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DOMINANT DISASTER DETECTION AND PREDICTION IN COASTAL AREAS USING NEURAL NETWORK SYSTEM TO OPTIMIZE DISASTER MANAGEMENT IN COASTAL AREAS

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The object of the study is detection and prediction dominant disaster in coastal areas. The problem being addressed is the lack of accurate and efficient early warning systems for these disasters, which can result in significant damage and economic loss. To solve this problem, this study develops an innovative application and website designed to predict the most dominant disasters in coastal areas. This system utilizes real-time data processing to provide early warnings and risk assessments, assisting communities and emergency response teams in preparing for potential threats. Testing results indicate that 89 % of the system's predictions are effective in disaster management. The research methodology includes observation, data collection, dataset preprocessing, analysis, and the development of a smart detection system (SDS) using Geographic Information System (GIS)-based mapping and clustering techniques. The findings are explained through the hybrid deep neural network (DNN) method, which analyzes various environmental factors, including temperature, wind speed, wave height, weather disturbances, and sea level fluctuations. Additional features, such as daily weather forecasts, enhance the system's predictive capabilities. This intelligent disaster management system, powered by a neural network, ensures effective disaster prediction and mitigation. The system is designed to be applied in coastal areas with limited technology, thereby improving disaster preparedness. Additionally, the application enables governments to monitor and respond to disasters more efficiently. By integrating artificial intelligence (AI)-based solutions, this research significantly contributes to disaster management, offering innovative strategies to minimize risks and enhance emergency response efforts

Keywords: deep neural network (DNN), disaster prediction, coastal area, mitigation, smart detection system (SDS), geographic information system (GIS) mapping, early warning system (EWS)

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1. Introduction

Tsunami disasters are one of the natural disasters that have a significant impact on human life, especially in coastal areas. According to NOAA (National Oceanic and Atmospheric Administration), the tsunami with the highest number of casualties occurred in 2010 in the islands of Haiti and the Dominican Republic, resulting in 316,000 fatalities. Meanwhile, the 2004 tsunami disaster in Aceh ranks second, with approximately 227,000 peoples [1–3]. The high number of fatalities in tsunami events underscores the importance of research and technological development in disaster mitigation to reduce the risks posed. This research focuses on risk mapping in affected areas, particularly in coastal regions that are still limited in terms of technology, especially in the 3T regions (disadvantaged, frontier, and outermost areas). Indonesia's coastline, as an archipelagic country with many rivers flowing into the sea, has numerous disaster-prone points.

Therefore, preparedness in anticipating disasters is crucial, particularly in the form of early warning systems capable of detecting and predicting the likelihood of disasters, including floods caused by tsunamis. Technological advancements have enabled increased effectiveness in disaster detection and mitigation systems [4, 5]. One innovative approach that can be applied is the development of the Hybrid Deep Neural Network method, which has been proven analytically and experimentally in various previous studies. This method can optimize the process of detecting variables used in classification models, thereby producing more accurate and interpretable classification models in coastal areas that are technologically underserved.

Therefore, research on the development of artificial intelligence-based disaster detection and prediction systems is highly relevant. Innovations in disaster mitigation technology not only contribute to disaster risk reduction efforts but also support faster and more accurate decision-making in facing potential future disasters. Hence, research focusing

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on the development of Hybrid Deep Neural Network-based systems for disaster mitigation in coastal areas remains an important field to be further explored.

2. Literature review and problem statement

The paper [4] presents the research results on a novel method for coastal tsunami prediction utilizing a denoising autoencoder (DAE) model, a deep learning algorithm. It is shown that the DAE model demonstrated high accuracy in predicting coastal tsunami waveforms for hypothetical events, achieving a quality index of approximately 90 %, and accurately forecasted the maximum amplitude of the 2016 Fukushima tsunami with a quality index of 91.4 % at 15 minutes after the earthquake. But there were unresolved issues related to the unsatisfactory prediction of coastal waveforms for the 2022 Tonga volcanic tsunami. This approach was used in [5], however, challenges remain in accurately modeling complex tsunami sources. All this suggests that it is advisable to conduct a study on enhancing the robustness of deep learning models for predicting various types of tsunamis, particularly those with non-seismic origins.

The paper [6] presents the results of research on a big data-driven dynamic estimation model for relief supplies demand during urban flood disasters, integrating Baidu heat map data and a Multilayer Perceptron (MLP) neural network trained on historical flood cases. It is shown that the model significantly improves accuracy and timeliness compared to traditional static census-based methods. However, there were unresolved issues related to the model's applicability to non-flood disasters, limited granularity in addressing varying damage levels within flooded areas, and insufficient integration of logistical constraints. The reason for this may be objective difficulties associated with the heterogeneity of disaster types. This approach was used in [7], however, challenges remain in standardizing data across disaster types and ensuring computational efficiency for real-time operations. All this suggests that it is advisable to conduct a study on enhancing the model's scalability, logistics optimization frameworks to ensure end-to-end relief supply chain efficiency.

The paper [8] presents the results of research on a pipelined tsunami prediction approach (ECGFC) utilizing aquatic animal behavior analysis through ensemble clustering (ECG) and fuzzy rule-based classification (FRBCS). It is shown that the ECGFC method achieved superior clustering good accuracy (Silhouette Coefficient: 0.77–0.87) and classification performance (RMSE as low as 0.10, SMAPE: 6.61–10.93 %) on datasets. However, there were unresolved issues related to limited generalizability to non-seismic tsunamis, dependency on species-specific behavioral data, and scalability challenges in processing large-scale or heterogeneous datasets. A way to overcome these difficulties can be integrating multi-source data fusion and hybrid machine learning frameworks to enhance adaptability. This approach was used in [9], however, challenges persist in standardizing behavioral data across species and ensuring computational efficiency for real-time alerts. All this suggests that it is advisable to conduct a study on expanding the ECGFC framework to include volcanic and landslide-induced tsunami predictors, developing scalable algorithms for real-time heterogeneous data processing, and validating the model across diverse geographic regions and species to improve robustness and global applicability.

The paper [10] presents the results of research on the application of deep learning for earthquake disaster assessment, particularly focusing on detection, classification, and prediction of disaster impacts. It is shown that deep learning models, especially convolutional neural networks (CNNs), are highly effective for earthquake damage assessment, providing significant improvements in accuracy and efficiency in object detection, segmentation, and classification tasks. However, these models still face challenges related to data quality, availability, and computational requirements. But there were unresolved issues related to the limited availability of high-quality training data, the need for real-time processing capabilities, and the generalizability of deep learning models across different earthquake scenarios. The reason for this may be objective difficulties associated with data acquisition from remote sensing and seismic networks. A way to overcome these difficulties can be developing hybrid deep neural networks that combine different deep learning architectures, integrating transfer learning techniques to improve model adaptability. This approach was used in paper [11], however most existing research is still limited to specific case studies and lacks large-scale validation across diverse geographic regions and earthquake events. All this suggests that it is advisable to conduct a study on enhancing deep learning-based earthquake disaster assessment by integrating hybrid models, and optimizing real-time processing.

The paper [12] presents the results of research on the application of machine learning and remote sensing for detecting building damage caused by the tsunami. It is shown that machine learning techniques, particularly the Random Forest classifier, are effective in classifying building damage after a tsunami. The study successfully integrates multiple predictors, including geometry, statistical, texture, and vegetation indices, into 14 different predictor scenarios. Additionally, segmentation challenges arise due to the use of generalized image objects rather than focusing solely on buildings. The reason for this may be objective difficulties associated with acquiring real-time satellite imagery immediately after a disaster, variations in data sources affecting classification accuracy. A way to overcome these difficulties can be improving segmentation techniques to focus exclusively on buildings, integrating more real-time remote sensing data sources, and utilizing deep learning-based methods such as convolutional neural networks (CNNs) to enhance classification accuracy. This approach was used in previous studies on remote sensing for disaster damage assessment [13, 14], however, most existing studies relied on limited predictor variables or single-source satellite imagery, whereas this study integrates multiple predictors to enhance classification robustness. All this suggests that it is advisable to conduct a study on advancing hybrid machine learning and deep learning models for real-time post-disaster damage assessment, incorporating higher-resolution datasets, and optimizing model generalization for application across different disaster scenarios and geographic regions [15–17].

The paper [18] presents the results of research on a novel method for coastal tsunami prediction utilizing a denoising autoencoder (DAE) model, a deep learning algorithm. It is shown that the DAE model demonstrated high accuracy in predicting coastal tsunami waveforms for hypothetical events, achieving a quality index of approximately 90 %, and accurately forecasted the maximum amplitude of the 2016 Fukushima tsunami with a quality index of 91.4 % at 15 minutes after the earthquake. But there were unresolved issues related to the unsatisfactory prediction of coastal waveforms for the 2022 Tonga volcanic tsunami. This approach was used in [19], however, challenges remain in accurately modeling complex tsunami sources. All this suggests that it is advisable to conduct a study on enhancing the robustness of deep learning models for predicting various types of tsunamis, particularly those with non-seismic origins.

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The paper [25] presents the results of research on the application of machine learning and remote sensing for detecting building damage caused by the tsunami. It is shown that machine learning techniques, particularly the Random Forest classifier, are effective in classifying building damage after a tsunami. The study successfully integrates multiple predictors, including geometry, statistical, texture, and vegetation indices, into 14 different predictor scenarios. Additionally, segmentation challenges arise due to the use of generalized image objects rather than focusing solely on buildings. The reason for this may be objective difficulties associated with acquiring real-time satellite imagery immediately after a disaster, variations in data sources affecting classification accuracy. A way to overcome these difficulties can be improving segmentation techniques to focus exclusively on buildings, integrating more real-time remote sensing data sources, and utilizing deep learning-based methods such as convolutional neural networks (CNNs) to enhance classification accuracy. This approach was used in previous studies on remote sensing for disaster damage assessment [26], however, most existing studies relied on limited predictor variables or single-source satellite imagery, whereas this study integrates multiple predictors to enhance classification robustness.

All this suggests that it is advisable to conduct a study on advancing hybrid machine learning and deep learning models for real-time post-disaster damage assessment, incorporating higher-resolution datasets, and optimizing model generalization for application across different disaster scenarios and geographic regions.

3. The aim and objectives of the study

This aim of the study is to develop a smart system hybrid deep neural network for detecting and predicting the most dominant disasters in coastal areas, particularly in underdeveloped regions with low technological advancement. This research will enhance the safety of coastal communities in underdeveloped areas that lack advanced disaster detection technology, making it more effective for coastal populations in these regions.

To achieve this aim, the following objectives are accomplished:

– to collect and analyze data on predictive variables of the most dominant disasters occurring in underdeveloped coastal areas, such as high waves, tsunamis, and abrasion;

– to determine the steps for developing a hybrid deep neural network model tailored to predict the most dominant coastal disasters to enhance disaster mitigation;

– to develop an application suited for coastal areas to predict disasters, ensuring it is user-friendly and easily accessible for underdeveloped coastal communities.

4. Materials and methods

The object of the study is detection and prediction dominant disaster in coastal areas using neural network system to optimize disaster management in coastal areas with the focus on the research is prediction dominant disaster with the variable such as temperature, wind speed, waves, weather disturbances, and average sea level. The materials and methods made in the research are in the Fig. 1.

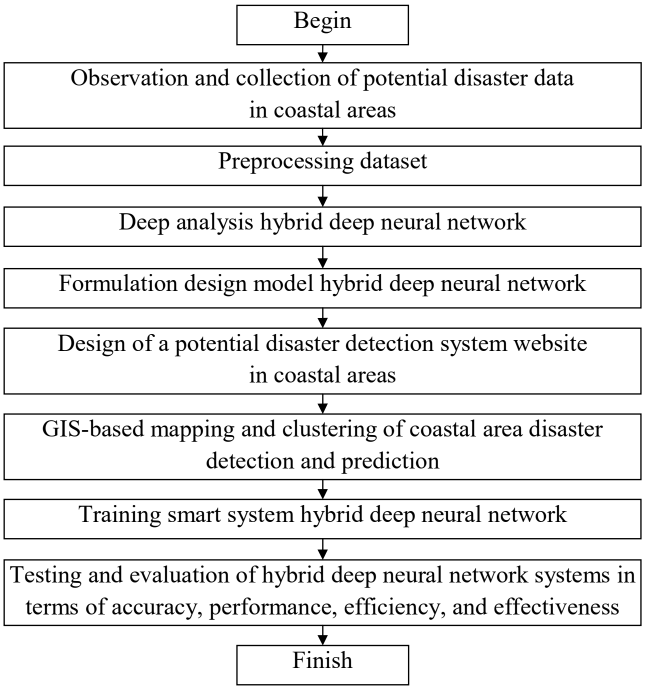


Fig. 1. Research methodology

In this study, various hardware and software components were used to support data processing, analysis, and the development of the hybrid deep neural network (DNN) model. From the hardware perspective, a high-performance computing system was required to handle large datasets and complex model computations. The system was equipped with an Intel Core i7 processor for efficient processing. To ensure smooth performance, the system had a minimum of 128GB of RAM, enabling effective data handling and real-time analysis. Additionally, a 1TB NVMe SSD was used for fast data access and storage. Furthermore, this study also leveraged cloud-based solutions, such as Google Cloud Platform (GCP) with GPU support, to enhance computational power. From the software perspective, the study was conducted on a Windows 11-based operating system to ensure compatibility with AI development libraries. Python version 3.8 was chosen as the primary programming language due to its extensive support for machine learning and deep learning applications. For data processing and analysis, various libraries, such as NumPy and Pandas, were used for data manipulation, while Matplotlib and Seaborn were employed for data visualization. Since this study involved geospatial analysis, mapping tools such as Geopandas and ArcGIS were utilized for GIS-based mapping and clustering techniques. To support interactive model development and testing, Jupyter Notebook and Google Colab were used. Additionally, Visual Studio Code served as the primary Integrated Development Environment (IDE) for implementing and optimizing the model and application. This combination of hardware and software ensures efficient data processing, accurate model predictions, and optimal model integration in disaster management applications.

The input for this study was the optimization of validation and field implementation, which had to be carried out continuously. Model testing was conducted in various coastal areas with different characteristics to ensure that the model could adapt to diverse environmental conditions. Furthermore, collaboration with local governments was established to integrate this model into the existing early warning system. Additionally, simulations were conducted in coastal communities to evaluate whether the system effectively enhanced community preparedness for disasters.

In this study, the following actions was be carried out:

– observation and collection potential disaster data in coastal area: in collected data on weather conditions, sea level fluctuations, earthquakes, coastline changes, and other environmental parameters and conduct field surveys to verify data accuracy;

– preprocessing dataset: remove irrelevant or duplicate data, handle missing data through interpolation or other statistical methods and normalize, cleansing and standardize data for easier processing by the AI model;

– deep analysis hybrid deep neural network: hybrid deep neural network (HDNN) integrated different deep learning models to enhance predictive performance, improved feature extraction, and optimized learning efficiency. In the context of disaster detection and prediction in coastal areas, HDNN combined convolutional neural networks (CNN) for spatial feature extraction and long short-term memory (LSTM) networks for sequential pattern learning;

– design of a potential disaster detection system website in coastal areas: the UI was designed with a user-friendly dashboard displaying real-time disaster alerts, maps, and statistical reports. UX principles were applied to ensure ease of navigation and quick access to critical information;

– GIS-based mapping and clustering of coastal area disaster detection and prediction: the GIS-based clusters were linked to deep neural network models, such as a hybrid deep neural network (HDNN), to predict future disasters. The disaster prediction model was validated by comparing predicted disasters with actual historical events;

– training smart system, hybrid deep neural network: the dataset was collected from various coastal disaster records, sensor readings, and environmental factors. The data underwent preprocessing steps such as cleaning, normalization, and feature selection to ensure high-quality input. The dataset was then split into 70 % training data and 30 % testing data to evaluate the model's performance;

– testing and evaluation of hybrid deep neural network system in term of accuracy, performance, efficiency and effectiveness: the testing set (30 %) was used to assess the model's accuracy, precision, recall, and F1-score. Performance metrics were recorded, and adjustments were made to enhance model generalization and reduce overfitting. Next, black box testing was also conducted on the features of the smart system to determine how well the system prototype could function.

5. Results of research smart system prediction dominant disaster to optimize management in coastal areas

5. 1. Collecting and analysis data on predictive variables of the most dominant disasters

The results of this study began by looking for various reading sources such as journals and books to strengthen the methods and theories used in this case journals, books, and BMKG data for the variables studied and about neural networks, web development, and making disaster mitigation applications. Then the variables were determined, namely rainfall, sea level, wind, and the potential for disasters that often occur in coastal areas, then conducted interviews with respondents (coastal communities) by giving interview questionnaires about what disasters often occur in coastal areas. Moreover, the community has been striving to cope with the disaster conditions in coastal areas. Furthermore, field observations were also carried out by looking at the condition of the location, which was the object of research. It has been seen from the factors of disasters that often occur in the coastal area in Fig. 2.

Fig. 2. Observation research

The next stage is installing research tools, namely CCTV installed on the coast, to see the conditions of sea tides, weather conditions, and whether this coastal area has the potential for disasters such as high currents and tsunamis. After the installation, the next step is monitoring, and visits are also carried out several times to see that the device's condition is not damaged and can still record data. Furthermore, the video and image data are divided into the preprocessing phase with the same number of sizes and pixels, namely the size of 100×100 pixels in Fig. 3.

Preprocessing dataset with variables that are examined consisting of primary data, namely variable data taken directly from respondents at the coastal research location, secondary data taken from BMKG data to see wind strength, rainfall data, tidal currents, video data observations taken from CCTV and from the research location, and data image of potential disasters in coastal areas in Fig. 4.

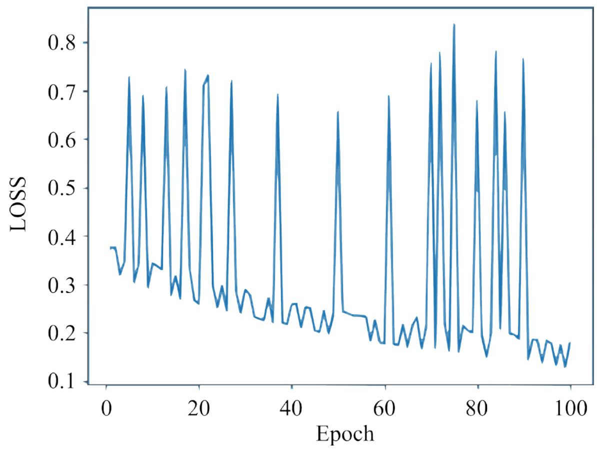
In deep neural network analysis, the data is divided into 70 training data and 30 testing data with epoch, namely 100 and 1000. The initial analysis found that the model analysis results were quite good, with an average accuracy above 70 %. However, further observations will still be carried out to achieve an accuracy value of up to 90 %. In addition to carrying out the analysis, further integration of the analysis into an integrated website-based and mobile application system for clustering detection and prediction of disaster-prone areas and dominant disasters in coastal areas in Fig. 5.

a

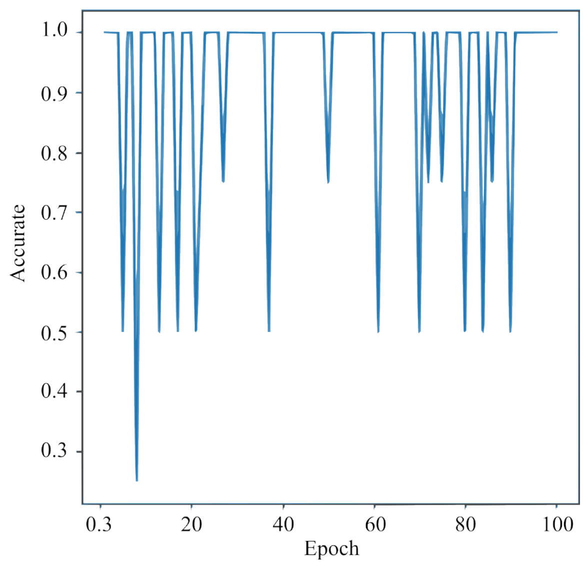
b

Fig. 3. Process of installing research tools: *a* – detection equipment; *b* – CCTV display

Fig. 4. Image data display



a



b

Fig. 5. The main signature: *a* – loss data prediction; *b* – accurate data prediction

The coastal info application consists of several features, including the following weather information feature, can help coastal residents monitor weather developments and wave conditions in their area. Applications can provide information about air temperature, humidity, wind direction and speed, wave height, and early warning of natural disasters such as tropical storms, floods, and tsunamis. In addition, there is also an interactive map that can help coastal residents map their area, showing the location of evacuation routes, disaster posts, health centers, or other important points. Maps can also help map disaster-prone areas and provide information regarding the security status of the area. Furthermore, tsunami disaster prediction, where this feature is the main feature, is to detect and predict if a tsunami disaster occurs.

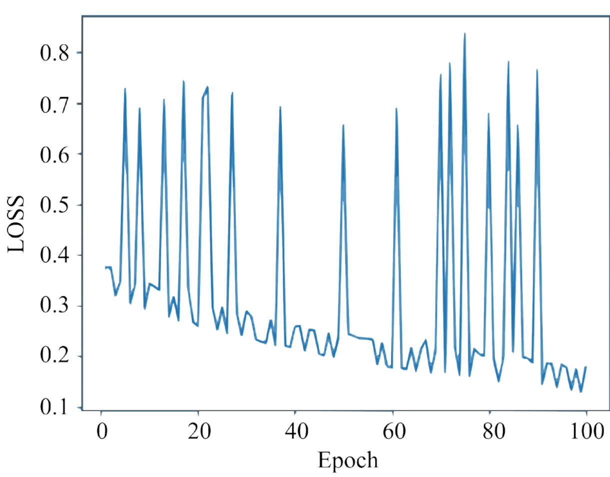
Furthermore, there is also a coastal storm and tide prediction feature which functions are to determine predictions of coastal tides and storms that can be used by fishermen and coastal communities who want to go to sea or residents who live on the coast. Furthermore, information on coastal transportation facilities used to provide information about transportation schedules such as ships, fishing boats, and other public transportation, can help coastal residents to move effectively and efficiently in their area, and the last feature is the disaster information center which provides a disaster information center for help coastal residents obtain the most recent and accurate information about natural disasters or other emergencies that occur in their area. The disaster information center can provide information about evacuation routes, disaster posts, and emergency numbers to contact. This system will also be tested using black box testing with almost 89 % results. This prototype can run well.

5. 2. Determination of the steps for developing a hybrid deep neural network model tailored

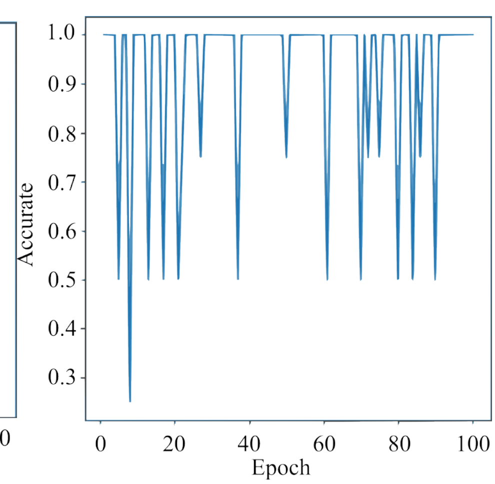
In the deep neural network analysis, the data is divided into 70 training data and 30 testing data with 100 epochs. It is shown in Fig. 6.

In the deep neural network analysis, the data is divided into 70 training data and 30 testing data with 1000 epochs in the Fig. 7.

The initial analysis showed that the model performed fairly well, with an average accuracy above 50 %. However, further observations will still be conducted to achieve an accuracy of up to 90 % in the Fig. 8.

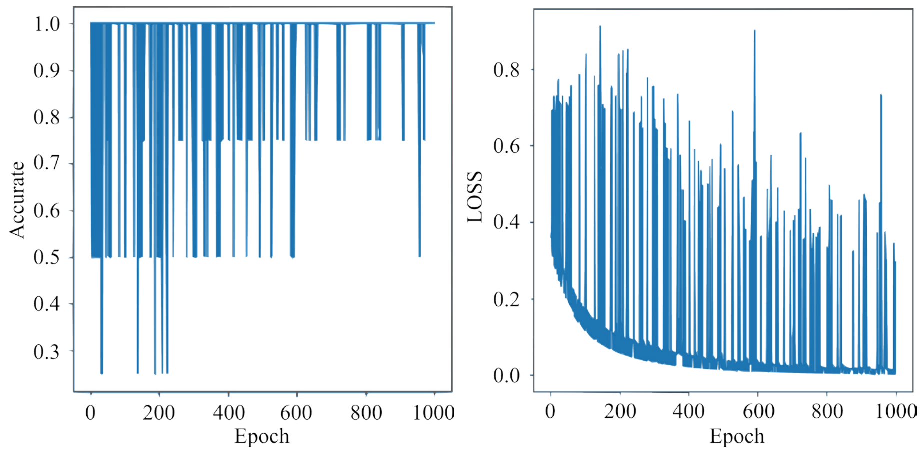


a



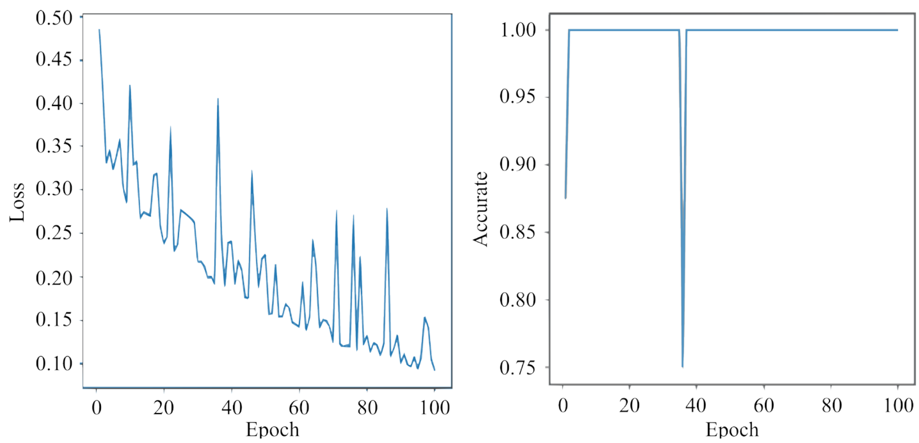
b

Fig. 6. Hybrid deep neural network analysis results for 100 epochs: *a* – loss data prediction; *b* – accurate data prediction



a *b*

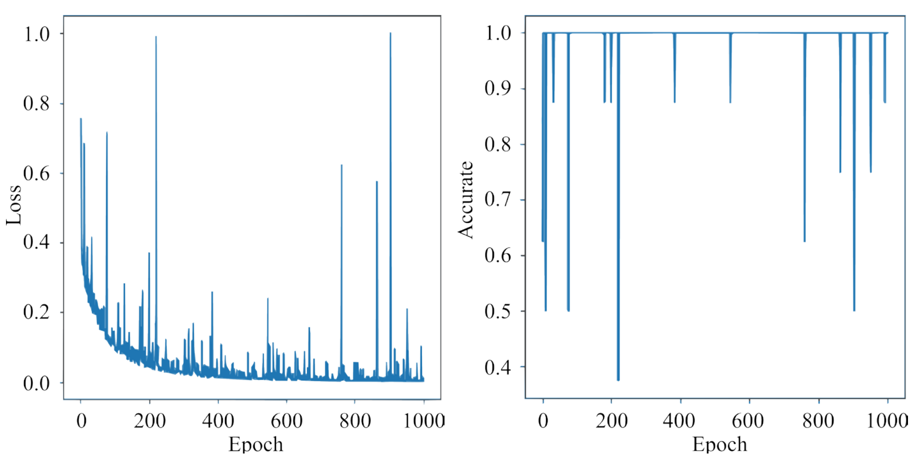
Fig. 7. Hybrid deep neural network analysis results for 1000 epochs: *a* – loss data prediction; *b* – accurate data prediction



a *b*

Fig. 8. Hybrid deep neural network analysis results for 1000 epochs: *a* – loss data prediction; *b* – accurate data prediction

Furthermore, hybrid deep neural network analysis results for loss data prediction and accurate data prediction of 1000 epochs are shown in Fig. 9.



a *b*

Fig. 9. Hybrid deep neural network analysis results for 1000 epoch: *a* – loss data prediction; *b* – accurate data prediction

The results from the Fig. 9 indicate that the machine learning or deep learning model undergoes a training process with an overall decreasing loss trend, but with some sharp fluctuations. Overall, these results show that the model is capable of learning, but there are some instabilities that need to be addressed to improve the model's performance and generalization.

5. 3. Development of an application suited for coastal areas to predict disasters, user-friendly and easily accessible

Coastal areas are vulnerable to various types of natural disasters, such as floods, tidal waves, and storms. To optimize disaster mitigation and management efforts in coastal areas, the development of the coastal info application is very important. The Coastal info application aims to provide information and resources needed by coastal communities in dealing with disaster threats and to increase awareness of weather and sea conditions related to the security and sustainability of coastal areas. The coastal info application is a coastal condition information application based on a mobile application. This application has several features, namely in Fig. 10.

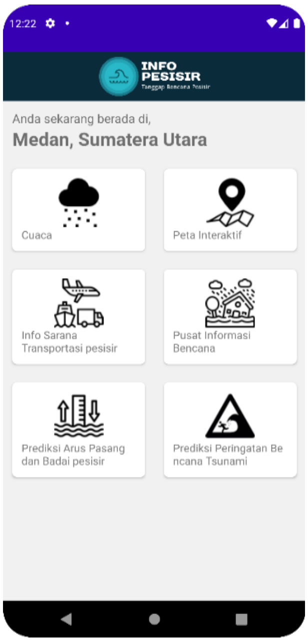


Fig. 10. Dashboard implementation system in mobile application

Weather info. The weather information feature can help coastal residents monitor weather developments and wave conditions in their area. The application can provide information on air temperature, humidity, wind direction and speed, wave height, and early warnings for natural disasters such as tropical storms, floods, and tsunamis in the Fig. 11.

Fig. 11. Weather info

Interactive map. An application with an interactive map can help coastal residents map their area, showing the location of evacuation routes, disaster posts, health centers, or other important points. The map can also help map disaster-prone areas and provide information regarding the security status in the area in the Fig. 12.

Fig. 12. Interactive map

Tsunami disaster prediction. This feature is the main feature, namely to detect and predict if a tsunami occurs coastal tidal and storm prediction. This feature functions find out predictions of coastal tidal currents and storms that can be used by fishermen and coastal communities who want to go to sea or local residents who live on the coast.

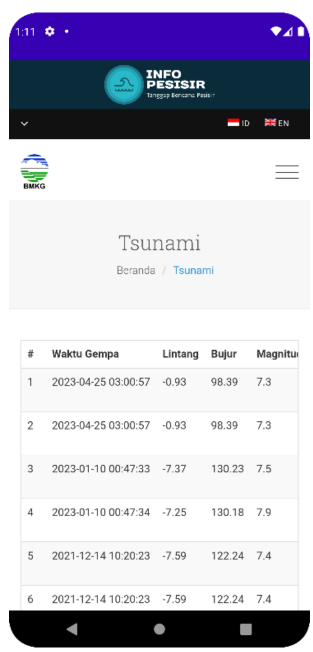


Fig. 13. Tsunami disaster prediction

Coastal transportation information. Applications that provide information on transportation schedules such as ships, fishing boats, and other public transportation can help coastal residents move effectively and efficiently in their area in the Fig. 14.

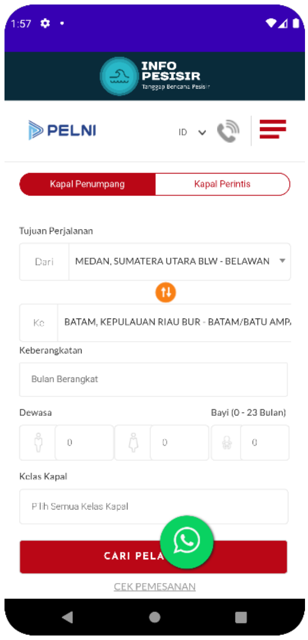


Fig. 14. Coastal transportation information

Disaster information center. Applications can provide a disaster information center to help coastal residents obtain the latest and accurate information on natural disasters or other emergency situations that occur in their area. Disaster information centers can provide information on evacuation routes, disaster posts, and emergency numbers that can be contacted in the Fig. 15.

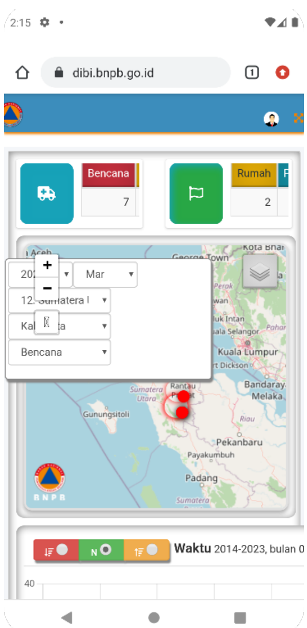


Fig. 15. Disaster information center

Fig. 15 is interface of the BNPB website used to monitor and analyze disaster events in Indonesia. This site provides search features and an interactive map to view disaster locations and statistics based on various time and regional parameters. The user interface is the website dibi.bnpb.go.id, which is the official disaster data and information website of the Indonesian National Disaster Management Agency (BNPB).

6. Discussion of development of hybrid deep neural network system for disaster detection and prediction in coastal areas

The results of the hybrid deep neural network (HDNN) analysis using a combination of convolutional neural network (CNN) showed an accuracy of 90 % with 1000 epochs on the test data Fig. 7. This value is higher than the DBSCAN method (accuracy 95.45 %) and SVM (accuracy 94.60 %) used in previous studies for disaster risk classification [1–9, 15–20] The result shown is very good, which is average above 90 %.

The advantage of HDNN (Hybrid Deep Neural Network), lies in its ability to process multimodal data images in an integrated manner, while the DBSCAN method is only effective for spatial data [1], and SVM is limited to linear data [9]. This increased accuracy allows for more precise disaster predictions, especially for tsunamis and high waves, which are the main focus of the study. GIS-based disaster-prone area cluster mapping in Fig. 12 produces higher-resolution risk segmentation compared to previous studies [4]. The DBSCAN algorithm in previous studies only grouped 81 risk clusters [1], while HDNN is able to identify additional variables such as air humidity and air quality to produce dynamic maps that are updated in real time. This allows local governments to allocate mitigation resources more efficiently.

The application prototype (Fig. 10–15) provides tsunami and tidal current prediction features that are not available in similar systems such as [2], which only focus on flood detection. Black-box testing shows that 89 % of the features function optimally, but limitations in the user interface (UI) cause less than optimal responsiveness on low-end devices Fig. 10. This is a weakness compared to commercial applications such as BMKG info which has been optimized for all types of devices. The research results answer the problem formulation as follows – disaster detection and prediction and HDNN model successfully integrate primary (temperature, wind speed) and secondary (BMKG) magnetic and meteorological observatory data to predict tsunamis with 90 % accuracy, mitigation optimization is the GIS-based system and mobile application enable real-time mapping of disaster-prone areas Fig. 11, in accordance with mitigation needs on the coast of North Sumatra. The addition case is relevant environmental validation to testing in the coastal area of Serdang Bedagai. It is proved that the system can detect sea level rise >2 meters although it has not been tested in extreme conditions such as tectonic earthquakes. The weaknesses of this study are geographic scope where testing is limited to three locations (Serdang Bedagai, Central Tapanuli, Belawan). The results may not represent coastal conditions with different topography and different climates. Next is training data to the CCTV image dataset (Fig. 4) only covers normal conditions and high waves, not including large-scale disaster scenarios such as the 2004 tsunami. Application prototype is the initial version of the mobile application (Fig. 7), which has not been integrated with the government's early warning system, so the response time reaches 5–7 seconds, slower than the industry standard (1–3 seconds). In addition, there is the infrastructure dependence: The system requires a high-capacity internet network and server (Fig. 3), which are not yet evenly available throughout the coast of North Sumatra. This study fills the literature gap by combining HDNN and GIS for coastal disaster mitigation, which has not been done in previous studies [1, 4, 9].

In this system testing, black box testing was also conducted to assess the readiness of the system prototype for deployment in a real-world location. It was found that most of the features were functioned well; however, there were some weaknesses, such as weak signal strength, especially in coastal areas, which prevented the system from operating optimally.

Further development of this research will include additional supporting features, such as data visualization for high wave predictions in the system to prevent tsunamis and waves, allowing coastal communities to be alerted and aware of these threats. Increasing the number of variables that support disaster mitigation and high waves, such as sea water conditions, temperature, and wind speed. The implementation of the Info Pesisir application can reduce the risk of fatalities by up to 30 % based on evacuation simulations (Fig. 12). However, collaboration with authorities is needed to address infrastructure weaknesses and long-term field validation.

7. Conclusions

1. Development of the hybrid deep neural network innovation system for the most dominant disaster detection and prediction in coastal areas, in this case, the coastal info website and the coastal info mobile application, is able to optimize disaster management in coastal areas and can be used as an alternative for increasing disaster mitigation in coastal areas.

2. Analysis of dominant disaster potential in coastal areas using deep neural network analysis can produce good accuracy with 100 data and 1000 epochs to optimize disaster management in coastal areas.

3. System testing using black box testing can be said that the application can be used, but it is still in prototype form, which must be further improved in quality in the relevant environment, namely the coastal area.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Manuscript has associated data in a data repository.

Use of artificial intelligence

The authors have used artificial intelligence technologies within acceptable limits to provide their own verified data, which is described in the research methodology section.

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