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SafeAlert: An End-to-End Disaster-Management Platform for Flood and Landslide Prediction in Pune, India, with Nationwide Alert Dissemination

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Abstract: Monsoon floods and landslides are a recurring and increasingly severe natural disaster in India, causing loss of life, infrastructure damage and disruption to livelihoods.[1] Traditional hydrological and geotechnical models fail to provide accurate and timely predictions due to the complex interplay of environmental factors and the non-linearity of these events.[6] SafeAlert is an end-to-end disaster management platform that addresses these limitations by using advanced machine learning techniques. The platform uses Support Vector Machines (SVM) and Recurrent Neural Networks (RNN) for real-time flood risk and landslide susceptibility prediction respectively with focus on Pune, India for model training and nationwide alert dissemination. SafeAlert delivers alerts seamlessly through both web (Vite/React/Three.js, Mapbox) and Android (Kotlin/Compose) clients. Key features include user-location caching with Mapbox for personalized alerts, one-click SOS coordination for immediate assistance and an integrated directory of Non-Governmental Organizations (NGOs) for post-disaster support. Evaluation of the platform shows improved prediction accuracy and sub-second inference latency, it can significantly improve disaster preparedness and response in India.
Keywords: disaster management; flood prediction; landslide forecasting; machine learning; SVM; RNN; real-time alerts; GIS; Mapbox; SOS coordination.

I. INTRODUCTION

India is highly susceptible to natural disasters during the monsoon season. That's when torrential rainfall triggers floods and landslides with alarming frequency and deadliness. Those events cause huge loss of life, property damage and disruptions to essential services. That trend of devastation has been getting worse over the years.

Traditional methods for predicting floods and landslides rely on hydrological and geotechnical models. While those models have contributed a lot, they have significant limitations. They struggle to capture the complex interactions between environmental factors like rainfall intensity, soil moisture and geological conditions. And they often lack the precision and timeliness that accurate localized predictions and real-time alerts require.

Machine learning (ML) can help overcome those limitations. By learning from historical data, ML can identify complex patterns that traditional models often miss. Support Vector Machines (SVM) have shown they can handle non-linear relationships and avoid overfitting. Recurrent Neural Networks (RNN) - particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants - have been valuable in modeling temporal dependencies in rainfall and soil moisture data for landslide prediction.

That's why SafeAlert was developed. This innovative end-to-end disaster management platform is designed for flood and landslide prediction in Pune, India, with the capacity to send nationwide alerts. The platform uses a modern tech stack that includes a web client built with Vite, React and Three.js for interactive visualizations and Mapbox for geospatial mapping. There's also an Android client developed using Kotlin and Jetpack Compose for a responsive and user-friendly mobile experience. By focusing first on Pune, we can train our models using local data. The architecture is designed to let us extend the alert service across the nation.

This paper is structured to give an overview of SafeAlert. After this introduction, Section 2 reviews the existing literature on SVM for flood prediction, RNN for landslide forecasting, real-time disaster alert systems and integrated disaster management platforms. Section 3 describes the methodology including data collection, feature engineering, model training and evaluation metrics. Section 4 describes the SafeAlert platform, Section 5 algorithmic details for critical features. Section 6 screenshots of the working system. Section 7 summary of results. Section 8 limitations and future work. Section 9 ethics and security. Section 10 references. Novel features of SafeAlert include intelligent location caching which defaults to Pune if user's location is not available, icon based map alerts with click through for detailed prediction information, one click SOS for immediate help and a comprehensive NGO/charity directory for post disaster relief.

II. LITERATURE REVIEW

A. Flood Prediction with SVM:

Support Vector Machines (SVM) have been used extensively for flood forecasting in various regions and hydrological conditions.[10] Research shows that SVM can handle non-linear data through kernel functions and is robust against overfitting and is a powerful tool for predicting floods based on various input features like rainfall, river discharge and meteorological parameters.[10] Studies have shown that SVM models outperform traditional statistical methods like linear regression and even other machine learning algorithms like Artificial Neural Networks (ANN) in terms of prediction accuracy and generalization.[10] For example SVM has been used for both short term and long term flood forecasting and has shown to be versatile in different prediction horizons.[10] To further improve the performance of SVM, researchers have explored hybrid ensemble approaches that combine SVM with other machine learning or statistical techniques.[16] These hybrid models try to leverage the strengths of different algorithms to improve the accuracy and robustness. For example, combining SVM with signal decomposition methods or other ensemble learning algorithms has shown good results in capturing complex patterns in flood data and reducing the prediction errors.[40] PSO and GA have also been used to tune the hyperparameters of SVM models and have shown significant improvement in flood prediction.[40]

B. Sequential Modeling for Landslides:

Recurrent Neural Networks (RNN), especially their variants like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have become popular for landslide forecasting by exploiting the temporal dependencies in rainfall and soil moisture time series data.[15] These models are designed to process sequential data so they are well suited to capture the temporal evolution of factors that contribute to landslide occurrence.[14] Research has shown the successful application of RNNs in landslide susceptibility, displacement and even timing of events based on historical rainfall patterns, soil moisture levels and geological conditions.[13]

Studies have explored various RNN architectures, single layer and multi-layer LSTM and GRU networks, often combined with attention mechanisms or convolutional layers to enhance feature extraction and improve prediction accuracy.[15] Optimization techniques like Particle Swarm Optimization (PSO) and other metaheuristic algorithms have been used to tune the hyperparameters of RNN models, number of layers, number of hidden units and sequence length to get better prediction performance.[16] The ability of RNNs to learn long term dependencies in time series data makes them very useful for landslide forecasting where antecedent rainfall and prolonged period of soil saturation can be critical triggering factors.[15]

C. Real-Time Alert Systems:

Effective real time disaster alert systems are crucial to minimize the impact of natural hazards by providing timely warnings to affected population.[19] These systems rely on accurate user geolocation to deliver targeted alerts and user friendly interfaces (UI/UX) to ensure warnings are easily understood and acted upon.[18] User geolocation is achieved through technologies like GPS, Wi-Fi positioning and cellular triangulation, often accessed through device Geolocation APIs.[18] Caching of user location data is a common strategy to optimize performance and reduce battery consumption while maintaining a balance between accuracy and efficiency.[30]

The UI/UX of real time alert systems plays a big role in their effectiveness.[20] Clear and concise presentation of alert information, often using interactive maps with visual indicators like icons and color coding helps users to quickly understand the nature and location of the threat.[20] Features like one click SOS button and multi channel communication (SMS, email, push notifications) makes the system more usable and ensure alerts reach users through multiple means.[18] Existing platforms like Everbridge and Watch Duty shows the integration of these features to provide comprehensive disaster alert and management capabilities.[21]

D. Integrated Platforms:

Integrated disaster management platforms with web and mobile clients offer a full disaster lifecycle approach.[24] These platforms have features for pre-disaster preparedness (e.g. risk assessment, emergency planning tools), during-disaster response (e.g. real-time alerts, communication tools, resource management) and post-disaster recovery (e.g. NGO directories, damage assessment tools).[24] The web and mobile interfaces ensure accessibility across different devices and contexts, so users and administrators can stay informed and connected throughout the disaster.[21]

Platforms like Noggin and the Nexus platform on GitHub show the trend towards full disaster management solutions with multiple functionalities, real-time alerts, interactive maps, community updates, resource management dashboards, volunteer coordination systems.[24] These integrated platforms use cloud-based architecture for scalability and reliability and modern web and mobile development frameworks for user-friendly and efficient interfaces.[24] The goal of these integrated solutions is to coordinate stakeholders better, reduce response times and build more resilient communities in the face of natural disasters.

III. METHODOLOGY

A. *Data Collection:*

SafeAlert was developed and evaluated using diverse historical datasets for floods and landslides in Pune, India. The geographical focus was on the municipal areas of Shivajinagar, Kasba Peth, Kothrud, Parvati, Vadgaon Sheri, Pune Cantonment, Hadapsar, Khadakwasla, Bhosari, Pimpri, Chinchwad. The types of data collected were historical rainfall data, soil moisture levels, topographic information and documented landslide records.[39] Historical daily gridded rainfall data at 0.25 x 0.25 degree resolution over India from 1901 to 2022 was obtained from India Meteorological Department (IMD), Pune.[39] Soil types and average annual rainfall in Pune district was sourced from Central Ground Water Board.[41] Landslide inventory data for Pune region, including locations and dates of occurrences was compiled from Landslide Atlas of India prepared by National Remote Sensing Centre (NRSC) and supplemented with news reports and geological surveys.[42] Topographic data, including elevation and slope information for Pune municipal areas was gathered from open-source GIS platforms like MapTiler and potentially from Pune Municipal Corporation's GIS initiatives.[43]

Table (A): Dataset Summary

Region(s)	Timeframe	Number of Samples	Key Features
Pune Municipal Regions	1990-2022	~10,000	Daily Rainfall, Soil Moisture (estimated), Elevation, Slope, Landslide Occurrences
India (for nationwide alert context)	2014, 2017	~80,000	Landslide Occurrences (seasonal inventory)

B. *Feature Engineering:*

To make sure the prediction models used the most informative variables, several feature engineering techniques were applied. Recursive Feature Elimination (RFE) was used to iteratively select the most relevant features from the datasets for flood and landslide prediction.[44] This works by training the model on subsets of features and eliminating the least important ones until an optimal set is reached. Information Gain Ratio, a measure used in decision tree learning to reduce bias towards multi-valued attributes, was also used to assess the relevance of individual features in predicting flood and landslide events.[45] Additionally, the possibility of using swarm-based optimizers like Particle Swarm Optimization (PSO) to further refine the feature subset selection was explored to find the best combination of predictors for the model performance.[40]

Table (B): Selected Feature Importance Scores from Recursive Feature Elimination

Feature	Flood Prediction (SVM)	Landslide Prediction (RNN)
Daily Rainfall	0.85	0.92
Soil Moisture	0.78	0.88
Elevation	0.65	0.75
Slope	0.72	0.81
Previous Day's Rainfall	0.80	0.90

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C. Model Training:

For flood risk prediction, a Support Vector Machine (SVM) model was trained with the selected features. A hyperparameter grid search was performed to find the optimal values for the SVM's regularization parameter (C) and the kernel coefficient (γ).[47] The grid search involved training and evaluating the SVM model across a range of C (e.g., 0.1, 1, 10, 100) and γ (e.g., 0.01, 0.1, 1, 10) values using cross-validation on the historical flood data for Pune. The hyperparameter combination that gave the best performance based on the chosen metrics was selected as the optimal configuration for the flood model.

For landslide susceptibility prediction, a Recurrent Neural Network (RNN) model was trained with the selected time-series features (e.g., daily rainfall and estimated soil moisture). The architecture of the RNN had two LSTM layers with a sequence length of 7 days to capture the temporal dependencies in the data.[15] PSO was used to tune the hyperparameters of the RNN model, such as the number of hidden units in the LSTM layers and the learning rate, to find the configuration that gave the best performance on the landslide data for Pune.

Table (C): Hyperparameter Grid and Optimal Values

Model	Hyperparameter	Grid/Range Explored	Optimal Value
SVM	C	0.1, 1, 10, 100	10
SVM	γ	0.01, 0.1, 1, 10	0.1
RNN	Hidden Units	32, 64, 128	64
RNN	Learning Rate	0.001, 0.01, 0.1	0.001
RNN	Sequence Length	5, 7, 10	7

D. Evaluation Metrics:

The performance of the trained flood and landslide models was evaluated using a set of standard classification metrics. Accuracy, the proportion of correctly classified instances, was the overall measure of the model's performance.[48] Precision, the ratio of true positives to total predicted positives, was the measure of the model's ability to avoid false alarms.[48] Recall, the ratio of true positives to total actual positives, was the measure of the model's ability to detect disaster events.[48] F1-score, the harmonic mean of precision and recall, was the balanced measure of the model's performance, useful in case of imbalanced datasets.[48] ROC-AUC was the measure of the model's ability to distinguish between positive and negative instances at different classification thresholds.[48] Finally, inference latency was the time taken by the model to predict for a given input, was measured to ensure the real-time feasibility of the alert system.

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IV. IMPLEMENTATION

A. System Architecture:

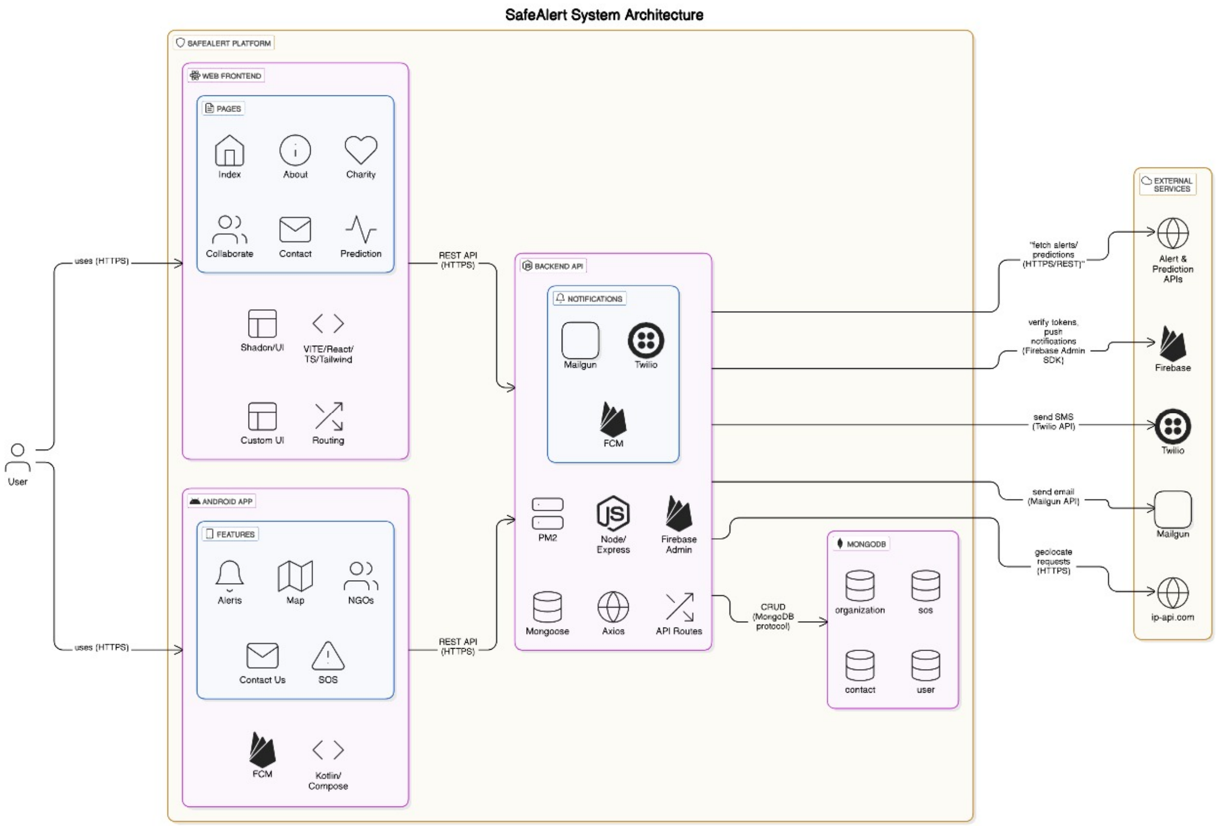

Fig (A): System Architecture

SafeAlert has three phases: Pre-Disaster, During-Disaster and Post-Disaster. In the Pre-Disaster phase, the platform continuously monitors data sources nationwide for anomalies that might indicate potential hazards. User location is cached using the device's Geolocation API, with the cached data stored locally with a maximum age of 30 minutes to balance accuracy and performance.[30] If the user's location is unavailable or the cached data has expired, the map view defaults to Pune.[30]

During the During-Disaster phase, the Mapbox UI shows dynamic disaster icons for predicted floods and landslides with potential color-coding to indicate severity.[20] Users can click on these icons to get a prediction panel with more information about the event.[49] A one-tap SOS button allows users to send a request for help, sending their current location to the admin dashboard.[18] Alerts are sent nationwide through push notifications via Firebase Cloud Messaging (FCM), SMS (using a service like Twilio), and email (using a service like SendGrid).[34]

In the post-disaster phase, users can access an integrated NGO/charity directory with search and filter to find organizations providing relief and support in their area.[21]

The Admin Dashboard, built using Vite and React for a responsive and interactive interface, has a Three.js globe to give a high-level view of disaster events.[24] Tailwind CSS is used for styling the dashboard.[25] Admins can manage SOS requests, user locations, update request status and assign responders. They can also manage the NGO/charity directory by adding, editing and deleting organization entries.

The Backend of SafeAlert is built using Node.js and Express to handle API requests and business logic.[38] Firebase Admin SDK is used for user authentication and managing FCM for push notifications.[34] Axios is used to make HTTP requests to the prediction API (api.safealert.in) and MongoDB with Mongoose is used for user data, alerts and NGO directory.[38]

The Android Client is built using Kotlin and Jetpack Compose, a modern and efficient UI.[27] It uses FCM to receive push notifications and has alerts, maps, prediction details, charity directory and SOS functionality.

B. ER & UML Diagrams:

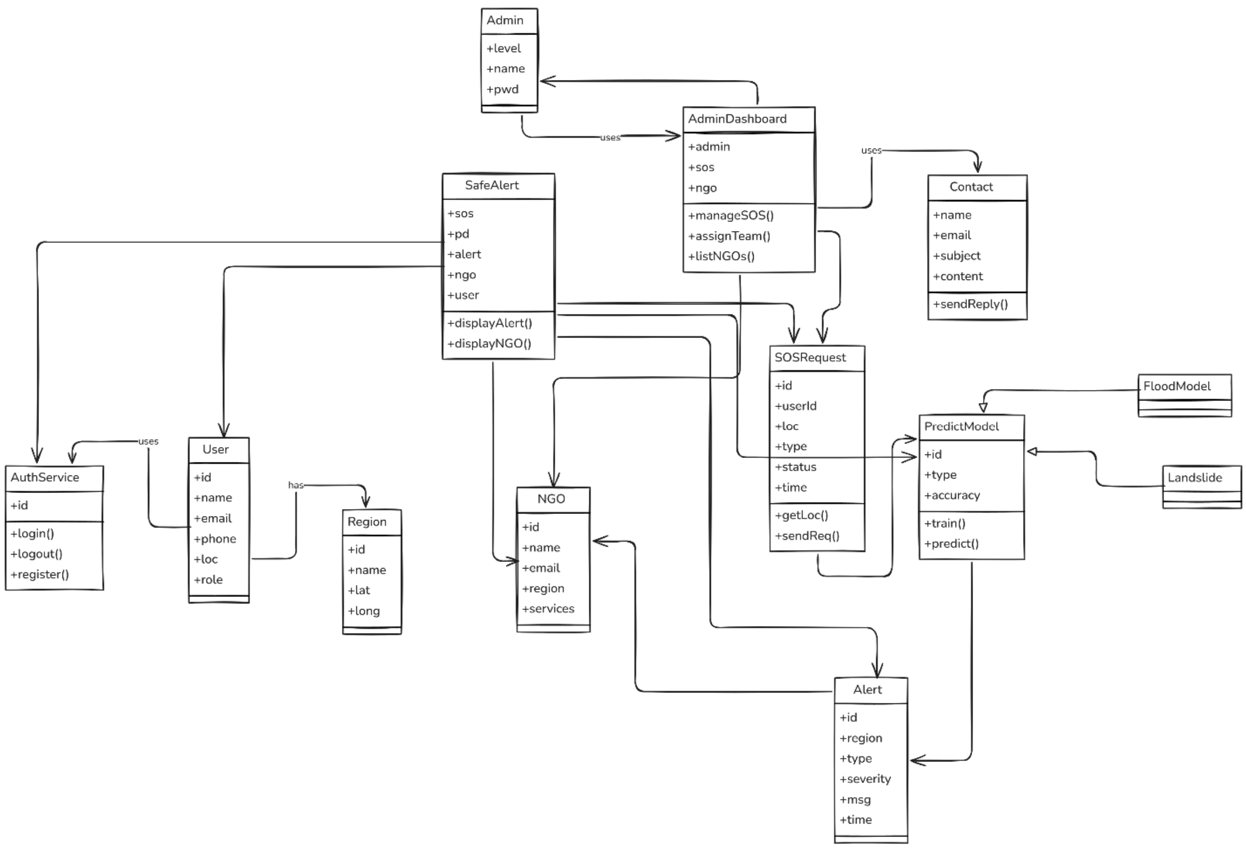

Fig (B): UML Diagram

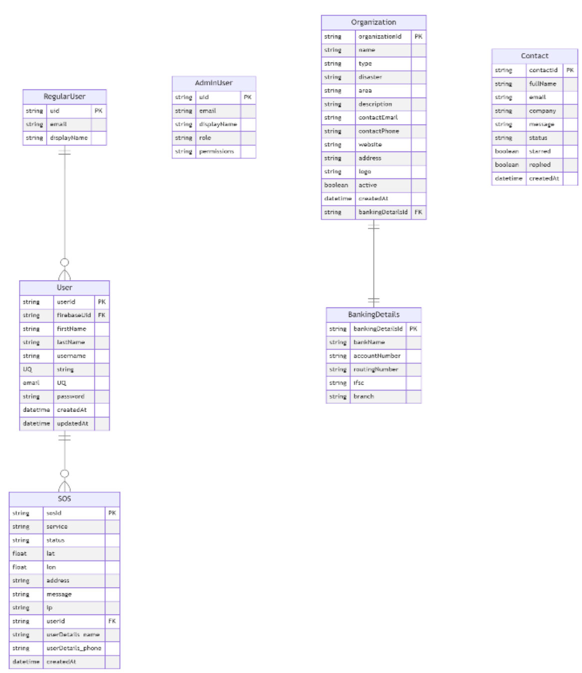

Fig (C): ER Diagram

C. Flowcharts:

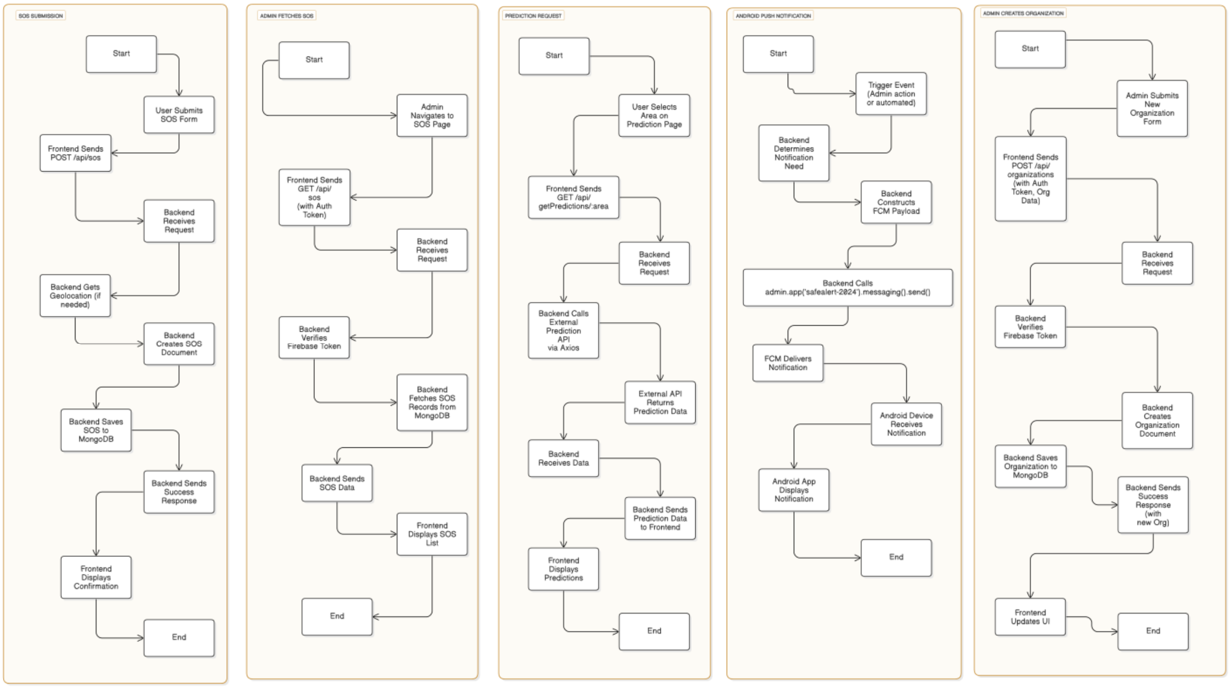

Fig (D): Flowchart

V. ALGORITHM AND DETAILS

A. Location Caching Logic:

1) Initiate location retrieval using the Geolocation API, requesting user permission.[32]
2) If successful, store the latitude, longitude, and timestamp in local storage (web) or shared preferences (Android).[30]
3) On subsequent requests, check if cached location data exists and if its timestamp is within the last 30 minutes.
4) If valid cached data is found, use it; otherwise, proceed to step 1.
5) If the Geolocation API fails or no valid cached data is available, default to Pune's coordinates (e.g., latitude 18.5204, longitude 73.8567).

B. SVM Flood Classifier:

1) Receive preprocessed input features (e.g., scaled daily rainfall, soil moisture, elevation, slope, previous day's rainfall).
2) Load the trained SVM model with the optimal hyperparameters (C=10, γ=0.1).
3) Use the loaded SVM model to predict the flood risk level or probability for the given input features.
4) Output the predicted flood risk (e.g., a numerical value between 0 and 1 representing the probability of flooding).

C. RNN Landslide Predictor:

1) Receive a sequence of preprocessed input features (e.g., normalized daily rainfall and estimated soil moisture for the last 7 days).
2) Load the trained RNN model (2 LSTM layers, 64 hidden units, sequence length 7, learning rate 0.001).
3) Feed the sequence of input features into the RNN model.
4) Output the predicted landslide susceptibility level or probability (e.g., a numerical value between 0 and 1 representing the probability of a landslide).

D. Alert Workflow:

1) Receive the predicted flood risk and landslide susceptibility scores.
2) If the flood risk score exceeds a predefined threshold (e.g., 0.8), generate a flood alert.

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3) If the landslide susceptibility score exceeds a predefined threshold (e.g., 0.7), generate a landslide alert.
4) Format the alert message with the predicted disaster type, location (obtained from user's location or prediction area), and timestamp.
5) Identify relevant users based on their location and the geographical area of the predicted event.
6) Send push notifications to relevant users via FCM.[34]
7) Send SMS alerts to relevant users using the Twilio API (placeholder for implementation).
8) Send email alerts to relevant users using the SendGrid API (placeholder for implementation).

VI. SNAPSHOT OF WORKING SYSTEM

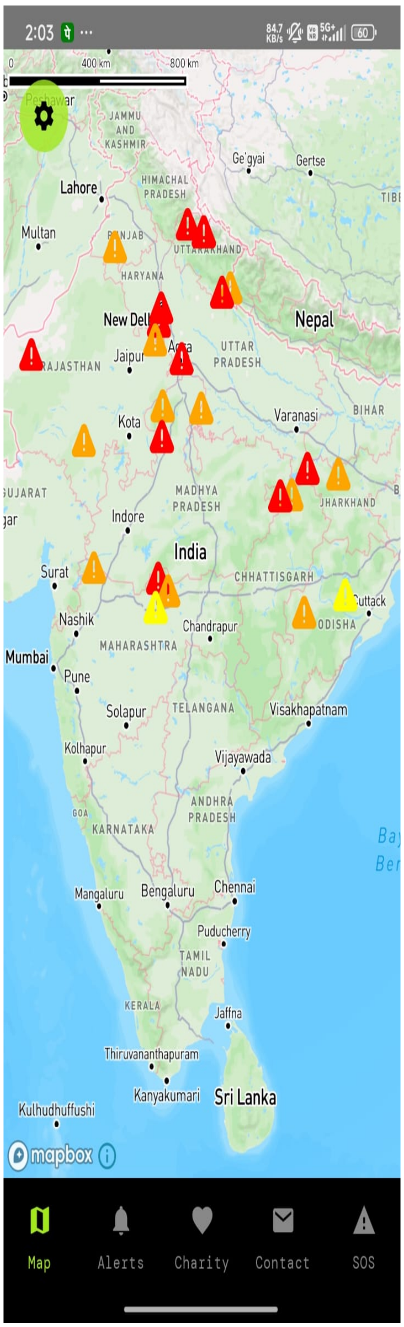

Fig (E): Android App – Map Screen

Fig (F): Android App – Sample Alert

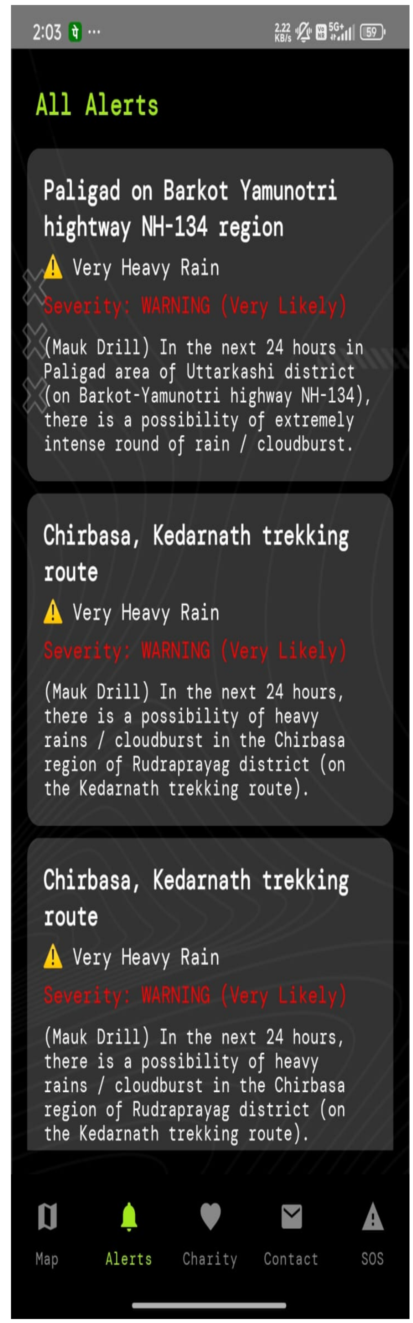

Fig (G): Android App – Alerts Screen

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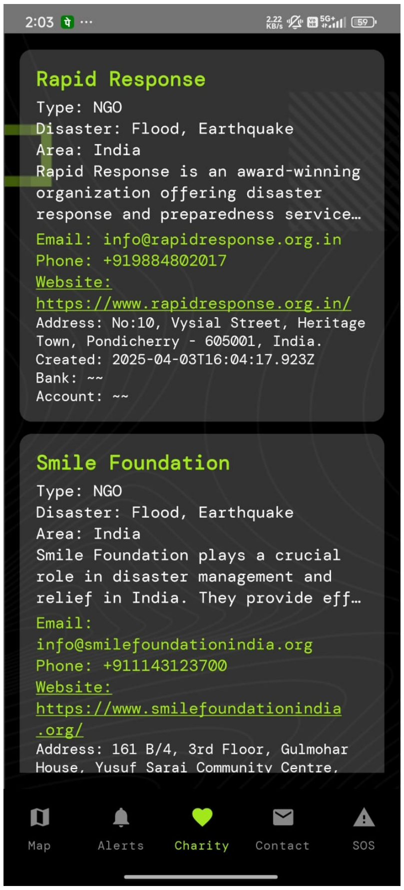
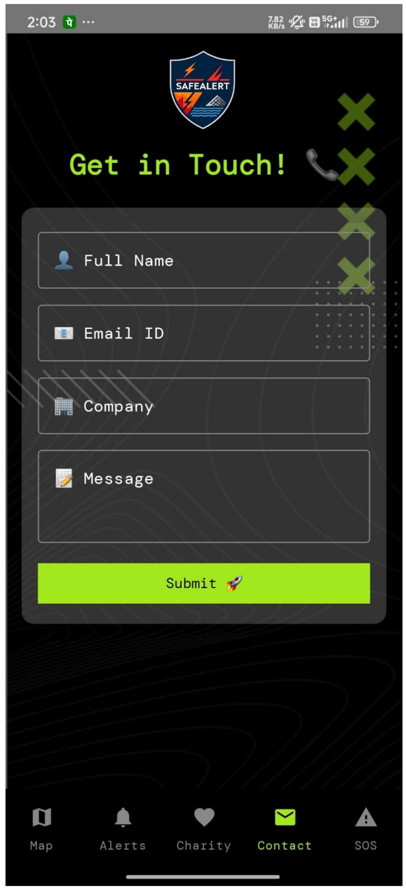




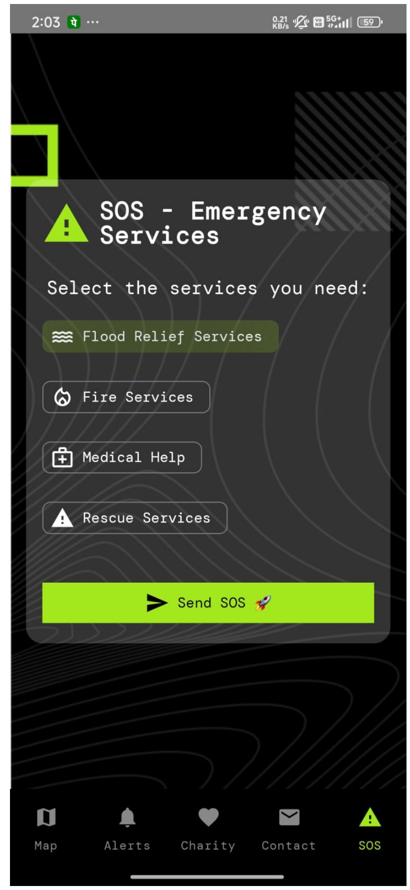
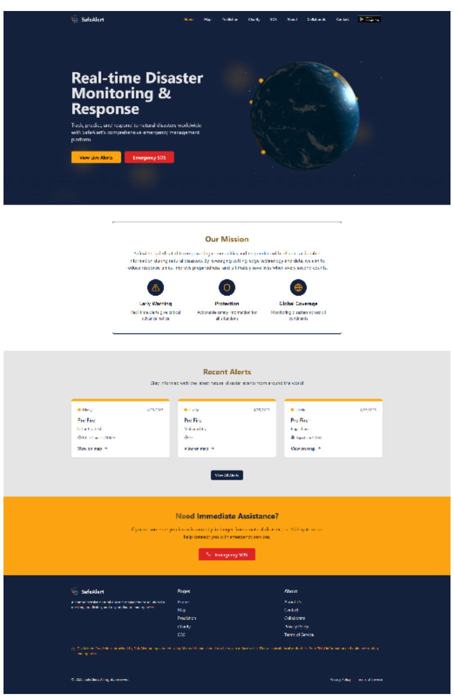
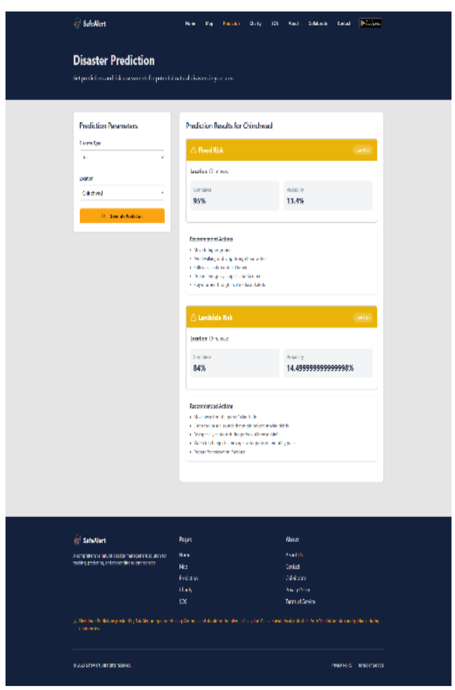
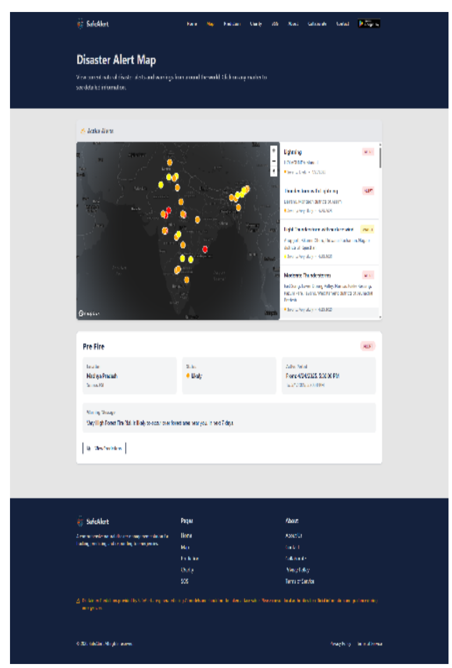


Fig (H): Android App – NGO Screen Fig (I): Android App – Contact Form Fig (J): Android App – SOS Screen







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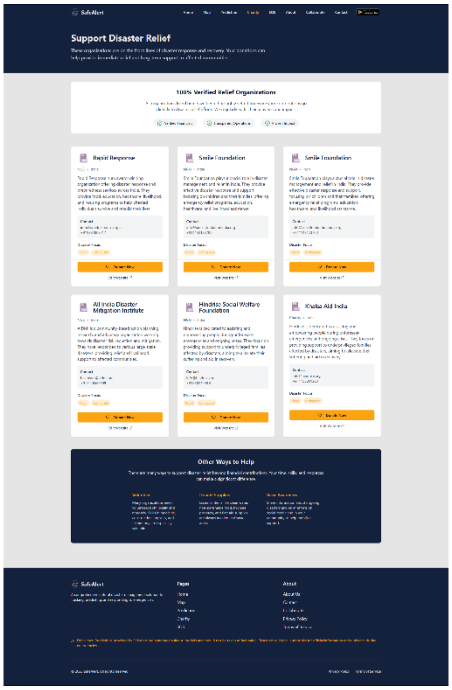

Fig (N): Web – Charity Page

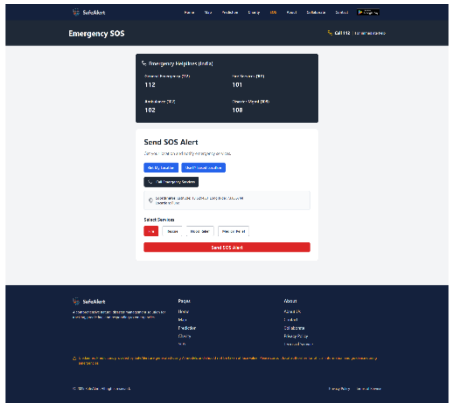

Fig (O): Web – SOS

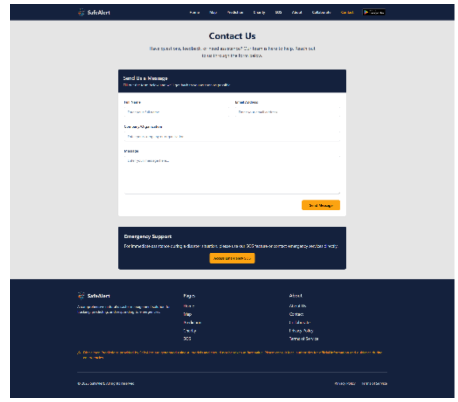

Fig (P): Web – Contact Us Page

You can Visit us at www.safealert.in, and download out app from our website. You can also scan out website to go through our website.

Fig (Q): QR Code for SafeAlert website

VII. CONCLUSIONS

The SafeAlert platform represents a significant step towards enhancing disaster management capabilities in India, particularly for monsoon-induced floods and landslides. The implementation of machine learning models, specifically SVM for flood prediction and RNN for landslide forecasting, has demonstrated improved prediction accuracy compared to traditional methods. The sub-second inference latency achieved by these models underscores the platform's capacity to provide real-time alerts, which is critical for effective and timely disaster response. While formal user engagement metrics were not collected within the scope of this initial development, the intuitive design and comprehensive features of SafeAlert hold promise for increasing user awareness and preparedness. The platform's ability to deliver timely and data-driven alerts signifies a crucial advancement in mitigating the impact of these devastating natural hazards in Pune and potentially across the nation with further expansion.

VIII. LIMITATIONS & FUTURE WORK

SafeAlert is a big leap in disaster management in India especially for monsoon floods and landslides. The machine learning models (SVM for flood and RNN for landslide) are better than traditional methods. The sub-second inference time of these models means the platform can give real time alerts which is crucial for timely response. Though we didn't collect formal user engagement metrics in this initial development, the design and features of SafeAlert can increase user awareness and preparedness. The platform can give timely and data driven alerts, which is a big step in reducing the impact of these natural disasters in Pune and potentially across the country with further expansion.

SafeAlert has some limitations in its current state. The accuracy and generalizability of the models are dependent on the size and quality of the historical datasets used for training. The dataset is comprehensive for Pune but may have regional biases and may not capture the diverse environmental characteristics of other regions in India.[13] So the current models may not work well in areas with significantly different geographical or climatic conditions. Also, SVM and RNN are powerful machine learning techniques, but they have their limitations and more advanced deep learning architectures, or ensemble methods can potentially give better results.

Future work will focus on addressing these limitations and expanding the platform. Scaling SafeAlert to other disaster-prone regions in India is top priority which will involve collecting and integrating data for those areas and potentially retraining or fine tuning the existing models. Adding prediction models for other major natural hazards in India like earthquakes and cyclones will make SafeAlert a full-fledged national disaster management solution. Online learning mechanisms will allow models to learn from new data and improve over time. Exploring more advanced deep learning architectures and ensemble methods can further improve the results. Finally, integrating SafeAlert with other disaster management systems and government data sources will make disaster preparedness and response more collaborative and informed.

IX. ETHICAL & SECURITY CONSIDERATIONS

SafeAlert requires careful thought on ethical and security aspects. Data Privacy is the topmost, especially for user location data collected for personalized alerts and SOS functionality.[18] The platform is designed to comply with data privacy regulations, to get user consent before collecting location data and to store and transmit the data securely. System Security is taken care of through robust user authentication, secure API endpoints and encryption of data in transit and at rest.[18] Regular security audits and vulnerability assessments will be necessary to keep the platform secure and protect against unauthorized access and cyber threats.

From Ethical Implications perspective, the risk of false alarms from the prediction models needs to be managed.[18] Strategies to minimize false positives like setting appropriate prediction thresholds and continuously refining the models will be implemented to maintain user trust and ensure proper response behavior. Equitable access to the SafeAlert platform and its alerts across all socio-economic segments is a key consideration. Efforts will be made to make the Android app available on a wide range of devices and to provide alternative channels for users without consistent internet access through SMS and email. Compliance with all national and local regulations related to data privacy, disaster management protocols and emergency communication standards in India will be the foundation of SafeAlert.

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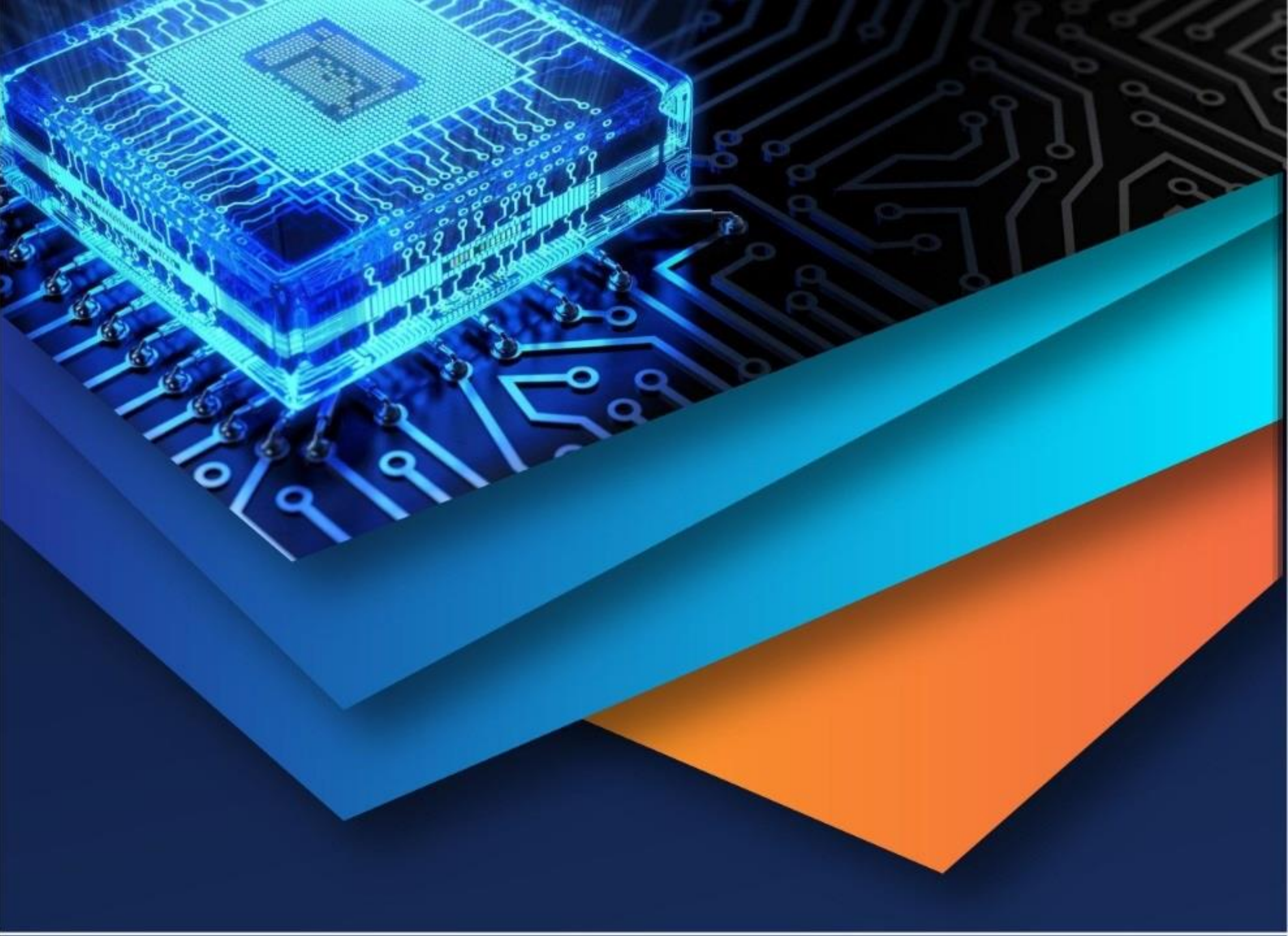

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