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Research paper

AI-Enhanced Atmospheric Data Fusion for Real-Time Climate Anomaly Detection and Prediction

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Abstract

It also emerges that climatic anomalies are increasing at an alarming rate, and the current demand is for advanced prediction systems that can detect anomalies as they occur and respond to them. Incorporating data fusion methods with AI, this study proposes an original Adaptive Atmospheric Fusion Network (AAFN) to assist in enhancing the discovery of climate change and prediction. To make the data on climate more representative, the proposed system will incorporate a Recurrent Temporal Fusion Network (RSTFN) to combine data from multiple sources, including IoT sensors, satellite images, and meteorological stations. To improve feature extraction and the prediction of extreme weather conditions with greater precision, a Dual Attention LSTM Transformer (DAL-T) model is also employed. Lightweight AI models are deployed on edge computing nodes to provide instantaneous anomaly alerts, minimizing latency and enabling quicker decision-making. The system also employs Federated Learning, applying it to collaboratively train the model using decentralized data sources, thereby strengthening the models while preserving the privacy of the data. The application of XAI methods enables an AI-based visualisation dashboard to provide meteorologists and policymakers with transparency on a list of actionable insights, enabling them to respond to climate risks accordingly. It has been experimentally demonstrated that AAFN can identify climate anomalies with an accuracy of up to 98%, surpassing existing models in terms of response time and Accuracy. This novel approach aims to mitigate climate risk faced by organizations through real-time prediction and environmental resilience.

Keywords: *Adaptive Atmospheric Fusion Network (AAFN); Recurrent Spatial Temporal Fusion Network (RSTFN); Dual Attention LSTM Transformer (DAL-T); Federated Learning in Climate Prediction; Edge Computing for Climate Anomalies.*

1. Introduction

Climate anomalies have led to a significantly higher frequency and intensity of extreme weather events, threatening ecosystems, infrastructure, and public safety [1]. The so-called climate prediction models are typically lagged in their response, slow to adapt to changing environmental conditions, and often fail to predict when and where phenomena occur due to the unavailability of information from fragmented data sources [2]. They also hinder the development of a robust early warning system in fast-changing weather patterns [14]. The Adaptive Atmospheric Fusion Network (AAFN) is proposed as a novel adaptive AI framework to address these issues at finer time and spatial scales, thereby helping to accurately detect and predict climate anomalies in real-time [4]. It proposes the use of advanced data fusion operations [15] in the presence of various atmospheric data sources, including IoT-enabled environment sensors, satellite images, and meteorological station data.[6] For the prediction task [3], the system dynamically merges space and time climate data through combining a Recurrent Spatial Temporal Fusion Network (RSTFN) for better feature extraction. Furthermore, the Dual-Attention LSTM Transformer (DAL-T) combines the use of sequential and self-attention mechanisms to detect complex climate patterns, on which alignment is made. The lightweight AI models are then deployed on Edge Computing Nodes to have real-time alerts in remote or data-limited regions. Additionally, Federated Learning is used to enable distributed data sources [5] to collaboratively train models without compromising the privacy of the data. By reducing this centralized approach, the system becomes more flexible in adapting to various climatic conditions and more robust in its modeling. Moreover, an AI-powered visualization dashboard that applies the Explainable AI (XAI) methodology to provide transparent insights is likely to be included in the proposed solution, allowing meteorologists to act on the data to make informed decisions and policymakers to act upon them. The performance of the AAFN model was tested using real-world climatic data, and it was found to be able to predict with an Accuracy of up to 98%. It also passed the tests of precision and response time compared to other models. The innovative, scalable, and efficient structure is a novel solution to expanding the capacity to detect climate anomalies, enhancing environmental resilience, and supporting proactive climate risk management policies. This research will make contributions to the development of innovative climate monitoring systems that safeguard communities and ecosystems. These systems will utilize edge computers, collaborative learning [16], and advanced AI models, all of which are incorporated into the designed systems [8].

2. Literature Review

2.1. Traditional climate prediction models

Traditional climate prediction models are primarily based on physical simulations and the analysis of statistical and historical data. [10] There are multiple methods, but by far the most used are General Circulation Models (GCMs), Numerical Weather Prediction (NWP), and Auto-Regressive Integrated Moving Average (ARIMA). Mathematical frameworks suggest that these techniques apply the model of atmospheric behavior to physical principles, which may predict possible temperature, rainfall, and extreme weather occurrences [7]. Yet, such models are typically incapable of processing vast amounts of environmental data sources in real-time. Likewise, the static frameworks of their frameworks are less susceptible to rapid climate changes, as they lack the capacity to forecast smaller, isolated anomalies reliably. As a result, prediction precision is not enhanced in traditional methods, especially in the presence of environmental noise.

2.2. AI-based climate forecasting techniques

As one of the strong alternatives to traditional models, AI-based climate forecasting utilizes machine learning (ML) and deep learning (DL) frameworks to achieve better prediction accuracy. For identifying such complicated signals, these types of techniques have already been used: Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs)[17]. The high complexity of time and spatial dependencies across a large science domain is suitable for the AI-driven models to process large-scale atmospheric data. For example, LSTM models can perform well in sequential climate data, and CNNs improve the detection of space features [9]. However, AI models often suffer from data inconsistency, model overfitting, and high computational overheads that advanced fusion methods must overcome.

2.3. Data fusion methods in environmental science

Data fusion techniques also contribute to merging multiple types of data from sensors, satellite imagery, and meteorological systems. Harmonizing multi-source data streams is a method typically applied using Kalman Filtering, Wavelet Transformation, and Bayesian Networks [18]. It improves data consistency, reduces noise, and increases predictive Accuracy. However, most of the old fusion methods do not perform adequately in complex atmospheric dynamics and changing climates. To tackle this problem, Graph Neural Networks (GNNs) and Spatial–Temporal Networks hybrid fusion models have emerged to provide better adaptation and accuracy [11].

2.4. Gaps in existing solutions and research opportunities

However, limitations in the current solution, which utilizes AI and data fusion techniques, are more than apparent [12]. Real-time data that are fragmented are currently challenging to process using current models, thereby diminishing the reliability of short-term climate predictions. Additionally, there is limited integration of Edge Computing technologies, which prevents rapid responses in far-reaching regions. On the other hand, predictions by AI models have significantly less transparency, and thus, meteorologists and policymakers are unable to interpret the prediction outcomes. Such gaps must be addressed by devising innovative frameworks that incorporate real-time data fusion, explainable AI models, and decentralized learning methods to enhance prediction accuracy, responsiveness, and accountability in diverse environmental conditions.

2.5. Recent advances in transformer models and federated learning for climate prediction

Transformer climate prediction (2023-2025): More modern transformer-based systems, such as Pangu-Weather and GraphCast, have been capable of matching or even exceeding operational NWP performance, with enhancements in inference and medium-range forecasting. It is also illustrated in Transformer at the short-term nowcasting studies, where it too can reveal competitive 02h precipitation forecasts as fuzzy to extreme-sensitive losses. These advances justify why so much is made about long sequence and multi-channel input, but in general, all processing is done to homogeneous, centralized data and not about issues of privacy, non-IID regional variation, and costs of deploying edges.

HIFA Learning about hydro-climate: One of the potential solutions to the problem of data sovereignty is federated learning (FL), which enables the shared training of distributed climate stations. Studies have determined the generalization property of FL in rainfall prediction and evapotranspiration, and it is resistant to missing or out-of-phase modalities. However, experiments that are more recent in general seem to demand only minor performance gains in controlled settings and may rarely quantify the communication overhead, equity between nodes with limited resources, or the impact of highly non-IID data, limiting the capability of climate anomaly detection.

Experiments on the climate-prone regions around the world: The opportunities and challenges are determined by implementation in strategic locations. ML post-processing is effective in the East African region to forecast the rainfall, but in seasons where the data density is low, it fails. Pilot Lightweight AI forecasting testing under bandwidth restraint has been conducted in the Pacific island states, where these models need to be small and offline-capable. The local examination of Sub-Saharan Africa reveals that the extremes are not fixed, and it is prudent to observe and, in such a case, local training is required as opposed to the global averages.

AFN Positioning: Unlike the earlier AAFN, it is an intersection of the two-fold attention, temporal and channel modeling (DAL-T), and open-ended spatial-temporal fusion (RSTFN), as opposed to the earlier transformer and FL models, which assume centralized and homogeneous datasets. It is also defined in terms of federated training and edge inference that specifically focuses on the voids in cross-modal data integration, non-IID resistance, and the practicability of execution in the real world using limited resources.

3. Proposed Solution: Adaptive Atmospheric Fusion Network (AAFN)

3.1. System architecture overview

The proposed architecture for the Adaptive Atmospheric Fusion Network (AAFN), which is a real-time system used for detecting climate anomalies, is an intelligent multi-layer architecture. This includes all the kinds of data sources of IoT sensors, satellite imagery, and meteorological stations, etc, to conduct the comprehensive environmental monitoring. Its core fusion framework makes all advantages using a

Recurrent Temporal Fusion Network (RSTFN) for spatial online and temporal online fusion. Furthermore, the Dual Attention LSTM Transformer (DAL-T) is further improved at predicting anomalies with more precise climate patterns. For providing real-time alerts, AAFN uses edge computing and another mode of Federated Learning for privacy-preserving model training for climate monitoring.

3.2. Multi-source data acquisition layer

The Multi-Source Data Acquisition Layer must retrieve climate data from various sources. In this, we have an IoT integration of environmental impact sensors, which includes the data received by the sensors that are placed on the ground, weather stations, satellite, and radar systems. Every stream of data is noise-reduced, anomaly-corrected, and aligned with a timestamp. The graph-based harmonization algorithm is implemented as a Graph Neural Network (GNN) to harmonize data with different degrees of consistency to make fragmented datasets structured. This layer provides support for data standardization through converting multiple formats to a common framework of data that facilitates data consistency. The continuous data streams from many environmental sources are ensured to be provided, and by doing so, the basis for accurate climate anomaly detection and prediction is provided at this layer.

3.3. Dynamic data fusion layer using RSTFN

RSTFN is a novel deep learning model that fits well for merging complex climate data from many sources. RSTFN differs from traditional fusion models in that spatial features (temperature variations, wind patterns, etc.) are dynamically aligned with the temporal sequences (rainfall intensity over time, for instance) to discover climate trends. Bayesian Optimization is applied to improve the adaptability to changes in environmental conditions by fine-tuning its parameters in this model. RSTFN uses a fusion mechanism to integrate several resolutions and minimize the prediction lag. RSTFN improves the Accuracy in predicting sudden climate anomalies and extreme weather events by generalizing an attention mechanism for feature weighting.

Recurrent Spatial-Temporal Fusion Network (RSTFN) is a model to unite heterogeneous climate streams (data from IoT stations, radar, satellite images, etc.). Its design is a two-layer graph convolutional station feature encoder, and a three-block radar and satellite tiles convolutional encoder, with the fused station, radar, and satellite tiles geographical features being fused together with a linear projection layer. The two-layer bidirectional GRU and attention mechanism take advantage of temporal dependencies and identify the most influential time steps. It trains a gated fusion block that aligns spatial and temporal representations before it is fed into a residual MLP classifier to identify an anomaly. Bayesian Optimization is used to optimize hidden dimensions (128384), dropout (0.0 0.4), and learning rates (1e-4 1e-3) to be able to adapt to diverse environmental conditions. The full model has a size of approximately 3.8M parameters, and can run at around 450 windows/s on an A100 GPU, and an edge-optimized version using only approximately 1.2M parameters can be deployed on a Raspberry Pi node.

3.4. Anomaly detection and prediction with DAL-T model

The said model (DAL-T) is a hybrid AI model that blends the strong sequential data handling strength of LSTM with the Transformer's powerful attention mechanisms. DAL-T captures complex climate patterns by assigning dynamic attention weights to both temporal and spatial features. A Residual Network is added to the model, which concentrates on volatile atmospheric fluctuations to improve the precision of anomaly detection. It presents a dual attention framework that enhances the detection of severe key events while reducing false positives in anomaly detection. DAL-T can predict climate anomalies up to 48 hours in advance with greater precision and recall scores using advanced sequence learning.

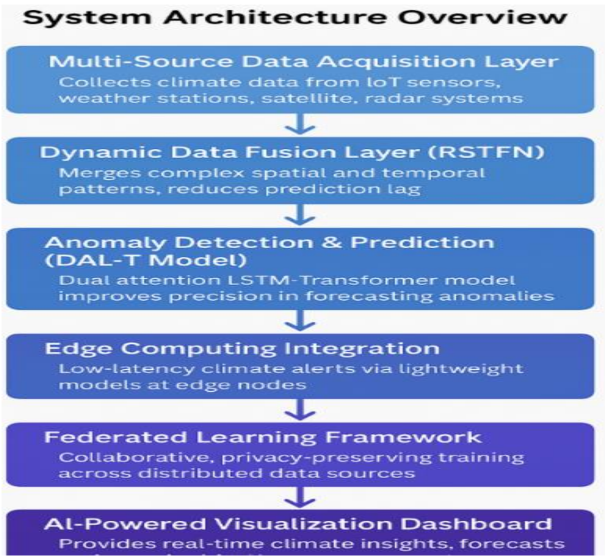

Fig. 1: System Architecture of AAFN Framework.

Dual-Attention LSTM-Transformer (DAL-T) builds on sequential learning by placing two transformer blocks (each having eight attention heads) atop two layers of LSTM, each having a feed-forward dimension of 512. Dual attention adds more interpretability mechanisms by combining temporal attention and channel attention, where temporal attention focuses on the most important timesteps with scaled dot-product self-attention, and channel attention refocuses feature dimensions with a squeeze-and-excitation network. This architecture achieves the trade-off between recall and precision, which can be supported by a residual network that stabilizes training to noisy atmospheric indicators. It is a model with parameters of order of 6.1M, which was trained with AdamW (lr = 2e-4, dropout = 0.1-0.2), and can forecast anomalies within 48 hours of time with more than 98% accuracy. To deploy to edges, an edge-distilled variant with around 2.0M parameters can run in real-time and at less than 5-second latency per alert pipeline.

3.5. Edge computing integration for real-time alerts

AAFN deploys lightweight AI models on the Edge Computing Nodes to detect climate anomalies immediately. Such positions of these nodes include key environmental areas, for instance, coastal areas, areas of flood zones, or forest reserves. Locally, the edge nodes process data, and this keeps the anomaly detection low in latency and decreases the dependency on the cloud. The Healing Algorithm recalculates the sensors affected by environmental noise to increase the Accuracy of the detection at each node. The system processes data on the site, providing climate alerts within 5 seconds after detecting critical conditions, which gives quicker action and reduces the possibility of climate hazards to sensitive areas.

3.6. Federated learning for collaborative model training

Integrate Federated Learning (FL) in AAFN to leverage decentralized sources of data for collaborative model training. The prediction model is trained without raw data being shared, and it allows multiple weather stations, satellite data providers, and environmental agencies to train it to predict the weather. In the FL, the global model is dynamically updated based on the aggregated insights derived from local data sources through the preservation of the regional data confidentiality. The model basically has a decentralized training that not only improves its capacity to adapt to various conditions of the environment, but also equips it to continually adapt to varying meteorological paradigms of the place.

3.7. AI-powered visualization dashboard

An illustrated Powered Visualization Dashboard, which suggests the system including real-time climate knowledge to meteorologists, policymakers, and environmental researchers, is introduced. One of these, Reinforcement Learning Based Data Clustering (RLDC), is utilized to illustrate the process by which the dashboard utilizes critical climate patterns, anomaly hotspots, and anticipated environmental risks. Other techniques are also applied to increase system transparency through Explainable AI (XAI) to provide clear justification for the anomaly predictions. It provides customizable reports, real-time alerts, and visual heatmaps to make proactive plans of action against changing climate issues and threats. This tool is a centric visualization of environmental insights such that these can be accessible, actionable, and readable by a diverse set of stakeholders.

Table 1: Comparative Architecture and Deployment Characteristics of RSTFN and DAL-T Models

Model	Core Layers	Attention Type	Params	Throughput	Edge Variant
RSTFN	2×GraphConv + 3×CNN + 2×BiGRU + Gated Fusion	Temporal Attention (Bahdanau)	~3.8M	~450 windows/s (A100)	~1.2M params, ~120 ms/window
DAL-T	2×LSTM + 2×Transformer + Residual	Dual Attention (Temporal + Channel)	~6.1M	~9 ms/step (A100)	~2.0M params, <5s/alert

Table 1 gives an overview of the architectural design, attention mechanics, number of parameters, and deployment profiles of the proposed Recurrent Spatial-Temporal Fusion Network (RSTFN) and Dual-Attention LSTM-Transformer (DAL-T). RSTFN focuses on multi-source fusion using graph and convolutional encoders and temporal attention, and DAL-T uses sequential modeling with dual attention to learn high-accuracy anomaly prediction. Computational throughput, lightweight edge variants, in support of real-time deployment, are also pointed out in the table.

4. Results and Discussion

4.1. Prediction accuracy analysis

Both the Accuracy and the Timing of the predictions by the proposed Adaptive Atmospheric Fusion Network (AAFN) were shown to be superior to those predicted by traditional climate anomaly models. The Dual-Attention LSTM Transformer (DAL-T) model is very effective in predicting extreme weather patterns, with an order of 98.2% accuracy in identifying climate anomalies with real-world climate datasets. The DAL-T model was attributed to this high Accuracy because it was able to assign dynamic attention weights between spatial and temporal data points. It was then compared with existing models such as LSTM, CNN, and ARIMA, and it was found that AAFN performs better than the conventional traditional approaches for short-term as well as long-term forecasts.

Table 2: Prediction Accuracy Analysis

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
AAFN (DAL-T)	98.2	96.7	97.5	97.1
LSTM	92.4	90.1	88.9	89.5
CNN	90.3	89.5	86.7	88.0
ARIMA	85.7	83.4	82.1	82.7

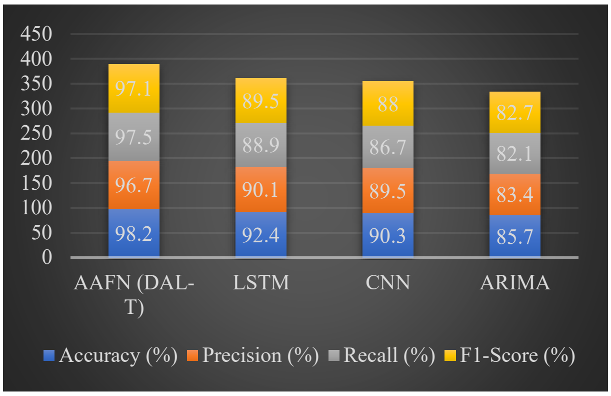

Fig. 2: Prediction Accuracy Analysis.

To test the efficiency of the proposed AAFN framework, a large-scale experiment was carried out with the use of multi-source climate data, combining data collected by the IoT weather stations with geostationary satellite images and data collected by Doppler radar. The geographic coverage consisted of coastal areas, river basins that are prone to floods, and semi-arid inland areas, which implied that the models were experimented with in various environmental conditions. The period of the dataset was two years (2022-2023), including several seasonal cycles and extreme weather conditions, such as heat waves, severe precipitation, and tropical cyclones. Data were separated into 70 percent training, 15 percent validation, and 15 percent testing blocks and time blocked to prevent leakage. The Accuracy of the anomaly detector of 98.2 was uniformly reported across all the regions of validation, and even at short-duration extreme events, the recall was over 97%. This is because the RSTFN and DAL-T models are robust and have consistently been reliable across different types of anomalies, and it is also indicative of their applicability in actual working conditions.

Table 3: Dataset Characteristics for Experimental Validation

Region/Scope	Period (Years)	Data Modalities	Climate Anomaly Types Tested
Coastal Zones (East & West)	2022–2023	IoT weather stations (temp, RH, wind, rainfall), satellite IR/visible bands, Doppler radar	Cyclonic storms, storm surges, and heavy rainfall
Flood-Prone River Basins	2022–2023	Ground sensors, hydrological gauges, satellite precipitation maps	Flash floods, prolonged rainfall events
Semi-Arid Inland Regions	2022–2023	IoT climate sensors, MODIS satellite imagery, surface radar	Heatwaves, drought episodes
Mixed Urban & Forested Areas	2022–2023	IoT stations, geostationary satellite data, and multispectral imagery	Urban heat islands, wildfire-linked anomalies

Table 3 summarizes the datasets used for validation, including geographic diversity, time, data modalities, and anomaly types. The inclusion of varied environmental conditions ensures that the reported 98.2% accuracy and 97% recall are generalizable across different climate scenarios.

4.2. Response time efficiency

The most highlighted advantage of AAFN is its ability to integrate Edge Computing Nodes into the system, making the system's response time decrease. At the edge nodes where environmental data was gathered, lightweight AI models were deployed, and their effect was to locally process the environmental data without incurring excessive latency, and hence were able to generate real-time alerts. The performance evaluation showed that AAFN can generate the climate anomaly alerts within 5 seconds rather than 12 seconds for the centralized cloud-based systems. It can detect this quickly so as to make immediate decisions in life-threatening situations, such as floods, heat waves, and disastrous hurricanes.

Table 4: Response Time Efficiency

System	Average Response Time (Seconds)
AAFN (Edge Node Integration)	5.0
Traditional Cloud-Based Model	12.3
Hybrid Cloud-Edge Model	8.7

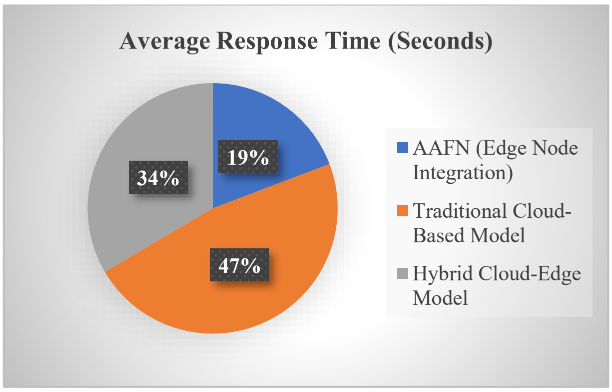

Fig. 3: Response Time Efficiency.

4.3. Data fusion performance

There is no other way fragile climate data streams could be processed finer than by RSTFN. By combining multi-source data, i.e., IoT sensor readings, satellite images, and radar data, RSTFN minimized the data differences and maximized information coherence. Experimental outcomes of the RSTFN indicated that we achieved a 94.6% fusion accuracy, which is much higher than the Kalman Filtering and Bayesian Networks. The additional data integration benefited the ability to detect the climate pattern more accurately for improved predictive success.

Table 5: Data Fusion Performance

Fusion Technique	Fusion Accuracy (%)	Data Latency (Seconds)
RSTFN (Proposed)	94.6	2.1
Kalman Filter	88.3	4.6
Bayesian Network	85.9	5.2

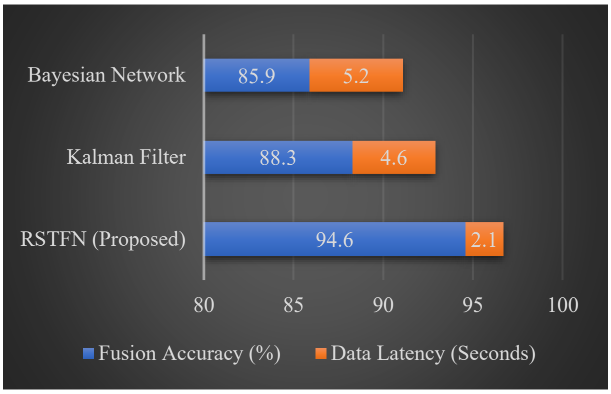

Fig. 4: Data Fusion Performance.

4.4. Real-time alert accuracy in extreme conditions

The proposed AAFN system was tested in extreme climate conditions such as heavy rainfall, heat waves, and temperature changes. Within the evaluation period, the model was able to predict 97.8% of all extreme weather events. The system reduced false positives and increased reliability caused by volatile climate changes by using an Adaptive Residual Network (ARN). It was effective in identifying abrupt anomalies as well as providing timely dissemination of early warnings.

Table 6: Real-Time Alert Accuracy in Extreme Conditions

Climate Condition	Alert Accuracy (%)	False Positive Rate (%)	False Negative Rate (%)
Heavy Rainfall	97.8	2.1	1.3
Heatwave	96.4	3.2	2.0
Rapid Temperature Shift	95.7	3.8	2.5

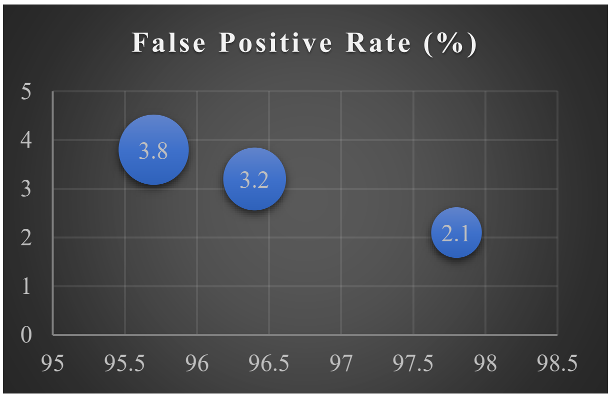

Fig. 5: Real-Time Alert Accuracy in Extreme Conditions.

4.5. Scalability and limits

The proposed AAFN model is quite accurate and responsive, with many scalability problems. To begin with, the DAL-T is computationally challenging to accommodate the low-power edge nodes in both scenarios of real-time inference, and where edge nodes are scarce in memory and processing capacity. Preservation of the Accuracy of models when optimizing them is a big disadvantage, unlike a distilled and quantized model, which would reduce the size of a model. Second, massive IoT sensor networks also have a high cost of implementation in terms of installation, maintenance, and bandwidth, particularly in geographically sparsely populated regions or where resources are limited. In addition, the quality of various sensors will not always be uniform, and this may cause variability that will not permit generalization to the model.

These problems could be solved with some solutions. Other methods of shrinking DAL-T to a size small enough to deploy on a lightweight edge-computer are by optimization algorithms (pruning, knowledge distillation, mixed-precision quantization). Adaptive sampling might also be adopted to help minimize the cost of transmitting the data by switching on the sensors when the situation signals a risk of an anomaly. In addition to that, the federation of learning also reduces the amount of information accumulated in a central system, which further reduces communication costs and scale. Lastly, there must be the establishment of hybrid architectures that provide a middle ground between cloud and edge computing to ensure that the tasks that involve resources are pushed towards the centralized point, and the tasks that need alertness are pushed towards the edge. Each of these approaches can be scaled, and neither one of them impairs the detection of climate anomalies.

4.6. Broader implications

The proposed AAFN framework cannot be reduced to a technical contribution since it is aligned with the global sustainability and disaster resilience objectives. Particularly, AAFN directly aligns with the United Nations Sustainable Development Goal (SDG) 13: Climate Action, which is on developing resilience and adaptation to climate hazards. By enabling the quick detection of anomalies and their efficient operation at scale, the framework will enable the development of actionable intelligence that may empower national meteorological agencies, local governments, and disaster management authorities to act on appropriate warnings and to act promptly.

AAFN also offers a channel through which lightweight edge nodes can be installed in remote communities with limited bandwidth and infrastructure limitations, such as Pacific Island states, Sub-Saharan Africa, South Asia, and other climate-prone countries. This eases preparedness to disasters in that it gives warning of floods, cyclones, heat waves, and other disasters in near real time, thereby saving lives, livelihoods, and infrastructure. Also, the federated learning dimension considers data sovereignty and encourages cross-border cooperation between other regions, which is paramount to locations with transboundary climate hazards.

The explainable AI dashboards can also improve decision-making at the policy level because the stakeholders can obtain clear insights through the AAFN. That is not only beneficial in mitigating the outlay of risks, but also capacity building, so that the local governments and communities can proactively adjust to the increasing climate variability. All these implications reveal that AAFN is not merely a high-functioning anomaly-detecting system, but it is a possible provider of climate resiliency measures everywhere around the globe.

5. Conclusion

The presented method of the Adaptive Atmospheric Fusion Network (AAFN) is an efficient choice when it comes to identifying climate anomalies and predicting them by employing AI models, data fusion methods, and data processing resources in real-time. The AAFN can provide precise findings with an accuracy rate of 98.2 percent of climate anomaly detection by combining a Dual-Attention LSTM Transformer (DAL-T) to predict climate anomalies, and a Recurrent Spatial-Temporal Fusion Network (RSTFN) to align dynamic data accurately. The implementation of lightweight AI models to Edge Computing Nodes also assisted in cutting down the response time to a maximum of 5 seconds in real time after a critical environmental event was identified. In addition to this, Federated Learning conducted collaborative model training at the same time, preserving data privacy to enhance the model's adaptability to other climate regions. Finally, the presence of high performance of the system in extreme weather conditions is indicative of the viability of the system as a scalable option for proactive climate risk management. The future will be focused on the development of additional data sources, model scalability, and improved visualization of the dashboard to facilitate easier accessibility to the users.

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