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LONG SHORT TERM MEMORY APPROACH FOR SHORELINE CHANGE PREDICTION ON ERETAN BEACH

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Abstract—*Eretan Beach is one of the beaches in Indramayu and has a reasonably severe abrasion rate from year to year. The Eretan coastline always experiences significant changes due to erosion every year. Therefore, it is necessary to study changes in the coastline at Eretan beach. This study obtained coastline data from the Google Earth engine using CoastSat, a python-based open-source toolkit, from 1992 – 2022. The open-source geographic information system software used to process the data is the Quantum Geographic Information System. This study aims to analyze the Long Short-term Memory (LSTM) algorithm in predicting shoreline changes at Eretan Beach. The eight optimizer functions in the LSTM are used with nine different scenarios to analyze the algorithm's performance. The results of this study show that RMSProp has the best performance compared to other optimizers. The RMSE and MAPE values on the RMSProp are 35.06258 and 2.2923 on the training data and 9.2457 and 1.06786 on the test data. In addition, from the predictions for the next ten years at transect point 251, it was found that there would be an increase in the coastline.*

Keywords: *eretan shoreline change, long short-term memory, shoreline change, shoreline change prediction.*

Intisari—*Pantai Eretan merupakan salah satu pantai yang ada di Indramayu dan memiliki tingkat abrasi yang cukup parah dari tahun ke tahun. Garis pantai Eretan selalu mengalami perubahan yang signifikan karena erosi setiap tahunnya. Oleh karena itu, diperlukan kajian tentang perubahan garis pantai di pantai Eretan. Dalam penelitian ini, data garis pantai diperoleh dari mesin Google Earth menggunakan CoastSat, sebuah toolkit open-source berbasis python, pada periode 1992 – 2022. Perangkat lunak sistem informasi geografis open-source yang digunakan untuk mengolah data adalah Quantum Geographic Information System. Tujuan dari penelitian ini adalah untuk menganalisis algoritma Long Short-term Memory (LSTM) dalam memprediksi perubahan garis pantai di pantai Eretan. Delapan fungsi pengoptimal dalam LSTM digunakan dengan sembilan skenario berbeda untuk menganalisis kinerja dari algoritma. Hasil dari penelitian ini didapatkan RMSProp memiliki kinerja terbaik dibandingkan dengan pengoptimal lainnya. Nilai RMSE dan MAPE pada RMSProp adalah sebesar 35.06258 dan 2.2923 pada data latih dan sebesar 9.2457 dan 1.06786 pada data uji. Selain itu, dari prediksi sepuluh tahun kedepan pada titik transek 251, didapatkan bahwa akan terjadi peningkatan garis pantai.*

Kata Kunci: *perubahan garis pantai eretan, long short-term memory, perubahan garis pantai, prediksi perubahan garis pantai.*

INTRODUCTION

Indramayu is one of the districts located on the north coast known as Pantura. The length of the coastal area is around 147 km that stretches from the border of Cirebon to Subang regency [1]. According to the reference, 45.6 km of the coastline undergone abrasion. Further, Indramayu has potential to experience abrasion around 8.23 ha/year [2]. According to Bappeda-Jabar data reported by Kasim in [3], the district experienced the longest abrasion namely around 48.57 km from all coastal areas in west java. Moreover, the value of accretion of the district also far exceeded the stable value. It is recorded that the district experienced 46.37% accretion whereas the stable value is 5.57%. One of the factors that influenced the significant change is development activities.

According to the work of Kasim as mentioned in [3], the beaches of the north coast of Indramayu were dominated by abrasion over a 12-year period starting from 1991 to 2003. Around 50.98% of the beaches experienced abrasion and 40.02% of the beaches undergone accretion. The research was conducted using modified single transect technique and end point rate method. These results indicate that the coastal area of Indramayu is undergoing destructive changes.

Further, it also mentioned in the research that one of beaches that experienced significant shoreline change is Eretan beach. In the reference, the rate of shoreline change of Eretan beach has been conducted. The author calculated the rate change of the north coastline including the coastal area of Eretan (Indramayu regency) and Subang regency. It is reported that the average annual rate of change of accretion and abrasion on each shoreline grid was 1.80 – 12.78 m/year. The results lead to how important research about forecasting of shoreline change of the beach. There are many studies focused on forecasting of shoreline change in recent years, but there are few studies that took Indramayu's coastal area especially Eretan beach as a case study. The information motivates us to do this research.

In the work of Kusnanto et. al. as described in detail in [1], Coastlines of Indramayu Regency have still undergone abrasion. The three highest districts that experienced abrasion are Pasekan, Cantigi, and Kandanghaur. However, in the period the abrasion decreased from 1.125 ha down to 358 ha due to efforts of government and community. It is stated in the reference that at the time the community started planting mangroves and doing green activities. Whereas the government installed sea dike or sea wall as wave breakers. Details of the coastline change are given in Figure 1.

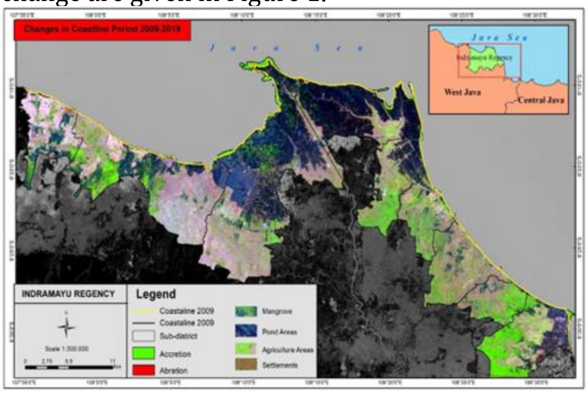

Figure 1. Coastline change in 2009 – 2019 of Indramayu Regency taken from [1]

Various methods to study shoreline change have been proposed. The methods are based on machine learning technique such as Support Vector Regression (SVR), Multi-layer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short Term Memory (LSTM), Random Forest (RF), and statistical model such as Error Trend Seasonality (ETS) and Autoregressive Integrated Moving Average (ARIMA).

In the work of Calkoen et. al. in [4], comparisons of traditional and machine learning methods were conducted to see shoreline change in area of Duck, North Carolina, USA. Around 37.000 Satellite-derived Shorelines (SDS) dataset are used to measure performance of each used methods. It is mentioned in the research that machine learning (ML) methods (e.g MLPs, CNNs, RNNs, and LSTM) outperform the classical methods such as ETS and ARIMA in terms of computational time. But the ML methods are slightly better accuracy than the classical methods. The ML methods performance depends on data and its quality.

In predicting sea level variation along West Peninsular Malaysia coastline, LSTM has better performance than SVR and ARIMA when the ocean and atmospheric variables were included in the model. Whereas ARIMA showed the best performance compared with the other methods when the ocean and atmospheric variable were excluded [5]. The LSTM method also showed better accuracy than the Empirical Orthogonal Function (EOF) method in predicting shoreline change of Nha Trang Coast in South Central Vietnam. Further, the method was also in good agreement compared with Seasonal Auto-regressive Integrated Moving Average (SARIMA) and Neural Network Auto-Regression (NNAR) [6].

Based on previously mentioned information, this research is focused on prediction of shoreline change in Eretan beach using LSTM method. In this study, the Eretan shoreline data was taken through satellite imagery using the Python CoastSat package for the period 1992 – 2022. Then the data was processed using the QGIS application to create baselines, transects and intersections to be used as parameters. After that, the shoreline data is predicted using LSTM method. The prediction is carried out for the next ten years.

The coastal area of Indramayu is mainly used for fish farming and salt production by the local citizens as their source of income [7]. Therefore, the destructive change of coastal area can cause economic loss. It is hoped that this research can provide an overview of changes in the Eretan shoreline so that policy makers can make wise decisions regarding development, economy, and

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other sectors, so that it has a positive impact on residents around the coast and other general public.

LSTM method is chosen in this research to predict the shoreline change of Eretan Beach in Indramayu due to its performance and advantages. The method can overcome the shortcomings of Recurrent Neural Network (RNN) algorithm namely vanishing gradient and exploding gradient by additional interactions per module (or cell) [8]. LSTM can store previous information as well as update it, then pass it on to the next layer without losing information.

Another advantage of LSTM compared to other artificial neural networks is the presence of a hidden layer, where the memory cell which is the computing unit effectively associates remote memory and input in time. LSTM is also able to predict numbers with certainty because this network can remember previous values and can calculate future values based on the accuracy of previous values [9].

Note that, study on shoreline change in Eretan beach was previously studied using LSTM in [10] and random forest in [11]. It is mentioned in [10] that optimizer functions such as RMSProp, Adam, Adamax, and Nadam are promising optimizer to increase performance of the LSTM method. Thus, those optimizer functions are used in this article. But the references did not mention any prediction of the shoreline. Therefore, the predictions distinguish the current article from the references. Another difference is data processing. In the current article, data obtained from Coastsat are processed using Quantum Geographic Information System (QGIS) whereas data in the references are processed using digitizer software.

All information mentioned above indicates that abrasion is a serious problem occurring in Indramayu. The study of the phenomena has been conducted by many researchers. But forecasting studies of the shoreline change are still lacking. Therefore, this research is focused to study the shoreline change in Eretan Beach in Indramayu using LSTM model and data obtained using CoastSat toolkit. The data are 31 years long from 1992 – 2022. Moreover, a ten-year forecasting becomes another purpose of this research.

MATERIALS AND METHODS

Study Area and Data

The research location is on Eretan Beach located in Kandanghaur village, Indramayu Regency, West Java (see Figure 2). The Area of Interest (AOI) of the research location is at the coordinates of 06°18'05"S and 107°62'18"E. In the process, the stages carried out in this research are data collection, data processing, data modeling, accuracy testing, and shoreline prediction.

Figure 2. The research location in Kandanghaur village.

The Shoreline data of Eretan beach are obtained through secondary data based on satellite imagery. An open-source python-based toolkit known as CoastSat is used to obtain the shoreline images for the period 1992 – 2022 (see Figure 3). CoastSat provides an interface to the GEE API to allow easy access to all Top-of-Atmosphere (TOA) reflectance images from the Landsat 5(TM), Landsat 7 (EMTþ), and Landsat 8 (OLI) Tier 1 collections and Sentnel-2 [12].

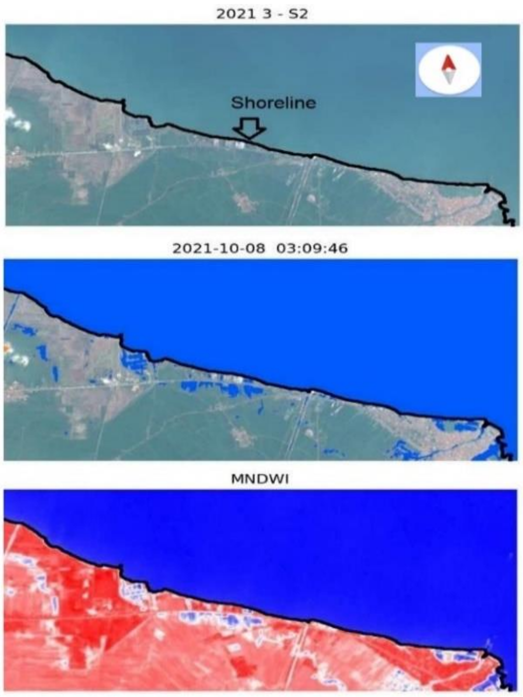

Figure 3. Shoreline Image of Eretan Beach using Coastsat [12].

The CoastSat toolkit can provide shoreline data. Besides the file in picture format, the toolkit also gives a file in geojson format as an output. In this research, obtaining shoreline data is quite challenging due to the clearness of the satellite data. Here, the image is chosen when the shoreline can be seen clearly as presented in Figure 3. The black line in the figure indicates the shoreline which is instantaneous interface between water and sand. Using the toolkit, time-series data of shoreline position are obtained and presented in Table 1 and Table 2. The obtained time-series data are used to develop the LSTM model.

Data Processing

Data processing is carried out using the Quantum Geographic Information System (QGIS) application to obtain vector data from raster processing. There are three kinds of vector data namely point, line, and polygon (area). The QGIS is an open-source geographic information system software from the Open-Source Geospatial Foundation (OSGeo). It can be run on a desktop with any operating system, such as Mac OS, Windows, Linux, or Android [13].

Several steps are conducted to process the shoreline data to obtain data on Eretan shoreline in period 1992 - 2022. The steps are digitization, area of interest (AOI) correction, creating baseline, creating transect, and measuring distance between intersect point to baseline.

a) Digitization

In this step, all geojson files obtained from the CoastSat toolkit are input in QGIS software. This process QGIS aims to create maps through a computer process. The result of the data mentioned in Table 1 is presented in Figure 4.

Figure 4. Result of Digitization step on Eretan Shoreline.

b) Area of Interest (AOI) Correction

The second step is AOI correction which aims to create an area that will become the research point by ensuring all the coastline data that has been obtained are within the area of interest. This process is done to ensure that there is no empty data in the area. The AOI data is obtained by forming an area. Starting from making a point on the map, then from the first point to the second point that is made will form a line, then if the last point is made the area (polygon) is formed see Figure 5 as illustration. Here, the interval distance between transects is 10 m with a 2 km transect length.

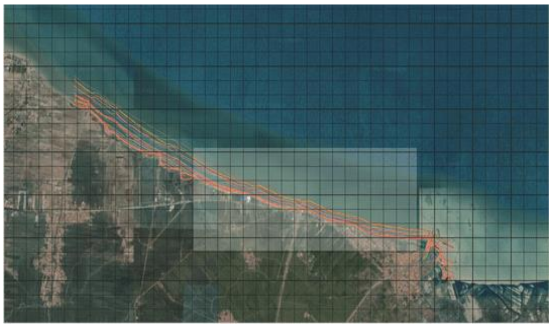

Figure 5. Correction of Area of Interest on Eretan Shoreline.

c) Creating Baseline

The next step is to create a baseline. Baseline creation in QGIS aims to obtain zero-point reference line data to measure shoreline changes [14]. Here, the baseline is the onshore type baseline or the baseline placed on land. After the baseline data each period is obtained on the Eretan shoreline, then the transects can be constructed because the baseline is closely related to transects [15].

d) Creating Transect

After obtaining baseline data in the previous step, then the transects can be determined. Transects are one of the methods used to measure the distance of movement of polyline boundaries. It is a straight line radiating from the baseline to the shoreline at user-defined intervals along the baseline [15]. Transect can also be interpreted as a line perpendicular to the baseline dividing the shorelines [14].

In this research, the transects were made automatically by using the Transect tool on the Vector Geometry menu. Technically, transects are created by simply inputting the distance between transects and selecting the layer to be transected. The interval distance between transects is 10 m with a 2 km transect length. Baseline and transect of the shoreline are given in Figure 6.

Table 1 Details of Obtained Shoreline Dataset

Year	Time of Data Taken	Source
1992	24/08/1992 02:16	Landsat 5
1993	28/09/1993 02:16	Landsat 5
1994	26/05/1994 02:13	Landsat 5
1995	14/06/1995 02:00	Landsat 5
1996	19/08/1996 02:10	Landsat 5
1997	06/08/1997 02:25	Landsat 5
1998	15/12/1998 02:32	Landsat 5
1999	12/08/1999 02:31	Landsat 5
2000	09/10/2000 02:44	Landsat 7

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Year	Time of Data Taken	Source
2001	19/04/2001 02:44	Landsat 7
2002	15/10/2002 02:41	Landsat 7
2003	25/04/2003 02:42	Landsat 7
2004	17/08/2004 02:42	Landsat 7
2005	21/09/2005 02:42	Landsat 7
2006	06/07/2006 02:43	Landsat 7
2007	05/10/2007 02:46	Landsat 5
2008	08/11/2008 02:37	Landsat 5
2009	22/07/2009 02:42	Landsat 5
2010	21/10/2010 02:46	Landsat 7
2011	17/05/2011 02:47	Landsat 7
2012	23/08/2012 02:49	Landsat 8
2013	18/08/2013 02:55	Landsat 8
2014	18/06/2014 02:53	Landsat 8
2015	21/06/2015 02:53	Landsat 8
2016	04/04/2016 02:53	Landsat 8
2017	10/06/2017 02:53	Landsat 8
2018	16/08/2018 02:53	Landsat 8
2019	11/06/2019 03:09	Sentinel 2
2020	20/06/2020 03:09	Sentinel 2
2021	08/10/2021 03:09	Sentinel 2
2022	20/06/2022 03:09	Sentinel 2

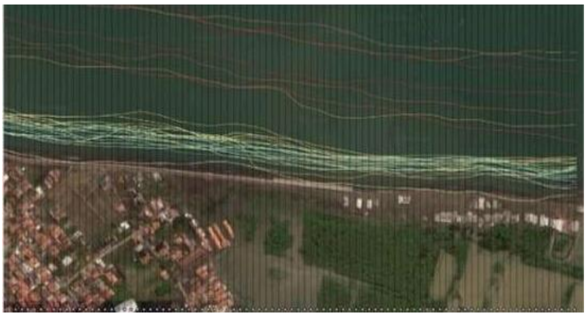

Figure 6. Baseline and Transect on Eretan Shoreline.

e) Measuring Distance between Intersect Point and Baseline

The measurement between intersection point and baseline can be done by using the Field Calculator tool in QGIS. The way to calculate it is by adding x and y coordinates of baseline. The intersect itself is a coordinate point obtained from the intersection of the transect line and the shoreline. The intersection is determined from the changes in the shoreline every year. Technically in QGIS, the process is done by using the Intersection feature on the Vector Geometry. Results of the intersect point are presented in Figure 7. Whereas an example of data of the distance measurement is given in Table 2.

Table 2 Example of Dataset of Eretan Shoreline

Index	Date	Transect id	Distance
0	2022-06-20 03:09:46	164	1024.581
1	2022-06-20 03:09:46	463	251.985
2	2022-06-20 03:09:46	177	951.438
3	2022-06-20 03:09:46	453	261.054
...	...	...	...
16287	1993-09-28 02:16:11	101	1343.621
16288	1993-09-28 02:16:11	315	705.050
16289	1993-09-28 02:16:11	7	1726.398
16290	1993-09-28 02:16:11	338	653.749
16291	1993-09-28 02:16:11	510	329.250

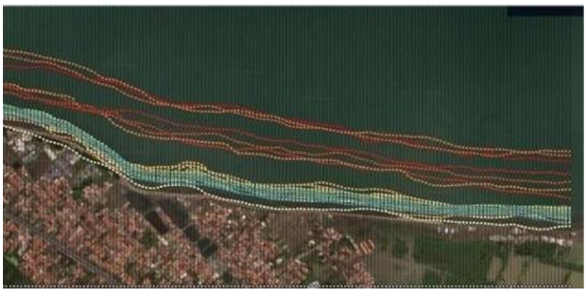

Figure 7. Intersect Points on Eretan Shoreline.

Data Modelling

After obtaining the time series data from QGIS as presented in Table 2, the next process is data modelling. Here the modelling is carried out using LSTM. Some steps must be conducted to do the modelling including data pivoting, plotting, data splitting, data windowing and data modeling using LSTM.

Pivoting data is done to arrange data to look similar in one field. It aims to make it easier to process because it can eliminate various anomalies that can make checking information more complicated. Then proceed with the plotting process. Plotting is the process of making plots.

The third process is data splitting. Data splitting is the process of determining the data to be used as training and testing data. The fourth process is data windowing. Windowing is the process of predicting the next data using the previous data. The process is transformation of time series data into cross sectional data [16].

The last process is data modeling using LSTM. Theoretical background about the method is abundant in references. For sake of clarity, a roughly introduction to the method is resumed here. For further reading please conduct previous mentioned references and these references [17]–[23]. It is stated that LSTM method was proposed first in 1997 to overcome shortcomings, vanishing and exploding gradients, of Recurrent Neural Networks (RNN) method. As an improvement of the RNN method, LSTM is a promising method to make predictions based on time series data [21].

The LSTM method is possible to resolve the RNN shortcoming due to its cell structure. The LSTM cell has four units such as input gate i_t, forget gate f_t , memory cell gate C_t, and output gate o_t.

Mechanism of the LSTM method in processing information can be governed in equations (1) – (6) [10], [24].

$$f_t = \sigma(W_f x_t + R_f h_{t-1} + b_f), \quad (1)$$

$$i_t = \sigma(W_i x_t + R_i h_{t-1} + b_i), \quad (2)$$

$$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o), \quad (3)$$

$$\widetilde{c_t} = \tanh(W_c x_t + R_c h_{t-1} + b_c), \quad (4)$$

$$C_t = f_t * c_{t-1} + i_t * \widetilde{c_t}\,, \quad (5)$$

$$h_t = o_t * \tanh(c_t), \quad (6)$$

where $\sigma, W, b, R, x_t, h_t$ represent the sigmoid function, weight value, bias value, weight value, input value, and output value, respectively. Further, performance of the method depends on its hyperparameter. In [10], values of time step, batch size, and hidden neuron can be set as 1 – 20, 2 – 64, and 1 – 400, respectively to get good performance. Other parameters such as loss function, activation function, and optimizer function can be adjusted.

Accuracy Measurement

After the model is created using the LSTM method, the next step is measurement of the model performance. In this study, the performance is measured using Root Mean Squared Error (RMSE) and Mean Absolut Percentage Error (MAPE) using equation (7) – (8) as described in [24]. Note that four optimizer functions such as Adam, Adamax, Nadam, and RMSprop are used to increase performance of the method. Here the LSTM method was performed with Python, Keras, and TensorFlow using parameters as given in Table 3.

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(a_t - b_t)^2} \quad (7)$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{a_t - b_t}{a_t}\right| \quad (8)$$

where a is predicttion of shoreline data and b is actual data.

Table 3. Parameters/Functions of the LSTM Method

Parameter/Function	Value
Hidden neuron (LSTM Cell)	64, 128, 256
Time step	1
Batch size	2, 4, 8
Epoch	100
Activation function	relu
Loss Function	MSE
Measurement of errors	RMSE, MAPE
Optimizer function	Adam, Adamax, Nadam, and RMSprop

RESULTS AND DISCUSSION

This research will provide an overview of shoreline changes that occur in Eretan Beach, Indramayu, as well as provide an overview of the prediction of Eretan shoreline changes for the next 10 years using LSTM. At the step of data collection using CoastSat, the Eretan shoreline data was obtained from each year as shown in Table 1. The shoreline data from each year in the 1992 – 2022 period is processed using QGIS to get data presented in Table 2. Then the prediction of the shoreline is calculated using LSTM. The accuracy testing of the model is conducted using RMSE and MAPE. Eightty percent of the data was used as training data, whereas the rest was used as testing data. By using eight optimizer functions, the results of RMSE and MAPE values at transect 251 of each optimizer function are shown in Table 4 – Table 7. The best results of the accuracy on data training and data testing are marked in bold letters to make it easier to notice.

According to results of the accuracy measurement presented in Table 4 – Table 7, the implementation of the LSTM method for forecasting shoreline changes on Eretan beach has produced promising results. Further, it was found that the RMSProp got the best performance followed by Adam, Nadam, and Adamax. The RMSprop optimizer outperforms the rest optimizers. The RMSE and MAPE of RMSprop are 35.06258 and 2.29232 for training. However, the RMSE and MAPE for testing are found 9.2457 and 1.06786 respectively. Those values are gotten when values of batch size and LSTM cell are 2 and 64 values for training and 2 and 256 for testing.

Table 4 Accuracy Measurement of Adam Optimizer

Batch Size	LSTM Cell	Train		Test	
		RMSE	MAPE	RMSE	MAPE
2	64	51.1816	3.5769	10.5456	1.1166
2	128	**38.8794**	**2.542**	10.4644	1.0754
2	256	40.6221	2.6336	**9.8033**	**1.0716**
4	64	50.3626	3.5249	10.491	1.1156
4	128	54.9444	3.8658	10.8973	1.1166
4	256	51.5205	3.6000	10.6031	1.1176
8	64	49.2966	3.4384	10.4668	1.1162
8	128	54.0327	3.7866	10.7474	1.1170
8	256	50.6033	3.5255	10.5919	1.1205

Table 5 Accuracy Measurement of Adamax Optimizer

Batch Size	LSTM Cell	Train		Test	
		RMSE	MAPE	RMSE	MAPE
2	64	50.7322	3.5321	10.5528	1.1180
2	128	53.3059	3.7020	10.8413	1.1790
2	256	53.6841	3.7539	10.7333	1.1181
4	64	50.4526	3.52	10.5487	1.1174
4	128	54.5169	3.8103	10.7952	1.1189

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Batch Size	LSTM Cell	Train		Test	
		RMSE	MAPE	RMSE	MAPE
4	256	51.3964	3.5757	10.6783	1.1356
8	64	**50.2922**	**3.5122**	**10.5033**	**1.1164**
8	128	52.8477	3.6748	10.7221	1.1438
8	256	51.0992	3.5558	10.6502	1.1328

Table 6 Accuracy Measurement of Nadam Optimizer

Batch Size	LSTM Cell	Train		Test	
		RMSE	MAPE	RMSE	MAPE
2	64	48.1664	3.3635	10.8778	1.1972
2	128	53.9095	3.7571	10.7336	1.1221
2	256	**39.6097**	**2.5963**	10.5026	**1.0738**
4	64	49.2149	3.4318	**10.4697**	1.1162
4	128	53.0404	3.7044	10.6557	1.1179
4	256	48.7682	3.4001	10.8291	1.1891
8	64	50.2210	3.5198	10.4698	1.1148
8	128	52.3653	3.6504	10.6307	1.1189
8	256	51.3247	3.5888	10.5790	1.1171

Table 7 Accuracy Measurement of RMSProp Optimizer

Batch Size	LSTM Cell	Train		Test	
		RMSE	MAPE	RMSE	MAPE
2	64	**35.0626**	**2.2923**	10.6901	1.0785
2	128	37.055	2.3976	9.9757	1.0735
2	256	39.3177	2.5324	**9.2457**	**1.0679**
4	64	49.3952	3.4459	10.4688	1.1162
4	128	53.3086	3.7263	10.6698	1.1177
4	256	50.6842	3.534	10.5709	1.1177
8	64	50.4447	3.5367	10.4893	1.1148
8	128	52.7091	3.6777	10.6369	1.1179
8	256	49.6777	3.5255	10.6353	1.147

These results indicate that RMSProp, Adam, and Nadam optimizer are promising optimizers for this case. But further study in this case is needed considering the difficulty of obtaining the dataset. Due to the lack of obtained satellite datasets, the shoreline dataset each year does not represent the shoreline for that year. Therefore, finding a better dataset will be a future work.To see illustration of the results, next plots of the best four optimizers are presented in Figure 8 – Figure 11. Performances of RMSprop, Adam, and Nadam given in Figure 8, Figure 9, and Figure 10, respectively are in better agreement with the actual data of Eretan shoreline compared with performance of Adamax optimizer described in Figure 11.

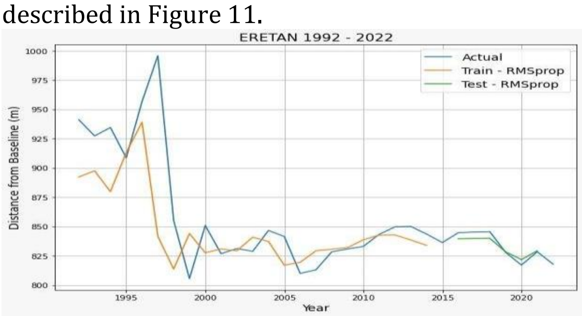

Figure 8. Plot of RMSProp performance.

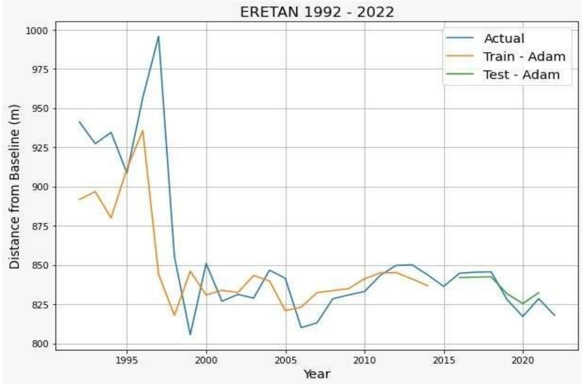

Figure 9. Plot of Adam performance.

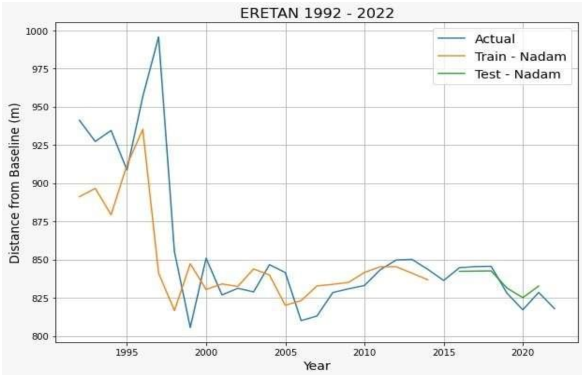

Figure 10. Plot of Nadam performance.

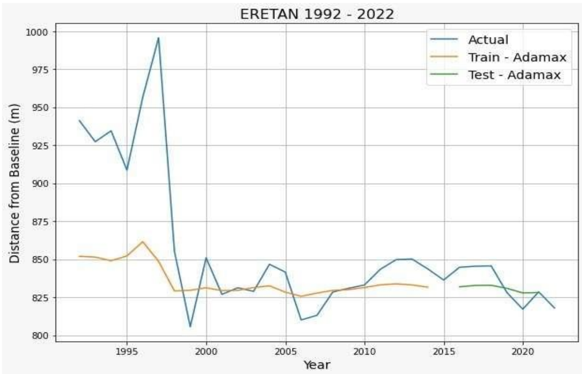

Figure 11. Plot of Adamax performance.

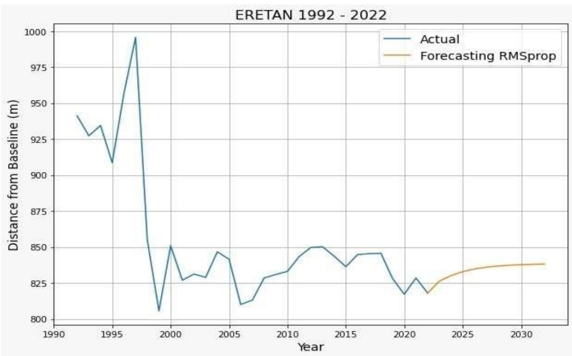

Figure 12. LSTM ten years forecasting

From the previous result, the best scenario of the LSTM is using RMSProp optimizer with two LSTM cells and two batch size 2. This scenario is used to predict shoreline changes within the next 10 years (2023–2032). The prediction of the shoreline at the 251 transect point is depicted in Figure 12. The figure shows that the prediction result of the shoreline changes at the 251 transect point shows slight accretion. This result, however, should be interpreted with caution as the lack of satellite datasets makes it challenging to obtain accurate data for each year. Moreover, another factor that influenced the data is the activity of land use growth near the shoreline. Hence, further investigation is needed to obtain a better understanding of the shoreline changes on Eretan beach. The investigation will be set as a future goal.

The prediction of shoreline changes using machine learning algorithms can help in developing effective strategies for managing coastal erosion. The findings of this study can be used by the government and other stakeholders to plan and implement measures to protect the beach from further erosion. Furthermore, this study highlights the importance of utilizing open-source tools for scientific research. The use of open-source tools, such as CoastSat and Quantum Geographic Information System, can significantly reduce the cost and increase the efficiency of research. This can also promote collaboration and knowledge sharing among researchers, which can lead to more effective solutions for addressing environmental issues.

However, this study has some limitations. Due to the difficulty of obtaining the dataset, the shoreline dataset for each year does not represent the shoreline for that year. Therefore, further study is needed to find a better dataset to improve the accuracy of the results. In addition, it is important to note that the prediction results are limited to a specific transect point and may not be representative of the entire beach.

Moreover, there are several challenges in managing coastal erosion. Climate change, sea level rise, and human activities are some of the major factors that contribute to coastal erosion. Therefore, effective strategies for managing coastal erosion must consider these factors. Coastal protection structures, such as breakwaters and groynes, can be effective in reducing erosion rates. However, these structures can also have adverse effects on the environment, such as altering sediment transport and affecting the habitats of marine species. Therefore, a balance must be struck between protecting the beach and preserving the environment.

The study on the shoreline change on Eretan Beach using the LSTM algorithm and various optimizer functions has provided valuable insights into the performance of these functions. The results indicate that the RMSProp, Adam, and Nadam optimizer functions are promising optimizers for this case, with the best performance achieved by RMSProp. The prediction of shoreline changes using machine learning algorithms can help in developing effective strategies for managing coastal erosion. The findings of this study can be used to develop effective strategies for managing coastal erosion and highlight the importance of utilizing open-source tools for scientific research. However, further study is needed to find a better dataset to improve the accuracy of the results. Effective strategies for managing coastal erosion must consider the challenges posed by climate change, sea level rise, and human activities while maintaining a balance between protecting the beach and preserving the environment.

CONCLUSION

The results of this research demonstrate the potential of using LSTM for predicting shoreline changes. The method provides a more accurate and efficient way of forecasting shoreline changes compared to traditional methods. The RMSProp optimizer function was found to have the best accuracy results for predicting shoreline changes using the scenario with a batch size of 2 and 64 LSTM cells for training, and a batch size of 2 and 256 LSTM cells for testing. The RMSE and MAPE values obtained for this scenario were 35.06258 and 2.29232 for training, and 9.2457 and 1.06786 for testing, respectively. The prediction of shoreline changes at the 251 transect point for the next ten years showed slight accretion. The implementation of the method can be further improved by obtaining more accurate datasets, especially satellite datasets, to increase the accuracy of the predictions. Finding more accurate database and increasing performance of the model are set as the future works.

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