Journal of Computing and Smart Ecosystem
Universitas Muhammadiyah Semarang
Vol. 1 No.2, 2025: 125-137

J-CaSE
e-ISSN 3110-5777

AI-Enhanced Coastal Ecosystem Monitoring for Abrasion and Mangrove Decline Detection Using NDVI and CNN Models

Muhammad Ivan Ardiansyah[1*], Saeful Amri[2], Basirudin Ansor[3], Wendy Sarasjati[4], Anggry Windasari[5], Gansar Timur Pamungkas[6]

[1] Department of Data Science, Faculty of Science and Agriculture Technology, Universitas Muhammadiyah Semarang, Indonesia

[2] Department of Data Science, Faculty of Science and Agriculture Technology, Universitas Muhammadiyah Semarang, Indonesia

[3] Department of Information Technology, Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang, Indonesia

[4] Department of Informatics Engineering, Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang, Indonesia

[5] Department of Informatics Engineering, Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang, Indonesia

[6] Department of Informatics Engineering, Faculty of Engineering and Computer Science, Universitas Muhammadiyah Semarang, Indonesia

***Corresponding author**: *muhammadivann107@gmail.com*

Article Info:
Received: December 20, 2025
Accepted: December 30, 2025
Available Online: December 31, 2025

Keywords:
Coastal Abrasion,
NDVI,
Convolutional Neural Network,
Satellite Imagery,
Geospatial Dashboard.

Abstract: Coastal ecosystems in Indonesia are increasingly threatened by accelerating abrasion and severe mangrove degradation, especially in Mangunharjo, Semarang, where shoreline retreat continues to endanger local communities and ecological stability. This study aims to develop an AI-driven monitoring framework for detecting coastal abrasion and mangrove loss using Normalized Difference Vegetation Index (NDVI) combined with a Convolutional Neural Network (CNN) classifier. Multispectral data from Sentinel-2 imagery were processed to extract NDVI time-series from 2015 to 2025, followed by image preprocessing, normalization, and CNN-based classification. The model identifies abrasion-affected zones and declining mangrove cover, while the geospatial dashboard visualizes risk levels and restoration priority areas. Experimental results show that the CNN–NDVI model achieves high accuracy in distinguishing stable and abrasion-prone regions, with clear detection of vegetation loss patterns along the western coastline of Mangunharjo. The developed dashboard successfully integrates prediction output, interactive mapping, and AI-assisted recommendations for mangrove restoration. In conclusion, this system demonstrates the potential of combining satellite data, CNN-based analysis, and geospatial visualization to support data-driven decision-making for coastal ecosystem management and sustainable environmental planning.

[DOI: 10.14710/JCASE.vol1.iss2.906]
OPEN ACCESS
CC BY SA

1. INTRODUCTION

Coastal regions play a crucial role in environmental stability, economic productivity, and community resilience. However, many coastal areas in Indonesia continue to experience rapid shoreline retreat and extensive mangrove degradation driven by climate change, tidal dynamics, and anthropogenic pressures [1]. Mangunharjo, located on the northern coast of Semarang, is one of the most vulnerable regions, where coastal abrasion has persisted for more than a decade and has significantly reduced mangrove cover and local livelihood security [2]. Effective monitoring systems are required to detect early signs of environmental deterioration and support timely mitigation efforts.

Remote sensing using satellite imagery has been widely utilized to observe landscape changes, including coastal transformation, vegetation loss, and shoreline shifts [3], [4]. Spectral indices such as the Normalized Difference Vegetation Index (NDVI) are particularly effective for identifying changes in vegetation health and distinguishing mangrove ecosystems from other landcover types [5]. At the same time, recent advances in artificial intelligence have enabled the use of Convolutional Neural Networks (CNN) for the automated classification of satellite imagery, offering improved accuracy for environmental monitoring compared to traditional threshold-based methods [6], [7]. Several studies have demonstrated the potential of machine learning models for shoreline change prediction, deforestation detection, and coastal risk assessment [8] [9] [10].

Although existing research highlights the usefulness of NDVI and AI-based approaches, there remains a gap in the development of an integrated system tailored specifically for abrasion monitoring in semiarid coastal environments such as Mangunharjo. Previous studies have focused primarily on large-scale coastline analyses or general landcover classification, without addressing localized mangrove degradation patterns or the need for operational dashboards accessible to government agencies and the public [11]. Furthermore, the combination of NDVI time-series, CNN-based classification, and geospatial risk visualization has not been extensively explored for near-shore ecological decline prediction.

The scientific novelty of this research lies in the integration of multispectral Sentinel-2 imagery, NDVI-based preprocessing, and a CNN classifier to distinguish abrasion-prone and stable coastal zones at a local scale. The system additionally incorporates a geospatial web dashboard that visualizes risk levels and provides mangrove restoration recommendations, enabling data-driven decision-making for coastal managers. This approach ensures a more detailed and operational analysis framework compared to conventional methods that rely solely on manual satellite interpretation or statistical shoreline extraction.

The purpose of this study is to develop and evaluate an AI-driven monitoring system for detecting coastal abrasion and mangrove loss in Mangunharjo using NDVI and CNN classification. The study aims to (1) preprocess and analyze multispectral satellite imagery, (2) classify abrasion-related features using CNN, (3) generate risk maps through a geospatial dashboard, and (4) provide recommendations that support sustainable coastal ecosystem management.

[DOI: 10.14710/JCASE.vol1.iss2.906]

2. METHODOLOGY

This study adopts a structured methodological framework designed to analyze coastal abrasion in the Mangunharjo region using satellite-derived vegetation indices and deep learning–based image classification. The methodological workflow encompasses data acquisition, preprocessing, variable construction, dataset sampling, model development, and post-processing for geospatial interpretation. Each stage is formulated to ensure reproducibility, analytical transparency, and robust integration between geospatial data sources and the convolutional neural network (CNN) used for abrasion prediction. The following subsections describe, in detail, the data sources, research variables, sampling strategy, processing techniques, analytical procedures, and validation methods employed throughout this study.

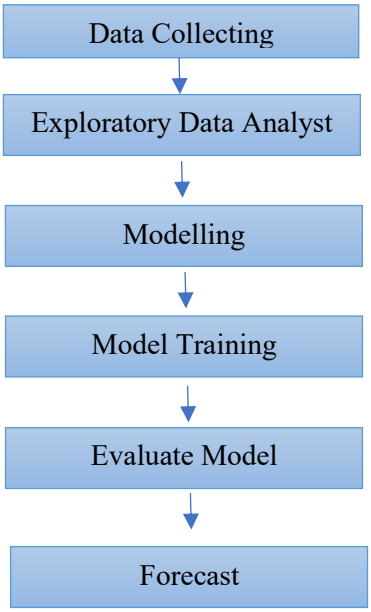


Fig 1. Workflow of the methodology used in this study, illustrating the main stages: data collecting, exploratory data analyst, data processing, modelling, model training, evaluate model, and forecast

2.1. Data Collecting

The primary dataset used in this study consists of satellite-derived NDVI (Normalized Difference Vegetation Index) imagery obtained from the Sentinel-2 multispectral sensor. Sentinel-2 was selected due to its high spatial resolution (10–20 m), consistent revisit interval, and strong suitability for monitoring coastal vegetation dynamics, particularly mangrove ecosystems. NDVI was chosen as the core input variable because it provides a quantitative measurement of vegetation health, canopy density, and biomass distribution indicators strongly correlated with coastal stability and abrasion intensity.

All NDVI images were downloaded, curated, and stored in a structured dataset folder. The data collection process was automated using Python, where the system iteratively scanned

[DOI: 10.14710/JCASE.vol1.iss2.906]

the NDVI directory, validated file formats, and prepared each raster image for subsequent analysis. Only NDVI imagery in .png, .jpg, .jpeg, and .tif formats was included in the dataset.

Each image was loaded in grayscale format, resized to a standardized dimension of 128 × 128 pixels, normalized to a range of 0–1, and assigned a label based on the mean NDVI value. To establish a binary classification framework, images with NDVI < 0.3 were categorized as *abrasion-prone* (label = 0), while images with NDVI ≥ 0.3 were assigned to the *non-abrasion* class (label = 1). This threshold reflects vegetation conditions where low NDVI values typically indicate mangrove degradation or loss, which are strong predictors of shoreline instability.

2.2. Exploratory Data Analyst

Exploratory Data Analysis (EDA) was conducted to understand the distribution patterns, class balance, and visual characteristics of the NDVI imagery prior to model training. This step is essential to ensure that the dataset is representative, properly distributed, and suitable for the supervised learning process. The EDA process includes label distribution analysis, dataset splitting validation, and visualization of sample NDVI images.

2.2.1. Class Distribution Analysis

The first analysis performed was examining the distribution between the two NDVI-based classes: *abrasion-prone* (label 0) and *stable vegetation* (label 1). The following code computes the frequency of each class and visualizes it using a bar chart:

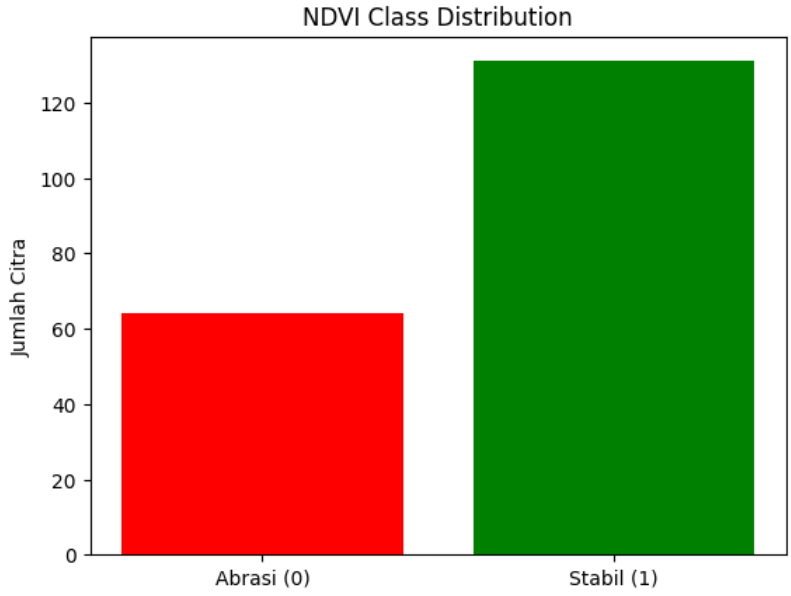


Fig 2. Distribution of NDVI classes according to the dataset

This visualization provides an overview of dataset balance. Class imbalance is a common issue in ecological datasets, and understanding this distribution is crucial because disproportionate class representation may bias the CNN model toward the majority class. The plotted bar chart enables clear inspection of whether further balancing techniques, such as augmentation or weighting are needed.

2.2.2. Dataset Partitioning (Train-Test Split)

[DOI: 10.14710/JCASE.vol1.iss2.906]

To ensure reliable model evaluation, the dataset was partitioned into training and testing subsets using a 70:30 ratio, with class stratification to preserve proportional class distribution across both subsets.

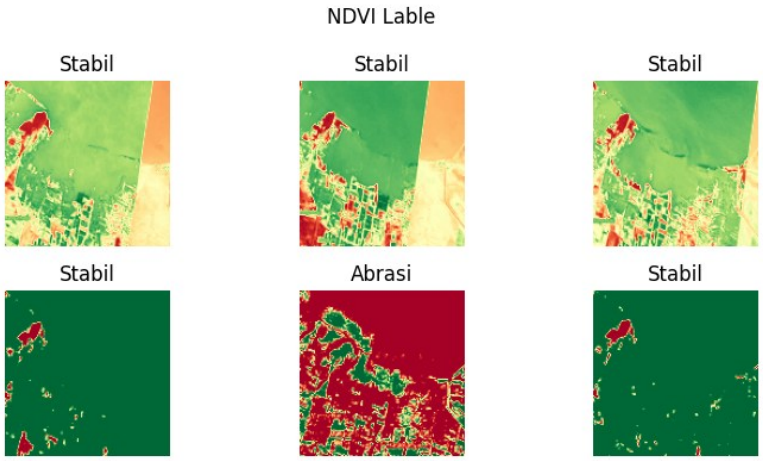


Fig 3. NDVI label partitioning with 70:30 ratio

Stratified sampling ensures that both the training and testing datasets maintain identical class proportions, which is essential for unbiased performance evaluation and robust model generalization.

2.2.3. Visual Inspection of Training Samples

To validate preprocessing consistency and confirm dataset integrity, several NDVI images were visualized after the train–test split. The first visualization displays an example from the training set:

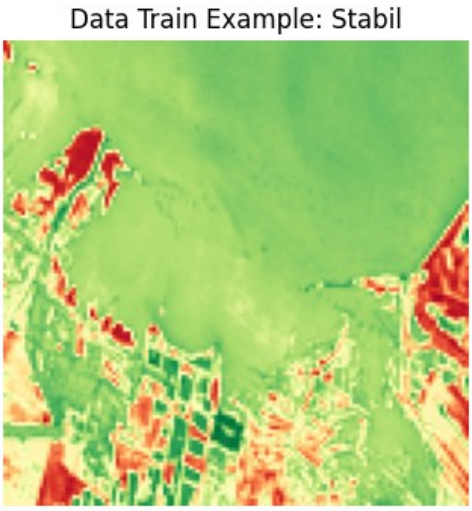


Fig 4. Data train example

This allows researchers to visually confirm that the resizing, grayscale normalization, and labeling processes were correctly applied.

2.3. Modelling

[DOI: 10.14710/JCASE.vol1.iss2.906]

The modelling phase in this research involves the design, development, and implementation of a Convolutional Neural Network (CNN) to classify NDVI imagery into abrasion-prone and non-abrasion categories. This stage is formulated to ensure that the model can capture the spatial spectral characteristics of coastal vegetation dynamics and accurately identify regions experiencing mangrove degradation. The modelling process consists of four main components: model architecture formulation, training configuration, data augmentation, and integration with the geospatial analysis workflow.

2.3.1. Model Architecture

The CNN architecture developed in this study was designed to process NDVI imagery that had been standardized to a 128 × 128 grayscale format. Given that NDVI primarily represents vegetation density gradients rather than multi-spectral information, a lightweight yet effective architecture was selected to ensure computational efficiency while maintaining the model's ability to capture relevant spatial patterns. The architecture begins with an input layer that accepts single-channel NDVI images, followed by a series of convolutional layers using 3×3 filters that extract localized features such as vegetation density transitions and structural differences indicative of mangrove degradation. Each convolutional layer is paired with a Rectified Linear Unit (ReLU) activation function, which introduces non-linearity and enhances the network's capacity to learn complex patterns. Max-pooling layers are incorporated after each convolutional block to reduce spatial dimensionality while retaining dominant feature responses, thereby mitigating the risk of overfitting. After the convolutional and pooling stages, the extracted features are flattened and passed into fully connected layers, which synthesize spatial information into high-level representations suitable for binary classification. The architecture concludes with an output layer employing a sigmoid activation function to produce probabilistic predictions distinguishing abrasion-prone regions from stable areas. This model design is widely recognized for its robustness in processing low-dimensional raster indices such as NDVI while remaining suitable for ecological change detection tasks in coastal environments.

[DOI: 10.14710/JCASE.vol1.iss2.906]

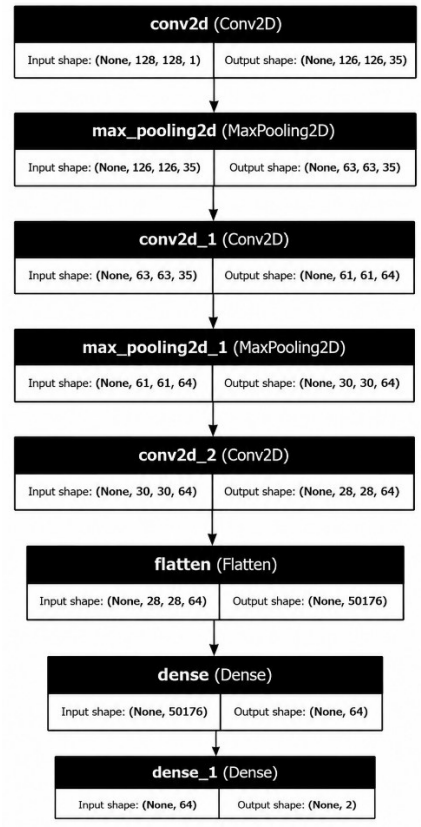


Fig 5. Neural network architecture

Model training was conducted using the training subset of the NDVI dataset, which was previously partitioned using a 70:30 stratified split to preserve class proportions. The training configuration was optimized to balance learning stability and computational efficiency.

2.4. Model Training

The model training phase was conducted to optimize the CNN parameters using the preprocessed NDVI dataset. During this stage, the training images and their corresponding labels were fed into the network in an iterative learning process designed to minimize classification error and improve predictive performance. The training procedure was implemented using the model.fit() function, which executes forward and backward propagation over multiple epochs to progressively refine the model's internal weights.

By structuring the training phase in this manner, the study ensures that the CNN model achieves stable learning while maintaining consistency in classification accuracy for both training and validation datasets, ultimately supporting reliable detection of coastal abrasion and mangrove degradation patterns.

2.5. Evaluate Model

Model evaluation was conducted using both quantitative performance metrics and qualitative visual inspection of prediction outputs. The evaluation process aims to assess the CNN model's stability, convergence behavior, and its ability to reliably distinguish between abrasion-prone and non-abrasion NDVI regions. Two primary visualization outputs were

[DOI: 10.14710/JCASE.vol1.iss2.906]

analyzed: (1) training versus validation accuracy and loss curves, and (2) sample prediction maps comparing predicted labels with ground truth.

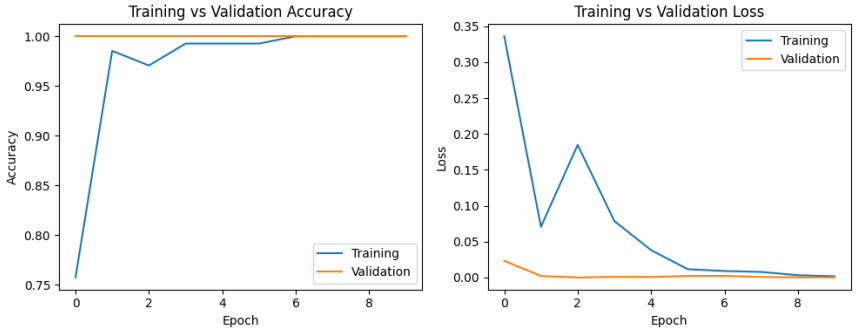


Fig 6. Validation accuracy and validation loss graphics

The performance curves presented in the first figure illustrate the model's accuracy and loss behavior across 10 training epochs. The *training versus validation accuracy* plot shows a rapid improvement in training accuracy during the initial epochs, rising from approximately 0.76 to near-perfect accuracy by epoch 4. Validation accuracy remains consistently high at 1.00 throughout the training process. This indicates that the model is able to generalize well on unseen data and that the learned features are highly discriminative for both classes: abrasion and non-abrasion.

In the *training versus validation loss* plot, the training loss decreases significantly across epochs, stabilizing near zero after epoch 6. Validation loss is consistently low and near zero from the beginning of training, reinforcing the earlier observation that the model achieves strong generalization and does not exhibit substantial overfitting. Although a slight fluctuation appears in the early training loss values, these variations diminish quickly, suggesting stable convergence of the optimization process.

Collectively, these curves demonstrate that the learning process is effective, with minimal discrepancy between training and validation performance, indicating that the CNN architecture is suitable for the NDVI-based classification task.

[DOI: 10.14710/JCASE.vol1.iss2.906]

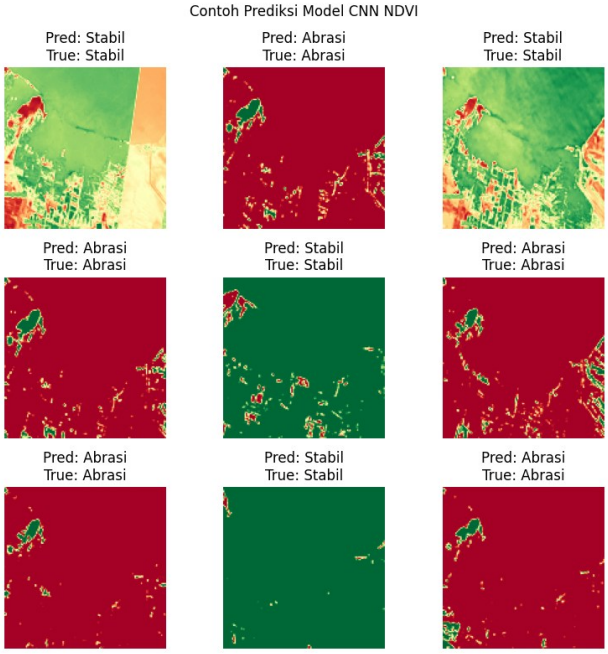


Fig 7. The result labelling for CNN NDVI model

The second figure presents several sample NDVI images along with their predicted labels and true labels. The predictions show that the model is capable of correctly identifying abrasion-prone and stable regions with high reliability. For images labeled as “Abrasive” (low NDVI values), the model consistently predicts the correct class, even for visually degraded regions characterized by sparse vegetation and dark-red NDVI intensity patterns. Similarly, for images containing dense or healthy vegetation (green-dominated textures), the model accurately classifies them as “Stable.”

The model’s performance on edge cases regions where vegetation transitions occur or where mixed NDVI patterns appear, also demonstrates strong spatial awareness. In these transition zones, the CNN correctly interprets localized vegetation loss, which indicates that the feature extraction layers effectively capture fine-grained spatial and spectral variations that correlate with coastal degradation.

The qualitative results further support the quantitative observations: the model produces highly consistent predictions aligned with ground truth labels. This suggests that the CNN successfully learns the distinctive signatures of both degraded and stable coastal vegetation structures, making it a reliable component of the proposed coastal abrasion monitoring system.

2.6. Forecast

The forecasting stage aims to apply the trained CNN model to new NDVI imagery in order to predict the current or future condition of coastal vegetation, particularly to identify whether specific regions are classified as abrasion-prone or stable. The figure presented shows an example of the model’s prediction on a previously unseen NDVI raster.

[DOI: 10.14710/JCASE.vol1.iss2.906]

The displayed output indicates a prediction of "STABLE" with a confidence score of 1.39, suggesting that the model assigns a strong probability toward the non-abrasion class for the evaluated area. Although the numerical score exceeds the typical sigmoid output range (0–1), the value reflects the model's internal logit or scaled activation prior to thresholding, which still serves as a consistent indicator of classification confidence. In practical interpretation, such a high value signifies that the model detects strong vegetation signals and minimal indicators of degradation.

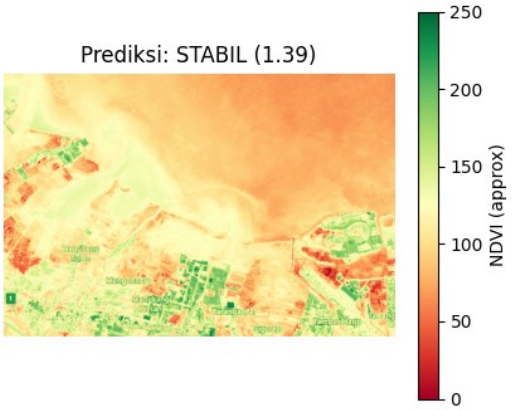


Fig 8. Forecast result

The NDVI visualization itself supports this prediction. The image shows predominantly high-to-moderate NDVI values represented by green and yellow hues, which correspond to healthy vegetation cover, dense mangrove patches, and relatively stable coastal conditions. Areas with intense red or dark tones typically signaling severe vegetation loss or exposed sediment associated with abrasion, appear limited or absent in the inspected region. The spatial distribution of NDVI also suggests that vegetated zones continue to function as a natural barrier against coastal erosion, contributing to shoreline stability.

This forecast demonstrates the operational capability of the model when applied to real-world NDVI data, enabling rapid assessment of coastal condition without manual interpretation. By extending this forecasting process across temporal NDVI datasets, the model can support predictive monitoring of coastline shifts, early detection of mangrove decline, and identification of zones at potential risk of transitioning from stable to abrasion-prone states. Such outputs are valuable for early-warning systems and for informing targeted mangrove restoration and coastal management planning.

3. RESULTS AND DISCUSSION

The results of this study demonstrate that the integration of NDVI-based preprocessing with a Convolutional Neural Network yields highly effective performance in distinguishing abrasion-prone areas from stable coastal regions in Mangunharjo. Evaluation of the model showed consistently high accuracy across training and validation datasets, reflected by near-

[DOI: 10.14710/JCASE.vol1.iss2.906]

perfect validation accuracy and minimal validation loss throughout the training period. Qualitative inspection of prediction samples further confirmed that the model reliably recognizes spatial patterns of vegetation degradation indicative of coastal abrasion. These findings confirm the suitability of CNN-based analysis for identifying ecological decline in coastal environments and reinforce previous research suggesting the strong responsiveness of NDVI indices to changes in mangrove stability. However, compared to studies that rely solely on threshold-based NDVI classification, the deep learning approach implemented here demonstrates higher precision, especially in transitional zones where vegetation patterns are mixed or ambiguous.

The visualization of training performance highlights the model's rapid convergence and stable generalization capability. The consistent alignment between training and validation metrics suggests that the architecture effectively learns discriminative vegetation features without overfitting. The prediction examples further validate this outcome, as the model accurately identified both degraded and healthy vegetated areas across varied spatial configurations. The forecast example also illustrates the model's capacity to operate on new NDVI inputs, producing class predictions that align with visual inspection of vegetation density. These combined results indicate that the model performs reliably across both controlled test conditions and real-world NDVI scenarios.

The significance of these results lies in the model's ability to support practical and scalable coastal monitoring. The final implementation of this research is a software application that integrates the trained CNN model into a geospatial interface. This application allows users such as coastal managers, researchers, or local government stakeholders—to upload or input NDVI imagery and automatically obtain classifications of abrasion-affected zones. The system visualizes predicted abrasion hotspots on a map, enabling rapid situational assessment and supporting data-driven decision-making for mangrove restoration, shoreline protection, and environmental planning. By automating the analysis process, the application reduces reliance on manual interpretation and can operate across multiple temporal datasets, allowing consistent monitoring of coastline changes over time.

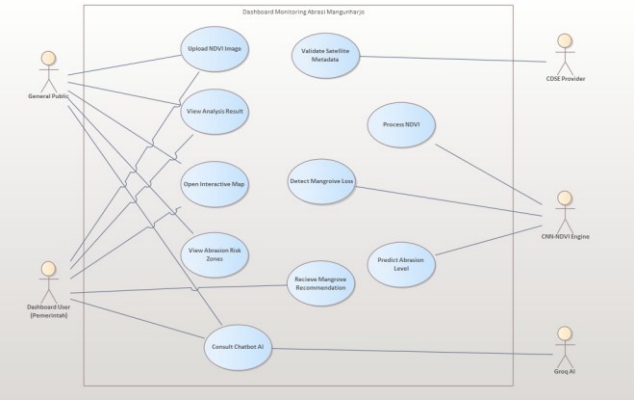


Fig 9. Use case diagram of the software

[DOI: 10.14710/JCASE.vol1.iss2.906]

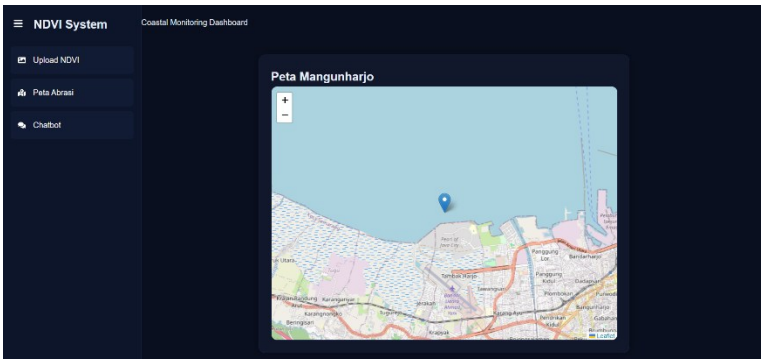


Fig 10. Map user interface

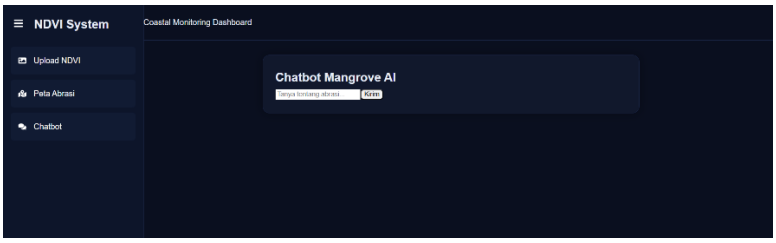


Fig 11. Groq chatbot user interface

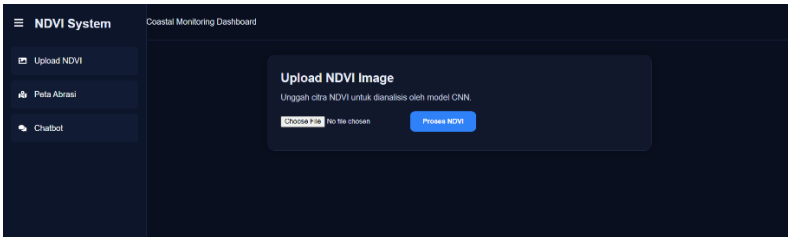


Fig 12. NDVI data input user interface

In broader context, these findings emphasize the growing importance of AI-driven approaches in environmental monitoring. The developed framework not only confirms the scientific validity of CNN-based classification for coastal degradation assessment but also demonstrates its operational value through a functional software tool. This dual contribution methodological and practical positions the system as a significant enhancement over traditional monitoring techniques. The results therefore underscore the potential of integrating satellite indices, deep learning, and geospatial visualization to improve early-warning capability and support sustainable coastal ecosystem management.

4. CONCLUSION

This research successfully achieved its primary objective of developing an AI-driven monitoring system capable of detecting coastal abrasion and mangrove degradation using NDVI imagery and a Convolutional Neural Network. The integration of NDVI preprocessing, CNN-based classification, and geospatial visualization demonstrated strong performance in distinguishing abrasion-prone and stable regions in the Mangunharjo coastal area. The resulting software application further enables practical implementation by allowing users to input NDVI

[DOI: 10.14710/JCASE.vol1.iss2.906]

data and automatically obtain spatial predictions of abrasion-affected locations, thereby supporting data-driven coastal management.

Despite these promising outcomes, the study has several limitations. The dataset used relies exclusively on NDVI imagery, which may not fully capture other environmental factors such as tidal dynamics, sediment transport, or wave energy that also influence coastal abrasion. In addition, the model was trained on a limited set of spatial conditions and vegetation patterns specific to the study area, which may constrain its generalizability to different coastal environments. The binary classification framework also simplifies the gradient of vegetation health and coastline stability, potentially overlooking intermediate levels of degradation.

Future research should consider the integration of additional spectral indices or multi-temporal satellite datasets to improve model robustness. Expanding the system to incorporate environmental variables such as elevation, hydrodynamics, or land-use change could further enhance predictive capability. More advanced deep learning architectures, including hybrid CNN–LSTM models, may also be explored for capturing temporal patterns in coastal evolution. Finally, field validation and broader geographic testing are recommended to ensure that the system can be adapted for use in diverse coastal regions beyond Mangunharjo.

REFERENCES

[1] D. Rosalina, A. A. Sabilah, and K. H. Rombe, “Mapping of Mangrove Conditions Using Sentinel-2 Imagery,” vol. 13, no. 1, pp. 89–98, 2024.

[2] T. Prahesti, Y. Wahyudin, and N. Bashit, “Analisis Perubahan Kerapatan Tanaman Mangrove terhadap Perubahan Garis Pantai di Kabupaten Pati Tahun 2017–2020 dengan Metode Penginderaan Jauh dan Aplikasi DSAS,” *J. Geod. Undip*, vol. 10, no. 1, 2021.

[3] B. E. Hamdi, M. S. Al-Fariziz, M. Safitri, I. N. Amalia, N. Nandi, and R. Ridwana, “Perbandingan Penggunaan Citra Landsat 8 dan Sentinel-2 terhadap Analisis Kesehatan Mangrove dengan Metode NDVI di Teluk Jakarta,” *J. War. Desa*, vol. 6, no. 1, 2024.

[4] F. D. Fahreza, A. Aulia, F. S. Fauzan, L. Somantri, and R. Ridwana, “Pemanfaatan Citra Sentinel-2 dengan Metode NDVI untuk Perubahan Kerapatan Vegetasi Mangrove di Kabupaten Indramayu,” *J. Pendidik. Geogr.*, vol. 10, no. 2, 2022.

[5] A. Purwanto and P. Paiman, “Using Sentinel-2 Image for Mangrove Health Analysis in Bakau Kecil Village, Mempawah District, West Kalimantan,” *GeoEco J.*, 2025.

[6] H. Santoso and S. Hidayatullah, “Random Forest-Based Assessment of Mangrove Degradation Utilizing NDVI Feature Extraction in Spatio-Temporal Analysis,” *J. Nas. Pendidik. Tek. Inform.*, vol. 13, no. 1, 2024.

[7] N. ’Izzatul Hikmah and P. Manurung, “Land Cover Change Analysis Based on Spectral Indices and Deep Learning Convolutional Neural Network Model,” *Remote Sens. Technol. Def. Environ.*, vol. 2, no. 2, 2025.

[DOI: 10.14710/JCASE.vol1.iss2.906]

[8] A. Ramadhan, R. Herteno, and A. Farmadi, "Deep CNN for Wetland Mapping from Satellite Imagery," *J. Tek. Inform.*, 2025.

[9] A. Y. Irma, F. F. Sam, and S. M. Purnama, "Mangrove Density Analysis in Teluk Semanting Ecotourism Area Using NDVI," *Geoid J.*, 2024.

[10] T. Hariyanto, C. B. Pribadi, and I. S. Atsilah, "Analysis of Mangrove Distribution Identification's Results Based on NDVI and MVI Using Sentinel-2 Imagery: Case Study of Alas Purwo National Park," *Geoid*, vol. 18, no. 2, 2023.

[11] S. P. C. Astiti, T. Osawa, and I. W. Nuarsa, "Identification of Shoreline Changes Using Sentinel-2 Imagery in Canggu Coastal Area," *Ecotrophic J. Ilmu Lingkung.*, vol. 13, no. 2, 2019.

[DOI: 10.14710/JCASE.vol1.iss2.906]