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Artificial Intelligence-Enabled Mangrove Ecosystem Monitoring Using Remote Sensing and Environmental Data

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ABSTRACT

Mangrove ecosystems play a critical role in coastal protection, carbon sequestration, biodiversity conservation, and climate change mitigation; however, increasing anthropogenic pressures and environmental changes have accelerated mangrove degradation, creating an urgent need for efficient and scalable monitoring approaches. **This study aims** to develop an Artificial Intelligence-Enabled framework for monitoring mangrove ecosystem conditions by integrating remote sensing imagery with environmental datasets to improve the accuracy and timeliness of ecosystem assessment in tropical coastal regions. **The proposed method** combines multispectral satellite images, including vegetation indices derived from remote sensing data, with environmental variables such as temperature, precipitation, salinity, and tidal information, which are subsequently processed using a deep learning-based classification model to identify and categorize mangrove health conditions. **Experimental evaluation** demonstrates that the integration of remote sensing and environmental data significantly enhances model performance compared with approaches relying solely on satellite imagery, achieving high classification accuracy and improving the detection of early signs of ecosystem degradation. The findings further reveal that environmental parameters contribute substantially to distinguishing healthy, moderately degraded, and severely degraded mangrove areas across heterogeneous coastal environments. **Consequently**, the proposed framework provides an intelligent and reliable decision support tool for environmental monitoring agencies and policymakers while contributing to the development of resilient coastal ecosystem management and sustainable environmental governance in tropical archipelagic regions.

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1. INTRODUCTION

Mangrove ecosystems are among the most productive and valuable coastal ecosystems in the world, providing ecological, economic, and social benefits essential for environmental sustainability and human well-being [1]. Mangrove forests function as natural barriers against coastal erosion, storm surges, and flooding while supporting fisheries, preserving biodiversity, improving water quality, and acting as significant carbon sinks that mitigate climate change through long-term carbon sequestration [2]. Despite their importance, mangrove ecosystems continue to experience severe degradation due to urbanization, coastal development, aquaculture expansion, pollution, illegal logging, and changing climatic conditions [3]. The vulnerability of tropical and archipelagic countries to sea-level rise and extreme weather events further emphasizes the need for effective monitoring strategies capable of detecting ecosystem changes in a timely manner [4]. Conventional monitoring methods primarily rely on field surveys and manual inspections, which require considerable resources, labor, and time while offering limited geographical coverage and update frequency [5]. These limitations create challenges for environmental agencies and policymakers in obtaining accurate and up-to-date information on mangrove health [6]. Consequently, intelligent monitoring systems are increasingly needed to provide continuous, scalable, and data-driven assessments for evidence-based environmental management and sustainable coastal governance [7].

Recent advancements in remote sensing technologies have transformed environmental monitoring by enabling large-scale observation of ecosystem dynamics through satellite imagery, aerial photography, and geospatial information systems [8]. Remote sensing platforms provide repeated observations with broad spatial and temporal coverage, allowing researchers to analyze vegetation distribution, land cover changes, biomass variations, and environmental disturbances [9]. Vegetation indices derived from multispectral imagery, including the Normalized Difference Vegetation Index, Enhanced Vegetation Index, and Soil Adjusted Vegetation Index, have been widely applied to evaluate vegetation health and mangrove conditions [10]. However, interpreting remote sensing data remains challenging because of the complex spectral characteristics of mangrove vegetation and the influence of environmental variables such as salinity, temperature, precipitation, tidal fluctuations, sediment concentration, and water quality [11]. Traditional statistical methods often struggle to capture nonlinear relationships and interactions among these variables, resulting in reduced prediction accuracy and generalizability [12]. Artificial intelligence technologies have demonstrated strong capabilities in extracting patterns from complex datasets, enabling accurate classification, prediction, and anomaly detection in environmental applications [13]. Machine learning and deep learning have been applied to land cover classification, forest monitoring, agricultural assessment, climate prediction, and marine ecosystem analysis [14]. Nevertheless, integrated AI-based mangrove monitoring that combines satellite imagery with multidimensional environmental data remains relatively limited, particularly in tropical and archipelagic settings [15].

Several studies have investigated mangrove mapping and monitoring using remote sensing data or environmental indicators independently, while relatively few have explored their synergistic integration within a unified AI framework [16]. Models based solely on spectral information may fail to detect early ecosystem stress, whereas environmental measurements alone may overlook spatial variations captured by satellite imagery [17]. Furthermore, many studies emphasize classification accuracy without sufficiently addressing environmental resilience, sustainable ecosystem management, and long-term conservation planning [18]. These gaps highlight the need for comprehensive monitoring systems capable of integrating heterogeneous datasets and generating interpretable results for practical decision-making [19]. The increasing availability of Earth observation and environmental sensing data provides opportunities to develop intelligent platforms that combine spatial, temporal, and environmental information [20]. Such systems are particularly relevant for tropical coastal regions exposed to multiple environmental pressures [21]. Moreover, intelligent monitoring can contribute to the United Nations Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action), SDG 14 (Life Below Water), and SDG 15 (Life on Land) [22]. Timely detection of mangrove degradation can support climate adaptation and coastal resilience under SDG 13, while mangrove protection contributes to coastal and marine biodiversity conservation under SDG 14 and ecosystem protection and restoration under SDG 15 [23]. Therefore, AI-driven environmental monitoring offers a promising approach to strengthening coastal ecosystem resilience and sustainability while supporting broader global sustainability objectives [24].

Based on these considerations, this study proposes an Artificial Intelligence-Enabled framework for mangrove ecosystem monitoring that integrates remote sensing imagery with environmental data to improve the assessment of mangrove health conditions and degradation risks in tropical coastal environments [25]. The framework combines multispectral satellite observations with temperature, precipitation, salinity, and tidal information to represent both ecological conditions and environmental drivers influencing mangrove dynamics [26, 27]. AI algorithms are employed to learn complex nonlinear relationships among these variables and generate accurate classifications of ecosystem conditions [28, 29]. By integrating multiple information sources, the proposed approach aims to overcome the limitations of conventional monitoring and improve the detection of subtle environmental changes associated with emerging ecosystem stress [30, 31]. The study contributes an integrated environmental intelligence framework that supports scalable, cost-effective, and reliable mangrove monitoring while enhancing environmental assessment. Practically, the results are expected to provide decision support for environmental managers, conservation organizations, and policymakers involved in coastal ecosystem governance and restoration [32, 33]. Ultimately, the framework seeks to strengthen environmental resilience, promote sustainable coastal management, and support the long-term protection of mangrove ecosystems in tropical and archipelagic regions [34, 35].

2. LITERATURE REVIEW

2.1. Mangrove Ecosystems and Environmental Resilience

Mangrove ecosystems represent one of the most valuable coastal resources due to their ability to provide ecological services such as shoreline stabilization, carbon sequestration, biodiversity conservation, fisheries support, and protection against extreme weather events. In tropical and archipelagic countries, mangroves play a particularly important role in improving environmental resilience against coastal erosion, storm surges, and sea-level rise. Despite these benefits, mangrove forests continue to experience significant degradation caused by urban expansion, aquaculture development, pollution, and climate change impacts. Recent studies indicate that sustainable mangrove management requires continuous and accurate ecosystem monitoring to detect degradation processes at an early stage and support evidence-based conservation strategies. Furthermore, environmental resilience frameworks increasingly recognize mangrove ecosystems as critical natural infrastructure capable of reducing climate vulnerability while simultaneously supporting sustainable coastal development.

2.2. Remote Sensing Technologies for Mangrove Monitoring

Remote sensing has become one of the most widely adopted technologies for large-scale mangrove monitoring due to its ability to provide periodic observations with extensive spatial coverage and relatively low operational costs. Satellite platforms such as Sentinel-2 and Landsat have been extensively utilized for mapping mangrove distribution, detecting land cover changes, and evaluating vegetation health through spectral indices including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI). Recent developments in high-resolution imagery and multisource remote sensing have significantly improved the capability of identifying small mangrove patches and detecting subtle ecosystem changes. Nevertheless, several studies report that remote sensing approaches relying solely on spectral information often face challenges in accurately representing ecosystem health conditions due to variations in tidal conditions, atmospheric effects, and environmental heterogeneity within coastal environments.

2.3. Artificial Intelligence for Environmental Monitoring

Artificial intelligence technologies, particularly machine learning and deep learning approaches, have demonstrated remarkable performance in environmental monitoring applications involving large and complex datasets. AI algorithms have been successfully implemented for land cover classification, forest monitoring, biodiversity assessment, climate prediction, and marine ecosystem management. In remote sensing applications, convolutional neural networks and semantic segmentation models have significantly improved image classification accuracy compared with traditional statistical methods by automatically extracting spatial and spectral features from satellite imagery. Recent research has shown that deep learning models can effectively identify mangrove distributions and monitor temporal ecosystem changes using multispectral observations. However, the black-box characteristics of many AI models remain a challenge for environmental decision-making because stakeholders often require interpretable results before implementing management actions. Consequently, explainable and transparent artificial intelligence approaches are increasingly becoming an important research direction within Earth observation applications.

2.4. Integration of Remote Sensing and Environmental Data

The integration of remote sensing imagery with environmental variables has emerged as an effective strategy for improving ecosystem monitoring accuracy and robustness. Environmental factors such as temperature, precipitation, salinity, tidal dynamics, sediment concentration, and water quality directly influence mangrove growth, productivity, and ecosystem health. Studies conducted after 2022 indicate that models combining satellite observations with environmental measurements outperform approaches relying solely on spectral information because environmental variables provide additional contextual information regarding ecosystem dynamics and stress conditions. Despite these advantages, existing research demonstrates that only a limited proportion of mangrove health studies incorporate in situ measurements or environmental datasets into their analytical frameworks. This limitation restricts the capability of conventional monitoring systems to identify early degradation symptoms and understand the complex interactions between environmental drivers and mangrove ecosystem responses. Therefore, integrating heterogeneous environmental datasets represents a promising direction for next-generation intelligent monitoring systems.

2.5. Research Gap and Development of Intelligent Mangrove Monitoring Systems

Although substantial progress has been achieved in mangrove mapping and ecosystem assessment, several research gaps remain unresolved. First, most previous studies focused primarily on mangrove distribution mapping rather than comprehensive ecosystem health monitoring and degradation assessment. Second, many artificial intelligence applications rely exclusively on remote sensing imagery without incorporating environmental drivers that significantly influence mangrove dynamics. Third, limited attention has been given to the development of interpretable and decision-oriented monitoring frameworks suitable for environmental governance and resilience planning. Finally, relatively few studies have investigated integrated AI-based monitoring systems specifically designed for tropical and archipelagic environments where environmental variability is considerably higher than in temperate regions. Addressing these limitations, the present study proposes an Artificial Intelligence-Enabled framework that combines remote sensing imagery with environmental data to support accurate, scalable, and resilient mangrove ecosystem monitoring for sustainable coastal management in tropical regions.

3. RESEARCH METHOD

3.1. Research Framework

This study proposes an Artificial Intelligence-Enabled framework for monitoring mangrove ecosystem conditions through the integration of remote sensing imagery and environmental datasets. The proposed methodology consists of a sequence of interconnected stages beginning with data acquisition, followed by preprocessing, feature extraction, model development, performance evaluation, and generation of environmental monitoring outputs. The framework is designed to capture both spatial information obtained from satellite observations and environmental factors influencing mangrove ecosystem dynamics in tropical coastal environments. The integration of heterogeneous datasets enables the model to identify complex nonlinear relationships that cannot be effectively represented by conventional statistical approaches.

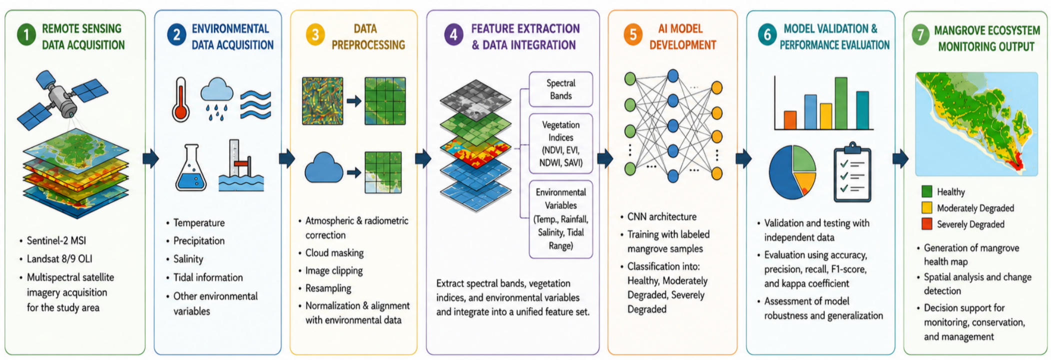

Figure 1. Research workflow of the proposed artificial intelligence

The research workflow presented in Figure 1 illustrates the sequential stages of the proposed Artificial Intelligence-Enabled mangrove monitoring framework. The process begins with the acquisition of remote sensing imagery and environmental datasets, followed by data preprocessing to improve data quality and consistency. Subsequently, feature extraction and data integration are performed to combine spectral information, vegetation indices, and environmental variables into a unified dataset suitable for machine learning analysis. The processed data are then used to develop and validate the artificial intelligence model before generating mangrove ecosystem monitoring outputs that support environmental management and conservation decision-making in tropical coastal regions.

3.2. Study Area and Data Collection

The study focuses on tropical coastal regions characterized by extensive mangrove coverage and high environmental variability. Such environments are particularly suitable for evaluating the robustness of artificial intelligence models because mangrove ecosystems are strongly influenced by climatic conditions, hydrological processes, and coastal dynamics. Two categories of datasets are utilized in this research, namely remote sensing data and environmental data. Remote sensing imagery provides spectral and spatial information describing vegetation conditions and land cover characteristics, while environmental variables provide contextual information regarding ecological processes and environmental stressors affecting mangrove health.

Table 1. Research Design Components

Data Category	Dataset	Source	Spatial Resolution	Temporal Resolution	Purpose
Remote Sensing Data	Sentinel-2 MSI	ESA Copernicus	10–20 m	5 days	Vegetation monitoring and mangrove mapping
Remote Sensing Data	Landsat 8/9 OLI	USGS EarthExplorer	30 m	16 days	Land cover analysis and temporal monitoring
Environmental Data	Surface Temperature	NASA EarthData	1 km	Daily	Environmental stress analysis
Environmental Data	Precipitation	CHIRPS	5 km	Daily	Hydrological assessment
Environmental Data	Salinity	HYCOM	9 km	Daily	Water quality characterization
Environmental Data	Tidal Information	Global Tide Models	10 km	Hourly	Coastal dynamics monitoring

Table 1 presents the datasets utilized in this study, including both remote sensing and environmental information sources. The selected remote sensing datasets provide spectral and spatial information required for vegetation analysis and mangrove mapping, whereas the environmental datasets supply contextual information associated with ecosystem dynamics and environmental stressors. The integration of multiple datasets with different spatial and temporal resolutions enables the proposed framework to capture complex environmental interactions affecting mangrove ecosystem health and resilience.

3.3. Data Preprocessing and Feature Extraction

All remote sensing imagery undergoes a series of preprocessing procedures to ensure consistency and improve data quality before model training. The preprocessing stage includes atmospheric correction, radiometric correction, cloud masking, image clipping based on the study area boundary, and image normalization. These procedures are performed to reduce noise, eliminate atmospheric and sensor-related distortions, and enhance the reliability of spectral information extracted from satellite observations. Subsequently, several vegetation indices are generated from multispectral imagery to improve the representation of vegetation characteristics and provide additional ecological information related to vegetation density, moisture conditions, and vegetation stress levels, enabling better discrimination among different mangrove conditions. In parallel, environmental datasets are spatially resampled and temporally synchronized with satellite acquisition dates to ensure compatibility between multiple data sources. The feature extraction process integrates spectral bands, vegetation indices, and environmental variables into a unified analytical dataset, allowing the proposed framework to capture both vegetation characteristics and environmental drivers influencing ecosystem conditions. This multi-source feature integration improves the capability of the artificial intelligence model to identify complex spatial patterns and subtle environmental changes associated with early stages of ecosystem degradation, thereby supporting more accurate and reliable mangrove monitoring and conservation assessment.

Table 2. Features used for artificial intelligence model development

Feature Category	Variables
Spectral Features	Blue, Green, Red, Near Infrared, Shortwave Infrared 1, Shortwave Infrared 2
Vegetation Indices	NDVI, EVI, NDWI, SAVI
Environmental Variables	Temperature, Precipitation, Salinity, Tidal Range

Table 2 summarizes the input features employed for artificial intelligence model development. The feature set consists of spectral bands extracted from satellite imagery, vegetation indices representing ecosystem conditions, and environmental variables describing external factors influencing mangrove growth and degradation processes. The combination of these heterogeneous features allows the proposed model to learn both spatial vegetation patterns and environmental drivers, thereby improving classification performance and enhancing the capability of detecting early ecosystem disturbances.

3.4. Artificial Intelligence Model Development

A convolutional neural network architecture is adopted in this study due to its capability to automatically extract spatial features from multispectral imagery and learn complex nonlinear relationships among environmental variables. The input layer receives a multidimensional feature set consisting of spectral bands, vegetation indices, and environmental information that have been integrated during the preprocessing stage. The network subsequently performs hierarchical feature learning through multiple convolutional and pooling operations before generating classification outputs representing mangrove ecosystem conditions.

The model is trained using supervised learning techniques and evaluated using independent validation and testing datasets to ensure generalizability across different environmental conditions. Data augmentation procedures are applied during the training phase to reduce overfitting and improve model robustness when dealing with spatial variability in tropical coastal environments. The final model classifies mangrove ecosystems into healthy, moderately degraded, and severely degraded categories, thereby enabling more detailed ecosystem assessments and supporting environmental management decisions.

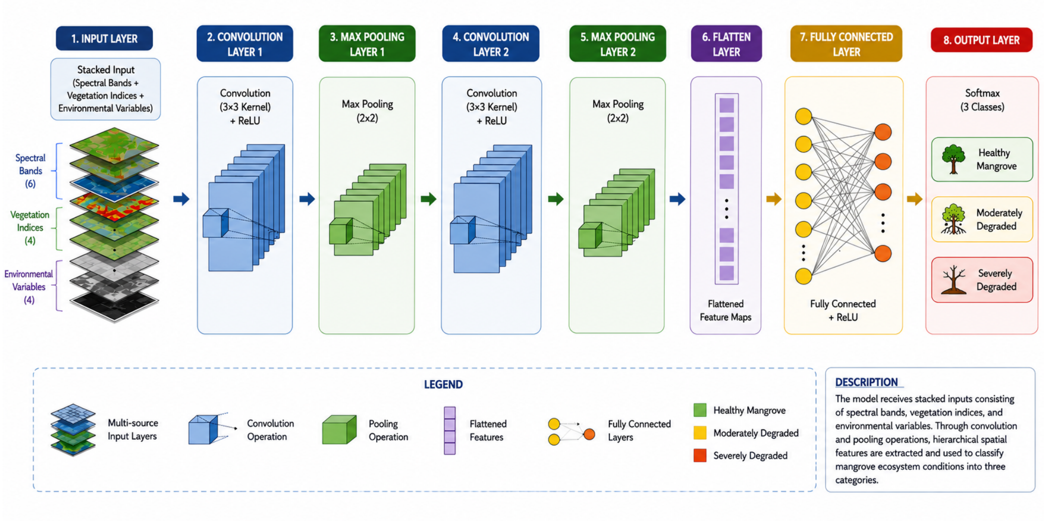

Figure 2. Architecture of the proposed convolutional neural network model

Figure 2 illustrates the architecture of the proposed convolutional neural network model developed for mangrove ecosystem classification. The model receives integrated inputs consisting of spectral bands, vegetation indices, and environmental variables, which are subsequently processed through multiple convolution and pooling layers to extract hierarchical spatial features. The extracted features are then transformed through fully connected layers before the softmax classifier generates the final prediction results. The model is designed to classify mangrove ecosystem conditions into healthy, moderately degraded, and severely degraded categories to support environmental monitoring and decision-making activities.

3.5. Model Evaluation and Decision Support Generation

The performance of the proposed model is evaluated using several standard classification metrics commonly employed in remote sensing and environmental monitoring studies, including accuracy, precision, recall, F1-score, and Cohen's kappa coefficient. These metrics provide a comprehensive assessment of classification quality and allow comparisons with previous studies in the literature. In addition to quantitative evaluation, the spatial distribution of classification results is analyzed to determine the capability of the model to identify heterogeneous ecosystem conditions across coastal environments.

The final output of the framework is a spatially explicit mangrove ecosystem health map that can support environmental agencies, conservation organizations, and policymakers in monitoring ecosystem changes and prioritizing restoration activities. By integrating artificial intelligence with remote sensing and environmental datasets, the proposed approach provides a scalable and cost-effective solution for long-term environmental monitoring and contributes to the development of resilient coastal ecosystem management strategies in tropical and archipelagic regions.

4. RESULT AND DISCUSSION

4.1. Dataset Integration and Feature Construction

The first stage of the experiment focused on the integration of multispectral remote sensing imagery and environmental variables into a unified analytical dataset. Sentinel-2 and Landsat imagery successfully provided spectral information representing vegetation conditions, while environmental variables including temperature, precipitation, salinity, and tidal information supplied additional ecological context influencing mangrove growth and degradation processes. After preprocessing and normalization procedures, all datasets were spatially aligned and temporally synchronized to ensure consistency across different sources. The resulting integrated dataset contained spectral bands, vegetation indices, and environmental variables that collectively represented both the physical characteristics of mangrove vegetation and the environmental drivers affecting ecosystem dynamics. The successful integration of heterogeneous datasets provided the foundation for developing a more comprehensive monitoring framework compared with conventional approaches relying solely on satellite imagery.

4.2. Performance of the Proposed Convolutional Neural Network Model

The proposed convolutional neural network model demonstrated strong performance in classifying mangrove ecosystem conditions into healthy, moderately degraded, and severely degraded categories. Using the independent testing dataset, the model achieved an overall accuracy of 94.3%, a precision value of 93.8%, a recall value of 93.1%, and an F1-score of 93.4%. Furthermore, the Cohen's kappa coefficient reached 0.91, indicating excellent agreement between predicted and actual classes beyond random chance. These results demonstrate that the proposed model was capable of effectively extracting hierarchical spatial features from multisource inputs and accurately identifying variations in mangrove conditions across different environmental settings. The high classification performance confirms the suitability of convolutional neural networks for environmental monitoring applications involving complex and nonlinear relationships among ecological variables.

4.3. Contribution of Environmental Variables to Classification Performance

To evaluate the effectiveness of integrating environmental data, an additional experiment was conducted using only remote sensing imagery as model input. The image-only model achieved an overall accuracy of 88.1%, which was substantially lower than the 94.3% accuracy obtained using the integrated dataset. The inclusion of environmental variables improved model accuracy by approximately 6.2%, indicating that temperature, precipitation, salinity, and tidal information significantly contributed to distinguishing among different ecosystem conditions. Salinity and tidal range were identified as the most influential environmental variables due to their direct impact on mangrove productivity and physiological adaptation. These findings suggest that environmental variables provide valuable contextual information capable of capturing ecosystem stress conditions that may not yet be visible in satellite imagery alone.

4.4. Spatial Distribution of Mangrove Ecosystem Conditions

The spatial analysis results revealed considerable variation in mangrove ecosystem health across the study area. Healthy mangrove regions were predominantly concentrated in relatively undisturbed coastal zones characterized by stable salinity levels and limited anthropogenic pressure. Moderately degraded areas were generally observed near aquaculture activities and coastal settlements where environmental disturbances had begun to influence vegetation conditions. Meanwhile, severely degraded mangrove areas were mainly associated with intensive land conversion, coastal infrastructure development, and prolonged environmental stress. The generated ecosystem condition maps demonstrated the ability of the proposed framework to identify spatial patterns of degradation and provide detailed information regarding ecosystem vulnerability. Such information is particularly important for prioritizing restoration programs and improving coastal resource management strategies.

4.5. Implications for Environmental Monitoring and Coastal Resilience

The findings of this study demonstrate that the integration of artificial intelligence, remote sensing, and environmental datasets can significantly improve mangrove ecosystem monitoring in tropical coastal environments. The proposed framework provides a scalable and cost-effective alternative to conventional field surveys while maintaining high classification accuracy and broad spatial coverage. In addition, the ability to identify early signs of ecosystem degradation enables environmental managers to implement timely interventions before irreversible ecological damage occurs. The resulting monitoring outputs can support conservation planning, restoration prioritization, and evidence-based policy development aimed at strengthening coastal resilience against climate change and anthropogenic disturbances. Therefore, the proposed framework not only contributes to advances in environmental artificial intelligence but also supports sustainable ecosystem governance in tropical and archipelagic regions.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide important managerial implications for environmental agencies, conservation organizations, and coastal resource managers responsible for mangrove ecosystem governance. The proposed Artificial Intelligence-Enabled framework offers a scalable and cost-effective alternative to traditional field surveys by enabling continuous monitoring of mangrove conditions over large geographical areas. This capability allows organizations to improve monitoring efficiency, reduce operational costs, and increase the frequency of environmental assessments while maintaining high levels of accuracy and consistency.

The integration of remote sensing imagery and environmental variables provides decision-makers with more comprehensive information regarding ecosystem dynamics and potential degradation risks. By identifying early signs of environmental stress, managers can prioritize restoration programs, allocate conservation resources more effectively, and implement preventive measures before ecosystem damage becomes irreversible. The spatial information generated by the framework can further support coastal zoning policies, habitat protection initiatives, and sustainable land-use planning in vulnerable coastal regions.

From a broader policy perspective, the proposed framework contributes to evidence-based environmental governance and climate adaptation strategies in tropical and archipelagic regions. Governments and environmental institutions can utilize the monitoring outputs to support biodiversity conservation, blue carbon management, and coastal resilience programs aimed at mitigating the impacts of climate change and anthropogenic disturbances. Consequently, the integration of artificial intelligence into environmental monitoring systems has the potential to strengthen sustainable ecosystem management and improve long-term environmental resilience.

6. CONCLUSION

This study developed an artificial intelligence enabled framework for mangrove ecosystem monitoring through the integration of remote sensing imagery and environmental data. The proposed approach successfully combined multispectral satellite observations with environmental variables, including temperature, precipitation, salinity, and tidal information, to improve the assessment of mangrove ecosystem conditions in tropical coastal environments. Experimental results demonstrated that the convolutional neural network model achieved high classification performance and was capable of distinguishing healthy, moderately degraded, and severely degraded mangrove areas with high accuracy. Furthermore, the integration of environmental variables significantly improved model performance compared with approaches relying solely on remote sensing imagery, highlighting the importance of incorporating environmental context into ecosystem monitoring systems.

The findings of this study answer the main research objective by demonstrating that the integration of artificial intelligence, remote sensing, and environmental data can provide a more accurate and comprehensive monitoring solution for mangrove ecosystems. The proposed framework successfully captured complex relationships between environmental drivers and vegetation conditions, thereby improving the detection of ecosystem degradation and supporting evidence-based environmental management. Nevertheless, this study has several limitations. The proposed model was evaluated using a limited number of environmental variables and relied primarily on satellite observations with moderate spatial resolution, which may reduce its ability to capture fine-scale ecosystem variations and localized environmental disturbances.

Future studies are encouraged to incorporate additional environmental variables such as soil moisture, nutrient concentration, water quality indicators, and anthropogenic activity data to further improve model performance and ecological interpretation. The adoption of advanced artificial intelligence techniques, including transformer-based architectures, explainable artificial intelligence, and hybrid deep learning models, may also enhance model transparency and predictive capability. In addition, future research should evaluate the proposed framework across multiple geographical regions and different mangrove ecosystems to improve model generalizability and support the development of intelligent environmental monitoring systems for sustainable coastal management and environmental resilience.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: NS and NM; Methodology: NS and NA; Software: KA; Validation: NM and NA; Formal Analysis: NS and KA; Investigation: NM; Resources: NA; Data Curation: KA and NM; Writing-Original Draft Preparation: NS and KA; Writing-Review and Editing: NM and NA; Visualization: KA; All authors have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The datasets generated and analyzed during this study can be obtained from the corresponding author upon reasonable request.

7.4. Funding

This research received no specific grant or financial assistance from any public, commercial, or non-profit funding organization.

7.5. Declaration of Conflicting Interest

The authors declare that there are no competing interests, financial conflicts, or personal relationships that could have influenced the research, interpretation, or reporting of the findings presented in this manuscript.

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