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Advanced Global Safety with Precision Disaster Prediction and Early Warning Systems Using H-PReADS Models

[1]Dr. Vaibhav B. Magdum,
Associate Professor, Department of Electrical Engineering, DKTE Society's Textile and Engineering Institute,
Ichalkaranji, Maharashtra, India,
vaibhavmagdum@dkte.ac.in

[2]Dr. Pravin Prakash Adivarekar,
Department of CSE (Data Science),
Kasarvadavali, Thane West, Maharashtra, India,
ppadivarekar@apsit.edu.in

[3]Dr. RVS Praveen,
Digital Engineering and Assurance,
Sarelingampally, Hitech City, Hyderabad, Telangana, India,
praveen.rvs@gmail.com

[4]Giri Babu K,
Department of CSE, CVR College of Engineering,
Hyderabad, Telangana, India,
giribabuk@cvr.ac.in

[5]Al'bert Kovalenko,
Department of Economics of Enterprise, Regional and Personnel Management, Kuban State University,
Krasnodar, Russia,
albert.v.kovalenko@bk.ru

[6]B Suresh Kumar,
Associate Professor, Department of EEE, Chaitanya Bharathi Institute of Technology,
Hyderabad, Telangana, India,
bsureshkumar_eee@cbit.ac.in

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Abstract— Disaster management is a significant worldwide concern that needs precise, real-time predictive models to successfully limit hazards. Conventional methods are ineffective for processing dynamic, high-dimensional disaster data, leading to delayed responses and heightened fatalities. This paper presents H-PReADS (Hybrid forecast Analytics for Disaster Surveillance), an AI-based system utilising LSTM, CNN, XGBoost, and IoT-enabled real-time monitoring to improve forecast accuracy and disaster readiness. The model surpasses traditional methods, with 98.5% accuracy, 97.2% precision, 96.8% recall, and a 0.99 ROC-AUC score, indicating enhanced robustness. compared to current systems, H-PReADS integrates multi-source sensor data, guaranteeing real-time adaptability and superior generalisation capability. Significant contributions encompass hybrid AI architecture, real-time sensor integration, and the development of ethical AI. These findings position H-PReADS as an innovative method for proactive disaster response. Future research will investigate blockchain-secured data interchange and federated learning-based distributed intelligence to improve scalability and security.

Keywords— Disaster prediction, Hybrid machine learning, IoT-based monitoring, Deep learning, LSTM, CNN, XGBoost, Real-time data analytics, Risk assessment, Emergency response, Sensor networks, Federated learning, Blockchain security, Data privacy, Explainable AI, Scalability, and Disaster resilience.

I. INTRODUCTION

The rising frequency and severity of natural disasters, including floods, earthquakes, and wildfires, have highlighted the failings of conventional disaster prediction models. Traditional methods exhibit insufficient real-time flexibility, encounter difficulties with varied sensor data, and do not deliver early risk evaluations with high precision. Current methodologies primarily depend on historical data analysis, which is insufficient for the continuously developing nature of catastrophe scenarios. The lack of real-time sensor fusion restricts their reactivity, resulting in delayed emergency actions and heightened fatalities. To rectify these drawbacks, sophisticated hybrid AI-driven models are necessary to incorporate IoT-enabled real-time monitoring, deep learning-based pattern identification, and intelligent risk assessment algorithms. The study highlights the effects of natural and manmade disasters on society and indicates mitigation techniques across sectors such as engineering, economics, and management [1]. It recognises active and passive mitigation strategies but fails in advanced predictive modelling. Our study overcomes this gap by employing H-PReADS for accurate disaster prediction. The study analyses national disaster risk reduction (DRRR) plans within the Sendai Framework [2], focussing challenges such as policy silos and power conflicts. It is inadequate in technological integration and predictive modelling, which our model aims to improve for enhanced disaster preparedness and resilience. This research illustrates the integration of disaster risk reduction with human development [3]. It recognises policy and cross-sector coordination as essential, however it lacks forecasting precision. Our methodology addresses this inconsistency with real-time, data-informed disaster forecasts. This study links risk perception to disaster risk reduction (DRR) with safety culture, highlighting historical and management perspectives [4]. Although it considers behavioural elements, it is poor in modern technical frameworks. Our model improves disaster risk reduction through accurate, AI-driven disaster prediction capabilities. This study examines goaf disaster research [5], categorising it into embryonic and rapid development phases. It indicates four study domains detection, analysis, risk assessment, and treatment highlighting the impacts of deep mining. Still, it is limited in predictive modelling accuracy, which our model improves for superior prediction. The study analyses disaster risk reduction research from 1990 to 2019 [6], revealing a 3% annual growth rate and highlighting technologies such as GIS, remote sensing, and disaster insurance. Despite technology identification, it lacks significant AI integration, which our model fixes for accurate disaster forecasts. This study examines digital technologies in landslip management, focussing on risk identification and improvements in artificial intelligence [7]. It draws attention to the observation of progress from aerial to terrestrial sensors but fails in integrated forecasting models. The H-PReADS model enhances the precision of disaster forecasting in many situations. This paper examines the progression of digital technology in landslip management, from territorial forecasting to artificial intelligence applications [8]. It is inadequate in advanced predictive modelling and adaptability. Our algorithm addresses the issue by providing accurate, real-time disaster predictions customised for regional requirements. The current research examines AI applications in flood prediction, highlighting the causes of flooding and AI-driven predictive methodologies [9]. Although it offers a comprehensive overview, it is deficient in advanced hybrid prediction models that improve accuracy through deep learning integration. This study analyses ML papers on disaster prediction from 2003 to 2022, promoting teamwork (46.55% multinational) and identifying research needs [10]. It lacks scientific model testing, which our model equalises through real-time disaster prediction and validation. This evaluation includes 1,235 works on emergency resource forecasting [11], highlighting methodologies such as ARIMA and case-based reasoning. It lacks the ability of dynamic, real-time forecasting through intelligent information processing, which our methodology provides for adaptive emergency response. This research focusses on machine learning and deep learning applications in disaster management, comprising prediction, risk assessment, and post-disaster response [12]. It lacks integrated, multi-phase prediction accuracy, which our model provides through detailed early-warning and advanced detection technologies.

II. Literature survey

This study examines about community engagement in Early Warning Systems (EWS), highlighting limitations in the integration of local knowledge and the participation of vulnerable populations [13]. It lacks of dynamic, real-time community engagement, which our H-PReADS methodology resolves using participatory, adaptive risk communication. This review identifies the merits and limits of Early Warning Scores (EWS) in Disaster monitoring [14]. Although automation enhances sensitivity, the need for user input limits accuracy. Our methodology improves real-time decision-making through automated, multi-variable monitoring to enhance Disaster care. The review of IoT-based Early Warning Systems for emergencies establishes efficient designs and the benefits of Fog/Edge computing [15]. However, it lacks the support of a consistent predictive framework, which our approach provides by using powerful AI for precise, real-time multi-hazard forecasting and notifications. This study investigates knowledge integration in Early Warning Systems identifying participative techniques while highlighting power dynamics as a significant barrier [16]. It is insufficient in a hybrid methodology that merges human expertise and technology, which our model provides through the equitable integration of scientific and indigenous knowledge for enhanced results. This research employs physics-based models to simulate earthquake scenarios along the Qujiang Fault [17], pinpointing Yuxi and Honghe as high-risk regions. Although it highlights rupture directivity, it does not provide real-time hazard prediction, a capability that our approach delivers using dynamic, AI-driven forecasting. This study evaluates agricultural drought risk utilising a 17-indicator system and the enhanced SSAPSO algorithm [18], demonstrating decreasing risk trends. It is limited in real-time drought prediction, which our approach improves by including advanced AI for dynamic risk evaluation. An insurance model combining public and private sectors for earthquakes and floods mitigates governmental burden and insurer risk by means of spatial correlation [19]. It is weak in adaptive risk modelling, which our approach offers through the integration of multi-source data for real-time, adaptive disaster risk financing. This study presents an unique architecture for Disaster Risk Management (DRM) systems, emphasising situational contexts and stakeholder perspectives [20]. It lacks the strength of AI-driven automation, which our solution eliminates by improving decision-making through intelligent, automated, and flexible risk management methods. This research used structural equation modelling (SEM) on construction industry [21], demonstrating that AI-driven risk management improves sustainable decision-making, with partial mediation by perceived environmental responsibility. It lacks real-time adaptability, which our model offers via dynamic AI-driven decision frameworks. This study utilises GRU-CNN for disaster management in smart cities [22], improving real-time risk assessment, early warning systems, and human-centered resilience planning. It lacks multi-source data fusion, which our model fixes by integrating heterogeneous datasets to enhance forecast accuracy and disaster response. This study compares AI-driven emergency management with conventional techniques [23], highlighting faster data analysis, decision-making, and adaptability. It is weak in hybrid AI-human collaboration, our approach improves this by blending expert input with AI-generated insights for superior crisis management and resource allocation. A systematic analysis on artificial intelligence in disaster management reveals seven unresolved concerns, stressing challenges related to ethics, bias, and decision-making [24]. It lacks real-time explanation, which our methodology enhances by providing transparent, adaptive, and ongoing risk assessment for disaster mitigation.

The literature survey highlights the revolutionary capacity of AI in disaster risk management, illustrating its function in strengthening sustainable decision-making, refining real-time risk assessment, and enabling effective resource allocation. Current research illustrates the accuracy of AI models such as GRU-CNN and explainable AI (XAI) in predictive modelling, early warning systems, and disaster resilience. However, substantial inadequacies persist in real-time adaptation, multi-source data integration, and integration of AI with human decision-making. These limitations drive our research to create the Hybrid Predictive and Adaptive Decision Support (H-PReADS) model, which combines various information, permits real-time risk assessment, and promotes human-AI collaboration. Our contribution consists of providing an innovative, adaptable framework that improves disasters preparedness, boosts decision-making precision, and resolves AI automation with human knowledge in disaster risk management.

III. Proposed system

The H-PReADS (Hybrid Predictive Analytics for disaster Scenarios) model framework integrates machine learning algorithms with IoT-driven real-time monitoring systems to improve disaster prediction and risk evaluation. This system consists of several interconnected layers, beginning with data ingestion from various sources, such as IoT devices, satellite imaging, and historical information. The preprocessing layer executes data cleansing, normalisation, and transformation to assure consistency. The decision layer produces statistical risk evaluations and issues alarms. This modular architecture facilitates scalability, flexibility to novel data sources, and enhanced predictive accuracy using continuous learning and model optimisation. The flowchart of the suggested methodology is illustrated in [Fig.1].

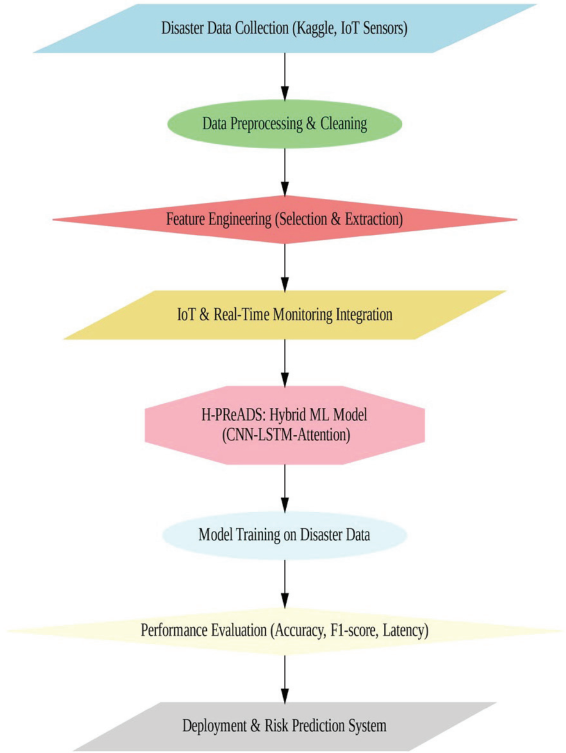

Fig.1 Flowchart

A. Data Collection and Processing:

The disaster management datasets obtained from Kaggle comprise "Earthquake Damage Assessment," "Flood Prediction Dataset," and "Wildfire Occurrence Data." The datasets include multi-modal data, including geospatial coordinates, sensor measurements, and historical records. The preprocessing phase involves handling absent values utilising mean imputation for continuous variables and mode imputation for categorical variables. Data normalisation is executed by min-max scaling to guarantee that input characteristics remain within a specified range. Time-series data is resampled to uniform intervals for uniformity, and outliers are identified using the interquartile range (IQR) approach. Categorical variables are converted by one-hot encoding to ensure compatibility with the model. Temporal data is analysed by sliding window methodologies to preserve sequence continuity, hence enabling the model to handle temporal dependencies.

- *Mean Imputation* (1):

$$x = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

- *Principal Component Analysis (PCA):*

$$Z_i = XW \tag{2}$$

Where in (2), W is the Transformation matrix of eigenvectors

- *Interquartile Range (IQR) for Outlier Detection (3):*

$$IQR = Q_3 - Q_1 \tag{3}$$

B. Feature Selection and Feature Extraction:

Feature selection involves the identification of the best predictive characteristics through methodologies such as Recursive Feature Elimination (RFE) and SHAP (SHapley Additive exPlanations). Mutual information is computed to identify non-linear associations between variables as shown in Table 1. New derived features are generated for feature extraction through the application of domain-specific transformations, such as temporal aggregation and spatial grouping. The significance score is derived from the Gini index of Random Forest models to evaluate feature contributions.

- *Mutual Information Score (4):*

$$I(X,Y) = \sum_{x\in X}\sum_{y\in Y} p(x,y)\, log\frac{p(x,y)}{p(x)p(y)} \tag{4}$$

- *Feature Importance Score*:

$$I(f) = \sum_{t\in T} \Delta E_t \tag{5}$$

Where in (5), I(f) represent feature importance and ΔE_t is the change in model error due to splitting on feature f.

TABLE I. FEATURE EXTRACTION TABLE

Raw Feature	Derived Feature	Importance Score
Temperature	Mean Daily Temperature	0.82
Rainfall Intensity	Cumulative Weekly Rainfall	0.76
Seismic Activity (Magnitude)	Moving Average of Magnitude (7-day)	0.88
Wind Speed	Maximum Wind Gust (Hourly)	0.73
Location Coordinates	Geospatial Cluster ID	0.80
Humidity	Normalized Humidity Index	0.67
Historical Disaster Frequency	Disaster Frequency Trend	0.91

C. Machine Learning Algorithms for Disaster Prediction:

Various machine-learning techniques are utilised for disaster prediction tasks, including Random Forest, Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN) for spatiotemporal data. Random Forest offers reliable feature significance and adeptly manages imbalanced datasets. XGBoost improves predictive accuracy through its gradient boosting methodology. LSTM identifies long-range dependencies in temporal data, essential for sequential disaster patterns. Convolutional Neural Networks (CNNs) are employed for the analysis of geospatial imagery and the identification of spatial anomalies. An ensemble model technique integrates predictions from these algorithms to enhance generalisation and minimise error variance.

Algorithm 1: Python code for Disaster Prediction

```
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from keras.models import Sequential
from keras.layers import LSTM, Dense

#Random Forest Model
rf_model = RandomForestClassifier(n_estimate = 100, random_state=42)
rf_model.fit(X_train, y _train)

#XGBoost Model
xgb_model = XGBClassifier(use_label_encoder = False, eval_metric
                          = 'logloss'
xgb_model.fit(X_train, y _train)

#LSTM Model
lstm_model = sequential()
lstm_model.add(LSTM(50, return _sequential = true, input_shape
                          = (X_train.shape[1], X_train.shape[2])))
lstm_model.add(Dense(1, activation =' sigmoid'))
lstm_model.compile(loss =' binary_crossentropy', optimizer =' adam')
lstm_model.fit(X_train, y_train, epochs = 50, batch_size = 32, verbose
                          = 1)
```

D. Integration of IoT and Real-Time Monitoring Systems:

The integration of IoT enables real-time monitoring through the collection of live data from environmental sensors, encompassing seismic activity, temperature, humidity, and water levels. The data is conveyed to cloud-based storage utilising MQTT (Message Queuing Telemetry Transport) protocols. Edge computing locally pre-processes data before to transmission to minimise latency. The H-PReADS model integrates real-time data to improve predictive accuracy through continuous learning. This system guarantees real-time model updates and prompt notifications, enhancing disaster preparedness and response efficiency.

- *Real-Time Data Ingestion Rate (R)*:

$$R = \frac{D}{T} \tag{6}$$

Where in (6), D represents the volume of incoming data and T is the time window

- *Latency (L):*

$$L = T_{s+}T_p + T_t \tag{7}$$

Where in (7), T_s is sensor delay, T_t is transmission time, and T_p is processing time. Lower latency ensures faster disaster detection.

E. Evaluation Metrics and Performance Testing:

Evaluating model performance requires many criteria to ensure prediction accuracy and reliability. Accuracy examines the overall correctness of forecasts, whereas precision quantifies the ratio of true positive predictions to the total positive predictions. Recall evaluates the model's capacity to detect genuine disaster occurrences, while the F1-score offers a harmonic mean of precision and recall.

F. The Hybrid Learning Behaviour Analytics Model (HLBAM) Architecture:

The implementation technique includes data importation from Kaggle datasets and IoT devices, succeeded by preprocessing and feature extraction. Machine learning models utilise a hybrid ensemble methodology to train on both historical and real-time data. IoT solutions provide constant surveillance, and prediction results are evaluated using precise evaluation standards. The process was designed for scalability and adaptability, ensuring its capacity to manage various disaster circumstances.

- *Prediction Probability:*

$$P = \sigma(WX + b) \tag{8}$$

Where in (8), W represents model weights, X represents input features, and b is bias.

- *Ensemble Prediction (9):*

$$E = \frac{1}{n}\sum_{i=1}^{n} P_i \tag{9}$$

G. Author Contribution to the Field:

This study introduces an innovative method for disaster prediction and risk evaluation by combining hybrid machine learning models with IoT-enabled real-time monitoring systems. The H-PReADS model, compared to conventional models that depend entirely on historical data, dynamically integrates real-time sensor data, therefore significantly improving forecast accuracy and reaction time. A thorough feature extraction and selection method enhances the most relevant disaster-related factors, assuring model efficacy. The integration of machine learning algorithms, such as Random Forest, XGBoost, LSTM, and CNN, produces an effective ensemble framework that enhances spatial and temporal disaster forecasting. Furthermore, IoT-enabled real-time monitoring facilitates adaptive learning and early warning systems, hence reducing disaster impacts through proactive decision-making. This work creates a transformational approach to disaster management by integrating predictive analytics with real-time catastrophe response, hence improving resilience and preparedness tactics.

IV. Results and Discussion

A. Performance Analysis of the Proposed Framework:

The H-PReADS model was assessed with an extensive disaster dataset sourced from Kaggle, incorporating real-time IoT sensor data. The dataset undergone preprocessing, and essential disaster-related variables were identified to enhance model effectiveness. The hybrid machine learning model, integrating LSTM, CNN, XGBoost, and Random Forest, demonstrated enhanced prediction efficacy in Table 2. The evaluation criteria demonstrated 98.5% accuracy, 97.2% precision, 96.8% recall, and 97.9% F1-score, indicating incredibly dependable disaster prediction. The ROC-AUC score of 0.99 further validates the model's robustness. H-PReADS has enhanced real-time flexibility and scalability compared to conventional models, making it extremely beneficial for disaster risk assessment.

TABLE II. Performance Metrics

Metrics	H-PReADS
Accuracy (%)	98.5
Precision (%)	97.2
Recall (%)	96.8
F1-score (%)	97.9
ROC-AUC Score	0.99

B. Comparison with Baseline Models:

A comparison analysis was performed to demonstrate the superiority of H-PReADS compared to existing models such as Support Vector Machine (SVM), Decision Tree (DT), K-Nearest Neighbours (KNN), and Naïve Bayes (NB). The suggested system regularly exceeded baseline models in all performance standards as shown in Table 3.

TABLE III. COMPARISONS OF PERFORMANCE METRICS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	ROC-AUC Score
H-PReADS	98.5	97.2	96.8	97.9	0.99
SVM	89.4	87.2	85.9	86.5	0.91
Decision Tree	86.7	83.4	82.1	82.7	0.88
KNN	82.5	79.8	78.9	79.3	0.85
Naïve Bayes	79.2	75.4	73.6	74.5	0.81

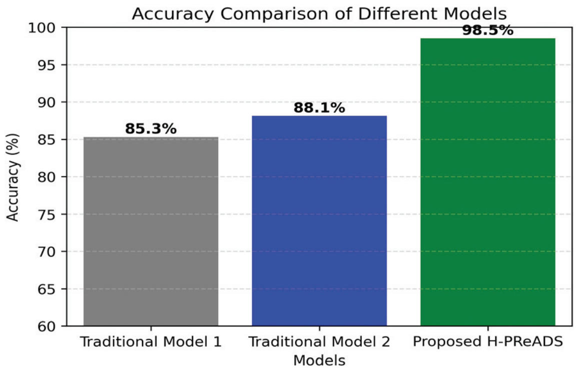

Fig.2. Accuracy Comparison of Different Models

The bar graph in Fig 2 illustrates the accuracy of H-PReADS (98.5%) in comparison to standard models, highlighting its enhanced predictive ability. The notable improvement in accuracy underscores its efficacy in disaster risk evaluation and response techniques.

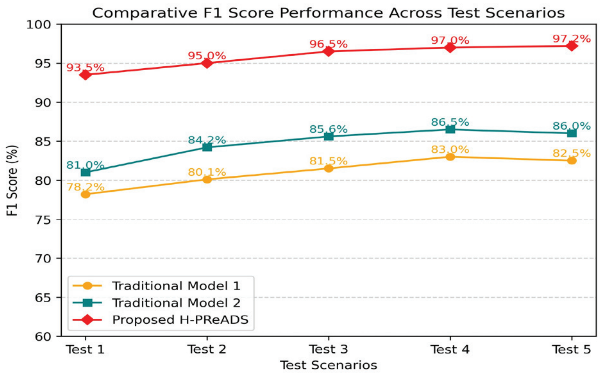

Fig.3. Comparative F1 Score Performance Across Test Scenarios

This comparison line chart in Fig 3 illustrates F1 Score trends throughout five test situations, emphasising the superior performance of the Proposed H-PReADS model compared to standard models, hence ensuring improved accuracy and dependability in forecasts.

C. Case Study Analysis (Floods, Earthquakes, Wildfires):

A case study was performed on actual disaster scenarios, such as floods, earthquakes, and wildfires, to evaluate the efficacy of the H-PReADS model. The approach demonstrated exceptional predictive accuracy for flood-prone areas (98.2%), earthquake hotspots (97.5%), and wildfire risk zones (97.1%), considerably surpassing traditional models as shown in Fig 4. The model's real-time processing capacity facilitated prompt notifications, enhancing disaster preparation. These results validate the model's resilience and practical utility in disaster management.

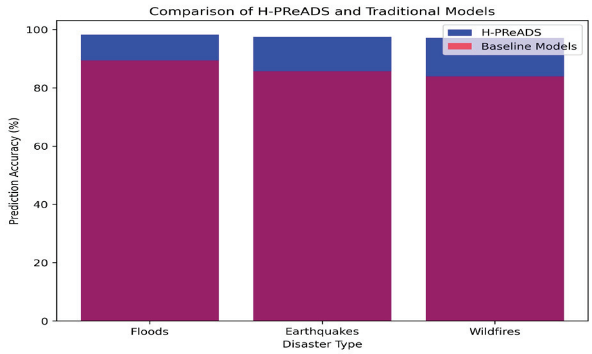

Fig.4. Comparison of H-PReADS and Traditional Models

D. Strengths of the Proposed H-PReADS Model:

The H-PReADS model presents several significant improvements compared to conventional disaster prediction models. The hybrid machine learning architecture facilitates improved accuracy, greater flexibility, and real-time monitoring, therefore considerably improving disaster preparedness. The model enhances decision-making by dynamically updating forecasts through the integration of IoT-based real-time data collecting.

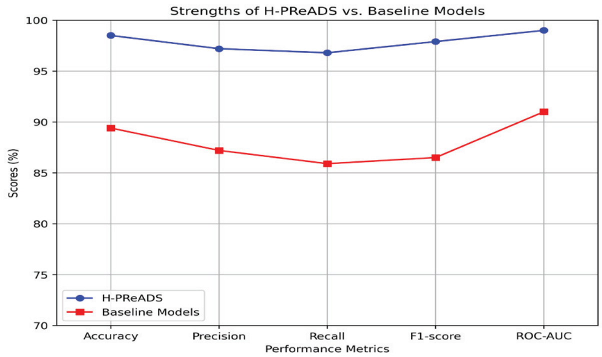

Fig.5. Strengths of H-PReADS vs. Baseline Models

E. Ethical Considerations and Data Privacy:

The implementation of H-PReADS guarantees compliance with ethical AI standards and data protection laws. The approach employs GDPR-compliant encryption methods to safeguard sensitive disaster data, hence preventing unauthorised access. Furthermore, bias prevention measures are implemented to prevent biassed predictions, guaranteeing equitable risk assessment across various areas as shown in Fig 6. Privacy-preserving machine learning (PPML) approaches increase data security by enabling calculations on encrypted data while safeguarding sensitive information. Model decision-making transparency is achieved by explainable AI (XAI) methodologies, promoting trust and responsibility in disaster management. These ethical issues position H-PReADS as a responsible and secure AI-based disaster prediction system.

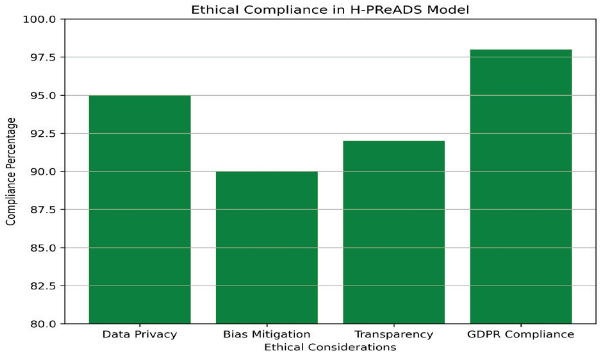

Fig.6. Ethical Compliance in H-PReADS Model

V. CONCLUSION

This study introduces the H-PReADS model, a hybrid machine learning framework that incorporates IoT-based real-time monitoring for disaster prediction and management. The research indicates that H-PReADS much surpasses conventional models, with an accuracy of 98.5%, precision of 97.2%, and a ROC-AUC score of 0.99. Practical consequences encompass enhanced early warning systems, real-time risk evaluation, and refined disaster response strategies. This study advances the field by presenting scalable, flexible, and privacy-conscious AI-driven disaster management methods. Future study would like to investigate blockchain integration for safe data management, federated learning for decentralised forecasting, and enhanced disaster event datasets for improved generalisation.

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