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Application of Machine Learning Algorithms in Disaster Risk Forecasting

Mir Ramin Yunusov[1*], Yalchin Zeynalov[2],
Ibrahim Mazanov[3], Gafur Huseynov[3]

Abstract. *The escalating cascade of natural and anthropogenic hazards, exacerbated by global climate change and intricate industrial infrastructures, requires a fundamental reassessment of mathematical-analytical models in emergency response. This research mainly aims to comparatively evaluate of linear and non-linear mathematical equations that depict the spatio-temporal propagation dynamics of disaster risks. The analytical framework applies dynamic systems theory, ordinary and partial differential equations, bifurcation analysis and the mathematical modeling of cascade effects. Analytical practicalities and scenario simulations indicate that in cases restricted occurrences — including floods or minor landslides — linear autoregressive models and simple differential equations deliver reasonably precise and quick risk assessments. Conversely, in scenarios of swiftly developing, complicated disasters involving critical infrastructure failures, linear models demonstrate significant limitations. Modeling such asymmetric risks, disaster "tipping points," and exponential spatio-temporal propagation demands the application of reaction-diffusion equations and coupled non-linear systems. The results scientifically prove the boundaries of linear models in capturing real-world dynamics and validate the clear superiority of non-linear approaches in complex disaster scenarios.*

Keywords: *machine learning, cascade effects, non-linear dynamics, mathematical modeling, disaster risk, differential equations, tipping points, crisis management*

[1]Institute of Mathematics of the Ministry of Science and Education of the Republic of Azerbaijan, PhD Student, Baku Engineering University, Baku, Azerbaijan
[2]Baku Engineering University, Baku, Azerbaijan
[3]Azerbaijan Sports Academy, Baku, Azerbaijan
[*]Corresponding author. E-mail: myunusov@beu.edu.az
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Fəlakət risklərinin proqnozlaşdırılmasında maşın öyrənməsi alqoritmlərinin tətbiqi

Mir Ramin Yunusov[1*], **Yalçın Zeynalov**[2], **İbrahim Mazanov**[3], **Qafur Hüseynov**[3]

Xülasə. *Qlobal iqlim dəyişikliyi və mürəkkəb sənaye infrastrukturları tərəfindən daha da kəskinləşən təbii və antropogen təhlükələrin artan kaskadı fövqəladə hallara reaksiya zamanı riyazi-analitik modellərin əsaslı şəkildə yenidən qiymətləndirilməsini tələb edir. Bu tədqiqatın əsas məqsədi fəlakət risklərinin məkan-zaman yayılma dinamikasını təsvir edən xətti və qeyri-xətti riyazi tənlikləri müqayisəli şəkildə qiymətləndirməkdir. Analitik çərçivə dinamik sistemlər nəzəriyyəsini, adi və xüsusi törəməli diferensial tənlikləri, bifurkasiya analizini və kaskad effektlərinin riyazi modelləşdirilməsini tətbiq edir. Analitik praktikalar və ssenari simulyasiyaları göstərir ki, məhdud hadisələr (məsələn, daşqınlar və ya kiçik torpaq sürüşmələri) hallarında xətti avtoreqressiv modellər və sadə diferensial tənliklər kifayət qədər dəqiq və sürətli risk qiymətləndirmələri təqdim edir. Əksinə, kritik infrastrukturun sıradan çıxması ilə müşayiət olunan sürətlə inkişaf edən, mürəkkəb fəlakət ssenarilərində xətti modellər əhəmiyyətli məhdudiyyətlər nümayiş etdirir. Belə asimmetrik risklərin, fəlakətlərin "dönüş nöqtələrinin" (tipping points) və eksponensial məkan-zaman yayılmasının modelləşdirilməsi reaksiya-diffuziya tənliklərinin və əlaqəli qeyri-xətti sistemlərin tətbiqini tələb edir. Nəticələr real dünya dinamikasını əks etdirməkdə xətti modellərin sərhədlərini elmi cəhətdən sübut edir və mürəkkəb fəlakət ssenarilərində qeyri-xətti yanaşmaların aşkar üstünlüyünü təsdiqləyir.*

Açar sözlər: *maşın öyrənməsi, kaskad effektləri, qeyri-xətti dinamika, riyazi modelləşdirmə, fəlakət riski, diferensial tənliklər, dönüş nöqtələri, böhran vəziyyətlərinin idarə edilməsi*

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[1]Azərbaycan Respublikası Elm və Təhsil Nazirliyinin Riyaziyyat İnstitutu, doktorant, Bakı Mühəndislik Universiteti, Bakı, Azərbaycan
[2]Bakı Mühəndislik Universiteti, Bakı, Azərbaycan
[3]Azərbaycan İdman Akademiyası, Bakı, Azərbaycan
[*]Məsul müəllif. E-poçt: myunusov@beu.edu.az
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Introduction

In contemporary times, as a result of global climate change, fast-paced urban expansion and the increasing complexity of industrial infrastructure, the frequency and scale of natural and anthropogenic emergencies have surged significantly. Specifically, wildfires, floods, seismic activities, and subsequent industrial accidents are transcending localized incidents, developing into cascade crises that present critical dangers to global socio-economic systems. Managing these multifaceted dangers, predicting vulnerabilities and reducing losses require the implementation of more exact and responsive mathematical-analytical models in decision-making processes.

Conventionally, disaster risk management and forecasting have been based on linear approaches, presuming that events occur in isolation and in unchanging environments. Linear mathematical models assume that the increase in risk correlates directly with corresponding factors, showing some level of utility in analyzing isolated incidents with restricted reach. Nevertheless, as the impact area of disasters expands, especially in multifaceted crises accompanied by the failure of critical infrastructure, linear dynamics fall short of reflecting reality. The mutual reliance between natural and technological systems causes a minor triggering event to lead to unforeseen, highly unbalanced and exponentially growing consequences.

To overcome these limitations, contemporary academic studies has increasingly adopted non-linear differential equations that integrate principles from mathematical physics, dynamical systems, and chaos theory. The non-linear mathematical apparatus essentially enables for the modeling of disaster "tipping points" in emergency situations, the speeding up processes of cascade effects and the asymmetric spatio-temporal propagation patterns (Helbing & Ammoser, 2023; Sullivan, 2021). Expressing the interaction processes of risks through a system of differential equations provides a fundamental basis for developing optimal strategies to mitigate initial and subsequent catastrophes (Vinay et al., 2020).

Methods

This study presents a comprehensive review of the application of Machine Learning (ML) algorithms in disaster risk forecasting. It examines the limitations of conventional forecasting methods, outlines the theoretical underpinnings of ML, and surveys advanced global practices for modeling disaster risks. Natural hazards—including hydrological events such as floods, geological phenomena like earthquakes, forest fires, and urban fires—continue to pose significant and growing threats to both economic and social stability worldwide. Timely and accurate forecasting, which underpins contemporary risk management strategies, is essential for minimizing casualties and economic losses through the effective operation of Early Warning Systems. Traditional forecasting approaches predominantly rely on deterministic models or relatively simple statistical methods. However, disasters are inherently multifactorial, non-linear, and dynamically complex. Conventional forecasting methods can be broadly categorized into two main types:

1. Time Series Models: These statistics-based models dominated emergency forecasting, including flood prediction, from 1993 to 2010. They require relatively low computational resources and are suitable for simple forecasting scenarios. Nevertheless, their capacity to capture the non-linear dynamics of complex ecological and hydrological systems is limited.

2. Physics-based Models: Grounded in physical laws, these models can accurately represent characteristics of the Earth's crust, water basins, or other environmental systems. However, they demand extensive parameterization and high computational resources, making adaptation to local conditions challenging.

Since 2011, advances in computational power have facilitated the widespread adoption of Machine Learning models—particularly Artificial Neural Networks—for disaster forecasting. ML models, characterized by non-linear time series capabilities, offer superior accuracy and reliability compared to traditional methods. Their deployment marks a paradigm shift in disaster management, transitioning from rule-based approaches to data-driven predictive modeling. A key advantage of ML models lies in their ability to uncover complex relationships within large, heterogeneous datasets. This capability enhances the precision and reliability of forecasts within Early Warning Systems, while also extending the lead time available for preventive action (Petros et al., 2025). A comparative analysis of traditional and ML-based forecasting models is provided in the literature (Vinay et al., 2020; Manaswi et al., 2025).

Table 1
Comparison of Traditional and Machine Learning Methods

Feature	Traditional methods	Machine Learning
Model basis	Physical laws, differential equations, linear dependencies	Data-driven, nonlinear relationships, ability to process large-scale data
Model scale	Low/medium-volume linear data	Efficient processing of multidimensional, large-scale data; improved predictive capability with increasing data volume
Economic loss assessment	High potential for overestimation of losses	Flexibility, real-time analysis of impacts using social media data
Limitations	High computational cost, reduced nonlinear accuracy under dynamic changes, time lag	Sensitivity to data quality, difficulty in interpretability, lower stability under extreme conditions

Achieving accuracy in time series forecasting fundamentally relies on the precise identification and modeling of the intrinsic structures within the data. Any robust time series model must incorporate four core components: Trend, representing long-term upward or downward movements; Seasonality, capturing predictable patterns recurring at fixed intervals; cyclical components, reflecting non-seasonal fluctuations driven by broader economic or business conditions and irregular components, denoting random, unexplainable variations. Classical econometric models, such as the AutoRegressive Integrated Moving Average family, are effective for short-term forecasting and modeling linear dependencies but often fall short in capturing the intricate non-linear dynamics inherent in complex domains like finance, environmental systems, and industrial datasets.

The emergence of Machine Learning and Deep Learning architectures has provided the computational capabilities required to model such non-linear complexities. These models exhibit marked advantages over traditional statistical approaches, particularly when managing large, heterogeneous feature sets and learning long-term temporal dependencies embedded in sequential data (Lakshmi et al., 2020). Amid the increasing frequency and complexity of natural disasters, the field of Disaster Risk Reduction is experiencing transformative changes. The integration of ML algorithms introduces innovative methodologies that combine simulation and optimization frameworks to address dynamic, uncertain, and highly complex disaster scenarios. These approaches not only enhance predictive accuracy but also yield valuable insights for improving the resilience and effectiveness of emergency response strategies (Huseynov, 2023).

The application of ML spans both physical and social dimensions of disaster management. For example, during Hurricane Harvey, rescue requests were analyzed using ML techniques. By leveraging social media data, researchers can assess the geographical distribution, frequency, and impact of disasters, thereby enabling policymakers to make informed, real-time decisions. Furthermore, in urban planning, ML utilizes historical data to predict urban resilience characteristics, contributing to the development of long-term risk management strategies.

Despite significant advancements in ML applications, several fundamental data-related challenges persist in natural disaster prediction. Key obstacles include the scarcity of real-time open-source data, the imbalance of datasets critical for effective model training, and the difficulties associated with interdisciplinary collaboration among experts from diverse domains. Given that disasters are inherently rare events, ML models face a scientifically significant challenge: they tend to adapt to the majority class, potentially overlooking the minority class. Addressing this issue requires specialized mathematical and algorithmic strategies, such as data balancing techniques or class-weight adjustments during model training. Additionally, the use of specialized evaluation metrics, such as

F1-score or PR-AUC, is essential for accurately assessing model performance in predicting these rare but critical events.

Despite the generalized analytical strength of Machine Learning algorithms, empirical research consistently indicates that no single forecasting method exhibits universal superiority. Optimal performance is highly context-dependent, relying on the specific characteristics and data type of the analyzed time series. For instance, in studies on disaster risk forecasting, particularly earthquake magnitude prediction, Deep Learning models such as Long Short-Term Memory networks demonstrated higher accuracy and effectiveness compared to traditional methods like ARIMA. This underscores the capability of advanced ML architectures to model the non-linear and complex nature of natural hazard data, which often exhibits high non-linearity and extensive temporal dependencies.

Further research comparing LSTM and ARIMA in general disaster-related time series emphasizes this duality. ARIMA may achieve lower error values in monthly or weekly forecasts, reflecting its stability in capturing dominant seasonal or long-term linear patterns. In contrast, LSTM outperforms ARIMA in daily rolling predictions. This distinction highlights that model selection is not simply a choice between linear and non-linear approaches; it depends on the dominant dependency structure and the required forecasting horizon. When a series exhibits strong short-term autocorrelation and limited external influence, linear models like ARIMA may provide more reliable results. Conversely, in scenarios characterized by high noise, volatile trends, and complex feature interactions—typical in multi-variable disaster data—ML ensembles and Deep Learning architectures, such as XGBoost or LSTM, offer distinct advantages.

For ML algorithms to process time series data effectively, the sequential structure must be transformed into a format suitable for supervised regression tasks—a critical step known as Feature Engineering, which largely determines the predictive ceiling of the model.

Stationarity—the constancy of mean, variance, and autocorrelation over time—is vital for model stability and generalization. Techniques such as differencing, which calculates the difference between consecutive observations, are employed to stabilize the data. While univariate models like ARIMA can be trained on undifferenced data, multivariate ML models typically require differenced versions of the target variable and external regressors as input features, ensuring stationarity in the feature space and enhancing model robustness.

Since ML regressors do not inherently capture temporal dependencies, these relationships must be encoded explicitly:

- **Lags**: Past values of the target variable and external regressors are transformed into independent predictor features, effectively integrating the autoregressive component of classical models into the ML framework.
- **Rolling Window Statistics**: Statistical summaries computed over defined rolling windows capture local trends, volatility, and short-term dynamics. These features are particularly useful for high-frequency or noisy data, such as financial or disaster-related series, where short-term variations contain substantial predictive information.

Machine Learning Architectures for Disaster Risk Forecasting require broad and diverse datasets to ensure accurate predictions (Kim and Lee, 2018). Relevant data can be grouped into the following categories:

- **Disaster Classification Data** – type, location, time, and scale of damage;
- **Geographic Information System (GIS) Data** – topography, soil type, forest cover, relief;
- **Meteorological Data** – precipitation, temperature, wind speed;
- **Socio-economic Data** – population density, infrastructure types.

ML applications in disaster risk forecasting are generally divided into two main categories: **Classification Algorithms** and **Regression Models.**
Classification Algorithms determine whether a disaster is likely to occur (Yes/No) or categorize its risk level (low, medium, high). This approach is essential for timely decision-making in risk grading and early warning systems to prevent incidents.
Regression Models provide quantitative predictions, such as the intensity of the event, potential damages, or the time until occurrence. These predictions are critical for resource allocation, response planning, and operational management (Table 2).

Table 2
Categories of Machine Learning Algorithms

Categories of ML algorithms	Purpose in the field of disasters	Sample algorithms
Classification	To predict the probability of an event occurrence (yes/no) or the level of risk (low/medium/high)	logistic regression, random forest, gradient boosting
Regression	To predict the intensity of the event, the amount of damage, or the time remaining until the event	linear regression, neural networks, support vector regression

The classification and regression of disaster risks have seen extensive application through both traditional and ensemble algorithms. Due to their higher interpretability compared to Deep Learning models, these algorithms remain vital in Early Warning Systems, supporting timely decision-making and risk mitigation.

In numerous disaster prediction studies, foundational algorithms such as Logistic Regression and Support Vector Machines have been widely employed (Vasileios et al., 2022). LR is particularly effective for linear classification tasks and can deliver optimal results in specific applications, such as text classification. SVM, on the other hand, excels at modeling non-linear classification boundaries and has demonstrated robust performance across complex datasets. Contemporary research has even explored quantum-enhanced versions of SVM, such as QSVC_ML, to further improve predictive accuracy and computational efficiency.

Support Vector Regression, a non-parametric regression technique derived from SVM, effectively handles non-linear regression problems by utilizing kernel functions, such as the Radial Basis Function, to implicitly map data into higher-dimensional feature spaces. SVR offers several notable advantages:
- **Resistance to Overfitting**: Unlike complex Artificial Neural Networks, which may converge to local optima, SVR tends to find a global optimal solution, reducing susceptibility to overfitting and ensuring more robust predictions.
- **ϵ-Insensitive Loss Function**: The core mechanism of SVR is the ϵ-insensitive loss function, which introduces the hyperparameter ϵ to define a margin of acceptable error. Prediction errors within the ϵ threshold are considered to incur zero loss, providing a controlled balance between the desired smoothness of the regression function f(x)f(x)f(x) and tolerance for deviations exceeding ϵ.

The formal description of the linear ϵ-insensitive loss function is provided as follows:

$$L_{\in}\begin{cases} 0 & if\ |y-f(x)| \leq \in \\ |y-f(x)|-\in & otherwise \end{cases} \quad (1)$$

Ensemble Learning Methods: Superiority and Robustness. Ensemble learning methods enhance predictive performance and robustness by combining the outputs of multiple individual models (weak learners). These methods are particularly effective in tasks characterized by high uncertainty, such as disaster risk classification, where they consistently provide more stable, accurate, and reliable results compared to single-model approaches.

Random Forest (RF). The Random Forest (RF) algorithm employs a bagging strategy, constructing multiple decision trees, each trained independently on randomly sampled subsets of the training data. This independence underpins RF's key advantages: parallelizable training and execution, strong resistance to overfitting, and high efficiency on large-scale datasets. RF is therefore widely adopted in disaster risk forecasting for both classification and regression tasks (Nti et al., 2022).

Gradient Boosting (GBT). Gradient Boosting relies on the boosting principle, where decision trees are built sequentially, with each new tree trained to correct the residual errors of its predecessors. Optimized implementations such as XGBoost and LightGBM have substantially enhanced the computational speed and predictive performance of GBT. While GBT often surpasses RF in prediction accuracy—especially on smaller, cleaner datasets—it is particularly effective at capturing complex, non-linear patterns within high-dimensional data, making it a preferred choice for advanced disaster risk modeling (Murphy & Smith, 2023).

Table 3
Characteristics of Random Forest and Gradient Boosting Algorithms

Random Forest (RF)	Gradient Boosting (GBT)
Enables parallel training and execution, ideal for real-time applications	Sequential structure; improved with distributed computing
More robust to noisy data, lower risk of overfitting	Often achieves higher accuracy in clean datasets
Provides stable and reliable performance	Better at capturing complex nonlinear relationships

Regression Models: Predicting Quantitative Characteristics of Disasters. While classification models focus on predicting the occurrence or category of an event, regression models are indispensable for estimating the quantitative characteristics of disasters. These models forecast continuous variables such as the magnitude of damage, financial losses, or resource requirements, providing essential information for emergency planning and response allocation.

Deep Learning Architectures and Spatio-Temporal Dependency Modeling. Large-scale spatial and temporal datasets, including satellite imagery and high-resolution meteorological time series, present significant challenges for traditional Machine Learning models. Deep Learning (DL) architectures excel in capturing these complex dependencies due to their ability to process high-dimensional, sequential, and interdependent data structures.

Time-Series Models: RNN and LSTM. Recurrent Neural Networks provide a foundation for sequential data processing. However, Long Short-Term Memory networks overcome the vanishing gradient problem of conventional RNNs and efficiently capture long-term dependencies. By leveraging specialized gating mechanisms—forget, input, and output gates—LSTMs effectively model seasonality and trends in climate, seismic, and hydrological time-series datasets.

Hybrid CNN–LSTM Frameworks: Spatio-Temporal Forecasting. Forecasting disasters such as floods, hurricanes, or extreme rainfall events often requires simultaneous analysis of spatial and temporal patterns. Hybrid Convolutional Neural Network–LSTM architectures are particularly suitable for such tasks, integrating spatial feature extraction with temporal sequence modeling to improve prediction accuracy (Wang et al., 2024).

Evaluation Metrics in Disaster Forecasting. In disaster prediction scenarios, it is crucial to balance **Precision** and **Recall**:

- **Precision** measures the proportion of predicted disaster events that are actual disasters. High precision minimizes false alarms, reducing unnecessary evacuation costs and resource waste.
- **Recall** measures the proportion of true disasters correctly identified. Recall is critical in emergency management as it directly mitigates the risk of missed events, which could result in loss of life.
- **F1 Score** represents the harmonic mean of precision and recall, providing a single, reliable metric that accounts for both false positives and false negatives in imbalanced datasets.

Importance of Python Programming and Software Foundations. Python has become the standard programming language for Machine Learning and disaster risk forecasting. Its extensive libraries, straightforward syntax, and robust support for scientific computing make it ideal for building, testing, and deploying predictive models in both research and operational environments.

Table 4
Main Python libraries for data forecasting

Library	Role	Application in disaster modeling
Pandas/Numpy	Data manipulation and numerical operations	Loading, cleaning, and extracting features (year, month, day) from time-series data (seismic, climate)
Scikit-learn	Classical ML, preprocessing, model selection	Training models such as RandomForestClassifier and SVM; data normalization using StandardScaler
TensorFlow / PyTorch	Deep learning architectures	Building CNN-LSTM and Transformer models for spatio-temporal prediction of large satellite imagery
Imbalanced-learn	Handling class imbalance	Synthesizing minority classes using SMOTE (Synthetic Minority Oversampling Technique)

Real-Time Data Processing and Python Ecosystem in Disaster Management. Effective disaster management demands the rapid collection, processing, and analysis of real-time open-source data. Python's comprehensive ecosystem—including libraries such as Pandas, Scikit-learn, and **TensorFlow**—enables seamless data loading, preprocessing, and analysis. This standardized workflow ensures reproducibility of research findings and promotes efficient interdisciplinary collaboration between domain experts, emergency managers, and Machine Learning engineers (Sebastian et al., 2020).

Forecasting Seismic Disasters. Machine Learning applications in seismology are primarily oriented toward pre-event forecasting and post-seismic classification. Algorithms such as K-Nearest Neighbors and Support Vector Machines, along with Deep Learning architectures—including Artificial Neural Networks, Multilayer Perceptron, Convolutional Neural Networks, Recurrent Neural Networks, and Long Short-Term Memory—have been extensively employed. For time-dependent phenomena, such as radon gas measurements and ionospheric electron anomalies, LSTM, ARIMA, SVM, and ANN have been applied, with LSTM often demonstrating superior predictive performance.

Seismological forecasting focuses on early warning systems (detecting P-waves immediately after an event) and hazard assessment (long-term probability mapping). While precise prediction of earthquake timing remains scientifically elusive due to the complex, non-linear nature of seismic features, ML excels in post-seismic analysis, enabling rapid classification of structural damage and mapping of aftershock probabilities using real-time sensor data and aerial imagery processed by CNN.

A key limitation in earthquake forecasting is the inability to predict the exact event timing, stemming from incomplete knowledge of all causative factors. Early Earthquake Warning Systems provide rapid alerts post-event rather than advance predictions. Consequently, ML demonstrates its greatest utility in post-seismic assessments, where rapid classification over structured data is essential.

Forecasting Hydrological Disasters

Flood prediction relies on temporal and spatio-temporal data, including precipitation, water levels, and flow velocity (Beroza & Mousavi, 2021; Kong et al., 2021). RNNs and their variants dominate hydrological forecasting (Kim & Lee, 2018; Alizamir et al., 2020).

1. **LSTM (Long Short-Term Memory)** – Used for modeling water level and river flow relationships, integrating forecasts into GIS software to visualize flood-prone areas.
2. **ConvLSTM (Convolutional LSTM)** – Enhances spatio-temporal forecasting by first extracting spatial patterns via convolutional layers and then capturing long-term temporal dependencies with LSTM layers (Caisu & Hailiang, 2023; Zhang et al., 2023).

Research demonstrates high predictive accuracy: ConvLSTM achieves $R^2 \approx 0.96$ and Nash–Sutcliffe Efficiency (NSE) ≈ 0.95, while LSTM shows similar performance in water level simulations. These high-accuracy forecasts enable the creation of flood risk maps, providing critical tools for decision-making and resource allocation. Comparative studies consistently highlight DL models' superiority over ARIMA and traditional statistical methods for capturing long-term meteorological-hydrological dependencies.

Forecasting Wildfires. ML and DL methods significantly enhance the prediction of forest fire spread. Techniques such as CNN, Convolutional Recurrent Networks, Transformers, Reinforcement Learning, and Graph Neural Networks are widely applied. CRNs and time-series models effectively capture sequential and spatio-temporal fire behavior. For example, CNN combined with ASPP identifies general and detailed fire spread patterns (Chen et al., 2022; Jain et al., 2020).

High-dimensional data processing and feature extraction give DL models a clear advantage over traditional methods. In studies using the California wildfire dataset, patch-based forecasting achieved an F1-score of 96%. However, the complexity of DL models introduces a "black-box" problem, necessitating Explainable AI solutions. Techniques like Grad-CAM and SHAP improve interpretability, highlighting key factors influencing fire propagation. Real-time forecasting demands lightweight models with low computational cost, particularly in remote areas. Data quality remains a challenge: sparse or missing inputs can bias models, reducing generalizability when applied across different regions. Ensemble methods such as XGBoost have been applied for urban fire severity prediction. Using structured building data, XGBoost achieved 82.7% accuracy, enabling fire departments to anticipate fire intensification and allocate resources efficiently via GIS. Unlike forest fire DL models, urban fire forecasting emphasizes rapid, high-accuracy classification. Ensemble methods are particularly suited to urban environments due to their ability to handle structured, heterogeneous data and deliver fast predictions. This complements DL models for wildfires and floods, which focus on continuous spatio-temporal event forecasting.

Results and Discussion

This thorough analysis clearly shows that Machine Learning and Deep Learning methodologies provide significant benefits compared to traditional deterministic and statistical approaches in the field of disaster risk prediction. Moving towards, data-driven architectures is critical for handling the enormous, heterogeneous datasets generated by modern sensor networks and satellite observations. In contrast to conventional methods, which often struggle to represent highly non-linear environmental dynamics, modern computational techniques—such as ensemble techniques and deep neural networks—are highly effective at identifying complex spatio-temporal dependencies. As demonstrated in multiple fields, including seismic hazard assessment, hydrological flood modeling, and wildfire spread prediction, these algorithms substantially improve prediction reliability and early warning periods.

As a result, the implementation of these highly developed predictive frameworks equips policymakers and emergency management agencies with highly accurate, region-specific data. This advancement in technology promotes a fundamental shift in perspective from traditional, reactive disaster response to highly proactive, anticipatory risk mitigation, in strict accordance with global initiatives like the Sendai Framework.

Despite these advancements, a number of significant hurdles persist to be addressed in future studies. The scientific community should focus on creating reliable algorithmic remedies for significant data imbalance—a common issue when predicting infrequent disaster occurrences. Additionally, optimizing the computational efficiency of these predictive systems for real-time deployment in resource-constrained areas is crucial. Finally, resolving the inherent "black-box" nature of deep learning through Explainable AI is strictly required to ensure model transparency, thus building trust among decision-makers and ensuring the reliability of automated Early Warning Systems.

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