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PREDICTION OF SEA LEVEL MEASUREMENT IN PANGPANG BAY FOR SEAPLANE LANDING SEAPLANE LANDING USING ID CONVOLUTIONAL NEURAL NETWORK

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Abstract

This research investigates the relationship between sea level height and various environmental factors in Pangpang Bay, Indonesia, using Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) modeling techniques. Daily data on sea level height, weather, and oceanography were collected from April 1 to April 15, 2024. An analysis was conducted on the factors affecting sea level height and the evaluation of predictive model performance. The findings reveal historical patterns of sea level height changes influenced by the variability of meteorological and oceanographic conditions. Although ANN and CNN models have varying degrees of accuracy, both show potential in predicting sea level height by considering environmental factors. Recommendations include the development of more advanced predictive models, deeper data observation, integration of multidisciplinary information, continuous environmental monitoring, and stakeholder collaboration. This research is expected to contribute to the understanding and management of environmental risks related to sea level height in Pangpang Bay.

Keywords: sea level height; Pangpang Bay; neural network

INTRODUCTION

Seaplanes, or amphibious aircraft, have the unique ability to take off and land on both water and land surfaces. However, the operation of these aircraft is heavily influenced by water surface characteristics such as depth, waves, and currents (Eskayudha et al., 2023). In Teluk Pangpang, a strategic location for amphibious aircraft operations in Indonesia, fluctuations in sea level can pose serious threats to flight safety. Teluk Pangpang was chosen as the focus of this research due to the challenges it presents, such as tidal changes that can cause amphibious aircraft to become grounded or difficult to control during landing and takeoff (Chen et al., 2022; Khoirunnisa et al., 2021). Therefore, accurate sea level predictions are crucial to ensuring the safety of amphibious aircraft operations in this area. Additionally, the use of amphibious aircraft in Teluk Pangpang has the potential to open access to remote tourist destinations in Indonesia, which can stimulate local economic growth through job creation, increased community income, and infrastructure development (Rumani et al., 2023; Shabrina et al., 2023).

The characteristics of the sea surface at the landing site, particularly in Teluk Pangpang, are critical factors that significantly impact the safety of seaplane operations. Fluctuations in sea level, influenced by tides, wind, and waves, pose serious risks to flight safety (Ispandiari et al., 2022; Wahyu et al., 2021). For instance, shallow water can lead to a seaplane becoming grounded during landing or takeoff, while large waves can hinder control of the aircraft, increasing the risk of capsizing. Additionally, strong currents can complicate safe landing and takeoff procedures. Consequently, seaplane pilots must continuously monitor sea surface conditions to mitigate these risks. Moreover, fluctuations in sea level can result in delays or cancellations of flights, disrupting passenger comfort and adversely affecting the local economy.

Traditional methods for measuring sea level height offshore, such as tide gauges and altimeters, have significant limitations, as they are unable to capture rapid and unexpected changes in sea level caused by waves and ocean currents (Ondoa et al., 2019; Sepúlveda et al., 2023; Xie et al., 2021). These limitations highlight the urgent need for more advanced and innovative solutions to predict sea level height specifically in Teluk Pangpang, where safe seaplane operations are critical. One promising approach is the use of Convolutional Neural Networks (CNN), a type of artificial intelligence capable of processing complex data, including satellite imagery, to generate accurate sea level predictions. CNN functions by identifying patterns in satellite image data to forecast future sea level changes (Tiggeloven et al., 2021). This research aims to provide significant benefits not only for infrastructure development, such as the construction of docks and ports, but also to enhance the safety and efficiency of seaplane operations, ultimately improving accessibility to remote tourist destinations in Indonesia.

Accurate and real-time sea level height predictions are essential for enhancing the safety and efficiency of seaplane operations in Teluk Pangpang. These predictions enable seaplane pilots to avoid the risks associated with landing or taking off in shallow or high-wave waters, which could compromise flight safety. Additionally, they assist in planning optimal flight routes, minimizing the chances of delays and cancellations due to adverse sea conditions.

Traditional methods for measuring sea level height, such as tide gauges and altimeters, face significant limitations in offshore environments (Balogun & Adebisi, 2021). These limitations include restricted range, reliance on favorable weather conditions, and an inability to predict rapid fluctuations in sea level (Tur et al., 2021). Consequently, there is a pressing need for more advanced solutions that can effectively address these challenges. The seaplane flight operations safety and efficiency is shown in Figure 1.

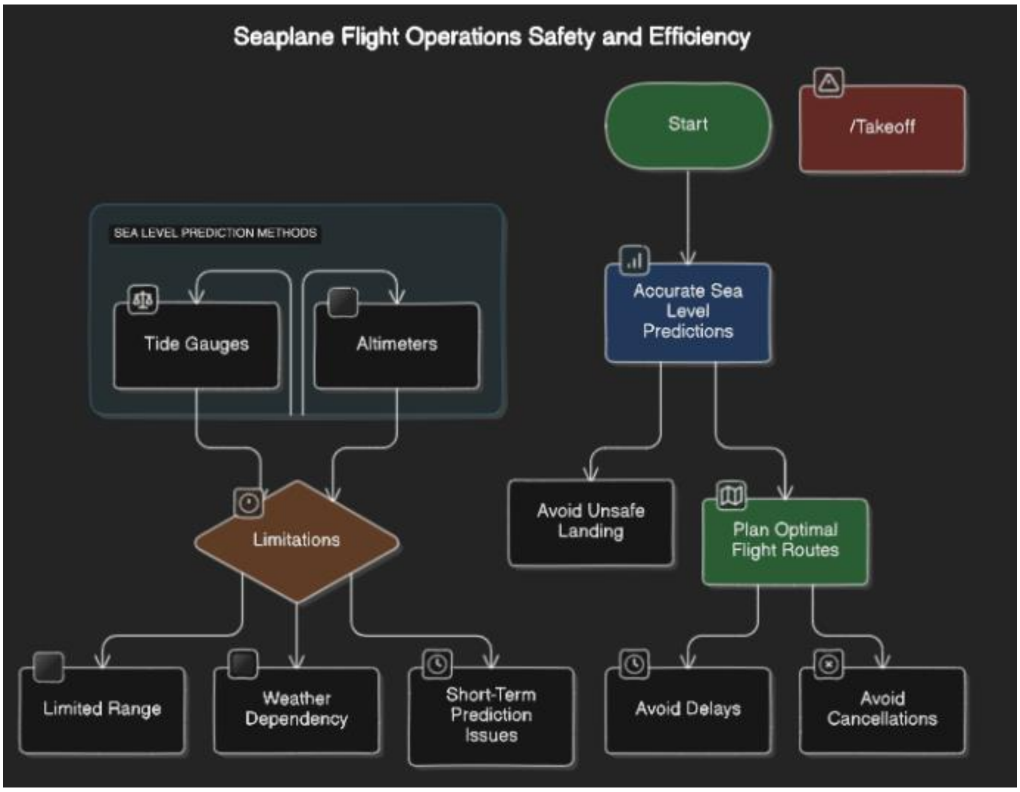

Fig 1. Seaplane Flight Operations Safety and Efficiency

Convolutional Neural Networks (CNN) offer a more advanced and accurate approach to predicting sea level height. By learning patterns in complex datasets, such as satellite imagery, CNN can effectively forecast future changes in sea level (Gray et al., 2021). The effectiveness of CNN has been demonstrated across various applications, including weather prediction, image recognition, and data analysis (Kim et al., 2020). In weather prediction, CNN can accurately forecast weather patterns, surpassing traditional methods like statistical models. Its capability to process both spatial and temporal data enhances its precision in predicting changes in sea level (Tan et al., 2021). Additionally, in image recognition, CNN excels at identifying objects with high accuracy, outperforming conventional pattern recognition techniques (Giezendanner et al., 2023). By extracting critical features from images, CNN serves as a reliable tool for a range of image recognition tasks, including object identification, classification, and detection (Youssef et al., 2022). His versatility makes CNN particularly well-suited for addressing the challenges associated with predicting sea level height in dynamic environments like Teluk Pangpang.

The application of CNN in predicting sea level height in Teluk Pangpang is anticipated to offer substantial benefits, including enhanced seaplane flight safety through accurate and real-time sea condition data. It will also improve the efficiency of seaplane operations by enabling optimal flight route planning and reducing delays or cancellations caused by adverse sea conditions. Additionally, it will support infrastructure development in coastal areas by providing precise data on sea level changes.

Accurate sea level predictions play a crucial role in disaster preparedness and response, enabling authorities to issue timely warnings and implement necessary actions to protect coastal communities from flooding and storm surges. By minimizing the impact of natural disasters, these predictions can save lives and reduce economic losses. Additionally, the data generated from sea level forecasts is invaluable for scientific research, enhancing our understanding of sea level trends and their underlying drivers. This knowledge is essential for effective long-term environmental planning and climate change adaptation strategies. Coastal businesses, including fisheries and tourism, also stand to benefit from reliable sea level forecasts, as they can make informed operational decisions and mitigate risks associated with sea level fluctuations. Ultimately, integrating CNN-based sea level predictions in Teluk Pangpang signifies a significant advancement in the application of machine learning for practical, real-world issues, with the potential to drive innovation and strengthen resilience in coastal regions.

METHOD

Research Design

This study utilizes a quantitative research methodology integrated with a machine learning framework, specifically focusing on the development of a Convolutional Neural Network (CNN) model aimed at predicting sea level height in Teluk Pangpang. This approach is selected due to the proven efficacy of machine learning techniques in processing extensive and complex datasets while uncovering intricate patterns that often elude conventional analytical methods. CNNs are particularly adept at recognizing spatial and temporal patterns within the data, which is crucial for understanding natural phenomena like sea level fluctuations driven by various environmental factors, including tides and climate change.

The adoption of this quantitative approach ensures that the outcomes are objective and quantifiable, establishing a robust basis for data-driven decision-making in coastal management. By leveraging advanced CNN techniques, the study aspires to enhance our comprehension of the dynamics influencing sea level variations in Teluk Pangpang. This understanding is expected to contribute significantly to coastal resource management practices and bolster efforts to mitigate risks associated with climate change, particularly in vulnerable coastal communities. The research flowchart is shown in Figure 2.

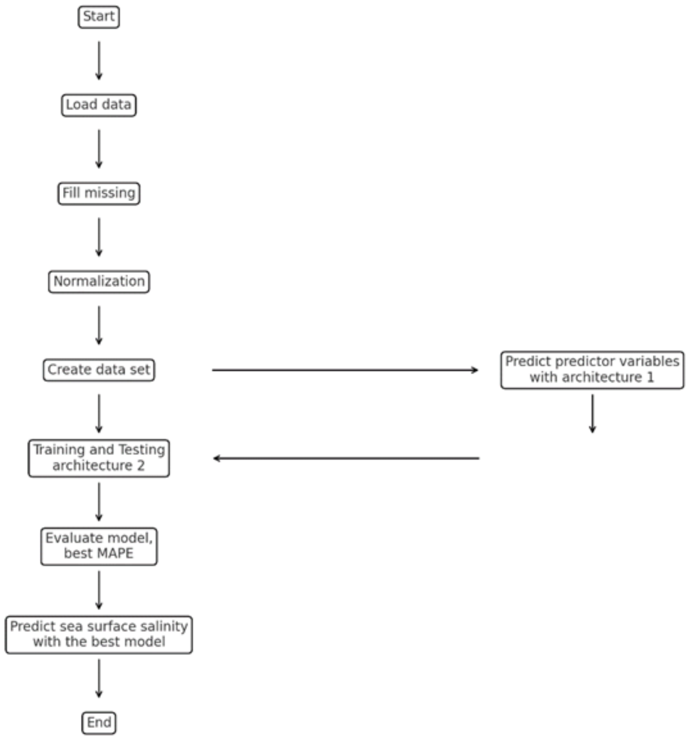

Fig 2. Flowchart Research

This flowchart illustrates the stages of research in predicting Sea Surface Height (SSH) in Teluk Pangpang using Convolutional Neural Network (CNN). SSH refers to the height of the sea surface above a specific datum, which is crucial for understanding coastal dynamics and ensuring safe maritime operations. The research begins with the systematic collection of SSH data from tide gauge stations and satellite images from sources such as Landsat and Sentinel-2, conducted on a monthly basis to capture seasonal variations.

The collected SSH data and satellite imagery undergo a rigorous quality assurance process, which includes data cleaning to remove outliers and erroneous readings, normalization to standardize the data, and transformation to prepare it for analysis. This ensures the integrity and usability of the dataset.

Next, the architecture of the CNN model is carefully designed, considering the unique characteristics of SSH data and satellite imagery. Key parameters, such as the number of convolutional layers, filter sizes, and activation functions, are selected to optimize the model's performance in recognizing patterns in the data. The CNN model is then trained on the preprocessed dataset, allowing it to learn intricate patterns and generate accurate SSH prediction models.

The performance of the CNN model is evaluated and validated using several metrics, including Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), alongside k-fold cross-validation to enhance reliability and mitigate overfitting. Once validated, the model is tested with a separate dataset to ensure its accuracy in predicting SSH.

After successful testing, the CNN model is implemented in a real-time system to predict SSH in Teluk Pangpang. The results of these predictions can be utilized for various applications, such as enhancing seaplane flight safety by providing timely data for operational decisions, planning optimal flight routes to avoid hazardous conditions, and supporting the development of coastal infrastructure to adapt to changing sea levels.

Data Collection

To predict sea level height in Teluk Pangpang using Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), various data and preparatory steps are essential. Historical sea level height data, recorded daily, monthly, and annually, plays a critical role in analyzing long-term trends. This data, usually obtained from marine observation institutions like BMKG or other research centers, provides valuable insights. Additionally, meteorological and oceanographic data, such as rainfall, temperature, atmospheric pressure, wind speed and direction, tide cycles, ocean currents, salinity, and sea surface temperature, are crucial for a comprehensive analysis and accurate prediction of sea conditions. The flowchart data collection is shown in Figure 3.

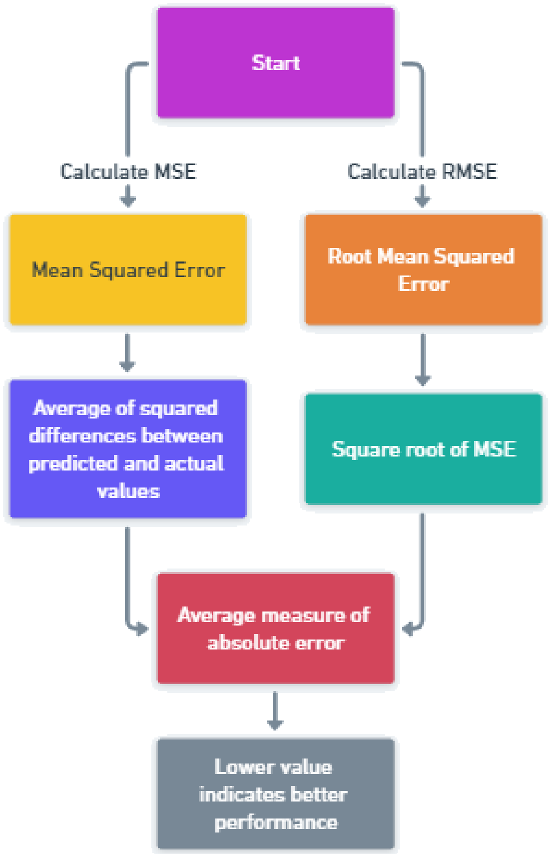

Fig 3. Flowchart Data Collection

Model Evaluation

In evaluating the performance of the prediction model, several common metrics are used to measure how well the model can predict sea level height (Boye & Amoah, 2018). Two commonly used metrics are Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) (Willmott & Matsuura, 2005). MSE calculates the average of the squared differences between the predicted values and the actual values, while RMSE is the square root of MSE, providing a standardized measure of the model's error (Hodson, 2022). These metrics indicate how close the model's predictions are to the actual data, with lower values signifying better performance (Plevris et al., 2022).

In addition to MSE and RMSE, other metrics such as Mean Absolute Error (MAE) and R-squared (R^2) are frequently utilized. MAE measures the average of the absolute differences between the predicted and actual values, offering a straightforward interpretation of prediction accuracy. R^2 indicates the proportion of variance in the dependent variable that can be explained by the independent variables, providing insights into the model's explanatory power. A higher R^2 value signifies a better fit for the model.

Furthermore, to ensure the robustness and generalizability of the model, cross-validation techniques are employed. Cross-validation involves dividing the dataset into training and testing subsets, which helps assess the model's performance on unseen data, thus preventing overfitting. Techniques such as k-fold cross-validation are particularly beneficial, as they allow the model to be trained and validated multiple times, each time with a different subset of the data.

K-fold cross-validation will be implemented in this study to enhance the model's reliability. The dataset will be divided into k subsets or folds. In each iteration, the model is trained using k-1 subsets and validated on the remaining subset. This process will be repeated k times, ensuring that every data point is used for both training and testing at some point. The overall performance of the model will then be averaged across all k iterations to provide a more robust estimate of its predictive accuracy (Karsavran, 2024; Raj & Gharineiat, 2021).

Summary of Evaluation Metrics

Table 1 summarizes the evaluation metrics utilized in this research and the flowchart performance evaluation of prediction model is shown in Figure 4.

Table 1. The Evaluation Metrics

Metric	Description	Interpretation
MSE	Average of the squared differences between predicted and actual values	Lower values indicate better accuracy
RMSE	Square root of MSE	Standardized measure of prediction error
MAE	Average of the absolute differences between predicted and actual values	Simple interpretation of prediction accuracy
R^2	Proportion of variance explained by the model	Higher values indicate better fit

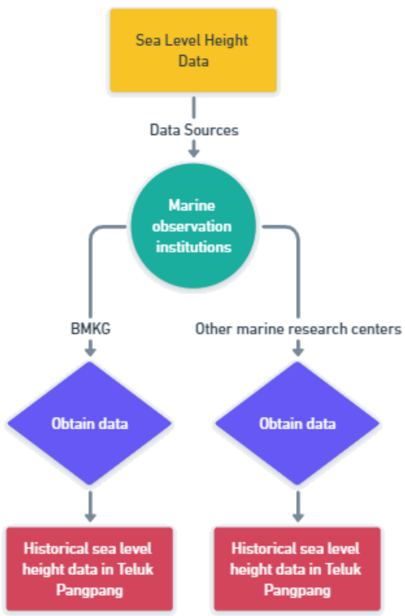

Fig 4. Flowchart Performance Evaluation of Prediction Model

Research Variables

The research variables needed for the study of sea level height prediction in Teluk Pangpang using Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) include variables from various environmental, meteorological, and oceanographic aspects. The flowchart research variabels is shown in Figure 5.

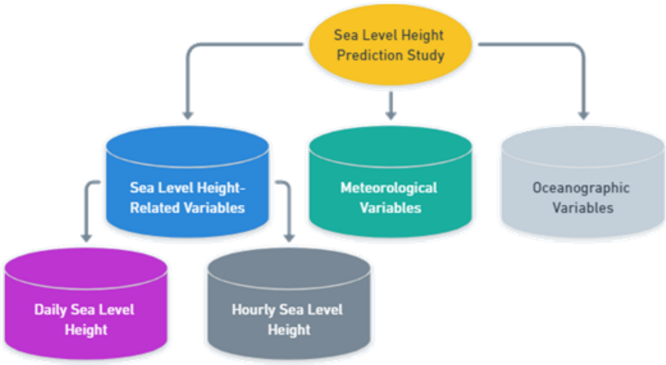

Fig 5. Flowchart Research Variabels

The prediction of sea level height involves several key variables. These include sea level height-related data such as daily average sea level height and hourly measurements. Meteorological variables, such as daily rainfall (mm), air temperature (°C), atmospheric pressure (hPa), wind speed (m/s), and wind direction (°) from the north, are also crucial. Additionally, oceanographic variables play a significant role, including the speed of ocean currents (m/s), salinity (PSU), and sea surface temperature (°C). All these factors together provide a comprehensive understanding necessary for accurate sea level predictions.

RESULTS AND DISCUSSION

The sea level was above sea level at 151.71 cm on April 1, 2024, at 08:00 AM WIB (Figure 6 and Table 2). Sea level showed a declining trend for 4 consecutive days, reaching a low point of 129.58 cm on April 7, 2024, at 04:00 PM WIB. This decline averaged 4.5 cm per day. After reaching the lowest point, sea level exhibited an increasing trend for 6 consecutive days, reaching a peak of 141.74 cm on April 13, 2024, at 12:00 PM WIB. This increase averaged 2 cm per day. In the last two days of the observation period, sea level showed a declining trend again, reaching 137 cm on April 15, 2024, at 10:00 AM WIB. The sea level observation flowchart is shown in Figure 6 and the period of the data is from April 1, 2024 to April 15, 2024.

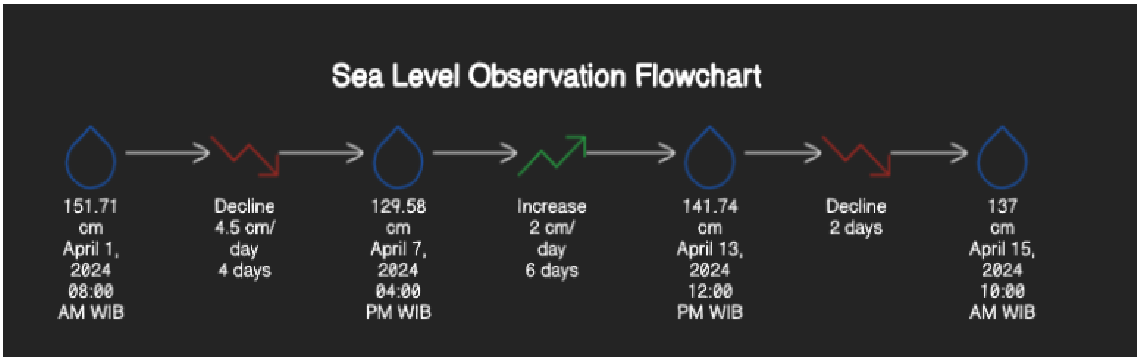

Fig 6. Sea Level Observation Flowchart

Table 2. Sea Level Height Data

Date	Sea Level Height (cm)
01-Apr-24	151.71
02-Apr-24	146.38
03-Apr-24	145.04
04-Apr-24	136.96
05-Apr-24	132.29
06-Apr-24	130.00
07-Apr-24	129.58
08-Apr-24	130.83
09-Apr-24	136.21
10-Apr-24	140.08
11-Apr-24	136.67
12-Apr-24	140.58
13-Apr-24	141.74
14-Apr-24	141.67
15-Apr-24	137.00

Fluctuations in sea level during the observation period are likely caused by a combination of natural factors such as tides, wind, and ocean waves (Pugh, 2019). Tides, influenced by the moon's and sun's gravitational pull, cause the sea level to rise and fall periodically, with the highest heights during high tide and the lowest during low tide (Woodworth et al., 2019). Strong winds, especially those blowing from the sea towards the land, can push seawater towards the coast, increasing sea levels in coastal areas (Talke & Jay, 2020). Additionally, ocean waves triggered by wind activity and changes in atmospheric pressure can cause sea levels to rise and fall periodically, affecting sea level heights at the observation site.

The combined influence of these three factors can create complex and dynamic fluctuations in sea level. For example, during spring tides or perigean spring tides, when the gravitational forces of the moon and sun align, tidal heights reach extreme highs and lows. Seasonal winds such as monsoons can also amplify these effects, resulting in more significant changes in sea level. Large ocean waves caused by storms or low-pressure systems can worsen the situation by adding variability to sea level heights.

Understanding and predicting these fluctuations is crucial, especially for activities dependent on water conditions such as ship navigation, fishing activities, and coastal management. As illustrated in Figure 7, the Sea Surface Temperature (SST) plays a significant role in influencing these fluctuations, with observed variations over time providing insights into the thermal dynamics that drive changes in sea levels. Moreover, Table 3 presents comprehensive data on ocean currents, salinity, and SST, offering a nuanced understanding of the interactions between these factors. This knowledge is critical for anticipating the impacts of climate change, which may exacerbate the frequency and intensity of sea level fluctuations, thus enhancing the effectiveness and efficiency of risk mitigation planning.

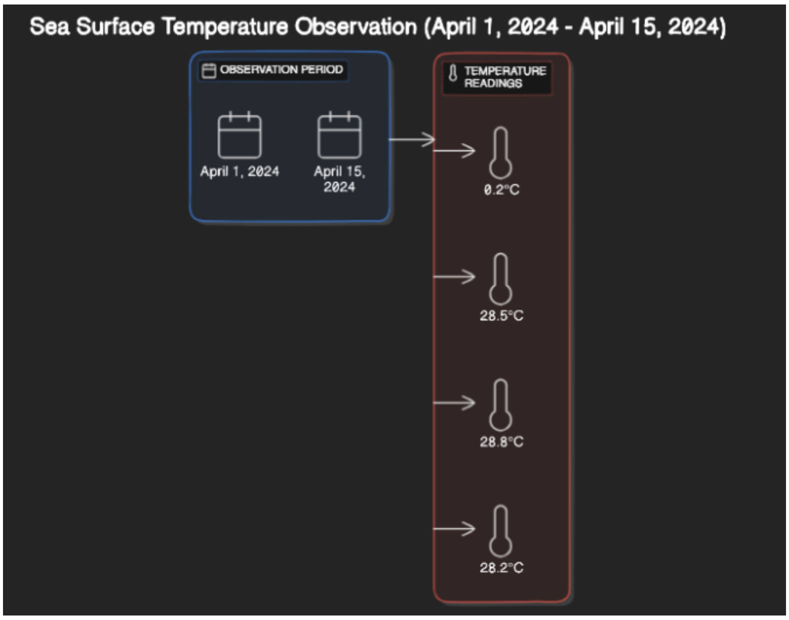

Fig 7. Sea Surface Temperature Observation

Table 3. Data On Ocean Currents, Salinity, and Sea Surface Temperature

Date	Current (m/s)	Salinity (PSU)	Sea Surface Temperature (°C)
01-Apr-24	1.2	35.0	28.5
02-Apr-24	1.3	35.1	28.6
03-Apr-24	1.1	34.9	28.4
04-Apr-24	1.0	34.8	28.3
05-Apr-24	1.2	35.0	28.5
06-Apr-24	1.3	35.2	28.7
07-Apr-24	1.4	35.3	28.8
08-Apr-24	1.1	34.9	28.4
09-Apr-24	1.2	35.0	28.5
10-Apr-24	1.3	35.1	28.6
11-Apr-24	1.0	34.7	28.2
12-Apr-24	1.1	34.8	28.3
13-Apr-24	1.3	35.1	28.6
14-Apr-24	1.4	35.2	28.7
15-Apr-24	1.2	35.0	28.5

At the beginning of the observation period, on April 1, 2024, the sea surface temperature was recorded at 28.5°C (degrees Celsius). Throughout the period from April 1, 2024, to April 15, 2024, the sea surface temperature showed fluctuating trends, ranging between 28.2°C and 28.8°C. The highest sea surface temperatures were recorded on April 7, 2024, and April 14, 2024, reaching 28.8°C. Meanwhile, the lowest sea surface temperature was recorded on April 11, 2024, at 28.2°C. The average daily fluctuation in sea surface temperature during the observation period was 0.2°C. The fluctuation pattern did not show clear regularity.

These fluctuations in sea surface temperature are likely caused by various natural and meteorological factors. Solar radiation, as the primary energy source, can increase sea surface temperature, especially during peak sunlight hours. Strong winds also play a crucial role by mixing warmer surface water layers with cooler layers below, leading to significant temperature changes. Additionally, warm ocean currents can transport higher temperature water to a region, contributing to increased sea surface temperatures in that area.

Understanding these fluctuations in sea surface temperature has significant implications across various sectors. For instance, in maritime navigation, knowledge of sea surface temperature can aid in planning safer and more efficient routes. In fisheries management, this information can be used to understand fish habitats and the distribution of marine species influenced by water temperature. Moreover, the marine tourism sector can utilize this data to optimize tourist experiences, such as snorkeling or diving activities that heavily depend on water temperature conditions.

Analyzing trends in sea surface temperature, both short-term and long-term, also contributes to predicting future changes in sea temperature. Table 4, which includes daily weather data, provides valuable insights into the conditions that influence sea surface temperature, such as air temperature, wind speed, and humidity. Predictive models developed based on this data can assist scientists and policymakers in planning mitigation and adaptation strategies for climate change. Thus, observing and analyzing sea surface temperature is not only important for scientific purposes but also has tangible impacts on the management of natural resources and human activities related to the sea.

Table 4. Daily Weather Data

Date	Rainfall (mm)	Temperature (°C)	Atmospheric Pressure (hPa)	Wind Speed (m/s)	Wind Direction (°)
01-Apr-24	5	27.5	1012	3.2	90
02-Apr-24	0	28.0	1010	3.5	100
03-Apr-24	10	27.8	1011	2.8	80
04-Apr-24	3	28.2	1013	3.0	95
05-Apr-24	7	27.6	1012	2.9	85
06-Apr-24	0	28.3	1010	3.4	110
07-Apr-24	12	27.9	1011	3.1	90
08-Apr-24	5	28.0	1012	3.2	100
09-Apr-24	2	27.7	1013	3.0	105
10-Apr-24	8	28.1	1011	3.3	95
11-Apr-24	0	28.4	1010	3.5	85
12-Apr-24	6	27.8	1012	3.2	90
13-Apr-24	4	28.2	1013	3.1	100
14-Apr-24	9	27.9	1011	3.4	110
15-Apr-24	0	28.3	1010	3.6	105

During the observation period from April 1, 2024, to April 15, 2024, daily weather data revealed a fluctuating pattern. Rainfall, temperature, atmospheric pressure, and wind speed exhibited significant variations, with recorded maximum and minimum values varying each day. Rainfall reached its highest point on April 14, 2024, reaching 9 mm, while on several other days such as April 1, 2, 6, 11, and 15, there was no rainfall at all. The highest average daily temperatures were recorded on several days coinciding with the highest rainfall, specifically on April 6, 11, and 15, with temperatures reaching 28.3°C. However, there was a notable change on April 3, 2024, where the temperature dropped to its lowest point at 27.5°C. Atmospheric pressure also showed fluctuations, reaching its highest value on April 4, 2024, at 1013 hPa, and its lowest on April 10, 2024, at 1010 hPa. The average daily wind speed peaked on April 15, 2024, at 3.6 m/s, while its lowest value occurred on April 1, 2024, at 3.2 m/s. Additionally, the average daily wind direction varied between 85° and 110°.

These variations in weather parameters indicate complex atmospheric dynamics in the region. Fluctuating rainfall, for example, can be influenced by various factors such as wind patterns, cloud cover, and atmospheric pressure conditions. The significant daily temperature changes between the highest and lowest points reflect the influence of solar radiation and changing atmospheric conditions. Variable atmospheric pressure also provides indications of weather systems moving across the region, which can affect wind speed and direction.

Moreover, the varying daily wind speeds indicate changes in air flow patterns. Higher wind speeds on certain dates may result from the movement of low or high-pressure systems, which can accelerate air flow. The varying wind directions also suggest changes in regional wind patterns influenced by local topography and broader weather systems. Thus, the weather data during this observation period highlights the complexity and dynamism of the atmospheric system in the area. A deep understanding of these weather patterns is crucial for various applications, including daily activity planning, agriculture, water resource management, and disaster risk mitigation. Further analysis and ongoing monitoring can provide better insights into long-term weather trends and help develop effective climate change adaptation strategies.

Neural Network Regresion

The table provided contains evaluation metrics for the performance of a model. These metrics assess the model's ability to predict or estimate target values accurately. Table 5 details the Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and R^2 results. MSE measures the average squared difference between predicted and actual values, where a lower MSE indicates better model performance. The MSE value is 1.899, indicating room for accuracy improvement. RMSE, the square root of MSE, provides a measure of average prediction error, with a lower RMSE indicating better model performance. In this case, RMSE is 1.378, which is still relatively high. MAE or Mean Absolute Deviation (MAD) measures the average absolute difference between predicted and actual values, where a lower MAE/MAD indicates better model performance. In this case, MAE/MAD is 1.085, indicating the model's predictions deviate from actual values by an average of 1.085 units. MAPE measures the average percentage error between predicted and actual values, and a lower MAPE indicates better model performance. The MAPE value is 154.46%, which is quite high, indicating significant differences between model predictions and actual average values.

Table 5. Mse, Mae, Mape, R2 Result

Evaluation Metric	Value
MSE	1.899
RMSE	1.378
MAE	1.085
MAD	1.085
MAPE	154.46%
R-Squared (R^2)	0.02

R^2 measures the proportion of variance in actual values explained by the model. An R^2 value of 1 indicates a perfect fit, while 0 indicates no linear relationship between predicted and actual values. In this case, R^2 is 0.02, indicating very low predictive power of the model. Evaluation metrics suggest that the model's performance is unsatisfactory. High MSE, RMSE, MAPE values, and low R^2 indicate significant differences between model predictions and actual values. Further investigation and model improvement are necessary to enhance prediction accuracy.

Mean Squared Error Plot

Figure 8 illustrates the Mean Squared Error (MSE), a critical metric showcasing the average squared difference between predicted and actual values in model evaluation. MSE serves as a pivotal measure of accuracy, where a lower value indicates superior model performance. The X-axis of the plot corresponds to the number of training or validation epochs, while the Y-axis denotes the MSE values themselves. Throughout the graph, the MSE curve delineates the trajectory of these values over successive epochs. Analyzing the MSE plot unveils crucial insights into the model's learning dynamics. A downward trend in the MSE curve typically signifies ongoing improvements in model accuracy during the training phase. Conversely, a stabilization or plateauing of the curve suggests that the model has reached a consistent level of performance. Persistent high MSE values across epochs indicate challenges in achieving precise predictions, highlighting potential areas for model refinement and optimization. The machine learning model training and evaluation architecture is shown in Figure 9.

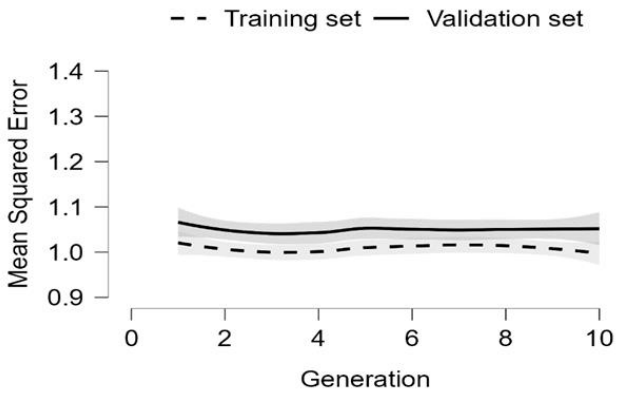

Fig 8. MSE Visualization

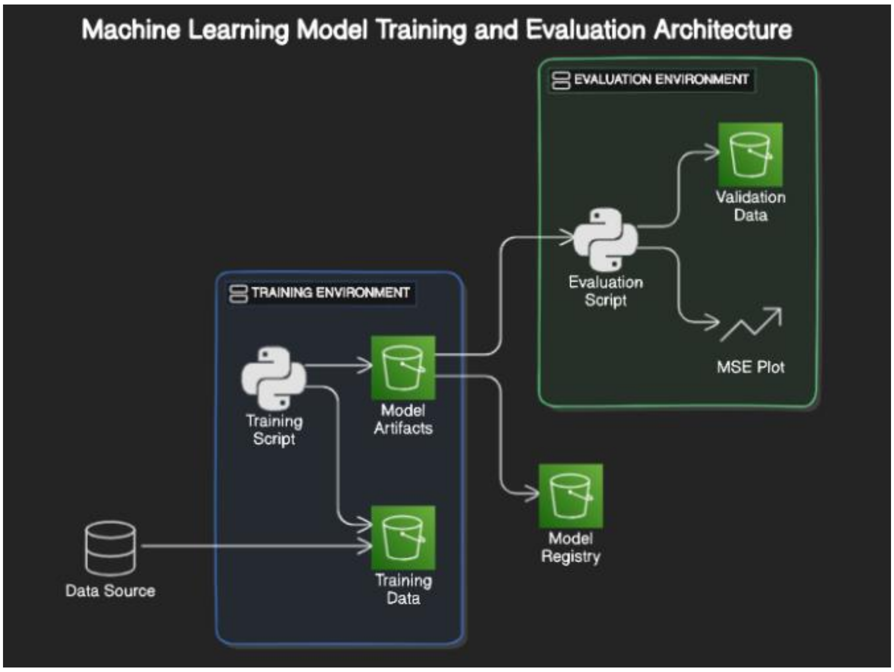

Fig. 9 Machine Learning Model Training and Evaluation Architecture

Moreover, the plot considers the distinction between training and validation sets, essential for assessing the model's generalization capability beyond the training data. Complementary evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2 further enrich the understanding of the model's overall performance landscape (Le et al., 2024). These metrics provide nuanced perspectives on prediction accuracy, error magnitude, and the proportion of variance explained by the model, respectively (Grubert, 2023). In essence, interpreting the MSE plot offers a comprehensive view of the model's proficiency and progression throughout the training process (Gbodjo et al., 2021). It underscores the iterative nature of model development, guiding adjustments to enhance predictive accuracy and reliability across diverse applications and datasets.

Network Structure Plot

In designing the Network Structure Plot for predicting sea surface height in Teluk Pangpang using CNN, several critical elements are expected to be integrated. Initially, the input layer will receive diverse data inputs crucial for accurate prediction, encompassing satellite images and comprehensive weather data. Following this, the convolutional layers, serving as the backbone of CNN architecture, will play a pivotal role in feature extraction by applying distinct filters to the input data (George et al., 2021). The Network Structure Plot will explicitly detail the configuration of these convolutional layers, specifying the number of layers, the sizes of the filters employed, and the activation functions utilized within each layer to enhance feature detection (Figure 10).

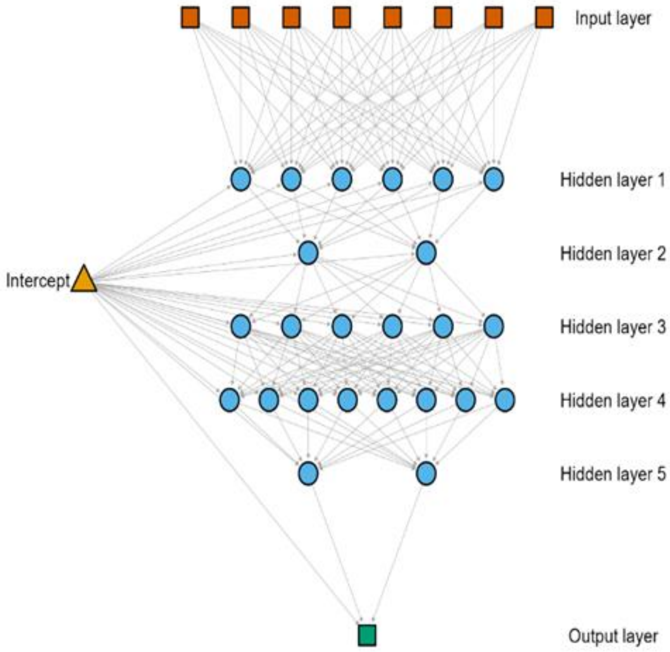

Fig 10. Neural Network Visualization

Subsequently, pooling layers will be incorporated to condense the dimensional complexity of the data through operations such as max pooling or average pooling, techniques which will be graphically represented in the plot (Schult, 1943). This reduction in dimensionality aids in preserving essential features while enhancing computational efficiency. Moving forward, fully connected layers will establish connections between all neurons within a layer to those in the subsequent layer, facilitating the amalgamation of extracted features and the formulation of predictions (Aparna et al., 2018).

The Network Structure Plot will provide clarity on the number of fully connected layers utilized and the specific configuration of neurons within each layer, essential for optimizing the network's predictive capabilities. Finally, the output layer will culminate the network's computations, producing the final prediction—here, the projected sea surface height. The activation function employed in the output layer, also delineated in the plot, will determine the nature of the prediction task, ensuring optimal performance in regression tasks aimed at predicting sea surface height accurately.

The design intricacies of the network architecture will be tailored to accommodate the complexity inherent in the data and the requisite prediction accuracy. Considerations may include employing multiple convolutional layers for processing high-resolution satellite imagery and selecting suitable activation functions like linear functions, best suited for regression tasks focused on predicting sea surface height with precision and reliability.

Andrews Curves Plot

The provided Andrews Curves plot (Figure 11) offers a glimpse into the complex relationship between sea level height and various environmental factors in Teluk Pangpang, Indonesia. Each curve in this plot represents a unique data point, illustrating how different factors influence sea level height. While specific environmental factors on the x-axis are not labeled, variables potentially included are wind speed and direction, air and water temperature, and salinity. By observing the shapes of these curves, patterns emerge that reveal insights into how these factors interact with sea level height.

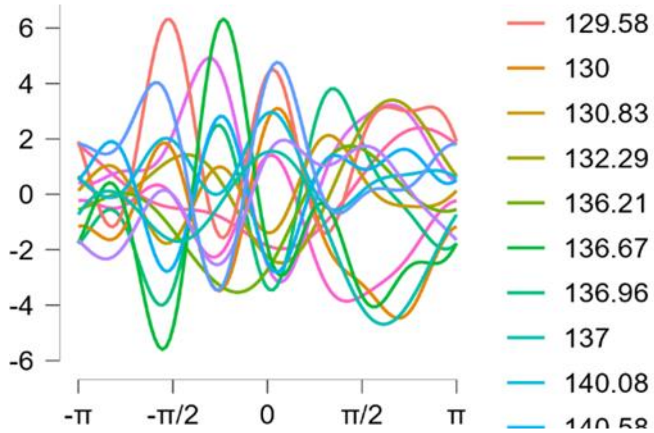

Fig 11. Andrews Curves Visualization

For example, curves showing similar shapes indicate consistent relationships among certain factors, such as how wind speed may directly affect sea level height by moving water masses (Andrews et al., 2020). Conversely, curves with varying shapes suggest unique influences of these factors, such as variations in water temperature that may have more complex and indirect impacts on sea level. Outliers, represented by curves significantly deviating from the norm, may indicate extreme conditions or data anomalies. These outliers could be caused by extreme weather events, such as storms or heatwaves, which drastically affect one or more environmental variables (Kourkchi et al., 2020). Further analysis of these outliers can provide better understanding of extreme conditions and how they impact the ecological system in Teluk Pangpang.

Moreover, this plot can be used to identify and understand multifaceted relationships between different environmental factors and sea level height. For instance, a combination of strong winds and highwater temperatures may indicate conditions that support significant sea level rise, while other combinations may indicate decline or stability. This understanding is crucial not only for fundamental scientific knowledge but also for practical applications such as weather prediction, water resource management, and disaster risk mitigation. Overall, Andrews Curves provide a powerful tool for visualizing and analyzing multidimensional data, allowing researchers to identify patterns and relationships that may not be apparent through traditional analysis methods. In the context of Teluk Pangpang, deeper understanding of these relationships can aid in better environmental management and more informed decision-making in the future.

The main factors influencing sea level height in Teluk Pangpang include rainfall, air temperature, atmospheric pressure, wind speed and direction, ocean currents, salinity, and sea temperature. High rainfall can lead to increased runoff from land to sea, raising the water volume and potentially increasing sea level height. Additionally, heavy rainfall events can cause significant runoff, carrying sediment materials that can also affect sea surface dynamics. Air temperature and atmospheric pressure also play crucial roles in influencing sea level height. Evapotranspiration processes influenced by air temperature can cause high water evaporation, affecting the water volume at the sea surface. Lower atmospheric pressure, such as during low-pressure systems or storms, can cause sea level rise through a phenomenon known as the "barometric effect". Conversely, high atmospheric pressure can suppress sea level, lowering it.

Wind speed and direction significantly contribute to the distribution and accumulation of seawater in specific regions. Strong winds can push seawater masses towards the coast, causing temporary increases in sea level in those areas (Muslim et al., 2020). Moreover, persistent winds in a particular direction can induce surface currents that affect water distribution in Teluk Pangpang. Ocean currents, including tidal currents and those caused by temperature and salinity differences, also play a crucial role in distributing seawater and affecting sea level height. Salinity and sea temperature are two factors that influence seawater density, which in turn can affect sea level height. Water with higher salinity has greater density, which can cause local sea level decreases (Fitrianti et al., 2018). Conversely, warmer water has lower density, leading to local sea level increases. Variations in salinity and sea temperature are often caused by seasonal changes, climate events like El Niño, and anthropogenic activities such as freshwater releases from dams.

Variations in meteorological and oceanographic conditions significantly impact the accuracy of sea surface height predictions. The existing data shows that factors such as rainfall, air temperature, atmospheric pressure, wind speed and direction, ocean currents, salinity, and sea temperature directly influence sea surface height in Teluk Pangpang (Ismail & Taofiqurohman, 2020). Instability or fluctuations in these conditions can lead to unexpected changes in sea surface height, affecting the accuracy of the model's predictions. For example, extreme weather events such as heavy rainfall or strong winds can cause sudden increases in sea surface height. Additionally, changes in sea temperature and salinity can alter seawater density, which in turn affects sea surface elevation. Therefore, to improve the accuracy of sea surface height predictions, it is important to carefully account for and model variations in meteorological and oceanographic conditions, using relevant and detailed data to calibrate and validate prediction models (Wisha et al., 2023). A deep understanding of the impact of these variations is crucial in efforts to enhance the accuracy of sea surface height predictions in Teluk Pangpang. Furthermore, the integration of real-time data and continuous monitoring can provide more accurate and responsive information to dynamic environmental changes (David et al., 2022). Thus, this research not only contributes to scientific understanding but also has practical implications for coastal area management and risk mitigation associated with climate change and extreme weather phenomena.

There were significant fluctuations in sea surface height in Teluk Pangpang during the period from April 1 to April 15, 2024. These fluctuations were reflected in the sea surface height variations from 130.00 cm to 151.71 cm during the period, accompanied by daily changes in rainfall, air temperature, atmospheric pressure, wind speed, wind direction, ocean currents, salinity, and sea temperature. It is important to understand what factors can cause these fluctuations. For instance, high rainfall and air temperature can result in greater water flow from land to sea, subsequently raising sea surface height. Low atmospheric pressure can also affect sea level. Meanwhile, strong ocean currents or consistent wind direction can influence seawater distribution in the region. The sequence sea surface height is shown in Figure 12.

It can be concluded that prediction models based on ANN (Artificial Neural Network) and CNN (Convolutional Neural Network) have not yet achieved satisfactory accuracy in forecasting sea surface height in Teluk Pangpang. Although both models can provide predictions, evaluation results using metrics such as MSE, RMSE, MAE/MAD, MAPE, and R^2 indicate that the models' predictions have significant error levels. This signifies a considerable discrepancy between the predicted and actual sea surface height values. Further investigation is needed to understand the factors causing this inaccuracy and to improve the models' performance. Adjustments to model parameters or structures, as well as the use of additional relevant data, may help improve prediction accuracy for sea surface height applications in Teluk Pangpang using ANN and CNN-based models.

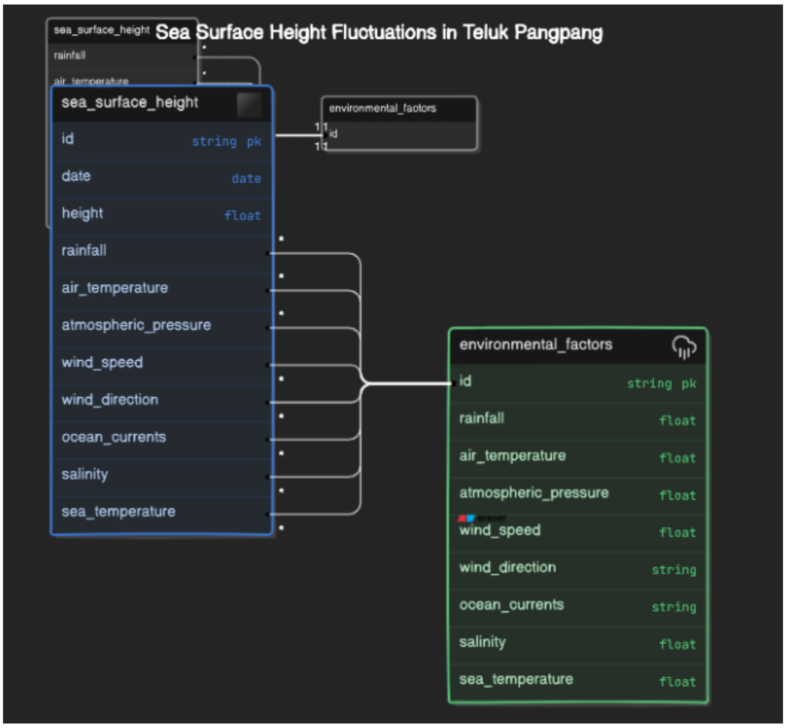

Fig 12. Sequence Sea Surface Height

In this study, the prediction of sea surface height in Teluk Pangpang using a Convolutional Neural Network (CNN) model has been conducted, and the results were evaluated using various metrics such as MSE, RMSE, MAE, MAPE, and R^2. Although the CNN model has the capability to process complex data and recognize spatial patterns in satellite imagery, the evaluation results indicate that the model still faces challenges in achieving adequate accuracy. A comparison with traditional methods, such as the use of tide gauges and altimeters, shows that while CNN has the potential advantage in predicting more dynamic short-term fluctuations, traditional methods still provide more stable results in the long term.

The main advantage of CNN in this context is its ability to process large and complex datasets more efficiently and to recognize patterns that may not be detected by traditional analysis methods. CNN can integrate various environmental variables simultaneously and provide predictions that are more adaptive to rapidly changing environmental conditions. However, challenges in model calibration and validation, as well as limitations in the available data, may diminish these advantages. Therefore, while CNN demonstrates great potential, its application in predicting sea surface height in Teluk Pangpang still requires further refinement.

These findings have significant practical implications, particularly for amphibious aircraft (seaplane) operations in Teluk Pangpang. More accurate predictions of sea surface height can substantially enhance flight safety. For instance, by utilizing predictions generated by the CNN model, seaplane pilots can avoid landing or taking off in shallow waters or areas with high waves, which could jeopardize flight safety. Additionally, optimal flight route planning can be carried out by considering the predicted sea surface conditions, thereby reducing the risk of flight delays or cancellations due to unfavorable sea conditions.

In terms of efficiency, more accurate predictions can also aid in more efficient operational planning. For example, predictions about sea surface height fluctuations can be used to optimize flight schedules, minimize waiting times, and reduce fuel consumption. Moreover, this predictive data can also support decision-making in coastal infrastructure development, such as the construction of docks and ports, making them more resilient to changing environmental conditions.

Although this research provides valuable insights into the use of CNN for predicting sea level height, there are several limitations that need to be addressed. One of the main limitations is the constraint on input data, where the availability of richer and more detailed data on meteorological and oceanographic variables could improve the model's accuracy. Additionally, the limitation in the calibration of the CNN model, particularly in setting optimal parameters, also presents a significant challenge.

For future research, it is recommended to expand the scope of the data used by including more environmental variables and utilizing a longer historical dataset. Furthermore, exploring more complex CNN model structures or employing hybrid models that combine CNN with other machine learning approaches could help enhance predictive performance. Future studies should also consider testing the model under various extreme weather scenarios to ensure that the model can still provide accurate predictions under the most challenging conditions.

CONCLUSION

Based on the presented research findings, it is evident that sea surface height in Teluk Pangpang is intricately influenced by a spectrum of environmental variables including wind speed and direction, air and water temperature, rainfall, and salinity. The analysis, depicted through Andrews Curves plots, reveals nuanced and dynamic interactions among these factors and the sea surface height. Despite the absence of specific labels for each environmental factor in the plot, the distinctive shapes of the curves provide valuable insights into their respective impacts on sea surface height. The research highlights that the historical patterns of sea surface height fluctuations exhibit variability across different daily meteorological and oceanographic conditions. Utilizing prediction models such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN), the study discerns varying levels of accuracy in forecasting sea surface height, with ANN demonstrating superior performance compared to CNN. Moreover, the research underscores the significant influence of meteorological and oceanographic conditions on the predictive accuracy of sea surface height models.

However, while ANN has shown better performance, it is crucial to note the inherent limitations and challenges in both modeling approaches. The differences in accuracy between ANN and CNN models may stem from various factors, including the specific architecture of the neural networks, the quality and quantity of the input data, and the complexity of the environmental interactions being modeled. This suggests a need for further refinement and optimization of these models to enhance their predictive capabilities. Despite these challenges, this study contributes significantly to the understanding of the intricate relationship between environmental factors and sea surface height in Teluk Pangpang. It lays a robust foundation for future advancements in developing more refined and accurate prediction models. By integrating comprehensive data analysis techniques and leveraging advanced neural network architectures, future research endeavors aim to enhance predictive capabilities and support informed decision-making in managing coastal environments and marine resources effectively.

In conclusion, while the current models provide valuable insights, ongoing research and development are essential to address the limitations and improve the robustness and accuracy of sea surface height predictions. This will ultimately facilitate better management and conservation strategies for coastal regions, highlighting the critical importance of continued investment in scientific research and technological innovation.

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REFERENCES

Andrews, K., Bowman, A., Rijal, U., Chen, P.-Y., & Zhou, Z. (2020). Improved contacts and device performance in MoS2 transistors using a 2D semiconductor interlayer. *ACS Nano*, *14*(5), 6232–6241.

Aparna, S. G., D'souza, S., & Arjun, N. B. (2018). Prediction of daily sea surface temperature using artificial neural networks. *International Journal of Remote Sensing*, *39*(12), 4214–4231.

Balogun, A.-L., & Adebisi, N. (2021). Sea level prediction using ARIMA, SVR and LSTM neural network: assessing the impact of ensemble Ocean-Atmospheric processes on models' accuracy. *Geomatics, Natural Hazards and Risk*, *12*(1), 653–674.

Boye, C. B., & Amoah, V. I. (2018). Performance evaluation for mean sea level prediction using multivariate adaptive regression spline and artificial neural network. *Ghana Mining Journal*, *18*(1), 1–8.

Chen, J., Xiao, T., Wang, M., Lu, Y., & Tong, M. (2022). Numerical study of wave effect on aircraft water-landing performance. *Applied Sciences*, *12*(5), 2561.

David, C. P., Custado, M. J., Sekhon, N., & Ibarra, D. E. (2022). Forecasting tropical ENSO-induced drought conditions using sea surface height in the Western Pacific. *All Earth*, *34*(1), 55–65.

Eskayudha, D. B., Yamamoto, K., Kanehira, T., Nakashima, T., & Mutsuda, H. (2023). A proposed seaplane float in water entry problem and landing in waves using particle based method. *Journal of Advanced Research in Numerical Heat Transfer*, *13*(1), 31–38.

Fitrianti, N., Haryanto, Y. D., Simamora, E. V. S., Bintari, H. F. A., Hartoko, A., Anggoro, S., & Zainuri, M. (2018). Analysis of daily wind circulation toward sea level rise in Semarang. *IOP Conference Series: Earth and Environmental Science*, *162*(1), 12018.

Gbodjo, Y. J. E., Ienco, D., & Leroux, L. (2021). Benchmarking statistical modelling approaches with multi-source remote sensing data for millet yield monitoring: A case study of the groundnut basin in central Senegal. *International Journal of Remote Sensing*, *42*(24), 9285–9308.

George, T. M., Manucharyan, G. E., & Thompson, A. F. (2021). Deep learning to infer eddy heat fluxes from sea surface height patterns of mesoscale turbulence. *Nature Communications*, *12*(1), 800.

Giezendanner, J., Mukherjee, R., Purri, M., Thomas, M., Mauerman, M., Islam, A. K. M., & Tellman, B. (2023). Inferring the past: A combined CNN-LSTM deep learning framework to fuse satellites for historical inundation mapping. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2155–2165.

Gray, P. C., Chamorro, D. F., Ridge, J. T., Kerner, H. R., Ury, E. A., & Johnston, D. W. (2021). Temporally generalizable land cover classification: A recurrent convolutional neural network unveils major coastal change through time. *Remote Sensing*, *13*(19), 3953.

Grubert, D. A. da V. (2023). *A synergistic approach to sugarcane yield forecasting using machine learning, remote sensing, and process-based modeling*. Universidade de São Paulo.

Hodson, T. O. (2022). Root mean square error (RMSE) or mean absolute error (MAE): When to use them or not. *Geoscientific Model Development Discussions*, *2022*, 1–10.

Ismail, M. F. A., & Taofiqurohman, A. (2020). Sebaran spasial suhu, salinitas dan densitas di perairan Kepulauan Sangihe Talaud Sulawesi Utara. *Jurnal Kelautan Tropis*, *23*(2), 191–198.

Ispandiari, A. R., Fauzi, I., Kartikasari, D., Sadiah, S., Shabrina, N., & Gutami, N. I. (2022). Identifikasi awal risiko kecelakaan seaplane pada Bandar Udara Perairan. *G-Tech: Jurnal Teknologi Terapan*, *6*(2), 201–210.

Karsavran, Y. (2024). Evaluation of the performance of SVR and ANN Models in Sea Water Level Prediction for the Izmir Coast of the Aegean Sea. *International Journal of New Findings in Engineering, Science and Technology*, *2*(1), 1–7.

Khoirunnisa, H., Wibowo, M., Hendriyono, W., & Wardani, K. S. (2021). Hydrodynamic and boussinesq wave modeling for the N219 amphibious aircraft seaplane dock development plan in Panjang Island. *Majalah Ilmiah Pengkajian Industri; Journal of Industrial Research and Innovation*, *15*(2), 87–96.

Kim, Y. J., Kim, H.-C., Han, D., Lee, S., & Im, J. (2020). Prediction of monthly Arctic sea ice concentrations using satellite and reanalysis data based on convolutional neural networks. *The Cryosphere*, *14*(3), 1083–1104.

Kourkchi, E., Tully, R. B., Eftekharzadeh, S., Llop, J., Courtois, H. M., Guinet, D., Dupuy, A., Neill, J. D., Seibert, M., & Andrews, M. (2020). Cosmicflows-4: The catalog of∼ 10,000 tully–fisher distances. *The Astrophysical Journal*, *902*(2), 145.

Le, X.-H., Huynh, T. T., Song, M., & Lee, G. (2024). Quantifying predictive uncertainty and feature selection in river bed load estimation: A multi-model machine learning approach with particle swarm optimization. *Water*, *16*(14), 1945.

Muslim, T. O., Ahmed, A. N., Malek, M. A., Abdulmohsin Afan, H., Khaleel Ibrahim, R., El-Shafie, A., Sapitang, M., Sherif, M., Sefelnasr, A., & El-Shafie, A. (2020). Investigating the influence of meteorological parameters on the accuracy of sea-level prediction models in Sabah, Malaysia. *Sustainability*, *12*(3), 1193.

Ondoa, G. A., Almar, R., Castelle, B., Testut, L., Léger, F., Sohou, Z., Bonou, F., Bergsma, E. W. J., Meyssignac, B., & Larson, M. (2019). Sea level at the coast from video-sensed waves: Comparison to tidal gauges and satellite altimetry. *Journal of Atmospheric and Oceanic Technology*, *36*(8), 1591–1603.

Plevris, V., Solorzano, G., Bakas, N. P., & Ben Seghier, M. E. A. (2022). Investigation of performance metrics in regression analysis and machine learning-based prediction models. *8th European Congress on Computational Methods in Applied Sciences and Engineering (ECCOMAS Congress 2022)*.

Pugh, C. J. (2019). *Crystal engineering and structural solutions of organic molecular materials.* The University of Liverpool (United Kingdom).

Raj, N., & Gharineiat, Z. (2021). Evaluation of multivariate adaptive regression splines and artificial neural network for prediction of mean sea level trend around Northern Australian coastlines. *Mathematics*, *9*(21), 2696.

Rumani, D. D., Wicaksono, A. W., Wiyono, D. S., & Mardhika, A. (2023). Pemulihan penerbangan dan pengembangan potensi wisata nasional dengan pembangunan water aerodrome. *Jurnal Penelitian*, *8*(2), 175–188.

Schult, D. (1943). *Exploring network structure, dynamics, and function using NetworkX*.

Sepúlveda, I., Cao, B., Haase, J. S., & Murphy Jr, M. J. (2023). Optimizing Simultaneous water level and wave measurements from multi-GNSS interferometric reflectometry over 1 year at an exposed coastal site. *Earth and Space Science*, *10*(6), e2022EA002767.

Shabrina, N., Arianto, D., Wardani, K. S., Qonita, Z., Ispandiari, A. R., Gutami, N. I., & Manti, M. F. (2023). Session assessment of seaplane operations: The case of marine tourism development on Gili Iyang Island, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *1166*(1), 12050.

Talke, S. A., & Jay, D. A. (2020). Changing tides: The role of natural and anthropogenic factors. *Annual Review of Marine Science*, *12*(1), 121–151.

Tan, C.-K., Tan, C.-P., & Shaun Wes, N. (2021). Information technology students' preferences on blended learning. *Computational Science and Technology: 7th ICCST 2020, Pattaya, Thailand, 29–30 August, 2020*, 91–100.

Tiggeloven, T., Couasnon, A., van Straaten, C., Muis, S., & Ward, P. J. (2021). Exploring deep learning capabilities for surge predictions in coastal areas. *Scientific Reports*, *11*(1), 17224.

Tur, R., Tas, E., Haghighi, A. T., & Mehr, A. D. (2021). Sea level prediction using machine learning. *Water*, *13*(24), 3566.

Wahyu, A., Wiyono, D. S., Mardhika, A., & Parjan, P. (2021). Rencana operasi penerbangan seaplane di Teluk Pang – Pang Banyuwangi dan dampaknya terhadap lingkungan. *Jurnal Penelitian*, *6*(4), 278–291.

Willmott, C. J., & Matsuura, K. (2005). Advantages of the Mean Absolute Error (MAE) over the Root Mean Square Error (RMSE) in assessing average model performance. *Climate Research*, *30*(1), 79–82.

Wisha, U. J., Wijaya, Y. J., & Hisaki, Y. (2023). Sea level variability in the equatorial Malacca Strait: The influence of climatic–oceanographic factors and its implications for tidal properties in the estuarine zone. *Climate*, *11*(3), 70.

Woodworth, P. L., Melet, A., Marcos, M., Ray, R. D., Wöppelmann, G., Sasaki, Y. N., Cirano, M., Hibbert, A., Huthnance, J. M., & Monserrat, S. (2019). Forcing factors affecting sea level changes at the coast. *Surveys in Geophysics*, *40*(6), 1351–1397.

Xie, S., Chen, J., Dixon, T. H., Weisberg, R. H., & Zumberge, M. A. (2021). Offshore sea levels measured with an anchored spar-buoy system using GPS interferometric reflectometry. *Journal of Geophysical Research: Oceans*, *126*(11), e2021JC017734.

Youssef, A. M., Pradhan, B., Dikshit, A., & Mahdi, A. M. (2022). Comparative study of Convolutional Neural Network (CNN) and Support Vector Machine (SVM) for flood susceptibility mapping: A case study at Ras Gharib, Red Sea, Egypt. *Geocarto International*, *37*(26), 11088–11115.