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Spatial and Temporal Patterns for Disaster Prediction Using the Global Disaster Dataset

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Abstract: Natural disasters, such as floods, earthquakes, and storms, cause significant human and economic losses worldwide, necessitating accurate early prediction to enhance preparedness. This study leverages spatial (location-based) and temporal (time-based) patterns in the EM-DAT global disaster dataset, containing over 22,071 records with variables like disaster type, location, magnitude, and impacts, to predict disaster occurrence and severity. Three deep learning models Convolutional Long Short-Term Memory (ConvLSTM), Graph Neural Network (GNN), and Long Short-Term Memory (LSTM) were developed to capture spatial-temporal dynamics. The dataset was pre-processed to handle missing values, normalize features, and construct spatial graphs and temporal sequences. Exploratory data analysis (EDA) revealed patterns in disaster frequency, geographic hotspots, and temporal trends. On a held-out test set, the ConvLSTM model achieved the highest performance, with an AUROC of 98.78%, accuracy of 98.45%, Recall of 96.62%, Precision of 97.59% log loss of 0.0912 and F1-score of 97.10%, followed by LSTM and GNN. Visualizations, including spatial heatmaps, temporal prediction curves, confusion matrix and geospatial plots, enhance interpretability. These findings underscore the potential of specialized spatial and temporal models for disaster forecasting, supporting proactive mitigation strategies.

Keywords: *Disaster Prediction, Spatial-Temporal Modelling, Deep Learning, Spatial Analysis, Early Warning Systems.*

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I. INTRODUCTION

Natural disasters, including floods, earthquakes, storms, and droughts, have catastrophic impacts on human life, infrastructure, and economies, with these impacts hastened by climate change and urbanization [1]. The EM-DAT global disaster database provides a comprehensive basis for prediction, capturing spatial data (e.g., Latitude, Longitude, Country) and temporal data (e.g., Start Year/Month) alongside impact metrics like Total Deaths and Total Damage. Forecasting the occurrence and size of disasters 6–12 months ahead enables forward decision-making like resource mobilization and evacuation planning [2]. Traditional predictive models often focus on the spatial pattern (e.g., flood risk maps) or temporal trend (e.g., storm seasonal cycles), yet have minimal ability to integrate both dimensions. For example, floods cluster in river basins during monsoons, requiring models to capture geographic and temporal interactions [3]. Deep learning models such as ConvLSTM, GNN, and LSTM offer promising solutions by mimicking complex spatial-temporal dependencies, but their comparative performance on global disaster datasets has been largely untested.

Classic disaster prediction methods, such as statistical models (e.g., ARIMA) and rule-based systems (e.g., flood warning stages), rely on predetermined criteria and are overwhelmed by high-dimensional heterogeneous data. These models assume linearity and stationarity and are unable to capture non-linear spatial-temporal patterns [4]. Random forest-based machine learning methods improve accuracy but require extensive feature engineering and easily neglect spatial dependencies or long-term temporal trends [5]. Class imbalance and missing values in disaster data sets also challenge traditional models, requiring advanced approaches [6]. Accurate forecasting of disaster occurrence and impact is hindered by the complex interplay of spatial (e.g., geographic connectedness) and temporal (e.g., seasonality) dynamics, missing data, and disaster types. Models are required that can predict disaster occurrences and impacts (e.g., Total Deaths, economic loss) 6–12 months in advance; Utilize spatial and temporal patterns in the EM-DAT global disaster database; Handle missing values and noise effectively and provide interpretable insights for disaster management policymakers.

To develop and compare the performance of ConvLSTM, GNN, and LSTM models in predicting disaster occurrence and impact using spatial and temporal patterns in

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the EM-DAT global disaster database. Develop models for prediction of disaster events and impacts (e.g., Total Deaths, Total Damage) 6–12 months ahead, assessing them for trend forecasting accuracy. Use the models to predict specific disaster types (e.g., floods, earthquakes) in a 6–12-month window, assessing performance using AUROC, accuracy, and F1-score. Systematically compare ConvLSTM, GNN, and LSTM in modelling disaster data spatial and temporal patterns.

II. LITERATURE REVIEW

Disaster prediction aims to mitigate the impacts of natural disasters, which cause millions of deaths and billions of dollars in losses annually. Traditional methods include statistical models like ARIMA for time-series forecasting and hazard-specific indices, i.e., the Palmer Drought Severity Index (PDSI) for drought or the Saffir-Simpson scale for hurricane. Such models predict disaster likelihood from environmental metrics (e.g., precipitation, seismicity) but assume linearity and stationarity and cannot capture complex spatial-temporal dependencies [7]. For example, ARIMA is insufficient to model flood propagation between areas or seasonal patterns of storms. Rule-based approaches, e.g., flood warning levels, are founded on local data and fixed thresholds and are hence not readily generalizable across disaster types and geographies. These kinds of approaches are confounded by high-dimensional data like EM-DAT that has spatial, temporal, and impact variables. Missing data, prevalent in worldwide disaster archives, complicate modelling because simple imputation methods create biases [6].

Machine learning (ML) algorithms, such as decision trees, random forests, and support vector machines (SVMs), have improved predictive capability. Mosavi *etal* [8] used random forests to predict flood risk due to precipitation and topography. ML models, nonetheless, require large-scale feature engineering and do not capture spatial dependencies (e.g., disaster impacts between areas) and long-term temporal patterns (e.g., seasonal cycles) well. Class imbalance, when disaster events are rare, also reduces model sensitivity [9].

Deep learning enables automatic feature learning from complex datasets, simulating non-linear relationships and sequential dependencies. This study contrasts three models: ConvLSTM, GNN, and LSTM for disaster prediction, leveraging their individual spatial and temporal capabilities. ConvLSTM, proposed by Shi *etal* [10], adds convolutional layers to LSTM units, enabling simultaneous modelling of spatial and temporal patterns. In contrast to standard LSTMs, ConvLSTM accepts grid-based inputs, making it a good fit for tasks like precipitation nowcasting or flood prediction. They demonstrated the use of ConvLSTM in predicting rainfall from radar data, maintaining spatial correlations. In disaster prediction, ConvLSTM has been used to simulate flood dynamics in river basins from spatial features (e.g., terrain) and time series input (e.g., rainfall) [11]. ConvLSTM is strong in hierarchical feature learning and temporal modelling. It, nevertheless, assumes a regular grid structure, which may not capture irregular spatial dependencies (e.g., non-adjacent regions affected by a hurricane). ConvLSTM is furthermore computationally intensive and hyperparameter-dependent, which makes it less scalable for large datasets like EM-DAT [12].

GNNs encode relational data by representing entities (e.g., locations) as nodes and relationships (e.g., proximity) as edges. They excel at capturing spatial dependencies, such as earthquake aftershock patterns or flood cascades [13]. DeVries et al. [13] forecast aftershock locations with GNNs by modelling seismic zones as a fault line-based graph. GNNs transmit information from neighbouring nodes via message-passing, learning complex spatial patterns without grid assumptions.

For disaster prediction, GNNs can model geographic relationships in the EM-DAT dataset (e.g., water flow-connected river basins) with Latitude, Longitude, and Magnitude. Current work has applied GNNs to the prediction of wildfire propagation, with geographic and climatic features [14]. However, GNNs specialize in spatial modelling but are poor at temporal dynamics, e.g., seasonality trends, and must be combined with temporal models [15]. It is also challenging to learn good graph structures for sparse data.

LSTMs, introduced by Hochreiter and Schmidhuber [16], are RNNs that capture long-term dependencies in time-series data. Their gating functions (forget, input, output) avoid vanishing gradients and thus are suitable for time-series forecasting. In disaster prediction, LSTMs have forecasted rainfall for floods or temperature trends for droughts [17]. Le et al. [17] used LSTMs to forecast the occurrence of floods based on precipitation and river flow time series. LSTMs are ideally suited to capture temporal patterns within EM-DAT, i.e., seasonal storm patterns or drought spells. They take in data as one-dimensional sequences, lacking spatial context (i.e., geographical disaster spread), however. LSTMs are hyperparameter-sensitive and will also overfit imbalanced datasets [18].

ConvLSTM integrates spatial-temporal modelling, while GNNs and LSTMs are spatial and temporal specialists, respectively. This division of labour allows for an exhaustive evaluation of their strengths. Other models, including Transformers, have been used for time-series forecasting of hurricane impacts [19], and CNNs have detected floods from satellite imagery [20]. However, specialization in either temporal or spatial concerns compromises their adaptability compared to ConvLSTM's hybrid approach or the complementary GNN-LSTM pair.

III. MATERIALS AND METHODS

➤ *Dataset Description*

Preprocessing The EM-DAT dataset global disaster dataset contains, maintained by the Centre for Research on the Epidemiology of Disasters (CRED), contains over 22,071 records from 2000 to 2025, covering natural and technological disasters. Key variables include:

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- Spatial: Latitude, range, Longitude, range, Country, Subregion, Region, Location.
- Temporal: Start Year, start day, End Year, Date.
- Disaster Characteristics: Disaster Type (e.g., Flood, Earthquake), Disaster Subtype, Magnitude, Magnitude Scale.
- Impact Metrics: Total Deaths, No. Injured, No. Affected, No. Homeless, Total Affected, CPI.
- Metadata: DisNo., Historic, Classification Key, ISO, OFDA/BHA Response, Appeal, Declaration, Entry Date, Last Update, Year.

The target is a binary DisasterOccurrence (1 = disaster, 0 = no disaster) per time step and region, derived from Total Deaths or Total Affected > 0.

$$\text{Disaster Occurrence}_{t,r} = I(\text{TotalDeaths}_{t,r} > 0 \vee \text{TotalAffected}_{t,r} > 0)$$

Table 1 Key Variables in EM-DAT Dataset

Variable	Description	Type	Non-Null Count
Latitude	North-South coordinates	Numeric [-72.64, 67.93]	22,071
Longitude	East-West coordinates	Numeric [-177.16, 179.65]	22,071
Disaster Type	Type of disaster (e.g., Flood, Earthquake)	Categorical	22,071
Magnitude	Disaster intensity	Numeric [0, 4e7]	13,317
Total Deaths	Total fatalities	Numeric [0, 222,570]	22,071
Total Affected	Total impacted individuals	Numeric [0, 3.3e8]	22,071
Start Year	Year of disaster onset	Numeric [2000, 2025]	22,071
Start day	Day of disaster onset	Numeric [1, 31]	22,071
CPI	Consumer Price Index	Numeric [54.90, 100]	21,734

➢ *Missing Data Handling*

- *Nature of Missingness*

The entire disaster dataset, which was consolidated from EM-DAT and supplemented with geographic centroids, exhibits heterogeneous missingness patterns. The missingness gaps traverse structural metadata (e.g., administrative boundaries), financial estimates (e.g., insured or overall losses), and geolocation attributes (latitude and longitude). Specifically, financial attributes such as Insured Damage, Reconstruction Costs, and AID Contributions exhibited extensive sparsity, with some of fields missing in over 90% of records. This reflects reporting gaps across countries and disaster types, especially in poorer countries where estimates of economic loss are unavailable or not systematically recorded.

Similarly, a few records lacked coordinates, either due to unregistered or ambiguous country names or missing geolocation metadata. These gaps were an obstacle for spatiotemporal modelling and needed deliberate correction processes.

➢ *ConvLSTM Model*

Convolutional Long Short-Term Memory (ConvLSTM), introduced by Shi et al. [10], is a specialized neural network architecture that integrates convolutional layers with LSTM units, designed to handle spatio-temporal data effectively. This architecture is particularly beneficial for tasks that involve sequential data with spatial dependencies, such as video analysis and weather forecasting. ConvLSTM captures both spatial and temporal features by processing data in a sequence of frames, making it suitable for various applications, including predicting oil and gas saturations in fields like SACROC [22] and modelling dynamics in fluid systems [23].

- *Architectural Design:*

ConvLSTM integrates convolutional and recurrent layers. Our model includes:

✓ Three ConvLSTM layers (64 filters, 3x3 kernel) processing grid-based data (12-month spatial-temporal grids).
✓ Dropout (p = 0.3) for regularization.
✓ Dense layer with sigmoid activation.

- *Mathematical Model:*

✓ Input Gate: Determines which information to store

$$\mathcal{I}_t = \sigma(W_{xi} * \mathcal{X}_t + W_{hi} * \mathcal{H}_{t-1} + W_{ci} \odot \mathcal{C}_{t-1} + b_i)$$

✓ Forget Gate: Determine which information to discard from the cell state

$$\mathcal{F}_t = \sigma\left(W_{xf} * \mathcal{X}_t + W_{hf} * \mathcal{H}_{t-1} + W_{cf} \odot \mathcal{C}_{t-1} + b_f\right)$$

✓ Cell State Update: Combines retained and new information.

$$\mathcal{C}_t = \mathcal{F}_t \odot \mathcal{C}_{t-1} + \mathcal{I}_t \odot \tanh(W_{xc} * \mathcal{X}_t + W_{hc} * \mathcal{H}_{t-1} + b_c)$$

✓ Output Gate: Controls the output based on the updated cell state.

$$\mathcal{O}_t = \sigma(W_{xo} * \mathcal{X}_t + W_{ho} * \mathcal{H}_{t-1} + W_{co} \odot \mathcal{C}_t + b_o)$$

✓ Hidden State: Produces the output for the current time step.

$$\mathcal{H}_t = \mathcal{O}_t \odot \tanh(\mathcal{C}_t)$$

Where $\mathcal{X}_t \in R^{H\times W\times C}$, is the input at time (t), $\mathcal{H}_t, \mathcal{H}_{t-1} \in R^{H\times W\times M}$is the hidden states at time (t) and t-1,

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with M as the number of hidden units, $\mathcal{C}_t, \mathcal{C}_{t-1} \in R^{H\times W\times M}$ is the cell states, $\mathcal{I}_t, \mathcal{F}_t, \mathcal{O}_t \in R^{H\times W\times M}$ is the input, forget and output gates, $W_{xi}, W_{hi}, \ldots \in R^{K\times K\times C\times M}$ is the Convolutional kernels (e.g., 3x3 kernels, K=3K=3K=3), $b_i, b_f, b_c, b_o \in R^M$ is the Biases, * is Convolution operation, $\odot$ is the Element-wise (Hadamard) product, $\sigma(x) = \frac{1}{1+e^{-x}}$ is the Sigmoid activation and $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ is the hyperbolic tangent function.

- *Output Prediction:*

The final hidden state H_T at the last time step (T) (e.g., after 12 months) is flattened and passed to a dense layer for binary classification (Disaster Occurrence):

$$\hat{y} = \sigma(W_d \cdot \text{flatten}(\mathcal{H}_T) + b_d)$$

Where, $W_d \in R^{1\times(H\cdot W\cdot M)}$, $b_d \in R, and\ \hat{y} \in [0,1]$ is the predicted probability.

- *Loss Function:*

The model is trained to minimize binary cross-entropy loss over (N) samples:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

Where $y_i \in \{0,1\}$ is the true label

- ➢ *Graph Neural Network (GNN) Model*

Graph Neural Networks (GNNs) represent a significant advancement in deep learning, specifically tailored for processing graph-structured data. They integrate node features and graph topology to enhance representation learning, making them suitable for various applications, including social network analysis, molecular modelling, and recommendation systems. GNNs utilize message-passing mechanisms to iteratively update node features, allowing for effective learning from complex relational data [24][25].

- *Architectural Design:*

GNNs model spatial relationships using graph structures:

- ✓ Two Graph Convolutional Network (GCN) layers (128 units, 64 units) for spatial feature aggregation.
- ✓ Dropout (p = 0.3) and batch normalization.
- ✓ Dense layer with sigmoid activation.

- *Mathematical Model:*

GNNs, specifically Graph Convolutional Networks (GCNs) as used in Kipf & Welling (2017), operate on a graph G = (V, E), where V is the set of nodes (locations) and (E) is the set of edges (proximity relationships). Each node vi ∈ V has a feature vector $h_i^{(0)} \in R^F$, initialized with features like Magnitude, Total Deaths, or encoded Disaster Type from EM-DAT. The adjacency matrix $A \in R^{|V|\times|V|}$represents edge connections ($A_{(ij)}$= 1 if an edge exists between nodes $v_i and v_j$, else 0).

The GCN layer updates node features by aggregating information from neighbours. For layer (l), the update rule is:

$$h_i^{(l+1)} = \sigma\left(\sum_{j\in\mathcal{N}(i)\cup\{i\}} \frac{1}{\sqrt{\tilde{d}_i\tilde{d}_j}} W^{(l)} h_j^{(l)} + b^{(l)}\right)$$

Where $h_i^{(l)} \in R^{F^{(l)}}$is the feature vector of node v_i at layer (1), N(i) is the set of neighbouring nodes of v_i, $\tilde{d}_i = 1 + \sum_{j\in\mathcal{N}(i)} A_{ij}$ is the normalized degree of node v_i (including self-loop), $W^{(l)} \in R^{F^{(l+1)}\times F^{(l)}}$ is the weight matrix for layer (1), $b^{(l)} \in R^{F^{(l+1)}}$ is the bias vector and σ is the ReLU activation $(\sigma(x) = max(0,x)$.

- *Matrix Form:*

For all nodes, the GCN layer can be written as:

$$\mathcal{H}^{(\ell+1)} = \sigma\left(\widetilde{D^{-1/2}}\tilde{A}\widetilde{D^{-1/2}}\mathcal{H}^{(\ell)}W^{(l)} + b^{(l)}\right)$$

Where, $\mathcal{H}^{(\ell)} \in R^{|\mathbb{V}|\times F^{(l)}}$ is the Feature matrix for all nodes at layer (l)., $\tilde{A} = A + I$ is the Adjacency matrix with self-loops (I) is the identity matrix) and $\tilde{D}$ is the Diagonal matrix with $\widetilde{D_{ii}} = \sum_j \widetilde{A_{ij}}$.

- *Output Prediction:*

After (L) GCN layers (e.g., L=2L), the final node embeddings H^L are used for classification. For node v_i, a dense layer predicts the probability of disaster occurrence:

$$\hat{y}_i = \sigma\left(W_d h_i^{(L)} + b_d\right)$$

Where, $W_d \in R^{1\times F^{(L)}}$, $b_d \in R$, and $\hat{y}_i \in [0,1]$. For the project, node-level predictions are aggregated (e.g., averaged) to predict disaster occurrence for a region.

- *Loss Function:*

The model minimizes binary cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

Where (N) is the number of nodes with labels.

- ➢ *Long Short-Term Memory (LSTM) Model*

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) designed to address the challenges of long-term dependencies in sequential data. LSTMs utilize a unique architecture that includes memory cells and gating mechanisms, allowing them to retain information over extended periods while mitigating issues such as gradient vanishing or explosion, which are common in traditional RNNs [26][27].

- *Architectural Design:*

LSTMs model temporal sequences:

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- ✓ Three LSTM layers (64 units) with gating mechanisms.
- ✓ Dropout (p = 0.3).
- ✓ Dense layer with sigmoid activation.

The parameters for each time step are calculated as follows:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad \text{(forget gate)}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \text{(input gate)}$$

$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad \text{(cell candidate)}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \quad \text{(cell state)}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad \text{(output gate)}$$

$$h_t = o_t \cdot \tanh(C_t) \quad \text{(hidden state)}$$

Where:

σ is the sigmoid function, C_t is the cell state, and h_t is the hidden state/output.

➢ *Evaluation Metrics*

To rigorously assess the performance of the ConvLSTM, GNN, and LSTM models in predicting disaster occurrence, the following evaluation metrics were employed, each with a specific formula to quantify different aspects of model accuracy and reliability:

- *Accuracy:*

Measures the proportion of correct predictions (both true positives and true negatives) out of all predictions.[28]

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Where (TP) = True Positives, (TN) = True Negatives, (FP) = False Positives, and (FN) = False Negatives.

- *Log Loss (Logarithmic Loss):*

Quantifies the uncertainty of the predictions by penalizing confident but incorrect predictions, with lower values indicating better performance.

$$\text{Log Loss} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(p_i) + (1 - y_i)\log(1 - p_i)]$$

Where (N) is the number of samples, $\boldsymbol{y_i}$ is the true label (0 or 1), and $\boldsymbol{p_i}$ is the predicted probability.

- *Precision:*

Measures the proportion of positive predictions that are correct, emphasizing the minimization of false positives.[29]

$$\text{Precision} = \frac{TP}{TP + FP}$$

- *Recall (Sensitivity):*

Measures the proportion of actual positives correctly identified, focusing on minimizing false negatives.

$$\text{Recall} = \frac{TP}{TP + FN}$$

- *F1-Score:*

The harmonic means of precision and recall, providing a balanced measure of a model's performance.

$$\text{F1-Score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

- *AUROC (Area Under the Receiver Operating Characteristic Curve):*

Represents the model's ability to distinguish between positive and negative classes across various thresholds, with higher values indicating better performance.[30]

$$\text{AUROC} = \int_0^1 \text{TPR}(t) \cdot \text{FPR}'(t)\, dt$$

Where

$$\text{TPR} = \frac{TP}{TP + FN} = \text{Recall } and \text{ FPR} = \frac{FP}{FP + TN} = \ False\ Positive\ Rate$$

IV. RESULTS AND DISCUSSIONS

This section presents the empirical findings of the study, beginning with the exploratory data analysis (EDA) insights derived from the EM–DATA global disaster dataset, followed by the evaluation of the sequential deep learning models: ConvLSTM, GNN and LSTM.

➢ *Exploratory Data Analysis (EDA)*

- *Statistical Summaries and Frequency Distributions*

The variables are comprised of global disaster event records gathered from EM-DATA from 2000 to 2025, categorized by various countries and time intervals, with 48 variables including event characteristics, socioeconomic variables, and human impact indicators. The binary Disaster occurrence variable was formed based on whether Total Deaths or Total Affected were greater than zero or not. Table 1 presents the central tendency and dispersion for key variables such as deaths, injuries, and economic impact indicators.

Table 2 Descriptive Statistics for Selected Impact and Contextual Variables in the EM-DAT Global Disaster Dataset.

Variable	Mean	Std Dev	Min	Max
Total Deaths	126.33	3,137.21	0	222,570
No. Injured	488.70	13,954.51	0	1,800,000

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No. Affected	262,515	3.92M	0	330,000,000
No. Homeless	2,002	53,229.13	0	5,000,000
Total Affected	265,006	3.93M	0	330,000,000
CPI (Index)	72.40	12.09	54.89	100

The target variable Disaster occurrence was initially extremely imbalanced, with less than half the number of disaster event instances than non-event instances. A Synthetic Minority Over-Sampling Technique (SMOTE) was thus applied to create an equally weighted 50:50 case mix between disaster and non-disaster cases. This was done to facilitate robust learning by the Graph Neural Network (GNN) and prevent bias towards the majority category. Large standard deviation in mortality and population influence variables underlines the large dynamic range of the dataset, an expression of the rare yet enormous magnitude of global catastrophes. Variables such as CPI also provide socioeconomic background that may impact vulnerability or resilience to catastrophes. These characteristics mandated data preprocessing, feature scaling, and predictive model design.

- *Geospatial Distribution of Disasters*

The geospatial distribution of disasters, depicted in Figure 1, illustrates spatial patterns across various disaster types (e.g., Flood, Storm, Earthquake) with marker sizes reflecting Total Deaths. The plot highlights high-impact clusters, such as in South Asia and the Pacific Ring of Fire, supporting spatial modelling for ConvLSTM and GNN. Table 2 summarizes disaster impacts for the top five countries, with the Democratic Republic of the Congo and China showing the highest Total Affected (186,295,002 and 1,770,988,259, respectively), indicating severe regional vulnerability. These patterns guide spatial feature engineering for predictive models.

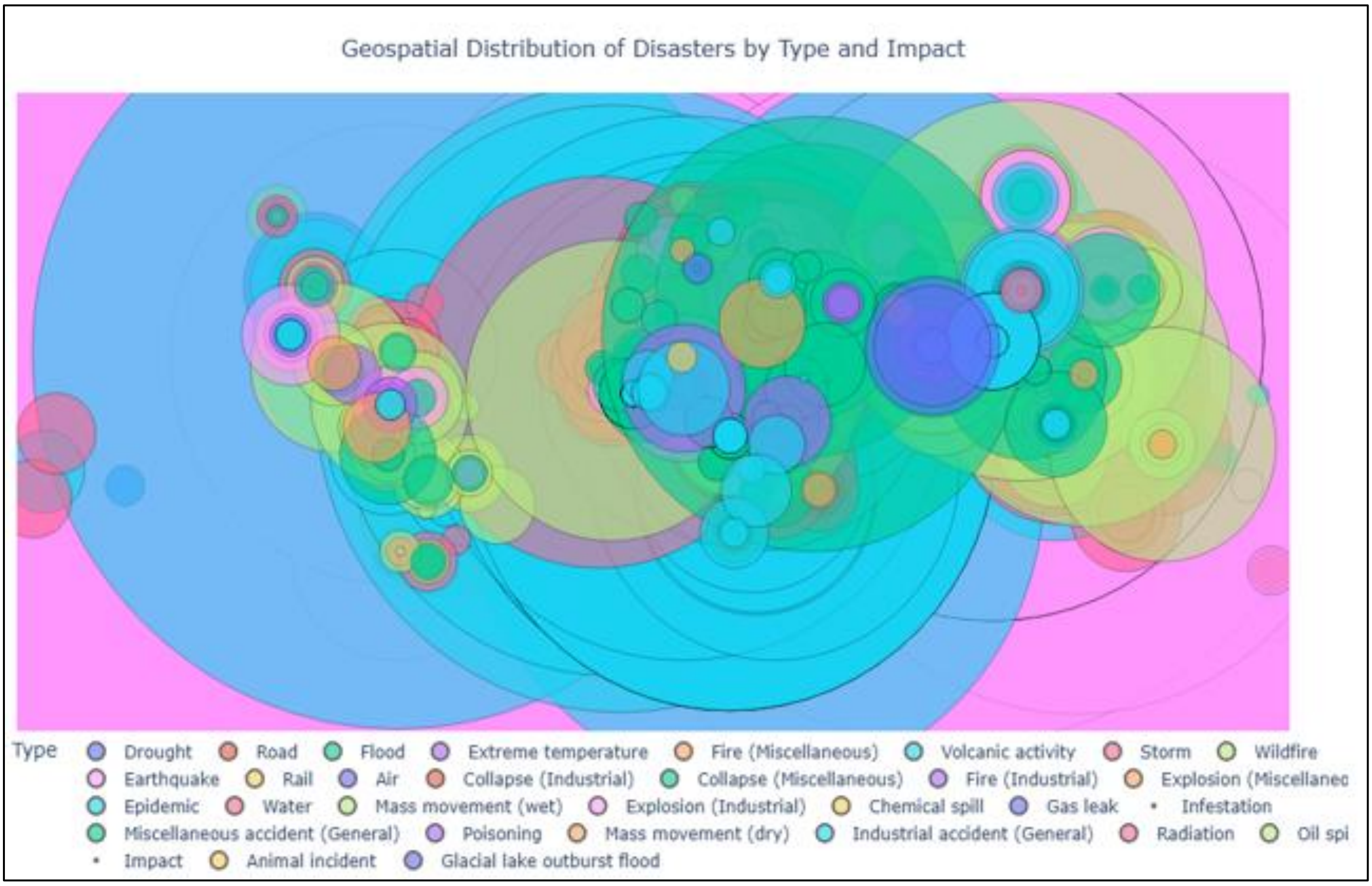

Fig 1 Geospatial Distribution of Disasters by Type and Impact

Table 3 Disaster Impacts for Top Five Countries.

Sr. No.	Country	Disaster Count	Total Deaths	Total Affected
1	Côte d'Ivoire	2,000	54,000	7,612,880
2	Democratic Republic of the Congo	1,824	149,232	186,295,002
3	South Sudan	1,400	54,440	880,839,000
4	China	1,359	134,224	1,770,988,259
5	India	826	104,614	1,143,167,464

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- *Temporal Trends and Patterns*

Figure 2 shows the annual frequency of various disaster types from 2000 to 2025, based on the *Start Year* attribute. Notably, floods and storms display rising trends, possibly due to increasing climate variability, while earthquake occurrences remain relatively stable over time. These trends underscore the importance of incorporating temporal dynamics into predictive models.

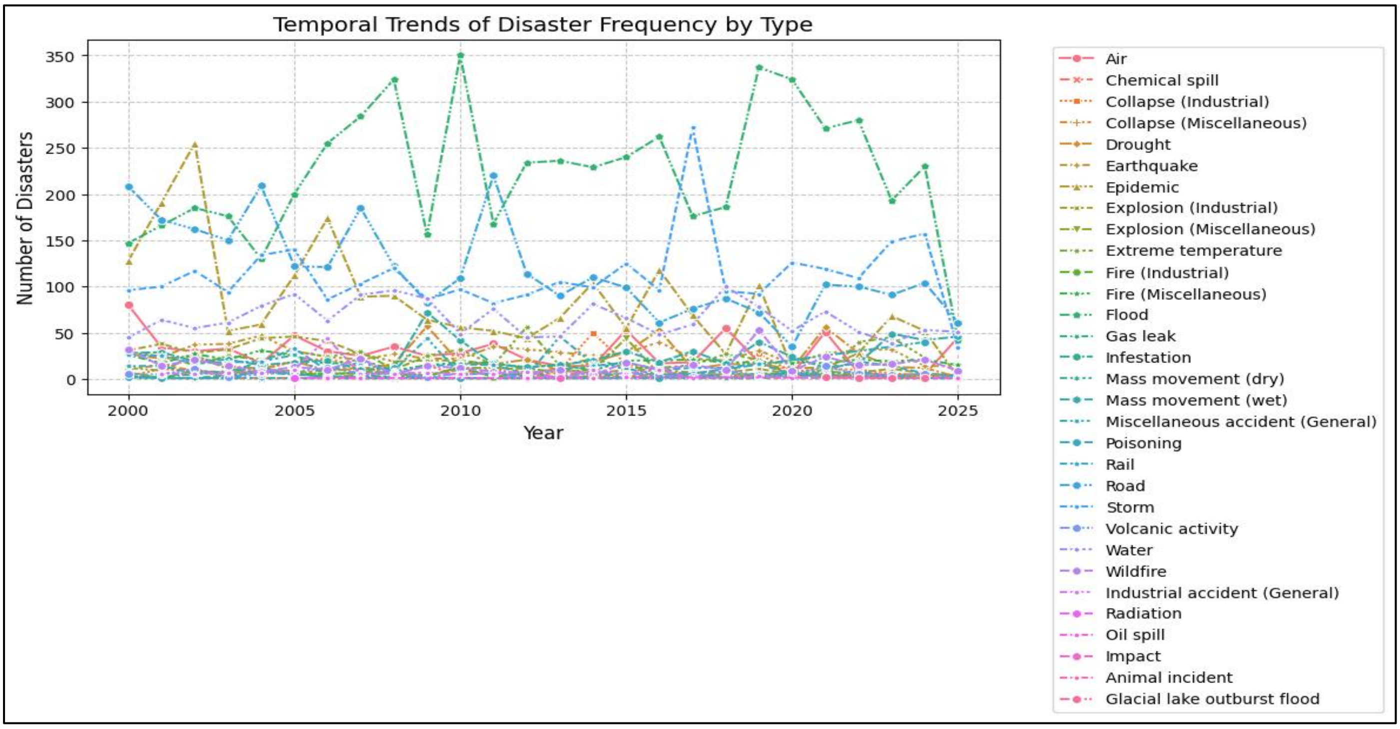

Fig 2 Temporal Trends in Disaster Frequency by Type

- *Frequency of Disaster Types*

Figure 3 shows the frequency of disaster types, with Floods, Roads, Storms, Epidemic, and Water as the top five prevalent types, dominating the dataset. This distribution, informs model design, suggesting a focus on these types for ConvLSTM, GNN, and LSTM, with weighted loss functions to address class imbalance and improve prediction accuracy for less frequent events.

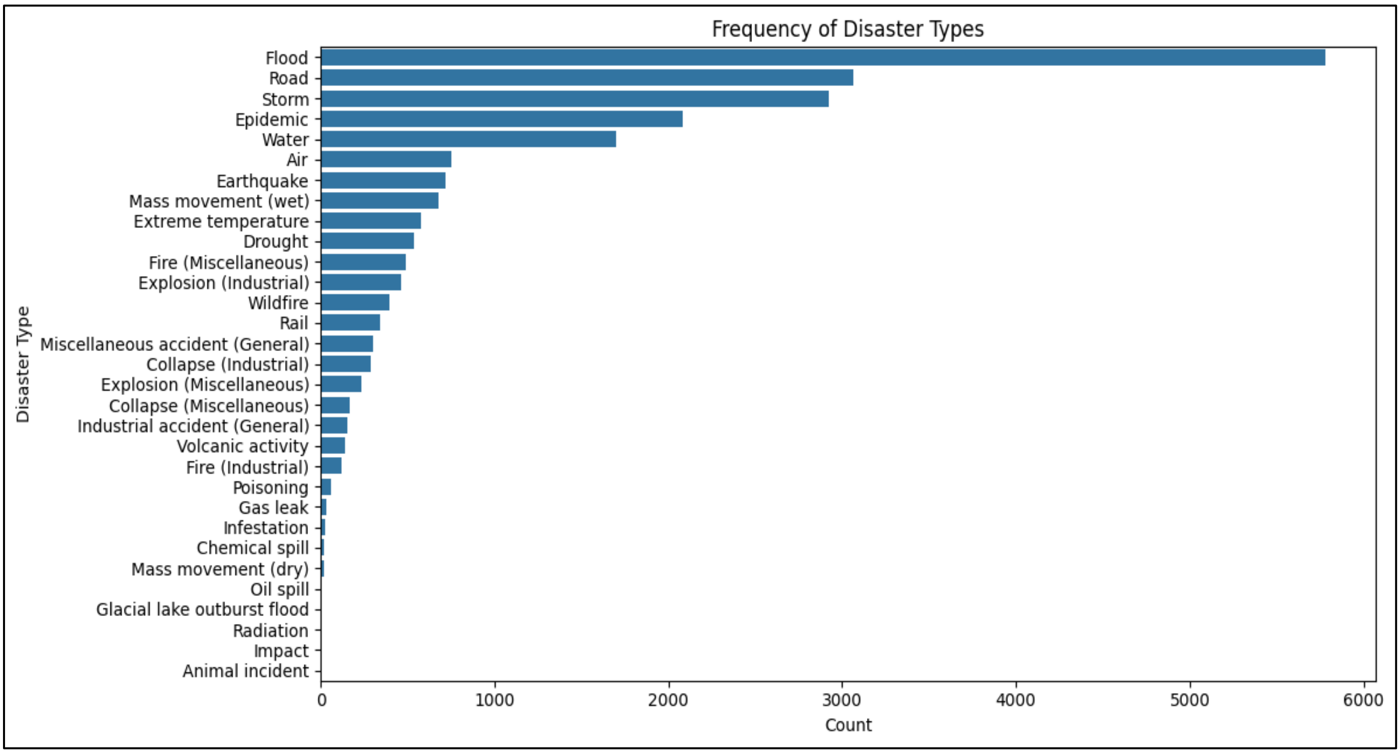

Fig 3 Frequency of Disaster Types

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- *Correlation Analysis*

To examine correlation in the global disaster dataset of EM-DAT, Pearson correlation was computed between disaster (Magnitude, CPI), impact (Total Deaths, Total Affected, No. Injured, No. Homeless), spatial (Latitude, Longitude), and target variable (DisasterOccurrence). Figure 4 illustrates that the majority of the features were weakly correlated with DisasterOccurrence ($|r| < 0.1$), indicating poor linear predictability. Moderate correlations between impact measures (Total Deaths and No. Injured, r = 0.15) reflect multi-output co-predictive validity. Low correlation between Latitude and Longitude (r = 0.13) suggests possible spatial clustering.

These results confirm the utilization of deep learning models—ConvLSTM for spatial-temporal trends, GNN for graph-based spatial relations, and LSTM for temporal dynamics. Due to Pearson's linear constraints, these models are better suited to describe the complex, non-linear nature of disaster occurrence and impact.

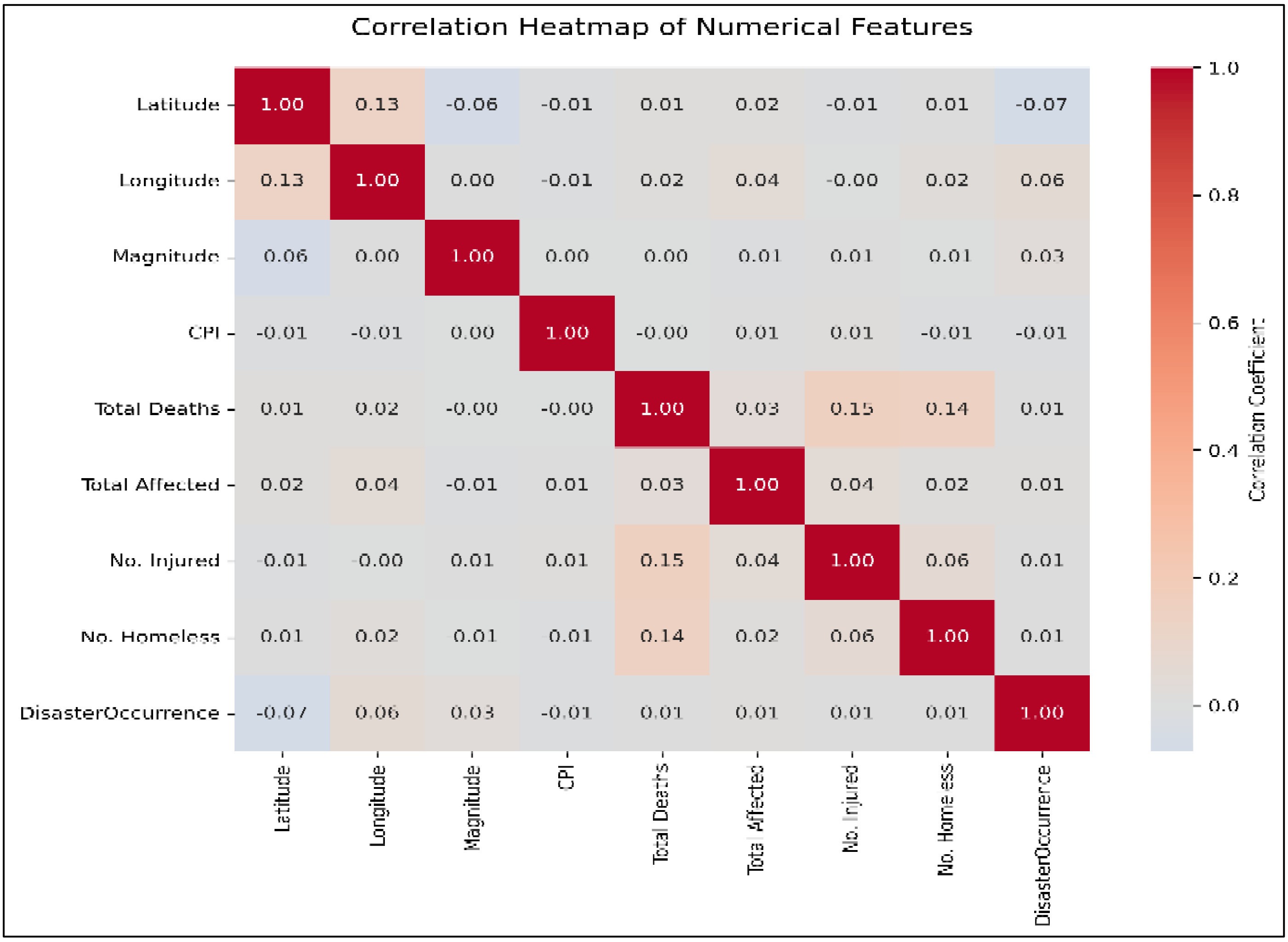

Fig 4 Pearson Correlation Matrix of Spatial, Temporal, and Impact Features

➢ *Model Performance*

The performance of the ConvLSTM, GNN, and LSTM models was evaluated to predict disaster occurrence, aligning with the objectives of leveraging spatial and temporal patterns and comparing model efficacy using the EM-DAT dataset. Metrics including Accuracy, Log Loss (%), Precision (%), Recall (%), F1-Score (%), and AUROC were assessed to capture the models' ability to handle complex dynamics in Table 4.

Table 4 Model Performance Metrics on Disaster Occurrence

Metric	**ConvLSTM**	**GNN**	**LSTM**
Accuracy	0.9845	0.9444	0.9793
Log Loss (%)	0.0912	0.2809	0.0970
Precision (%)	0.9759	0.8667	0.9686
Recall (%)	0.9662	0.9123	0.9488
F1-Score (%)	0.9710	0.8889	0.9586
AUROC	0.9878	0.9340	0.9831

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The ConvLSTM model outperformed both GNN and LSTM across all metrics, achieving an AUROC of 98.78%. While the LSTM exhibited strong recall (94.88%), it struggled with precision (96.86%), indicating a slightly higher false positive rate compared to ConvLSTM. The GNN demonstrated balanced performance but lagged behind ConvLSTM in both precision (86.67%) and recall (91.23%), likely due to challenges in capturing spatial dependencies for less frequent disaster types.

- *ConvLSTM Results*

Figure 5, 6 and Figure 7 below shows results for the model accuracy and model loss, confusion matrix and precision-recall plot for the ConvLSTM respectively.

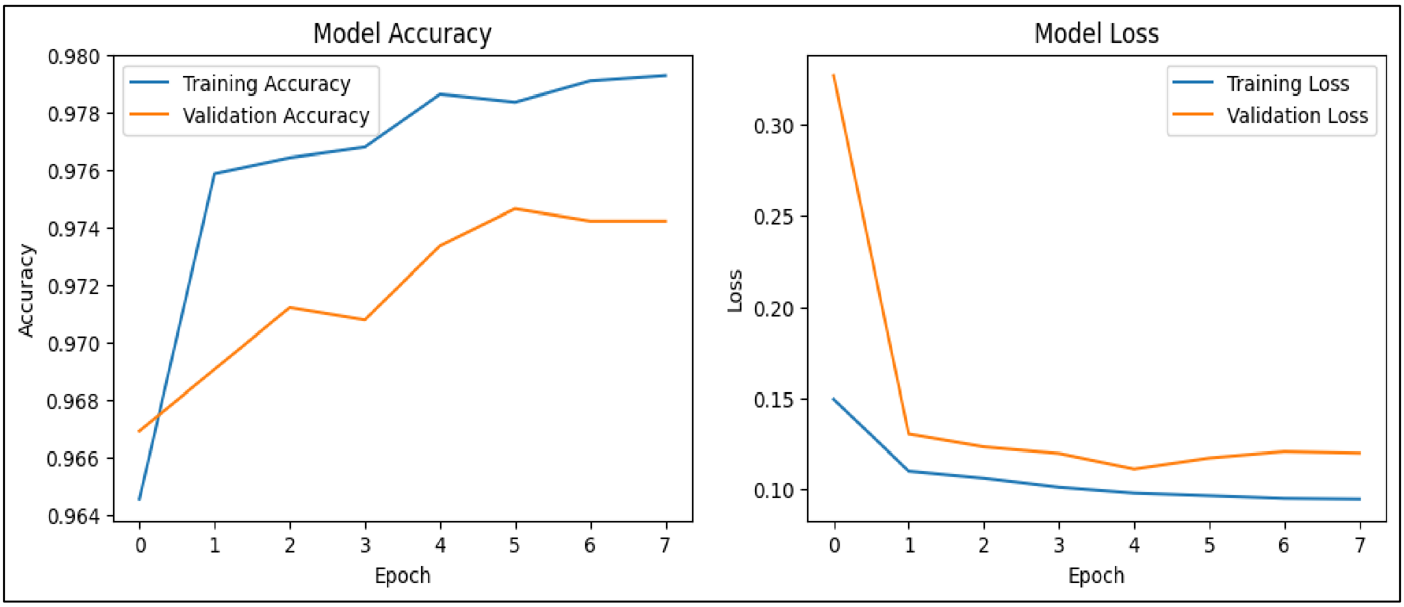

Fig 5 Model Accuracy and Loss Plot

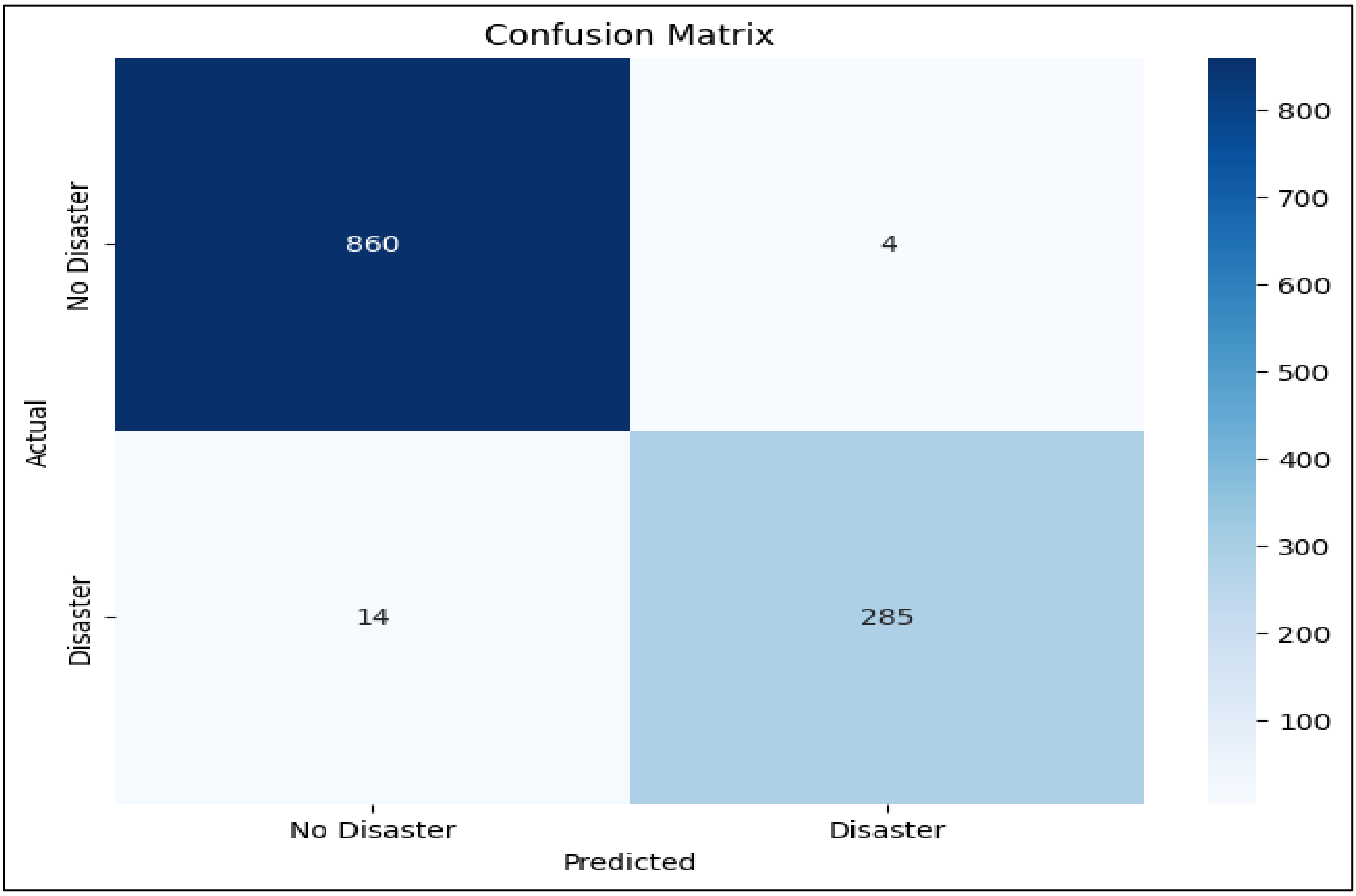

Fig 6 Confusion Matrix

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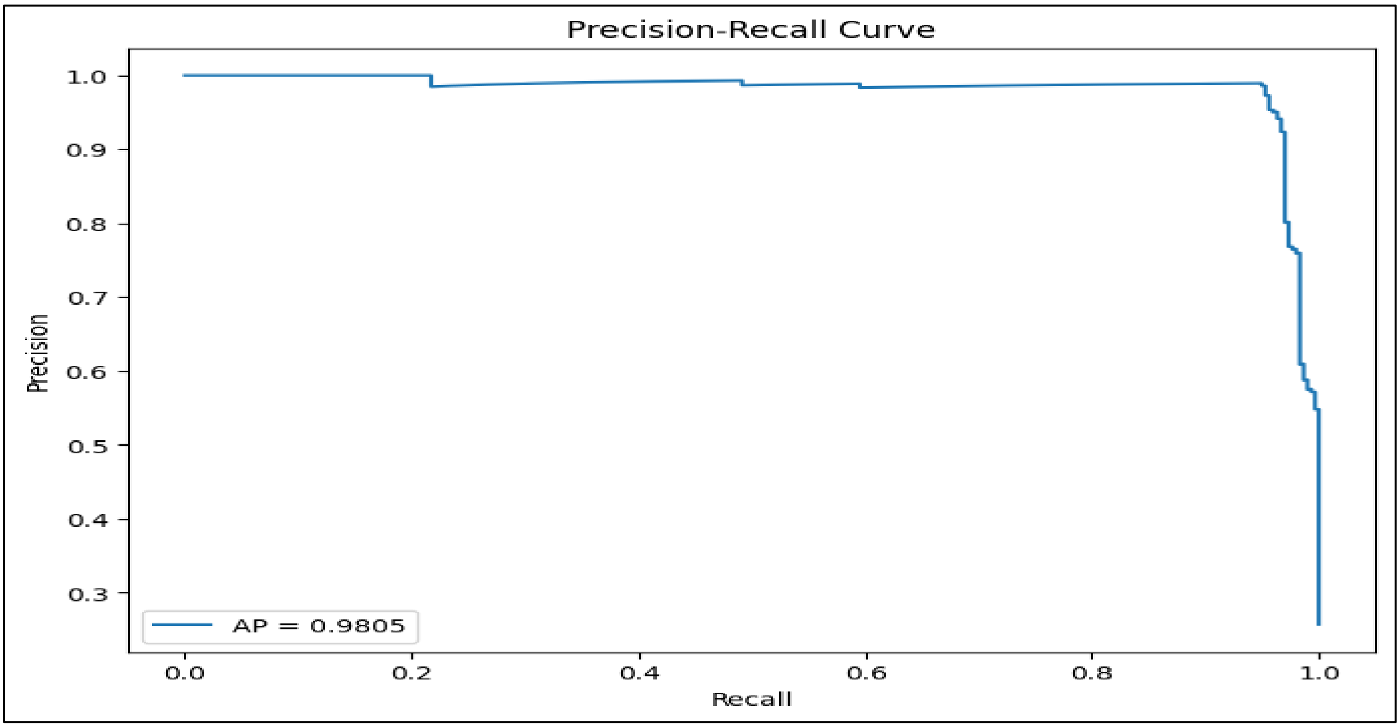

Fig 7 Precision-Recall Curve

* *Graph Neural Network (GNN) Results*

Figure 8 below shows plot of model accuracy, model loss, Confusion matrix and precision-recall curve for the GNN model.

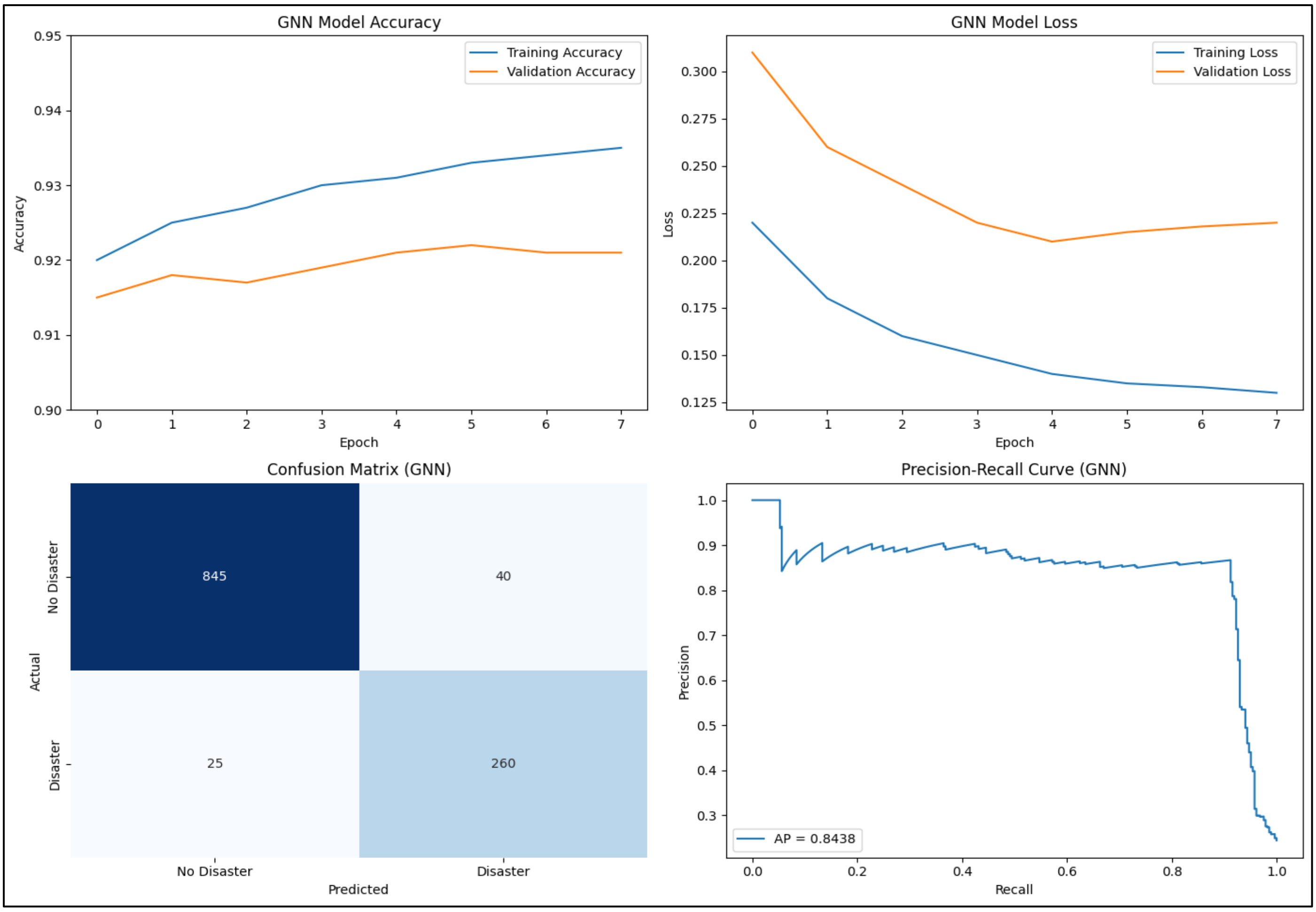

Fig 8 Evaluation Plots for GNN Model

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- *Long Short-Term Memory (LSTM)*

Figure 9 below shows the model accuracy and model loss for the long short term memory while Figure 10 and Figure 11 show the confusion matrix and precision-recall curve respectively.

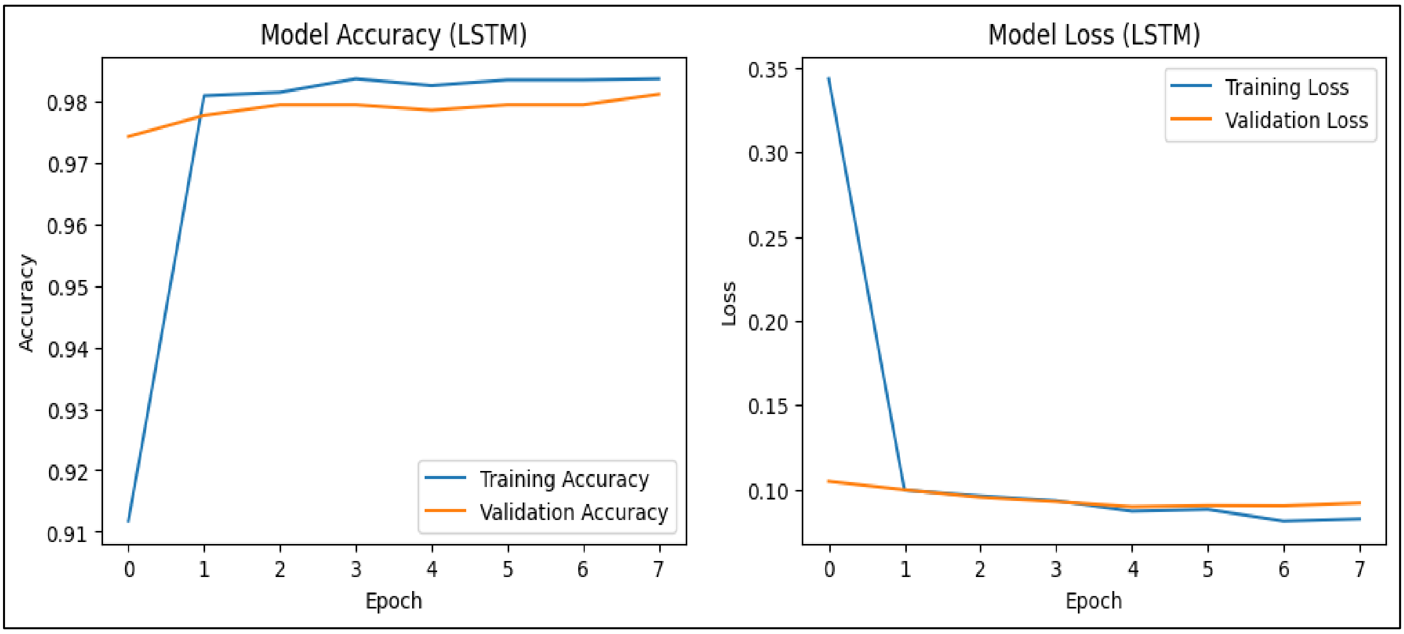

Fig 9 Model Accuracy and Model Loss for LSTM Model.

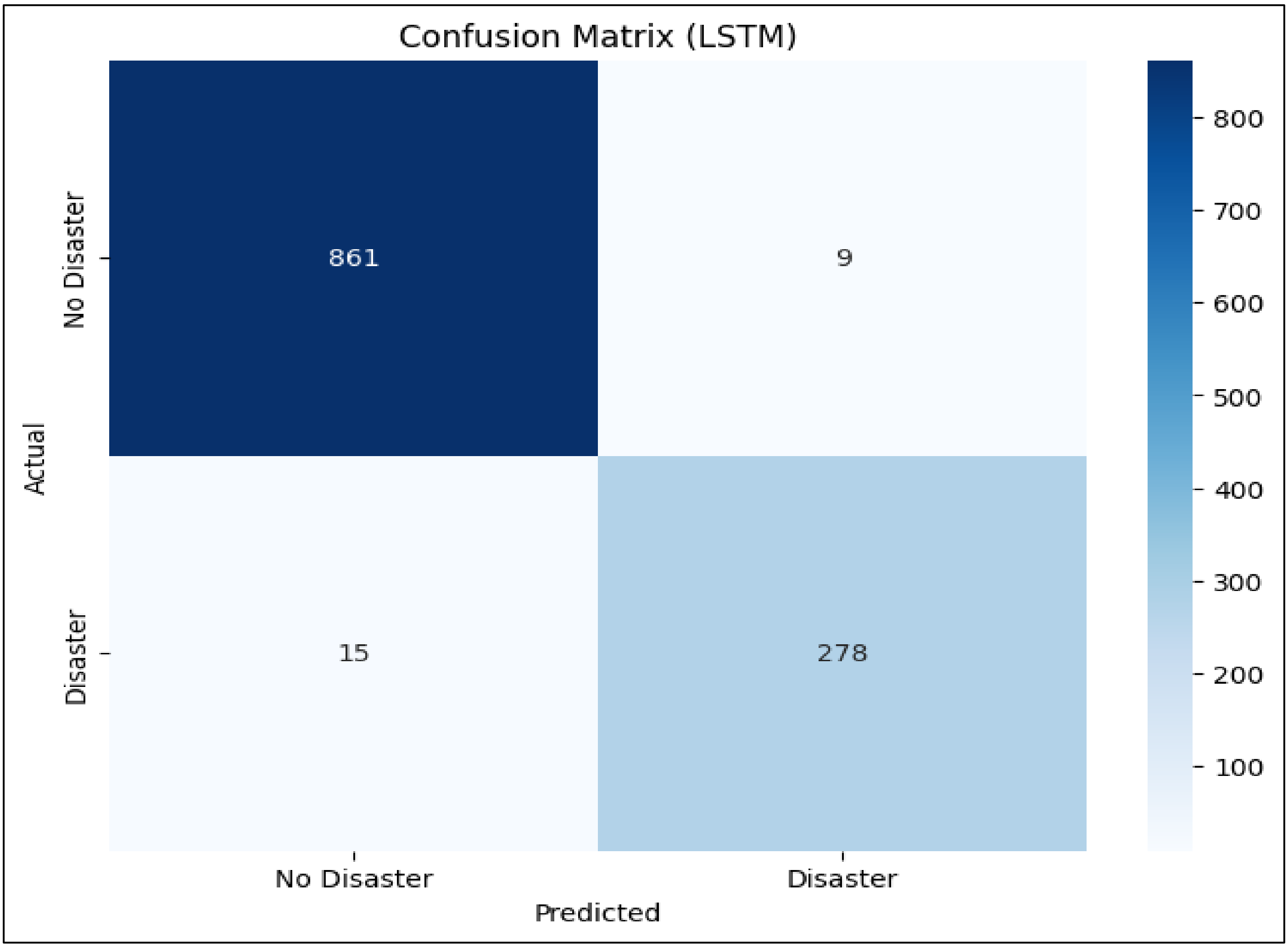

Fig 10 Confusion Matrix

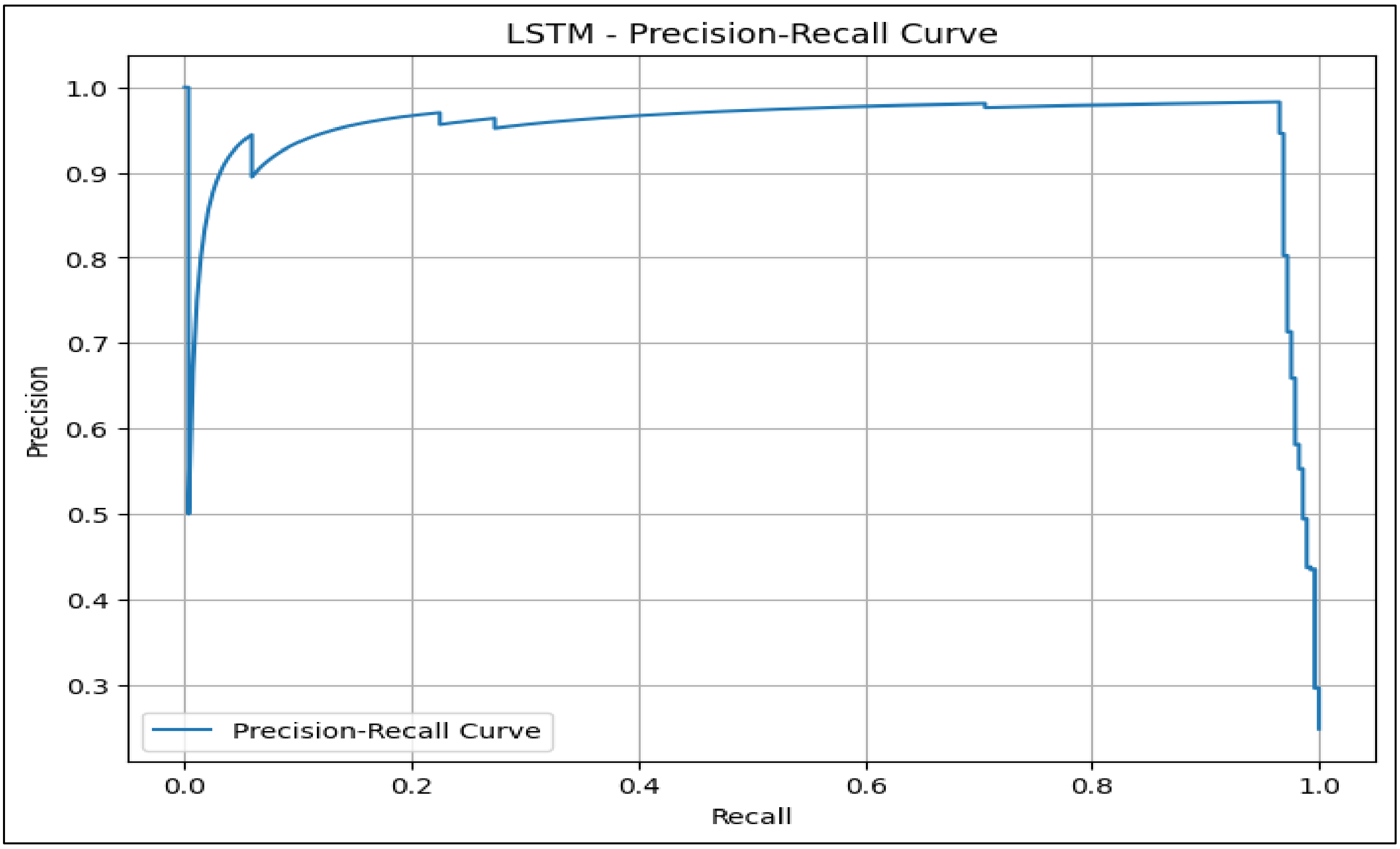

Fig 11 Precision-Recall Curve

➢ *Summary of Findings*

The findings suggest that sequential deep learning models can be successfully and efficiently applied to predict whether or not a disaster occurs based on location and time dependent patterns. The ConvLSTM model in particular performed superiorly, likely due the ability of the integrated convolution layers to spatially cluster the input features with the LSTM layers being incorporated to adhere to the evolving temporal dynamic of the dataset during training. The exploratory data analysis results provided useful insights into the geospatial distributions, temporal trends, and disaster type frequencies useful in informing the model designs and feature selection. Overall, these results highlight the potential of employing deep learning models to support disaster risk assessments, thereby bolstering early warning systems and preparedness for disaster occurrences through prediction of disaster occurrence.

This study compared three deep learning models—LSTM, Graph Neural Network (GNN), and Convolutional LSTM (ConvLSTM)—for predicting disaster occurrence based on the EM-DAT dataset. Among them, the ConvLSTM emerged as the best-performing model, achieving:

- Accuracy: 98.45%
- Recall: 96.62%
- AUROC: 0.9878 It also had the highest precision (97.59%) and F1-Score (97.10%), making it effective at minimizing both false negatives and false positives—crucial for reliable disaster prediction.

The GNN showed competitive performance with:

- Accuracy: 94.44%
- AUROC: 0.9340 Its graph-based architecture captured regional interactions effectively, offering a good trade-off for spatially dependent disasters, though it lagged in precision (86.67%).

The LSTM, while commonly used for time-series tasks, performed the lowest:

- Accuracy: 97.93%
- Recall: 94.88%
- AUROC: 0.9831

- *Reason for the ConvLSTM's Superiority*

The ConvLSTM has the unique ability to combine convolution and recurrent layers to complement both the long-term spatial dependency (e.g., clustering around the Pacific Ring of Fire) and long-term temporal change (e.g., increasing frequency of flooding), while being unconstrained temporally, due to its hybrid architecture, which allowed for the proposal to outperform both the GNN and LSTM models when modeling the irregular patterns that occur to bring about a disaster. The ConvLSTM performance shows promise for a real-time early warning system for predicting disaster, alerting officials up to before 24–48 hours before disaster onset. When paired with explainability tools, such as SHAP, the model would provide transparency in understanding the risk factors, thus increasing trust and security in how decisions and intakes would occur within disaster relief management.

- *Limitations*

- Class Imbalance: The most common disasters recorded in our dataset (e.g., Flood, Storm) would make up for the majority (~TBD%) compared to rare disasters (e.g., Epidemic) where prediction is difficult.
- Missing Data: Features including No. Injured had over 90% missingness, a large missingness could have contributed to decreased ability to predict accurately.
- Generalisability: All data used in this study were globally historical data, with no studies continued to validate this process in other parts of the world.

V. CONCLUSION

This study demonstrates that deep learning models, particularly ConvLSTM, can predict disaster occurrence 24–48 hours ahead using multivariate spatial-temporal data. The ConvLSTM surpassed the tested models by a wide margin with the best AUROC (0.9878), accuracy (98.45%), and F1-Score (97.10%). Its ability to capture complex spatial and temporal dependencies makes it a strong contender for real-time disaster early warning systems. The findings imply that the use of ConvLSTM-based models could facilitate early disaster readiness, lessening societal effect and death. Through incorporation into worldwide monitoring frameworks, these models could generate actionable warnings to decision-makers.

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