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Smart Wildfire Prediction and Risk Mapping System using AI and Remote Sensing Data

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ABSTRACT: Wildfires are among the most devastating natural disasters, causing severe ecological damage, economic losses, and threats to human life. The increasing frequency and intensity of wildfires due to climate change and anthropogenic activities highlight the need for intelligent, timely, and accurate monitoring systems. Traditional wildfire detection approaches largely depend on satellite observations or manual reporting, which often result in delayed alerts and limited predictive capability. This paper presents a Smart Wildfire Prediction and Risk Mapping System that integrates artificial intelligence (AI) with remote sensing data to provide both real-time wildfire detection and long-term risk prediction. The proposed system combines a real-time pipeline using lightweight deep learning models for immediate fire detection with a batch-processing pipeline that leverages historical satellite imagery, vegetation indices, meteorological data, and terrain features to predict wildfire risk. A Hybrid Fusion Risk Model (HFRM) integrates outputs from both pipelines to generate dynamic wildfire risk maps and alerts. Experimental results demonstrate that the fusion-based approach improves prediction accuracy and significantly reduces false alarms compared to standalone models. The proposed system is scalable, adaptive, and suitable for large-scale deployment in forest fire management applications.

KEYWORDS: Wildfire Prediction, Remote Sensing, Deep Learning, NDVI, NBR, Risk Mapping, Fusion Model, Artificial Intelligence

I. INTRODUCTION

Wildfires pose a serious threat to ecosystems, biodiversity, infrastructure, and human settlements across the globe. In recent years, wildfire events have increased in both frequency and intensity due to rising global temperatures, prolonged droughts, deforestation, and changes in land-use patterns. Early detection and accurate prediction of wildfire-prone regions are essential for minimizing damage and enabling timely intervention by disaster management authorities.

Remote sensing technologies provide continuous and large-scale observations of forest regions and have become an important tool for wildfire monitoring. Satellites such as MODIS, VIIRS, Sentinel-2, and Landsat supply thermal and multispectral data that can be used to detect fire activity and assess vegetation conditions. However, satellite-only systems often suffer from detection delays, cloud interference, and limited capability to predict future fire risk. Recent advances in artificial intelligence, particularly machine learning and deep learning, have shown strong potential in extracting complex patterns from large-scale environmental data. This research proposes an integrated AI-driven wildfire prediction system that combines real-time fire detection with batch-based wildfire risk assessment, enabling proactive decision-making and effective disaster response.

II. LITERATURE REVIEW

Several studies have investigated the use of AI and remote sensing for wildfire detection and prediction. FCDNet introduced a lightweight convolutional neural network optimized for real-time wildfire core detection using drone-based thermal imagery, achieving fast inference and low computational cost [1]. While effective for immediate detection, the approach does not consider long-term fire risk prediction.

RFWNet proposed a multiscale deep learning architecture that integrates spatial and spectral features from satellite imagery to improve wildfire detection accuracy [4]. Although the model demonstrated high detection performance, it required substantial computational resources, making it less suitable for real-time applications.

Jain et al. conducted a comprehensive survey of machine learning techniques for wildfire prediction, highlighting the effectiveness of Random Forest and other ensemble methods in identifying fire-prone areas using vegetation indices and meteorological variables [7]. However, most surveyed models operate in offline mode and lack real-time adaptability.

Zhu et al. presented a deep learning-based approach for wildfire prediction using satellite imagery and weather data, emphasizing the importance of temporal modeling through neural networks [8]. Despite promising results, the approach relied on computationally intensive models and did not integrate real-time fire detection.

These studies demonstrate that existing approaches typically focus either on real-time detection or offline prediction. There is a clear research gap in developing a unified framework that combines both capabilities, which motivates the proposed work.

III. DATASETS USED

The proposed Smart Wildfire Prediction and Risk Mapping System utilizes multiple datasets collected from satellite platforms, meteorological sources, and historical records to ensure accurate and reliable wildfire detection

and prediction. These datasets are broadly categorized into real-time datasets and batch (historical) datasets, each serving a specific purpose within the system architecture. Real-time datasets are primarily used for immediate wildfire detection and rapid response. Satellite-based fire products from MODIS and VIIRS provide near real-time information on active fire hotspots, brightness temperature, and confidence levels. These datasets enable the system to identify potential fire events shortly after ignition. In addition, thermal and RGB imagery captured by drones is used to obtain high-resolution, localized views of fire-affected areas, which helps in confirming fire presence and reducing false alarms. Live meteorological data from weather sensors supplies critical parameters such as temperature, humidity, and wind speed, which influence fire behavior and spread.

Batch or historical datasets are used for long-term wildfire risk prediction and pattern analysis. Sentinel-2 and Landsat-8 multispectral satellite images provide detailed surface reflectance data that is used to compute vegetation indices such as NDVI and NBR. These indices help assess vegetation health, fuel availability, and burn severity. ERA5 reanalysis data provides historical weather information, including temperature, rainfall, wind speed, and humidity, which are essential for understanding climatic conditions associated with wildfire occurrence. Digital Elevation Model (DEM) data is used to extract terrain features such as elevation and slope, which significantly influence fire spread. Additionally, historical fire occurrence records are used as ground truth data for training, validation, and evaluation of machine learning models.

By combining these diverse datasets, the system achieves a comprehensive understanding of both current fire activity and long-term wildfire risk factors.

IV. METHODOLOGY

The methodology of the proposed Smart Wildfire Prediction and Risk Mapping System is designed to integrate real-time wildfire detection with batch-based historical risk prediction into a single, unified framework. The approach ensures timely identification of active fire events while also assessing long-term wildfire susceptibility based on environmental and climatic factors. This section explains the complete workflow of the system, including data acquisition, data flow, database design, model processing, fusion of predictions, and system interaction.

The methodology begins with the acquisition of data from multiple heterogeneous sources. Real-time data is continuously collected from satellite platforms such as MODIS and VIIRS, drone-based thermal and RGB cameras, and live weather sensors. These sources provide immediate information related to thermal anomalies, fire hotspots, and current environmental conditions. In parallel, batch data is periodically collected from high-resolution satellite imagery

such as Sentinel-2 and Landsat, historical meteorological datasets from ERAS, Digital Elevation Models (DEM), and historical wildfire records. This combination of real-time and historical data enables both fast detection and accurate risk prediction.

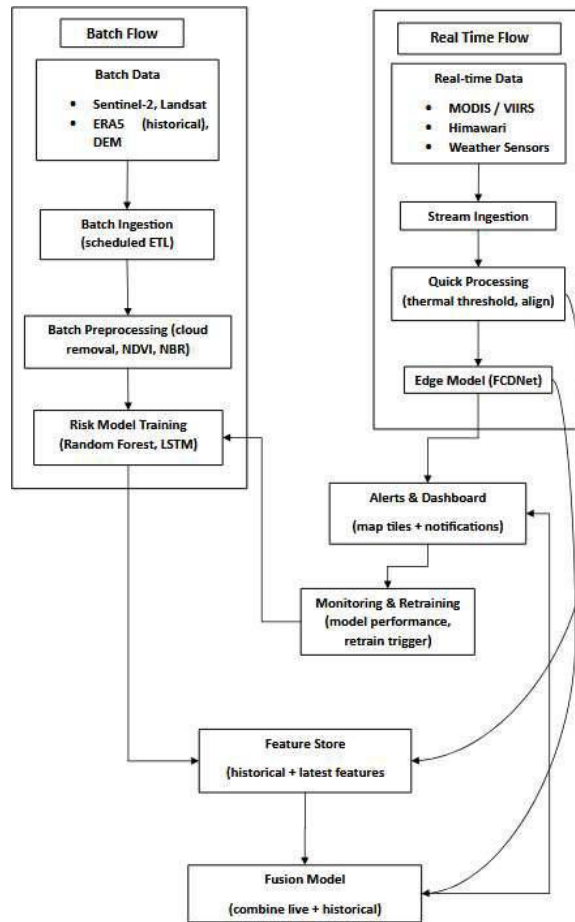


Fig 1 - System Architecture

After data acquisition, all incoming data is passed through the ingestion layer. Real-time data streams are ingested using low-latency streaming mechanisms such as Kafka or MQTT to ensure continuous processing. Batch data is ingested through scheduled ETL pipelines that periodically fetch and store large volumes of satellite and weather data. This ingestion process ensures synchronization, reliability, and fault tolerance across both real-time and batch pipelines.

The movement of data through the system is represented using a Data Flow Diagram. The data flows from input sources to preprocessing units, then to model processing units, and finally to output components such as risk maps and alert systems. The Data Flow Diagram helps in understanding how data is transformed at each stage and how different components interact within the system.

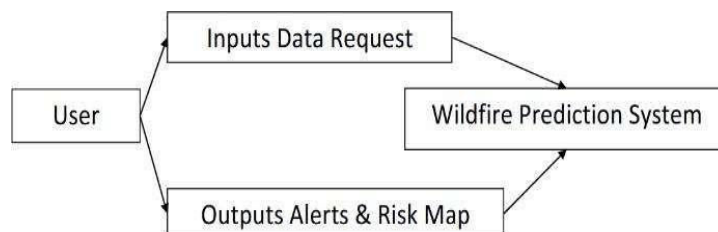


Fig 2 - Data Flow Diagram

Following ingestion, preprocessing and feature extraction are performed separately for real-time and batch data to meet their respective requirements. Real-time preprocessing focuses on speed and includes thermal thresholding, noise filtering, and basic spatial alignment to quickly detect potential fire regions. Batch preprocessing involves more detailed operations such as cloud masking, atmospheric correction, resampling, and temporal alignment. Vegetation indices such as NDVI and NBR are computed during this stage to assess vegetation health and burn severity. Weather and terrain features such as temperature, humidity, wind speed, elevation, and slope are also extracted.

The extracted features are stored in a structured database for efficient access and management. To represent the organization of stored data, an Entity Relationship (ER) diagram is used. The ER diagram defines key entities such as Satellite Data, Weather Data, Vegetation Indices, Fire Events, Risk Predictions, and Model Information, along with their relationships. This database design supports efficient storage, retrieval, and analysis of large-scale wildfire-related data.

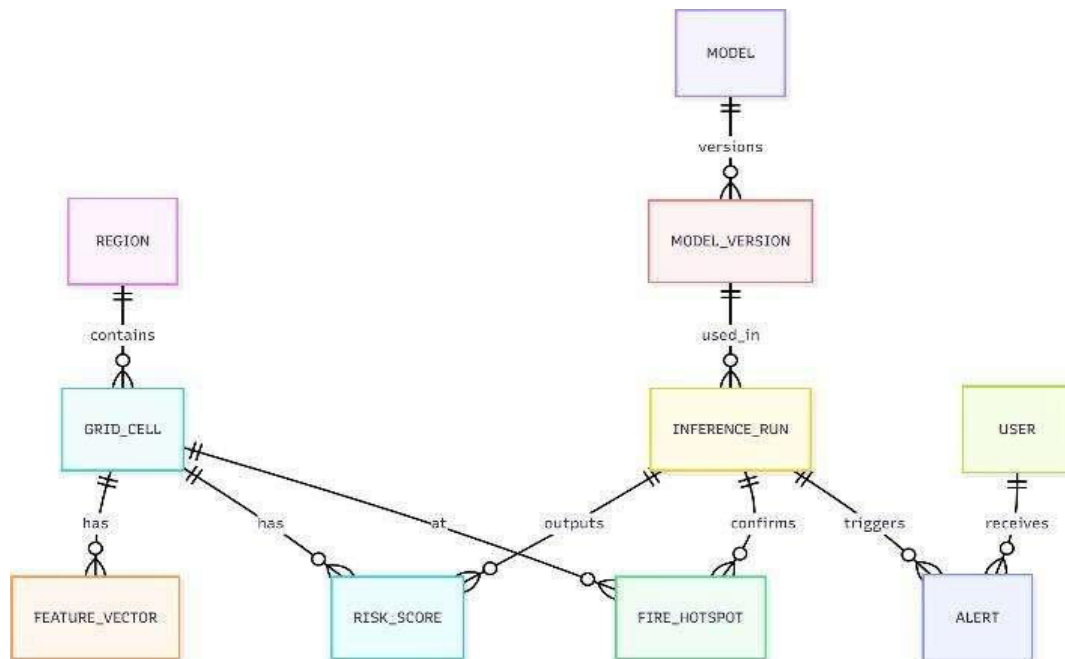


Fig 3 - Entity Relationship (ER) Diagram

Once the data is preprocessed and stored, model-based analysis is performed. Real-time fire detection is carried out using lightweight deep learning models such as FCDNet or Mobile U-Net. These models analyze thermal and satellite imagery to detect active fire regions with low latency. Batch-based wildfire risk prediction is performed using machine learning models such as Random Forest and XGBoost, which analyze vegetation, weather, and terrain features to estimate spatial fire risk. Additionally, LSTM networks are used to capture temporal dependencies in historical weather and vegetation data to predict short-term fire risk trends.

To combine the outputs from real-time detection and batch prediction models, a fusion-based approach is employed. A Hybrid Fusion Risk Model integrates real-time fire detection confidence scores with batch-based historical risk predictions and environmental indicators. This fusion process produces a final wildfire risk score for each spatial grid cell, ensuring that both immediate fire activity and long-term susceptibility are considered. The fusion approach significantly reduces false alarms and improves prediction reliability.

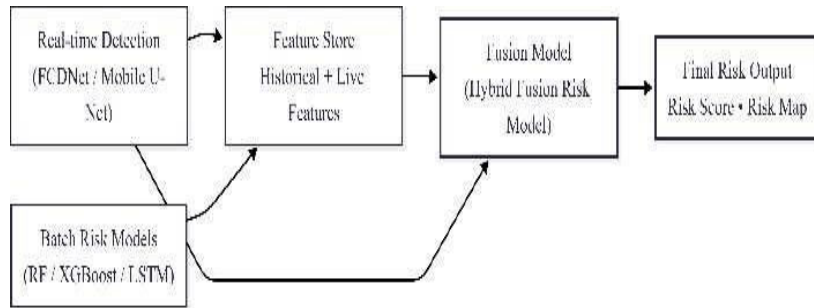


Fig 4 - Fusion Model Interaction Diagram

The interaction between users and the system is represented using a UML Use-Case diagram. The diagram identifies key actors such as forest officers, disaster management authorities, and system administrators. It illustrates how users interact with the system to view risk maps, receive alerts, monitor fire events, and manage data and models. This diagram helps in understanding the functional behavior of the system from a user perspective.

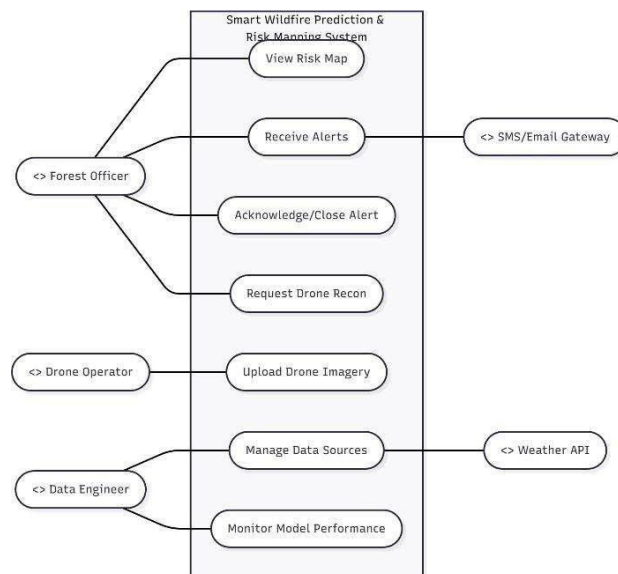


Fig 5 - UML Use-Case Diagram

Finally, the system includes a monitoring and retraining mechanism to ensure continuous improvement. Model predictions are continuously evaluated against actual fire events to assess performance. When prediction accuracy degrades or data drift is detected due to changing environmental conditions, retraining is triggered using updated datasets. Updated models are redeployed into the system to maintain accuracy and adaptability over time.

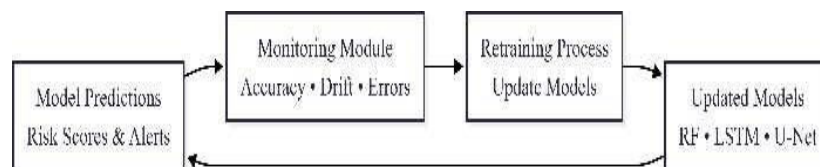


Fig 6 - Monitoring and Retraining Feedback Loop

In summary, the methodology integrates data acquisition, preprocessing, feature extraction, AI-based modeling, fusion of predictions, and continuous monitoring into a cohesive workflow. By combining real-time detection with batch-based risk prediction and incorporating structured system design diagrams, the proposed methodology provides a robust, scalable, and effective solution for wildfire prediction and risk mapping.

V. MATHEMATICAL MODEL

The mathematical model of the proposed Smart Wildfire Prediction and Risk Mapping System provides a formal representation of how wildfire risk is computed using environmental, historical, and real-time data. The objective of the model is to estimate a wildfire risk score for each spatial region by integrating vegetation conditions, weather parameters, terrain characteristics, historical fire patterns, and real-time fire detection outputs.

The entire forest region under study is divided into fixed spatial grid cells. Each grid cell represents a geographical area for which wildfire risk is independently assessed. Let the total number of grid cells be denoted by N . For each grid cell i , a feature vector is constructed using relevant environmental and fire-related parameters. The feature vector for grid cell i is defined as:

$$X_i = \{V_i, W_i, T_i, H_i, E_i, F_i\}$$

where V_i represents vegetation-related features, W_i denotes wind speed, T_i represents temperature, H_i denotes humidity, E_i represents terrain features such as elevation and slope, and F_i denotes historical fire occurrence frequency. These features collectively capture the major factors influencing wildfire ignition and spread.

Vegetation conditions are quantified using spectral indices derived from satellite imagery. The Normalized Difference Vegetation Index (NDVI) is used to assess vegetation health and fuel availability and is computed as:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

where NIR represents near-infrared reflectance and RED represents red band reflectance. Higher NDVI values indicate healthy vegetation, while lower values suggest dry or sparse vegetation, which is more susceptible to fire.

To assess burned areas and fire severity, the Normalized Burn Ratio (NBR) is used. NBR is calculated as:

$$NBR = \frac{NIR - SWIR}{NIR + SWIR}$$

where $SWIR$ represents shortwave infrared reflectance.

Lower NBR values indicate burned or fire-affected areas and help in identifying fire impact and recovery.

Batch-based wildfire risk prediction models learn the relationship between historical features and fire occurrence. These models approximate a function that maps the feature vector X to a wildfire risk probability:

$$P_i^{Batch} = f_{Batch}(X)_i$$

where P_i^{Batch} represents the long-term wildfire risk probability for grid cell i . Machine learning models such as Random Forest and XGBoost are used to estimate this probability based on historical data, while LSTM models capture temporal dependencies in weather and vegetation patterns.

For real-time fire detection, deep learning models analyze incoming thermal or satellite imagery at the pixel level. Let p represent the input pixel value at location p . The real-time fire detection model produces a probability score

indicating the likelihood of fire presence:

To obtain a grid-level real-time fire probability, pixel-level probabilities within a grid cell are aggregated as follows:

$$P_{real-time} = \frac{1}{M} \sum_{p=1}^M P_{fire}$$

where M is the total number of pixels within grid cell i .

To combine long-term risk prediction and real-time fire detection, a fusion-based approach is adopted. The final wildfire risk score for each grid cell is computed using a weighted combination of batch-based and real-time probabilities:

$$R_i = \alpha P_{real-time} + \beta P_{batch}$$

where α and β are weighting factors such that $\alpha + \beta = 1$. The values of these weights can be dynamically adjusted depending on system requirements, such as giving higher importance to real-time detection during active fire conditions.

The continuous wildfire risk score R_i is mapped to discrete risk categories to facilitate interpretation and visualization. The risk levels are defined as:

$$\begin{aligned} \text{Low, } R_i &< 0.3 \\ \text{Risk;} &= \{\text{Medium, } 0.3 \leq R_i < 0.6 \\ \text{High, } R_i &\geq 0.6 \end{aligned}$$

These categories are used to generate color-coded wildfire risk maps and trigger alerts when high or critical risk levels are detected.

To ensure long-term reliability, a monitoring mechanism evaluates prediction accuracy by comparing predicted risk scores with actual fire events. If the prediction error exceeds a predefined threshold, retraining of models is initiated using updated datasets. This adaptive mechanism allows the system to respond to changing environmental conditions and maintain prediction accuracy over time.

In summary, the mathematical model integrates vegetation indices, meteorological variables, terrain features, historical fire patterns, and real-time fire detection outputs to compute a reliable wildfire risk score. The fusion-based formulation ensures that both immediate fire activity and long-term susceptibility are effectively captured in the final risk assessment.

VI. EXPERIMENTAL RESULTS

The performance of the proposed Smart Wildfire Prediction and Risk Mapping System was evaluated using a combination of historical satellite imagery, meteorological data, terrain information, and recorded wildfire events. The experiments were conducted to assess the effectiveness of individual models as well as the overall performance of the fusion-based approach. The evaluation focuses on prediction accuracy, robustness, and the ability of the system to reduce false alarms while providing timely alerts.

The study area was divided into fixed spatial grid cells, and predictions were generated for each grid cell over the selected time period. Historical data from multiple years was used for training, while recent data was reserved for validation and testing. Standard evaluation metrics such as

accuracy, precision, recall, and FI -score were used to assess model performance. For real-time detection, the false alarm rate and detection accuracy were also analyzed to evaluate system reliability.

The batch-based wildfire risk prediction models demonstrated strong performance in identifying high-risk regions. Random Forest models provided stable and interpretable results, particularly in regions where vegetation and terrain features played a dominant role. XGBoost achieved higher overall accuracy due to its ability to capture complex nonlinear relationships between vegetation indices, weather parameters, and terrain features. LSTM models performed well in capturing temporal patterns in weather and vegetation data, making them effective for short-term risk forecasting, especially during seasonal transitions.

Table I - Performance Comparison of Batch-Based Risk Prediction Models

Model	Accuracy (%)	Precision	Recall	F1-Score
Random Forest	84.2	0.82	0.80	0.81
XGBoost	87.6	0.86	0.84	0.85
LSTM	85.1	0.83	0.82	0.82

Real-time fire detection models were evaluated using thermal and satellite imagery. Lightweight deep learning architectures such as FCDNet and Mobile U-Net achieved fast inference with high detection accuracy, making them suitable for real-time deployment. However, when used independently, real-time models showed a higher false alarm rate due to transient thermal anomalies, cloud effects, and sensor noise.

To address this limitation, the fusion-based approach was evaluated by combining real-time detection outputs with batch-based risk predictions. The Hybrid Fusion Risk Model significantly improved overall system performance by filtering out spurious detections and reinforcing predictions in historically high-risk regions. The fusion model achieved higher detection accuracy and a substantially lower false alarm rate compared to standalone approaches.

Table 2 - Comparison of Standalone and Fusion-Based Approaches

Approach	Detection Accuracy (%)	False Alarm Rate (%)
Real-time only	82	18
Batch only	85	15
Fusion Model	91	9

In addition to numerical evaluation, qualitative analysis was performed using wildfire risk maps generated by the system. The risk maps clearly highlighted regions with high and critical wildfire susceptibility and showed strong agreement with known fire-prone areas. Temporal analysis indicated that the system successfully adapted to changing weather and vegetation conditions, particularly during peak fire seasons.

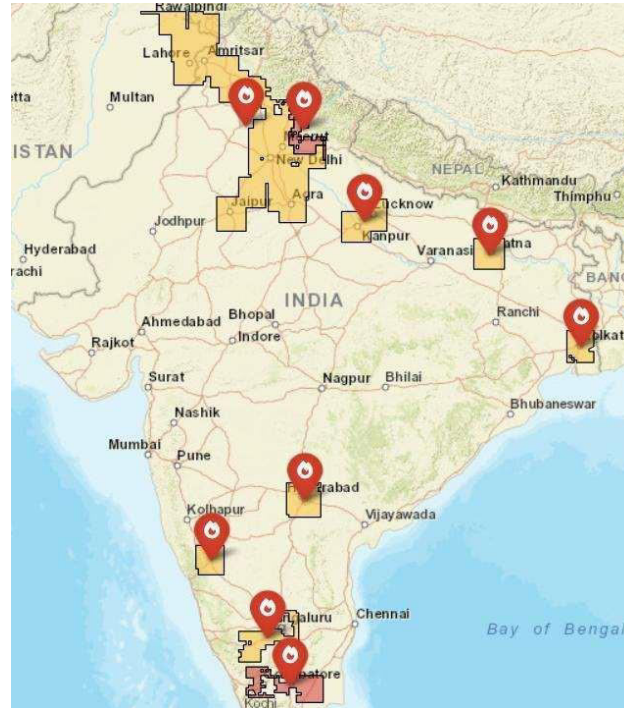


Fig 7 - Sample Wildfire Risk Map Generated by the Proposed System

Overall, the experimental results demonstrate that integrating real-time fire detection with batch-based historical risk prediction through a fusion model leads to more accurate and reliable wildfire risk assessment. The proposed system outperforms individual models and provides a balanced trade-off between early detection and prediction stability, making it suitable for real-world wildfire monitoring and decision support.

VII. APPLICATIONS

The proposed Smart Wildfire Prediction and Risk Mapping System has a wide range of practical applications across environmental monitoring, disaster management, and public safety domains. By integrating real-time detection with long-term risk prediction, the system supports proactive decision-making and efficient resource utilization in wildfire-prone regions.

One of the primary applications of the system is in forest fire early warning systems. Forest departments and environmental agencies can use the generated wildfire risk maps and real-time alerts to identify high-risk zones before fire outbreaks occur. Early warnings enable timely preventive actions such as controlled burns, deployment of firefighting resources, and restriction of human activities in vulnerable areas.

The system is also highly useful for disaster management and emergency response planning. During active fire events, real-time detection helps authorities quickly identify fire locations and assess their severity. Combined with risk maps, the system supports evacuation planning, prioritization of response efforts, and coordination among

firefighting teams. This leads to reduced response time and minimized damage to life and property. Another important application is in environmental monitoring and forest management. Long-term wildfire risk analysis helps in assessing forest health, vegetation stress, and the impact of climate change on fire behavior. The system can also be used for post-fire assessment by analyzing burned areas and monitoring vegetation recovery over time using satellite-derived indices.

The proposed system can be integrated into smart city and IoT-based safety platforms. By combining wildfire predictions with ground-based sensor networks and communication systems, automated alerts and decision-support tools can be developed for urban areas located near forest regions. This integration enhances public safety and supports smart infrastructure planning.

In addition, the system has potential applications in insurance and risk assessment. Insurance companies and land management agencies can use wildfire risk predictions to assess exposure, estimate potential losses, and develop data-driven risk mitigation strategies. The system also supports academic and research applications, providing a scalable framework for studying wildfire patterns, climate variability, and the effectiveness of AI-based environmental monitoring solutions.

VIII. CONCLUSION

This research presented a Smart Wildfire Prediction and Risk Mapping System that integrates artificial intelligence with remote sensing data to address the challenges of early wildfire detection and accurate risk assessment. By combining real-time fire detection with batch-based historical risk prediction, the proposed system overcomes the limitations of traditional wildfire monitoring approaches that rely on a single data source or processing method. The use of deep learning models for real-time detection and machine learning models for long-term risk prediction enables the system to provide timely alerts while maintaining high prediction accuracy.

The incorporation of a fusion-based decision mechanism further enhances system reliability by integrating immediate fire signals with historical environmental patterns. Experimental results demonstrate that the fusion approach significantly improves detection accuracy and reduces false alarms compared to standalone real-time or batch-based models. The generated wildfire risk maps and alerts provide actionable insights for forest authorities, disaster management agencies, and emergency responders, supporting informed decision-making and effective resource allocation.

IX. FUTURE WORK

Although the proposed system demonstrates strong performance, several enhancements can be explored in future work. The integration of additional data sources such as ground-based IoT sensors and higher-resolution satellite imagery can further improve detection accuracy and spatial resolution. Automated online learning and continuous retraining mechanisms can be developed to adapt models to changing environmental and climatic conditions in real time.

Future extensions may also include fire spread modeling to predict the direction and speed of wildfire propagation, enabling more effective evacuation and containment planning. Deployment of the system on cloud-edge hybrid infrastructures can improve scalability and reduce latency for large-scale monitoring. Additionally, the framework can be extended to support global wildfire monitoring and integrated with decision-support systems for comprehensive disaster management and climate impact analysis.

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