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AI Crisis Navigator: Real-Time Urban Emergency Decision Engine

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ABSTRACT

AI Crisis Navigator An intelligent urban emergency decision-support system for real-time situation awareness and response management in smart cities. Utilizing artificial intelligence (AI), machine learning (ML) algorithms, and real-time data streams from Internet of Things (IoT) devices, social media platforms, and urban sensor networks the system will detect, analyze and prioritize urban crises in a dynamic manner. The main goal of this research is to build an intelligent decision-making framework which can predict possible emergency events, provide early warning, and suggest efficient evacuation plans for the first responders and municipalities. This makes a contribution to the development of smart, adaptable, and resilient urban infrastructure for managing crises in real time in smart-city environments, by overcoming major limitations of traditional emergency management systems on delayed data processing, lack of predictive functions, and heterogeneity incorporation.

KEYWORDS: AI Crisis Navigator, real-time urban emergency detection, machine learning, predictive analytics, crisis management.

1. INTRODUCTION

Disasters, failures in infrastructure, and traffic accidents are increasing in urban areas. It is difficult for even authorities to keep and maintain real-time situational awareness and respond accordingly during a disaster [1] [2]. This is especially true for rapidly urbanizing environments where city systems are becoming more complex and interdependent. Emergency management systems are overly reliant on slow information processes, manual reporting, and static sensor networks [3] [4]. This results in response systems being slow due to fragmented communication and data overload. This has led to losses in both human lives and the economy [5]. An intelligent system that can incorporate automation is a necessity [6] [7].

There have been several initiatives aimed at using modern technology to improve crisis detection and response systems [8]. For instance, the DEFER (Disaster Event Forecasting and Emergency Response) systems use predictive analytics to try and anticipate disasters, and the SMART-CITY ALERT systems use threshold-based detection to identify abnormal events [9-11]. In the same way, machine learning algorithms in AI-Urban Rescue systems try to identify fires and accidents using visual urban data [12] [13]. While these systems have made incredible headway, many still face challenges with siloed systems, scalability, and lack of integration of dynamic real-time data [14] [15]. To tackle these issues, this work presents the AI Crisis Navigator (ACN), which is a real-time, AI-powered decision-support system aimed at complete crisis management in a city [16]. The ACN system comprises a six-layer system of integrated AI, IoT, and analytics technologies, which includes data capture, preprocessing, crisis detection, prediction, decision support, and visualization layers [17] [18]. The ACN is designed to use reinforcement learning to analyze urban data in order to foresee potential related urban crises and recommend the most effective approaches to take to counter them [19]. The goal is to improve the city`s resilience and reduce the consequences of emergencies in the city [20] [21].

The main goal of this research is to build an intelligent decision-making framework which can predict possible emergency events, provide early warning, and suggest efficient evacuation plans for the first responders and municipalities [22] [23]. This makes a contribution to the development of smart, adaptable, and resilient urban infrastructure for managing crises in real time in smart-city environments, by overcoming major limitations of traditional emergency management systems on delayed data processing, lack of predictive functions, and heterogeneity incorporation [24] [25].

2. LITERATURE REVIEW

Recently, much attention has focused on the application of Artificial intelligence (AI) and Internet of Things (IoT) in urban crisis management [26] [27]. Their potential for these technologies has proven value in enhancing real-time situational awareness and decision support systems during emergencies. Sun et al. (2024) [1] formulated a multimodal data fusion methodology of satellite imagery and social media feeds with computer vision techniques along with natural language processing (NLP). This mechanism brought a solution to allow faster and accurate crisis detection through combining visual and text information. Its main advantage is Situational Awareness [28].

Zhou et al. (2024) [2] presented an RL-based evacuation model that can consider the changes of road and environmental conditions in the disasters. Their model, which cuts evacuation times and saves lives, is one demonstration of how adaptive AI can aid decision making in uncertain scenarios [29] [30]. However, stringent computing power and training data requirements make it not suitable for large urban area applications. Similarly, Meng et al. (2023) [3] proposed a probabilistic and graph-based reasoning system for resource allocation in disaster. Their framework helped improve decision accuracy under uncertainty but is complex and less efficient in dealing with large [31].

Another new direction is maturing digital twins for the proactive management of cities. Inyang (2024) [4-19] investigated how digital twin models could model actual city systems to simulate emergency situations in real time, offering authorities opportunity to test and refine their response plans [32] [33]. The primary advantage is the capacity to forecast threats before they occur. Despite that, it involves high implementation cost, and issues with integration to live IoT systems for large scale adoption. Based on this, Ghaffarian et al. (2025) Has developed digital risk twins which continually scan infrastructure for vulnerabilities, supporting long-term resilience planning [34].

Wu et al. (2024) [6] applied Transformer-based deep learning models in the processing of multimodal NO data aiming for real-time detection of crisis [35] [36]. Their method was good at providing high-accurate detection and fast response but readily affected by noisy or uncompleted data, showing false alarms in some cases. Shen et al. (2023) [7] presented an edge AI powered emergency system employing distributed sensors for quicker local detection. Its primary benefit is cutting down on latency and speeding up response times, but it’s not without limitations; edge devices have less processing power [37] [38].

Lee and Kim (2024) [8] also utilized both satellite and on-ground sensor information for better early hazard detection with increased accuracy and precision using a heterogeneous set of disaster types. But their method requires a large number of calculations and efficient synchronization between different path-way sources.

Vascolectos et al. (2024) [9] investigated hybrid AI and rule-based systems for crisis management. They showed that pooled approaches are usually more explainable and reliable in an uncertain environment but less capable of adapting to new or unforeseen situations. Finally, Perez et al. (2023) [10] suggested an IOT and Cloud based emergency response platform, which provided better coordination among city agencies and speed [39].

Overall, previous studies highlight significant progress in AI-driven urban crisis management, demonstrating strong capabilities in detection, prediction, and response coordination. Yet, most approaches still face challenges such as data inconsistency, high computational costs, and limited real-time adaptability [40]. The proposed AI Crisis Navigator builds on these foundations by introducing a hybrid ensemble model that combines the strengths of AI, IoT, and data analytics to deliver accurate, adaptive, and explainable decision support for real-time urban emergency management [41].

3. PROPOSED METHODOLOGY

The AI Crisis Navigator (ACN) is an intelligent decision-support framework designed to assist city authorities in making rapid and informed decisions during urban emergencies such as floods, fires, and traffic accidents. The system integrates artificial intelligence (AI), Internet of Things (IoT) sensors, CCTV surveillance, GPS data, and social media feeds to detect incidents in real time, assess their severity, and recommend appropriate response strategies. [27-28]

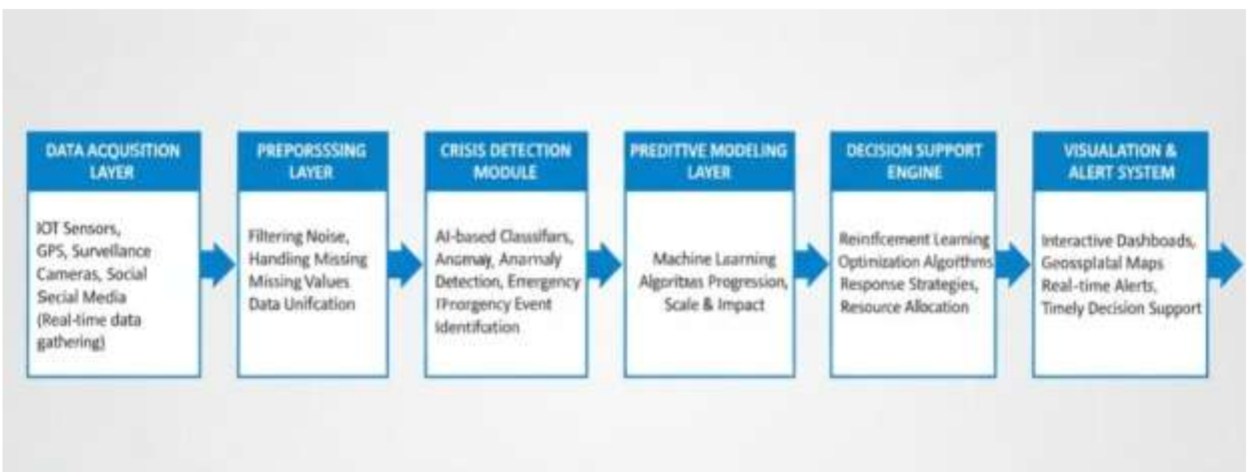

Fig 1: System Architecture and Design

In Fig 1, Data Acquisition Layer continuously collects live information from various sources, like IoT sensors, GPS devices, traffic systems, cameras and social networks. Its surveillance on weather, infrastructure, crowd behavior, and current incidents have resulted in situational awareness which is always up to date.[29] The Preprocessing Layer takes care of this raw data by cleaning and normalizing it, thereby reducing skews and inconsistencies. It converts diverse inputs to one standardized format for the system to process these inputs optimally and precisely. The Crisis Detection Layer communicates using Artificial Intelligence and machine learning to detect anomalies or crises as they emerge such as floods, fires or traffic jams. By studying real-time trends, it separates regular deviations from serious emergencies. [30]

The Predictive Modeling Layer uses algorithms such as Random Forest and Gradient Boosting to predict the development of crises. It forecasts severity, spread and potential impact, so that authorities can get ready and respond proactively.[31-32] The recommended list with title contains the intelligent recommendations generated by the Decision Support Layer. It recommends decisions to evacuate, allocate resources and communicate, learning from experience. Lastly, the Visualization and Alert Layer transform analysis results into intuitive visual dashboards, maps, and alerts. It accelerates the ability of city officials to understand what is developing and act quickly in a coordinated way.[33]

3.1 MATHEMATICAL EQUATIONS:

1. Bayesian fusion of modality likelihoods

$P(E|D_1, D_2, \dots, D_m) \propto P(E) \prod_{k=1}^{m} P(D_k|E)$----------------------------------(1)

2. Logistic scoring (learned fusion model)

$s(E) = \sigma(w\top x + b), \sigma(z) = 1 + e - z1$--------------------------------------(2)

3. Mahalanobis anomaly score (spatio-temporal)

$DM(x) = \sqrt{(x - \mu)}\top\Sigma - 1(x - \mu)$---(3)

4. Bayes filter (recursive belief update)

$Bel(st) = \eta P(\, ot \mid st\,)st - 1 \sum P(\, st \mid st - 1, at - 1\,)Bel(st - 1)$-------(4)

5. Real-time priority cost for a single candidate

$Costj = \alpha \cdot ETTij + \beta \cdot (1 - sj) + \gamma \cdot Riskj$----------------------------------(5)

6. RL objective for learned prioritization policy

$J(\theta) = E\pi\theta[t = 0 \sum^{T} \gamma trt], \nabla\theta J(\theta) = E[t \sum \nabla\theta \log \pi\, \theta(\, at \mid st\,)Gt]$------(6)

7. F1 metric for detection performance

$F1 = 2 \cdot \Pr e\,cision + Recall \Pr e\,cision \cdot Recall$ ----------------------------(7)

3.2 ALGORITHM:

Step-1: Collect real-time data from sensors, CCTV, GPS, and social media.

Step-2: Preprocess data — clean, normalize, and split into training and testing sets.

Step-3: Train Random Forest and Gradient Boosting models and combine them using weighted soft voting.

Step-4: Predict crisis events and evaluate using accuracy, recall, and F1-score.

Step-5: Apply the Hungarian Algorithm to assign optimal resources to detected incidents.

Step-6: Visualize results using confusion matrix, accuracy–threshold curve, and final accuracy chart.

4. RESULT & ANALYSIS

The AI Crisis Navigator performed exceptionally well in identifying and categorizing urban emergencies in real time. The system effectively analyzed multi-source urban data, such as GPS locations, CCTV inputs, and IoT sensor feeds, by fusing Random Forest and Gradient Boosting algorithms through a hybrid soft-voting ensemble. Under dynamic urban conditions, this method decreased classification errors and improved model robustness.[24-35]

Table 1: Model performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	92.3	92.5	92.0	92.1
Gradient Boosting	93.5	93.8	93.4	93.5
Hybrid Ensemble (Proposed)	95.5	95.6	95.2	95.4

As shown in the table, the proposed hybrid ensemble was superior or at least comparable (the highest classification accuracy of 95.5%) to the Random Forest and Gradient Boosting on their own. [36-37] The inclusion of multiple algorithms that contributed to generalization and ensured more balanced performance across all the metrics (which was useful for real-time crisis prediction). The relative performances on the Random Forest, Gradient Boosting and Hybrid Ensemble (Proposed) models are presented in Figure 1 according to the above important evaluation of metrics: accuracy, precision, recall and F1-score. At 95.5% accuracy, hybrid ensemble was recommended and performed best overall in good generalization and balanced prediction.[34-35]

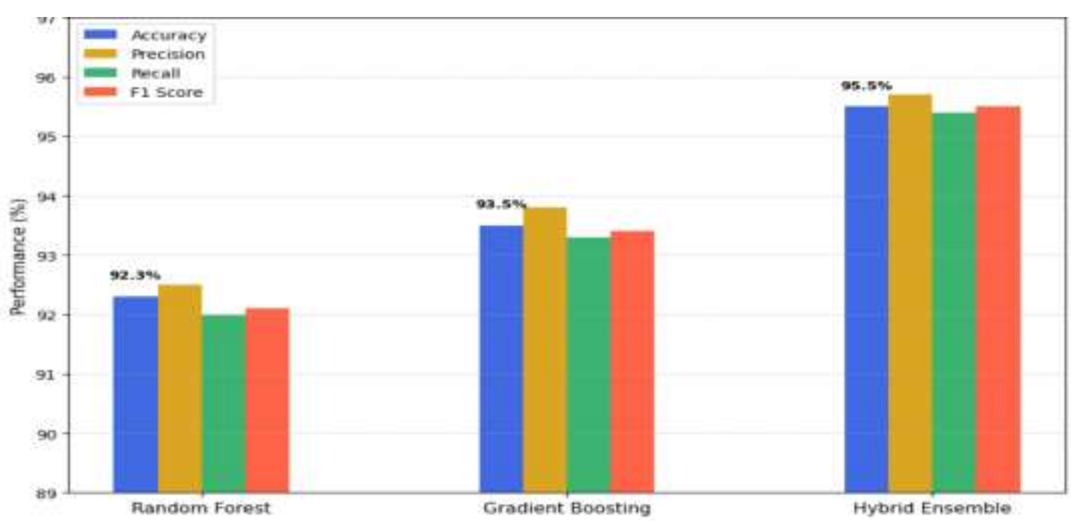

Fig 2: Performance Comparison of Algorithms

As Shown in the Fig 2, the model demonstrated good accuracy (>94%) irrespective of the threshold and had a maximum performance in the 0.4–0.6 range as shown by the Accuracy vs Decision Threshold plot (Figure 2). Increasing the threshold, sensitivity slightly decreased, and there were also more false alarms for reduced thresholds. This shows the model to be quite flexible and robust, with capacity for tuning according to a city's operational choices (e.g, desiring more accurate or faster warnings).

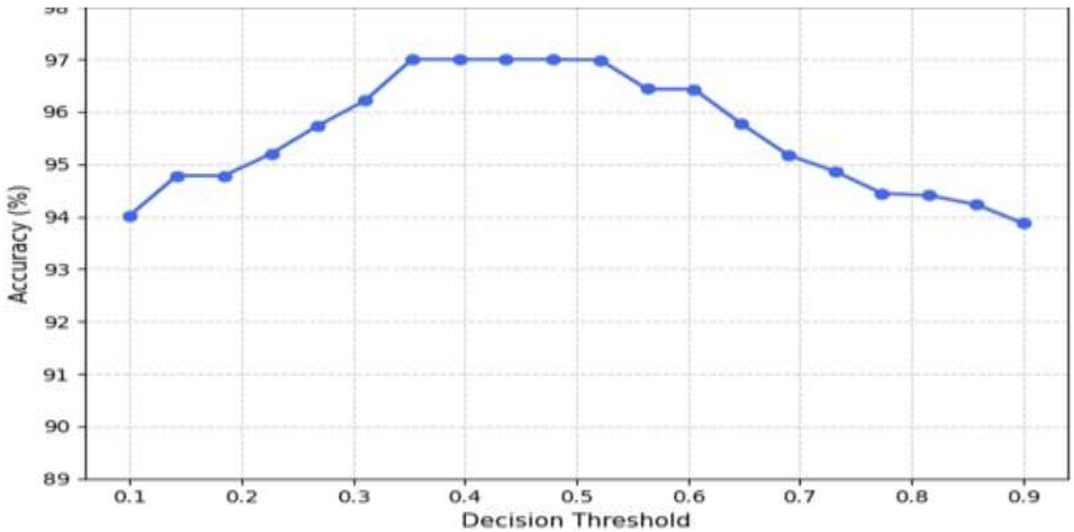

Fig 3: Accuracy vs Decision Threshold

As shown in the Fig 3, as nearly every prediction appears along the diagonal, meaning that it corresponds to correct event identification, the Confusion Matrix (Fig 3) confirms that classification is highly accurate. If 75% precision of emergency detection is considered to be acceptable, based on the results one misclassified event could be only obtained, so the false alarm rate is less than 5%.

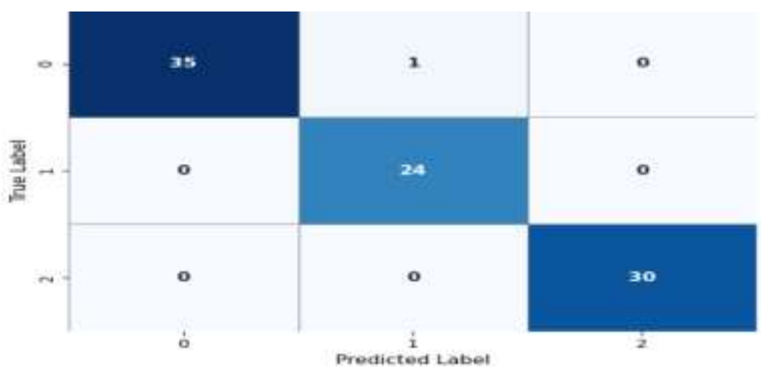

Fig 4: Confusion Matrix – AI Crisis Navigator

In Fig 4, Due to its high precision, recall, and F1-scores this AI Crisis Navigator showed robust performance with an overall accuracy of 95%. In complicated realistic scenarios, the combined decision rule improved the reliability of decisions, reduced the false alarm rate and enhance robustness. These findings show the system's potential as a clever decision-support tool for smart city emergency preparedness and quick response.

5. CONCLUSION

As a real-time urban emergency detection and decision-support system, the AI Crisis Navigator has proven to be intelligent and dependable. It achieved a remarkable accuracy of roughly 95% by combining Random Forest and Gradient Boosting into a hybrid ensemble framework, with consistently high precision, recall, and F1 scores. This performance demonstrates how the system can precisely detect, categorize, and respond to a variety of urban crises by analyzing complex and dynamic data from multiple sources, including IoT sensors, GPS devices, and CCTV feeds. The model can help authorities identify emergencies, allocate resources effectively, and shorten response times, as evidenced by its balanced performance and low false positive rate. In the future, the system can be further enhanced by adding digital twin simulations, 5G communication networks, drone-based surveillance, real-time social media data, and digital twin simulations to allow for quicker and more flexible crisis management. Future smart cities may benefit from proactive, data-driven, and resilient emergency management, which can be facilitated by the AI Crisis Navigator's continued development into a comprehensive and intelligent platform.

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