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Deep Learning for Tidal Flood Prediction in West Pandeglang Waters, Banten

Nevin Adel Ramaputra[1], Asep Sandra Budiman [2], Willdan Aprizal Arifin [3]

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***Abstract* - Tidal flooding poses a significant threat to coastal areas, exacerbated by rising sea levels. In West Pandeglang Waters, Banten, frequent tidal floods impact communities, necessitating accurate prediction models for effective disaster mitigation. This study aims to develop a deep learning-based tidal flood prediction model using Keras and TensorFlow. The model incorporates oceanic and atmospheric variables, including sea surface height, wave characteristics, wind components, and precipitation data from 2003 to 2023. To address data imbalance, Synthetic Minority Over-sampling Technique (SMOTE) and MinMax scaling were applied, ensuring balanced class distribution. The model was trained and evaluated using a dataset comprising 11,808 samples, achieving an accuracy of 86% and an area under the curve (AUC) of 0.93. These results indicate a strong capability to differentiate between flood and non-flood conditions. The study demonstrates the effectiveness of deep learning in predicting tidal floods, providing valuable insights for early warning systems and coastal management in flood-prone regions.**

Keyword – Coastal Flooding, KERAS TensorFlow, MinMax Scaller, Sea Level Rise, SMOTE Resampling

I. Introduction

Sea level rise significantly impacts the frequency and severity of tidal flooding in coastal areas. Studies show that changes in tidal range are correlated with sea level variations, potentially increasing the risk of tidal flooding in some areas[1]. The impacts are widespread globally, with studies in Indonesia showing varying vulnerability to tidal flooding in coastal areas[2]. These studies emphasize the need for comprehensive flood risk assessments considering sea level rise and tidal changes. Coastal regions worldwide are also increasingly threatened by tidal flooding, driven by rising sea levels and land subsidence, which exacerbate the frequency and severity of inundation events [3]. In Indonesia, the coastal area of West Pandeglang Waters in Banten Province is particularly vulnerable, with tidal flooding affecting 1,232 hectares across four sub-districts. This vulnerability is compounded by land subsidence rates of 1-14 cm/year and the region's exposure to extreme weather events [4]. The 2018 Sunda Strait tsunami, which generated waves up to 6 meters high and inundated areas 200 meters inland, further underscored the urgent need for improved disaster preparedness and accurate flood prediction systems in the region [5]. Traditional flood prediction methods often fail to capture the complex interactions between environmental variables, such as tidal fluctuations, rainfall, and wind patterns, resulting in unreliable forecasts and inadequate mitigation strategies [6].

Recent advancements in deep learning have demonstrated significant potential for addressing these challenges. Deep learning models, mainly those built using KERAS TensorFlow, have achieved remarkable success in handling complex, nonlinear datasets across various domains, including hydrology and environmental science [7]. For example, deep learning has been effectively applied to predict river flooding and storm surges, outperforming traditional methods by capturing intricate patterns in environmental data[8]. These successes highlight the potential of deep learning for tidal flood prediction, particularly in data-scarce regions like West Pandeglang. However, the application of deep learning in this context remains underexplored, with existing studies primarily relying on traditional modeling approaches that fail to account for the dynamic nature of coastal flooding [9]. A critical challenge in developing accurate flood prediction models is the issue of imbalanced datasets, where rare but high-impact flooding events are underrepresented. This imbalance often leads to biased predictions that favor non-flood scenarios, reducing the model's effectiveness in real-world applications [10]. To address this, resampling techniques such as random oversampling and synthetic minority oversampling (SMOTE) have been proposed to balance datasets and improve model performance [10]. By integrating these techniques with deep learning, more robust and reliable flood prediction models for West Pandeglang Waters can be developed.

This study proposes using deep learning, explicitly leveraging KERAS TensorFlow, to develop a tidal flood prediction model for West Pandeglang. By incorporating tidal data, wind, and other environmental variables, this approach aims to provide accurate and timely flood forecasts, enabling better disaster preparedness and

[1]Nevin Adel Ramaputra, Departement of Marine System Information, Faculty of Serang, Indonesia University of Education, Serang, 42116, Indonesia, Email: adelnevin@gmail.com
[2]Asep Sandra Budiman, Center For Climate and Atmospheric Research, National Research and Innovation Agency’s, Bandung, 40135, Indonesia, Email: asep036@brin.go.id
[3]Willdan Aprizal Arifin Departement of Marine System Information, Faculty of Serang, Indonesia University of Education, Serang, 42116, Indonesia, Email: willdanarifin@upi.edu

coastal management strategies. The study also addresses the challenge of imbalanced datasets through resampling techniques, ensuring that rare but critical flooding events are adequately represented in the model.

II. METHOD

A. Model Structure

The research model has one input layer, two hidden layers (dense, dense, dense_relu), one dropout layer, one Gaussian layer, and two output layers. The structure model is shown in Figure 1. This model structure is designed for binary classification or probabilistic regression tasks. The sigmoid in the output layer indicates that the model generates probability values. This simple structure is suitable for datasets with small input dimensions and simple tasks, such as prediction or classification with limited data[11].

The dense_input layer takes preprocessed data from a data input file, where features have been scaled for better convergence during training. The first dense layer is a fully connected layer that applies linear transformations, allowing the model to capture initial feature relationships. The dense_relu layer follows, incorporating the ReLU activation function, which helps the model learn complex patterns by introducing non-linearity while avoiding issues like vanishing gradients. The dropout_6 layer randomly deactivates a fraction of neurons during training to enhance generalization and prevent overfitting. Additionally, the gaussian_noise_6 layer injects random noise into the data, making the model more robust to variations and improving its ability to generalize to unseen tidal flood scenarios. The output layer represents the final prediction stage, combining all learned features. Finally, the output_sigmoid layer applies a sigmoid activation function, transforming the output into a probability value between 0 and 1, which is ideal for binary classification-predicting whether a tidal flood will occur. With this structure, your model effectively learns from past tidal flood data to make accurate future predictions. To optimize performance, you can fine-tune the architecture by adjusting the number of neurons, dropout rate, or activation functions.

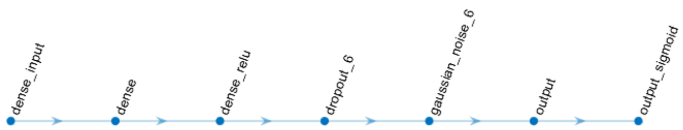


Figure. 1. Model Structure

B. Data

In this study, several types of data were used, which were downloaded from the site *https://bnpb.go.id/* as reference data for flood events in the selected area and from the site *https://data.marine.copernicus.eu/* for data used as variables. The variable data used include Sea Surface Height Above Sea Level (SLA), Significant Wave Height (SWH), Mean Wave Direction (MWD), Mean Wave Period (MWP), 10m u-component of wind, 10m u-component of wind, Total Precipitation. Data used to process deep learning models. The data spans from 1 January 2003 to 31 December 2023 (20 Years).

C. Resampling, Scaling, and Tidal Flood Class

The flood data obtained earlier was used as a time indicator to determine the class of all variable data used. From the results obtained during the classification, the class value is obtained for all variables with class 1 as many as 289, which is categorized as "Flood Class," and class 0 as many as 7380, which is classified as "Non-Flood Class." The data used in this study experienced data imbalance problems, so data enhancement or resampling and data scaling are required to maximize the results. Resampling techniques are widely used to address class imbalance in deep learning datasets. Random oversampling (ROS) and undersampling (RUS) are common approaches, along with hybrid methods like SMOTE and its variants[12]. However, the effectiveness of these techniques depends on dataset characteristics such as imbalance ratio, size, dimensionality, and class overlap[13]. RUS can severely impact model performance, especially with highly imbalanced datasets,

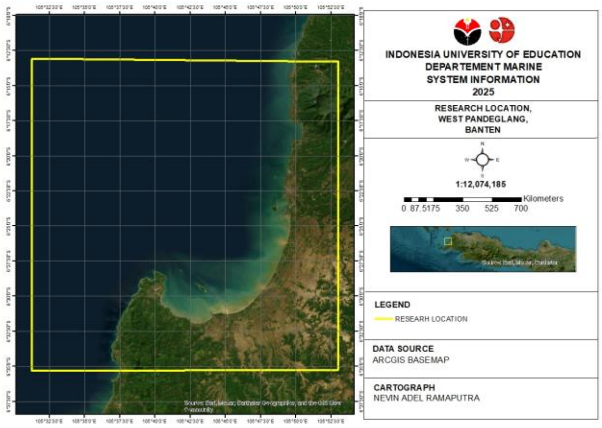


Figure. 2. Research Location Map

while SVM-SMOTE shows promise when paired with Random Forest and Gaussian Naïve Bayes classifiers[14]. In the context of breast cancer classification, standard class imbalance techniques can counteract bias towards the majority class but may not improve AUC-ROC performance[15]. Applying cleaning strategies to neural network outputs rather than input features alone may yield better results in big data scenarios[12].In this research, the resampling technique is SMOTE with scaling using MinMax Scaller. The resampling and scaling techniques produced data that was initially unbalanced, with 7380 for class "0" and 289 for class "1" to 11808 data with class '1' of 5904 and class "0" of 5904. This result makes the data balanced and gives better accuracy.

D. Research Location

This research location covers the area in the west waters of Pandeglang Regency, Banten, with a longitude of 105.5 - 106.05° and a latitude of -6.75 - (-6.05)°. Figure 2 shows that the research location includes several areas that often experience tidal floods, including Carita, Panimbang, Labuan, and Pagelaran.

III. RESULTS AND DISCUSSION

The research results obtained reveal the vulnerability of the research location area. Extreme waves and abrasions are also still a big problem in tidal flooding. As in Table 1, the potential danger of extreme waves and abrasion in pandeglang is high. In Table 2, the potential vulnerability of pandeglang to extreme waves and abrasion is in the medium class; this explains that tidal flooding in the region has a high enough vulnerability, with 26,550 people affected. Table 3 shows the risk level of extreme waves and abrasion in the Pandeglang area, which is the highest risk level from its neighboring regions due to the potential danger and the number of people affected by this disaster. Waves are also a significant indicator of the occurrence of this tidal flood disaster. According to Gaol[16], natural and anthropogenic factors make coastal areas increasingly vulnerable to tidal flooding. Sea level rise due to climate change and land subsidence due to excessive groundwater extraction exacerbate flood risk in low-lying coastal regions[17].

From the table data related to the potential vulnerability of the population and dangers to extreme waves and abrasion above, Pandeglang District can be categorized as an area with a high level of risk even though it is still at a moderate vulnerability. Still, the potential for dangers in this area has a high potential. This high potential and risk can also be seen in Table 4; the table explains the potential and risk in the area used as the research location; four sub-districts are included in the

TABLE 1.
POTENTIAL DANGER OF EXTREME WAVES AND ABRASION IN BANTEN REGENCY. (SOURCE : ANALYSIS DATA NATIONAL DISASTER RISK ASSESSMENT DOCUMENT, 2021)

District	Danger				Class
	Low (Ha)	Medium (Ha)	High (Ha)	Total	
Lebak	161	45	1.232	1.438	High
Pandeglang	2.766	1.512	2.857	7.121	High
Serang	1.268	209	1.362	2.840	High
Tanggerang	626	60	195	882	High

TABLE 2.
POTENTIAL POPULATION EXPOSED TO EXTREME WAVES AND ABRASION DISASTERS IN BANTEN REGENCY. (SOURCE : ANALYSIS DATA NATIONAL DISASTER RISK ASSESSMENT DOCUMENT, 2021)

District	Total Population Exposed	Potential Population Exposure in Groups (People)			Class
		Age Vulnerable Population	Poor Population	Disabled Population	
Lebak	10.273	1.095	1.447	36	Medium
Pandeglang	26.550	2.677	4.276	80	Medium
Serang	21.272	2.168	2.046	60	Medium
Tanggerang	7.461	746	911	13	Medium

TABLE 3.
DISASTER RISK LEVEL OF EXTREME WAVES AND ABRASION IN BANTEN REGENCY. (SOURCE : ANALYSIS DATA NATIONAL DISASTER RISK ASSESSMENT DOCUMENT, 2021)

District	Danger Class	Vulnerability Class	Capacity Class	Risk Class
Pandeglang	High	High	Medium	High
Lebak	High	High	Medium	Medium
Tanggerang	High	High	Medium	Medium
Serang	High	High	Medium	Medium

TABLE 4.
POTENTIAL AND RISK OF ROB FLOODING AT THE RESEARCH SITE.

District	Potenial and Risk
Carita	High
Panimbang	High
Labuhan	High
Pageralaran	High

research location with high potential and risk of tidal. Flooding.

In Table 5, the four sub-districts are located in the coastal area and have a history of tidal floods recorded from the official website *https://www.bnpb.go.id/*, with a total of 14 occurrences in the last 20 years; this also makes the area highly vulnerable to tidal floods (BNPB, 2024).

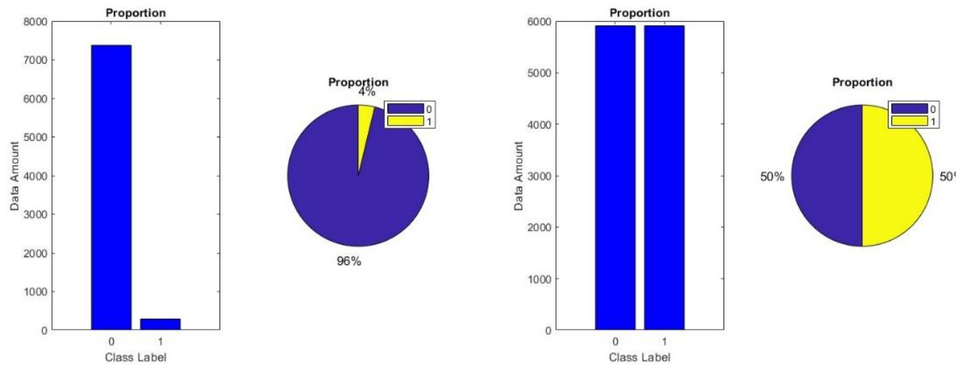
In deep learning models for flood prediction, classes are divided into two main categories: "flood" and "no flood". According to Razali [18], this binary approach allows the model to learn to distinguish conditions at risk of flooding based on the parameters Sea Surface Height Above Sea Level (SLA), Significant Wave Height (SWH), Mean Wave Direction (MWD), Mean Wave Period (MWP), 10m u-component of wind, and Total Precipitation obtained from the Copernicus website.

TABLE 5.
FLOOD EVENTS IN THE STUDY AREA (BNPB, 2024).

Date	Disaster	Area (Sub-District)	District	Province
1/3/2023	Flood	Panimbang, Picung	Pandeglang	Banten
12/30/2022	Flood	Patia, Sobang	Pandeglang	Banten
12/28/2022	Flood	Pagelaran	Pandeglang	Banten
12/27/2022	Flood	Patia, Sobang, Cisata, Panimbang, Sukaresmi	Pandeglang	Banten
3/19/2022	Flood	Carita, Labuan, Panimbang	Pandeglang	Banten
3/1/2022	Flood	Labuan, Panimbang, Pagelaran, Mandalawangi, Cisata, Carita, Cadasari	Pandeglang	Banten
12/6/2021	Flood	Labuan, Sukaresmi, Carita, Panimbang	Pandeglang	Banten
11/7/2021	Flood	Sukaresmi, Carita	Pandeglang	Banten
1/28/2021	Flood	Sukaresmi, Labuan, Carita, Pagelaran, Patia, Sindangresmi	Pandeglang	Banten
12/7/2020	Flood	Picung, Panimbang, Cikeusik, Angsana , Cigeulis, Sukaresmi Patia, Cibitung, Pagelaran, Munjul, Sindangresmi	Pandeglang	Banten
11/22/2020	Flood	Cigeulis, Panimbang	Pandeglang	Banten
5/25/2020	Flood	Pagelaran	Pandeglang	Banten
1/10/2020	Flood	Sobang, Sukaresmi, Pagelaran, Sindangresmi, Panimbang	Pandeglang	Banten
11/7/2021	Flood	Patia,Panimbang	Pandeglang	Banten

Multiple oceanic and atmospheric factors influence tidal flooding. Sea Surface Height Above Sea Level (SLA) has the highest impact because rising sea levels directly lead to flooding, especially during high tides or storm surges. Significant Wave Height (SWH) also plays a major role, as larger waves push more water inland, worsening floods[19]. Total Precipitation contributes by overwhelming drainage systems, especially when combined with high tides[20]. Wind components (U and V at 10m height) can either increase or decrease flooding by pushing seawater toward or away from the coast [21]. Mean Wave Direction (MWD) and Mean Wave Period (MWP) have a moderate impact, as wave energy and direction influence how water moves toward land[22]. Overall, SLA, SWH, and precipitation are the strongest predictors of tidal flooding, while wind and wave characteristics modify their severity.

After dividing the classes into two main categories, namely "flood" and "not flood", the results obtained before resampling the data are shown in Figure 3 (a) . The results of the data used are very far apart for the "flood" and "not flood" classes; this is because, in the last 20 years, there were only 14 occurrences of tidal floods, which makes the proportion for class data unbalanced into a model. This data imbalance is unsuitable for deep learning modeling; it poses significant challenges for deep learning models in various domains. An unbalanced data distribution can negatively impact classification performance.[23].



(a) **(b)**

Figure. 3. Proportion Data Before (a), and Proportion Data After Resampling (b)

Therefore, the data resample technique is needed to balance the proportion of data classes; in this study, the data resample technique used is SMOTE with the scaling

TABLE 6.
POTENTIAL AND RISK OF ROB FLOODING AT THE RESEARCH SITE.

Parameter of Performance	Value
Accuracy	0.86
F1 Score	0.86
AUC	0.93
Precision for class 1	0.86
Recall for class 1	0.86

method min-max smaller. The Synthetic Minority Over-sampling Technique (SMOTE) technique is consistently used to balance the dataset and improve model accuracy [24]. In Figure 3 (b), the proportion of data after resampling the data gets maximum results, where the “flood” and “not flood” classes already have comparable Proportions; this will improve the results of the Performance of the model built.

From the previous data's resample, the clustering results are used for deep learning modeling using the KERAS TensorFlow algorithm in Google Collab. Recent research has shown the versatility of KERAS TensorFlow in various prediction tasks, and it performs well in prediction. As shown in Table 6, the results of the previous data modeled with the KERAS TensorFlow algorithm were high; the model achieved an accuracy of 0.86, indicating that 86% of the predictions were correct[25]. This model has separated positive and negative classes well.

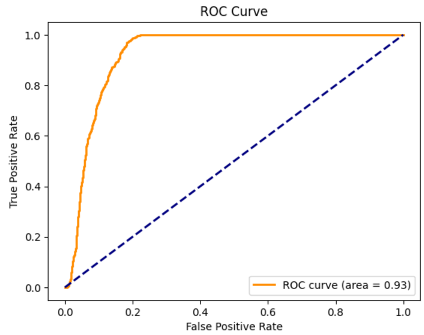


Figure. 4. ROC Curve

In Figure 4, the ROC curve result with an AUC of 0.93 strongly argues that the deep learning model built with KERAS and TensorFlow is highly effective in predicting tidal floods. A model with such a high AUC demonstrates a strong ability to differentiate between flood and non-flood cases, suggesting that it can reliably identify critical flood events. This level of performance is crucial for early warning systems, where accurate predictions can help mitigate potential disasters. Moreover, the steep rise in the ROC curve at lower false favorable rates indicates that the model achieves high sensitivity early on. This means it correctly detects most flood cases without excessively misclassifying non-flood cases as floods. Such a property is fundamental in flood prediction, where missing a flood event (false adverse) could have severe consequences.

However, despite the high AUC, it is essential to consider the trade-off between precision and recall. A model that prioritizes high recall may trigger more false alarms, potentially leading to unnecessary evacuations or resource deployment. On the other hand, focusing too much on precision could result in missing actual flood events. About 49% of the original data has class 0 (Not Flooded), while about 51% has class 1 (Flooded) in Figure 5 (a). Meanwhile, the model predicts about 51% of class 0 and 49% of class 1 in Figure 5 (b). These results show that the model's predictions are close to the original data distribution, indicating that the model performs reasonably well. The model can capture the distribution of classes 1 and 0 accurately. Still, the slight difference in the proportion of the original data and the proportion of the Predicted data suggests the model may still have some

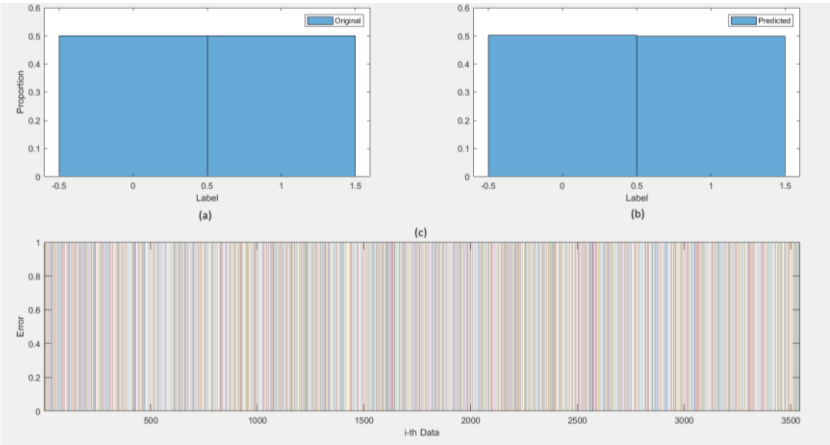


Figure. 5. Proportion Data Original (a), Proportion Data Predicted (b), Error Line (c)

bias or prediction errors. The errors appear to be relatively uniformly distributed, indicating that the model errors are spread evenly across the data points and are not concentrated in any particular region in Figure 5 (c). This uniform distribution of errors implies that the model's performance is consistent across the different data instances. Still, the presence of these errors suggests there is room for further improvement in the accuracy and generalizability of the model. Although the model accurately predicts class scores, error plots suggest room for development, optimization, and improvement—prediction performance of the model.

Figure 6 (a) shows that the flood prediction application has been designed, has seven input variables, and has a scatter plot display that gives a more informative impression. In Figure 6 (b), it can be seen that the flood prediction application can predict the value of class 0 (Not Flooded) correctly and accurately, with an informative display on the scatter plot and line graph as an average marker of the variables inputted. In Figure 6 (c), it can be seen that the flood prediction application can predict the value of class 1 (Flood) well and accurately, with an informative display on the scatter plot and line graph as an average marker of the variables inputted

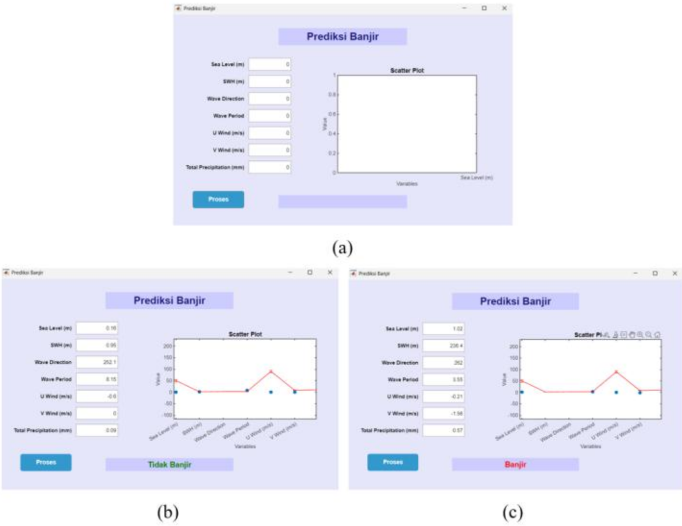


Figure. 6. Application Tidal Flood Prediction (a), Predition of Class “Not Flood” (b), Predition of Class “Flood” (c)

IV. CONCLUSION

This study successfully developed a deep learning-based tidal flood prediction model for West Pandeglang Waters, Banten, using Keras and TensorFlow. By integrating multiple oceanic and atmospheric variables, the model demonstrated high accuracy (86%) and strong classification performance (AUC 0.93) in distinguishing flood and non-flood events. The application of SMOTE resampling and MinMax scaling effectively addressed dataset imbalance, enhancing model reliability in predicting rare but significant tidal flooding events. These findings highlight the potential of deep learning in improving flood forecasting and coastal disaster mitigation strategies.

However, while the model achieved promising results, there are areas for further development. Future research should explore real-time data integration to enhance predictive accuracy and response efficiency. Additionally, incorporating more complex hydrodynamic variables and ensemble learning techniques could further improve model robustness. The findings of this study emphasize the importance of data-driven approaches in coastal management and disaster preparedness, supporting policymakers in designing effective early warning systems. Advancements in deep learning models for tidal flood prediction will be crucial for mitigating risks in vulnerable coastal regions, ensuring community resilience against climate-induced hazards.

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