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SHORT-TERM STORM SURGE PREDICTION USING THE LSTM ON MYANMAR COASTAL REGION

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Abstract

The height of the water above the typical expected astronomical tide is known as storm surge, and it is the extraordinary rise in the sea surface that occurs during a storm. The surge is brought on by storm winds pushing water ashore. The angle of the coast line with the storm track, the storm's intensity, speed, and size, as well as the local bathymetry, all influence the storm surge amplitude at any given location. The coastal areas are especially vulnerable to the tropical cyclones. Southeast Asian coastal regions, including Bangladesh, India, Sri Lanka, Myanmar, and Pakistan, frequently experience storm-related storm surges. The long short-term memory (LSTM) algorithm is utilized to analyze sequential data, allowing for rapid processing of historical data and generating highly accurate predictions. In this paper, the model for prediction of storm diameter, wind direction and height of storm surge is proposed. This model leverages a LSTM approach, known for its effectiveness and accuracy in such implementations. In applying this, the storm surges that occur in the coastal areas of Myanmar are predicted using a Long Short-term memory neural network.

***Keywords*: storm surge, LSTM, astronomical tide, tropical cyclone, coastal areas.**

1. Introduction

The risk for storm surges caused by strong tropical cyclonic storms creates a danger to the nations surrounding the Bay of Bengal. There is serious concern about the damage caused by storm surge flooding in the coastal regions of Bangladesh, India, and Myanmar. Storm surges are especially dangerous in Bangladesh and Myanmar's situated deltaic areas. Cyclones in the Bay of Bengal travel in a north-westerly path until they reach India's east coast. These cyclones frequently alter course and recurved in a northerly or north-easterly direction, striking the Bangladesh and Myanmar coasts. Myanmar is the largest country in continental Southeast Asia with a total surface area of 676,578 square kilometers (261,228 square miles) and a population of 56.2 million. Nearly the whole east coast of the Bay of Bengal is covered by its 2,000 km long shoreline. Due to the nation's propensity for high rainfall, floods frequently happen in regions that are crossed by rivers or wide streams during the mid-monsoon season, which runs from June to August. In addition, the nation is vulnerable to drought, landslides, earthquakes, tsunamis, and cyclones. On May 2 and 3, 2008, Myanmar was devastated by a category 3 cyclone named Nargis and it caused storm surge with 3.6 meters (12 feet). Pre-existing environmental deterioration, such as overexploitation of natural resources, soil erosion, and deforestation, especially of mangroves, increased the impact of the cyclone. Accurate and fast predictions of storm surges are of paramount importance, as they play a critical role in protecting the lives and economic well-being of countless individuals. Timely and precise storm surge forecasts are essential for safeguarding the livelihoods and ensuring the safety of millions of people in vulnerable regions. In this paper, we have created a dataset using the storm that occurred in Myanmar and its information, and first calculated the storm surge height using the equation [1]. The obtained storm surge height and storm's factors are trained and the next storm surge height and storm information are predicted using the Long Short-term memory neural network method. The rest of the paper is structured as follows. The background method based on machine learning techniques in prediction will be covered in section 2. Following that, in section 3, we provide the implementation and evaluation the result. The architecture of the proposed system will be discussed in section 4. The limits of the simulation will be discussed in section 5. Section 6 offers the paper conclusion, in the end.

1. Related Works

Storm surge forecasting techniques are generally classified into two categories: numerical model-based and empirical/ statistical-based techniques. Numerical models are increasingly employed in the study of storm surges as a phenomenon, their effects on natural and human ecosystems, and their responses to storm surges due to advances in processing power and storage capacity. In [10] used Artificial Neural Network (ANN) for storm surge prediction to overcome these constraints—such as typhoon characteristics, rainfall, and coastal topography. Four input variables are considered: pressure, wind direction, wind velocity, and harmonic analysis of the tide level. Observed storm surge data from Taiwan's Jiangjyun station is used to train and test the model. The correlation coefficient (CC) and normalized root mean squared error (RMSE) are used to assess the model's efficiency. ANN had a learning rate of 0.05, a momentum factor of 0.9, and six neurons in the hidden layer. The ANN model is applicable to many locales and offers precise storm surge forecasts. The study showed that how ANN can be used to enhance storm surge predictions and lessen the effects of extreme weather. In [3] described two machine learning approaches to hurricane-related water level prediction as well as the overall storm surge forecasting and prediction problem. They used a hybrid technique that combines simulation and machine learning with data and scientific expertise. Two datasets generated from ADCIRC storm surge model and have been simulated using two models (geospatial grid based model, image and numerical data regression model). One dataset is eight stations surrounding a central point, or node, near Wrightsville Beach provided time-series data of wind speed, air pressure, and water level. These data were then extracted to construct a 3x3 grid with 20 km spacing. Another dataset is a simulated spatial grid that depicts a lengthy channel with a comparatively small width. This is typical of big coastal rivers in eastern North Carolina, including the Cape Fear River. The water level residual at the central node was predicted using an Artificial Neural Network (ANN) that was built using time-series data inputs from a 3x3 grid and comprises of 28 input feature time-series at each of the nine nodes time-series input comprises three days where the data is recorded in 30-minute intervals for each node and added a lag between the input data and the moment to forecast the water level. They adjusted the lag times and eliminating specific inputs to know how to affected the predictions. Due to its huge area and dispersed grid points, the geospatial grid-based model was unable to anticipate the storm surge accurately. In image and numerical data regression model, they combined Multilayer Perceptron and Convolutional Neural Network to predict water level and water level image. While models with more information perform better overall, those that exclude the sloping effect produce better estimates at the hurricane's peak surge. Using cyclone parameters and a hybrid model of neural network, this research predicts the storm surge of the northeast coast of Taiwan. The storm's position, central pressure, wind direction, radius of cyclone, forward speed, and destinations are all converted to local pressure and wind and used as input in this model. Authors collected 14 historical typhoon data and surge height up to 1.8m from the Central Weather Bureau. They predicted the storm surge height with time lag 1hr, 2hrs, 4hrs, 6hrs and 8hrs. They compared the results and measured the performance with the root mean square error, coefficient of correlation and coefficient of efficiency of six parametric models in [2]. The study [9] evaluated five single machine learning algorithms, including Decision Tree, Naive Bayes, K-nearest neighbors, XGBoost, and SVM. Additionally, six ensemble machine learning algorithms were also evaluated, which included Bagging, Random Forest, AdaBoost, Gradient Boost, Voting, and Stacking. These algorithms were assessed using a storm surge dataset from the South China Sea region to predict the occurrence of storm surges. The evaluation aimed to compare the performance of single and ensemble machine learning algorithms in storm surge prediction.

2. Methodology

Time series forecasting using Long Short-Term Memory (LSTM) is a contemporary method for developing rapid and accurate forecasting models. Following a comprehensive time series analysis, we constructed the architectural model. Neural networks, particularly LSTM, are adept at learning complex nonlinear relationships, making them highly effective for recurrent neural network applications. Consequently, LSTM is considered one of the most successful types of neural networks for supporting multivariate sequence prediction problems.

3.1 Data collection and preparation

Predicting storm surges involves utilizing various datasets to gather relevant information about past storm events, coastal conditions, atmospheric variables, and oceanographic data. In this study, two historical Storm dataset are applied. The first dataset encompasses storm surge occurrences along the coast spanning from the North Atlantic Ocean to the Gulf of Guinea. The second dataset pertains to storm surge occurrences derived from storms within the Bay of Bengal and Myanmar Coastal Region. Specifically, storm data from the Bay of Bengal and Myanmar coast spanning from 2000 to 2021 were sourced from the Joint Typhoon Warning Center. Given the limited availability of storm-related information for Myanmar, the mean value from RAD to GUSTs (Gusts under Storm Threats) was used and calculate storm surge heights.

Two distinct methodologies are employed for calculating storm surge along the coast of Myanmar. The first method entails computation based on air pressure variation, while the second method relies on the impacts of onshore wind stress. In this study, the calculation of storm surge involves the utilization of an equation (1) that accounts for variations in air pressure. This methodological approach forms the basis of our analysis, providing a rigorous framework for understanding and predicting storm surge dynamics.

$$S_p = (1013 - P_c) * 0.033 \qquad (1) \qquad [6]$$

where pressure at the storm centre (Pc) is measured in millibars, while storm surge (Sp) is measured in feet of sea water. The resulting feet are multiplied by 0.3048 and converted to meters.

3.2 Preprocessing

First of all, normality tests are used to determine whether the set of data is distributed that is consistent with a normal distribution. The continuous data normality can be tested using a variety of techniques. In this article, we tested the data normality using skewness, kurtosis, and box plotting. Data are deemed normally distributed when $P > 0.05$, which indicates acceptance of the null hypothesis. Skewness is a metric for symmetry, or more accurately, how asymmetric the normal distribution is. Kurtosis is a metric for a distribution's peakiness. Sometimes, the term "kurtosis (proper)" refers to the initial kurtosis value. A box plot, which is essentially an interval scale, is utilized for estimate, which inherently involves data abstraction. The data is interpreted and analyzed using boxplots. The data can also be visualized using it. A graphical form of the method used to show how the data vary within the data distribution is the boxplot. Rectangles are used to graphically depict the frequency distribution of continuous series in a histogram. The class interval is represented by the graph's x-axis, and the various frequencies that correlate to the various class intervals are displayed on the y-axis. In a histogram, the width of the rectangles represents the class interval widths, and the length of the rectangles represents the corresponding frequency. The diagram is two-dimensional [19].

3.3 Prediction using LSTM neural network

LSTM is a variation of the RNN (Recurrent Neural Network) model designed to handle extended time-series data, whereas traditional RNNs are limited to learning short-term information. One of the critical issues with RNNs is the vanishing gradient problem, which hinders their ability to learn from long sequences. LSTM models overcome this problem during training by incorporating mechanisms to maintain and manage long-term dependencies. An LSTM model achieves this through its unique architecture, which includes three gates: the input gate, the forget gate, and the output gate. The input gate controls the addition of new information to the cell state, the forget gate removes irrelevant data from the cell state, and the output gate determines the next hidden state based on the filtered information from the cell state. These gates enable the LSTM model to effectively retain and utilize relevant features while discarding irrelevant ones, thus allowing it to recall and process long-term time-series data efficiently [20]. The simple process flow of LSTM network is depicted in Fig.1.

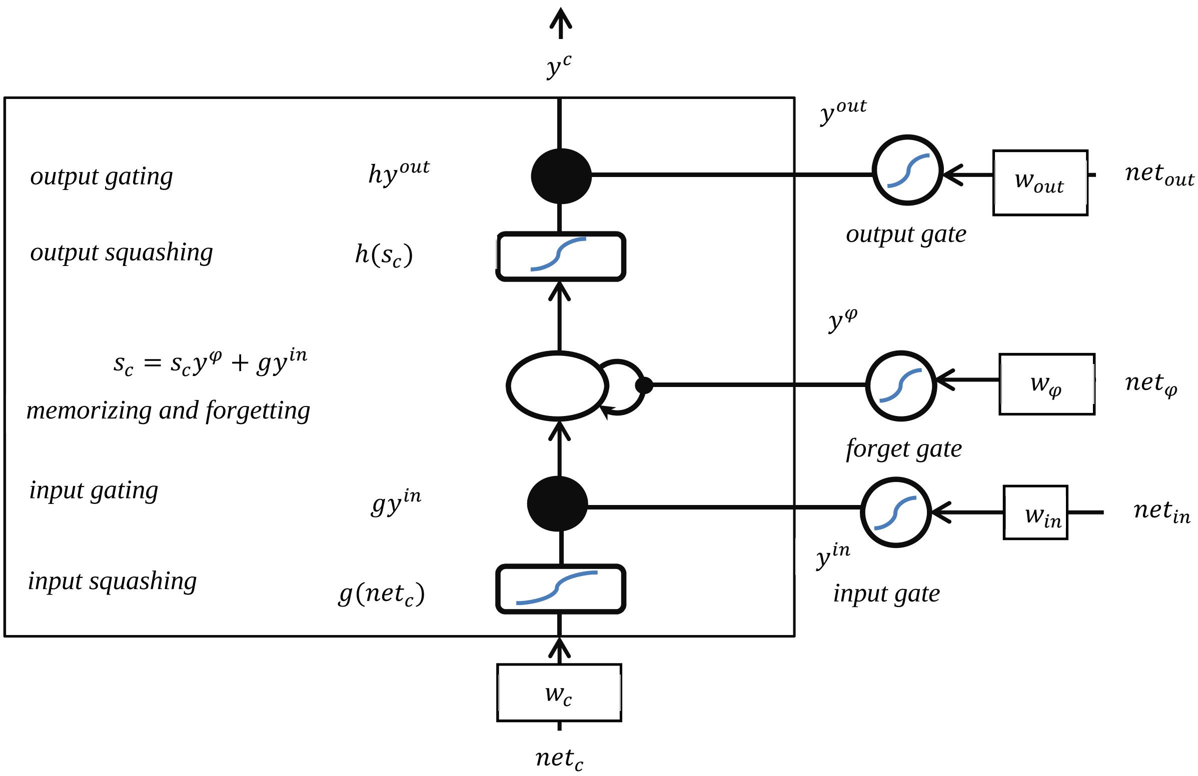

Fig.1 Process Flow of Long Short-Term Memory Network

4. The Architecture of the Proposed System

Prediction of storm surge is essential for saving lives, protecting infrastructure, safeguarding the environment, and building resilient coastal communities in the face of increasingly frequent and severe storms. This work aims to provide the accurate storm surge prediction system for Myanmar. The system applied LSTM model on two different datasets. The overall architecture of this system is illustrated in Fig. 2.

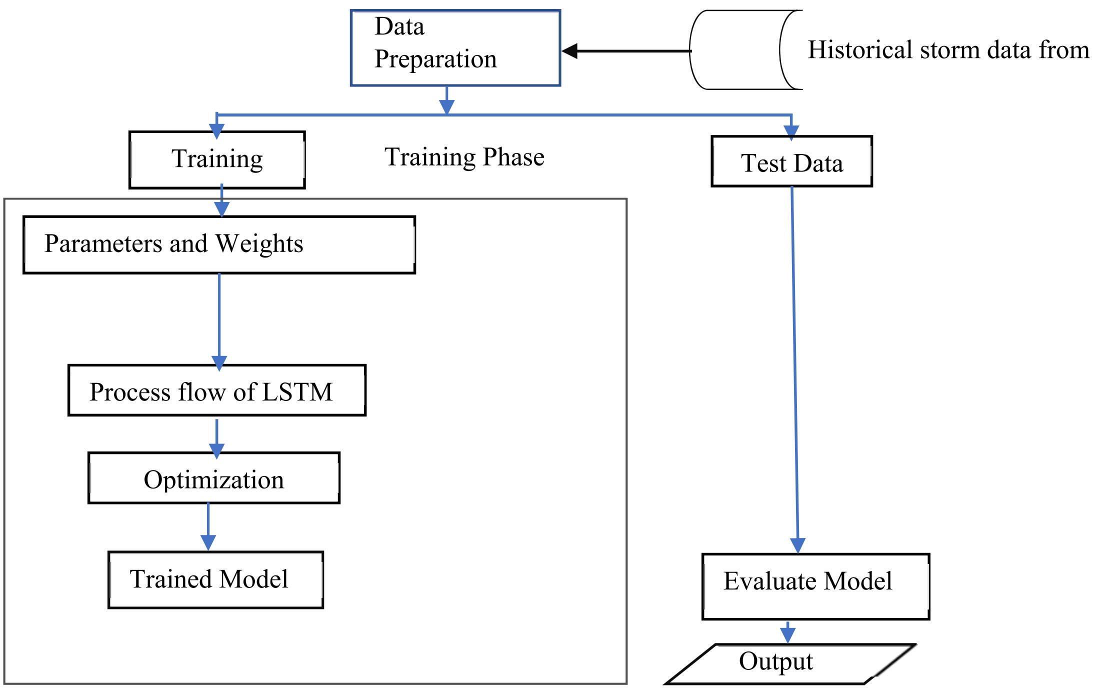

Fig.2 Architecture of the Proposed System

5. Experiments

This system performs a set of preliminary experiments to evaluate the effectiveness of preprocessing and prediction model on two datasets.

5.1 Dataset description

In the experiments, the both datasets are divided into two parts, 80% for training and 20 % for testing. To scale the data between 0 and 1, applied MinMaxScaler. The detailed information of two datasets used in this work are described in Table 1 and Table 2.

No.	Attribute Name	Description
1	Date	Date from 2011-1-1 to 2015-1-1
2	wind_u10	is used to describe the zonal component of the east-west wind velocity at a height of ten metres above the surface.
3	wind_v10	The meridional component of the north-south wind velocity at a height of ten metres above the surface
4	Sea level pressure (slp	The atmospheric pressure at sea level. The difference in pressure between the center of the storm and the surrounding areas influences the strength and extent of the surge.
5	Weight	The weighting or importance assigned to different input variables or features in the model.
6	atmospheric pressure	Barometric pressure, is the force exerted by the weight of the atmosphere on a surface
7	strong winds	High-speed air movements that can have significant impacts on the environment
8	momentum of the stormUnits	the movement or velocity of a storm system.
9	Surge	The abnormal rise in sea level along a coastline due to the combined effects of low atmospheric pressure, strong winds, and the momentum of the stormUnits

Table 1. Detail Information of Dataset 1

No.	Attribute Name	Description
1	YYYYMMDDHH -Cautionary Date-Time-Group	09999123123 to 0000010100. (notice the four-digit year)
2	LatN/S	The hemisphere index, expressed in tenths of degrees, for the DTG, ranging from 0 to 900
3	LonE/W	Longitude (tenths of degrees) for the DTG, is the hemisphere index; E/W ranges from 0 to 1800
4	VMAX	Maximum sustained wind speed- ranges from 0 to 300 knots
5	MSLP	Minimum sea level pressure – (1 – 1100) MB
6	RAD	Stands for wind intensity- measured in Knots- (kts) for the following defined radii: 35, 50, 65, or 100
7	RAD1	The radius of the circle component indicated in the radius code, if it is a full circle; if it is a semicircle or quadrant, the radius of the stated wind intensity between 0 and 1200 nm.
8	RAD2	The radius of the circle component indicated in the radius code, if it is a full circle; if it is a semicircle or quadrant, the radius of the stated wind intensity between 0 and 1200 nm.
9	RAD3	(Counting clockwise from the quadrant indicated in the radius code) 0 through 1200 nm is the radius (nm) of the stated wind intensity for the third quadrant, if full circle or semicircle, this field is not used.
10	RAD4	If this field is left empty or only partially filled in, If quadrant, the radius (nm) of the fourth quadrant's stated wind intensity (counting clockwise from the quadrant indicated in the radius code) from 0 to 1200 nanometers.
11	RADP	Pressure of the last closed isobar, measured in milli bars - (900–1050) mb
12	RRP	Radius of the last closed isobar)-(0 – 9999) nm in nanometers
13	MRD	Maximum Wind Radius- 0 to 999 nm
14	GUSTS	wind gusts during a storm - (0 – 995) kt
15	Surge	the height of the storm surge (m)

Table 2. Detail Information of Dataset 2

5.2 Data preprocessing

In this system, the normality test of the both datasets are not Gaussian distribution. The Kurtosis and Skewness of normal distribution for the first surge data are 5.37 and 0.89. The Kurtosis and Skewness of normal distribution for the second surge data are 430.23 and 12.9. The surge heights from the first dataset are shown below in a box plot by quarterly and by year in (see Fig. 3). The surge heights from the second dataset are shown below in a box plot by quarterly and by year in (see Fig. 4). The surge distribution of first dataset and second dataset are show below in (see Fig.5 and Fig.6) respectively.

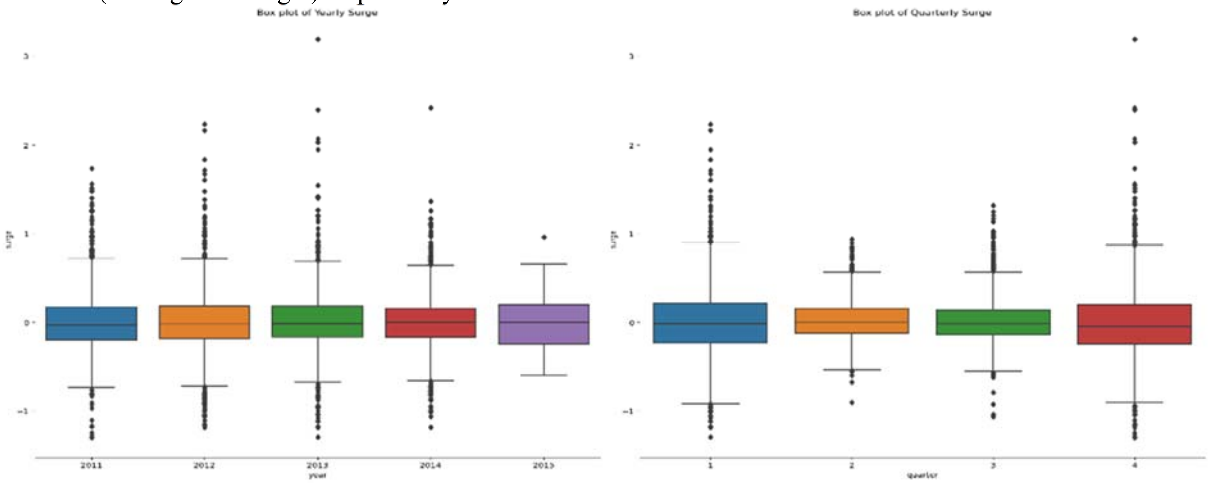

Fig. 3. Box plot of Yearly and Quarterly Surge for the first dataset

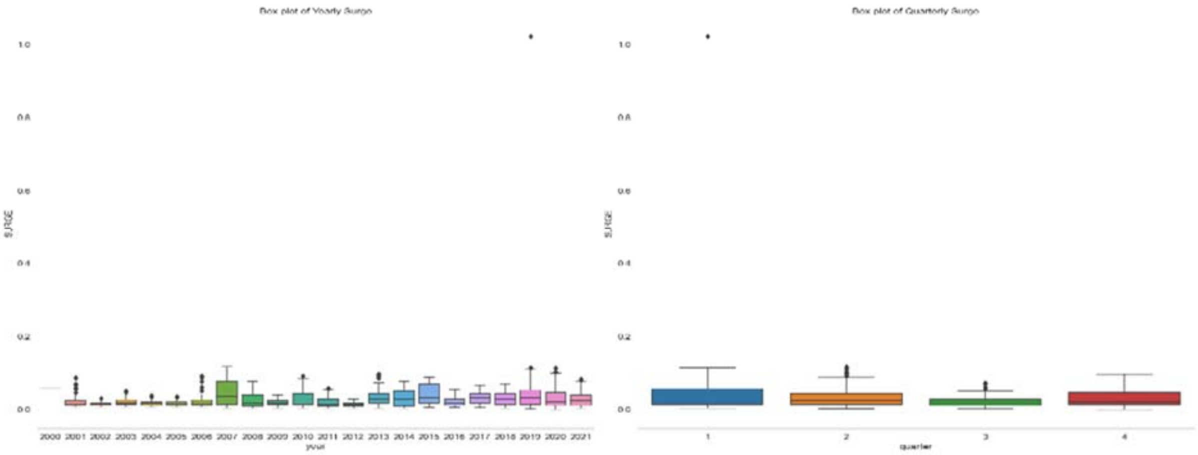

Fig. 4. Box plot of Yearly and Quarterly Surge for the second dataset

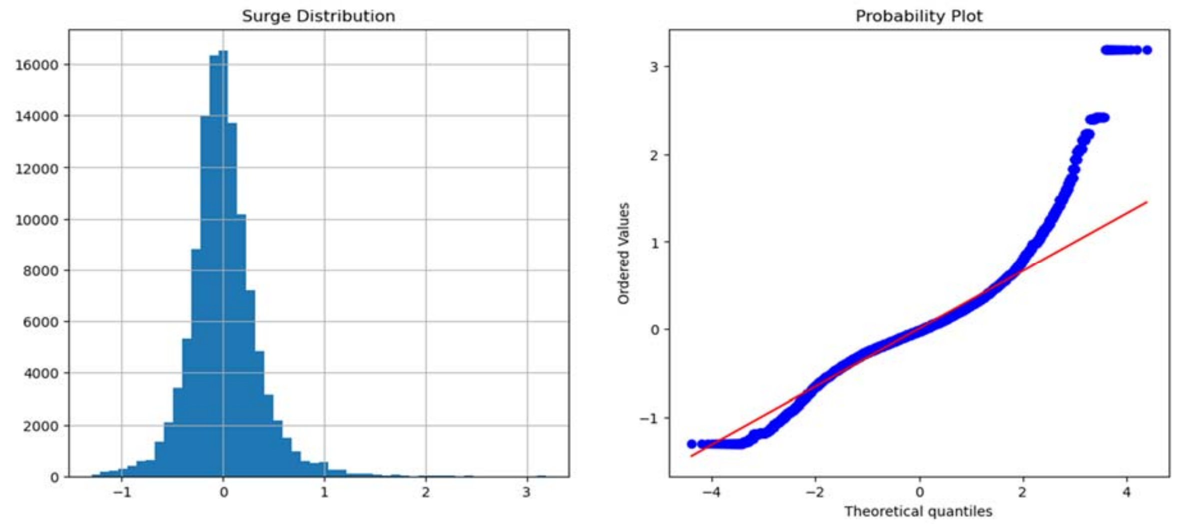

Fig. 5. Surge distribution of first dataset

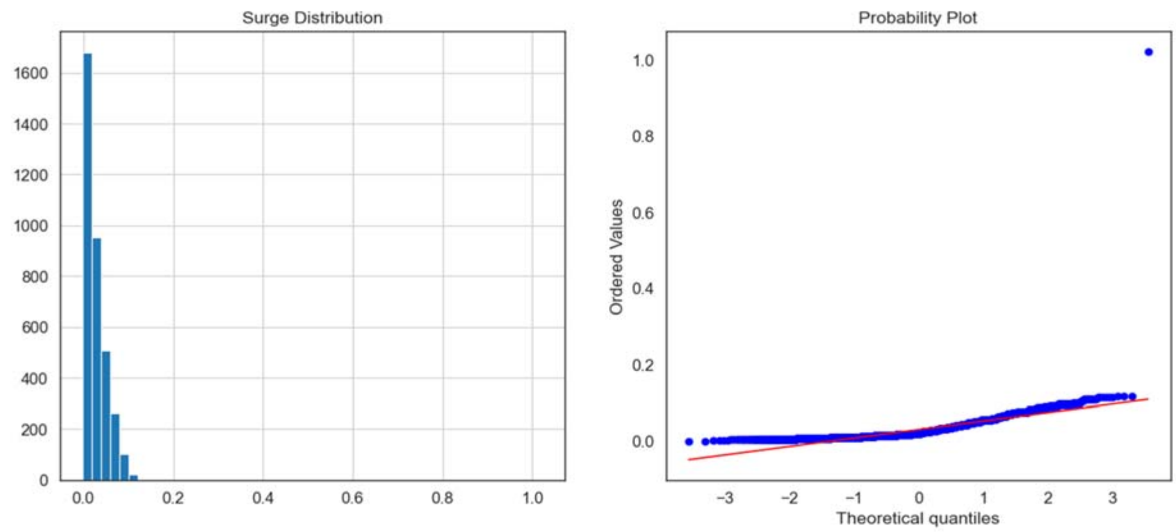

Fig. 6. Surge distribution of second dataset

Average Surge Resampled over Day, Week, Month, Quarter and Year of first dataset and second dataset are show below in (see Fig.7 and Fig.8) respectively.

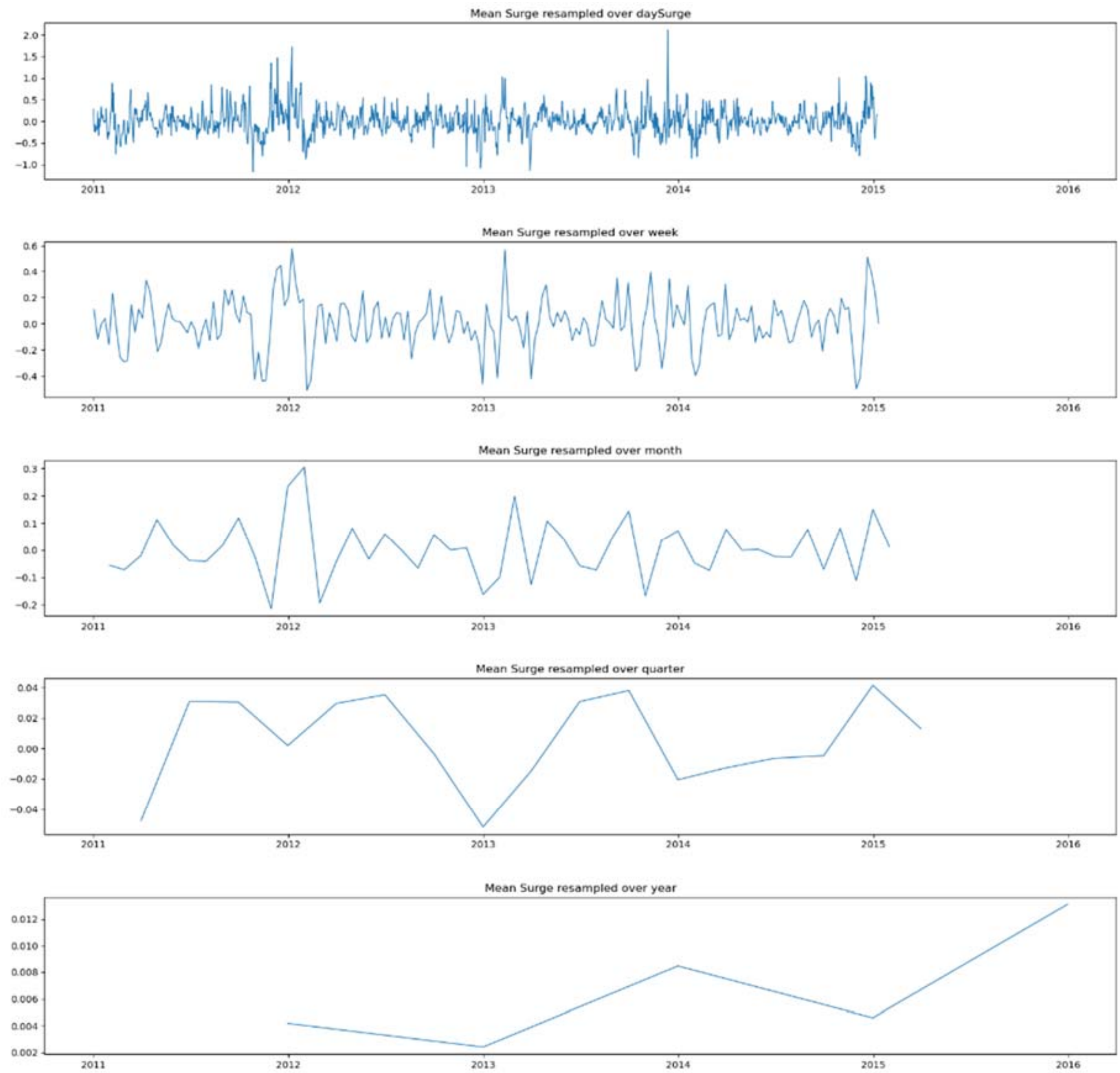

Fig. 7. Average Surge Resampled over Day, Week, Month, Quarter and Year of first dataset

Fig. 8. Average Surge Resampled over Day, Week, Month, Quarter and Year of first dataset

5.3 Model implementation and evaluation

This study implements a two-layer LSTM network utilizing the ADAM optimization function. In the case of the first dataset, the input consists of 3 timesteps and 9 features, while the output comprises 1 timestep with 9 features. Conversely, for the second dataset, the input involves 4 timesteps and 15 features, with the output retaining 1 timestep and 15 features. Both datasets undergo training for 100 epochs, utilizing batch sizes of 300 and 3, respectively. The evaluation metrics employed for assessing model performance include mean squared error for loss computation and accuracy measurement. The loss and accuracy of these two datasets are shown in (see Fig.9 and Fig.10).

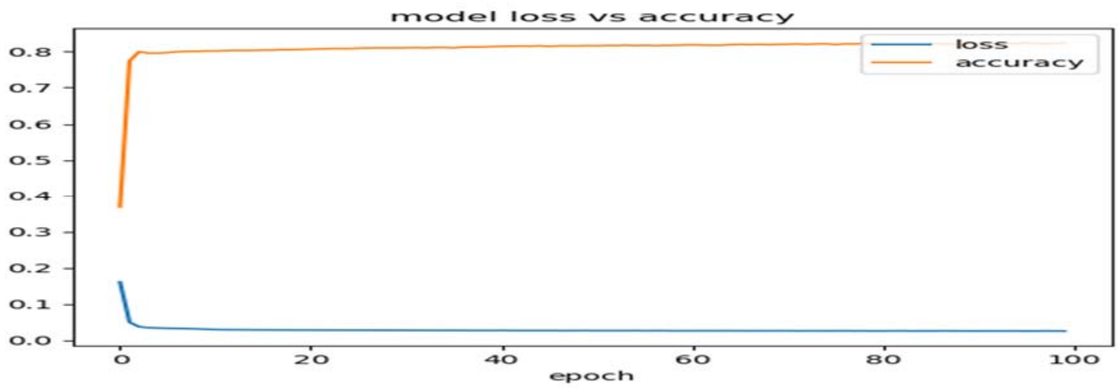

Fig. 9. The loss and accuracy of model using First dataset

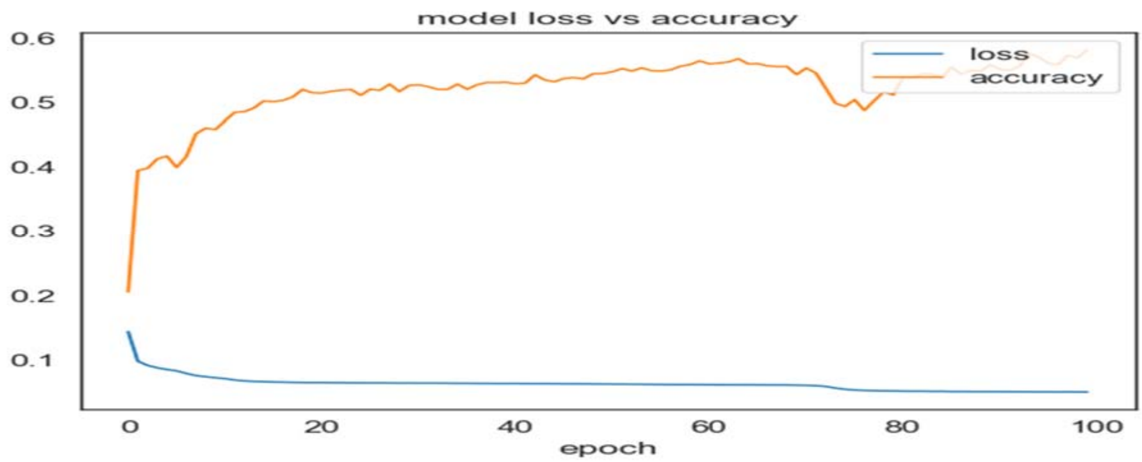

Fig. 10. The loss and accuracy of model using Second dataset

5.4. Discussion

Based on the analysis presented in Figures 9 and 10, it is evident that the LSTM model trained on Dataset 1 demonstrates higher accuracy compared to the model trained on Dataset 2, despite similar loss values observed in both models. Dataset 1 comprises a significantly larger number of data instances, providing an ample dataset for training the deep LSTM model effectively. Conversely, the limited amount of data in Dataset 2 contributes to the lower accuracy achieved by the model trained on this dataset. Furthermore, an increase in the number of epochs correlates with a reduction in loss across both models, indicating the iterative improvement of model performance with prolonged training duration.

6. Conclusion

This study shows the performance of LSTM using two different datasets. The first dataset is the wind_velocity based storm surge dataset. The second dataset is a dataset that calculates surge based on air pressure variation. There are two differences in training data using LSTM. The two parameters, input_timesteps and batch_size, differ depending on the data size, but remaining are the same. However, LSTM predicts all input features (multivariate), including storm surge, without significantly decreasing its accuracy. Using the LSTM model, where will the storm hit in Myanmar? What will be the wind speed? Storm diameter, wind direction and storm surge will be predicted every 6 hours.

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