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Original Article

AI-Driven Decision Systems for Real-Time Disaster Prediction

Dr. Pooja Agarwal

Professor, Aligarh Muslim University, India.

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ABSTRACT

Both natural and man-made disasters are very impactful to the surroundings, infrastructure, and human life. Proper and timely forecasting of disasters is essential in the reduction of the disaster. The conventional disaster prediction models are based on analysis of previous history and simple statistical methods which could be not capable of offering real-time and adaptive decision-making options. The present paper includes an in-depth research concerning AI-based decision systems of real-time disaster predictions that combine the latest machine learning (ML), deep learning (DL), and real-time sensor networks. We suggest an approach based on multi-layered which involves combining real-time data collection, AI-enhanced predictive analytics, and automated decision-making to improve disaster preparedness and response. The system resorts to ensemble learning, recurrent neural networks (RNNs), and spatiotemporal modeling and manages to predict the occurrence of a flood, earthquake, wildfire, and storm with high accuracy. The system is shown in one of the case studies that use actual real-time sensor data on the environment and satellite images to prove the efficiency of the system. It is shown that there is substantial increase in accuracy of prediction and response time over traditional systems. The given strategy is focused on scalability, flexibility, and resilience to different disaster risks. In addition, the combination of AI and Internet of Things (IoT) and Geographic Information System (GIS) allows developing a real-time decision support system that can support the government agencies, emergency responders, and communities with making proactive and data-driven decisions. The study indicates the possibilities of AI-powered systems in shifting disaster management to a predictive instead of a reactive and prevention system.

KEYWORDS

AI, Machine Learning, Deep Learning, Disaster Prediction, Real-Time Decision Systems, IoT, GIS, Ensemble Learning, Spatiotemporal Modeling, Emergency Management.

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1. INTRODUCTION

1.1. Background

Both natural and artificial disasters are still causing massive economic, social and human damages to the world on annual basis. The classical methods of disaster management are more reactive in nature as they are pegged on emergency responses whenever a disaster has struck, which can significantly hamper its intent to minimize the damage and casualties. In turn, predictive disaster management also seeks to preempt hazardous events and facilitate proactive responses, which will decrease the suffering and property damage of humans. With newly introduced possibilities and innovations in the field of Artificial Intelligence (AI) and the Internet of Things (IoT), the transformation of disaster prediction systems into real-time and data-driven structures became possible. AI methods, such as machine and deep learning, have the ability to process complex and large datasets (both in volume and variety), identify complicated patterns and create correct predictions despite uncertain and volatile circumstances. The rationale behind the implementation of AI-based strategies is based on their capacity to combine all forms of data such as environmental inclinometers, aerial photos, past disaster history, and social media feeds to build a very detailed picture of possible danger. Between them, IoT sensors can provide twenty-four-hour control of temperature, rainfall, river levels, and seismic activity, and satellite images can allow studying the spatial distribution of flood areas or wildfires. By using historical data and crowdsourcing information in the social media, AI models can determine correlations and warning signs that are not evidently observed in the traditional approaches. In addition to this, these systems can improve decision-making in uncertain situations by giving executable information, including risk information, the optimal allocation of resources, and evacuation data. With the help of the predictive abilities of AI and real-time information about the environment, these systems can turn disaster management into a more proactive than reactive paradigm and thus positively impact the response times, save human lives, and reduce the number of economic losses at a massive scale.

1.2. Needs of AI-Driven Decision Systems

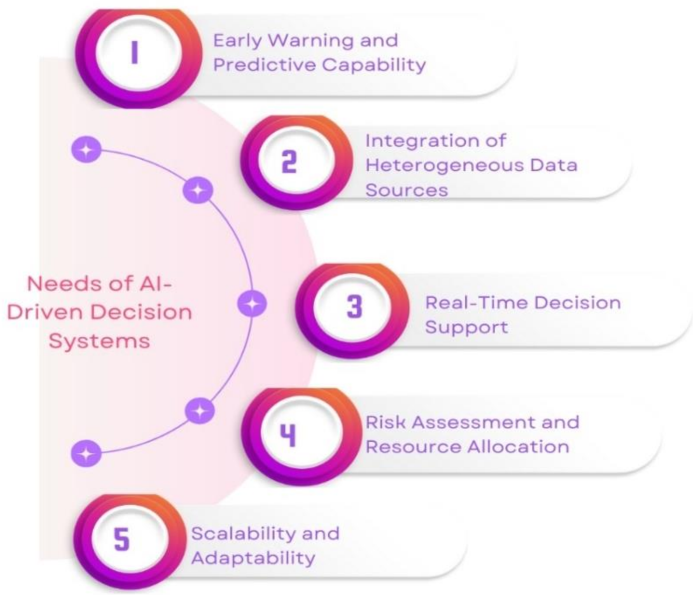

Fig 1 - Needs of AI-Driven Decision Systems

1.2.1. Early Warning and Predictive Capability

Precise predictive information and early alerts is one of the key requirements of AI-based decision systems in the case of disaster management. Conventional disaster management is very much dependent on assessments after the occurrence and this has always led to slow response and more casualties. Based on historic data, live sensor data, and satellite photos, AI models could predict the likelihood of a disaster (floods, wildfire, storm, or earthquake) and notify of such occurrences before a disaster complies with its prediction capabilities. Such anticipatory potential allows the government and societies to mitigate in advance cutting down human, and economic consequences of calamities.

1.2.2. Integration of Heterogeneous Data Sources

The prediction of disasters is based on the processing of various and heterogeneous data of various types, such as IoT sensors, GIS information, satellite data, meteorological data, and even social networks. The conventional systems are unable to handle and process such massive and multi-format data. They can be combined effectively in AI-driven frameworks and identify sophisticated patterns and correlations that would have been unseen otherwise. This unification would guarantee an all-inclusive situational awareness, essential in making informed decisions in time.

1.2.3. Real-Time Decision Support

One more important requirement is real-time decision support. In a disaster, the speed of making decisions is critical in the allocation of resources, in the planning of evacuations, and the control of emergency response professionals. A system consuming sensor data and updating predictions around-the-clock has the capability to be implemented by artificial intelligence and refresh predictions whenever the situation changes, enabling authorities to make sound decisions about the situation at any given time. Real-time analysis assists in reducing the delay, resource optimization, and minimizing the mismanagement tendency in the case of emergency situations.

1.2.4. Risk Assessment and Resource Allocation

Risk assessment and resource allocation are also required to be done using AI-driven systems. These systems are able to rank important areas and direct emergency planning by quantifying the probability and intensity of possible disasters. Simulation of various resource allocation tasks (deployment of medical teams, relief supplies or evacuation shelters, etc.) can be achieved with advanced algorithms in order to optimize the use of limited resources.

1.2.5. Scalability and Adaptability

Lastly, AI-based decision systems would be necessary to be scalable and adaptable since the world of disaster management is characterized by unpredictable and dynamically changing conditions. Such systems are able to scale to handle high volumes of data in multiple regions, handle new kind of disasters, and keep on learning on new data to guarantee better predictive capabilities over time.

1.3. Real-Time Disaster Prediction in Decision Systems

The real-time disaster prediction has become an essential part of the modern decision support systems that ensure prompt reaction by the authorities on the threats, which are about to occur, and reduce the extent of possible harm. In contrast to the classical methods that utilize post-event measurements or the stationary historical data, the system of real-time predictions on the environment, geospatial, and meteorological indicators constantly follows early warning signs of disasters, including floods, wildfires, earthquakes, and storms. The combination of IoT sensor networks enables the gathering of real-time and high-frequency data which consists of rainfall intensity, river water levels, wind speed, temperature and seismic activity. Such sensor measurements create granular and recent insights into the state of the environment that can result in certain trends and deviations pointing to an imminent disaster when fed into AI models. Besides sensor data, satellite imagery and remote sensing will also provide important spatial data, which will be used to identify the changes in terrain, vegetation, water body and storm formations. With both spatial and temporal information integrated, AI-based models, including Long Short-Term Memory (LSTM) networks and CNN-RNN hybrids, are able to not only analyze the development of the environmental phenomena over time but also map the geographic scopes of possible hazards. The twin feature is vital in proper early warning and risk evaluation especially in the areas that are subject to compound or Multi- Hazards. There is also enhanced decision-making through real-time disaster prediction systems that offer practical insights, such as risk rating, the best evacuation paths and resource distribution plans. The use of dynamic updates using live information ensures that emergency responses would be flexible in the changing scenario to minimize as much delay as possible and avoid mismanagement of the key assets. Moreover, through predictive intelligence, law enforcement agents are able to provide early warnings to society members and conduct prior preparations, and the loss of lives and financial resources is reduced. Altogether, real-time prediction of disasters converts the conventional approach of disaster management as reactive to proactive, data-driven, and highly responsive models, which offere substantial enhancement of both the accuracy and promptness of emergency response.

2. LITERATURE SURVEY

2.1. AI in Disaster Prediction

A new technology that has come into play is Artificial Intelligence (AI), which is a tool that facilitates disaster prediction and enables the analysis of large volumes of complex data within a short time and with accuracy. Conventional machine learning (ML) models, are the Support Vector Machines (SVM), the random forest, and the XGBoost, which have been heavily used to predict natural disasters, e.g., earthquakes and floods. These models are very good at finding the trends in historical data and early warning systems are able to predict upcoming risks. In addition to traditional ML, deep learning (DL), algorithms, such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) have also been demonstrated to be especially effective to spatiotemporal modeling and to a detection of disasters based on images. In sequential data, RNNs, and LSTMs are able to encapsulate the temporal characteristics important in predicating events such as wildfires, whereas CNNs are very effective in processing satellite or aerial images to forecast a storm, flood, or landslide. Also, hybrid solutions that integrate ML and DL have proven to be promising since they have utilized the merits of both methods to enhance the predictability of complex disaster events that have multiple, related variables. These artificial intelligence frameworks will enable a faster decision-making process, which will eventually reduce the effects that disasters have on a community and infrastructure.

2.2. Real-Time Decision Systems

The complement of disaster management is real-time decision systems that are able to integrate AI predictions with operational strategies to act on. These systems are highly dependent on the Internet of Things (IoT) to collect real-time environmental observations in the form of distributed sensor networks, i.e. river water level, seismic activity sensors, or weather weather stations. Visualization tools based on Geographic Information System (GIS) enable disaster authorities to superimpose prone areas on map and interpret risk patterns and organize their resources more efficiently. Timely notifications to the government, first responders as well as communities and other impacted groups can be generated through automated alert systems through the use of AI algorithms and this greatly saves the time of responding to an emergency. The systems can be used to fill the gap between making predictions and taking action, enabling proactive disaster management, which ensures optimal utilization of the necessary resources and protection of human lives.

2.3. Challenges and Gaps

However, AI-based disaster prediction and management systems are subject to a number of challenges, even though the development has been impressive. Using non-homogeneous and noisy data gathered through various sources, such as satellite images, sensor data, and social media feeds, which can differ in format, quality, and credibility is one of the key problems. The technical challenge of coming up with scalable structures that would handle this data real time is still pending particularly on large scale disasters where quick response is essential. Moreover, the predictability of the model is essential in the situation of high stakes as decision-makers should know the reasons, why AI gives predictions so they could rely on it and apply it. To prevent misunderstanding and increase responsibility in disaster management, it is necessary to ensure the transparency of AI models. The solutions to these challenges are critical in coming up with strong, reliable, and trustworthy AI-driven disaster management solutions.

3. METHODOLOGY

3.1. System Architecture

The disaster management system being proposed would have a multi-layered architecture that would entail the incorporation of data collection, analysis, prediction and decision making in order to make a timely and effective response to the disaster. The different layers have been optimized to support a particular segment of the workflow, hence its accuracy, scalability and applicability in real-time.

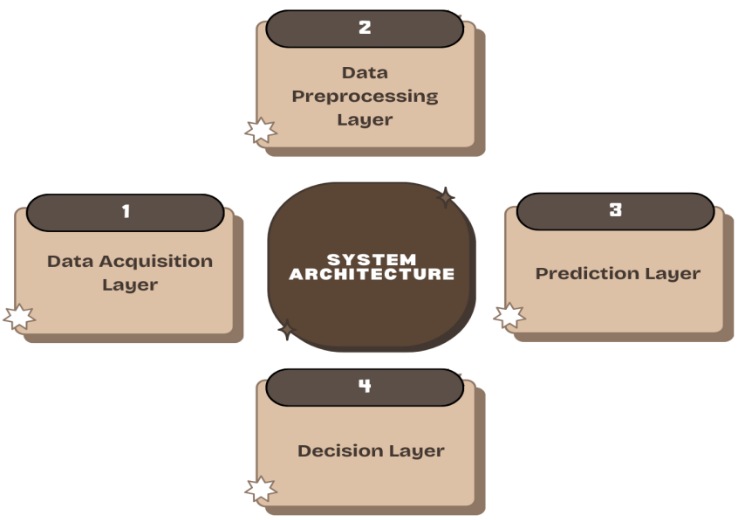

Fig 2 - System Architecture

3.1.1. Data Acquisition Layer

The Data Acquisition Layer forms the backbone of the system since it collects real-time and past data of various sources. The types of parameters measured by IoT sensors placed in strategic places include rainfall, river water, seismic, temperature, and humidity. Satellite pictures are capable of supplying an enhanced visual information on identifying massive environmental alterations including forest fires, floods, or cyclones. There are also weather stations, which provide the meteorological information, the speed of the wind, atmospheric pressure, and predictions of rain. Such a wide variety of sources can help the system form a complete dataset to quite accurately predict the future of a disaster, based on the current state and the changes throughout the history.

3.1.2. Data Preprocessing Layer

The Data Preprocessing Layer converts raw data into a form of data that the prediction models can analyze using the raw data by cleansing and transforming it into a format considered appropriate to the prediction models. Noise filtering eliminates unnecessary or incorrect data point of IoT sensors and satellite images to enhance data quality. Normalization makes sure that the model inputs have features which have varying values like temperature and rainfall which are normalised. The extraction methods used in features recognition determine the most important variables that affect disaster occurrence, e.g. the river flow speeds in case of floods or vegetation indices in the case of wildfires. This preprocessing step is essential because it helps to minimize the computational complexity, maximise the model performance and maximise prediction reliability.

3.1.3. Prediction Layer

The Prediction Layer will use advanced machine learning models and deep learning models to predict possible disasters. Conventional algorithms such as the Random Forest can be used to analyze a structured tabular datatype of events such as floods and earthquakes. Deep learning models, including Long Short- Term Memory (LSTM) networks, are used to model temporal information in sequential data, and as a result, they can easily predict dynamic events such as wildfires. Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) can be used in a combination form to study both the spatial and temporal variations, thus capable of detecting storms and any other complex disasters accurately. This layer generates probabilistic forecasts that illustrate the probable frequency and magnitude of possible disasters, deliverable information on the second step.

3.1.4. Decision Layer

Predictions are converted into disaster management action plans using the Decision Layer. The predicted extent and geographical location of the disaster is assessed using risk assessment algorithms to prioritize the affected regions. Resource allocation modules represent the best allocation of emergency personnel, implementing medical aid, food, and shelter. The evacuation planning algorithms propose route secure defections and timeless to the afflicted population to reduce the loss of life and congestion. Combined with predictions and operational measures, this layer will ensure that legislative bodies and response units could make appropriate, prompt decisions that will reduce the consequences of a disaster and preserve human life and property.

3.2. Data Collection

Any disaster prediction system based on AI relies upon data collection because the quality, diversity, and volume of data directly determine the rate of model accuracy and reliability. The fact that data in the proposed system is collected using various supplementary sources gives the system an all-embracive coverage of the environmental conditions and disaster events. The training of machine learning and deep learning models is based on historical data on disasters. These data sources are authoritative sources like the United States Geological Survey (USGS) and the National Oceanic and Atmospheric Administration (NOAA), which are found to give extensive information about past activities that included quakes, floods, hurricanes and other disasters. These datasets usually incorporate such parameters as magnitude, location, duration, frequency, and assessment of damage that assist AI models in learning patterns and correlations that are likely to occur before disasters. Besides historical databases, current data of the IoT sensors is constantly used to observe the environmental conditions that may indicate a possible disaster. Parameters measured using sensors include temperature, humidity, rain fall, water level in rivers and seismic activities. This streaming data allows the system to notice small variations in the conditions of the environment, and this is important in the cases of early warning systems that need early attention. When sensor networks of IoT are installed in important areas, there is a detailed picture of local experience, and the prediction models are equipped with precise and current data. Besides, satellite images are used to monitor large scale environmental effects otherwise hard to measure using ground based sensors. Remote sensing satellites provide high-resolution images, which the system can analyze to detect vegetation changes, soil moisture, river routes, storms development as well as coastal erosion. When they are subjected to convolutional neural networks and other image processing methods, these images can help in giving information of the size and severity of a possible disaster in its spatial terms. The fusion of the past, current (i.e., the IoT sensor measurements) and the satellite images guarantees the presence of the strong multi-dimensional data that improves the precision of prediction, promotes the timely reaction to the disaster and eventually leads to the development of more efficient mitigation measures.

3.3. Feature Extraction

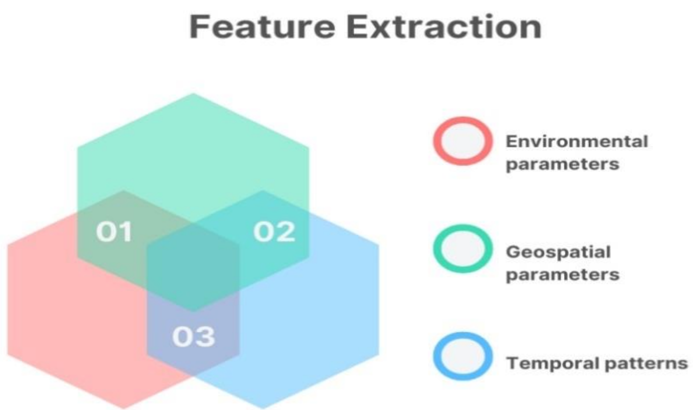

Fig 3 - Feature Extraction

3.3.1. Environmental Parameters

The environmental parameters are important environment-related predictors of natural disasters since they directly affect the intensity and frequency of occurrence of a natural disaster like flood events, storms, and wildfires. The major variables are rainfall, temperature, wind speed, humidity and soil moisture that give understanding of the weather pattern and environmental conditions. As an example, high moisture levels and surplus rainfall can cause the occurrence of flooding, whereas high temperature and low humidity can lead to the possibility of wildfires. The system is able to quantify environmental risks through extraction and analysis of these parameters that are collected by the IoT sensors, weather stations, and satellite data to give credible inputs to prediction models.

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3.3.2. Geospatial Parameters

Geospatial parameters offer physical features of the terrain and is very important in disaster prediction and assessment of risk. They are elevation, slope, closeness to water bodies, type of soil and land use. Also, regions by rivers run a higher risk of being flooded and steep slopes increase the chances of landslides during downpour. Integration of the geospatial properties into the AI models will enable more precise predictions by the system and specific mitigation strategies since the system will comprehend both spatial relationships and patterns of vulnerability. These parameters are usually extracted and mapped using Geographic Information Systems (GIS) to get to understand them.

3.3.3. Temporal Patterns

The temporal patterns deal with the time-varying characteristics of environmental and geospatial variables and assists the system to identify episode trends, season cycles and anomalies prior to disasters. As an illustration, monsoon seasons can cause frequent flooding of certain areas, and long-term droughts can contribute to the heightened vulnerability of wildfires. Providing the system with historical data to analyze trends with respect to time allows it to identify those trends that remain not visible in the one-time point observations. Such methods like anomaly detection and time-series analysis are used to recognize the unique shifts of the environmental conditions, as a result of which AI models will predict disasters in a better way and give a warning.

3.4. Machine Learning Models

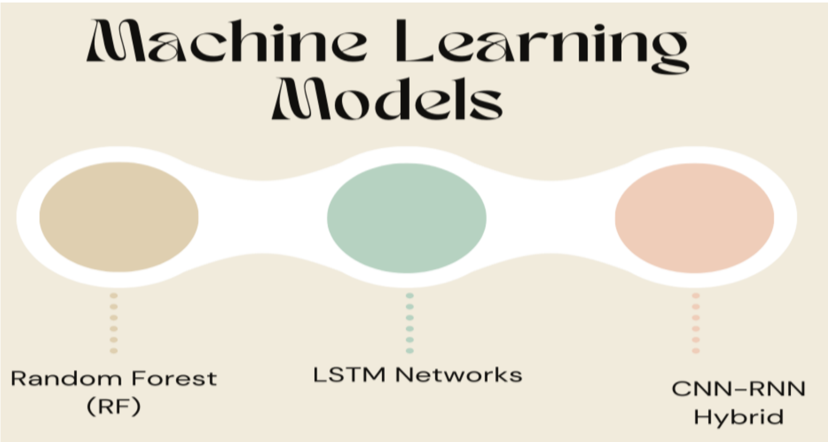

Fig 4 - Machine Learning Models

3.4.1. Random Forest (RF)

Random Forest (RF) is a popular ensemble learning algorithm, which is an integration of several decision trees to enhance accuracy and minimize overfitting in forecasting. RF is especially useful in structured and tabular data, including past events of floods, landslides and precipitation measurements in predicting disasters. RF can categorize regions by their potential to experience a disaster through analyzing the input characteristics such as rainfall intensity, soil type and river levels among others. This means that it is a credible tool in discovering the key determinants of the environment and geospatial dimension to determine proactive disaster management and early warning systems, given that it can be applied to high-dimensional data and its features ranked in terms of importance.

3.4.2. LSTM Networks

The Long Short-Term Memory (LSTM) networks refer to a category of recurrent neural network (RNN), with the sole purpose of learning long-term dependencies in it. LSTMs are especially asked to predict the disasters which change over time, e.g., earthquakes, wildfires, seasonal floods. Horizons of sensor measurements, past history of past disasters and weather scenarios allow LSTMs to be trained to sort out patterns that anticipate an event e.g. progressive seismic wave sequence an increase in temperature. Their memory cells and gating systems enable them to store significant information about time and filter the irrelevant information, which makes them very suitable in the real-time prediction and early warning systems.

3.4.3. CNN-RNN Hybrid

CNN-RNN hybrid model is a model that integrates the capabilities of Convolutional and Recurrent neural networks to provide spatial and temporal processing of disaster data. CNNs can extract spatial features of a high-resolution satellite image, like the area of a flood or a wildfire or the pattern of a storm, whereas the RNNs capture how these features change over time. This hybrid methodology would be especially useful in complex disasters, where environmental changes, both spatial and temporal, are dynamic in nature, such as a hurricane or a flood of the whole area. The CNN-RNN model can better forecast and give early warnings of an impending disaster due to the combination of spatial and time data, which is more reliable.

3.5. Decision Support Layer

The Decision Support Layer is the last phase of the AI-based disaster management system and it converts the predictions into actionable measures that will help authorities make timely and effective decisions. The risk scoring is at the centre of this layer and it measures the likelihood and the possible effect of a disaster to a particular area. Risk scoring is based on the inputs of machine learning and deep learning models, and to categorize the areas into low, moderate, and high-risk areas, it assesses environmental, geospatial, and temporal parameters. These scores allow the authorities to give priority to the interventions, resources to be allocated in the most beneficial way, and the communities at the risk of the impending disaster are determined. This element will help advance situational awareness and make informed decisions by offering a well-defined and numerically measurable level of risk. The other important consideration of the Decision Support Layer is in finding out the most appropriate evacuation routes. The geographic Information System (GIS) mapping tools combine real time forecasts, topographical information, road system, and population density to know the reasonable and secure evacuation routes. When dealing with emergency cases like floods, wild fires or storms, it is necessary to ensure the rapid and secure route is chosen as a way of reducing the number of casualties and traffic. The system is also capable of dynamically updating evacuation recommendations as the situation evolves so that real time evacuation recommendations can be provided to the residents to move out of danger zones. Lastly, resource allocation simulation helps those in power to schedule the allocation of essential resources such as emergency personnel, medical assistance, food and temporary housing. Simulation models do an evaluation of allocation strategies depending on the expected severity of the disaster, geographic transmission, and people requirements. The optimization of resources placement helps the system to deliver the aid to the affected regions as quickly as possible and make it possible to have response teams working efficiently even in the situation of high pressure. Collectively, the risk scoring, evacuation planning, and resource allocation will be a holistic decision support system, which transforms the predictive intelligence into actionable plans to enhance the preparedness, speed of response, and general resilience of communities to disasters.

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4. RESULTS AND DISCUSSION

4.1. Experimental Setup

The experiment to compare the proposed disaster prediction system based on AI was set up in a way that would guarantee efficient training of the model, proper evaluation, and repeatability of outcome. It was written in Python, a python ecosystem that gives rich access to machine learning, deep learning, and data processing libraries and frameworks. The central libraries were TensorFlow to implement and train a deep learning network like LSTM and CNN-RNN hybrid and Scikit-learn to execute a classic machine learning network, such as a Random Forest and Support Vector Machine. The fact that Python is flexible, and has a comprehensive documentation, means it is a perfect fit when it comes to covering data preprocessing, feature extraction, model training, as well as evaluation, within the same development environment.

The hardware infrastructure has been chosen carefully to be able to support the computational requirements of deep learning models. The computation power of training complex networks and especially CNNs with high resolution satellite imagery or LSTMs with long time sequences is very high. To do this, NVIDIA GPUs were used, which provide parallel processing in their design, which facilitates the acceleration of computations of matrices and the process of backpropagation. Multiplication by acceleration with a GPU took a considerable amount of time, enabling exploration of a range of hyperparameter settings and model architectures to trade off across performance. In order to strictly evaluate the performance of the models, a number of evaluation measures were used. Accuracy is the sum of correctness of predictions giving a general indication of correctness of the models with all classes. Precision is a measure of the fraction of successful positive predictions made, of all positive predictions, which is important in reducing false alarms in disaster detection.

Recall is used to assess how well the model can correctly recognize all the actual positive cases so that important disaster events are not missed. F1-Score which is a harmonic mean of both the precision and the recall, is a balanced metric of performance of a model, particularly when there is an imbalanced dataset where occurrences of disasters are infrequent relative to the normal conditions. Through a combination of these measures, the experimental design would be able to provide a comprehensive assessment, both in terms of predictive accuracy and reliability of the AI models when applied in a disaster management real-life situation.

4.2. Prediction Performance

Table 1: Prediction Performance

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	88%	85%	83%	84%
LSTM	91%	89%	90%	89.5%
CNN-RNN	93%	91%	92%	91.5%

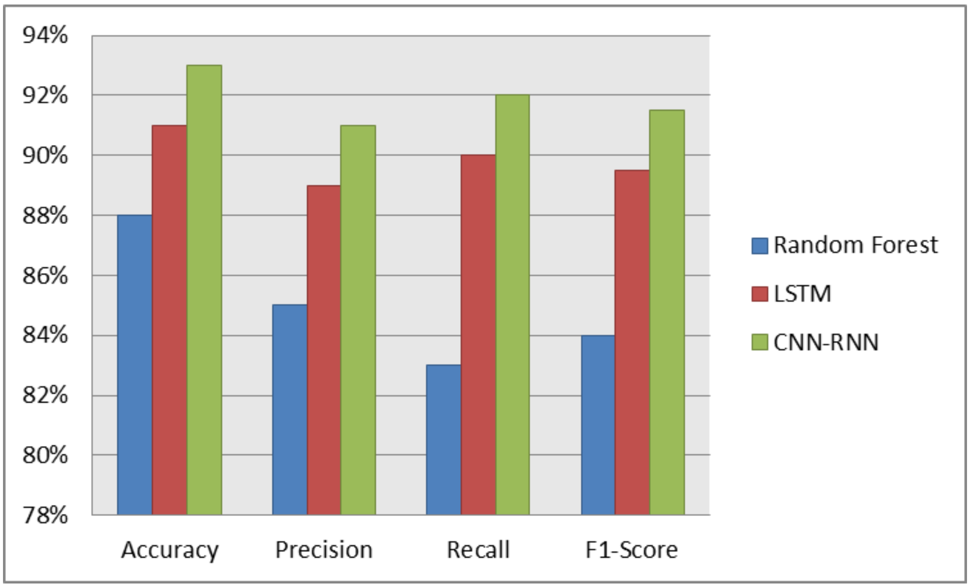

Fig 5 - Graph representing Prediction Performance

4.2.1. Random Forest

The Random Forest (RF) model was very pertinent in the prediction of the organized disaster-related information with a percentage of accuracy being 88. The pattern in the environmental and geospatial features of floods and landslides was sufficiently represented in its ensemble approach where it combines two or more decision trees. The specificity of 85 is an indication that the majority of the regions that were marked as high-risk were true hazards whereas the recall of 83 is an indication that the model was able to identify the majority of regions that actually were disaster prone. Random Forest with an F1-score of 84 is an excellent compromise between precision and recall, and is therefore an effective option when initial risk assessment and decision support are required in structured data.

4.2.2. LSTM

The Long Short-Term Memory (LSTM) network is a temporal sequence model that achieved better results compared to traditional models in learning temporal dynamics of individual disaster data, e.g., seismic activity with earthquakes or temperature variations with wildfires. The accuracy of LSTM was 91, which was a measure of its capability to learn time-dependent relationships in historical and real-time sensor information. The precision and recall of 89% and 90 percent respectively of the model imply that in addition to having a minimum number of false alarms, the model identifies the majority of the actual acts of disaster, which is crucial in the context of the early warning systems. The achieved F1-score of 89.5% supports the idea that the given model is quite effective in terms of balancing sensitivity and reliability and thus can be utilized in the endeavors of disaster prediction as a time-series model.

4.2.3. CNN-RNN

CNN-RNN hybrid showed the best results of the evaluated models with accuracy of 93%. The hybrid model combining the spatial feature of CNN that utilizes satellite images and the temporal sequence modeling technique of RNN effectively achieved both spatial and time trends in the occurrences of disasters. Its accuracy of 91% means that the predictions of the disaster areas are mostly true and a recall of 92% means that the model can be used to pick the actual incidents of the disaster and minimise the chances of the warning missing. The F1-score of 91.5 percent validates the overall power of the model as it is true that the combination of spatial and temporal information is beneficial in improving the accuracy of outcome of predictions and as a source of reliable feedback on total disaster management and early warnings system.

4.3. Discussion

The metrics of the experiment prove that hybrid CNN-RNN model is always better than the conventional machine learning models, including Random Forest when it comes to disaster prediction. This is the best performance due to its capability to get spatiotemporal features which are naturally existent in environmental and satellite data. Whereas standard models have been successful with tabular structured data, they can sometimes prove to be incapable of capturing complex spatial relations or moving time sequences. The CNN aspect of the hybrid model are used to extract spatial information in the satellite images, which can be of flood areas, fire area, or even shape of a storm, which gives the system the ability to identify the high-risk areas with large accuracy. In the interim, the RNN-based component, especially LSTM units, will be able to consider the temporal dependencies in the sequential sensor readings or past catastrophe-related history as the model will be able to identify patterns and predict the eventual occurrence that evolves over time. The result of such a combination is that the place of the possible disaster and the time are correctly forecasted, which is essential in the context of the early warning mechanisms. Moreover, real-time sensor data, incorporated into the model, can be regarded as an important contributor to the practical value of the presented model. The system is notified of dynamic updates of its predictions as the environment changes in response to continuous streams of environmental data, such as temperature, rainfall, humidity, seismic activity, and river water levels. This real time feedback enhances the responsiveness of the early warning mechanisms and reduces the rate of false negative and guarantees that emergency alerts are sent at the right time where alarm signs of potential hazards are met. The system uses a combination of complex deep learning algorithms and live sensor networks to ensure a higher degree of predictive reliability and accuracy that is impossible to offer using traditional models. Besides that, the potential of the hybrid model to deal with heterogeneous data sets, including not just sensor measures that are numeric but also temporal and high-resolution images, gives it a high level of versatility across the types of disasters, such as floods, wildfires, earthquakes, and storms. This and its high accuracy and precision, as well as recall, indicate the effectiveness of the model as a comprehensive disaster management tool. Altogether, CNN-RNN hybrid, combined with an IoT-driven real-time data, provides a solid framework of optimizing early warning systems as well as directing resource allocation and reducing the human and economic effect of natural disasters.

5. CONCLUSION

This study shows that artificial intelligence-based decision support systems have a huge potential towards better disaster management and prediction in real-time. The proposed system contributes to the multiphase combination of machine learning (ML) and deep learning (DL) models with Internet of Things (IoT) sensor networks and Geographic Information System (GIS)-based visualization tools, presenting a holistic proactive mitigation of a disaster. Conventional disaster management systems tend to consider stagnant historical data or delayed information and this may result in slow responses and sub optimum resource utilization. Conversely, AI-oriented models will be capable of reviewing both previous and current data, finding trends and patterns that indicate a threat. Random Forest, LSTM networks and CNN-RNN hybrid models integration allows the system to process a variety of data types, such as structured tabular data, time series, and high-resolution satellite images. Such a multi-model strategy leads to a high level of prediction accuracy, which is proved by the fact that the hybrid model based on CNN-RNN has shown excellent performances in terms of revealing both spatial and temporal patterns of a number of different disaster types, such as floods, wildfires, storms, and earthquakes.

The fact that the system considers the IoT data of sensors is associated with the high level of early warnings. The system continuously monitors environmental conditions like rain, river level, temperature, humidity, and seismic and thus provides real time updates to predictions. The visualization that is based on GIS also helps to transform these forecasts into practical knowledge, mapping the dangerous areas, outlining evacuation, and modeling resource distribution. These parts combined will create a solid decision support framework that enhances situational awareness, shortens response times, and assists the authorities to allocate resources effectively during an emergency.

Going forward, the future will be concerned with multi-disaster integration where the system can monitor and predict a number of different disaster types in the same area which is very important due to the rising popularity of compound disasters driven by climate change. Another priority area is cloud deployment since it would offer scalable computing capabilities, process large amounts of data, and allow the disaster management authorities in various localities access to such services in real-time. Along with it, the creation of explainable AI (XAI) models will be necessary to introduce more confidence in predictions because the ability to see the reason behind AI-based warning messages and suggestions on where to allocate resources will make the decision-makers more confident in their choice. With the areas being covered, it is possible to make the system a complete integrated, scalable, and interpretable platform to cope with the proactive disaster management and reduce the harm to human and economic lives in response to the natural hazards it will eventually be possible to create resiliency in communities against a natural hazard.

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