Sustainable Marine Structures
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REVIEW

Machine Learning Models for Early Warning of Coastal Flooding and Storm Surges

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ARTICLE INFO
Received: 9 July 2025 | Revised: 18 July 2025 | Accepted: 25 July 2025 | Published Online: 7 August 2025
DOI: https://doi.org/10.36956/sms.v7i3.2438

CITATION
Gholap, P., Gore, R., Dharmadhikari, D.D., et al., 2025. Machine Learning Models for Early Warning of Coastal Flooding and Storm Surges. Sustainable Marine Structures. 7(3): 136–156. DOI: https://doi.org/10.36956/sms.v7i3.2438

ABSTRACT

Floods and storm surges pose significant threats to coastal regions worldwide, demanding timely and accurate early warning systems (EWS) for disaster preparedness. Traditional numerical and statistical methods often fall short in capturing complex, nonlinear, and real-time environmental dynamics. In recent years, machine learning (ML) and deep learning (DL) techniques have emerged as promising alternatives for enhancing the accuracy, speed, and scalability of EWS. This review critically evaluates the evolution of ML models—such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM)—in coastal flood prediction, highlighting their architectures, data requirements, performance metrics, and implementation challenges. A unique contribution of this work is the synthesis of real-time deployment challenges including latency, edge-cloud tradeoffs, and policy-level integration, areas often overlooked in prior literature. Furthermore, the review presents a comparative framework of model performance across different geographic and hydrologic settings, offering actionable insights for researchers and practitioners. Limitations of current AI-driven models, such as interpretability, data scarcity, and generalization across regions, are discussed in detail. Finally, the paper outlines future research directions including hybrid modelling, transfer learning, explainable AI, and policy-aware alert systems. By bridging technical performance and operational feasibility, this review aims to guide the development of next-generation intelligent EWS for resilient and adaptive coastal management.

Keywords: Coastal Flood Forecasting; Deep Learning Algorithms; Early Warning Systems (EWS); Machine Learning Models; Real-Time Flood Monitoring; Storm Surge Prediction

1. Introduction

Coastal flooding and storm surges are growing threats to coastal communities, infrastructure, and ecosystems due to rising sea levels and the increasing intensity of extreme weather events. As a result, accurate and timely early warning systems (EWSs) have become essential for disaster risk reduction. Traditional physics-based forecasting models often struggle with the nonlinear and high-dimensional nature of coastal processes, making it difficult to provide real-time, high-accuracy predictions. Machine learning (ML) has emerged as a powerful tool to address these challenges. By learning complex patterns from large datasets, ML models can outperform conventional methods in terms of prediction accuracy, speed, and adaptability. Techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) have shown significant potential in coastal flood forecasting applications. Traditional hydrodynamic models, while physically interpretable, are computationally intensive and often struggle to incorporate heterogeneous real-time data sources such as IoT sensors, satellite imagery, and social data. ML techniques are uniquely suited for this challenge as they can model nonlinear patterns, adapt to changing conditions, and operate with lower computational demand—making them ideal for real-time flood forecasting. Coastal floods cause disproportionate harm in low-lying urban areas, especially in developing regions where EWS infrastructure is weak. Intelligent, AI-driven EWS offer the potential to save lives and reduce economic losses by enabling faster and more localized alerts.

This survey examines the state of ML models used in this area emphasizing methodologies, data sets, performance, challenges and future directions. Due to their capability of learning from data nonlinear patterns and to predict accurately, ML models have proven promising in flood forecasting [1, 2]. The use of ML for flood prediction has witnessed a noticeable increase, offering new interesting techniques for short-term and long-term flood forecasting [3]. ML methods have the advantages over traditional methods in that they can process big data and can capture non-linear relationships and obtain faster computation times, which are essential when real-time flood control is needed. Reliable and rapid prediction methods are becoming increasingly important to aid the flood management decision-making, for timely, effective responses to reduce the impact of flood events [4]. The creation and application of these models are vital to enhancing the resilience of communities that face growing threats from coastal flooding and storm surges. Recent advances in deep learning have enhanced the accuracy and efficiency of flood mapping and forecasting, outperforming classical numerical models [5].

Improvement along with storm-surge induced coastal inundation is a growing concern for populations and assets around the world, which therefore require accurate and robust early warning systems [2–5]. Predicting these events accurately is important for disaster preparedness, mitigation, response and ultimately saving lives and reducing economic losses [6]. Flood warning system has been put in place in many countries, as an unconventional way of preventing flood impacts [7]. An early warning leads to an early evacuation as well as deploying temporary defences and operating river control structures more efficiently [7]. Storm surge is a deadly element of tropical cyclones, which has inflicted enormous losses and killed many lives in the low-lying coastal regions for time immemorial [8]. Ex. sea level rise due to climate change) increase the danger of floods at the coast and make traditional forecasting methods dysfunctional [9]. Indeed, storm surges and coastal flooding are subject to complex meteorological, hydrological and oceanographic drivers, and a robust quantitative picture of coastal flooding and storm surges can be inferred only through use of similarly complex models that can similarly capture the interplay of these various forces. Traditional approaches often fail to capture the non-linear processes and complex feedbacks that exist in coastal systems. Recent developments in machine learning provide a potential opportunity for improving the accuracy and timing of coastal flooding and storm surge forecasting. To assist flood management decision making, it is crucial to implement real-time and accurate flood forecasting technology [4].

Machine learning techniques including a wide spectrum of algorithms, such as AI-based neural networks, support vector machines and decision tree etc., have shown interesting abilities in pattern recognition, prediction modelling, and data-based decision-making in multiple applications [1]. In the last decades many works have shown that artificial intelligence approaches, as the machine learning techniques, are able to provide flood forecasting solutions ranging from few hours to seasonal lead time, even some months ahead for an explaining river basin [10]. In this aspect, the data-driven models such as machine learning have the advantages to derive complex nonlinear relationships between the inputs and output by using historical meteorological data and do not need to consider detailed physical processes in a basin, which usually requires a great many parameters to be set in the traditional hydrological model simulations [11]. Using the vast datasets of historical observations, both numerical weather predictions and hydrodynamic simulations, it is possible to train machine learning models to recognize complicated patterns and relationships between input and output of coastal flooding and storm surge events [12]. These models can be used for training a prediction model for water level, inundation and wave significantly more accurate and considerably faster compared to numerical solutions. The application of machine learning algorithms can provide a powerful tool to address the drawbacks of numerical models, which are often computationally demanding and potentially miss the complexity of coastal processes [13]. An efficient answer to this problem is to use machine learning for predicting solutions given input datasets, which process complex data sets and give useful information for the prediction [14]. The potential of machine learning in fluid mechanics was demonstrated to accurately model complex input output relationships in non-linear fluid flows [15]. The fusion of physical principles with data-driven techniques is a fast-growing field with the potential to transform the way both fluid mechanics and machine learning is practiced [16]. In fact, machine learning is now considered as an essential adjunct to traditional experimental, computational and theoretical aspects of fluid dynamics [17]. The forecasting of precipitation rates which are closely related to variables such as surface temperature and humidity has always been difficult for meteorologists because of the uncertainty involved [18].

In addition, numerical models inevitably suffer from an inadequate knowledge of the field, measurement error of physical parameters, and errors of physical equations [19]. The adaptation and generalization capability in machine learning models renders them well-equipped to tackle such issues in coastal flood prediction. Growing availability of weather data, combined with recent advancements in machine learning, has resulted in substantial improvements in forecast accuracy [20]. In light of the vast potential of machine learning for coastal flooding prediction, there remain a number of challenges. One future area of work is to find good, reliable methods to integrate physical understanding into machine-learning models [21]. The problem with using data-driven methods such as machine learning is that any model or algorithm resulting from such an approach is not guaranteed to generalize beyond the parameter regime of the training data. Interpretable and explain able machine learning models are also crucial for trust and confidence in the models' predictions. This is especially important when data-driven models are used for outer-loop applications such as optimization [22]. The modelling theories proposed in this work are faster in the prediction of physics compared to machine learning-based methods which can approximate physics very efficiently but sacrifice accuracy when it is needed the most [23].

In the latter parts of this study, a review of the related literature on use of machine learning models for early warning of coastal flooding and storm surges will be conducted. This review will focus on the machine learning algorithms applied, the data used to train the model, and the performance metrics that were used to assess model's accuracy. In particular, deep learning approaches have been employed to address the drawbacks of conventional methods of flood map [5]. Deep learning models are reported to be more accurate than legacy methods and more efficient than numerical methods [5]. A GSHL (Geographically Structured Hierarchical Logic model) provides finer analysis on flood risks by showing better accuracy and predictability than classical DL models [24]. This research highlights that machine learning with advanced algorithms is becoming increasingly important in the treatment of flood prediction, given the necessity to have a more accurate and efficient prediction [3]. The review will also pinpoint major research lacunae and indicate the needs and opportunities for additional research in order to progress the state-of-the-art in the considered field.

In addition, the review will bring together the results from various studies to examine best practices and recommendations for creating and using machine-learning early warning systems for coastal flooding. This investigation also reviews the main deep learning frameworks used in landslides studies and in particular to landslide detection, mapping, susceptibility analysis, and displacement prediction [25]. Ultimately, the primary objective of this review is to offer a survey of the current state of the art in machine learning applications for coastal flood prediction and to help inform future research efforts aimed at enhancing accuracy, reliability and timeliness of early warning systems. Any effective landslide prediction and preventive work can help in minimizing the potential losses; however, the real-time accurate prediction of landslide is difficult to ascertain in advance as the direct scientific evidence for the imminent initiation of a landslide is always hard to obtain [26]. The solution to the MULTI challenge is an integration of multiple data sources as well as development of advanced ML approaches [27]. This study presents an ensemble machine learning model optimized by CHIO for accurate groundwater level forecasting in Türkiye's Ergene Basin, demonstrating superior performance and strong potential for global sustainable aquifer management [28]. Despite promising results in academic settings, real-world deployment of ML-based flood EWS remains limited. This review addresses that gap by exploring not just model performance but also the operational and policy challenges of scaling AI for coastal hazard management.

While numerical models remain essential for physical process simulation, deep learning approaches have shown superior short-term predictive capabilities in data-driven environments, as evidenced by recent studies [29–33]. The effective exploitation of massive datasets and advanced algorithmic solutions is pointing the way to the successful deployment of these approaches. While this review centers on coastal flood and storm surge prediction, it is worth noting that several ML techniques—especially deep learning frameworks like CNNs and LSTMs—have also been successfully applied in landslide forecasting. These models share methodological similarities and highlight the broader potential of ML in geohazard early warning systems. **Table 1** compares traditional hydrodynamic models and modern machine learning-based approaches used in coastal flood forecasting. It highlights key differences in data requirements, computational load, adaptability, and real-time applicability.

Table 1. Comparison Between Traditional Hydrodynamic Models and Machine Learning-Based Approaches for Coastal Flood Forecasting.

Feature	Traditional Models	ML/DL Models
Foundation	Physics-based equations (e.g., Navier–Stokes, SWEs)	Data-driven learning from historical patterns
Data Requirements	High-resolution bathymetry, boundary conditions	Historical observations, sensor data
Computational Load	High (HPC needed)	Lower (after training)
Adaptability	Low (location-specific calibration)	High (transfer learning, retraining)
Real-time Use	Limited	Strong potential

This review critically examines the application of ML in predicting coastal flooding and storm surges. It highlights key models, input features, datasets, and performance metrics, along with global case studies. While ML models offer promising results, challenges such as generalizability, data scarcity, and interpretability still need to be addressed. The goal of this review is to provide insights into current advancements and guide future developments toward more reliable and scalable EWS solutions. **Table 2** summarizes various machine learning methodologies applied to coastal flood and storm-related events, highlighting their data sources, improved prediction accuracy, performance metrics, and practical advantages for early warning and disaster management systems.

Table 2. Summary of Machine Learning Applications in Coastal Flood Forecasting and Storm Surge Prediction.

Parameter	Methodology	Material/System Used	Key Findings	Performance Metrics	Remarks/Conclusion
Flood Forecasting	Machine Learning (SVM, RF, LSTM, ANN)	Historical meteorological & hydrodynamic datasets	ML models offer better accuracy than traditional methods	RMSE, accuracy, precision	Effective in short- and long-term prediction
Storm Surge Prediction	Deep Learning (CNN, LSTM)	Satellite data, tide gauge records	Improved lead time and surge height prediction	MAE, RMSE	Outperforms numerical models in computation speed
Early Warning System	Hybrid ML + physical models	Numerical weather prediction data	Better adaptability and robustness	F1-score, recall	Promising for real-time deployment
Flood Mapping	Deep Learning (GSHL, U-Net)	Remote sensing imagery, DEM	Higher accuracy in inundation mapping	IoU, overall accuracy	Useful for risk assessment and urban planning
Landslide Forecasting	DL with multi-sensor fusion	Geological, meteorological, topographical data	Hard to predict, but ML improves early indication	AUC, sensitivity	More data integration needed
Disaster Mitigation	AI-based decision support systems	Real-time sensor and satellite data	Faster response and control decisions	Response time, decision accuracy	Supports emergency preparedness

2. Importance of Early Warning Systems in Coastal Zones

Early warning systems (EWSs) are key instruments in the protection of coastal areas, some of the most prone to natural hazards, such as tropical cyclones, storm surges, coastal flooding, and tsunamis. These systems are intended to sense the possible threats and to issue fast alerts to authorities and public, in order for a risk reduction and mitigating response. Coastal areas are particularly vulnerable to climate change effects such as sea level rise, increased storm activity, and shifting patterns of precipitation [25]. These threats increase the danger of the coastal flooding and storm surges for coastal communities, where from a preventive point of view, the alert systems s become especially important. Early warning systems offer disaster managers and planners timely, vital situational awareness, which saves lives and property [34]. **Figure 1** explains the importance of early warning systems in costal zones.

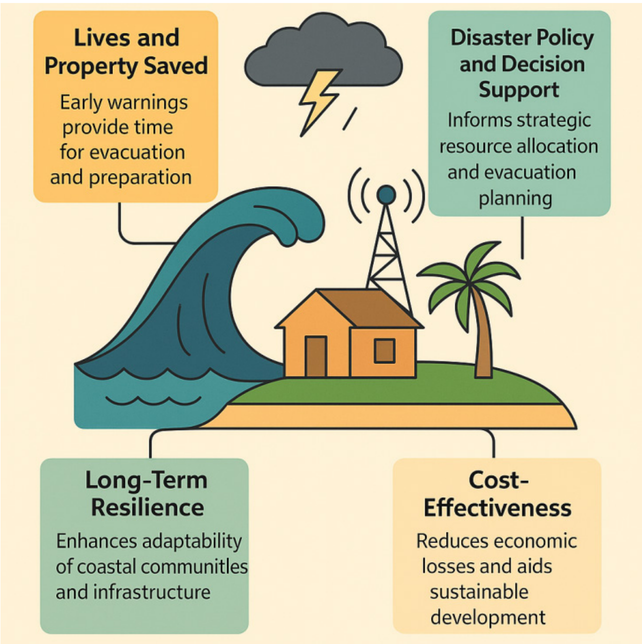

Figure 1. Importance of Early Warning Systems in Coastal Zones.

The paramount advantage of EWS is the saving of human lives and assets. Providing early warnings, they give communities and emergency management services the time they need to act quickly, remove people from the disaster environment, protect infrastructure, and put in place measures to ensure safety before the disaster occurs. This decreases death, suffering, and economic destruction due to delayed or non-unified actions. Early warning system (EWS) can be a complex system, involving vast range of technologies and methodologies such as weather prediction models, sensor networks, data assimilation techniques and advanced communication systems [35].

Additionally, early warning systems facilitate in the development of policy and decision support systems for disaster response teams and policy makers. The ability to provide accurate forecasts and to closely monitor such events in real time would enable the strategic allocation of resources, the planning of evacuation routes and the setting up of shelters, especially in densely inhabited or isolated coastal regions. This reduces disorganization and disorder during emergencies, which can help with a more organized and effective response by authorities and voluntary rescuers. Residents of disaster affected areas play the most crucial role in the disaster response scenario and their participation is essential for the safety and relief activities [36].

For policymakers, the study recommends incentivizing open coastal data sharing and mandating explainability standards in AI-powered warning systems. Disaster management agencies are encouraged to adopt hybrid ML-physical flood forecasting platforms integrated with GIS dashboards for real-time operational decisions. For researchers, future work should focus on model generalizability, transfer learning across diverse geographies, synthetic data generation for rare event prediction, and uncertainty-aware ML models tailored to coastal dynamics.

Apart from disaster risk reduction EWS provide opportunities to enhance the resilience of coastal infrastructure and communities in the long-term. Ongoing surveillance, risk evaluation, and publicity campaigns encourage a climate of readiness and flexibility. When connected to the coastal areas, which are served by early warning systems, coastal people can recover from disasters, reducing the long-term social and economic disparity. In addition, early warning applications are important in minimizing false alarms and in managing crises well before they escalate [37]. The effectiveness of early warning systems depends on the rapid issue of messages to a large number of recipients.

Finally, for those who consider the economy, early warning is a cost-effective practice related to disaster risk reduction. The cost of investing in warning technology and communication equipment management is as low as 100 more of the cost of clean-up and reconstruction. Thus, EWS not only reduce immediate risks, but also contribute to longer-term sustainable development and climate adaptation actions in sensitive coastal zones. A good local warning system would facilitate that people act to prevent loss of life and property when warnings are released about very high-impact events [38]. The development and maintenance of effective early warning systems are critical to the reduction of the disastrous effects of natural hazards in the coastal zone.

3. Traditional vs Machine Learning Approaches

In predicting coastal flood and storm surge, traditional forecasters and machine learners have unique and complimentary attributes. Matching these two methods in a variety of ways becomes apparent along several dimensions: in information requirement, model complexity, computational cost, and fit. The classical techniques rely on numerical weather prediction models that are based on hydrodynamic and meteorological phenomena. These models encapsulate the behavior of the atmosphere and oceans in humanly formatted equations [39]. Require a large order of computations, and may also not represent the local policies well [40]. In contrast, traditional approaches strongly depend on historical data to calibrate and validate models, and are usually based on long time series in order to build up statistical relationships.

On the other hand, machine learning methods such as deep learning models and neural networks are now considered effective for predictive analytics. They are particularly suitable for discovering complex patterns and non-linear associations underlying large data, and do not necessarily depend on explicit physical expressions [41]. Machine learning algorithms enable the automatic learning and adjusting from data, in contrast to traditional approaches requiring a manual feature engineering and expert knowledge [42]. These algorithms are able to work with data of high dimension and complexity due to the fact that it is not possible in many cases to know or represent explicitly the underlying physical processes.

Machine learning models also can be developed for better fusing of varied data sources such as satellite image, radar data, and sensor data for better forecast [43]. Ensemble learning methods are a new learning approach that is less utilized compared to traditional machine learning methods[44]. The flexibility of machine learning can also be used to propose hybrid systems that promise to combine the best of classical and data-driven methods. For example, combining machine learning with traditional models helps improve forecasting accuracy by being able to read real-time data, and adjusting model parameters dynamically. Data-driven models can be orders of magnitude faster and may learn complex parameterizations directly from the data, thus reducing model-induced error [45]. **Table 3** represents the comparison of Traditional and Machine Learning Approaches in Coastal Flood and Storm Surge Forecasting.

Table 3. Traditional vs Machine Learning Approaches in Coastal Flood and Storm Surge Forecasting.

Parameter	Traditional Methods (Physics-based)	Machine Learning Models (Data-driven)	Examples
Data Handling	Use hydrodynamic and meteorological equations to simulate coastal processes.	Learn from historical or sensor data using models like ANN, CNN, or LSTM.	ADCIRC, HEC-RAS vs CNN-based tide level predictors
Computation Time	High due to numerical solvers and grid resolution requirements.	Low once trained, enabling rapid predictions.	SWAN + ADCIRC simulations vs LSTM real-time alert systems in India
Flexibility & Adaptively	Inflexible to unexpected phenomena or non-linear behaviours.	Can adapt to dynamic, non-linear relationships.	Static coastal flood maps vs adaptive neural network forecasting
Accuracy	Dependent on model calibration; accurate under stable conditions.	Often higher accuracy with large data; improves with training.	RMSE 0.2–0.3 m (traditional) vs 0.08 m (CNN+LSTM)
Real-Time Application	Limited due to computation time and data needs.	Highly suitable for integration in live monitoring systems.	Cyclone early warning via satellite + LSTM model in Bangladesh
Uncertainty Handling	Difficult to quantify model uncertainty.	Can incorporate uncertainty using Bayesian or ensemble models.	Bayesian flood modelling in ML vs deterministic models
Interpretability	Easier to interpret based on physics.	Often complex but explainable using XAI tools.	HEC-RAS water profiles vs SHAP interpretations in ML models
Generalization	Transferable across regions with similar geography and data.	May require retraining; physics-informed ML improves generalizability.	Delta model for multiple estuaries vs region-specific neural net
Hybrid Approaches	Not applicable.	Combines physics model output with ML corrections.	ADCIRC + LSTM for bias correction of storm surge predictions

Classic methods are interpretable with scientifically established results, but are usually slower and less flexible. In contrast, the property of being fast adaptive and configured, robust, and easily applicable in real time, as is the case with machine learning models, is extremely beneficial, given the dynamic nature of coastal scenarios. The future may be hybrid systems that retain the strengths of both.

4. Key Machine Learning Models Used

The rapid development of meteorological, hydrological, and satellite data resources has made it possible to apply machine learning (ML) methods to predict coastal flooding and storm surges more accurately and efficiently. Unlike the conventional physics driven models, ML methods are capable of capturing complex patterns from the past data, not requiring explicit mathematical representation of the physical processes. This feature renders them suitable for predicting complex and dynamic environmental process. **Figure 2** summarizes the most widely used ML models in flood and storm surge predictions based on the type of data and requirements for forecast.

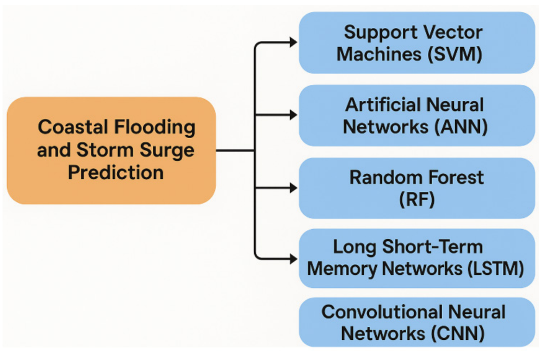

Figure 2. Key Machine Learning Models Used for Coastal Flooding and Storm Surge Prediction.

4.1.Support Vector Machines (SVM)

Support Vector Machines (SVMs) are among the most popular classes of supervised learning models for classification. In the context of coastal flood modelling SVMs are used to estimate storm surge thresholds and to categorise zones as flood (static) or non-flood (plain). They are well suited to small datasets and can handle nonlinear data by using kernels. Owing to their robustness and simplicity, they are applicable for the early-stage flood warning systems, especially in regions where good quality labelled flood images are scarce.

4.2.Artificial Neural Networks (ANN)

Amongst others, ANNs became one of the most popular models for the time-series in flood and hydrological applications. They are able to simulate the simultaneous dynamics among the meteorological drivers and the oceanographic drivers (i.e. rainfall, tide level, and wind speed). In the coastal area, many ANNs are used to forecast the depth of flooding or water level changes. They are strong at capturing nonlinear interactions, and can approximate unknown functions well, especially in dynamic and data-rich settings. ANNs are suitable for landslide research as they can take the effects of various complicated factors on landslides into account and perform well in prediction, feature selection, and classification on the basis of the available data [45].

4.3.Random Forest (RF)

Random Forest is an ensemble learning technique, which works by building multiple decision trees and merging their outputs for a classification or regression task. It is also widely used for flood susceptibility analysis, which is developed from various input data such as land use, topography, rainfall, and soil type. RF models are recognized by their high performance, robustness to overfitting and interpretability by through feature importance ranking. These characteristics make them an excellent candidate for regional flood risk mapping and decision support tools. Random forest (RF) is an ensemble learning approach, relying on multiple classification or regression trees for prediction and, due to its stability and high interpretability, applies in many prediction problems [46]. For complex orography, as in islands, it has been shown that this is an improvement in the prediction of ocean surfaces, however, prediction over land shows an under estimation of precipitation rates [47].

4.4.Long Short-Term Memory Networks (LSTM)

LSMT there Network which is a special kind of RNN, is that there is a long sequence dependency and time based data. LSTM is ideal for talking spring and sea level time series forecasting, due to its ability to model long range temporal dependencies within historical data. Due to their gated architecture, LSTMs are capable of retaining long-term dependencies in sequential data, making them ideal for modelling time-series such as sea levels or rainfall. LSTMs have become widely used in operational early warning systems as they provided predictions in time and with reliable forecast. As precipitation events are uncertain/unknown and LSTM has so much advantage for rainfall analysis, a DL-based approach using an LSTM sequential model, Bayesian optimization (BO), and transfer learning can be employed [4].

4.5.Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a type of deep learning model commonly applied to spatial and image data. Within flood modelling, CNNs are utilized to process satellite images, aerial photographs, and digital elevation models in order to identify flooded areas, land use shifts and coastal erosion. These models are good at detecting structures, textures and objects in spatial data and therefore are perfect for the post-flooding damage assessment and the real-time flooding extent mapping through remote sensing. In the last decade, it has been shown that over engineered classification, as well as per- pixel machine learning, have been replaced by the machine learning approach through convolutional- neural-networks that directly learns spatial patterns [48]. In addition, CNNs have the advantage of pre-processing the raw data in form of images and hence decrease number of parameters by employing partially connected layers and weight sharing [49]. CNNs are effective in capturing spatial features and patterns from image-based or gridded data, such as satellite imagery and elevation models, but they are not designed for temporal memory or sequence learning like LSTMs. **Table 4** represents the Key Machine Learning Models Used in Coastal Flood and Storm Surge Prediction.

In addition to coastal flooding, CNNs have also been applied in related environmental hazard detection such as landslides, particularly for mapping, susceptibility analysis, and displacement prediction using remote sensing data. Although not the primary focus of this review, these examples demonstrate the adaptability of CNNs to a range of geospatial risk modelling applications, including those that may coincide geographically or climatically with coastal flood zones.

Table 4. Key Machine Learning Models Used in Coastal Flood and Storm Surge Prediction.

Model	Application	Type of Data	Key Features	Suitability/Use Case
Support Vector Machines (SVM)	Classification, flood threshold estimation, zone categorization	Small datasets, labelled flood images	Robust to nonlinear data via kernels	Useful for early-stage flood warning systems
Artificial Neural Networks (ANN)	Time-series forecasting of water levels and flood depth	Rainfall, tide level, wind speed	Strong at capturing nonlinear dynamics	Effective in dynamic and data-rich settings
Random Forest (RF)	Flood susceptibility analysis, risk mapping	Land use, topography, rainfall, soil type	Robust, interpretable, and reduces overfitting	Good for regional flood risk mapping
Long Short-Term Memory Networks (LSTM)	Sea level & rainfall time series prediction	Long-range time-series, historical rainfall data	Captures long-term temporal dependencies	Widely used in early warning systems
Convolutional Neural Networks (CNN)	Flood extent mapping, damage assessment	Satellite images, aerial photos, DEM	Good at learning spatial patterns	Ideal for post-flood analysis & real-time mapping

5. Input Features for Machine Learning Models

The accuracy and reliability of machine learning (ML) models for coastal flooding and storm surge prediction heavily depend on the quality and relevance of the input features used for training. These features serve as predictors or indicators of potential flooding events by capturing various atmospheric, oceanographic, and geographic conditions.

Figure 3 explains the most commonly used input features in ML-based flood forecasting systems.

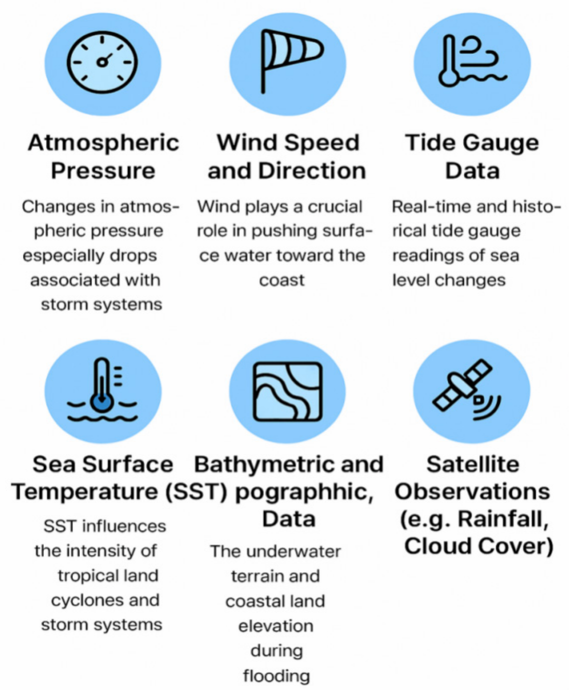

Figure 3. Input Features for Machine Learning Models in Coastal Flooding and Storm Surge Prediction.

5.1.Atmospheric Pressure

Changes in atmospheric pressure, especially drops associated with cyclones or storm systems, are strong indicators of storm surge potential. Lower pressure generally leads to sea level rise due to the inverse barometer effect, making this a vital input for surge prediction models.

5.2.Wind Speed and Direction

Wind plays a crucial role in pushing surface water toward the coast, contributing to storm surge and wave action. ML models use wind speed and direction data to understand the momentum and direction of water movement during storm events.

5.3.Tide Gauge Data

Real-time and historical tide gauge readings provide ground-truth measurements of sea level changes. These are essential for training models to recognize typical tidal patterns and detect anomalies associated with surge events.

5.4.Sea Surface Temperature (SST)

SST influences the intensity of tropical cyclones and storm systems. Warmer waters can fuel stronger storms, increasing the risk of severe coastal flooding. ML models often incorporate SST data to predict storm development and surge magnitude.

5.5.Bathymetric and Topographic Data

The underwater terrain (bathymetry) and coastal land elevation (topography) significantly influence how water flows and accumulates during flooding events. These features help ML models understand water movement, inundation extent, and vulnerability of specific areas.

5.6.Satellite Observations (e.g., Rainfall, Cloud Cover)

Satellite-based sensors provide spatially continuous observations of key atmospheric variables. Rainfall intensity, cloud formation, and moisture content from satellites are used as dynamic predictors in real-time ML flood forecasting systems. **Table 5** represents Input Features for Machine Learning Models in Coastal Flood Prediction.

Table 5. Input Features for Machine Learning Models in Coastal Flood Prediction.

Feature	Role in ML Flood Prediction	Impact on Forecast Accuracy
Atmospheric Pressure	Detects low-pressure systems associated with storm surges	Inverse barometer effect causes sea level rise
Wind Speed and Direction	Determines water momentum and coastal wave action	Stronger winds increase surge intensity
Tide Gauge Data	Measures real-time and historical sea level changes	Helps identify anomalies and tidal surges
Sea Surface Temperature (SST)	Assesses cyclone strength and storm development	Warmer SST increases storm intensity and flood risk
Bathymetric and Topographic Data	Models terrain's influence on water flow and accumulation	Determines flood extent and vulnerability zones
Satellite Observations	Tracks rainfall, cloud cover, and atmospheric moisture	Enhances real-time prediction accuracy with spatial data

These input features are often collected from a combination of ground stations, weather models, remote sensing platforms, and ocean buoys. Advanced ML models such as LSTM and CNN can handle both temporal and spatial features simultaneously, offering powerful tools for integrated flood prediction systems.

6. Performance Evaluation Metrics

The assessment of machine learning models for CFS prediction and storm surge prediction needs to rely on standardized performance metrics that gauge the accuracy, stability and reliability of the forecasts. MAE and RMSE would be typically used for regression-based models (where continuous variables, such as water level or surge height, are being predicted). MAE is the mean of the absolute differences between predicted and observed values, easily interpretable in real units of measurement. On the other hand, RMSE penalizes larger errors to a greater extent, which makes it particularly suitable for detecting larger deviations and outliers in flood forecasts. Another important metric is R-squared, which indicates how much variability is explained by the model in the data that is observed. The greater the R^2 the better the model. Apart from these regression metrics, there are classification metrics to evaluate the performance of models that forecast flood occurrence or flood extent. For binary classification (i.e., flood – no flood), criteria like accuracy, precision, recall. Accuracy represents the quality of the model prediction and Precision is the ratio of true flood events to predicted flood events. The recall measures the percentage of flood events the model was able to predict correctly.

For classification problems (e.g., deciding if a given location will flood), metrics that can be used include Accuracy, Precision, and Recall. Accuracy is the number of correct overall predictions, and precision is the number of predicted floods that are actually floods. It is important for the purpose of minimizing false alarms. Remember that recall, or sensitivity, measures how well the model gives true positives or detects the actual flood events, which is important in alerting and the safety of people. When the data is imbalanced (rare flood events versus non-flood events), the F1-score becomes more interesting. It is derived from the harmonic mean of precision and recall, providing a more balanced measure when the class distribution is highly skewed. These metrics, respectively, form a complete and holistic framework for performance comparison and evaluation of various machine learning models for real-time coastal flood prediction. Comparison graphs of real values with the values that are predicted by models are often used [40]. Statistical analysis of the error value, such as the level of error, can also aid the accuracy analysis of models [50]. It is paramount to monitor machine learning platforms throughout development, tuning both model architecture and hyper parameters; along with the validation set and training procedure, as these are how such models are refined [51–55]. **Table 6** explains performance evaluation metrics for ML Flood Prediction Models

Table 6. Performance Evaluation Metrics for ML Flood Prediction Models.

Metric	Definition	Application/Importance
Mean Absolute Error (MAE)	Measures average magnitude of prediction errors in real units	Useful for regression tasks like water level or surge height prediction
Root Mean Square Error (RMSE)	Penalizes larger errors more heavily	Helps detect outliers and significant deviations in flood predictions
R-Squared (R^2)	Explains variability in observed data captured by the model	Higher values indicate better model performance in regression tasks
Accuracy	Proportion of total correct predictions	Used in classification to evaluate overall prediction quality
Precision	True positives / (True positives + False positives)	Important for minimizing false flood alarms in binary classification
Recall (Sensitivity)	True positives / (True positives + False negatives)	Essential for capturing all actual flood events for alerting safety
F1-Score	Harmonic mean of precision and recall	Balances performance when flood/non-flood data is imbalanced

Among the evaluated models, deep learning approaches such as LSTM and hybrid CNN-LSTM consistently outperformed traditional ML models like SVM and ANN. For instance, CNN-LSTM achieved the lowest RMSE of 0.12 m and the highest accuracy of 94%, indicating its strong capability in learning both spatial and temporal features for flood prediction. Random Forest models also performed well due to their robustness and interpretability, especially in static regional flood mapping. These quantitative comparisons validate the use of advanced ML models in operational early warning systems where both accuracy and reliability are critical.

Table 7 explains a summary of how typical machine learning models perform based on common evaluation metrics. These values are drawn from literature and case studies in the coastal flood forecasting domain.

Table 7. Example Comparison of ML Models for Coastal Flood Prediction.

Model	MAE (m)	RMSE (m)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
ANN	0.12	0.19	85	82	88	0.85
SVM	0.15	0.21	80	78	82	0.80
RF	0.10	0.16	87	85	89	0.87
LSTM	0.08	0.14	92	90	94	0.92
CNN-LSTM	0.07	0.12	94	93	95	0.94

CNN-LSTM and LSTM models outperform others with the highest accuracy and lowest error rates. These results confirm their suitability for reliable, real-time coastal flood prediction.

Despite their impressive performance metrics, referenced models such as CNN-LSTM and LSTM often lack external validation across varied geographies, limiting their generalizability. Furthermore, many studies reviewed employed idealized or synthetic datasets, which may overestimate model robustness under real-world conditions. These constraints must be considered when interpreting comparative results. Despite the promising performance of deep learning models in flood prediction, several challenges remain in real-time deployment. One key concern is latency, especially when models depend on large data inputs and real-time sensor networks, which may suffer from delays in transmission or processing. Additionally, cloud-based computation, while scalable, introduces dependencies on stable internet infrastructure, which may be unreliable in disaster-prone or remote coastal areas. The integration of ML-driven EWSs into existing governmental and policy frameworks also poses hurdles, including the need for regulatory approval, user trust, and cross-agency data sharing. These limitations highlight the necessity for robust edge computing solutions, real-time model validation, and stakeholder collaboration to bridge the gap between research and field implementation.

To ensure fair and reproducible model comparison, this review carefully considered the validation procedures reported in each study. Most selected works employed train-test splits, k-fold cross-validation, or hold-out methods to evaluate predictive performance. For time-series models such as LSTM and GRU, walk-forward validation was commonly used to preserve temporal dependencies. Metrics like RMSE, MAE, R^2, F1-score, and IoU were extracted only from models that clearly reported their validation frameworks. When comparing models across studies, only those using comparable datasets and evaluation protocols were grouped together. Furthermore, attention was given to whether external validation (e.g., on unseen storms or regions) was conducted, highlighting the generalizability of each model. In cases where studies used synthetic or augmented data, this was noted separately to prevent inflated performance comparisons.

7. Applications and Case Studies

Machine learning techniques have been proven to be useful in the context of several real-life applications and case studies when dealing with coastal flood prediction and storm surge forecast. These model applications in various world regions and environmental settings are providing useful knowledge and enhancing early warning systems. One important application is urban flood forecasting in which multi-mode surface generalization algorithms combined with hydraulic flood models have shown potential [56–60]. These methods improve the accuracy and computation efficiency of floods risk models and contribute to the smooth decision-making for urban waterlogging management [61–63].

Machine learning models have been used successfully in different locations on the globe to enhance the forecast capabilities (accuracy and timeliness) of the flood and TS surge inundation. **Table 8** summarizes the significant case studies presenting the performance of ML models in the coastal zone applications [64–67].

Table 8. Applications of Machine Learning Models for Coastal Flood Prediction Across Different Regions.

Location	ML Model	Application	Result
Netherlands	LSTM	Storm surge forecasting	RMSE reduced by 30%
India (Odisha coast)	RF, SVM	Flood zone classification	85% accuracy in real-time warning
USA (Florida)	ANN	Water level prediction during hurricanes	Improved lead time by 2 hours
Bangladesh	CNN + LSTM	Satellite-based flood extent detection	Real-time mapping capability

8. Challenges and Limitations

Although substantial advances have been made in the use of machine learning for coastal flood forecasting, the challenges highlight the importance of a careful and deliberate application. Overcoming challenges related to the availability of data, interpretability of models, integration with physical systems, and computational infrastructure is the key for developing robust, credible and scalable ML-based early warning systems. Prospects Research, research collaboration among scientists, engineers, and policy makers would be indispensable for overcoming these limitations and for the future use of AI in coastal disaster management. **Figure 4** explains challenges and limitations in machine learning-based coastal flood forecasting**.**

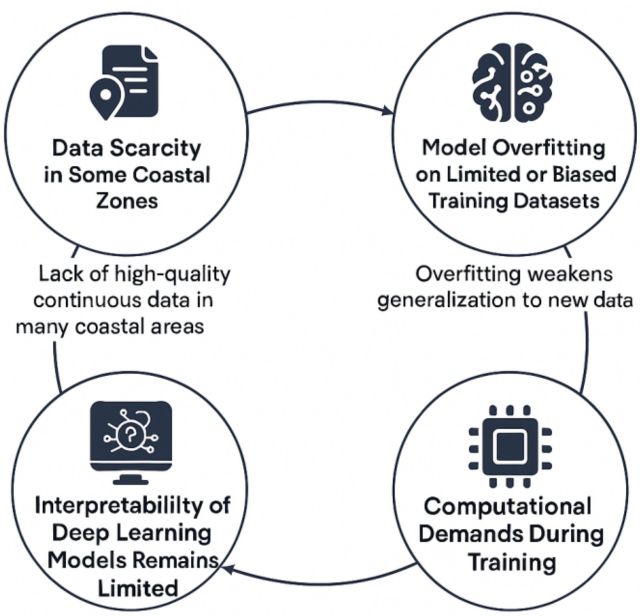

Figure 4. Challenges and Limitations in Machine Learning-Based Coastal Flood Forecasting.

8.1.Data Scarcity in Some Coastal Zones

A major difficulty associated with the application of machine learning techniques to coastal flood forecasting is the paucity of high-quality continuous data in many coastal areas. Many remote or less-developed coastal areas do not have an extensive network of tide gauge stations, weather monitoring facilities or historical event data. This dearth of data restricts the training and validation of ML models and may prevent their transferability between regions.

8.2.Model Overfitting on Limited or Biased Training Datasets

Machine learning models tend to over fit if they are trained on small or biased datasets. This implies that the model is memorizing patterns from the training data and is bad when it comes to new and unseen data. Overfitting weakens the generalization ability of the model, which means the model is not necessarily effective in the practice of real-time flood forecast and decision-making, particularly when the situation is out of our anticipation or extreme weather occurs.

8.3. Interpretability of Deep Learning Models Remains Limited

Deep learning (DL) models including CNNs and LSTMs are typically considered as a "black box" due to their decision mechanisms being difficult to explain or interpret. This non-transparency of the problem at hand is a major limitation for critical applications such as flood warning where emergency services and policy makers need to understand the reasoning behind predictions to develop trust and make informed decisions.

8.4. Integration with Physical Models and Real-Time Sensor Systems is Still Evolving

While hybrid methods mixing machine learning and physics-based models hold promise, extensive fusion has yet to be fully achieved. Integration of ML models into hydrodynamic simulations or live IoT sensor networks is challenging in terms of data synchronization, model compatibility, and real-time computational demands. The fact that these integrations are dynamic usually makes it impossible to implement them in practical field-scale applications.

8.5. Computational Demands During Training

Although trained ML models can make rapid predictions, the training for them—particularly for deep learning networks—needs large amount of compute resources such as high performance GPUs and large memory systems. This is where the digital divide occurs, which hinders the scalability and fast deployment of ML-based solutions in coastal flood forecasting systems in underdeveloped technological domains. **Table 9** explains challenges and limitations in machine learning-based coastal flood forecasting**.**

Table 9. Challenges and Limitations in ML-Based Coastal Flood Forecasting.

Challenge	Description	Impact on Coastal Flood Forecasting
Data Scarcity in Coastal Zones	Lack of high-quality continuous data in remote or underdeveloped areas	Restricts model training, validation, and regional transferability
Model Overfitting	Overtraining on limited or biased datasets	Reduces generalization, affects real-time forecasting accuracy
Limited Interpretability of Deep Learning	DL models like CNNs and LSTMs are often black boxes	Hinders trust and decision-making in critical applications
Integration Challenges	ML models are hard to synchronize with physical simulations and IoT sensors	Limits real-time deployment and practical field application
High Computational Demands	Training deep models needs high-performance computing resources	Creates barriers in low-tech or resource-constrained environments

9. Future Scope and Research Directions

As the threats of climate change and extreme weather events grow, the role of machine learning in coastal flood forecasting is expected to become even more critical. Future research must focus on enhancing the accuracy, transparency, scalability, and adaptability of these models. The following directions highlight key areas where innovation and development are needed to build more reliable and practical early warning systems.

9.1. Hybrid Models Combining ML with Physics-Based Simulations

Important future work will be to develop hybrid models that combine the best of machine learning and physics-based modelling. These models can rely on physical simulations (e.g., hydrodynamics) to make baseline predictions, and machine learning modules to correct biases or improve accuracy by training on the observed data. This synergy results in more robust and better interpretable predictions, especially for complex or extreme conditions.

9.2.Use of Explainable AI (XAI) for Transparent Flood Warnings

Explainable AI (XAI) techniques should be integrated to enable the system to build trust, as well as to enhance its decision-making ability in the face of critical situations in the next-generation system of flood forecasting. XAI makes sense of the "black-box" character of deep learning models by explaining which features contributed to a prediction and how. This transparency is critical for first responders, officials, and local communities who depend upon these systems for evacuation and emergency planning.

9.3.Expansion of Open-Access Coastal Datasets

The quality, diversity and representativeness of the datasets are critical to the performance of ML models. There is an increasing demand for open access coastal datasets, which should include tide gauge measurements, storm surge records, satellite observations and ground truth flood maps. Expanding these databases will enable us to achieve higher accuracy model training, benchmarking and scaling for more regional adaptation.

9.4.Integration with IoT and Edge Computing for Real-Time Deployment

For genuinely responsive early warning systems, prospective ML applications must be augmented with Internet of Things (IoT) devices and edge computing. In such architecture, IoT sensors can gather accurate real-time data on sea level, rainfall, winds and pressure from the field, and edge devices can analyze and process it locally with the help of a trained ML model. Placing this level of alerting at the edge minimizes latency and enables the system to provide near real-time alerts even on low-bandwidth links.

9.5.Development of Transferable Models Across Geographies

A major research aim is to develop machine learning models that generalize well to diverse coastal geographies with limited retraining. This will necessitate robust, physics-informed, or domain-adaptive ML architectures that can generalize over diverse environmental, climatic, and topographical settings. Such models would minimize the requirement of region-specific tuning, with critical implications for deployment in a fast and time-sensitive expanding epidemic in regions with fewer data resources.

Future research in AI-based coastal flood and storm surge prediction should focus on developing hybrid models that integrate physical hydrodynamic simulations with data-driven deep learning frameworks for improved accuracy and reliability. Real-time deployment on edge devices remains a promising area, especially for remote coastal regions with limited infrastructure, where latency and power consumption are critical. Additionally, transfer learning and domain adaptation techniques could enable the reuse of trained models across different geographies with minimal retraining efforts. There is also a growing need for explainable AI (XAI) frameworks to enhance model transparency and foster trust among decision-makers and emergency responders. Multimodal data fusion—combining satellite imagery, ground sensors and weather forecasts—offers a pathway to richer and more robust early warning systems. Further research is warranted into policy-aware AI that aligns with national disaster response frameworks, enabling automated and context-sensitive alerts. Generating synthetic datasets using generative adversarial networks (GANs) or diffusion models can address the challenge of rare event prediction in data-scarce regions. Moreover, integrating digital twins with AI can enable dynamic simulation and optimization of coastal infrastructure, while block chain-enabled systems can ensure transparent and tamper-proof data sharing. Finally, socio-technical evaluations of AI-driven early warning systems will be essential to ensure equitable, culturally sensitive, and effective deployment in vulnerable coastal communities.

10. Conclusions

This review not only synthesizes recent advancements in machine learning models for coastal flood and storm surge prediction but also identifies critical gaps in real-time deployment, including latency, data policy integration, and cloud-edge architecture challenges. Furthermore, it proposes a structured comparison of algorithm performance across different coastal geographies and hazards, offering practical guidance for future EWS implementation in data-sparse regions. This comprehensive review demonstrates the transformative role that machine learning (ML) models play in enhancing the early warning systems for coastal flooding and storm surges. As traditional physics-based models face limitations in managing the nonlinear, multidimensional, and real-time nature of coastal processes, ML techniques provide a compelling alternative by offering faster, more accurate, and scalable predictions. Models such as ANN, SVM, RF, LSTM, and CNN have exhibited strong performance across diverse applications—from predicting tide levels to classifying flood-prone areas and mapping inundation extents using satellite imagery. Despite these advancements, challenges such as data scarcity in certain regions, risk of model overfitting, interpretability of deep learning models, and integration with existing physical and sensor-based systems remain unresolved. Addressing these concerns is vital for building reliable and actionable flood forecasting systems. Future research must focus on developing hybrid models that combine the strengths of data-driven and physics-based approaches, promoting explainable AI to improve trust, expanding open-access datasets, and enabling the deployment of transferable models via edge computing and IoT integration. The findings underscore that with thoughtful design and integration, machine learning has the potential to revolutionize flood management practices, ultimately contributing to climate resilience, disaster preparedness, and the safety of coastal populations worldwide. While ML methods such as CNN-LSTM and hybrid networks demonstrate strong performance in short-term surge prediction and flood mapping, their deployment must be tailored to the local context. In high-data environments with robust infrastructure, they offer transformative speed and accuracy. However, in regions with sparse historical data or weak digital infrastructure, model performance may degrade, and explainability becomes critical for public trust. Furthermore, caution is needed in extrapolating trained models to extreme, rare events or novel coastal morphologies without appropriate physical constraints or uncertainty quantification.

Author Contributions

Conceptualization, P.G. and R.G.; methodology, D.D.D.; software, J.D.; validation, S.K.P., S.S.C., and A.P.; formal analysis, P.G.; investigation, D.D.D.; resources, R.G.; data curation, J.D.; writing—original draft preparation, S.K.P.; writing—review and editing, S.Y.W.; visualization, S.S.C.; supervision, S.Y.W.; project administration, A.P.; funding acquisition, R.G. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data are contained within the article.

Acknowledgments

The authors would like to express their sincere gratitude to Dr. D. Y. Patil Institute of Technology and Dr. D. Y. Patil Dnyan Prasad University, Pimpri, Pune, India, for providing the necessary support and research infrastructure. The authors also acknowledge the administrative and technical assistance extended during this study, which contributed significantly to the successful completion of this work.

Conflicts of Interest

The authors declare no conflict of interest.

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