Leveraging Transdisciplinary Engineering in a Changing and Connected World
P. Koomsap et al. (Eds.)

doi:10.3233/ATDE230644

The Design of Machine Learning for Searching Casualty People in the Gulf of Thailand

Athakorn KENGPOL [a,1] and Chawantorn CHANCHITTAKARN [b]
[a] *Advanced Industrial Engineering Management Systems Research Center, Department of Industrial Engineering, Faculty of Engineering, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand*
[b] *Lieutenant Commander of the Royal Thai Navy, Industrial Engineering, Faculty of Engineering, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand*

Abstract. This research designs a machine learning model for the Royal Thai Navy (RTN) in searching casualty locations and the time of the following suffering incident occurring in the Gulf of Thailand. From collecting information on the RTN's search and rescue (SAR) operations in 2019 - 2022, there were 146 incidents, and several casualties did not survive. It was found that the delays in assisting were the main reason for the loss. Therefore, the machine learning predictions can support the RTN's SAR operations. The Long-short Term Memory (LSTM) is used to create the machine learning predicting model, and the outputs are in terms of the Latitude, the Longitude, and the days after the previous incident, while the root means square error (RMSE) is used to test the validity of the predicting model. The result shows that the RMSE of testing data of the Latitude, Longitude, and the days after the previous incident prediction are 0.906 degree-North, 0.507 degree-East, and 5.633 days, respectively. In practice, the following suffering incident is predicted: on the Latitude 12.017 degrees-North, the Longitude 101.786 degrees-East and happening in the next 41 days after the previous incident, which is far from the actual incident, approximately 11.5 nautical miles, and the incident occurred after the predicted value of 14 days. Using machine learning allows the RTN SAR teams to prepare for disaster relief in advance. For this reason, the Royal Thai Navy SAR operations can increase the chances of meeting those in need and increasing the chances of survival.

Keywords. Machine Learning, AI, Long-short Term Memory, Search and rescue operations, The Royal Thai Navy

Introduction

The Royal Thai Navy has maritime sovereignty obligations with the most prominent operating area in the sea [1]. In 2019-2022, the Royal Thai Navy conducted searching and rescuing (SAR) operations for 146 cases; the location of the incidents are shown in Figure 1. The suffering incidents happened in coastal communities in the Gulf of Thailand, including a drowning man, a patient in a boat, a boat leak or sinking, illegal fishing, a broken ship, a patient on the island, a lost vessel, a boat crashing, and a fire

[1] Corresponding Author, Mail: athakorn@kmutnb.ac.th.

boat. Every incident had injuries or deaths even after entirely saving those lives. It was found that they couldn't help all casualties because they didn't know the future incidents, and the losses couldn't cope in time. Especially the man overboard (MOB) incident [2] that kills the most sufferers in the total number of cases. Hence, the prediction of the following incident information supports this SAR operation finding suffering people to reduce mortality and loss.

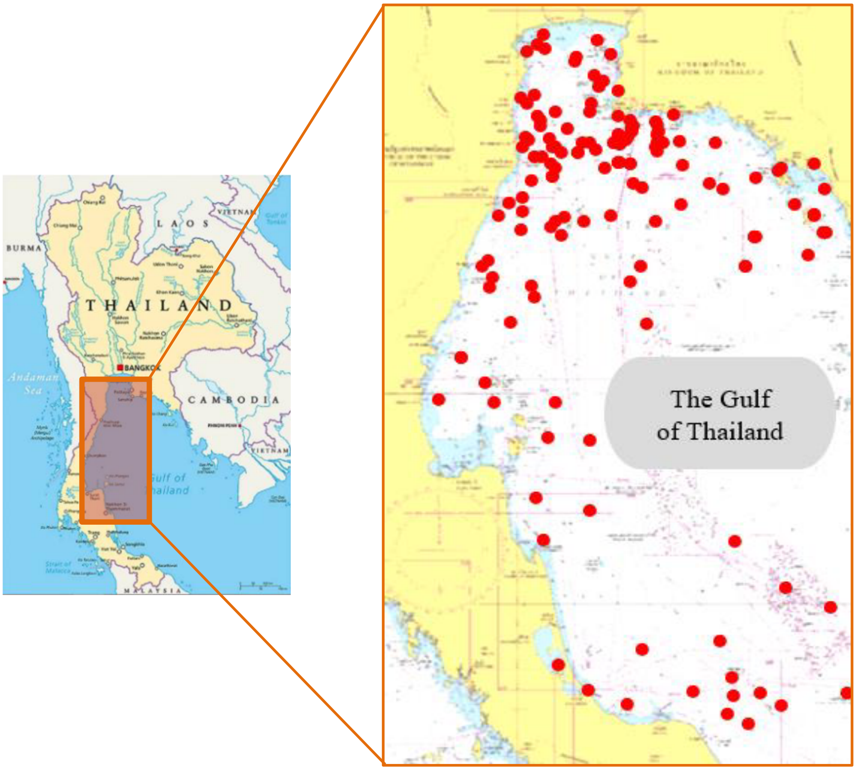

Figure 1. The location of 146 suffering incidents in the Gulf of Thailand.

1. Literature Review

1.1. The Incidents in the Gulf of Thailand

The sufferers have continued to occur in the Gulf of Thailand. The local fishermen within Thailand and from neighbours dwell in the Gulf of Thailand, and some need more skills to survive in the sea. Therefore, suffering incidents are usually happening. The Thai community and migrant workers [3] can also be sufferers of broken boats and patients in a ship, which are shown in Figure 2.

Figure 2. The migrant workers suffered from a broken ship.

1.2. Long short-term memory

The RNN network is shown in Figure 3, where A is neural network information, X_t is the input value, and h_t is the output value for each step. The Long short-term memory or LSTM network is an improved recurrent neural network (RNN) designed to avoid long-term dependence [4]. The LSTM model is widely used to implement sequential data modelling and time series forecasting [5]. Each neuron contains a memory cell capable of storing the previous information used by the RNN or forgetting it if necessary [6]. The LSTM network is shown in Figure 4, where X_t is the input value, C_{t-1} is the output value, and h_t and h_{t-1} are hidden layer states at the time t and t-1, respectively.

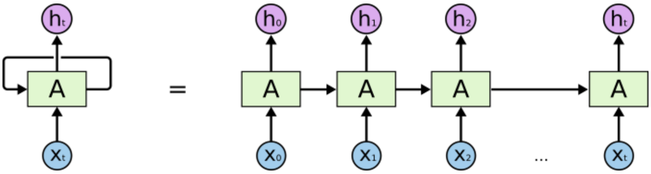

Figure 3. RNN network [6].

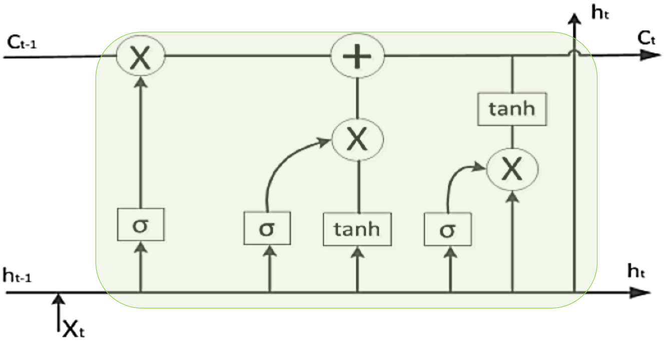

Figure 4. LSTM network [7].

2. Methodology

The research designed the LSTM model to predict the following incident regarding location and time. The research implementation is divided into four steps, as shown in Figure 4.

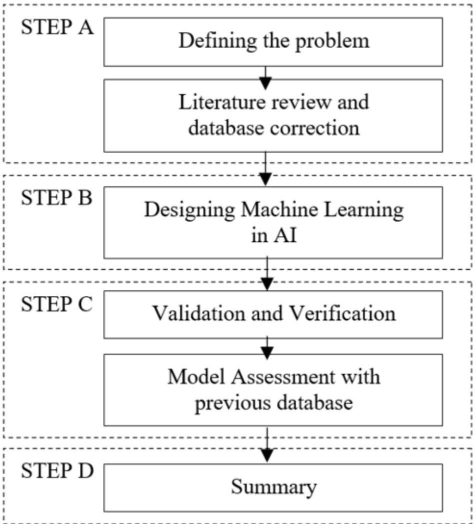

Figure 4. research implementation.

2.1. Step A: Defining the problem and Literature review and database correction

The implementation began with step A, defining the problem, literature review, and database correction. The last four years, the Navy's SAR operations information is sorted from the past to the present and transformed into the input data, including the Latitude, the Longitude and the days after the previous incident.

2.2. Step B: Defining Machine Learning

This step is designing machine learning. The LSTM network is used to create the three prediction models for predicting the three parameters, with the Latitude and the Longitude as the incident location and the days after the previous incident as the occurring time of the following incident.

2.3. Step C: Validation and Verification and Model Assessment with the previous database

From the prediction model in step B, the root means square error (RMSE) is used for validating the output. The prediction models are adjusted according to the lowest RMSE [8]. After that, the following suffering incident is predicted.

2.4. Step D: Summary

The 147th suffering incident (the following incident), which the proposed LSTM models predict, is compared with the actual incident in terms of distance (Nautical Mile: NM) and timing (Days).

3. Results

A machine learning LSTM model is created, and the following incident is predicted, which can be used to support the Royal Thai Navy's SAR operation. Each implementation result is following:

3.1. Defining the problem and Literature review and database correction

In the Gulf of Thailand, the Royal Thai Navy joined the 147 SAR operations in 2019-2022. Some of the Navy's SAR operations are shown in Figure 5. The suffering incidents information is transformed into input values, including the Latitude, the Longitude and the days after the previous incident. The example of the input value transforming is shown in Figure 6. After that, all the input data transformed are sorted according to the chronological order shown in Table 1.

Figure 5. The Navy's SAR operation.

Information: On 3 August 2021 at 6.20 am, the fisher boat name "N. Doungdee" notified that a Thai crew fell into the sea at Latitude 13 degrees 20 Lipda North / Longitude 100 Degrees 39 Lipda East. Neighbouring ships are searching.

Data	Value
Latitude (ºN)	13.333
Longitude (ºE)	100.650
The days after the previous incident (days)	3

Figure 6. The information transformation.

Table 1. The input data.

No.	Date	Latitude (ºN)	Longitude (ºE)	The days after the previous incident (days)
1	18-12-2019	7.074	101.959	1
2	19-12-2019	11.500	100.333	19
3	07-01-2020	11.633	101.167	0
…	…	…	…	…
146	18-07-2022	12.141	100.285	6

3.2. Step B: Defining Machine Learning

In almost all suffering incidents recorded, the casualties are fishermen, who have to work or go to work in the fish-rich area while these fish habitats have been changed according to the year's season. Hence, suffering incidents can be indicated that it is under sequencing. The LSTM model can learn long-term dependencies between time steps in time series and is suitable for creating the prediction model by the sequence data. Therefore, it matches creating the suffering incident prediction model. The purpose of this study is to predict the following suffering incident. Hence, the prediction model structure is designed to predict the following suffering location in the Gulf of Thailand in Latitude and Longitude and the day after the last incident, as shown in Figure 7.

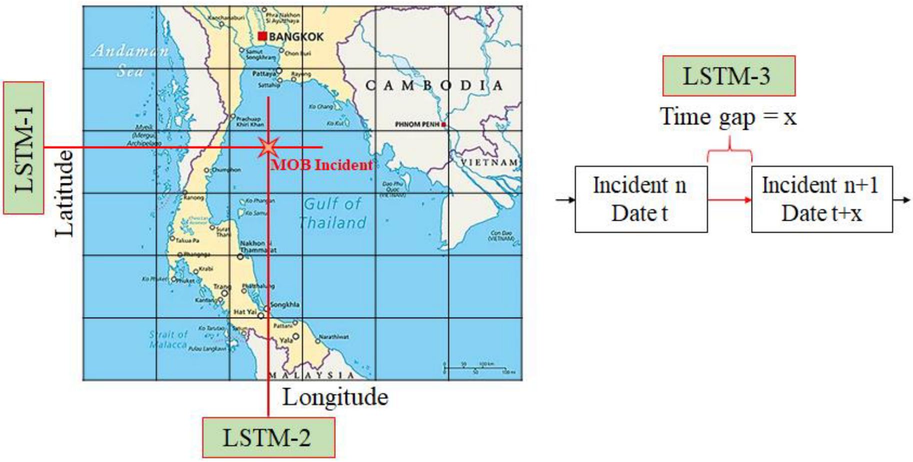

Figure 7. The prediction model structure.

The predicting models are performed on Intel (R) Core (TM) i5-10300H, CPU 4.5 GHz, RAM 8GB DDR4 SO-DIMM. The data are analyzed by using the Google COLAB applications. The model's parameters must be defined, including look back, a node of each layer, learning rate, momentum and epochs, for making the appropriate model.

3.3. Step C: Validation and Verification and Model Assessment with the previous database

The proposed prediction model separates the data with 80% and 20% for training and testing, respectively. In other words, the 1st-117th data is used for training the model, and the 118th-146th data is used for testing the models. The RMSE is used to evaluate the models. From the models created, the RMSE of the Latitude, the Longitude, and the day after the previous incident of both training and testing are shown in Table 2.

Table 2. RMSE of the Latitude, the Longitude, and the day after the previous incident prediction.

RMSE	Training	Testing
Latitude (Degree-North)	0.947	0.906
Longitude (Degree-East)	0.405	0.507
The day after the previous incident (Days)	4.198	5.633

Figures 8-10 compare the prediction value in the group of test data with the actual data for the Latitude, Longitude, and the day after the previous incident, respectively.

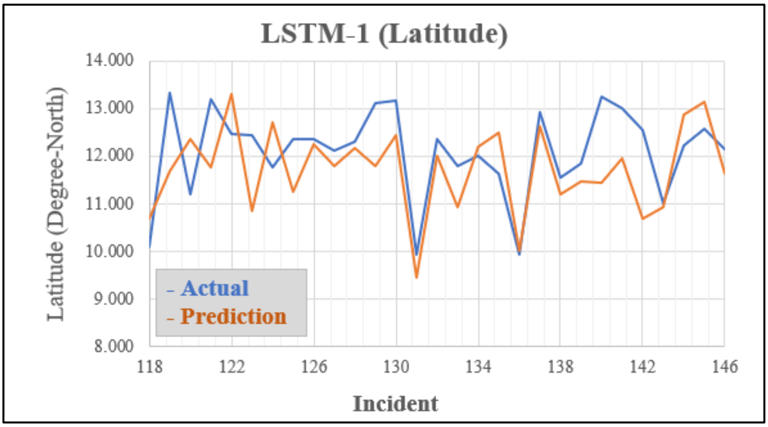

Figure 8. The Latitude predicting model.

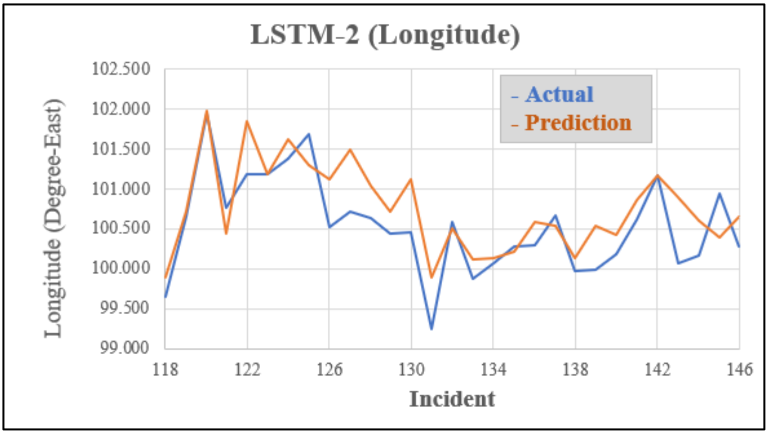

Figure 9. The Longitude predicting model.

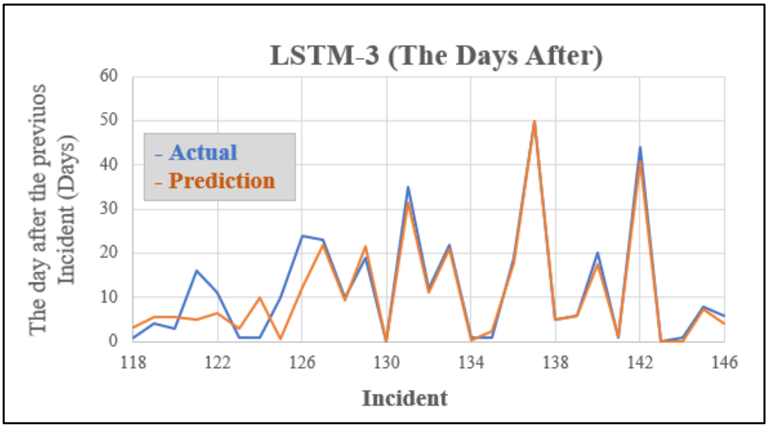

Figure 10. The days after the previous incident predicting model.

3.4. Step D: Summary

Table 3. The prediction of the following incident.

The 147th incident	Prediction	Actual
The Latitude	12.017 ºN	12.085 ºN
The Longitude	101.786 ºE	101.969 ºE
The days after the previous incident	41.33 Days	55 Days

Figure 11. The distance from the prediction to the actual location.

The result has shown that the following suffering incident is predicted: on the Latitude 12.017 degrees-North, the Longitude 101.786 degrees-East and happening in the next 41 days after the previous incident. Eventually, the 147th incident occurred on the Latitude of 12.085 degrees-North, a Longitude of 101.969 degrees-East, and 55 days after the previous incident, as shown in Table 3. Hence, the location by the prediction is far from the actual approximately 11.5 nautical miles, as shown in Figure 11, and the incident occurred after the predicted value of 14 days.

4. Conclusion

The contribution of this study is the prediction model created by machine learning and the data of suffering people in the Gulf of Thailand. The proposed predictive models can support Navy operations in the Gulf of Thailand. In practice, knowing the predicted incident data allows SAR teams to prepare for disaster relief in advance. For this reason, the Royal Thai Navy SAR operations can increase the chances of meeting those in need and increasing the chances of survival.

In addition, the forecasting results can support decision-making in selecting patrol sites to carry out peacekeeping operations in the Gulf of Thailand. The continuous improvement of the model's accuracy is necessary because it can decrease the area and budget for searching or patrolling.

Acknowledgements

The research was carried out in the Department of Industrial Engineering, and funded by Faculty of Engineering, King Mongkut's University of Technology North Bangkok. The authors are deeply grateful to All Naval Area Command for the related data and invaluable advice until this study comes to completion.

References

[1] A. Kengpol and C. Chanchittakarn, The influence of vertical centrifugal casting on nickel aluminum bronze alloy for using in the Royal Thai Navy, *Applied Science and Engineering Progress*, 2021, Vol. 14, pp.503-510.

[2] Government of Western Australia Department of Commerce, *Man overboard prevention and response*, Code of practice, 2010.

[3] M. Aoki, Thailand's Migrant Worker Management Policy as Regional Development Strategy, *ERIA Research Project Report No.19*, 2017.

[4] C. Zeng et al., Parking Occupancy Prediction Method Based on Multi Factors and Stacked GRU-LSTM, *IEEE Access*, 2022, Vol.10, pp.47361-47370.

[5] H. N. Bhandari et al., LSTM-SDM: An integrated framework of LSTM implementation for sequential data modeling, 2022, *Software Impacts*, Vol.14.

[6] H. Sak, A. Senior and F. Beaufays, Long Short-Term Memory Based Recurrent Neural Network Architectures for Large Vocabulary Speech Recognition, *Computer Science: Neural and Evolutionary Computing*, 2014, https://research.google/pubs/pub43895/, accessed July 6 2023.

[7] P. Kaibei1, B. Wei1 and W. L. Yi, Passenger flow forecast of railway station based on improved LSTM, *2nd International Conference on Advances in Computer Technology, Information Science and Communications (CTISC)*, 2020, pp. 166-170.

[8] M. Elsaraiti and A. Merabet, Application of Long-Short-Term-Memory Recurrent Neural Networks to Forecast Wind Speed, *Applied Sciences*, 2021, Vol.11(5), 2387.