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MODELLING OF AN INTELLIGENT AUTOMATIC IDENTIFICATION SYSTEM FOR TRACKING OF VESSELS IN MARITIME SECURITY SURVEILLANCE

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ABSTRACT

Over the years the maritime industries have faced many challenges of insecurity, theft, piracy and maritime terrorism among other problems which have often threatened the lives and peace of onboard vessels and hence demand immediate solutions. To solve this, an artificial intelligence-based system has been proposed using a support vector machine, convolutional neural network, fuzzy logic, genetic algorithms and artificial neural network among others, this study has recorded great success in the recognition of vessels and trajectory approximations but there is still need for a system which can predict the position of an online vessel and also recognize the vessel with a high rate of accuracy. This was proposed to be addressed in this research using a machine learning approach to develop an improved model to optimize the performance of the Automatic Identification Systems (AIS).The result achieved 89.55% success in correct prediction of vessel latitude position and also 87.1% for longitude prediction which gives a percentage deviation of 10.45% for latitude and 12.9% for longitude which signifies that a good vessel prediction success has been recorded.

Keywords: Genetic Algorithm Artificial Neural Network, AID, Maritime, Insecurity, Vessel

1. INTRODUCTION

According to the United Nations Conference on Trade and Development (UNCTD), it was revealed that shipping is the only international industry that has the most effect on globalization with over 90% of the world's commercial activities taking place in the maritime industry among more than 150 countries (UNCTD, 2008). The rapid growth of the shipping industry especially due to the advancement of Asia and the European Union among other continents has also made the sector a target for threats and attacks (Sheng and Yin, 2018; Xu et al., 2019; Gao et al., 2020). The maritime industry remains the only means to ship items via cargo and crew of men between continents (Sklet, 2006; Zhang et al., 2020). The AIS is a technology that can detect and broadcast vessel information automatically such as speed and location, to manage traffic and avoid vessel collision. According to the International Convention for Safety of Life at Sea (SOLAS, 2014), International Maritime Organization (IMO) regulation (IMO, 2008), the AIS is a mandatory facility for all cargo ships (with a gross tonnage larger than 300GT) and passenger ships due to its advantages of providing dynamic and static data of maritime traffic patterns such as speed over ground, latitude, longitude, course over ground, maritime mobile service identify, calls signs, vessels images among others. However, the ability of the system to be manually controlled and turned off most of the time disconnects its communication from the control center offshore and has limited its reliability as a result. This is because when it is turned off, the vessels become impossible to track and hence many illegal activities can be activated onshore which is not good for the industry, or the economy and thus has remained a big problem today. The AIS system as a vessel tracking system is not autonomous and can be manually turned off to perform illegal activities in the maritime environment and this has remained a big problem. This problem makes the AIS system unreliable enough to provide the necessary safety integrity in offshore environments and tracking of maritime vessels. This lack of safety integrity in the AIS has resulted in many casualties, and economic losses due to diversion of goods, via theft, among other issues which has remained a challenge waiting to be addressed. The benefit of solving this problem will help manage the issues of insecurity, oil theft, and piracy among other general insecurity problems that occur on shore. This study will concentrate on the development of an autonomous automatic identification system for the Nigerian Maritime Administration and Safety Agency (NIMASA) vessel traveling the Gulf of Guinea within the coordinates of 10° South to 30° North and 30° West to 15° East.

2. MARITIME SECURITY: AN OVERVIEW

Currently, maritime safety and security face several threats which are both natural and man-made. Natural threats can be grouped into climatogenic, such as hurricanes or storms; and seismogenic, such as earthquakes followed by tsunamis. The man-made threats include anthropogenic activities (for example oil pollution) and different unlawful actions such as piracy, armed robbery, drug trafficking, warlike activities, illegal fishing, illegal border crossing, illegal commercial activities, and many others (Samantha et al., 2017). Monitoring vessel activity can help local management institutions assess compliance with protected area and/or fisheries regulations. Vessel tracking technologies, such as the Automatic Identification System (AIS), inform an understanding of vessel use for the marine environment through time and space. The International Maritime Organization (IMO) requires all transiting ships of greater than 300 gross tonnage and all commercial passenger vessels, to broadcast static information on a vessel and its voyage and dynamic information on the vessel’s geo-location, heading, and speed throughout the voyage (IMO, 2018). Automatic Identification System (AIS) data has helped to detect illegal fishing model underwater noise pollution and inform risk assessments of collisions between ships and large whales (Samantha et al., 2017). Since AIS was not originally designed for environmental management, there are limitations to the use of AIS in this capacity (Gil et al., 2017).

3. METHODOLOGY

The methodology begins with the data collection which was acquired and extracted to train the Characterization of Automatic Identification System (AIS) machine learning algorithm for the location estimation of the vessel and also the intelligent recognition. These models were integrated to improve the performance of the existing AIS using Matlab programming and then evaluated considering parameters for success. In this work, coastal data was collected, and the varieties of datasets collected presented variable data structures and formats of the vessel behavior during navigation. The study proposed the use of a sparse filtering algorithm for the extraction of the coastal data.

3.1 Data collection

The data used for this research was collected at the Nigerian Maritime Administration and Safety Agency (NIMASA). The case study vessel considered for the data collection is Matrix Pride Vessel with International Maritime Organization (IMO) number 9228796, on 12 December 2021 navigating at the Gulf of Guinea within the coordinates of 10° South to 30° North and 30° West to 15° East. The parameters considered for the data collection include name, speed, course, position, longitude and latitude. The setup for the data collection is presented in Figure 1;

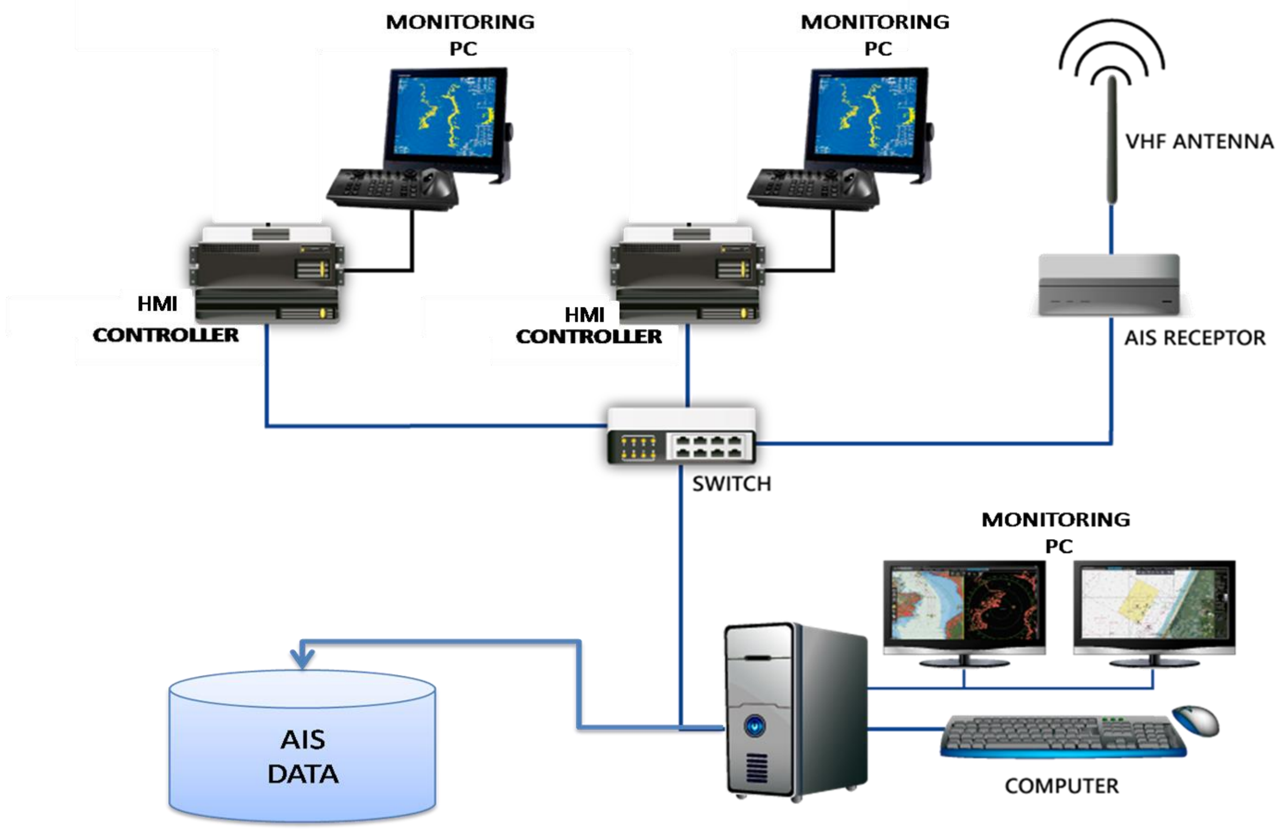

Figure1: The setup for the data collection

3.2 The Sparse Feature Extraction Filter Model

The sparse feature extraction filter model helps in identifying and extracting information from a specific dataset. The sparse algorithm Xuguo et al. (2020) identifies the dataset X in rows and columns as (n and p) where n presents the observation features and p the measurements. Then n and p are transformed into a weighted matrix (w) using the model in equation 1;

ϕ(u)=√(u^2+10^(-8)) 1

Where ϕ is a smooth negative symmetric function that estimates the absolute value function (u). These output matrixes originated from equation 1 and were harmonized for the rows (n) and column (q), then the weight (w) was optimized using a quasi-Newton optimizer to compute the normalization of the gradient functions until it satisfied the gradient tolerance value which is a scalar function presented in equation 2;

$$\tau = \max\left(1, \min(|f|, ||g_0||_\infty)\right) \quad 2$$

Where $|f|$the normalization of the objective is function and $||g_0||_\infty$ is the infinity normalization of the internal gradient function. The scalar function in equation 2 was used to normalize the matrix function $\hat{F}(i,j)$ to present the feature data in equation 3 for the row and 4 for the column of the vessel;

$$||\tilde{F}(i)|| = \sqrt{\sum_{i=1}^{n}(f(i,j))^2 + 10^{-8}} \quad 3$$

$$||\tilde{F}(i)|| = \sqrt{\sum_{j=1}^{q}(f(i,j))^2 + 10^{-8}} \quad 4$$

The matrix $\hat{F}$ is the extracted attributes for n and q parameters in the AIS dataset X. These features extracted in equation 3 and 4 are filtered using the objective function (h) in equation 5 which transforms the weight matrix for the data as;

$$h(W) = \sum_{j=1}^{q} \sum_{i=1}^{n} \hat{F}(i,j). \qquad 5$$

Where h (W) is the objective function as the normalization matrix $\hat{F}(i,j)$ of the processed data. In a case where the pair of the pixels are strictly positive integers, lambda (λ) was used to modify the objective function as shown in equation 6

$$h(W) = \sum_{j=1}^{q} \sum_{i=1}^{n} F(i,j) + \lambda \sum_{j=1}^{q} w_j^T w_j \qquad 6$$

Where w_j is the jth column of the matrix (w).The reason for the application of lambda parameters is to shrink the weight w of the image matrix.

3.2.1 The Pseudo Code of the Sparse Extraction (ALGORITHM 2)

1. *Start*
2. *Load AIS dataset (X)*
3. *Identify row and column as (n and p) in X*
4. *Compute the weights of X using equation 6*
5. *Initiate quasi-Newton optimizer*
6. *Normalize the gradient function of the optimizer with scalar function (equation 7)to harmonize X*
7. *Generate output extracted data*
8. *Initialize objective function (h)*
9. *Transform the weight (X) with (h) as equation 10*
10. *Initialize lambda function(λ) for filter*
11. *If*
12. *Values of X are less than 1*
13. *Then*
14. *Activate lambda(λ)*
15. *Data output smooth*
16. *Data output as filtered vessel parameters*
17. *Else*
18. *Equation 10*
19. *End if*
20. *Return*
21. *End*

3.3 Development of the Machine Learning Based Vessel Trajectory Estimation Model

Euclidean model only measures similarity distance of clusters without considering angle, among other geographical coordinate parameters within the equator and hence not justified to measure certain key vessel navigation attributes like course and position. The Euclidean model was presented as;

$$D_e = \sqrt{\sum_{i=1}^{x} (y_A - y_B)^2} \qquad 7$$

Where $y_A$is training features; y_B is testing features; x is the number of features extracted; D_e is distance.

The model in equation 7 was used to measure and estimate the vessel speed only, however to predict the vessel course and expected position (Lat. Long.), there is need for a model which considers the variables of geographical coordinates and angles with respect to the equator, this was achieved using bearing model and Haversine model respectively. The bearing model to measure the expected vessel course is presented as (Feng et al., 2021);

$$a = \cos(laty) * \sin(longy - longx) \quad 8$$

$$b = \cos(latx) * \sin(laty) \sin(latx) * \cos(laty) * \cos(longy - longx) \quad 9$$

Where x and y are the north and south of the vessel, a is the latitude components of the north, b is the longitude component of the east, while the course is presented using the relationship between equation 8 and 9 to present the model in the equation 10;

$$\beta x, y = xtan2(a, b) \quad 10$$

The model in equation 4presents the expected vessel course considering the initial vessel position. To measure the expected vessel longitude and latitude distance along the Gulf of Guinea as shown in the figure 2

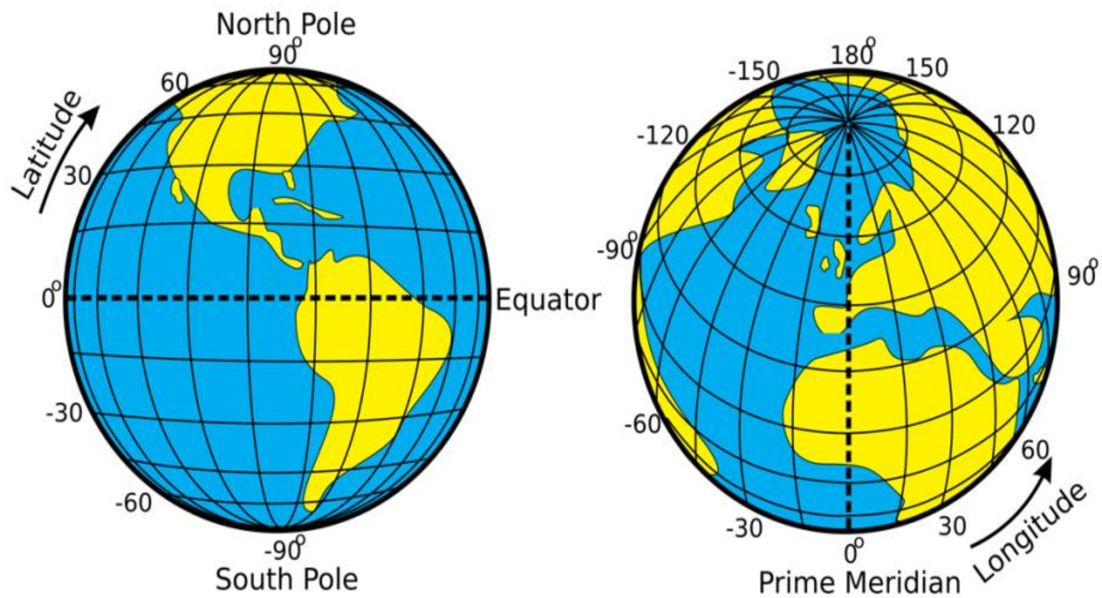

Figure 2: Global coordinate diagram with latitude and longitude.

The figure 1 was used to develop the latitude and longitude model of the vessel based on Haversine model in equation 10 (Gözde, 2019);

$$d = 2rsin^{-1}\left[\sqrt{sin^2(\frac{\varphi 2-\varphi 1}{2})} + \sqrt{cos(\varphi 1)cos(\varphi 2)sin^2(\frac{\psi 1-\psi 2}{2})}\right] \quad 10$$

Where ψ is longitude of points; φ is latitude of points.;

3.4. Modeling of the Rule Base Security System for vessel surveillance

The model was based on the longitude and latitude tolerance difference between the actual data and estimate data of the vessel by the algorithm. The standard for latitude tolerance is $\pm$0.075000 (0.356716) and $\pm$ 0.075000 (0.441897) for longitude was used to develop the security system. The figure 2 presents the flow chart of the model.

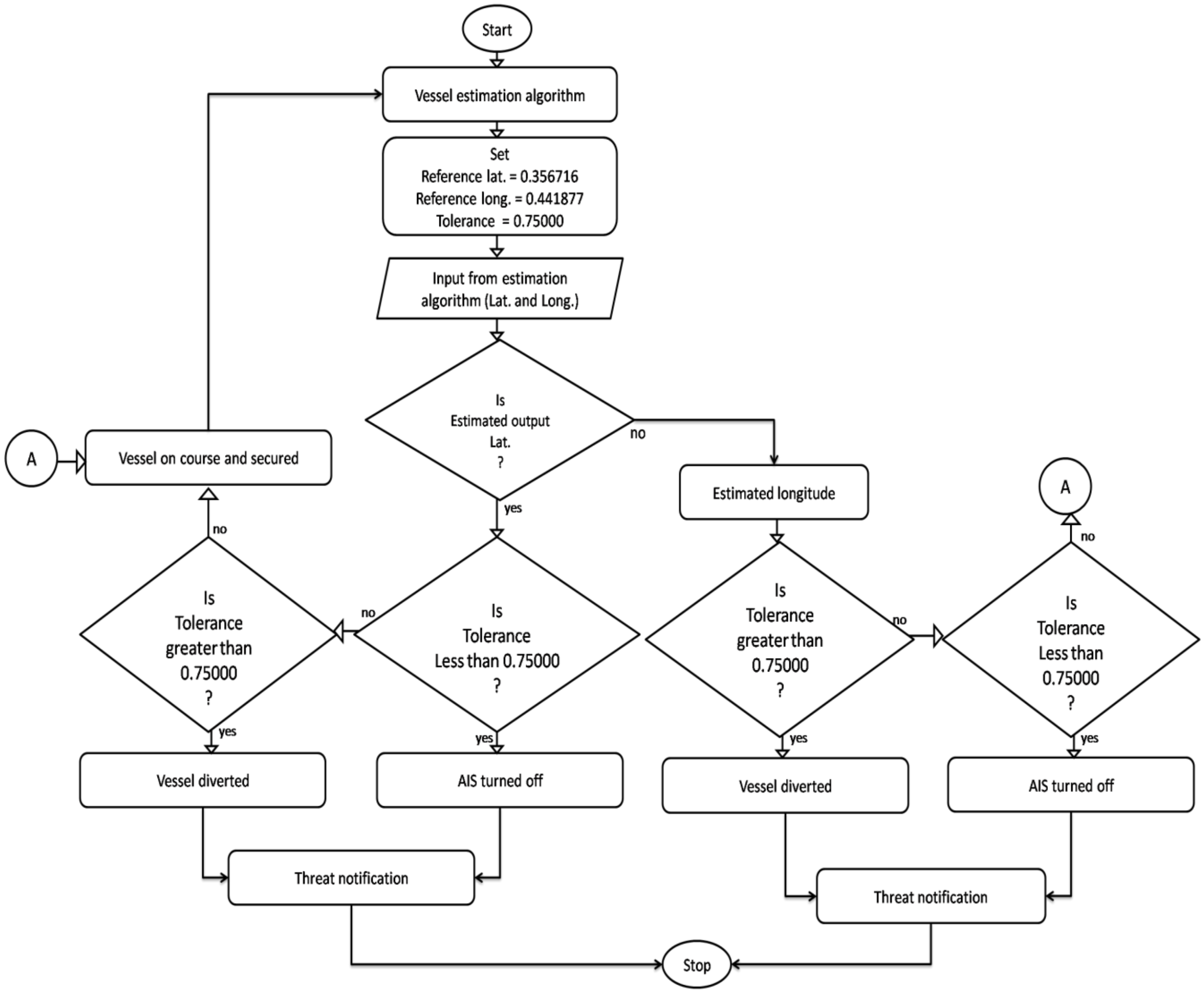

Figure 3: The flow chart of the security model

The input from the estimation output was compared with the tolerance value for the Latitude and Longitude respectively. When the tolerance is less than 0.750000, the average between the actual and estimated vessel latitude and longitude, then it indicates that the vessel is stagnant which implies AIS is turned off. When the reverse is the case for the latitude and longitude then the vessel is diverted, however when the coordinates are within the tolerance values then the vessel is on course and secured.

4. RESULTS AND DISCUSSION

4.1 Vessel recognition performance with sparse extraction algorithm

The sparse algorithm after extraction used an objective function to process the data and produce quality output for training with the vessel recognition algorithm. The performance of the algorithm was measured considering the average performance of the multiset which are trained, tested and validated sets, considering MSE and ROC analyzers as presented in figure 4; wile figure 5 presented the ROC results.

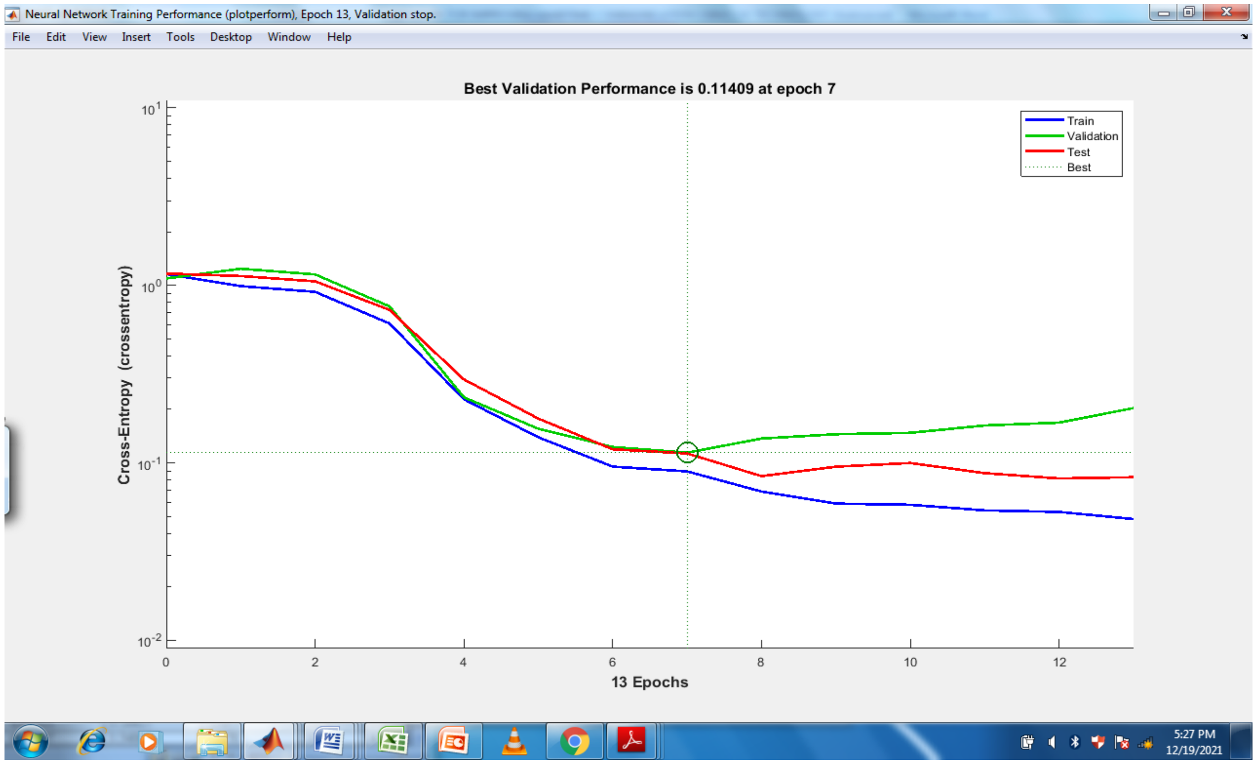

Figure 4: MSE performance with sparse algorithm

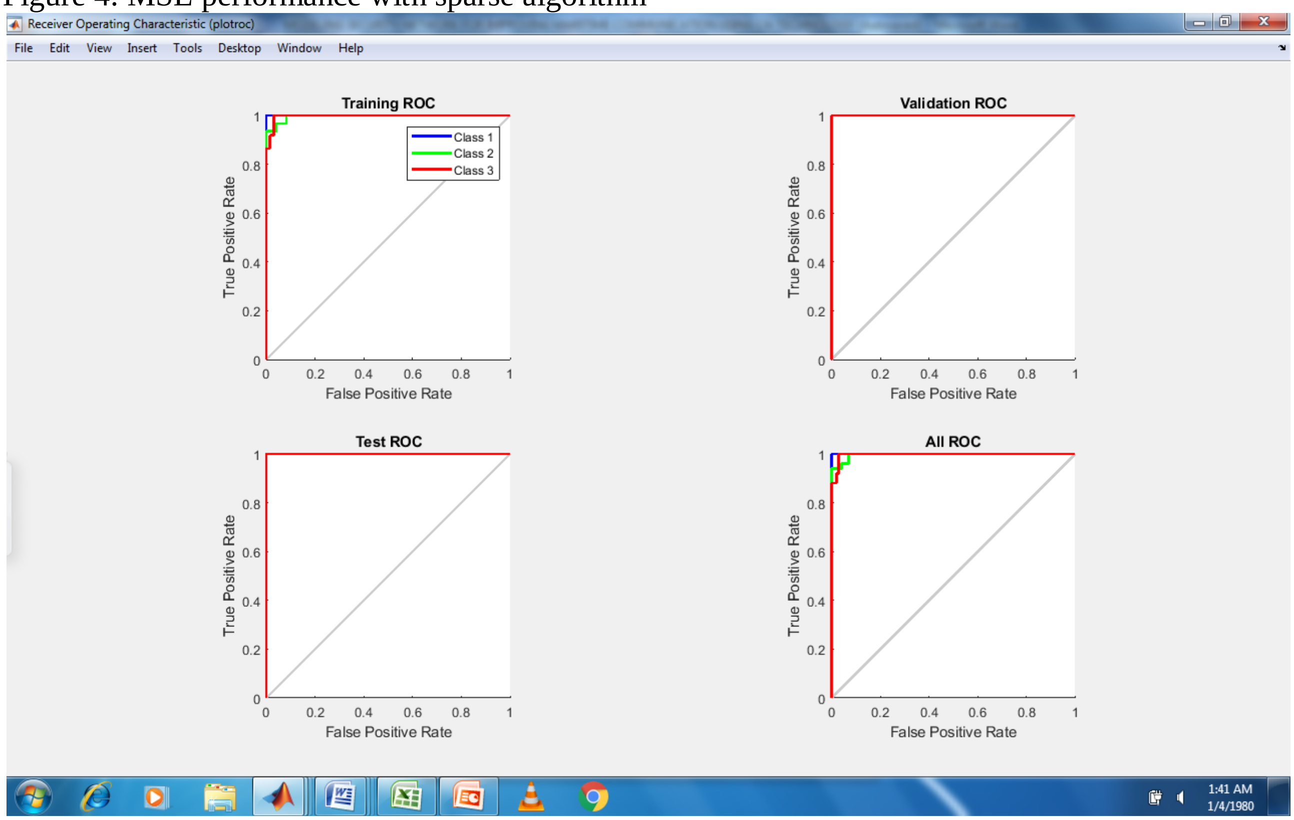

Figure 5: ROC performance with sparse algorithm

The MSE performance in figure 4 reported 0.11409 at epoch 7. The result implies that little error which is negligible was recorded during the training and testing process. Secondly, it was

observed that there was a better correlation between the multi-set patterns when compared with that of the clustering extraction algorithm, which implies that overshoot was not recorded in this result. To further evaluate the recognition algorithm, the ROC curve in Figure 5 was used;
Figure 5 presents a very good training, testing and validation regression performance. The result shows that the sparse extraction and filter algorithm which produced quality AIS data was important in providing a reliable vessel recognition result with ROC of 0.97 as against 0.82 with the clustering extraction algorithm. Since the result of the vessel recognition algorithm with sparse extraction was better, it is simply logical to use it as the main feature extraction model for the new system and validate the performance as in Table 1 using a tenfold cross-validation technique;

Table 1: Validation of the vessel recognition result

S/N	ROC
1	0.97
2	0.95
3	0.97
4	0.97
5	0.98
6	0.95
7	0.97
8	0.98
9	0.98
10	0.97
Average	0.97

The validation performance in Table 1 presents the average ROC result of the neural network-based vessel recognition algorithm with 0.97 which is very good as it shows that the algorithm was able to recognize vessels at a very high true positive rate. Having tested and validated the performance of the vessel estimation and recognition algorithms respectively, the system was integrated to improve the performance of the conventional NIMASA automatic identification system.

4.2 System Integration

This section presents the performance of the new AIS integrated at the NIMASA center to monitor vessel behavior at the Gulf of Guinea within the same coordinate as the case study vessel considered for data collection, and the predicted outcome is presented in Table 2;

Table 2: Performance of the new vessel trajectory estimation model at NIMASA

Date/Time (UTC)	Latitude (°)	Longitude (°)	Course	Speed (m/s)
2021-11-17 01:48:11	4.393085	2.279658	067.73	10.06
2021-11-17 01:49:52	4.411677	2.436509	242.08	08.99
2021-11-17 01:50:07	4.436035	2.229067	224.01	08.99
2021-11-17 01:53:21	4.396662	2.261179	064.70	10.32
2021-11-17 01:54:33	4.439605	2.203979	225.79	09.79
2021-11-17 01:55:02	4.412255	2.457085	242.08	11.75
2021-11-17 01:55:17	4.439696	2.244598	224.55	09.43
2021-11-17 01:58:22	4.400409	2.271405	065.24	10.41
2021-11-17 01:59:39	4.435822	2.221102	225.70	10.15
2021-11-17 02:00:11	4.424404	2.477689	243.59	11.57
2021-11-17 02:00:15	4.442017	2.260004	224.73	09.43

2021-11-17 01:48:12	3.503085	1.388658	068.62	10.95
2021-11-17 01:49:53	3.521686	1.546509	242.97	09.79
2021-11-17 01:50:08	3.531922	1.339067	224.90	09.83
2021-11-17 01:53:22	3.500761	1.220348	068.26	11.21
2021-11-17 01:54:34	3.571232	1.313978	224.01	10.68
2021-11-17 01:55:03	3.533129	1.567085	242.97	09.97
2021-11-17 01:55:18	3.549374	1.354598	225.73	10.32

From Table 2, it was observed that the AIS was able to monitor and estimate the behavior of the vessel at every step along the sea shores and provide real-time information on the estimated vessel location per time. The parameters considered produce different results and it was observed that the course produces a higher result (225.73) than others and should be considered first before other parameters.

5. CONCLUSION

The study successfully developed intelligent AIS using machine learning algorithms. The study collected all required data from NIMASA and a vessel tracking model for the monitoring of coastal vessel information system was also developed. The performance of the tracking algorithm was also evaluated using MSE with a value of 0.11409 and R-value of 0.97 when trained with sparse filter extracted data, thus indicating that the quality of data improves the performance of machine learning algorithms. The result achieved 89.55% success in correct prediction of vessel latitude position and 87.1% for longitude prediction which gives a percentage deviation of 10.45% for latitude and 12.9% for longitude signifies that a good vessel prediction success has been recorded, which implied that the model developed can correctly identify with cognitive sense the position of the vessel on shore and detect abnormally.

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