XB-RescueNet: Explainable Blockchain-Integrated Deep Learning Network for Real-Time Disaster Management

M. Satya Vijaya[1],A. Vasantha[2],G. Priyanka[3],B. Jayanthi[4],SK. Naseema[5]

Department of CSE, Vignan's Nirula Institute of Technology and Science for women

Palakaluru, Guntur, 522009, Andhra Pradesh, India.

Abstract

Strong situational awareness, rapid response, and unambiguous decision-making are essential for the effective and timely handling of natural disasters with recent advancements in deep learning, disaster events may now be automatically detected and their damage assessed using satellite and aerial photos. Remote sensing platforms and unmanned aerial vehicles (UAVs) survey impacted areas at a broad scale with high resolution. However, their practical usage is typically limited by challenges such as data security concerns, interoperability problems, problems with explainability in deep learning models, and dependable coordination among stakeholders. An explainable deep learning framework for integrated disaster management is presented in this research. It is protected by blockchain technology and makes use of analysis of images taken by drones and satellites. This method uses the distributed ledger technology of blockchain to guarantee the security, privacy, and trustworthiness of data as well as to facilitate the forecast of disasters, the categorization of damage, and the distribution of resources. Results from models and case studies demonstrate that disaster response operations can benefit from increased cybersecurity, improved communication, and faster coordination. This exemplifies the practicality of the framework.

Key Words: Explainable AI (XAI), Deep Learning, Blockchain Technology, Quantum Key Distribution (QKD), Disaster Management, Remote Sensing & UAV's.

Introduction

The number and severity of natural disasters have increased in the 21st century, wreaking havoc on people's lives, businesses, and infrastructure [1] [2]. Natural disasters such as floods, earthquakes, wildfires, and droughts are exacerbated by factors such as climate change [3], fast urbanization, and environmental degradation [4]. Natural catastrophes caused by climate change impacted more than 3.3 billion people and cost the world economy trillions of dollars between 2000 and 2020 [5]. Extreme consequences, such as population displacement and fatalities, befall vulnerable areas like India [6]. There are limitations to the modeling of complex environmental-social interactions [7], data imbalances [8], and data gaps in traditional disaster prediction approaches that rely on historical data [9].

Models like as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs) [10], and XGBoost enhance catastrophe classification even in the presence of noisy or incomplete data [11]. Neural networks, ML, and DL are examples of emerging technologies that offer potential solutions [12]. But there are still problems with trust and explainability with black-box AI models since they don't provide enough information for important decisions [13]. Data privacy and integrity assurance is equally critical [14]. When it comes to disaster management [15], blockchain technology's secure and decentralized architecture can improve trust, auditability, and data protection [16]. Full integration is still a way off, but it's showing promise in relief operations and insurance automation [17] [18].

2.Existance models

2.1 XAI-Based Flood Prediction & Early Warning Systems

This model is able to anticipate floods by making use of deep learning architectures such as CNNs and LSTM networks. It handles a wide variety of datasets [19], including hydrological models, river flow data, satellite photos, and rainfall patterns [20]. Different from LSTMs, which detect patterns in rainfall and water levels, CNNs extract features from photos [21].

Included are Explainable AI (XAI) methods such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) to guarantee that disaster management authorities can rely on and comprehend the forecasts [22]. By revealing which features affected the forecasts, these approaches throw light on important details like the most vulnerable regions. This aids authorities in making advance preparations for evacuations [23].

2.2 Earthquake Damage Assessment with DL + XAI

It is critical to swiftly evaluate building safety in earthquake-prone areas. This algorithm analyzes seismic data [24], building information, and sensor networks using deep learning techniques to forecast the amounts of damage [25]. To clarify why certain structures are designated as "high risk," it makes use of techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) and LIME [26]. Seismic stress zones or materials with a low resistance to seismic activity are two potential examples [27]. In order to minimize injuries and damage, engineers and emergency management teams can use the clear explanations to prioritize inspections, reinforce structures, or evacuate risky regions more effectively [28].

2.3 Blockchain-Based Disaster Relief Supply Chain

It is typically difficult to trace the distribution of help and relief after a disaster because supply chains are disrupted [29]. To keep tabs on necessities like food and medicine, this concept employs blockchain technology to build a distributed, public, and trustworthy record [30]. Donations, warehousing, and final distribution are all meticulously documented. In times of crisis, this promotes equitable distribution, safeguards against fraud, and strengthens relationships between donors and recipients [31]. The use of smart contracts can help streamline the approval and checkpoint processes involved in the supply chain [32].

3.Disadvantages

Despite the potential benefits to disaster preparedness, there remain substantial obstacles to the widespread use of XAI-based flood prediction systems in the actual world [33]. The lack of access to large volumes of labelled data in developing nations makes these models unreliable and inaccurate [34]. Deploying post-hoc explanation techniques such as SHAP or LIME in systems with limited resources is difficult due to their large processing requirements, and these tools may not always provide reliable insights, which could lead stakeholders astray [35]. Similarly, earthquake damage assessment algorithms frequently experience accuracy loss when deployed across different geographic contexts and struggle with limited or sparse datasets [36]. Disaster zones with limited internet connectivity can have slow speeds, high energy consumption, and hefty transaction fees when using blockchain-based rescue supply chain systems. However, these systems do provide transparency and security [37].

Literature survey

New developments in catastrophe categorization and assessment have made use of deep learning and transformer-based models [1-3]. Building damage segmentation was tackled by Weiwei Xiao et al. (2023) using a hierarchical framework [15] that integrated Siamese transformers, Segformer structures, and satellite imagery.[1] The researchers achieved good disaster-wide generalization but had challenges with class imbalance [5]. By utilizing lightweight transformers such as BERT-tiny within an NLP-based

OSEMN framework, Saima Saleem et al. (2024) were able to classify disasters in real-time using social media data on devices with minimal resources, using only text inputs [38].

Using deep ensemble CNNs with XGBoost and SVM, with the help of LIME and SMOTE for data balance [12] and explainability, Akella S. Narasimha Raju et al. (2025) investigated image-based methods.[3] Despite its good performance, their model did not use blockchain technology [9]. Two studies that focused on blockchain technology were Xuehong Gao et al. (2024) and Kulaea Taueveeva Pauu et al. (2024).[4-5] Xuehong and Kulaea both encountered problems with scalability and network stability, but their solutions included smart connected products for disaster relief manufacturing and the integration of federated learning with UAVs and differential [8] privacy for secure distributed disaster response [39]. Secure post-disaster data exchange, mostly in vehicle scenarios [13], was created by Huihui Wang et al. (2024) using a blockchain-based IoV framework [40].

Iskender Peker et al. (2023) utilized fuzzy MCDM methods to promote blockchain adoption in epidemic risk management;[17] Barry Sheehan et al. (2023) described a convergence of AI, blockchain, and parametric insurance for disaster financing [11]; and other researchers tackled broader frameworks and practical applications [41]. While YOLO-based drone monitoring by T. Neha et al. (2024) was successful in the field, it was severely constrained by lighting and occlusion.[19] An interpretable model was proposed by Muhammad Asim Saleem et al. (2025) utilizing XGBoost and neural networks [20]. It achieved good accuracy, although it faced regional bias and required considerable labelled data [10].

Proposed model

XB-RescueNet is a state-of-the-art system that integrates deep learning, blockchain technology, and quantum-secured communication to manage disasters in real-time. It uses Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), and Transformers to analyze various data sources, including sensor inputs, social media feeds, and satellite imagery. This allows for data-driven reactions to disasters such as floods, earthquakes, and wildfires, which are carried out quickly. Emergency responders can confidently comprehend and act on AI-generated warnings thanks to an integrated Explainable AI (XAI) layer that promotes transparency and trust. This layer provides visual heatmaps, decision graphs, and counterfactual explanations.

With the use of smart contracts that facilitate cooperation among governments, NGOs, hospitals, and individuals, XB-RescueNet integrates blockchain technology for unchangeable record-keeping and secure collaboration. Even in the most dangerous cyber environments, important communications are protected by Quantum Key Distribution (QKD) and quantum-resistant encryption. As a result of its global interoperability, which promotes cross-border cooperation and confidence, and its modular architecture, which allows dynamic adaption to different types of disasters without redesigning the system, XB-RescueNet is a strong and cohesive platform for international disaster relief operations.

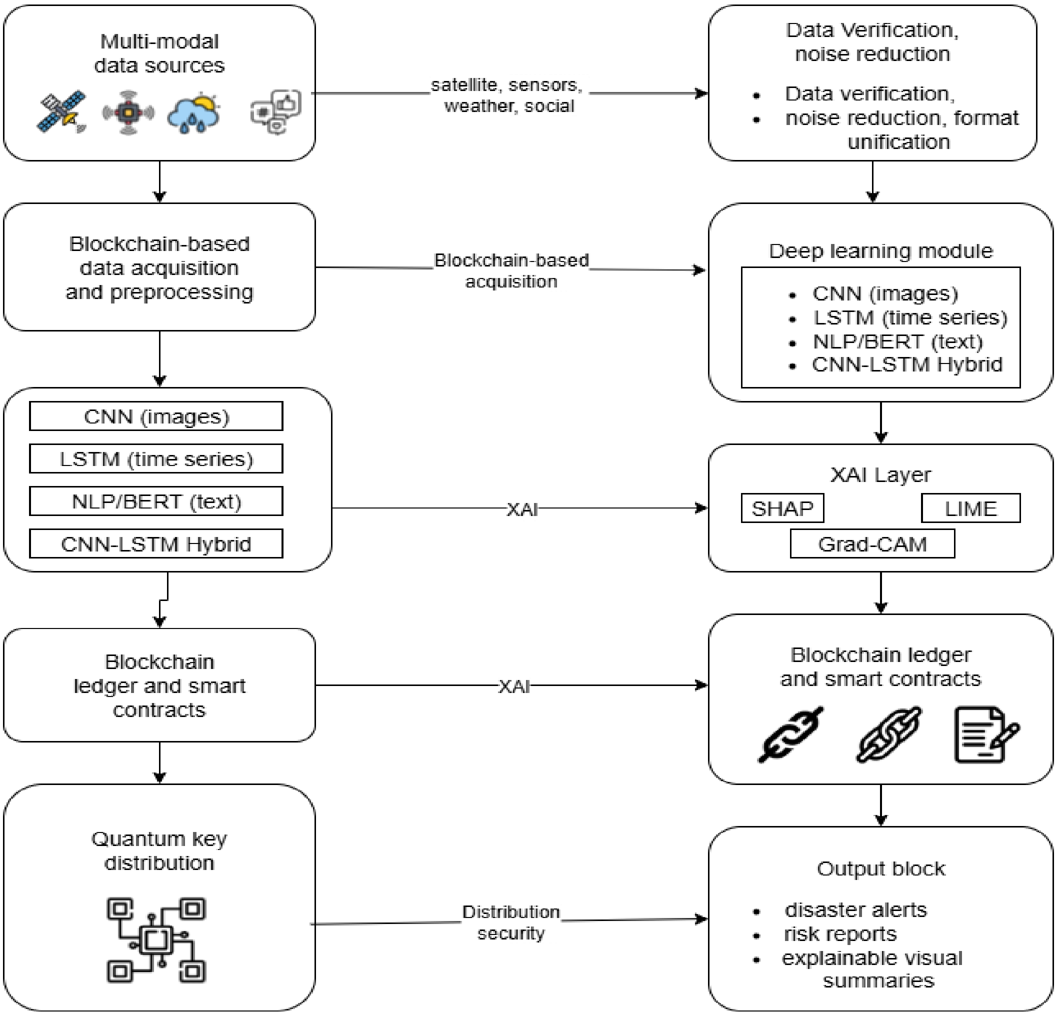

Fig a: Systematic diagram/ Architecture

Methodology

To guarantee precise, open, and protected emergency response, XB-RescueNet combines deep learning, blockchain technology, and quantum-secured cryptography into a real-time catastrophe management system. It is structured in six steps: collecting data from various sources (satellite images, internet of things sensors, social media), cleaning, extracting features, and balancing it. Then, for disaster assessment and prediction, it uses deep learning models (CNNs, LSTMs, Transformers, NLP). The insights provided to responders can be understood by a XAI layer that utilizes SHAP, LIME, and Grad-CAM. Quantum Key Distribution (QKD) safeguards communication and authentication amongst parties, while blockchain guarantees data integrity and automates collaboration through smart contracts. A simplified workflow of data collection, prediction, explanation, recording, action, and secure communication is made possible by the modular design of the system, which allows for worldwide collaboration and multi-disaster adaptability.

A. Multimodal Feature Extraction and Fusion using equation (1)

1. Image Features (CNN): Extract image features from satellite or drone images. Here, $I_t$is the input image from a satellite or drone, and f_{CNN} represents a convolutional neural network with parameters. θ_IThe CNN extracts spatial patterns and converts them into a feature vector v_t^Ithat captures disaster-related visual cues like floods or fires.

$$v_I^t = f_{CNN}(I_t; \theta_I) \qquad (1.1)$$

2. Sensor/Time-Series Features (LSTM): Process IoT sensor readings over a recent time window L. This represents sensor readings over a time window, such as water level or temperature. The LSTM captures temporal dependencies and trends, producing a feature representation v_t^Sthat reflects evolving disaster conditions.

$$v_S^t = f_{LSTM}(S_{t-L+1:t}; \theta_S) \quad (1.2)$$

3. Text/Social Media Features (Transformer): Encode social media or text data. This denotes textual data from social media or news sources, and f_{Trans} is a Transformer encoder. It learns semantic and contextual embeddingsv_t^T, providing insights from crowd-sourced and real-time textual reports.

$$v_T^t = f_{TR}(T_t; \theta_T) \quad (1.3)$$

4. Feature Fusion: Combine all features (Image + Sensor + Text). All extracted features are concatenated and passed through a fusion network. f_{fusion} This creates a unified representation v_t, allowing the model to combine different types of information for better disaster prediction.

$$z_t = g(v_I^t \oplus v_S^t \oplus v_T^t; \theta_g) \quad (1.4)$$

5. Final Prediction: The final prediction layer takes the fused feature vector v_t and outputs the predicted disaster type or severity level $\hat{y}_t$. This output is then used for alert generation and disaster assessment.

$$\hat{y}_t = h(z_t; \theta_h) \quad (1.5)$$

B. Total Loss Function (Combined Objective) Overall training loss using equation (2)

The total training loss combines several objectives, each weighted by coefficients α_i. This ensures the model maintains accuracy, understandability, security, efficiency, and privacy simultaneously.

$$L(\theta) = L_{task} + \lambda_{xai}L_{xai} + \lambda_{chain}L_{chain} + \lambda_{lat}L_{lat} + \lambda_{priv}L_{priv}$$

1.Task Loss

For classification tasks, cross-entropy loss measures prediction accuracy. For severity estimation (regression), Mean Squared Error (MSE) minimizes the difference between predicted and true values.

For classification: $L_{task} = -\frac{1}{N}\sum_{t}\sum_{c} y_{t,c} \log(\hat{y}_{t,c})$ (2.1.1)

For regression (e.g., severity): $L_{task} = \frac{1}{N}\sum_{t}(\hat{y}_t - y_t)^2$ (2.1.2)

2. Explainability Loss Encourages clear, simple explanations: This loss penalizes complex or unclear gradients. It promotes sparse and understandable feature attributions, improving model transparency for human experts.

$$L_{xai} = \frac{1}{N}\sum_{t}(\alpha \parallel S_t \parallel_1 + \beta D_{align}(S_t, M_t)) \quad (2.2)$$

3. Blockchain Integrity Loss Penalizes mismatch between local and on-chain data. This loss ensures consistency between local model outputs and blockchain-verified data. It maintains trust by penalizing any mismatched or altered information

$$L_{chain} = \frac{1}{N}\sum_{t} 1\left(H(data_t) \neq onchain_{hash_t}\right) \quad (2.3)$$

4. Latency Loss Ensures fast predictions: This loss penalizes the model whenever its inference time $\tau(\theta, x_t)$exceeds the maximum allowed latency τ_{max}.. It ensures that the model processes disaster data quickly, maintaining real-time responsiveness during emergencies.

$$L_{lat} = \frac{1}{N} \sum_t max\,(0, \tau(\theta, x_t) - \tau_{max}) \qquad (2.4)$$

5. Privacy Loss Maintains differential privacy: This loss enforces privacy-preserving learning by minimizing the difference between normal model parameters θ and their differentially private version θ_{DP} It protects sensitive data from leakage while maintaining model accuracy and integrity.

$$L_{priv} = \| \theta - \theta_{DP} \|^2 \qquad (2.5)$$

C. Explainability (XAI) Mechanisms using equation (3)

1. Grad-CAM (for images): Grad-CAM highlights image regions influencing the prediction for class c. It uses gradient-based importance weights α_k^c to visualize critical disaster areas in satellite images.

Normalized: $S_{GradCAM}^t(i, j) = ReLU\left(\sum_k \propto_k^C A_{ij}^k\right)$ (3.1.1)

$$\tilde{S}_t = \frac{S_t}{\sum_{i,j} St(i,j)} \qquad (3.1.2)$$

2.Integrated Gradients (for sensors/text): Integrated Gradients quantify the contribution of each input feature x_i. This helps identify which sensor or text elements most affect the model's decision.

$$\bar{I}G_i(x) = (\mathrm{x}\,i - x_i') \int_0^1 \frac{\partial F(x\prime + \dot{\alpha}(x - x\prime))}{\partial x_i} \alpha \qquad (3.2)$$

3.Counterfactual Explanation: Find a small change δ that changes the output class. Counterfactuals find minimal changes in input that alter the output. They show how sensitive the model is to input variations and enhance understanding.

$$\delta^* = \arg\min_{\delta} \| \delta \|_p + \gamma \ell_{CF}(x + \delta, y_{target}) \qquad (3.3)$$

D. Blockchain Integrity using equation (4)

1. Block Hash: This equation computes a unique cryptographic hash for each block using the previous hash, timestamp, data, and digital signature. It ensures immutability and traceability; any alteration in data changes the hash, preserving blockchain integrity.

$$h_t = H(h_{t-1} \,\|\, timestamp_t \,\|\, data_t \,\|\, \sigma_t) \qquad (4.1)$$

2. Merkle Root (for data batch): Each record is $r_i$hashed into l_i, and all hashes are combined into a Merkle root M. This compact representation allows fast verification of data batches and guarantees that stored disaster records have not been altered.

$$l_i = H(r_i), M = \mathrm{MerkleRoot}(l_1, \dots, l_n) \qquad (4.2)$$

3.Smart Contract Rule: This represents an automated blockchain rule. If the on-chain condition is $P(onchain_data)$satisfied, a predefined action is triggered. It ensures secure, transparent, and decentralized decision-making during disaster response operations.

If $P(onchain\_data) = True \Rightarrow Execute(action)$ (4.3)

E. Secure Communication (QKD Integration) using equation (5)

1. QKD Key Rate (simplified): This defines the minimum achievable quantum key distribution (QKD) rate R. It shows how key generation efficiency depends on quantum error rate e_b, ensuring secure and efficient key exchange between nodes.

$$R \geq q[1 - h(e_b) - f(e_b)h(e_b)] \quad (5.1)$$

where e_b= error rate, $h(\cdot)$= entropy function.

2. Encryption using QKD Key: Here, the message is encrypted using a quantum key K_{QKD} to produce ciphertext c. This quantum-secure encryption protects sensitive disaster data from interception during transmission.

$$c = Enc_{K_{QKD}}(m) \quad (5.2)$$

F. Evaluation Metrics using equation (6)

Accuracy measures how often the predicted disaster class $\hat{y}_t$ matches the true label y_t. It evaluates the correctness of the model's classifications.

$$Acc = \frac{1}{N}\sum_t 1\,(\hat{y}_t = y_t) \quad (6.1)$$

$$\tau_{avg} = \frac{1}{N}\sum_t \tau\,(\theta, x_t) \quad (6.2)$$

$$I = \sum_t 1\,(H(local_t) \neq onchain_t) \quad (6.3)$$

G. Online Update & Alert Decision Model update using equation (7)

Model parameters θ are updated continuously using a learning rate η_t and gradient information. This allows ongoing learning from new disaster data, keeping the model current.

$$\theta_{t+1} = (1 - \eta_t)\theta_t + \eta_t \nabla_\theta L(x_t, y_t; \theta_t) \quad (7.1)$$

Alert trigger: An alert is issued when the predicted disaster severity $\hat{y}_t$ exceeds a set threshold τ_a and is confirmed on the blockchain. This ensures accurate, verified, and timely disaster notifications.

$$Alert_t = 1(\hat{y}_t \geq \tau_a \wedge confirm\_onchain(h_t)) \quad (7.2)$$

H. Compact Combined Loss using equation (8)

This equation defines the final total loss combining task accuracy, explainability, blockchain consistency, and latency terms. Each term is weighted by λ to balance understandability, security, and real-time efficiency in the XB-RescueNet framework.

$$L(\theta) = -\frac{1}{N}\sum_t \sum_c y_{t,c} \log(\hat{y}_{t,c}) + \lambda_{xai}\frac{1}{N}\sum_t \| S_t \|_1 + \lambda_{chain}\frac{1}{N}\sum_t BCE\,(\sigma(H(data_t)), onchain_t) + \lambda_{lat}\frac{1}{N}\sum_t max\,(0, \tau(\theta, x_t) - \tau_{max}) \quad (8)$$

Results

1. F1 Score per Epoch

A measure that integrates recall and precision, the F1 Score is computed as the harmonic mean of the two. You can see how well the model handles false positives and false negatives as it learns by monitoring the F1 score over training epochs. A higher F1 score, particularly on the validation set, shows that the model accurately captures the classes without being overly or underly biased. Finding out which architecture is better at generalizing to new data is as easy as comparing F1 scores across models and epochs, which also aids in diagnosing underfitting and overfitting.

Table1: F1 Score per Epoch

Epoch	CNN Train F1	CNN Val F1	LSTM Train F1	LSTM Val F1	Hybrid Train F1	Hybrid Val F1
1	0.12	0.12	0.41	0.41	0.60	0.50
10	0.16	0.16	0.51	0.50	0.98	0.62
20	0.17	0.17	0.60	0.56	1.00	0.66
30	0.17	0.17	0.66	0.60	1.00	0.70
40	0.10	0.10	0.70	0.61	1.00	0.72
50	0.18	0.18	0.73	0.62	1.00	0.73

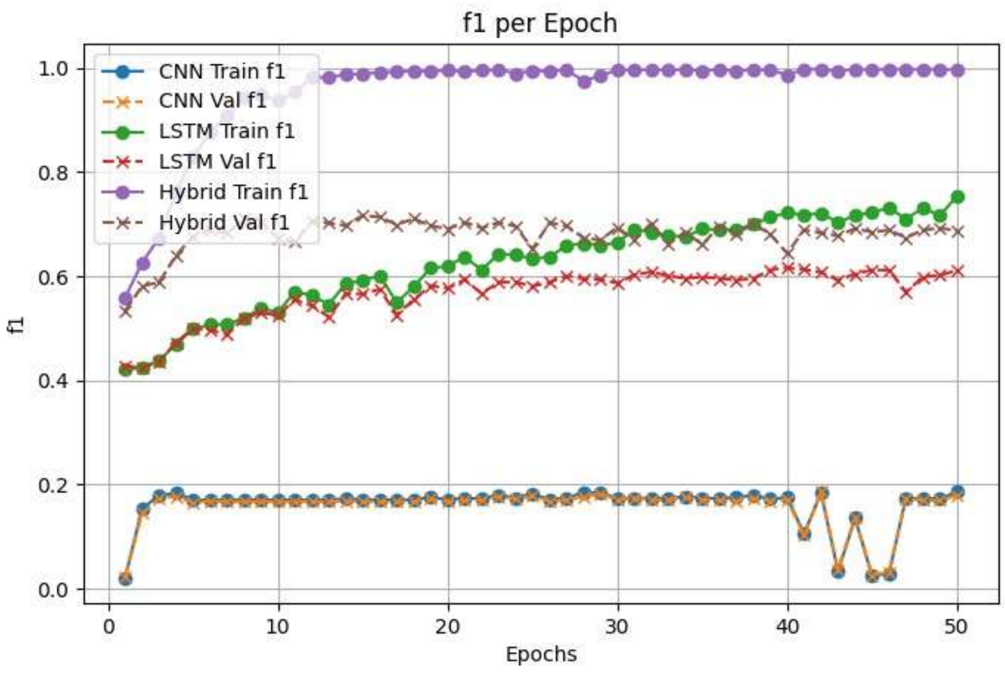

Fig1:F1 score per epoch

2. Loss per Epoch

The goal of the optimization process is to reduce loss, which is a measure of how off the model is in terms of its predictions compared to reality. The model's learning efficacy can be seen by plotting the loss for the training and validation sets across epochs. If the loss is going down on both sets, it means the model is learning well; if it's going down on training but going up on validation, it means overfitting, when the model learns from its mistakes instead of applying what it learned in the real world.

Table2: Loss per Epoch

Epoch	**CNN Train Loss**	**CNN Val Loss**	**LSTM Train Loss**	**LSTM Val Loss**	**Hybrid Train Loss**	**Hybrid Val Loss**
1	3.0	10.5	1.8	1.7	0.8	1.2
10	2.1	2.0	1.4	1.2	0.4	1.1
20	2.0	2.0	1.3	1.2	0.3	1.1
30	2.0	6.5	1.2	1.3	0.3	1.1
40	1.9	3.7	1.2	1.3	0.3	1.1
50	1.9	2.0	1.1	1.3	0.3	1.1

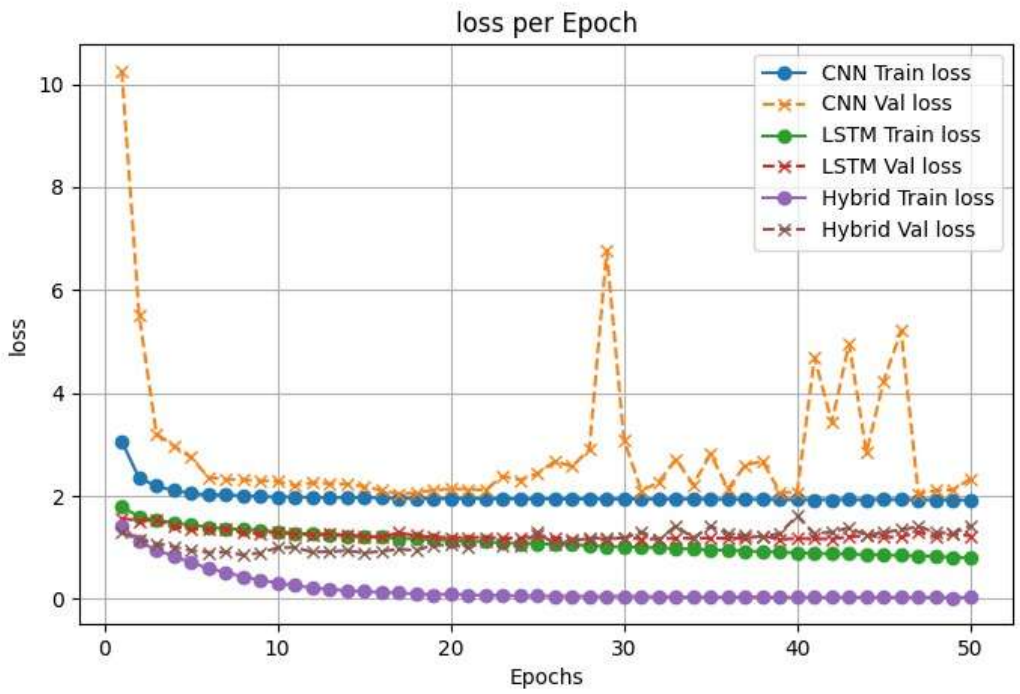

Fig 2:Loss per epoch

3. CNN Confusion Matrix

The number of samples that the model correctly identified as positive is known as precision. Keep an eye on this statistic per epoch to see how the dependability of predictions changes during training. Models with high precision, particularly on the validation set, seldom produce false alarms, which is essential in situations where false positives are expensive, like catastrophe detection, when resources are wasted due to a false alert.

Table3: CNN Confusion Matrix

Class	**Correct Predictions**
Infrastructure	287
Urban Fire	68
Wild Fire	62
Human Damage	51
Drought	23
Land Slide	88
Buildings Street	829
Wildlife Forest	224
Damage/sea	377
Disaster	206

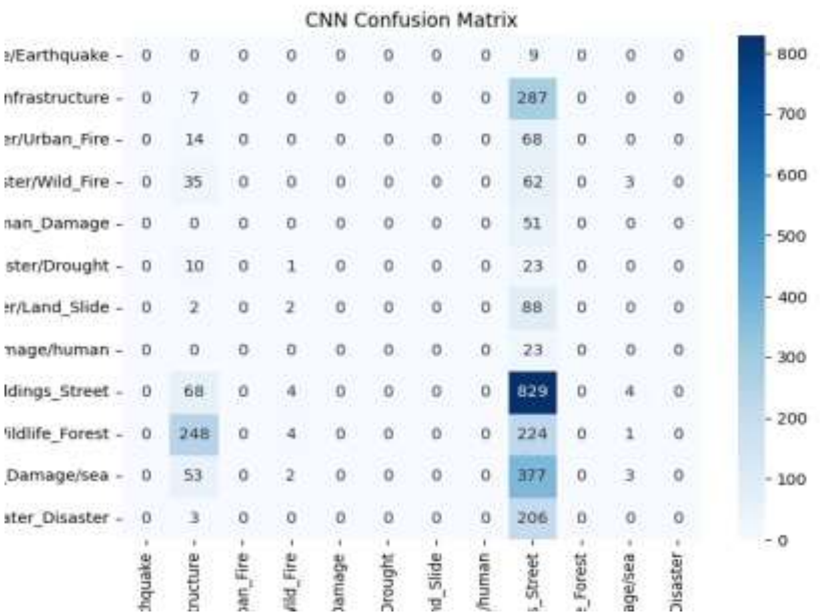

Fig 3: CNN Confusion Matrix

4. Precision per Epoch

The most basic indicator is accuracy, which is just the percentage of correct predictions made by the model. The general trend in accuracy over epochs shows that learning has progressed significantly. While helpful, this metric could be deceiving in a very unequal dataset if the dominant class is accurately predicted, leading to an inflated score regardless of the neglect of minority classes.

Table4: Precision per Epoch

Epoch	CNN Train Precision	CNN Val Precision	LSTM Train Precision	LSTM Val Precision	Hybrid Train Precision	Hybrid Val Precision
1	0.12	0.12	0.41	0.41	0.60	0.50
10	0.16	0.16	0.51	0.50	0.98	0.62
20	0.17	0.17	0.60	0.56	1.00	0.66
30	0.17	0.17	0.66	0.60	1.00	0.70
40	0.10s	0.10	0.70	0.61	1.00	0.72
50	0.18	0.18	0.73	0.62	1.00	0.73

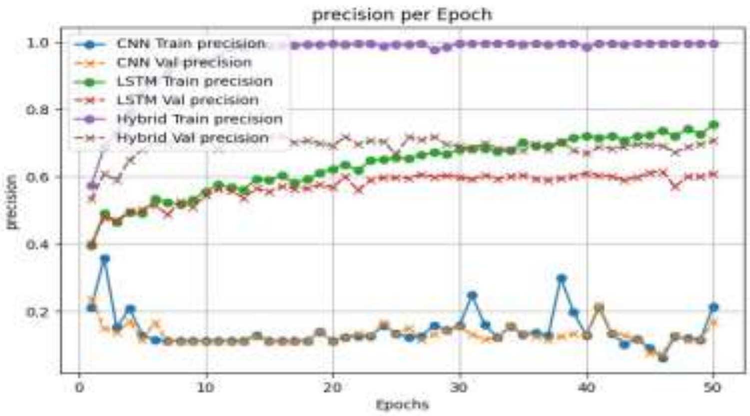

Fig 4: Precision per Epoch

5. Accuracy per Epoch

The confusion matrix delineates the class-specific advantages and disadvantages of a hybrid model's architecture, such as a CNN and LSTM combination. It shows how the two models worked together to enhance accuracy for classes that are difficult to categorize, or how certain confusions remain after the more complex arrangement.

Table5: Accuracy per Epoch

Epoch	CNN Train Acc	CNN Val Acc	LSTM Train Acc	LSTM Val Acc	Hybrid Train Acc	Hybrid Val Acc
1	0.29	0.14	0.40	0.50	0.60	0.62
10	0.31	0.16	0.51	0.57	0.98	0.70
20	0.33	0.16	0.60	0.61	1.00	0.72
30	0.33	0.16	0.66	0.64	1.00	0.73
40	0.32	0.10	0.70	0.61	1.00	0.73
50	0.33	0.16	0.73	0.62	1.00	0.73

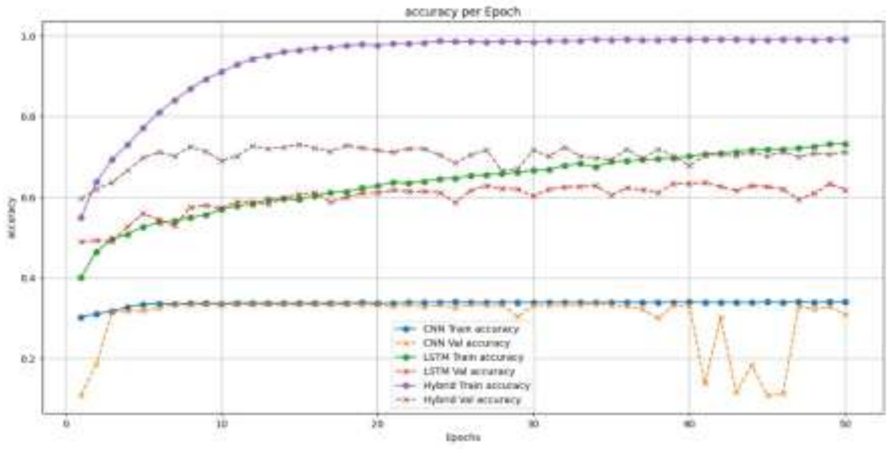

Fig 5: Accuracy per Epoch

6.Hybrid Confusion Matrix

The sensitivity or recall of a model is a measure of how many true positives it was able to identify. Crucial in domains affecting lives, such as emergency warning systems, monitoring recall each epoch enables detection of whether the model is omitting actual events (false negatives). While a high recall indicates that the model is effective at detecting all positive cases, it can lead to an increase in false positives if precision is not adequately balanced.

Table6: Hybrid Confusion Matrix

Class	**Correct Predictions**
Infrastructure	131
Urban Fire	18
Wild Fire	14
Human Damage	16
Drought	13
Land Slide	21
Buildings Street	831
Wildlife Forest	424
Damage/sea	360
Disaster	95

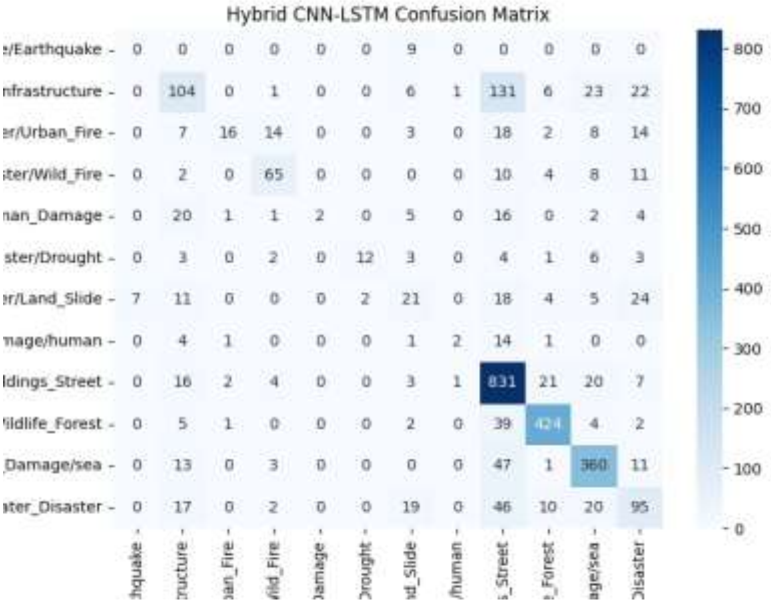

Fig 6: Hybrid Confusion Matrix

7. Recall per Epoch

The sensitivity or recall of a model is a measure of how many true positives it was able to identify. Crucial in domains affecting lives, such as emergency warning systems, monitoring recall each epoch enables detection of whether the model is omitting actual events (false negatives). While a high recall indicates that the model is effective at detecting all positive cases, it can lead to an increase in false positives if precision is not adequately balanced.

Table7: Recall per Epoch

Epoch	CNN Train Recall	CNN Val Recall	LSTM Train Recall	LSTM Val Recall	Hybrid Train Recall	Hybrid Val Recall
1	0.12	0.12	0.41	0.41	0.60	0.50
10	0.16	0.16	0.51	0.50	0.98	0.62
20	0.17	0.17	0.60	0.56	1.00	0.66
30	0.17	0.17	0.66	0.60	1.00	0.70
40	0.10	0.10	0.70	0.61	1.00	0.72
50	0.18	0.18	0.73	0.62	1.00	0.73

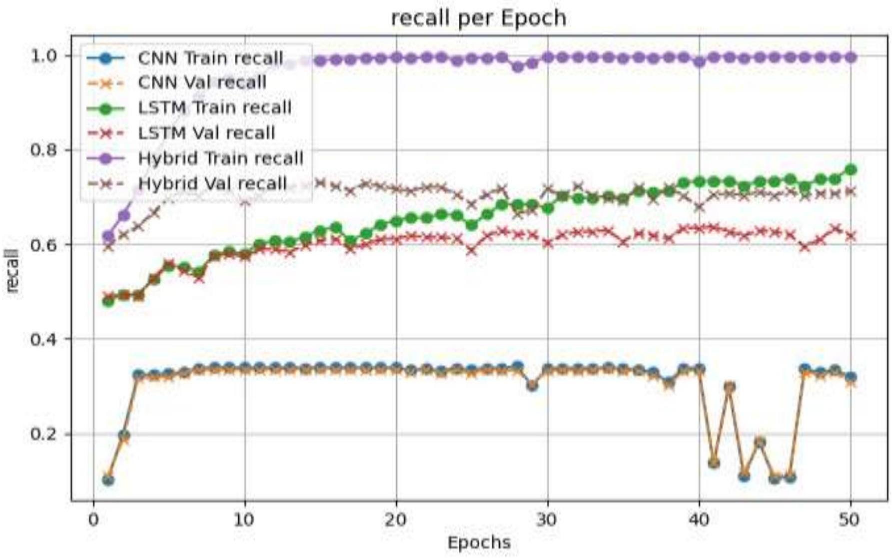

Fig 7: Recall per Epoch

8. LSTM Confusion Matrix

Similarly, the confusion matrix assesses the LSTM-based model's certainty in recognizing certain event types and its frequency of mistakenly identifying others. This directs focused methods for improvement or dataset augmentation and aids in further interpreting model-specific strengths in comparison to CNNs or hybrids.

Table8: LSTM Confusion Matrix

Class	**Correct Predictions**
Infrastructure	123
Urban Fire	20
Wild Fire	12
Human Damage	20
Drought	5
Land Slide	25
Buildings Street	669
Wildlife Forest	390
Damage/sea	333
Disaster	90

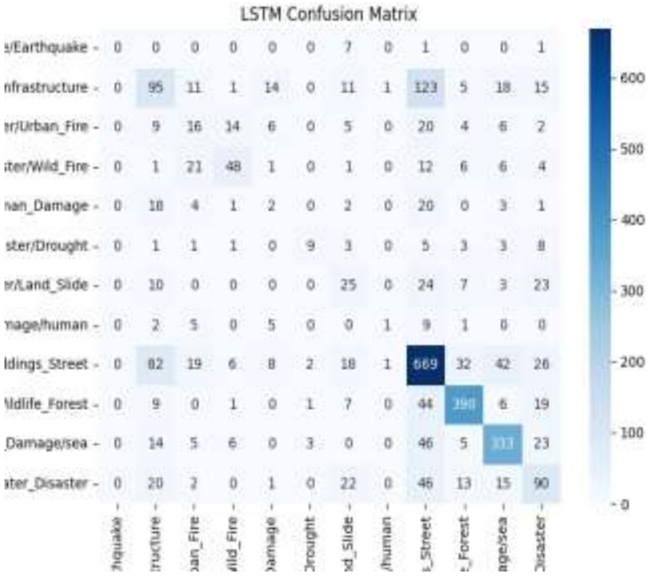

Fig 7: LSTM Confusion Matrix

Conclusion

For efficient and prompt catastrophe management, it is crucial to use cutting-edge technology. It highlights the ways in which explainable AI methodologies and recent advancements in deep learning might greatly enhance the use of multi-modal data sources, including drone and satellite photography, for natural disaster warning, classification, and response. The paper goes on to highlight how blockchain technology helps with data privacy, integrity, and trustworthy collaboration among various parties, while also solving a lot of problems with interoperability and security.

A decentralized blockchain ledger supports the proposed integrated system, which promotes openness and security, and provides interpretable AI modules for catastrophe prediction and resource distribution. The approach is realistic and effective for real-world crisis response scenarios, as shown in case studies and simulations, thanks to greater transparency, quicker coordination, and stronger cyber resilience.

The study also notes that there are problems with present models, such as a lack of data labeling, high computing demands, and regional biases, but it also promises better forecasts and more useful insights in the future. In sum, this study presents a fresh, interdisciplinary method that improves situational awareness, decision-making, and team reaction; it may be scalable to other kinds of disasters and other parts of the world. This all-encompassing plan has great potential to improve disaster management in the long run by making it more flexible, safe, and open.

References

[1]. W. Xiao, J. Su, Y. Chen and G. Cao, "Cross-Scale-Guided Fusion Transformer for Disaster Assessment Using Satellite Imagery," in *IEEE Transactions on Geoscience and Remote Sensing*, vol. 61, pp. 1-12, 2023, Art no. 4600512, doi: 10.1109/TGRS.2023.3298037.

[2]. S. Saleem, N. Hasan, A. Khattar, P. R. Jain, T. K. Gupta and M. Mehrotra, "DeLTran15: A Deep Lightweight Transformer-Based Framework for Multiclass Classification of Disaster Posts on X," in *IEEE Access*, vol. 12, pp. 153676-153693, 2024, doi: 10.1109/ACCESS.2024.3478790.

[3]. Lakshman Narayana, V., Rao, G.S., Gopi, A.P., Lakshmi Patibandla, R.S.M. (2022). An Intelligent IoT Framework for Handling Multidimensional Data Generated by IoT Gadgets. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_9

[4]. V. Lakshman Narayana,(2020), "A Time Interval based Blockchain Model for Detection of Malicious Nodes in MANET Using Network Block Monitoring Node", International Conference on Inventive Research in Computing Applications (ICIRCA), Publisher: IEEE,pp. 852-857, 9183256.

[5]. Tarakeswara Rao; R. S. M. Lakshmi Patibandla; V. Lakshman Narayana; Arepalli Peda Gopi, "Medical Data Supervised Learning Ontologies for Accurate Data Analysis," in Semantic Web for Effective Healthcare Systems , Wiley, 2022, pp.249-267, doi: 10.1002/9781119764175.ch11.

[6]. Chaitanya, Kosaraju, et al. "Predicting the Spread of Covid Disease Based on Chest X-Ray Images Using Convolutional Neural Network with Improved Accuracy." 2023 6th International Conference on Advances in Science and Technology (ICAST). IEEE, 2023.

[7]. Narayana, V.L., Gopi, A.P., Patibandla, R.S.M. (2021). An Efficient Methodology for Avoiding Threats in Smart Homes with Low Power Consumption in IoT Environment Using Blockchain Technology. In: Choudhury, T., Khanna, A., Toe, T.T., Khurana, M., Gia Nhu, N. (eds) Blockchain Applications in IoT Ecosystem. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-65691-1_16

[8]. Anusha, P. & Ravikiran, A. & Narayana, V. & Maddumala, V.R.. (2020). Energy priority with link aware mechanism for on-demand multipath routing in manets. International Journal of Advanced Science and Technology. 29. 8979-8991.

[9]. A.NareshV. PavaniM. Meghana Chowdarym. V.Lakshman Narayana (2020). Energy consumption reduction in cloud environment by balancing cloud user load. Journal of Critical Reviews. 7(7):1003-1010.

[10]. Suajtha, V. "Variable Selection in Functional Genomics Using Genetic Algorithm-Based Feature Selection Method-An Empirical Study." Journal of Engineering and Applied Sciences, 21 Sept. 2022. ISSN Online 1818-7803, ISSN Print 1816-949x.

[11]. Chaitanya, Kosaraju, and Sankara Narayanan. "Security and Privacy in Wireless Sensor Networks Using Intrusion Detection Models to Detect DDOS and Drdos Attacks: A Survey." 2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2023.

[12]. V. Pavani, S. Sri. K, S. Krishna. P and V. L. Narayana, "Multi-Level Authentication Scheme for Improving Privacy and Security of Data in Decentralized Cloud Server," 2021 2nd International Conference on Smart Electronics and Communication (ICOSEC), Trichy, India, 2021, pp. 391-394, doi: 10.1109/ICOSEC51865.2021.9591698.

[13]. Alapati, N., Prasad, B. V. V. S., Sharma, A., Kumari, G. R. P., Bhargavi, P. J., Alekhya, A., ... & Nandini, K. (2022, November). Cardiovascular Disease Prediction using machine learning. In 2022 International Conference on Fourth Industrial Revolution Based Technology and Practices (ICFIRTP) (pp. 60-66). IEEE.

[14]. V. Pavani, K. Divya, V. V. Likhitha, G. S. Mounika and K. S. Harshitha, "Image Segmentation based Imperative Feature Subset Model for Detection of Vehicle Number Plate using K Nearest Neighbor Model," *2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, Coimbatore, India, 2023, pp. 704-709, doi: 10.1109/ICAIS56108.2023.10073848.

[15]. Krisha, P.S., Peram, S.R. (2023). CT image precise denoising model with edge based segmentation with labeled pixel extraction using CNN based feature extraction for oral cancer detection. Traitement du Signal, Vol. 40, No. 3, pp. 1297-1304. https://doi.org/10.18280/ts.400349

[16]. Nagamani, T., Gopal, G. V., Lakshmi, G., Ramakrishna, K. V. S. S., Srija, N., & Gopi, A. (2025). Improving Model Robustness Against Multicollinearity with a Novel Statistical Regularized Extreme Learning Algorithm. *IAENG International Journal of Computer Science*, *52*(11).

[17]. Chaitanya, Ms Prathipati Silpa, et al. "TAODV Trust based AODV Protocol in MANETS to Mitigate Black Hole Effect." *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*. IEEE, 2023.

[18]. H. Wang, C. Wang, K. Zhou, D. Liu, X. Zhang and H. Cheng, "TEBChain: A Trusted and Efficient Blockchain-Based Data Sharing Scheme in UAV-Assisted IoV for Disaster Rescue," in *IEEE Transactions*

on Network and Service Management, vol. 21, no. 4, pp. 4119-4130, Aug. 2024, doi: 10.1109/TNSM.2024.3394162.

[19]. Peker, I., AR, I.M., Erol, I. *et al.* Leveraging blockchain in response to a pandemic through disaster risk management: an IF-MCDM framework. *Oper Manag Res* **16**, 642–667 (2023). https://doi.org/10.1007/s12063-022-00340-1.

[20]. Sheehan, B., Mullins, M., Shannon, D. *et al.* On the benefits of insurance and disaster risk management integration for improved climate-related natural catastrophe resilience. *Environ Syst Decis* **43**, 639–648 (2023). https://doi.org/10.1007/s10669-023-09929-8.

[21]. Kavishwar, S., & Uppal, S. K. (2020). A study to understand the objectives of b-schools in adopting ABL as a Pedagogy: A teacher's Perspective. *Sambodhi*. 43(04), 180-185.

[22]. Kavishwar, S (2024). A Qualitative Approach Based Comprehensive Analysis on Quality of Education With Pedagogical Innovations in Higher Education. *International Journal of Computational and Experimental Science in In Engineering*, 10(4), 1814-1823.

[23]. Joshi, M., Kothari, P. and Kavishwar, S. (2024). A Study on Determinants of Profitability in Indian Banks. *Journal of Informatics Education and Research*. 4(3), 22-26.

[24]. Kotadiya U, Arora AS, Yachamaneni T. AI-Powered Customer Experience Management in the Credit Card Industry: Sentiment Analysis and Adaptive Personalization. IJETCSIT [Internet]. 2021 Jun. 30 [cited 2026 Apr. 5];2(2):35-44.

[25]. Kotadiya U, Arora AS, Yachamaneni T. Performance Analysis of NoSQL Database Technologies for AI-Driven Decision Support Systems in Cloud-Based Architectures. IJERET [Internet]. 2022 Jun. 30 [cited 2026 Apr. 5];3(2):60-9.

[26]. B. K. Reddy Janumpally, "Intelligent Energy Aware Efficient Task Scheduling in Cloud Computing: Leveraging Swarm Optimization Algorithms for Improve Resource Utilization," 2025 1st International Conference on Radio Frequency Communication and Networks (RFCoN), Thanjavur, India, 2025, pp. 1-6, doi: 10.1109/RFCoN62306.2025.11085278.

[27]. Janumpally, Bharath Kumar Reddy. (2026). Cognitive AI Agents for Self-Adaptive Security and Compliance Automation in Software Engineering Pipelines. 10.1109/ICAUC68182.2026.11441048.

[28]. Tummuri, S. S. R. (2023). Quantization aware training techniques for efficient transformer-driven large language models. International Journal of Scientific Research & Engineering Trends, 9(2).

[29]. Tummuri, S. S. R. (2022). Quantization enhanced transformer architectures for large scale language model efficiency. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(3), 891–904.

[30]. Ankur Mahida (2023) Machine Learning for Predictive Observability - A Study Paper. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-252. DOI: doi.org/10.47363/JAICC/2023(2)235

[31]. "Ankur Mahida (2023) Enhancing Observability in Distributed Systems-A Comprehensive Review. Journal of Mathematical & Computer Applications. SRC/JMCA-166. DOI: doi.org/10.47363/JMCA/2023(2)135"

[32]. Jonnalagadda, Pawan Kalyan. "AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems." International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.

[33]. Jonnalagadda, Pawan Kalyan. "Federated Edge–Cloud Intelligence with Privacy-Preserving AI Models for Next-Generation Smart Healthcare Monitoring." United International Journal of Engineering and Sciences (UIJES), vol. 5, no. 4, Dec. 2025, pp. 46–57.

[34]. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.

[35]. Veginati, Navya. "Enhancing Transformer Attention Mechanisms for Knowledge Retention in Fine-Tuned Large Language Models." International Journal of Scientific Research in Science and Technology, vol. 11, no. 5, Sept.–Oct. 2024, pp. 864–871. DOI: https://doi.org/10.32628/IJSRST52310284

[36]. Racha, Ganesh. "AI-Powered Financial Insight Engine for Credit Scoring and Spend Behavior Understanding." International Journal of Scientific Research & Engineering Trends, vol. 10, no. 2, Mar.–Apr. 2024, pp. 1–8.

[37]. Racha, Ganesh. "Adaptive Quantum Blockchain for Secure IoT Resource Coordination." International Journal of Science, Engineering and Technology, vol. 11, no. 3, 2023.

[38]. R. Eswarawaka, S. K. Kudikala, S. C. Kuchi and V. Verma K., "The analysis on search engine optimization supported by six sigma methodology," 2017 International Conference on Innovative Mechanisms for Industry Applications (ICIMIA), Bengaluru, India, 2017, pp. 653-658, doi: 10.1109/ICIMIA.2017.7975544.

[39]. Albataineh, H., Kanmuri, V., Alaqqad, W., Nijim, M. (2024). Utilizing Machine Learning for Intrusion Detection in Smart Grid Systems. In: Daimi, K., Al Sadoon, A. (eds) Proceedings of the Third International Conference on Innovations in Computing Research (ICR'24). ICR 2024. Lecture Notes in Networks and Systems, vol 1058. Springer, Cham. https://doi.org/10.1007/978-3-031-65522-7_44

[40]. Jingar, N. K. (2022). Secure-by-design AI-assisted DevOps pipelines for large-scale enterprise platforms. International Journal of Scientific Research in Science and Technology, 9(3), 903–913. https://doi.org/10.32628/IJSRST2291348

[41]. Jingar, N. K. (2022). Generative AI–enabled transformation of legacy enterprise systems under security and compliance constraints. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(2), 760–770. https://doi.org/10.32628/CSEIT23906219