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Identification of IUU Transshipment Activity Using AIS Data

Dr. Shailender Kumar
Computer Science & Engineering
Delhi Technological University
Delhi, India
shailenderkumar@dce.ac.in

Harshit Muhal
Computer Engineering
Delhi Technological University
Delhi, India
harshitmuhal_2k18co145@dtu.ac.in

Ishan Chaudhary
Computer Engineering
Delhi Technological University
Delhi, India
ishanchaudhary_2K18co157@dtu.ac.in

Kirti Dabas
Computer Engineering
Delhi Technological University
Delhi, India
kirtidabas_2k18co176@dtu.ac.in

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***Abstract*—Transshipment at sea is the exchange of cargo and supplies between two vessels that are far from their home ports. Transshipment help in offloading caught fish so that the product can move to market quickly while fishing is still continued. However, illegal fishing has become widespread across the globe. Maritime natural resources are exploited by the widespread illegal transshipment activities which not only disrupts the natural ecological balance by selling of rare and endangered species to the sea market but slavery, trafficking, and bonded labor are some of the humongous problems that are faced today due to illegal transshipment activities as well. In this paper, we discussed the global patterns of transshipment behavior, boon and bane of using AIS data, and proposed a system integration consisting of a prediction and classification unit. The proposed prediction unit uses LSTM networks and for the classification unit, we explored both traditional machine learning methods (KNN, random forest, Logistic Regression, etc), deep learning algorithms (ANN) as well as ensemble models.**

***Index Terms*—Transshipment, IUU (Illegal, Unreported, and Unregulated), Automatic Identification System, Transshipment behavior, Vessel Track prediction**

I. Introduction

Illegal, unreported, and unregulated (IUU) fishing for a long while has been considered to be a food and monetary security risk by waterfront States. Because of the huge impact IUU fishing has on the food, economy, and security it is gaining tremendous attention in India recently[1]. Missing from this equation is the critical differentiation of how IUU fishing affects Indian public wellbeing and the consistency of individual Indian states inside the province and overall international maritime tending to IUU fishing.

The increase in the transshipment activity and the threats it poses to not only human population but to the ecological balance made the U.N. General Assembly, in line with the U.N. Food and Agriculture Organization (FAO), announce June 5 as "the International Day for the Fight against IUU Fishing." in 2018. According to the FAO, IUU fishing accounts for as much as 26 million tons of fish every year. [2] The financial worth of this catch has been set between $10 billion and $23 billion yearly. As indicated by a 2019 report disseminated in Marine Policy, India gave $277 million in sponsorships to its fishers, of which $174 million is acknowledged to add to harming fishing practices[3]. IUU fishing not only impacts the food and security but it also targets the prosperity of waterfront states, including India, in addition to further disturbing the aquatic ecosystem. The dangers brought by IUU fishing to the waters of the Indian Ocean have commonly been subsumed with other non-standard risks pertaining to security. Researches reveal that criminals use IUU fishing in the commission of various infringement, for instance, the smuggling of armed weapons, drugs and persons[4]. Most littoral States in the Indian ocean have immature economies damaged by deficiently implemented government plans, administrative structures tormented by defilement, and tangled issues of dismissal and minimization that as often as possible push desperation-stricken fishers to take on unlawful fishing practices and help criminal affiliations driving transnational illegal activities.

The AIS(Automatic Identification System) innovation, initially developed as a crash evasion system installed on ships for reporting purposes, is turning into a foundation of Maritime Situational Awareness(MSA). Traveler vessels, boats on international trip weighing 300 gross tons or more and vessels within their national boundaries with 500 tons or beyond are needed to be fitted with AIS.[5] The AIS information from the boats can be utilized to do statistical analysis and reporting besides collision avoidance.

The next section in the paper presents some preliminaries required for better comprehending the proposed work after which we have presented a detailed discussion of the existing work. In the following section, we have proposed a methodology that can be employed for the identification of IUU transshipment. Our method uses a pipeline of time-series LSTM models for the prediction of location, speed, and heading in case of missing AIS data which are then fed to the classification unit that finally classifies an episode as IUU transshipment activity.

II. Background

A. Automatic Identification System

The automatic Identification System (AIS) was originally used for avoiding collision between ships and tracking vessels[6]. It is used for safe navigation but can also be used for monitoring transshipment behavior [7]. AIS data includes different types of parameters like vessel name, Maritime Mobile Service Identity (MMSI), callsign, IMO, Navigational Status, Vessel type, Latitude, Longitude, Timestamp, Heading, Speed over ground (SOG), Draught, Course over ground (COG), Estimated Time of Arrival, etc.

All these parameters together form a package of information that is utilized for a plethora of purposes like the administration of vessels in oceans, protection of the environment [8], enhancing safety for navigational wellbeing by forestalling vessel crashes(very like utilizing GPS). [9] With AIS data, forbidden areas can be monitored and by measuring emissions of vessels, the quality of air can be improved as well. [10] The AIS data can be used to fill in as "ground truth" to approve or finish data of satellite pictures, radars and could assist with understanding the impact of climate conditions like the breeze, waves, ice, visibility, and tropical storms.[10]

While there are many benefits to AIS, there are also some limitations to it. AIS data contains voluminous information and has noise and data redundancy. [11] People can influence AIS data, it can be turned off or be misused to broadcast spoofed identity which may even include crafting a valid non-existent ship.[12] Besides, various things can influence the quality, like the medium/VHF transmission, AIS recipients being inaccessible, defective installation or position of the equipment[12]. AIS information can prompt incomplete tracks because of restricted collector range or irregular signals as a result of the revisit time and satellite's latency[10].

B. Problems posed by Transshipment

Several serious predicaments result from transshipment which forces managers to IUU fishing.[14] In [13] it has been highlighted that only 35-50% of the current catch in China is reported. It is a huge threat to sustainable markets as unregulated fishing leads to the extinction of vulnerable species on a local as well as on a global scale where markets are <14 km away [15][16].

Transshipment provides loopholes for companies to exploit regulations leading to human trafficking, transport of drugs, and money laundering besides illegal fishing which according to an estimate contribute between $10 and $23.5 billion worth of catch annually in the US alone [17][18].

The extent of illegal activities that take place alongside transshipment has been discussed in detail in [20][21]. These activities include forced labor and other human rights abuses. Miserable realities have been revealed which indicates the common occurrence of these violations in the fishing industry[22][23][24].

The importance of the eradication of transshipment is evident from the fact that the United Nations Food and Agriculture Organization has recognized transshipment as a vital objective in their International Plan of Action for intervention to decrease IUU fishing.[19]

C. Global Patterns of transshipment behavior

The AIS tracks of multiple vessels in vast oceans make a complicated web of relationships that can be used to pull out various patterns that can help in better understanding the transshipment behavior worldwide. Recognizing global patterns assists with marking a transshipment as illicit with more assurance relying on the Exclusive region, flag state, Economic Zone (EEZ), and other factors. It gives an important worldwide, open perspective on the size of the lead, its nearby normality, and the key individuals. It can give the initial push toward setting up a sound and straightforward method for assessing and managing these activities.

Flag of convenience (FoC) which refers to negligence by enforcement authorities and unguarded fishing is prevalent in some banner states. Frequently, vessel owners sail their ships under the banners of these states while in reality they have no connection to the banner state[26], for outsourcing labor. By "flagging out", ship owners can exploit less rigorous labor guidelines due to which they get an opportunity of utilizing cheap work force.[27] By analyzing AIS data its been found that the vessels belonging to Russian and US are transcendentally connected with appropriately flagged transshipment vessels, while Asian-flagged (China, Taiwan, South Korea, etc) fishing vessels are related with differently flagged transshipment vessels including a few FoCs (Panama, Liberia, Vanuatu)[6]. Since FoCs are flags of states portrayed by loose guideline and restricted oversight[30], IUU here is expected to be high and according to the 2017 Global Fishing Watch report on "The Global View Of Transshipment: Revised Preliminary Findings", transshipment activities are proportional to IUU percentages. This makes the encounters of reefers flying FoCs with the fishing vessel bound to enjoy illicit transshipment activities. On dissecting the networks of AIS, relations among EEZs and transshipment practices can be drawn.Analysis of data reveals clusters of regions with high volume of fishing , these regions lie close to the boundaries of EEZs[28]. Based on this finding it can be argued that a behavior of free-riding[29] is prevalent in the vessels sailing in the high seas near the EEZs , which take advantage of the useful holding of fisheries inside the EEZs of the nations.

All these patterns help in identifying a transshipment as being less or more likely to be illegal depending upon the area, route, port, flag, etc used by the vessel. For example, a transshipment happening in the EEZ of Russia is more likely to be engaged in illegal activities as compared to the one happening in Spain's EEZ[6].

III. Literature Review

In [31] a fuzzy logic based approach has been used to design a predictor system of predicting illegal transshipment. The system is composed of two sub-systems, (1) the prediction vessel movement system, and (2) the decision of illegal transshipment system. The output of the predictor subsystem produces trace of the ship motion patterns of mother ship (vessel delivering transshipment) and child ship (ship receiving transshipment) which are then used to determine the difference of the distance, speed of mother and child ships, and difference of heading between the two vessels. All of these variables are input for a fuzzy decision logic system.

For sub system 1 There are 5 input variables for identification of transshipment of ship 1 as the mother ship, namely: (1) Latitude Δx, (2) Longitude Δy, (3) change of Yaw rate Δr, (4) change of direction - and (5) change of ship velocity - v. These five data can be obtained from AIS data. In sub system 2 The allegations in motion patterns of ships in illegal transshipment activities are based on the motion pattern of COLREGS (Convention on the International Regulations for Preventing Collisions at Sea, 1972) regulations for anti collision. There are 3 motion patterns that are said to be a movement to avoid collisions. It is very unlikely that the two vessels will have a motion pattern in accordance with the COLREGS, unless it will perform illegal transshipment activities, so the three motion patterns are used to determine the possibility of illegal transshipment.

In [32] an approach has been proposed for the identification of IUU fishing and Illegal Transshipment using an integrated system of RNN predictor and ANN Identifier. The proposed approach comprises 3 subsystems namely (1) predictor unit, (2) selection unit, and (3) identification unit. The predictor unit supplies missing values namely latitude/longitude , speed and heading in AIS data resulting from missing trajectory information. The ANN identification unit comprises ANN selection and ANN decision subsystem. The output of the predictor unit is fed as input to the identification unit. The ANN unit is responsible for making decisions for both IUU transshipment and IUU fishing. ANN selection unit sorts data for IUU fishing and IUU transshipment identification. For identifying IUU transshipment, the variables under consideration are differences in values of speed ,heading and distance between the two ships suspected to be involved in the transshipment activity and for IUU fishing identification the time of casting , speed of the ship during hauling and casting are taken into account.

The authors of [33] explored a reinforcement learning-based approach for the identification of IUU fishing. In order to prosecute offending fishing vessels, authors in [33] used the Fuzzy Actor-Critic Learning (FACL) algorithm by modeling the IUU events as a Pursuer-Evader game in which the law enforcement vessels are the pursuers and unreported fishing vessels are the evaders. The critic and actors described in the approach of [33] are modeled as Fuzzy Inference Systems in which the agent has to realize rewards and punishments. This approach helps in simulating real-world IUU fishing pursuit events.

IV. Proposed Work

The block diagram for the design of the system is given in Fig 1.The system comprises two subsystems namely the prediction unit and the classification unit. As discussed in [12] AIS data suffers from missing values due to climatic conditions, overcrowding of ships, etc. These missing values have an impact on the overall accuracy of the classification unit. The function of the prediction unit is to supply these missing values in order to make the classification unit make predictions with greater accuracy. In our paper, we have used a time-series LSTM network to predict missing values, namely latitude/longitude, speed, and heading values. The data received from the output goes through data transformation and is then fed as input to the classification unit. To identify whether two adjacent ships are involved in an episode of transshipment, the classification unit then uses data namely the distance between the ships which can be found from latitude and longitude values, difference in headings, and difference in speed values.

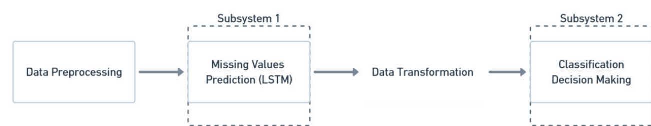

Fig. 1: System flow of proposed solution

A. Data Preprocessing

The AIS data for the prediction model (subsystem 1) was obtained from marinecadastre.gov/ais/ website which consisted of 6420411 rows , the dataset was split into a 70:30 train test split. For predicting the missing values for a vessel , the time series data was gathered by aggregating the values of the MMSI number of a ship. Prediction unit comprises of time-series LSTM model for each attribute. For each of the model, data was reshaped and transformed using appropriate time step value.

In [34] it has been argued that in order to classify an episode of rendezvous of a vessel as an episode of transshipment the parameters that contribute towards making the decision are the spatial distance (distance between the two vessels), difference in the speed and difference in heading values. The distance between the vessels can be found using the latitude-longitude of the vessels and haversine formula. A data transformation step has to be performed on the output from subsystem 1 to convert the values into the desired values of differences to be fed into subsystem 2.

The data set for the classification model (subsystem 2) was obtained from marinetraffic.com and it consisted of 4501 rows, the data has been split into 20:80 train test split .The data set comprises of distance (d) , difference in speed ,difference in heading and a label field , this data is then fed to the classification model for final decision.

B. Designing Prediction Model

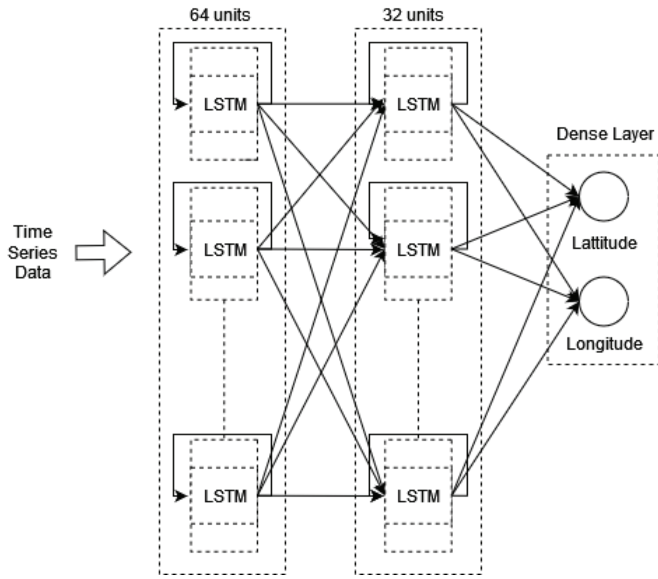

Fig. 2: Latitude & Longitude predicting LSTM model

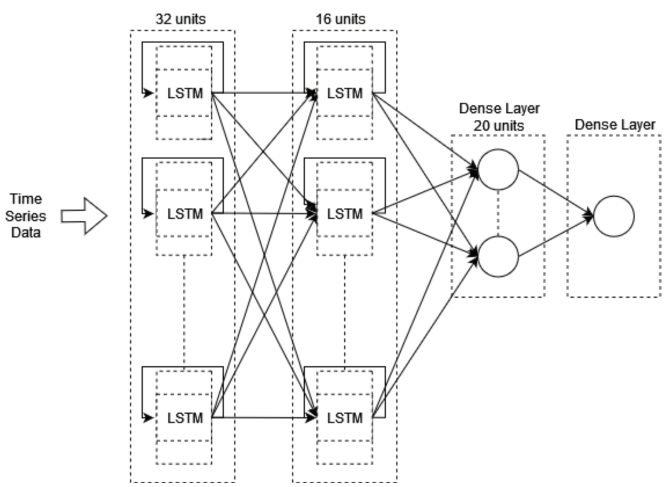

Fig. 3: Heading and Speed predicting LSTM model

LSTM is a sequential network that is capable of allowing information to persist. Unlike RNNs, they can handle the vanishing gradient problem and are often termed as advanced RNN. The equations involved in one unit of LSTM is shown in Fig. 4

Predictor model for latitude/longitude had 2 LSTM layers with 64, 32 units respectively followed by a Dense layer of 2

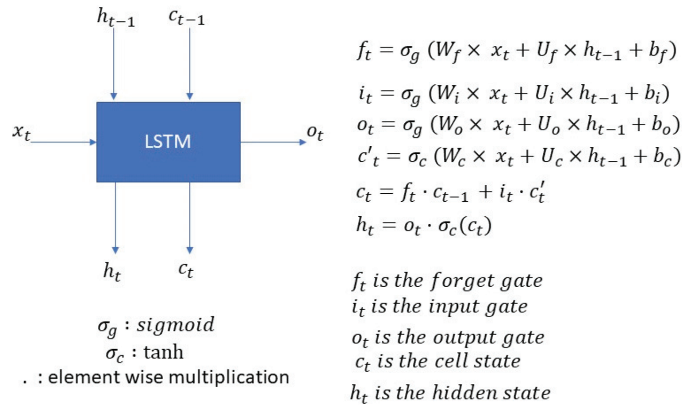

Fig. 4: Mathematical formulation of a single LSTM unit

units in the output layer. Both the LSTM layers have ‘relu’ activation function. Adam optimiser and ‘Mean Squared Error’ as the loss function were used to the compile the model with a time step of 10.

Predictor model for heading and speed had 2 LSTM layers with 32, 16 units respectively followed by a Dense layer of 20 units, output of which is fed to a dense layer of 1 unit in the output layer. Both the LSTM layers have ‘relu’ activation function while the Dense layers have ‘linear’ activation function. Adam optimiser and ‘Mean Absolute Percentage Error’ as the loss function were used to the compile the model with a time step of 10.

Tests and validation of trained models on various attributes have been given below.

- Latitude/Longitude Prediction
  The result for latitude and longitude prediction has been shown through the scatter plot in Fig. 5

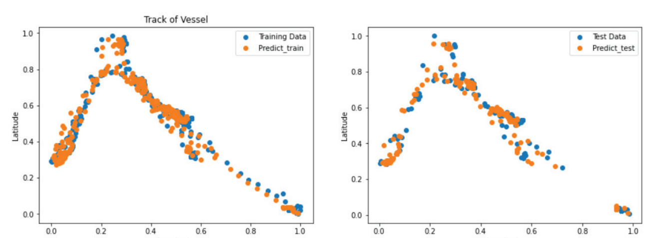

Fig. 5: Comparison between actual and predicted Track

  A snapshot of the map with test and predicted location of the vessel has also been plotted in Fig 6
- Heading Prediction
  The predicted heading value has been plotted along with the actual value in Figure 7
- Speed Prediction
  The predicted speed value has been plotted along with the actual value in Fig. 8

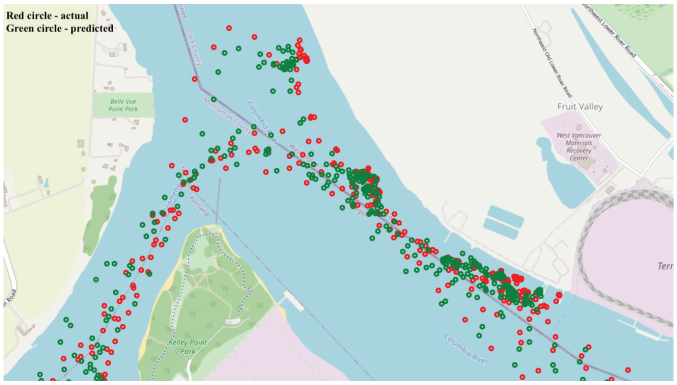

Fig. 6: Map showing actual and predicted Track of a vessel

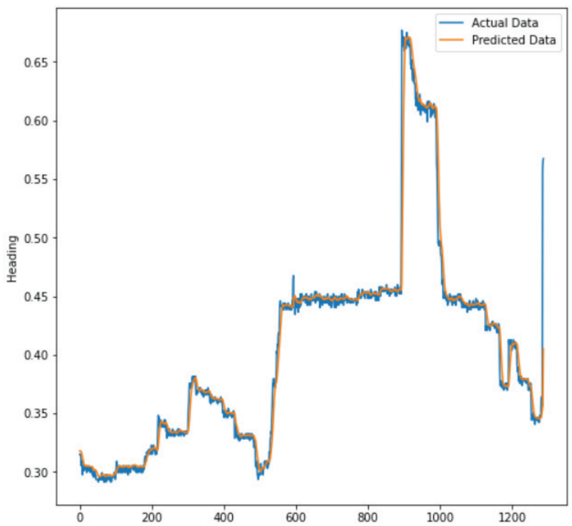

Fig. 7: Time-Series Graph Of Heading Attribute Showing Comparison Between Actual And Predicted Values

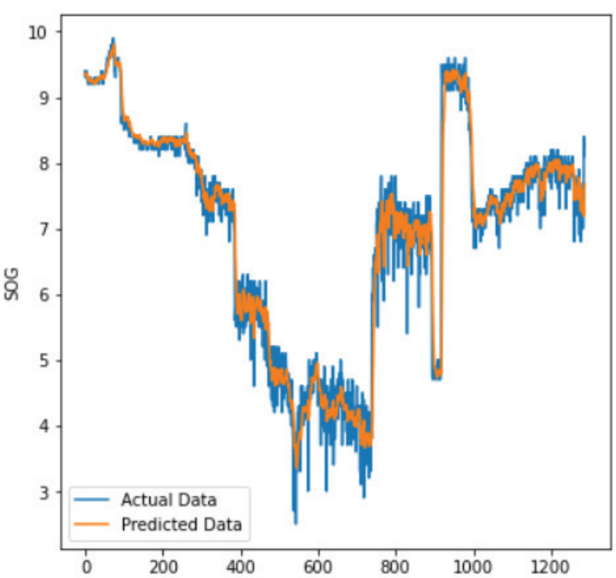

Fig. 8: Time-Series Graph Of Speed Attribute Showing Comparison Between Actual And Predicted Values

C. Designing Decision Model

For the experimentation, both traditional machine learning methods(KNN, random forest, etc), deep learning algorithms(ANN) and ensemble models have been explored and compared on the basis of four parameters namely accuracy, precision, recall and F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1{-}score = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN}$$

1) Machine Learning Models

a) Logistic Regression: It is a binary classification algorithm used to predict an event(0 / 1, True / False, Yes / No) given a sample of independent numerical and categorical variables. It fits the test sample using the logistic function to predict the probability of occurrence of an event. The hypothesis in a logistic regression model is of the form -

$$h\theta(X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X)}}$$

Logistic regression achieved an accuracy of 90.11% with a precision of 83.27% for the classification unit.

b) Random Forest Classifier: It is a supervised and tree-based ensemble machine learning approach. It is a technique grounded on a combination of decision trees. For random forest implementation, parameters controlling the size of the trees need to be selected. Various values for both parameters specifying the size and depth of the tree were tried, tested, and evaluated and we found the best performing model with n_estimators(size) = 20 and max_depth(depth) = 5 which has an accuracy of 96.11 and precision of 88.96.

c) KNN Classifier: KNN is a regression and classification algorithm which utilizes non parametric technique to analyze the class of a sample depending upon the class of its closest k neighbours. The fundamental hypothesis behind KNN is that it considers a group of k samples that are closest to obscure samples. From these k samples, the class of obscure samples is determined by working out the average of the class attributes of the k nearest neighbors. Subsequently, for this classifier, the k holds a significant place in the accuracy and performance of the KNN model. The distance between two sample points is calculated using the euclidean distance which is -

$$dist(\mathbf{x}, \mathbf{y}) = \left(\sum_{k=1}^{n} |x_k - y_k|^r \right)^{1/r}, r = 2$$

We tested values from 3 to 10 to identify the best-suited k value for the data set and got the best results (accuracy of 94.33 and precision of 88.61) for k=6.

d) Support Vector Machines: SVM is a statistical method which comes under supervised learning.It is a kernel-based non parametric algorithm. Kernel-based learning uses high-dimensional feature-space mapping of the input data which is described by a kernel function. For our paper, the kernel used for learning is the RBF(radial basis function) as it in general shows a good performance. The model shows promising results as the accuracy reaches a maximum of 91.22% and the precision is 91.45%.

2) Deep Learning Models

Artificial Neural Networks
In our paper, we trained 5 ANN models with different numbers of dense layers, number of units in hidden layers and hyper parameters . ANN models used are sequential models with relu as activation function for hidden dense layers and sigmoid function on the output layer. For training our models, the optimizer used by us was 'adam' and learning rate was 0.005. Each hidden dense layer is accompanied by a dropout of 0.3 and batch normalization layer. The architecture of the identification unit is given in Fig. 9
Performance metrics of the ANN models that were explored for subsystem 2 are given in the Table I

TABLE I: COMPARISON BETWEEN ANN MODELS

Units in Hidden Layers	Accuracy	Precision	Recall	F1-score
100,20,20	95.11	85.40	98.76	91.60
100,20	96.44	96.08	92.78	94.40
40,30	96.44	88.61	100	93.96
50,30	96.22	97.15	91.30	94.13
50	96.22	80.01	94.13	88.06

3) Ensemble Models
Ensemble models are a machine learning approach in which multiple models called base estimators are combined to make the final prediction. We have an ensemble

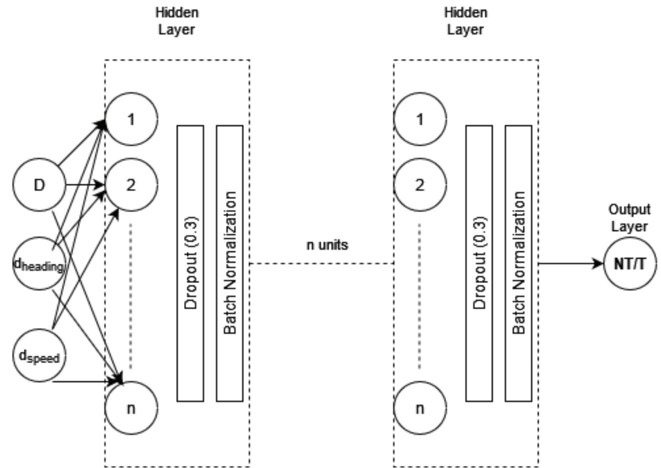

Fig. 9: PROPOSED ANN MODEL

of different models that combines machine learning and deep learning techniques predictions of which are combined using averaging. The different ensemble models that we tried are - a) Ensemble of Artificial Neural Network(ANN), Support Vector Machines(SVM) , Logistic Regression,Random Forest, K-nearest neighbors(KNN) b) Artificial Neural Network(ANN), Random Forest, K-nearest neighbors(KNN) c) Random Forest, K-nearest neighbors(KNN),Support Vector Machines(SVM).

V. RESULTS

For the prediction unit, the evaluation metrics which we have used is the Mean Absolute Percentage Error (MAPE) and for the classification unit we have used Accuracy, Precision, Recall, and F1-score. Table II shows the MAPE obtained for Latitude/longitude, Speed, and heading predictors while Table III shows the results of all the models that were explored for subsystem 2.

TABLE II: MAPE VALUES OF ATTRIBUTES IN THE PREDICTION UNIT

Parameter System	MAPE
Speed	0.038
Longitude	0.068
Latitude	0.029
Heading	0.017

TABLE III: COMPARISON OF MODELS

Model Name	Accuracy	Precision	Recall	F1-score
Artificial Neural Networks (ANN)	96.22	97.15	91.30	94.13
Logistic Regression (LR)	90.11	83.27	84.78	84.02
ANN+RF+KNN+SVM+LR Ensemble Model	93.4	87.5	92.17	89.77
Random Forest (RF)	96.11	88.96	98.42	93.45
ANN+RF+KNN Ensemble Model	95.11	95.05	88.96	91.91
K-nearest Neighbors (KNN)	94.33	88.61	92.91	90.71
RF+KNN+SVM Ensemble Model	95.0	94.69	88.96	91.74
Support Vector Machines (SVM)	91.22	91.45	82.37	86.67

Many architectures for ANN were explored and the ANN model with 2 dense layers having 50, 30 units and 'relu' activation function gave the best results. In this model, both the dense layers were followed by a dropout of 0.3 and a batch normalization layer. The deep learning ANN model outperformed all Machine learning as well as all the ensemble models. However, the ensemble models performed better than most of the machine learning models.

VI. Conclusion

In this paper, we presented the design and implementation of an integrated system capable of making decisions for IUU transshipment and predicting the missing values of AIS data necessary for the classification of a rendezvous of vessels as an episode of transshipment. The integrated system consists of 2 subsystems namely the prediction model and the decision model. We were able to train time-series LSTM models for filling missing AIS data for attributes latitude/longitude, speed and heading. All these models had good performance with mape values of 0.029, 0.068, 0.038, 0.017 respectively. We explored both the traditional machine learning, deep learning as well as the ensemble models. We presented a comparative analysis for these techniques and were able to get best accuracy as 96.22% with the ANN model.

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