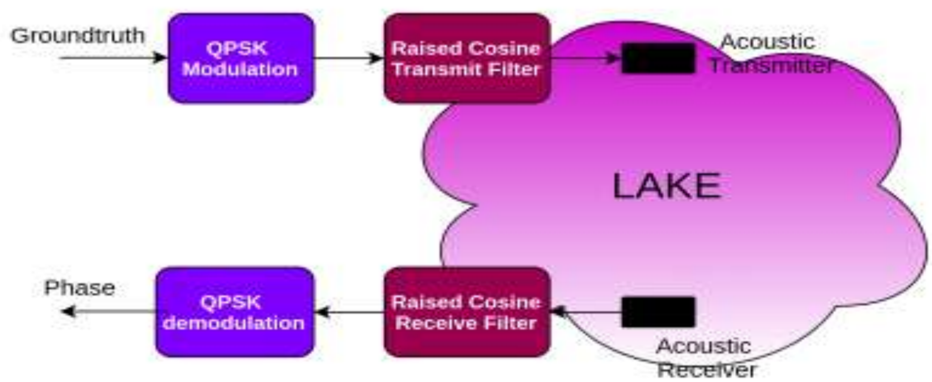

Fig no. 3:- Alternative Acoustics underwater Communication Channel.

Traditional Machine Learning In This Study

We made use of several more conventional machine learning models in order to ensure that they fulfilled the requirements outlined earlier. The k-Nearest Neighbor, the Random Forest, the Linear Regressor, and the Multi-Layer Perceptron are some of the models that fall into this category [10].

K Nearest Neighbor:

The k-nearest neighbors (KNN) is a supervised machine learning algorithm technique that may be used for both classification and regression issues. The algorithm believes that objects that are similar are close together, that is, related items are close together. The algorithm hinges on this assumption to capture the similarity between objects by calculating the distance between the objects or points. This algorithm is straightforward and simple to implement as it does not require creating a model nor tuning many hyper-parameters, the major hyper-parameter being the number of neighbors, K. We ran the KNN algorithm numerous times with different values of K to find the K that decreases the amount of errors we encounter while keeping the algorithm's capacity to properly make predictions.

Random Forest:

A random forest is a supervised machine learning approach based on decision tree algorithms. It makes use of ensemble learning, which is a technique for solving complicated problems by combining several simpler models. The random forest is made up of many decision trees and the resulting forest is trained either by bagging or bootstrap aggregation. The algorithm determines the outcome based on the decision trees' predictions and the final prediction is based on averaging the output of various trees. The performance of the predictions improves as the number of trees increases. It can also be applied to address problems involving regression and classification. Without hyper-parameter adjustment, random forest can provide a reasonable prediction and it also overcomes the problem of over fitting in decision trees.

Linear Regression:

Linear regression analysis is a statistical technique for predicting the value of one variable based on the value of another. Keras was used to create the many outfits that were shown. The datasets were shaped into a -dimensional tensor for the Keras dense layer, and the tensor was produced from a broad range of education instances (N) and samples in accordance with picture information (NS).

Deep Neural Network

A deep neural network (DNN) generally consists of many completely linked hidden layers numerous nodes, known as hidden units, make up each hidden layer. We utilised two alternative DNN architectures for this experiment. Four (4) thick layers make up the basic architecture **(See Fig no 4)**. This is the range of samples that are included in a transmitted picture, with the exception of the output dense layer, which has 578 nodes rather than 256. Rectified Linear Unit (ReLU) activation capabilities are used across the first three levels of the structure. We added hidden layers to the second structure in order to make the model more in-depth and to increase its overall performance on the disturbed dataset [11].

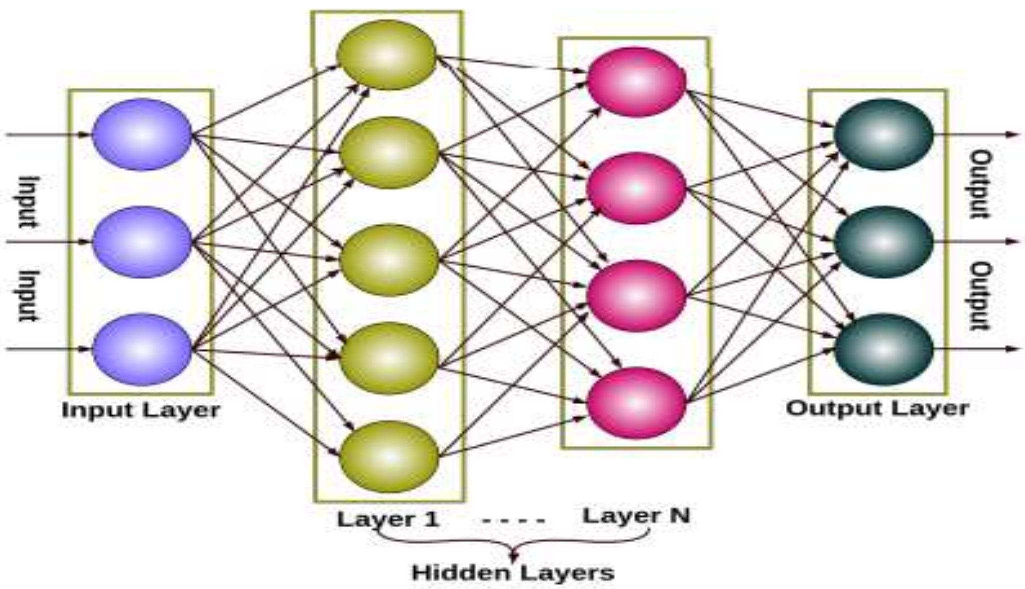

Fig no. 4:- Deep neural Network with N Hidden layers.

Uwsn Channel Model To Derive A Robust Channel Model For UWSN

Large Scale Deviation (LSD) refers to dynamism generated by numerous wavelength displacements, whereas Small Scale Dynamism (SSD) relates to single or few wavelength displacements. LSD is induced by system dislocations, which cannot be predicted using standard geometry. LSD and Nominal Conditions precedents the channel size and sound-speed parameters determine the nominal response of an acoustic channel, which may be evaluated using beam tracing models. Frequency-transmitted signal route loss affects received signal [12].

$$A(l,f) = A_0 l^k a(f)^l \quad \text{…..1}$$

$$0.11\frac{f^2}{1+f^2}+44\frac{f^2}{4100+f^2}+2.75\times10^{-4}f^2+0.003$$
…..2

Considering multi-path communication with different paths of length

$$H_p(f)=\frac{\Gamma_p}{\sqrt{A(l_p,f)}}$$
….3

$$\gamma_b(\theta_p)=\begin{cases}\dfrac{\rho_b\sin\theta_p-\rho\sqrt{\left(\frac{c}{c_b}\right)^2-\cos^2\theta_p}}{\rho_b\sin\theta_p+\rho\sqrt{\left(\frac{c}{c_b}\right)^2-\cos^2\theta_p}}, & \cos\theta_p\le\dfrac{c}{c_b}\\ 1, & otherwise\end{cases}$$
….4

For illustration, a realizable surface can be formed with reflection coefficient (yr), and the individual-bottom reflection can be derived as (7.4)

$$H(f)=\sum_p H_p(f)\,e^{-j2\pi f\tau_p}$$
…..5

To achieve a simple channel model, the approximated function

$$H_p(f)=\frac{\Gamma_p}{\sqrt{\left(\frac{l_p}{l_o}\right)^k a(f)^{l_p-l_o}}}H_o(f)$$
……6

$$a(f)^{-(l_p-l_o)/2}\approx a_0{}^{-(l_p-l_o)/2}$$
….7

$$H_p(f)\approx h_p H_o(f)$$

where the corresponding path gain is given in (7.9)

$$h_p=\frac{\Gamma_p}{\sqrt{\left(\frac{l_p}{l_o}\right)^k a_0{}^{l_p-l_o}}}$$
…..8,9

The frequency can be located anywhere like at the center frequency, or the edge frequency (lower or upper edge). In case frequency exists at the lower edge of the frequency range, it leads maximum path gain, while frequency at the upper edge may result minimum path gain.

Long Short Term Memory

The Long Short Term Memory (LSTM), the communities of recurrent neural networks include a variant that is known as the long short-term reminiscence (LSTM) set of rules. In addition to voice and language processing, RNNs are commonly used to issues that need sequential inputs [13]. The RNN is provided with a single symbol at a time from the input collection, and this information is saved in the hidden devices of its processors. These hidden units store statistics pertinent to the sequence's records, which include the history of all of the collection's previous input. These records may be retrieved at a later time **(See Fig no 5)**.

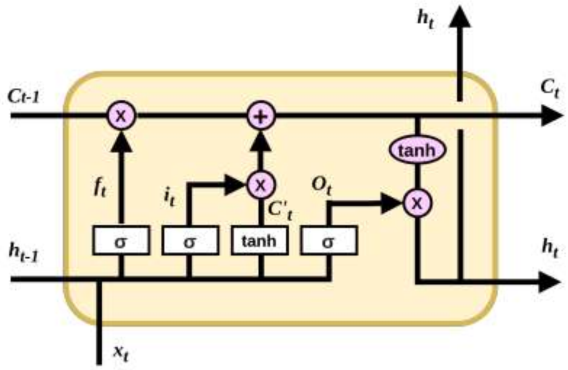

Fig no. 5:- A basic architecture ofLong Short Term Memory.

Resultand Discussion:-

The results of the tests that were run on data 1 and data 2 using both traditional machine learning methods and deep learning approaches are shown in table 1. These tests were completed on both sets of data. When evaluating the effectiveness of the version, the suggest absolute percentage mistakes ended up being the primary metric of choice (MAPE). It exceeds by a wide margin the standard deviation of the absolute percent mistakes found in all of the forecasts.

Performance Matrix

When examining problems with regression, the MAPE provides an interpretation that is wholly obvious from the perspective of relative error. It is favored in the assessment due to the fact that it presents the error in terms of probabilities, and the issue of excellent and bad faults cancelling each other out is eliminated. In a similar manner, MAPE provides the error expressed in terms of percentages [14].

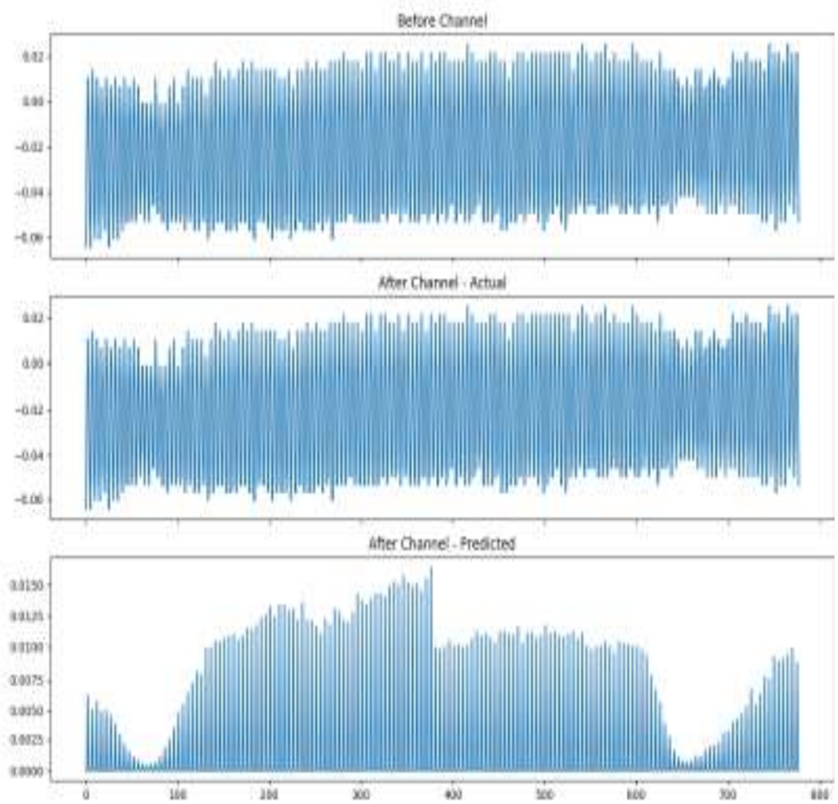

Fig no. 6:- Plot of Linear Regression.

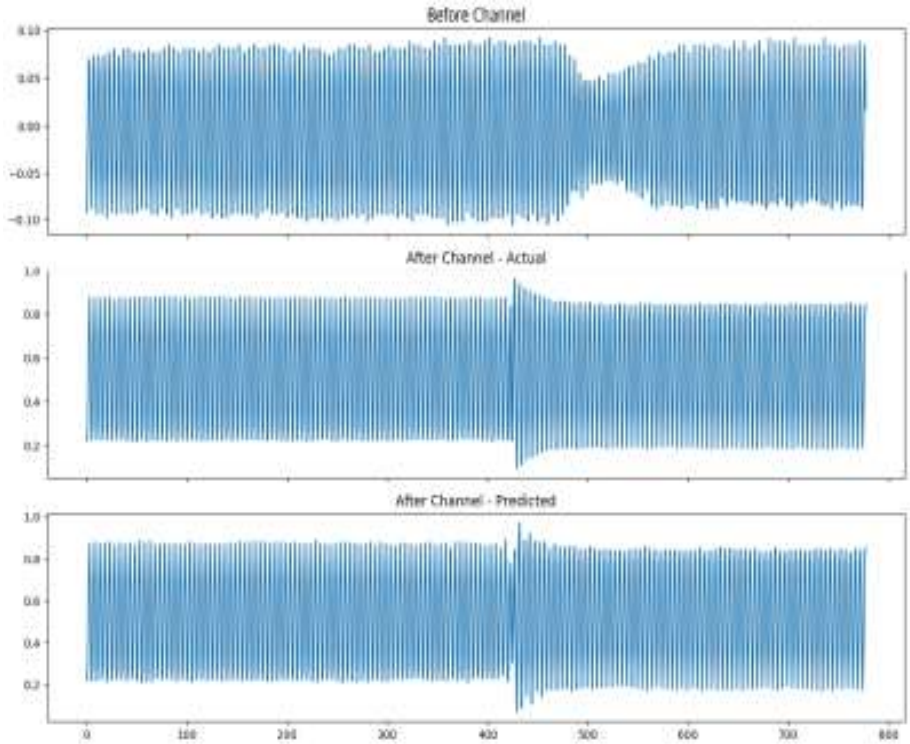

Fig no. 7:- Plot of LSTM.

Lower MAPE suggests higher accuracy. The model's overall performance worsened when applied to actual underwater data (Desk 1). This occurred without purpose. Performance of tool mastery tactics varies. The kNN approach performs better across both datasets (records 1 and statistics 2) Multi-layer perceptron and linear regressor has the least impact on device mastery models **(See Fig no 6, 7)**. This is because the kNN algorithm uses a weighted average of the distances between each point in the neighborhood.

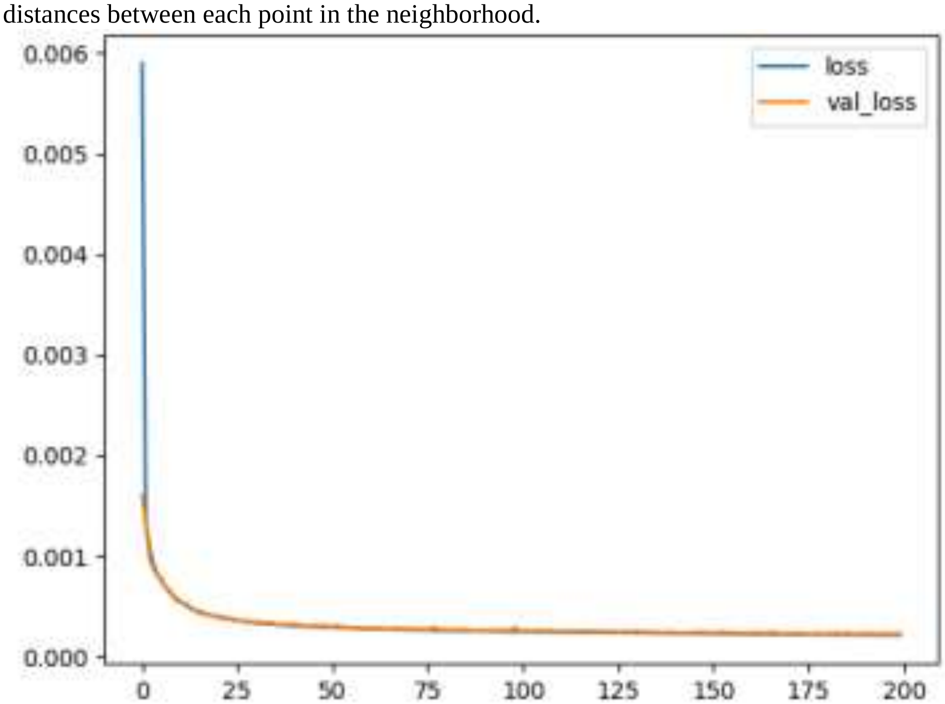

Fig no. 8:- Loss Curve for the LSTM Model.

Characterisation Of UWSN Channel Model

Here, a 13 kHz operational frequency range was chosen, and a 0.2-1 KM distance between the transmitter and receiver was kept constant **(See Fig no 8, 9 & 10)**.

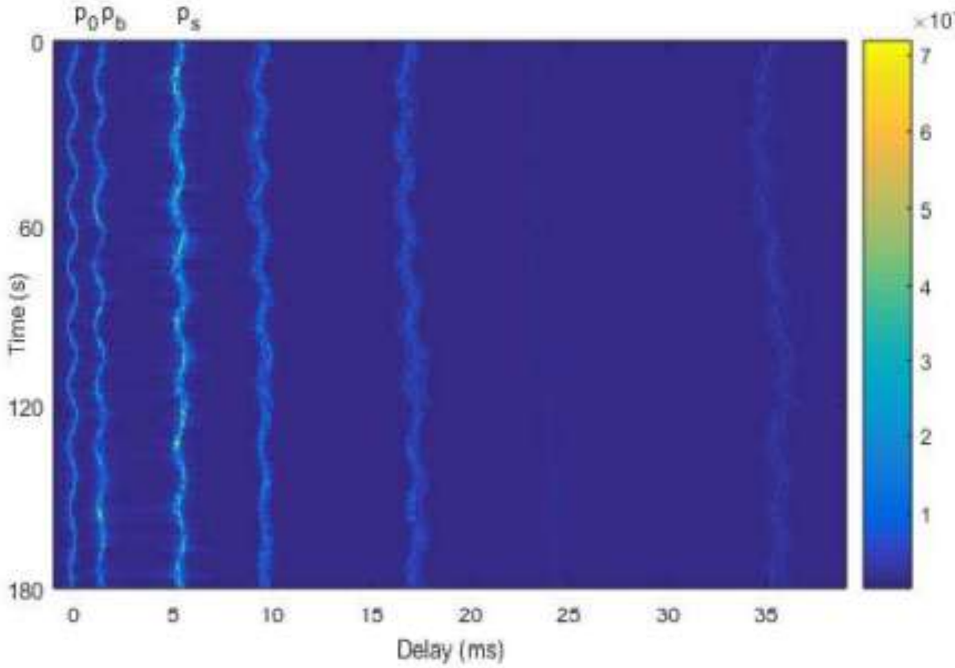

Fig no. 9:- Time Advancement of impulse response.

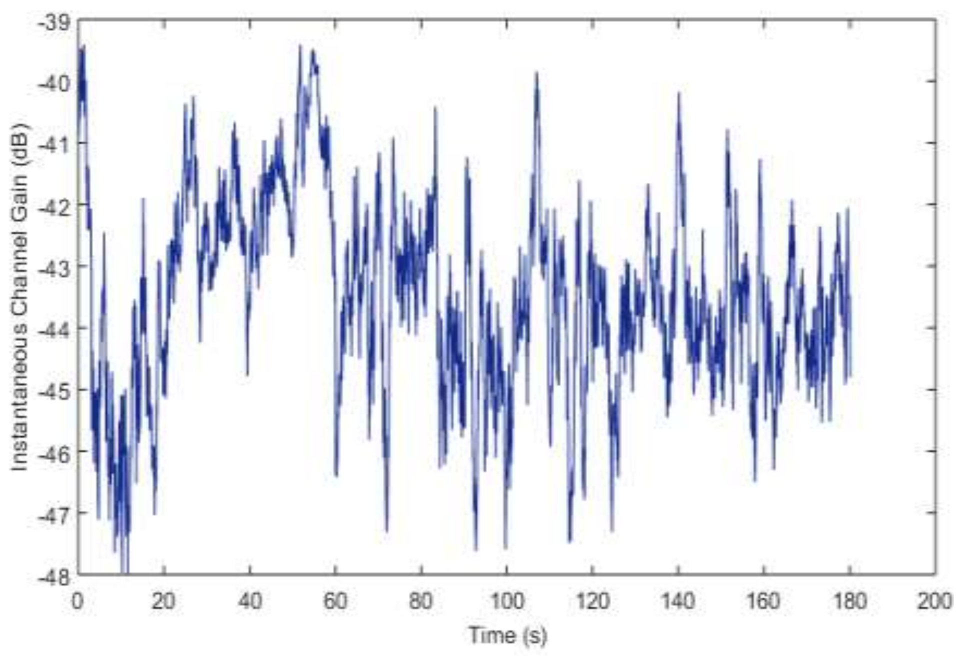

Fig no. 10:- Channel Gain.

Conventional Regression Methods With Traditional Features

The phrase "conventional characteristics" refers to the sign information that is created from the OFDM waveform within the context of this painting. The signal-to-noise ratio and the put-off spread are two instances of the data that are being referred to here. **(Table no1)** is a listing of the overall performance of the prediction based only on the features collected from the whole OFDM waveform. In addition to the delay spread, these functions include the time-area signal-to-noise ratio (SNR). The overall performance of the prediction is compared with CIR-based procedures with the help of this table. Although the overall performance of the majority of methods is pretty satisfactory, the decision tree has the best performance for KWAUG14, and linear regression has the best performance for SPACE08. Despite this, the overall performance of the majority of methods is quite satisfactory [15].

Table no. 1:- Maximum accuracy achieved by various authors.

NOTEWORTHY CONTRIBUTIONS BY VARIOUS AUTHORS WITH ACCURACY RATE			
S.NO	**AUTHOR**	**PUBLISHED YEAR**	**ACCURACY RATE**
1.	Yonglin Zhang	2022	**94.78%**
2.	Haibin Wang	2022	**89.56%**
3.	Yue Wang	2022	**85.34%**
4.	Qunfei Zhang	2022	**88.68%**
5.	Fabrice Meriaudeau	2022	**88.68%**
6.	OluwaseyiOnasami	2021	**93.56%**
7.	Damilola Adesina	2022	**94.78%**
8.	DorienHerre Mans	2021	**83.67%**
9.	Abigail Lee Leon	2021	**88.98%**
10.	Jian Zhang	2021	**96.78%**
11.	Xufeng Ma	2021	**94.34%**
12.	JongminAhn	2020	**97.46%**
13.	Wanjin Kim	2020	**81.90%**
14.	Xuetian Wang	2019	**76.67%**
15.	Shan Cao	2019	**77.89%**

Conclusionand Future Scope:-

In this study, we investigated the capabilities of deep learning and a few conventional machine learning algorithms to learn and appropriately simulate the underwater acoustic channel by the usage of actual underwater records accumulated from a water tank with disturbance and from a lake. These records were used to train the deep learning model, and the model was then used to correctly simulate the underwater acoustic channel. The records were obtained by collecting them from each of the respective locations. In order to accurately recreate the underwater audio channel in its whole, we combined the Deep Neural Community with a long rapid term memory. This was an excellent technique to do this.

The findings of a number of trials indicate that deep mastering is superior to traditional device mastering algorithms in terms of minimizing the suggest absolute percent mistakes made when modeling an underwater channel. This was determined by comparing the two types of algorithms. This method is one of a kind because, as opposed to modeling the channel via the use of mathematical approximations and assumptions, it models the channel through the use of real underwater data. This is an evaluation in comparison to other methodologies, each of which is reliant on certain mathematical approximations and assumptions.

Deep learning was successful in recreating underwater acoustic communications; nevertheless, it requires a significant quantity of data as well as intensive training in order to operate correctly. In this study, an enhanced UWSN routing protocol is created that takes use of the effectiveness of multipath SRLNC transmission over a suggested statistical acoustic channel model, IBF transmission, reduced Galois Field size, and SRLNC transmission with IBF. It makes the suggested system realization the best one for real-time applications.

The suggested system surpasses existing state-of-the-art systems in terms of better throughput, low latency, low energy consumption, etc., according to the MATLAB 2015a simulation. According to a performance comparison, the SRLNC-based routing protocol performs better than GPNC-based UWSN routing. The suggested SRLNC-based routing showed a PDR of 94.85 percent, while the average PDR of the GPNC protocol was determined to be 82.8 percent. In comparison to GPNC-based UWSN routing, SRLNC-based UWSN routing has 12.5 percent greater PDR. Even the suggested system has performed better with different node density.

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