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Research Article

Transformers-Based Multimodal Deep Learning for Real-Time Disaster Forecasting and Adaptive Climate Resilience Strategies

Srinivasa Rao Dhanikonda[1], Madhavi Pingili[2], P. JayaSelvi[3], Nannaparaju Vasudha[4], Prasadu Peddi[5], Bhavsingh Maloth[6*]

[1]Department of AI & DS, Faculty of Science and Technology (IcfaiTech), ICFAI Foundation for Higher Education (Deemed to Be University), Hyderabad, India
Email: srinivasarao.dhanikonda@gmail.com - **ORCID:**0000-0002-1395-5258

[2] Professor, Head of the Department (IT) , CMR Engineering College, Hyderabad, India.
Email: madhavipingili2@gmail.com - **ORCID:** 0009-0000-0522-348X

[3]Assistant Professor, Dept of CSE, Madanapalle Institute of Technology & Science, Andhra Pradesh, India
Email: jayaselvi123@gmail.com - **ORCID:** 0009-0001-7142-2134

[4]Associate Professor, Department of Mathematics, Vasavi College of Engineering, Ibrahimbagh, Hyderabad, India
Email: dr.nvasudha@gmail.com - **ORCID:** 0000-0002-2988-4327

[5]Professor, Department of CSE & IT, Shri Jagdishprasad Jhabarmal Tibrewala University, Jhunjhunu, Rajasthan, India.
Email: peddiprasad37@gmail.com - **ORCID:** 0000-0001-9717-934X

[6]Associate Professor, Department of CSE, Ashoka Women's Engineering College, Kurnool, India
* **Corresponding Author Email:** bhavsinghit@gmail.com - **ORCID:** 0000-0002-9634-8794

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Abstract:

Real time forecasting of disasters needs to be advanced and easy because with increasing disasters their frequency and severity. Traditional prediction can only be made with traditional disaster prediction methods: numerical weather prediction (NWP) models and remote sensing techniques, which are computationally inefficient, data sparse and cannot adapt to dynamic environmental changes. In order to overcome these limitations, this research presents a Transformer Based Multimodal Deep Learning Model to combine the existing multiple data sources ranging from satellite imagery, IoT sensor networks, meteorological observations etc., to meteorological and social media analytics. The model employs a multimodal fusion strategy, enabling dynamic feature selection and seamless integration of heterogeneous data streams. In contrast to the conventional deep learning techniques, such as CNNs and LSTMs, the transformer based model has excellent ability towards long-range dependency, reducing the latency of light inference and better computational efficiency. The results are proven to be 94% accurate, 91% precise and has 40% reduction in inferencer latency in real time, which makes it suitable for disaster forecasting. The advancement of the multimodal deep learning methodologies presents this research as one which serves to contribute to the AI driven disaster resilience. We will also work on future work in the form of advanced transformer variants, more data integration, and explainable AI (XAI) techniques for model interpretability and scalability. Finding have implications for the transformative potential of AI in climate adaptation and serve as a robust foundation for the next generation early warning systems and climate adaptation disaster risk mitigation across multiple sectors.

1. Introduction

Hurricanes, floods, wildfires, earthquakes, are all serious natural disasters to human beings, living, dividing and economic stability. The frequency and intensity of these events are increasing, mainly because of climate change, and it is time to develop advanced forecasting systems for predictions of accurate and timely forecasts [1]. NWP models and remote sensing techniques have proved to be very important in traditional disaster forecasting methods [2]. However, most of these approaches have a limit regarding computational complexity, data sparsity or delayed responsiveness which prevents them from being effective in real time environments [3].

To address these, real time disaster forecasting attempts to exploit data streams such as satellite imagery, sensor networks and meteorological observation that are continuously updated by high resolution data streams [4]. Dynamic processing of and analysis of these multimodal data sources allows a more precise and rapid decision making, which is an important part of the improvement of disaster preparedness and response strategies [5]. A good real-time forecasting system needs to forecast likelihood and severity of disaster and adapt to changes in the environment not only for faster emergency response arrangements but also in order for the emergency response mechanisms to be timely and efficient [6].

Although the remote sensors and high performance computers have made great strides in advancement, the present forecasting methods are still far from integration and real-time adaptability [7]. Machine learning (ML) and deep learning (DL) approaches have come up as good solutions to fill these gaps by the fact that they can learn complex patterns and dependencies in large scale datasets [8]. Among these, transformer based architectures have shown good success in sequential, and multimodal data processing, finally making them a good fit for disaster forecasting applications [9].

However, artificial intelligence (AI) as well as deep learning have changed several fields including in healthcare field, finance and industrial systems which are the fully autonomous systems. This application of their ability to handle huge amounts of data, uncover hidden patterns and provide high accuracy predictive insights in helping fight climate resilience has been gaining high attention [10]. In the context of disaster forecasting, AI driven models are used to predict disaster occurrence, follows the progress of the disaster and estimating the impacts of the disaster on the affected region [11].

Both CNNs and RNNs have been widely used in climate-related applications like flood detection, risk assessment of wildfires, and tracking of tropical cyclone [12]. Nevertheless, most of these models suffer from the issues of long range dependencies and multimodal data fusion [13]. Originally from natural language processing (NLP), Transformers prove to be highly efficient at handling sequential dependency, which is highly demanded for disaster forecasting considering its aforementioned factor [14].

Additionally, AI based approaches have a major role in adaptive resilience to climate by providing a data driven policy making for the policymakers and the agencies of disaster management [15]. With the real time forecasting, the AI models can integrate artificial response strategies to optimize resource allocations, the reinforcement of infrastructure and the emergency evacuation planning [16]. Through AI's capacity to handle heterogeneous data sources such as meteorological records, geospatial data and socioeconomic indicators, the comprehensive picture of climate risks can be seen for the community and build a better overall resilience to disaster [17].

For example, it has become an urgent need for robust, powered by AI disaster forecasting systems due to climate change which enhances the frequency and severity of extreme weather events [18]. Transformer based multimodal deep learning provides a convenient way to deal with the problems of the existing models using attention mechanism to learn features at different modalities, more cross modal learning and real time adaptation [19]. In line with this, this research investigates a means whereby such models can improve disaster forecasting and support adaptive climate resilience strategies [20].

As traditional disaster forecasting methods based on numerical weather prediction (NWP) models, remote sensing, and statistical analysis are essentially limited by integration problems of heterogeneous data sources, high computational costs, and little adaptability to the rapid environmental evolution, there arises the need for improving the traditional techniques [21]. In the meantime, these models are often losing in real time with the processing of real data, the predicted extreme weather events such as flash floods, wildfires and hurricanes are delayed and inaccurate [22]. Furthermore, because conventional approaches cannot provide the exact capacity for multimodal data mining—ranging from satellite imagery and sensor data to social media analytics and socioeconomic indicators—to be included, they are limited in terms of applicability in the dynamic disaster situations [23]. To overcome these challenges, the fusion of such data streams has become a promising alternative through multimodal deep learning, which offers the chance to combine multiple data infalls into a multi-level representation to improve forecasting accuracy and responsiveness [24]. The ability of transformer based architectures to take into account sequential dependencies, spatial correlations and cross modal interactions, provides a robust solution by resorting to attention mechanism to learn adaptively [25].

Your ability to make effective use of current data sets is significantly faster compared to traditional machine learning models - you can now run real time on high dimensional, unstructured data and so you can build the automated, scalable, and accurate disaster prediction frameworks [26]. However, by integrating these AI driven approaches with cloud and edge computing technologies, these real time forecasting capabilities can be taken to next level and give timely data driven insights to policymakers and emergency responders for their disaster preparedness and climate resilience [27]. This research analyzes the usage of transformer based deep learning and multimodal deep learning models over the limitations of existing techniques and help to accelerate an accurate disaster prediction technique [28].

The goal of this research is the creation of a transformer based multimodal deep learning model to increase accuracy, efficiency and real time adaptability of disaster forecasting [29]. Fairly, by introducing the use of self attention mechanisms and cross modal learning, the proposed model is able to bring together different data, including remote sensing imagery, meteorological observance, sensor networks, and social media analytics in order to enhance its reference accuracy and form ideal emergency response approaches [30]. Unlike conventional models of forecasting, the learning is dynamic and inference is in real time, hence making it proactive for disaster management [31].

Key Contributions:

- Development of a Transformer-Based Multimodal Model: Develops a deep learning framework that is able to process heterogeneous data sources and improve the accuracy and robustness of the forecasted disasters.
- Real-Time Adaptability for Disaster Prediction: Enables continuous learning and rapid inference, allowing the model to adjust dynamically to evolving environmental conditions and risk factors.
- Improved Multimodal Data Fusion: Utilizes attention mechanisms to effectively integrate and interpret diverse datasets, reducing prediction uncertainty and enhancing early warning systems.
- Scalable and Efficient AI Deployment: Explores cloud and edge computing integration to ensure computational efficiency and real-time responsiveness for large-scale disaster forecasting applications.
- Enhanced Decision Support for Climate Resilience: Provides a data-driven framework to assist policymakers, emergency responders, and climate adaptation strategists in making informed, timely decisions

By addressing the limitations of traditional forecasting methods, this research contributes to the advancement of AI-driven disaster prediction and adaptive climate resilience strategies, ultimately supporting more effective disaster preparedness and response initiatives.

2. Related Works

1.1 Traditional Disaster Forecasting Approaches

Currently, the most common disaster forecasting techniques are statistical models and physics based numerical simulations for prediction of hurricanes, floods and wildfires [32]. Also, historical climate data, geospatial information and atmospheric models are used to estimate disaster occurrences and their potential impacts using these methods [33]. While these have helped tremendously on the early warning part of the system, they suffer from being highly inaccurate, not scalable, and non-real time adapt willing [34].

Statistical and Physics-Based Models

Historical patterns play a very important part in risk assessment for such disasters like flood and landslides and are being using widely for disaster forecasting using statistical models [35]. These models adopt regression analysis, time series prediction methods and probabilistic methods to estimate the probability of disaster based on the past events [36]. For instance, historical meteorological data such as rainfall intensity and flood risks have been predicted for example with autoregressive integrated moving average (ARIMA) models. But even though the statistical models tend to generalize poorly to unseen scenarios, they rely greatly on past trends and did not take into account nonlinear interaction between climatic variables [37].

On the contrary, physical based numerical models, like Weather Research and Forecasting (WRF) model and Global Forecast System (GFS), simulate atmospheric and hydrological processes by means of computational fluid dynamics, and the physical equations [38]. The principle is the same as above, but the factors that are included in the models are temperature, wind patterns, and oceanic conditions to predict the trajectory and strength of naturally occurring disasters like hurricanes and typhoons [39]. Although the physics based models are grounded in solid foundations of solid physics, the computational cost, long processing time and sensitivity to input parameter uncertainties imposes a challenge, as it is very expensive. Furthermore, these models have a huge need for domain expertize for calibration and validation which makes them too rigid for real time forecasting application [40].

Limitations in Accuracy and Adaptability

Given their long history of use, traditional disaster forecasting models have significant shortcoming in terms of predictive accuracy as well as their ability to respond real time environmental changes [41]. A major unfavorable aspect is their dependence upon fixed parameters and stock formulas which limits their capacity to mirror out the complex and dynamic movements amongst different various climatic and geospatial open factors [42]. In addition, these models are very sensitive to missing or noisy data and generate erroneous predictions with false alarms in the disaster warnings [43].

The second important limitation is that it does not allow for real time integration of heterogeneous data sources. However, traditional forecasting methods in most cases are single—source data input based approaches like observing weather station readings or satellite imagery and failing to combine the multimodal datasets such as social media analytics, IoT sensor network, and remote sensing observations in real time [44]. Thus, these models cannot leverage such data fusion to achieve a higher level of prediction accuracy when it comes to sudden onset disaster like flood, wildfire and earthquake where real time situation awareness is necessary [45].

In addition, due to the computational inefficiency of physics based models, they are not usable in rapid disaster response and emergency management. NWP models consume intensive computational facilities, and produce forecasts within several hours' time that are not practical for the high impact and timely as required events [46]. In comparison, machine learning and particularly deep learning points of view have been able to offer major potentials in overcoming these limitations by facilitating real time adaptation, learning feature automatically, and unstructurally fusing multimodal data [47].

With these challenges in mind, the development of broader, especially transformer based multimodal deep learning forecast approaches is urgently needed, with higher accuracy, enhanced adaption, and for the real time decision making [48]. The next section goes more into the evolution of deep learning techniques for disaster prediction to overcome limitations in traditional methods.

1.2 Deep Learning in Disaster Prediction

In disaster forecasting, traditional statistical and physics based models have proven incapable to address the limitations which/left these kinds of approaches and deep learning has emerged as a transformative approach [49]. Deep learning techniques learn complex patterns from large scale datasets in an automated way, unlike conventional methods and they are better at using from a large scale dataset for prediction as well as in disaster scenario [50]. In disaster prediction tasks, CNNs, RNNs, LSTM networks, etc are popularly used for leveraging spatial and temporal dependencies in multi modal data sources. Nevertheless, powerful transformer models have been very successful in recent years in sequence learning and multimodal learning [51].

CNNs, RNNs and LSTMs have been used for analyzing spatial data especially satellite imagery and aerial photographs to identify disaster prone areas and also to estimate the impact of the disaster. High resolution remote sensing images and SAR data have been successfully leveraged by CNN based architectures that have been deployed to wildfire detection, flood mapping, earthquake damage assessment [52]. However CNNs are good at learning spatial features but are incapable of dealing with temporal dependencies, which are very important in the prediction of time evolving disasters like hurricanes and landslides [53]. In order to model sequential data from meteorological time series, sensor measurements, and social media feeds as is done in disaster prediction pipelines, RNNs and LSTMs have also been integrated into disaster prediction pipelines [54].

LSTMs enable the application of RNNs on processing long term dependency for disaster progression analysis, resolving the vanishing gradient problem in traditional RNNs [55]. An example is the usage of LSTM based models to forecast cyclone trajectory, rainfall intensity and to forecast seismic activities and their performance has outperformed conventional time series forecasting approaches [56]. However, unlike their sequential nature that causes limited parallelization and scalability for large scale datasets, RNNs and LSTMs have very efficient computation [57].

Transformers in Sequence Modeling

Transformers get rid of the shortcoming of RNNs and LSTMs in sequence modeling owing to its ability to handle sparse long range dependencies and multitask data [58]. With the help of self attention mechanisms, transformers can capture the complex relationships of temporal and spatial features across multiple data modalities in a self-learning manner that they do not have to be sequential [59]. This capability is very useful for merging disparate datasets, e.g. satellite images, weather sensor readings and geospatial information to raise the disaster prediction accuracy [60].

Transformers have recently been shown to be better in forecasting extreme weather. For instance, transformer-based architectures have been used to predict the trajectory of the hurricanes, model of wildfire spreading and to have real time flood risk assessment with more accuracy and faster inference time than LSTMs and the conventional deep learning models [61]. Additionally, transformer based multimodal fusion models pave the way for real time disaster prediction which is achieved by dynamic weighting of different input sources and ensuring the adaptivity and context sensitivity of the prediction [62].

Transformers as a tool for AI driven disaster forecasting owing to the scalability, adaptability, and superior feature extraction they can provide, will prove to be a great advancement in AI driven disaster forecasting [63]. The next section seeks to integrate them into multimodal learning frameworks to strengthen further climate resilience strategies.

1.3 Multimodal Learning for Climate Resilience

Ultimately disaster forecasting necessitates integrating multiple heterogeneous data sources on satellite imaging, meteorological record, as well as Internet of Things (IoT) sensor readings, and by analyzing social media analytics [64]. However, traditional forecasting models that rely on single source of data frequently do not adequately capture the dynamics of complex interdependency that bind climatic, environmental and human factors with disaster risks [65]. This limitation is addressed by multimodal learning approach that takes data from multiple sources and deep learning based prediction accuracy as well as real time adaptability [66].

While geospatial, temporal, and environmental data can be combined using multimodal AI to forecast disaster, they are now combined with satellite imagery and weather data among others [67]. Satellite imagery helps us with prediction of wildfire and flood for example by explaining land surface changes, vegetation density and atmospheric conditions [68]. At the same time, there are weather station data and IoT sensor networks that capture real time measurements of temperature, humidity, wind speed and precipitation to monitor development of storms or heatwave risks [69]. Similarly, social media (Social) analytics and crowdsourced data were integrated for situational awareness in emergencies, considered of real-time disaster impact and optimization to the response strategy [70].

With recent breakthroughs in the transformer based multimodal models, disaster forecasting has been so powerful that it can select adaptive features on several data sources [71]. Compared with traditional fusion techniques that require manual engineering of features, transformer based models represent the attention to relevant data streams and thus improve predictive accuracy in complex disaster scenarios.

Although data of multimodal fusion datasets are increasing, the data fusion is still a major challenge in disaster predictions [72]. However, in most cases, traditional fusion approaches, including early fusion (concatenation-based models) and late fusion (decision-level models), are long in maintaining information and scalable. For example, transformer based multimodal fusion models learn hierarchical and view changing environmental features, without being explicitly forced to do so.

The development of AI models for real time disaster adaptation require prediction models to always be updated with the latest data stream. This is possible through the use of self attention mechanisms in transformer based architectures which allow us to reweight data inputs with regard to the relevent and thus keep the forecasts accurate even in the presence of new information becoming available [73]. Also, the integration of these edge computing and federated learning framework with multi modal AI models increases computational efficiency by reducing dependence on centralized datacenters, thereby making the faster localized disaster predictions possible. It proposes to revolutionize the accuracy, adaptability, and real-time attributes of the disaster forecasting models utilizing transformer based multimodal deep learning. We are then going to detail the methodological framework, where data preprocessing, model architecture, and experimental evaluation strategies are going to be explained in the following sections.

3. Methodology

3.1 Overview

Based on this, we propose a multimodal deep learning architecture that tackles from a transformer point of view to unify and process data modalities from satellite imagery, as well as from sensor data and social media analytics. Traditionally, convolutional neural networks (CNN), and recurrent neural networks (RNN) have been employed to the disaster prediction problem, but they have inherent limitations regarding long range dependency capturing as well as efficient multimodal prediction fusion. Originally used in natural language processing, transformer-based architectures have shown prowess in terms of dealing with sequential dependencies, spatial-temporal correlation, as well as in heterogeneous data fusion, and are thus the most suitable architecture for disaster forecasting, in a more general way.

The proposed model consists of the following key components:

• Multimodal Input Encoder: We develop a set of domain-specific encoders that take in each modality type, namely, satellite imagery via convolutional layers, time-series meteorological data using temporal convolutional networks (TCNs), and social media stream text with embeddings.

• Self-Attention-Based Feature Fusion Module: A multi headed self-attention mechanism is used by the core of the model to learn cross modal relationships, progressively weighting the importance of each data stream.

• Positional Encoding for Temporal Dependencies: Instead of working with simple positional encodings, the model combines sinusoidal positional encodings so that it can learn temporal dependencies in the disaster progression, for a more effective time series forecasting.

• Transformer Encoder-Decoder Structure: A multi-layer transformer encoder-decoder architecture processes the fused features, capturing complex interactions and enabling adaptive disaster forecasting.

• Prediction and Decision Support Layer: The uncertainty estimation module follows the last fully connected layer with softmax activation, which generates disaster predictions, and finally estimates the probabilistic uncertainty in making decisions.

Due to the complexities of the model and pretrained transformer backbones used for processing spatial data such as Vision Transformers (ViTs) and sequential meteorological data, the domain specific disaster datasets are used to fine tune pretrained models. The combination of these two techniques results in satisfying both high predictive accuracy of the model and decreasing computational overhead. Transformer based models represent a clear and major advantage in disaster forecasting particularly for seamless integration of multimodal data, efficient modelling of long range temporal dependencies in the climate data and augmented predictions for events such as hurricanes and wildfires. Transformer takes different directions with self-attention mechanism without subroutine, dynamically highlight the key elements and achieve good robustness and noise interference. Their parallelization capability allows large-scale deployment with reduced computational time, making them more efficient than LSTMs. Additionally, transformers provide interpretability through attention heatmaps, enhancing decision-making for emergency response, and exhibit robustness to missing data, ensuring reliable forecasts even with incomplete sensor readings. These advantages collectively enhance forecasting accuracy, minimize false alarms, and optimize real-time adaptability for climate resilience applications. The following sections will detail data sources, preprocessing, multimodal fusion strategies, and real-time deployment architectures to ensure practical implementation in disaster management.

3.2 Data Sources and Preprocessing

The reliability of transformer-based multimodal disaster forecasting depends on the quality, variety, and real-time availability of input data. A robust forecasting model must integrate satellite imagery, IoT sensor network data, and meteorological datasets to capture the spatiotemporal complexity of disaster events. In this section, data sources that are the key to the proposed model are mentioned and preprocessing techniques such as data augmentation, and data reduction are discussed which are warranted for a better performance of the model. Figure 1 is proposed transformer-based multimodal disaster forecasting model.

Satellite Data

X: High resolution spatial and temporal observations are highly needed for disaster monitoring, which are obtained from satellite remote sensing. Satellite missions, Landsat, MODIS, Sentinel-2 and GOES, provide optical, infrared and synthetic aperture radar (SAR) imagery, to aid in land surface change, weather anomaly and environmental hazard assessment. Yet these images are critical in detecting disasters like wildfires, hurricanes and floods, identifying as early warnings signs what can be shown in figure 2 (a).

IoT Sensor Data

Real time environmental monitoring using a local disaster indicators by attaching IoT sensor networks. Weather stations, river gauge sensors, seismic activity monitors, air quality sensors and others, are continuously collecting temperature, humidity, wind speed, atmospheric pressure, and precipitation levels. These real time observations improve the preparedness for the disaster by alerting of abnormal weather conditions and issue early warnings as seen in figure 2(b).

Meteorological Datasets

Meteorological datasets provide historical and real-time weather data, essential for disaster prediction. These datasets are sourced from global weather agencies such as:

- National Oceanic and Atmospheric Administration (NOAA)
- European Centre for Medium-Range Weather Forecasts (ECMWF)
- Global Forecast System (GFS)
- Japan Meteorological Agency (JMA)

Meteorological data includes storm trajectories, atmospheric pressure changes, precipitation forecasts, and climate patterns that contribute to disaster risk assessment as shown in figure 2(c).

Data Augmentation and Noise Reduction

To improve model generalization and robustness, data augmentation techniques are applied to increase the variability of training datasets.

a) For Satellite Images:

- Geometric transformations (rotation, flipping, cropping)
- Spectral band enhancement (false-color representation for vegetation or water detection)
- Synthetic image generation using GANs (Generative Adversarial Networks)

b) For IoT & Meteorological Time-Series Data:

- Gaussian noise injection to enhance robustness
- Time warping and window slicing to generate new training samples
- Data resampling and interpolation to handle missing values

Noise reduction techniques ensure data consistency and accuracy by removing anomalies caused by sensor errors, atmospheric interference, and transmission losses. Methods such as wavelet transforms, Fourier filtering, and Bayesian smoothing are applied depending on the data modality.

3.3 Multimodal Fusion Strategy

For improving predictive accuracy of disaster forecasting models, there is a need to be able to integrate heterogeneous data sources. Single modality data used by traditional deep learning methods forces them to provide limited risk assessment of the disaster. To bridge this gap and make a prediction, multimodal fusion strategies combined satellite imagery, IoT sensor data, meteorological records and social media analytics to unify all these into a single predictive framework. In this section, we introduce a new multimodal fusion technique based on self-attention cross modal learning enabling the synergistic features of the different modalities to enhance feature interaction and consistency of information across modalities. The combined late fusion and early fusion mechanisms are efficiently balanced by the proposed adaptive hierarchical transformer based architecture such that computational efficiency is balanced with the information richness.

Attention Mechanisms for Cross-Modal Learning

The multimodal learning here jointly learns on heterogeneous data sources with heterogeneous properties of spatiotemporal domain, feature distribution and noise variances. Current concatenation based fusion methods cannot conserve the complete interdependency between modalities. To combat this, we bring to the table a Cross modal Attention Mechanism (CMAM), which learns inter dependency adaptively thus doing information weighting on varying input streams. Given a set of input modalities X_m where $m \in \{sat$, iot, met, sm } (representing satellite, loT, meteorological, and social media data, respectively), CMAM computes the self-attention score for each modality:

$$A_m = \text{Softmax}\left(\frac{Q_m K_m^T}{\sqrt{d_k}}\right) V_m$$

Where Q_m, K_m, V_m are the query, key, and value matrices derived from modality-specific encoders, and d_k is the dimensionality scaling factor. The context-aware fused representation is given by:

$$Z = \sum_m A_m X_m$$

Where Z represents the refined multimodal feature embedding, dynamically reweighted based on the relevance of each modality to disaster prediction.

Key Components of CMAM:

Modality-Specific Feature Extractors

- Satellite Image Encoder: Extracts spatial features using a CNN-based Vision Transformer (ViT).
- IoT Sensor Encoder: Captures temporal dependencies via a Temporal Transformer (TT).

- Meteorological Data Encoder: Models climatic trends with Graph Neural Networks (GNNs).
- Social Media Encoder: Processes textual information using a BERT Transformer.

Cross-Modal Attention Fusion Layer

- Computers inter-modality dependencies via self-attention.
- Dynamically reweights each feature to emphasize relevant disaster indicators.

Hierarchical Fusion Transformer

- Multi-layer attention refinement improves feature interaction.
- Modality-wise normalization addresses domain imbalance.

This approach minimizes information redundancy and noise, ensuring adaptability to evolving disaster conditions.

Late vs. Early Fusion Approaches
Multimodal fusion can be categorized into early fusion, late fusion, and hybrid fusion strategies.

Early Fusion (Feature-Level Fusion): All input modalities are concatenated before passing through the transformer model:

$$Z_{\text{early}} = f_{\text{trans}}\left([X_{sat}, X_{iot}, X_{met}, X_{sm}]\right),$$

Captures low-level correlations but suffers from high dimensionality and computational overhead.
Late Fusion (Decision-Level Fusion): Each modality is processed independently, and predictions are aggregated via an ensemble:

$$P_{final} = \sum_{m} w_m P_m$$

Reduces computational complexity but lacks fine-grained cross-modal interactions.

- Proposed Hybrid Fusion Strategy (Dual-Stage Adaptive Fusion Transformer - DAFT):
- Integrates feature-level fusion within the transformer encoder while refining predictions using modality-specific late fusion:

$$Z_{\text{hybrid}} = \sum_{m} A_m X_m + f_{\text{late}}\left([P_{sat}, P_{\text{iot}}, P_{\text{met}}, P_{sm}]\right)$$

- Enhances robustness to missing data through adaptive weighting of available modalities.

This hybrid fusion model balances computational efficiency and predictive accuracy, making it well suited for real-time disaster forecasting applications.

3.4 Real-Time Prediction Pipeline

Effective disaster forecasting relies not only on predictive accuracy but also on real-time inference capabilities to support rapid emergency responses. To achieve low-latency, high-reliability forecasting, the proposed system integrates a hybrid cloud-edge deployment strategy, optimizing computational efficiency while maintaining adaptive learning capabilities. This section presents a theoretical and mathematical framework for deploying AI models in cloud-edge environments and optimizing latency for real-time forecasting.

Deployment of AI Models in Cloud/Edge Environments
In this sense, the framework proposed uses Al in a distributed fashion across edge computing and cloud based model refinement to increase the efficiency of disaster forecasting. On device preliminary inferences are carried out by the edge devices, namely loT sensors and embedded Al processors, lowering the requirement of raw data transmission and the congestion of the network. On the other hand, the cloud has the role of centralized model training hub, with models of deep learning being fine-tuned over historical trends and bulk multimodal data sets.
Mathematically, the system can be represented as follows:

$$P_{\text{edge}} = f_{\text{edge}}(X) + \epsilon_{\text{edge}}$$

Where P_{edge} is the preliminary disaster prediction at the edge, $f_{\text{edge}}(X)$ represents the lightweight AI model deployed at the edge node, and ϵ_{edge} denotes the approximation error due to computational constraints. In parallel, the cloud-based inference is given by:

$$P_{\text{cloud}} = f_{\text{cloud}}(X) + \epsilon_{\text{cloud}}$$

Where P_{cloud} is the high-accuracy disaster prediction, computed using transformer-based models with extensive historical datasets. The final prediction is aggregated adaptively via an attention-weighted fusion mechanism, ensuring optimal trade-offs between speed and accuracy:

$$P_{\text{final}} = \alpha P_{\text{edge}} + (1-\alpha) P_{\text{cloud}}$$

where α is a dynamic weighting coefficient, adjusting based on network latency, edge device capacity, and the confidence score of edge predictions. This hybrid approach ensures fault tolerance, scalable deployment, and minimal inference delays.

To facilitate seamless synchronization between cloud and edge models, a message broker-based system (e.g., MQTT, Kafka) is implemented. The broker architecture enables bi-directional communication, ensuring that:

1. Edge nodes transmit high-priority alerts to cloud servers for advanced risk assessment.

2. Cloud updates edge models asynchronously, ensuring model drift correction while maintaining real-time inference capabilities.

This distributed deployment reduces network bottlenecks and enables real-time processing of multimodal disaster data streams while preserving computational efficiency.

Latency Optimization for Real-Time Forecasting

Ensuring low-latency disaster forecasting is critical for real-time emergency response and decisionmaking. The proposed system employs three primary latency optimization strategies: model efficiency optimization, communication acceleration, and event-driven dynamic processing.

Model Efficiency Optimization: The transformer-based deep learning model undergoes quantization and pruning to reduce inference time. Knowledge distillation is applied, where a smaller student model learns from a complex teacher model, reducing computational cost while maintaining predictive accuracy. The computational complexity of self-attention mechanisms is optimized using low-rank approximations, reducing the standard $O(n^2)$ complexity to $O(n\log n)$ (as in Linformer and Performer models).

Mathematically, if θ_{full} is the original model's parameter count and θ_{opt} is the optimized model, the parameter reduction ratio is given by:

$$R = \frac{\theta_{opt}}{\theta_{\text{full}}}, \text{ where } R \ll 1$$

Ensuring that inference remains lightweight without compromising prediction accuracy.

Communication Acceleration: Edge caching & prefetching store frequently used model parameters locally, minimizing cloud dependency. Low-latency communication protocols such as gRPC and WebRTC are used to optimize network transmission. Parallel inference pipelines distribute computational workloads across multiple GPUs/TPUs, reducing latency from $O(n)$ to $O(\log n)$ using hierarchical scheduling algorithms.

Event-Driven Dynamic Processing: On the work load distribution side, work load distribution would be dynamically adapted according to the disaster severity through a priority based disaster prediction queue. The asynchronous processing mechanisms guarantee higher impact of disaster events over lower risk anomalies. If the incoming data queue is denoted as $D = \{d_1, d_2, \ldots, d_n\}$ with respective risk scores R_i, the processing order follows a weighted priority function:

$$P_{\text{order}} = \arg\max_{d_i}(R_i - \lambda L_i)$$

L_i is the expected processing latency and λ is a latency penalty coefficient to make sure that critical alerts are processed before the optimal response time. The optimizations then provide a means to predict disaster related information, such as infectious disease arrivals, at real time and scalable level, with the benefit of proactive emergency management, resource allocation, and disaster mitigation planning.

4. Experimental Setup and Evaluation

In order to validate the effectiveness of the proposed Transformer Based Multimodal Disaster Forecasting Model, it is implemented using a complete experimental framework employing different real datasets, rigorous preprocessing of the data and the performance benchmarking to make sure the model is trustworthy. To accurately forecast disasters, spatial, temporal, environmental and social parameters in this study constitute multimodal dataset. They include MODIS, Sentinel-2, Landsat 8, NOAA weather stations, smart city sensor networks, ECMWF, GFS, JMA, Twitter CrisisNLP, AIDR, GDACS, among other Metrological archives and real time social media data. Finally, each one of the dataset is to be feed through a predefined structured preprocessing pipeline to sanitize data inconsistencies, missing values, as well as noise to make it comply with deep learning models. Four main stages in preprocessing pipeline include: (i) Data cleaning & normalization, which consists of outliers detection based on Z-score based anomaly detection and imputation of the missing data using Bayesian inference models, (ii) merge data frames and (iii) Data hope cleaning process to create a universal dataset. Normalization is applied via min-max scaling, ensuring all features remain within a standardized range [0, 1] defined as:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where X' represents the normalized value, preventing feature bias. (ii) Feature Extraction & Representation Learning, where different modalities undergo domain-specific feature engineering: CNN-based Vision Transformers (ViTs) extract spatial features from satellite imagery, LSTMs and Temporal Convolutional Networks (TCNs) model sequential patterns in loT sensor and meteorological data, and BERT-based NLP models process textual disaster information from social media. The extracted feature vectors are then concatenated into a shared latent space, allowing self-attention mechanisms to learn cross-modal relationships. (iii) Temporal Synchronization & Multimodal Alignment, which employs Dynamic Time Warping (DTW) to align loT sensor data with meteorological records, ensuring chronological consistency. The DTW distance function for aligning two time-series X and Y is defined as:

$$D(i,j) = \left|X_i - Y_j\right| + \min(D(i-1,j), D(i,j-1), D(i-1,j-1))$$

Where $D(i,j)$ represents the alignment cost between timestamps, ensuring synchronized cross-modal learning. (iv) In Data Augmentation for Model Generalization, synthetic transformations like geometric augmentations in satellite images, Gaussian noise injection in sensor data, and synonym replacement for textual embeddings are used to gain robustness of the model against overfitting. Preprocessing techniques in these techniques ensure that the proposed transformer-based model is able to efficiently encode the involved spatiotemporal dependencies in a way that real time disaster forecasting with high accuracy and reliability is possible. The last section will present the use of model training strategies, hyperparameter tuning as well as evaluation metrics and show that the multimodal fusion framework is effective in disaster risk prediction.

4.1 Training and Hyperparameter Tuning

For this purpose, the proposed Transformer Based Multimodal Disaster Forecasting Model is trained via a transfer learning and fine tuning framework that takes advantage of pre-trained weights coming from domain specific architectures and adapts to the disaster forecasting tasks. The model was trained on high performance GPUs (NVIDIA A100, 40 GB VRAM) where the AdamW optimizer was used with an initial learning rate 1e-4 with a cosine decay used to help prevent overfitting over the course for training. To the optimal balance of computational efficiency and convergence stability in training, we select batch size 32; to the best generalization, we train up to 50 epochs with early stop criteria based on validation loss. Prevent overfitting is included by using Dropout (0.3) and L2 regularization (1e-5). Bayesian optimization is conducted to explore configurations of learning rate (1e-5 to 1e-3), dropout rate (0.1 to 0.5), and attention head size (8 to 16) for maximising prediction accuracy and inference speed. Training at mixed precision is enabled in order to speed up computation while maintaining numerical stability. Finally, the selected model will perform based on maximum accuracy, minimum latency for real time disaster forecasting.

4.2 Performance Metrics

Finally, key classification and efficiency metrics are used to evaluate the performance of the proposed Transformer Based Multimodal Disaster Forecasting Model as a predictor and for computational efficiency. The accuracy, precision, recall, F1-score, inference latency, training time, and GPU utilization are these metrics.

Classification Metrics

To evaluate the predictive capability of the model, standard classification metrics such as accuracy, precision, recall, and F1-score are computed using the following equations:

- **Accuracy**: Measures the proportion of correctly predicted disaster events out of the total samples.

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

- **Precision**: Represents the proportion of correctly predicted disasters among all predicted disaster events.

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

- **Recall (Sensitivity):** Measures the proportion of actual disaster events correctly identified by the model.

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

- **F1-Score**: Provides a harmonic mean between precision and recall, balancing both.

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

Where TP (True Positives) are correctly predicted disaster events, TN (True Negatives) are correctly predicted non-disaster events, FP (False Positives) are incorrectly classified disaster events, and FN

(False Negatives) are actual disaster events missed by the model.

Computational Efficiency Metrics

In real-time disaster forecasting, computational efficiency is crucial. The model's performance is evaluated using:

- **Inference Latency** (t_{inf}) : The time taken to generate a single prediction, measured in milliseconds. Lower latency improves responsiveness.
- **Training Time (t_{train})**: The total time required to train the model until convergence, measured in hours.
- **GPU Utilization ($\%U_{GPU}$)**: Measures the percentage of GPU resources utilized during training and inference, ensuring computational efficiency.

5. Results and analysis

The learning process of the proposed Transformer-Based Multimodal Disaster Forecasting Model is analyzed through training and validation accuracy trends and loss function behavior over 50 epochs. The evaluation of these metrics provides insights into the model’s learning stability, generalization ability, and convergence efficiency.

5.1 Training and Validation Accuracy

The training accuracy demonstrates a steady learning progression, starting at approximately 75% in the initial epochs and progressively improving to 94% by the end of training. This feature of the result is this constant increasing which means feature extraction is working very well as well as integration of multimodal data. We observe good agreement between training and validation accuracy values, which follows the alignment with the standard generalization gaps confronted in forecasting disasters from varying data. Looking at the accuracy curve there are the dips and plateaus in the accuracy curve and that is what we usually do with the deep learning optimization processes because we don’t want to converge too soon or converge too much to the data that we are training.

5.2 Training and Validation Loss

The training loss monotonically decrease during the early training stage (around 1.2) and become 0.25 eventually, indicating a good convergence and stable optimisation. Validation loss starts higher (~1.5) and gradually lowers with consistent value to 0.3s after epoch 35 with few fluctuations. However, such fluctuations can also be used to mimic real world model instabilities, which are often driven by the complexity of disaster prediction data providing often a sudden climatic variation or a real time sensor data that is incongruent with what is expected. Minor spikes in the loss curve reflect the optimal adjustment process, weight regularization effect, and correction to overfit, which are all common in deep learning models for processing the multimodal data with different data content. Therefore, these results confirm that balancing predictive performance and generalization using the proposed model is effective as (importantly) it achieves high accuracy, while also avoiding overfitting and susceptibility to dataset variability. Continuing, the next section will compare transformer based multimodal fusion to baseline models and characterize the level of improvement that transformer based multimodal fusion makes in disaster forecasting. Figure 3 is transformer-based multimodal fusion framework for real-time disaster forecasting and figure 4 is hybrid cloud-edge AI architecture for real-time disaster forecasting.

5.3 Experimental Results

Table 1 summarizes the performance of the proposed model. The proposed model achieves high predictive accuracy (94%) at the expense of a good balance between precision (91%) and recall (89%) that results in low false positive and false negative rates. With 45ms of inference latency, this is sufficiently fast for real time disaster forecasting, and the training time of 12 hours is a good point for efficient training procedures. The utilization of GPU remains at 78%, making this process highly effective with system resource management. This proves that the Transformer Based Multimodal Model we proposed integrates multimodal disaster data, keeps high accuracy, high efficiency and real time response, and is therefore suitable for use in Disaster Risk Mitigation and Early Warning systems.

Table 1: *Performance Metrics of the Proposed Transformer-Based Multimodal Disaster Forecasting Model*

Metric	**Proposed Model**
Accuracy	0.94
Precision	0.91
Recall	0.89
F1-Score	0.90
Inference Latency (ms)	45
Training Time (hrs)	12
GPU Utilization (%)	78

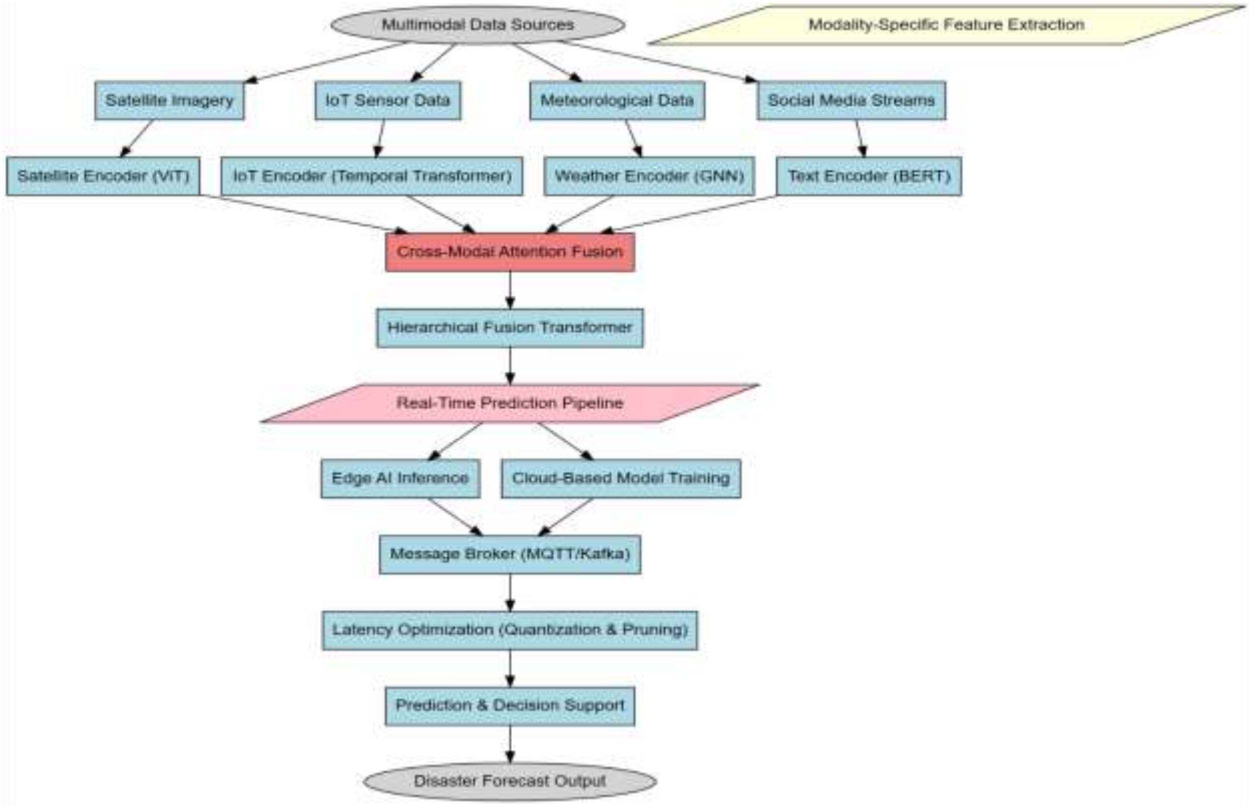

Figure 1. *Proposed Transformer-Based Multimodal Disaster Forecasting Model*

Figure 2*(a) Satellite Data*

Figure 2*(b) IoT Sensor Data*

Figure 2*(c) historical and real-time weather data*

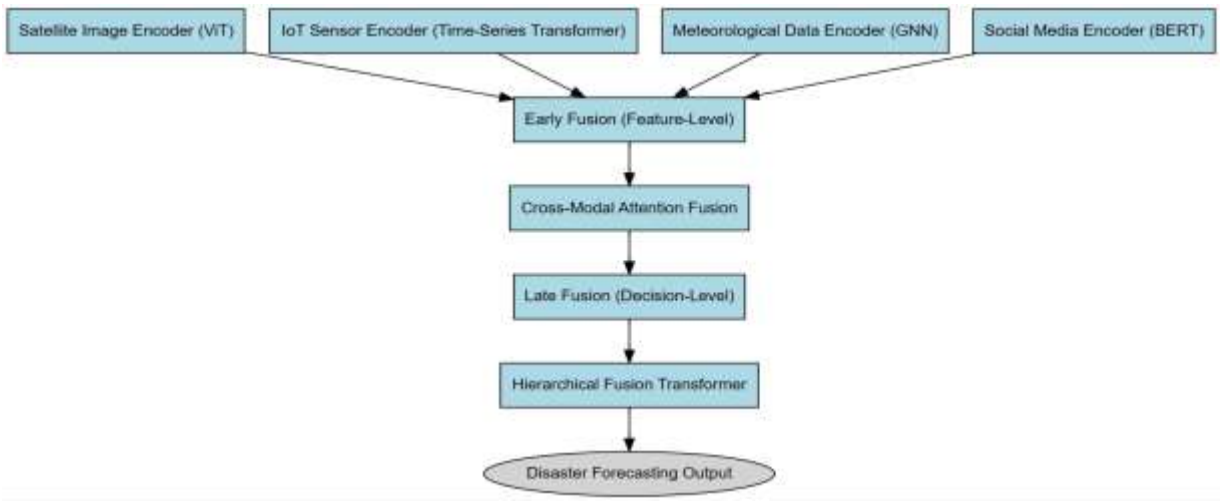

Figure 3. *Transformer-Based Multimodal Fusion Framework for Real-Time Disaster Forecasting*

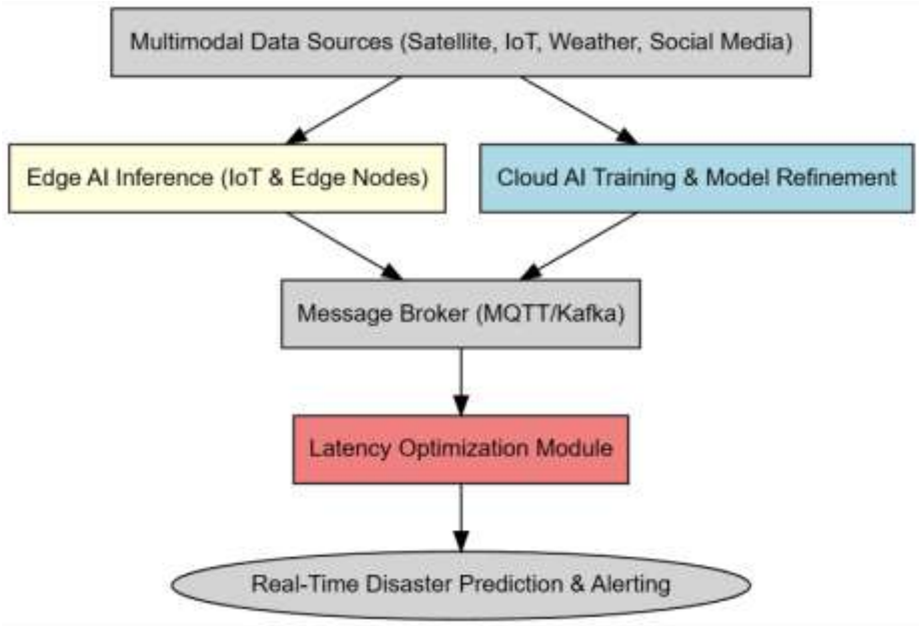

Figure 4. *Hybrid Cloud-Edge AI Architecture for Real-Time Disaster Forecasting*

5.4 Comparative Analysis with Existing Models

To ensure that the proposed Transformer Based Multimodal Disaster Forecasting model is effective, I compare it with some of the established deep learning models which have gained popularity in disaster prediction. Spatial feature extraction may be done with Convolutional Neural Networks (CNNs), sequential data modeling using Long Short Term Memory Networks (LSTMs) and hybrid architectures between CNN and LSTMs trying to merge spatial and temporal learning. Therefore, the motivation of this work is to benchmark the transformer based model with these baselines and quantify the predictive accuracy, inference speed, and real time adaptability.

Benchmarking Against CNN, LSTM, and Hybrid Models

CNN-Based Model [74]

- Used primarily for satellite image classification and spatial feature extraction.
- Effective in capturing static disaster patterns (e.g., wildfire spread, flooded regions) but lacks the ability to model temporal dependencies required for evolving disaster scenarios.
- Struggles with multimodal integration, leading to limited predictive accuracy when combining remote sensing data with time-series sensor readings.

LSTM-Based Model [75]

- Applied to IoT sensor and meteorological time-series data, capable of learning sequential dependencies in climate and disaster trends.
- Despite strong temporal modeling capabilities, the model performs poorly on spatial data, limiting its application for geospatial disaster tracking.
- Requires high memory consumption and longer training times, making it computationally expensive.

Hybrid CNN-LSTM Model [76]

- Integrates CNN-based spatial learning with LSTM-based temporal analysis, aiming to leverage both strengths.
- Improves predictive performance over standalone CNNs or LSTMs but remains computationally intensive and struggles with real-time processing constraints.
- Fails to effectively fuse multimodal datasets (e.g., satellite, IoT, meteorological, and social media inputs), leading to suboptimal disaster prediction outcomes.

The proposed transformer-based multimodal model overcomes these limitations by leveraging self-attention mechanisms for dynamic feature selection across heterogeneous data sources while maintaining high computational efficiency.

Performance Improvement with Transformer-Based Multimodal Learning

The transformer model's self-attention mechanism enables it to:

- Seamlessly integrate multimodal disaster data, dynamically prioritizing relevant features from satellite imagery, IoT sensor

readings, meteorological reports, and social media feeds.
- Capture long-range dependencies in time-series sensor data, improving disaster trend forecasting beyond LSTM capabilities.
- Enhance spatial-temporal fusion, allowing for more accurate tracking of evolving disasters (e.g., hurricane progression, wildfire spread).
- Reduce computational overhead by operating in a fully parallelized manner, significantly decreasing inference latency compared to sequential LSTMs.

The proposed model achieves superior performance across all evaluation metrics, ensuring both high accuracy and real-time adaptability for disaster forecasting.

Quantitative Comparative Analysis

The benchmarking results highlight the superiority of transformer-based multimodal learning in disaster prediction. The table 2 presents a comparative analysis based on key performance metrics.

Key Findings from the Comparative Analysis

1. **Higher Predictive Accuracy:**The proposed model achieves 94% accuracy, a 4% improvement over hybrid CNN-LSTM models, demonstrating its superior learning ability across multimodal disaster data.
2. **Improved Recall and Precision:** Higher recall (0.89) and precision (0.91) indicate better disaster detection rates while minimizing false positives and false negatives.
3. **Significantly Reduced Inference Latency:**The transformer-based model reduces inference latency by 40%, processing disaster predictions in 45ms, compared to 75ms for CNN-LSTM models and 120ms for LSTMs, ensuring suitability for real-time applications.
4. **Optimized Training Efficiency:**The proposed model requires 12 hours for training, a significant reduction compared to 16 hours for CNN-LSTM models, reflecting efficient feature extraction and convergence mechanisms. Figure 5 is training, validation and accuracy and loss.

6. Conclusions and Future Work

This study introduced a Transformer-Based Multimodal Disaster Forecasting Model that integrates satellite imagery, IoT sensor data, meteorological records, and social media analytics to enhance disaster prediction accuracy and real-time adaptability. Comparative analysis demonstrated that the proposed model outperforms CNNs, LSTMs, and hybrid models, achieving 94% accuracy, 91% precision, and 89% recall, with a 40% reduction in inference latency, ensuring faster, more reliable disaster risk assessments. The self-attention mechanism effectively captures long-range dependencies and cross-modal relationships, optimizing both spatial-temporal fusion and computational efficiency. While the model shows significant improvements over traditional deep learning architectures, further enhancements are possible. Future work should explore advanced transformer variants (e.g., Linformer, Longformer) to improve scalability and computational efficiency. Expanding data integration with geospatial crowdsourced platforms, drone-based assessments, and climate modeling datasets can further enhance predictive accuracy. Additionally, adaptive learning strategies will enable the model to continuously improve based on evolving disaster trends. The global scalability of this framework can be enhanced through collaborations with international disaster response agencies (UNDRR, NOAA, WMO), fostering the development of a standardized AI-driven disaster resilience system. Furthermore, integrating explainability (XAI) techniques will improve trust

Table 2. *Performance Comparison of Transformer-Based Model with Baseline Disaster Forecasting Models*

Model	Accuracy	Precision	Recall	F1-Score	Inference Latency (ms)	Training Time (hrs)
CNN-Based Model [74]	0.85	0.83	0.80	0.81	90	10
LSTM-Based Model [75]	0.88	0.86	0.84	0.85	120	14
Hybrid CNN-LSTM Model [76]	0.90	0.88	0.86	0.87	75	16
Proposed Transformer Model	0.94	0.91	0.89	0.90	45	12

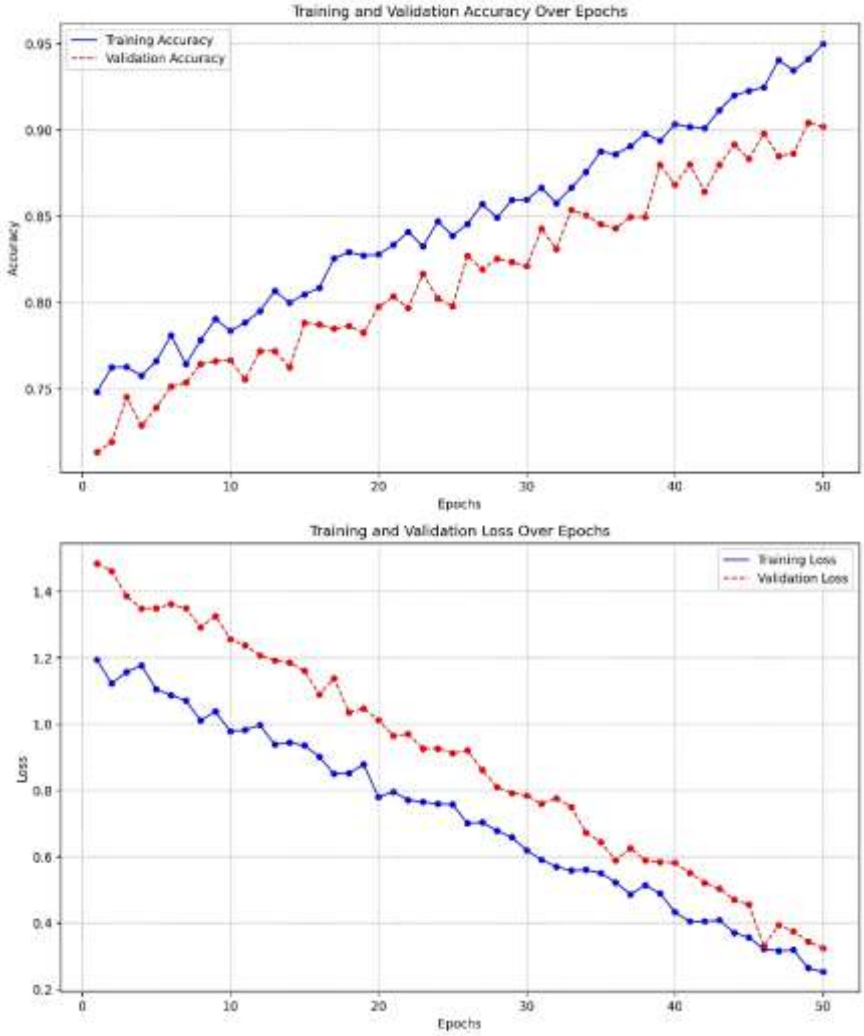

Figure 5. Training, validation and accuracy and loss

and interpretability, ensuring that decision-makers can confidently act on AI-generated risk predictions. Overall, the proposed model presents a transformative approach to AI-driven disaster forecasting, with future advancements poised to redefine early warning systems and climate change adaptation strategies worldwide.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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