Fine-Scale Forest Fire Monitoring and Early Warning via IoT and Remote Sensing

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Abstract:Forest fires pose a significant threat to natural habitats, leading to profound changes in the biological, chemical, and physical properties of forests. Accurate and timely prediction of fire occurrence is essential for proactive forest management and disaster mitigation. However, existing monitoring systems lack the precision and timeliness required for effective early fire detection and risk mitigation. This study proposes a hybrid wildfire monitoring and early alert framework that combines IoT ground sensors with remote sensing data to forecast forest fire risk, enabling proactive early warnings for forest protection and disaster mitigation. By collecting IoT sensors and satellite imagery, the data are refined through preprocessing steps that involve filtering out noise and intelligently estimating missing values, as well as satellite image correction. Followed by multi-modal feature fusion through locality-sensitive hashing and rank Gauss normalisation to create a uniform feature set. From the fused data, a convolutional neural network-based analytical model enhanced with triplet loss is applied to predict fire ignition probability and classify risk levels (high risk/ no risk). The findings indicate that the proposed model achieved an accuracy of 97.20%, a precision of 96.98%, a recall of 97.71%, and an F1-score of 97.34%, significantly outperforming existing architectures. These results validate the framework as a scalable, data-driven early warning solution for fine-scale wildfire prediction and sustainable forest management.

Keywords: Forest Fire Monitoring, Early Warning System, IoT Sensors, Remote Sensing, Convolutional Neural Network, and Disaster Mitigation

1. Introduction

Forest fires are unchecked or mismanaged fires that take place in grasslands and other natural terrain, which in most cases have considerable ecological, economic and social impacts [1]. Such fires have the potential to destroy vegetation, degrade biodiversity and release a lot of carbon dioxide in the air [2], and are a major source of threat to human safety. Wildfires are a long-standing phenomenon in the world, and their prevalence is rising amidst climate change, prolonged droughts, hot temperatures and other human activities [3]. A review of literature within 20-30 years revealed that wildfire events have increased significantly, especially in places like North America, Australia [4]. In the Mediterranean region, dry seasons and lightning sparks are among the factors contributing to an increase in fire incidences. History and satellite-based measurements have revealed that millions of hectares of forests are hit every year, and some areas are known to have repeated seasonal fires for decades [5], [6]. The ecological and economic effects of such fires are far-reaching, including depletion of vegetation cover, degradation of soil, smoke emissions, and other effects that pose a great danger to both wildlife and human beings [7]. In the past, monitoring relied on the capabilities of ground patrols and watchtowers. However, recent technological advances have enabled the integration of remote sensing (satellites and aerial drones), allowing for continuous surveillance [8]. These monitoring systems, combined with current computational methods, can produce approximate estimates of fire-prone regions, monitor the progress of current fires, and estimate possible outbreaks [9], thereby enabling effective preparations and resistance.

Artificial Intelligence (AI) has become a disruptive technology in the field of environmental surveillance and disaster management in recent years [10]. These calculation procedures enable machines to perform functions that previously required human intelligence. Deep learning (DL) is a subdiscipline of AI to determine intricate characteristics of large and heterogeneous data [11]. In the last ten years, the technologies have achieved considerable momentum, and multiple studies have shown that the technologies can process satellite images [12], Internet of Things (IoT) sensor data [13] and meteorological data with accuracy and speed never before possible. DL combined with IoT devices enable continuous tracking and offers a stream of data in constant motion inside forested areas [14]. On the same note, remote sensing platforms, such as satellites and drones, provide high-resolution space and time imagery that can identify vegetation conditions, thermal signals, and the presence of fire patches and hotspots [15]. With the aid of the integration of IoT sensor measurements and satellite-derived data, AI models can sufficiently acquire both time-dependent and space-dependent trends, which will allow making strong predictions with probability and risk classification [16]. The benefits of applying this to enhance proactive and timely warnings, and the safeguarding of large forested regions through proper and precise monitoring [17]. Therefore, the integration of AI has transformed traditional wildfire response in forest fire control methods to enhance situational awareness and enable proactive decision-making in real-time, thereby minimising ecological and socio-economic impacts.

1.1. Problem Statement

The benefits of forest fire monitoring and AI-based prediction are evident, but existing methods still have several unresolved issues. To begin with, a majority of satellite-based fire detection techniques have low temporal resolution [18], thus making it slow to detect small-scale ignition sources and limiting their ability to provide fine-scale early warnings. Moreover, the system based on IoT sensors can also be continuous, but due to the noise in data, it is usually restricted and is unable to assess the fire risk correctly [19]. In addition, the current models have a poor system of integrating multimodal data, a factor that makes the usefulness of the data streams' complementary information underutilised, thus lowering the strength of the predictions [20]. Also, many AI applications for wildfire risk prediction struggle with skewed data and poor feature representations [21], which limits their ability to generalise effectively across various forest regimes and changing climate dynamics. Despite the numerous approaches investigated, these outstanding challenges underscore the need for a fine-scale framework that enables more precise monitoring of forest fires and early warning systems to mitigate losses and damages from disasters. Thus, the proposed methodology has been developed to fill these gaps.

The major innovations introduced by this framework are listed as follows.

Develops a hybrid system of forest fire monitoring that combines the use of IoT sensors and remote sensing data to predict forest fire risk and make proactive early warnings to protect forests.

Processes of IoT data to handle missing values, satellite image processing, atmospheric correction and index retrievals to provide high-quality inputs.

Utilise Locality-Sensitive Hashing (LSH) to combine multi-modal features of IoT sensors and remote sensing data to generate a unified set of features in predicting fire risks.

Determines the probability of forest fires based on a CNN-based model with triplet loss as the optimal predictor of fire ignition potential and risk categorisation (high risk/ no risk).

The paper's layout and flow are organised as follows: Section 2 provides an overview of current wildfire monitoring approaches reported in the literature. Section 3 provides system methodology. The analysis and discussion of the results of the experiment are presented in Section 4. Lastly, Section 5 concludes the research and presents possible avenues of future research.

2. Literature Review

Forest fire monitoring has been a primary focus in most countries, with researchers such as Zheng et al. [22], Pang et al. [23], and Lin et al. [24] developed an AI-based prediction model to improve early detection and risk assessment. They proposed methods utilising convolutional neural networks (CNN) to extract informative features from forest blaze imagery, thereby capturing discrimination. Their proposed 15-layer CNN model detects the presence of high-risk fire zones by combining multi-source information, fire hotspots and past fire records (2003-2016) in China, utilising multiple AI methods. Similarly, LSTM architectures are integrated with GIS and remote sensing data to enhance predictive capabilities, and their correlation is assessed using multicollinearity testing to produce dynamic forest fire risk maps. Additional development was witnessed in work by Lai et al. [25] and Fitriany et al. [26], who used a sparse autoencoder-based DL with the balancing of data to predict fire. Based on Portuguese data in the Montesinho Natural Park, the prediction error decreased by 19.3 points, indicating improved future success in wildfire management. Meanwhile, in Indonesia, crowdsourced social media information was used in fire detection, with Twitter messages regarding forest fires in Riau, Sumatra (2014-2019), being processed. The results suggest that AI models, combined with unusual data sources like social media, could enhance national fire management systems. Nevertheless, these studies remained limited to multimodal integration against various forest conditions.

In parallel, researchers have investigated IoT-based sensor networks for the management of forest fires. A system that identifies wildfire occurrences using distributed IoT sensors was presented by Alkhatib et al. [27] and Lertsinsrubtavee et al.[28] to monitor the ecological conditions and detect fire hazards. This system has its ability to predict natural fire outbreaks hours in advance. It achieved this by continuously monitoring environmental conditions to enable the quantification of fire risk. They identified three active fire periods and three non-fire periods by selecting two for model training and the remaining for validation. A J48 decision-tree algorithm was applied and achieved an accuracy of 72% in distinguishing fire from non-fire events. Also, Mahaveerakannan et al. [29] and Haque et al. [30] integrated IoT data collection and AI-driven prediction to enhance the functions of early warning. They focused on object detection models with Efficient-Det being applied in detecting fire-related events. The use of a Calculus Optimisation was introduced to optimise the training of DL. Also, the incorporation of virtual sensors in the wireless sensor networks increased predictive ability in intricate fire situations caused by thunder or lightning. The effectiveness of using a hierarchical perceptron network to classify and predict early warning and fire scenarios using an experimental setting was proven. However, the issues of scalability and adjustability were not tackled.

Traditional wildfire prediction approaches had largely relied on satellite-based remote sensing for monitoring fire activity. Huot et al. [31] and Tian et al. [32] built a multivariate database of historical wildfires in the United States as a cumulation of 10 years of satellite images. This dataset is a fusion of both fire data and explanatory factors that provide an input with rich features to the ML models. The neural networks trained on this data demonstrated significant potential for predicting wildfire propagation. A different study, created by Avetisyan et al. [33] developed mountain fire in Muli County (March 2020) was analysed using a combination of meteorological, combustible, terrain, and human activity variables. The researchers identified the key factors influencing wildfire occurrence and assessed vegetation cover before and after two major fires in Sichuan Province using a random forest model. This enabled managers to correlate fire intensity with vegetation destruction, informing a more effective mitigation strategy. More inputs were recorded by Asadollah et al. [34] and Wang et al. [35], who utilised NASA satellite data and an ML classifier to simulate fire behaviour between 2000 and 2021. CMIP6 EC-Earth3-SSP245 climate data were used to develop the future fire projections (2030-2050). In addition, the classification was performed spatio-temporally, eliminating false hotspots of fire that were periodic or recurring sources of heat, and thus generating a dataset. This method was used in Hunan Province, and the mistakes in the detection of hotspots were minimised. Nevertheless, there were still difficulties when it came to the generalisation of different ecological areas.

Several studies have examined AI approaches for wildfire identification and forecasting. However, current models frequently fail to provide useful multi-modal data fusion, are unscaleable and cannot merge ground-level IoT data with satellite images to create accurate early warning messages. To overcome these weaknesses, the proposed work forms a hybrid framework that has been improved to facilitate proper forest fire monitoring and early warning.

3. Materials and Methodology

The architecture seeks to create a system for wildfire surveillance and proactive alerts by utilising a hybrid approach that integrates IoT ground sensors with satellite remote sensing data. Through the use of multi-source data acquisition, the framework further monitors the environment with the help of IoT sensors, and monitors the macro-level forest and fire indicators of the forest using high-resolution satellite images. The collected data undergo intelligent preprocessing to ensure they are cleaned and guaranteed. Thereafter, a multi-modal feature fusion layer would be used to integrate spatial information of remote sensing and time trends of IoT sensors using Locality-Sensitive Hashing (LSH) to align the results of feature integration correctly and Rank Gauss Normalisation to balance features appropriately.

The combined dataset is subsequently processed using an AI-based predictive model that employs a CNN with a triplet loss function to extract high-level information from the satellite images. Meanwhile, IoT trends are incorporated to enhance temporal perception and ensure robust, representative learning by comparing similar and dissimilar environmental patterns. While transformer-based and hybrid models are known for their ability to capture long-range dependencies and temporal dynamics, the proposed framework uses a CNN with triplet loss due to its computational efficiency, strong spatial feature extraction, and suitability for fine-scale fusion of heterogeneous data. The temporal patterns from IoT sensors are encoded as structured temporal grids and embedded alongside spatial features from remote sensing imagery. This allows the CNN to learn joint spatio-temporal representations without the overhead of transformer self-attention mechanisms, which are often data-hungry and less interpretable in low-resource, real-time forest monitoring settings. Moreover, the triplet loss enhances discriminative learning across fire/no-fire classes, compensating for temporal nuances by enforcing similarity-preserving embeddings. This enables advance warnings to protect the forest and prevent disasters. The system's operational workflow is visualised in Figure 1.

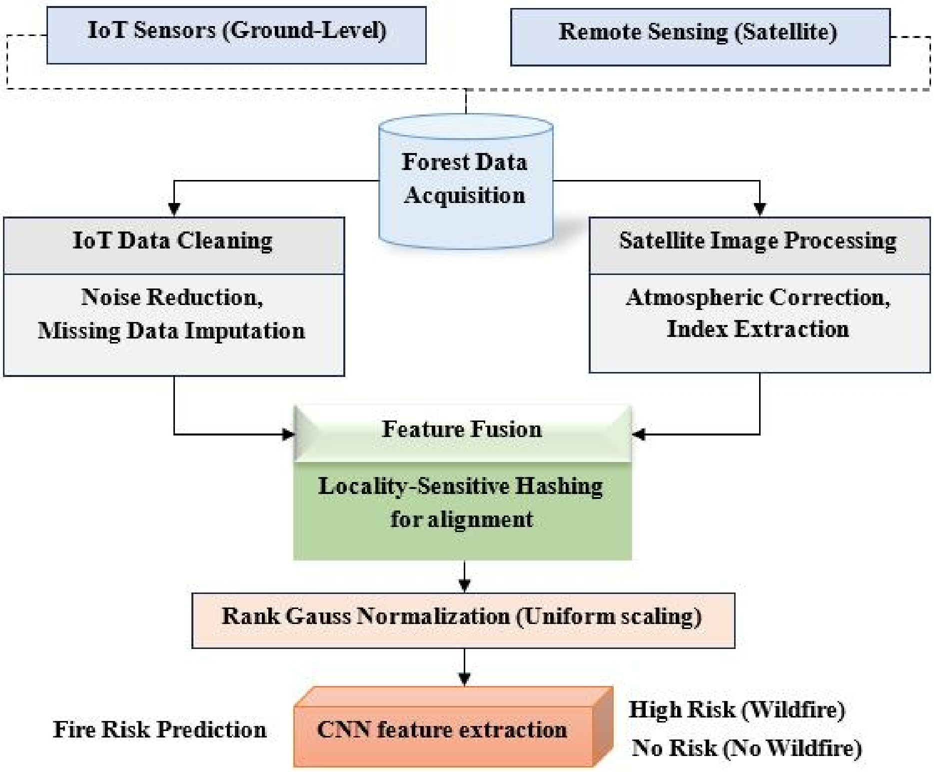

Figure 1: Proposed IoT-Remote Sensing Framework Architecture of Forest Fire Monitoring and Early Warning System.

3.1. Multi-Source Data Acquisition

3.1.1 IoT Sensors

The ground-level data comprises the IoT sensor data collected by the forest fire detection management system. These sensors are also strategically mounted in forest areas to monitor important environmental parameters (temperature, relative humidity, smoke concentration (CO/CO_2) and wind speed). The data include time and geo-tagging, providing temporal and spatial data on microclimatic changes, enabling the identification of early fire ignition evidence. This IoT information is developed through the deployment of low-power, wireless sensor nodes in forest areas that capture and transfer data in real-time, through communication protocols that tracking of the area, even where connectivity is low.

3.1.2 Remote Sensing Data (Aerial Level)

The satellite imagery is obtained to complement the ground measurements in areas of wildfires. These datasets will include high-resolution images of Earth that are taken by Earth observation satellites with multispectral and thermal sensors. The satellite images are acquired periodically to ensure temporal continuity, but can be used with drone observations to provide a better spatial resolution. The images show thermal deviations, vegetation droughtiness and burn markings to provide macro-level data on forest conditions that are difficult to detect with ground sensors. The data is interpreted to contain spectral indices, including normalised burn ratio and other vegetation indices, that illustrate potentially fire-prone regions or regions that are already burnt.

3.2. Intelligent Preprocessing

Raw data received by IoT and remote sensors is typically noisy and inconsistent, significantly undermining the performance of predictive models. Such problems are typical in the current methodology, as they are caused by the weaknesses in sensor precision. Thus, the framework will include a preprocessing step to optimise the quality and usability of the data to overcome these issues.

3.2.1. IoT Data Cleaning

- ***Noise Reduction***

In this context, Kalman filtering is used to minimise noise in measurements from IoT sensors. The Kalman filter is an optimal recursive estimator that is employed to estimate the current condition of a system by leveraging past observations with the new information obtained by the sensor, in effect separating actual environmental changes and random noise. When continuous streams of IoT data are filtered using this filter, a clean input signal is generated.

- ***Missing Data Handling***

In this case, Multiple Imputation by Chained Equations (MICE) will be used to address missing or incomplete data in the IoT sensor data. MICE operate through the sequential prediction of each of the missing values by a set of regression models in which a given variable with missing data is represented as a function of the other observed variables. In this process, initial approximate guesses of the missing entries are produced and then refined through repeated chaining steps, resulting in multiple possible imputed datasets. The average of these different imputations is then computed as the final value of each missing entry, producing the statistical reliability required and maintaining the underlying data distribution.

3.2.2. Satellite Image Processing

➢ ***Atmospheric Correction***

Under this, Radiative Transfer Models (RTMs) are used to preprocess satellite images, eliminating cloud cover and even atmospheric distortion. RTMs model radiation propagation in the Earth's atmosphere and include scattering, absorption and reflection of radiation by gases, aerosols and clouds. With the modelling of such interactions, the RTM can estimate and remove the atmospheric contributions of the observed satellite signal and, in effect, isolate the reflectance by the surface of the forest. When there are cloud-affected pixels, the model detects anomalies in spectral signatures caused by cloud presence and uses spatial and temporal interpolation with RTM outputs to correct them, ensuring the reflected surface properties.

➢ ***Index Extraction***

In this case, the satellite images are processed using the Normalised Burn Ratio (NBR) to determine the burnt or fire-prone regions in the forest. The NBR is based on the NIR and SWIR bands of satellite imagery by taking advantage of the fact that healthy vegetation strongly reflects the NIR band but absorbs the SWIR radiances. On the other hand, burnt areas are more reflective of SWIR compared to NIR.

The NBR generates a contrast map by computing the ratio $(\mathrm{NIR} - \mathrm{SWIR})/(\mathrm{NIR} + \mathrm{SWIR})$ for each pixel, indicating areas affected by or at risk of fire. In this flow, the index is used to correct small residual atmospheric and cloud terms by emphasising the spectral differences in vegetation health, but not atmospheric artefacts. The resultant NBR maps provide both quantitative indications and precise locations of forest conditions.

3.3. Multi-Modal Feature Fusion

In this context, combining data from multi-source sensors that contain IoT and remote sensor information represents the environment's imagery, identifies localised environmental variations, and reveals more general trends that contribute to forest fire risk. Nevertheless, the problem of heterogeneity and high dimensionality of IoT sensors data produces time-series vectors of continuous measurements of temperature, humidity, smoke and wind, whereas satellite images create high-dimensional space vectors (spectral indices and thermal anomalies). Locality-Sensitive Hashing (LSH) is applied to combine these modalities in a framework. It is a probabilistic dimensionality reduction algorithm that is used to condense complex, high-dimensional data into a simpler, low-dimensional representation, retaining the similarity relationships between them.

Given a set of IoT feature vectors (X) and satellite feature vectors (Y), LSH applies a family of hash functions $(\mathcal{H})$ to project these vectors into a shared hash space, as expressed in equations (1-4).

$$\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2, \dots, \mathrm{x}_i\} \subset \mathbb{R}^d \tag{1}$$

$$\mathrm{Y} = \{\mathrm{y}_1, \mathrm{y}_2, \dots, \mathrm{y}_j\} \subset \mathbb{R}^d \tag{2}$$

Each hash function h_i is defined as:

$$\mathcal{H} = \{h_1, h_2, \dots, h_i\} \tag{3}$$

$$h_i(\mathrm{v}) = \left\lfloor \frac{\mathrm{a}_i \cdot \mathrm{v} + b_i}{r} \right\rfloor, \mathrm{v} \in \mathbb{R}^d \tag{4}$$

Where a_i indicates a random vector $\mathbb{R}^d$ drawn from a p-stable distribution (Gaussian for Euclidean distance), b_i is a random offset, and r is the bucket width controlling the quantisation resolution. The product $a_i \cdot v$ captures the projection of the high-dimensional vector along a random direction, and the floor operation discretises the projection into hash bins. By applying L such functions in parallel, each feature vector is mapped to a hash code H, defined in equation 5.

$$H(\mathrm{v}) = (h_1(\mathrm{v}), h_2(\mathrm{v}), \dots, h_L(\mathrm{v})) \tag{5}$$

This mapping ensures that vectors that are close in the original space (representing similar environmental conditions or fire risk patterns) are highly likely to collide in the same hash bucket, effectively preserving locality. The fused feature set is then constructed by aligning IoT and satellite vectors that share common hash codes:

$$\mathcal{F}_{\mathrm{fused}} = \bigcup_{\mathrm{bucket}\ B} \{(\mathrm{x}_i, \mathrm{y}_j) | H(\mathrm{x}_i) = H(\mathrm{y}_j) = B\} \tag{6}$$

In equation (6), $\mathcal{F}_{\mathrm{fused}}$ represents the final multi-modal feature matrix used for downstream AI-based prediction. In this formulation, x_i and y_j are paired if they collide in the same hash bucket B, allowing the framework to efficiently align heterogeneous data streams without exhaustive pairwise comparisons, which would be computationally prohibitive. By using LSH in this manner, the framework achieves similarity-preserving fusion of IoT and remote sensing features, ensuring that both localised sensor trends and broader spatial patterns are jointly considered. This results in enhancing the system’s ability to identify high-risk regions for proactive forest fire warnings.

3.3.1 Uniform Scaling Function

Following the alignment of features, the fused data often contains heterogeneous distributions due to differences in measurement scales, units, and variability across sensor types and spectral indices. To ensure that all features contribute equally to the subsequent AI-based prediction model and to stabilise training convergence, the framework applies Rank Gauss Normalisation, which transforms arbitrary feature distributions into a standard Gaussian form. This approach handles skewed and heavy-tailed data in environmental and remote sensing measurements.

Given a feature vector $\mathcal{F}_{\mathrm{fused}} = [f_1, f_2, \dots, f_i]$ of length i, the Rank Gauss proceeds by first computing the rank of each element within the vector, as shown in equation (7).

$$r_i = \mathrm{rank}(f_i), i = 1,2, \ldots, n \tag{7}$$

Where r_i represents the sorted position of f_i within f, with $r_i = 1$ for the smallest value and $r_i = n$ for the largest. The rank is then rescaled into a uniform quantile in the interval [0,1] :

$$u_i = \frac{r_i - 0.5}{n} \tag{8}$$

In equation (8), u_i denotes the empirical cumulative probability associated with f_i, and the subtraction of 0.5 ensures centring within each quantile. Finally, the quantile is mapped onto a standard Gaussian distribution by applying the inverse of the normal distribution's cumulative function, as shown in equation (9).

$$f_i^{(\mathrm{norm})} = \Phi^{-1}(u_i), i = 1,2, \ldots, n \tag{9}$$

Where Φ^{-1} is the inverse of the standard normal function, producing a normalised value $f_i^{(\mathrm{norm})}$ with zero mean and unit variance, and approximately Gaussian distribution. In this formulation, $f_i^{(\mathrm{norm})}$ is now directly comparable across all features, allowing the AI model to learn patterns without bias from differences in scale or distribution shape.

By applying Rank Gauss Normalisation, the framework achieves uniform scaling across all sensor and satellite features, thereby mitigating the influence of extreme values, enhancing numerical stability, and improving the model's robustness and generalisation. This step involves multi-modal fusion, ensuring that heterogeneous environmental and spectral information contribute equally to the fire risk assessment.

3.4. Fire Risk Prediction

To enable fine-grained and reliable prediction of wildfire occurrence, a CNN integrated with a Triplet Loss learning strategy is employed. The CNN is responsible for hierarchical feature extraction from both remote sensing imagery and IoT sensor trends, whereas the Triplet Loss ensures that the learned embeddings preserve similarity between related samples (fire–fire, no fire-no fire) while maximising the separation between dissimilar instances (fire vs. no fire). This approach guarantees a discriminative representation learning and robust generalisation of heterogeneous data inputs. Figure 2 indicates the detailed CNN architecture for forest fire prediction.

To ensure reproducibility and transparency of the CNN–Triplet Loss model training for wildfire risk prediction, the following hyperparameters were employed: the model was trained using the Adam optimiser with a learning rate of 0.0003, a batch size of 64, and for 120 epochs with early stopping based on validation loss stagnation over 10 epochs. A triplet loss margin of 0.4 was used to enforce discriminative separation between fire and no-fire embeddings, while a dropout rate of 0.3 was applied after the fully connected layer to mitigate overfitting and enhance generalisation. These parameters were selected via grid search to balance predictive accuracy across heterogeneous IoT and remote-sensing inputs.

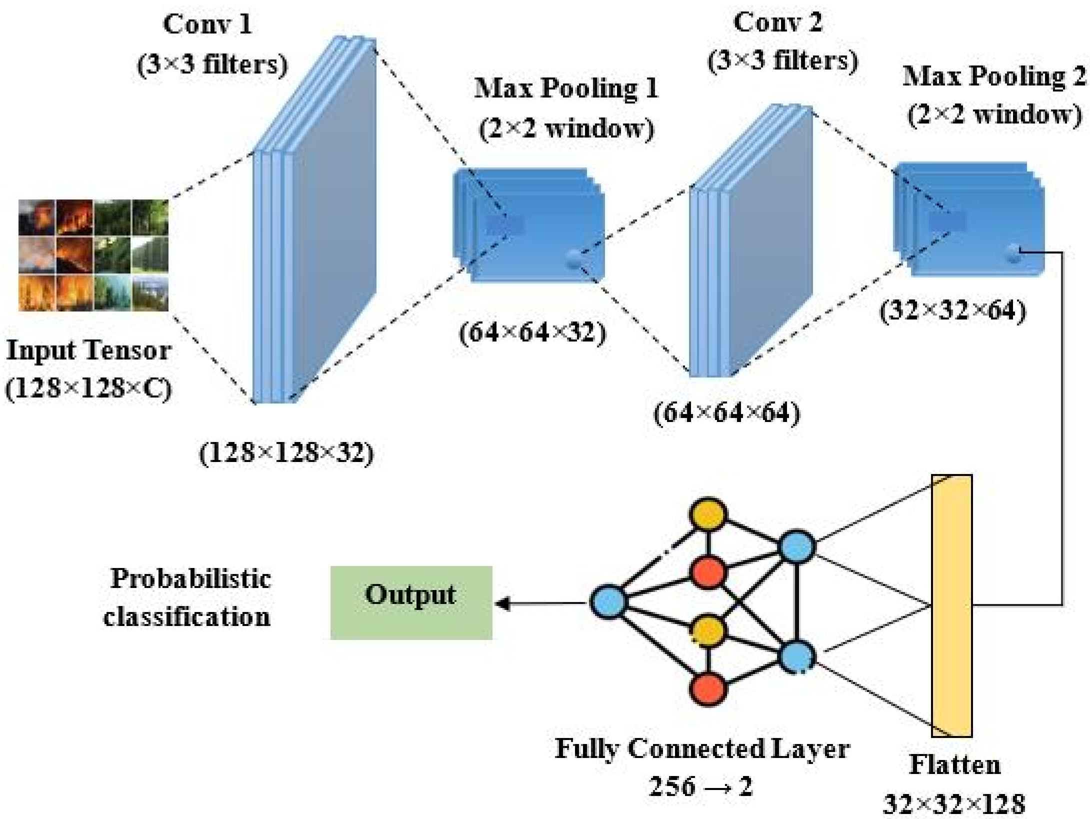

Figure 2: CNN Architecture for IoT and Remote Sensing-Based Wildfire Prediction

The CNN architecture processes an input tensor $X \in \mathbb{R}^{H\times W\times C}$, where H, W, and C denote the height, width, and channel depth of the input (multi-spectral satellite imagery combined with sensor-derived temporal grids). Each convolutional operation can be mathematically represented as in equation (10).

$$F_{i,j,k} = \sigma\left(\sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{c=1}^{C} W_{m,n,c,k} \cdot X_{i+m,j+n,c} + b_k\right) \tag{10}$$

Where $F_{i,j,k}$ is the activation at the spatial location (i, j) in the k-th feature map, $W_{m,n,c,k}$ are the learnable convolutional filter weights of spatial extent $M \times N$, b_k is the bias, and σ is the non-linear activation function (ReLU). This operation progressively extracts local spatial and temporal features relevant to wildfire dynamics.

The resulting feature maps are pooled to ensure translation invariance and dimensionality reduction. A max pooling operation is expressed as in equation (11).

$$P_{i,j,k} = \max_{(u,v)\in\Omega(i,j)} F_{u,v,k} \tag{11}$$

Where $P_{i,j,k}$ is the pooled activation, u, v are the feature map, and $\Omega(i,j)$ denotes the local neighbourhood window centred at (i,j). This reduces redundancy while retaining the strongest activation responses, which are indicative of wildfire patterns.

Once the deep features are extracted, the CNN projects the input sample x into an embedding space using a fully connected layer, as shown in equation (12).

$$z = f_\theta(x) \in \mathbb{R}^d \tag{12}$$

Where $f_\theta(\cdot)$ represents the CNN parameterised by weights θ, and z is the d-dimensional embedding vector $\mathbb{R}^d$. This learn an embedding where samples from the same class ("fire") are close, and those from different classes ("fire" vs. "no fire") are far apart.

To enforce this discriminative property, this work uses the Triplet Loss. For an anchor sample x^a, a positive sample x^p (same class), and a negative sample x^n (different class), the embeddings are computed as $z^a = f_\theta(x^a)$, $z^p = f_\theta(x^p)$, and $z^n = f_\theta(x^n)$. Thus, the Triplet Loss ($\mathcal{L}_{\text{triplet}}$) is then defined as in equation (13).

$$\mathcal{L}_{\text{triplet}} = \max\left(0, \|z^a - z^p\|_2^2 - \|z^a - z^n\|_2^2 + \alpha\right) \tag{13}$$

Where $\alpha > 0$ is the margin parameter. This ensures that the anchor-positive distance is at least α smaller than the anchor-negative distance, thereby pulling together similar samples while pushing apart dissimilar ones. In practice, the optimisation process leverages the gradient of the Triplet Loss with respect to the embeddings, guiding the CNN to refine its filters and parameters. The gradient with respect to the anchor embedding (∂) is given by equation (14).

$$\frac{\partial \mathcal{L}_{\text{triplet}}}{\partial z^a} = 2 \cdot (z^a - z^p) - 2 \cdot (z^a - z^n) \tag{14}$$

This indicates that the network simultaneously reduces the distance to the positive and increases the distance to the negative, thereby sharpening class boundaries. To further stabilise training, a SoftMax classification head is added to the embedding space, predicting the probability of fire ignition. The SoftMax probability (P) for the class $c \in \{0,1\}$ (no fire vs. fire) is expressed as in equation (15).

$$P(y = c|z) = \frac{\exp\left(w_c^{\top} z + b_c\right)}{\sum_{j=1}^{2} \exp\left(w_j^{\top} z + b_j\right)} \tag{15}$$

Where w_c and b_c are the class-specific weights and bias. This transforms the embedding into probabilistic predictions interpretable as ignition likelihood. The cross-entropy loss $\mathcal{L}_{\mathrm{CE}}$ is then used to guide the classifier, as shown in equation (16).

$$\mathcal{L}_{CE} = -\sum_{c=1}^{2} y_c \log\left(P(y = c|z)\right) \tag{16}$$

Where y_c is the ground-truth one-hot label. Combining this with the Triplet Loss, the final joint objective function becomes $\mathcal{L}_{\mathrm{final}}$, defined as in equation (17).

$$\mathcal{L}_{\mathrm{final}} = \lambda_1 \mathcal{L}_{\mathrm{triplet}} + \lambda_2 \mathcal{L}_{CE} \tag{17}$$

Here, λ_1 and λ_2 are weighting coefficients that balance representation learning and classification accuracy. This ensures discriminative embeddings and reliable probabilistic classification. This process produces a system capable of predicting the probability of wildfire ignition within the range of 0 to 1, expressed as a fire/no fire classification.

Algorithm 1: Pseudocode for CNN with Triplet Loss for fire risk prediction

Input: X (satellite images & IoT sensor data)

Output: Classification result P: {High Risk / No Risk}

Begin

For each input sample x in X do

$F \leftarrow$ Convolution (x, W, b) with activation σ

$P \leftarrow$ Max Pooling (F)

$z \leftarrow$ Fully Connected $(P;\ \theta)$

End For

Select triplets (x^a, x^p, x^n)

Compute embeddings: $z^\wedge a$

Cross-Entropy Loss: L_{CE}

Final Joint Loss: L_{final}

Update parameters: $\theta \leftarrow \theta$

For unseen input x:

Generate embedding z_{test}

Compute fire ignition probability $P \in [0, 1]$

If $P \geq$ threshold → Predict "High Risk (Wildfire)"

Else → Predict "No Risk"

End If

End For

End

4. Validation and Results

To confirm the suggested model, tests were conducted using IoT sensor data and satellite imagery. The entire implementation was done in Python on a 12th Gen Intel(R) Core (TM) i5-12400 (2.50 GHz) with 8 GB RAM (7.75 GB usable). The AI model was trained on a fused dataset comprising both IoT sensor streams and satellite images from forest areas with historical fire incidents. A total of 18,240 samples were obtained across different ecological zones to ensure generalisability. The dataset was first divided into three parts using stratified sampling: 70% for training, 15% for validation, and 15% for testing, to maintain class balance. After that, the model was evaluated using a 5-fold cross-validation protocol with a fixed random seed (42) to ensure reproducibility in the final reporting of accuracy, precision, recall and F1-score. This confirms the system's resilience and its fire-early warning capability in real-world scenarios.

4.1 *Performance Analysis*

This part presents evidence on the efficiency of the AI-based hybrid forest fire monitoring model through a wide range of experiments and comparative performance analysis. The performance of the AI architecture, including the integration of a CNN with triplet-loss optimisation, showed high learning efficiency, as it extracted small-scale spatial features from the integrated data. The findings support the validity and effectiveness of the suggested AI model as a way to issue early, fine-scale, and accurate warnings about forest fires and, therefore, contribute to swift response and efficient management of disasters.

To evaluate the predictive performance of the CNN-Triplet Loss model, a inclusive set of standard classification metrics was employed. These included (equations 18-23):

$$\text{Accuracy} = \left(\frac{TP+TN}{TP+TN+FP+FN}\right) \tag{18}$$

It measures the overall proportion of correctly classified instances.

$$\text{Precision} = \left(\frac{TP}{TP+FP}\right) \tag{19}$$

It quantifies the proportion of predicted fire events that were actual fires.

$$\text{Recall} = \left(\frac{TP}{TP+FN}\right) \quad (20)$$

It measures the model's ability to correctly identify actual fire events.

$$\text{F1} - \text{Score} = \frac{2\times \text{ Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (21)$$

It represents the harmonic mean of precision and recall to provide a balanced assessment.

$$FPR = \left(\frac{FP}{FP+TN}\right) \quad (22)$$

It indicates the proportion of non-fire events incorrectly classified as fire.

$$FNR = \left(\frac{FN}{FN+TP}\right) \quad (23)$$

It represents the proportion of actual fire events that the model misses.

In this context, TP, TN, FP, and FN represent the numbers of true positives, true negatives, false positives, and false negatives, respectively. For every fold in the k-fold cross-validation, all metrics were computed and their mean values were reported to provide a statistically robust and unbiased evaluation of the model's performance.

Figure 3: Probabilistic Satellite Contrast Map for Wildfire Classification

Figure 3 presents a comparative visualisation of satellite image samples. It portrays the no wildfire samples in urban and suburban areas with low ignition probabilities (0.01-0.05), and highlights wildfire samples with dense vegetation cover and thermal anomalies that have high ignition probabilities (0.95-0.98). This serves as a qualitative measure to demonstrate the model's discriminatory ability in distinctive fire-prone and safe areas. It validates the model's capacity to learn meaningful representations from heterogeneous data and classify fire risk by contrasting spatial features with corresponding probability scores. Thus, aiding early warning and disaster mitigation.

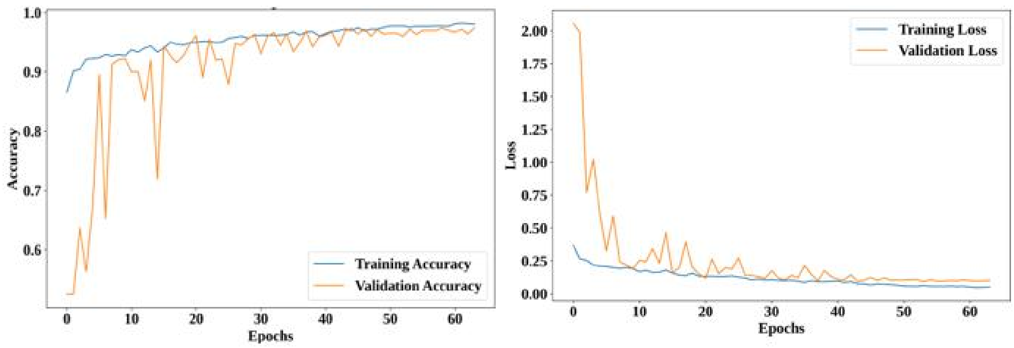

Figure 4: Performance Curve of CNN–Triplet Loss Model

The dynamics of training and validation of the proposed AI model are shown in Figure 4 during the 60 epochs. This shows an accuracy progression in which training accuracy increases gradually and reaches a plateau at 0.98. Whereas, validation accuracy varies at 97.20, indicating high generalisation. Also, the loss trajectory with training loss smoothly declining to 0.032 and validation loss stabilising around 0.054, confirms effective convergence and minimal overfitting. This validates the model's learning stability and robustness in predicting wildfire risk from fused IoT and satellite data for real-time early warning systems.

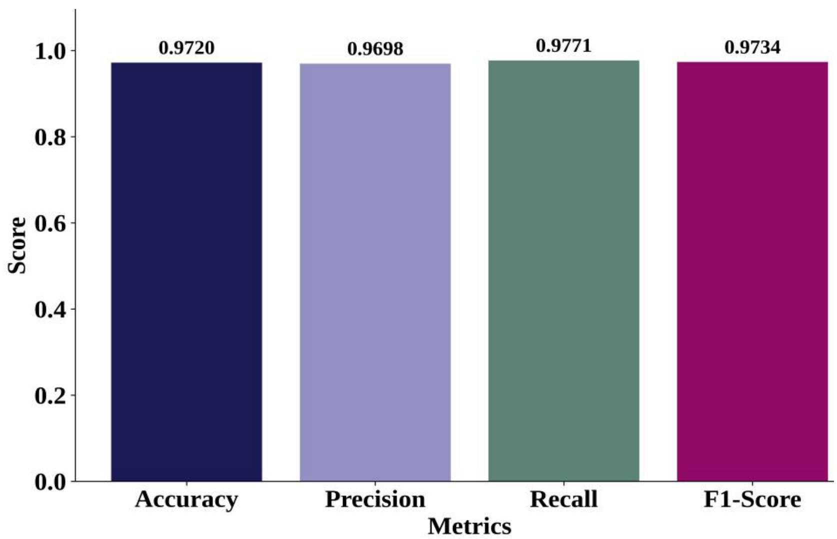

Figure 5: Classification Performance for Wildfire Risk Prediction

Figure 5 provides the classification metric, which summarises the performance of the proposed CNN-Triplet Loss model in terms of several metrics. The metrics evaluate the model's capability to detect high-risk wildfire areas compared to safe areas, utilising fused IoT and satellite data. The model had an Accuracy of 0.9720, a Precision of 0.9698, a Recall of 0.9771 and an F1-score of 0.9734, which is reliable in both detection and classification. Therefore, this model justifies its balanced performance by proving that it effectively minimises false positives and negatives, enabling forest fire management systems to issue timely and accurate early warnings.

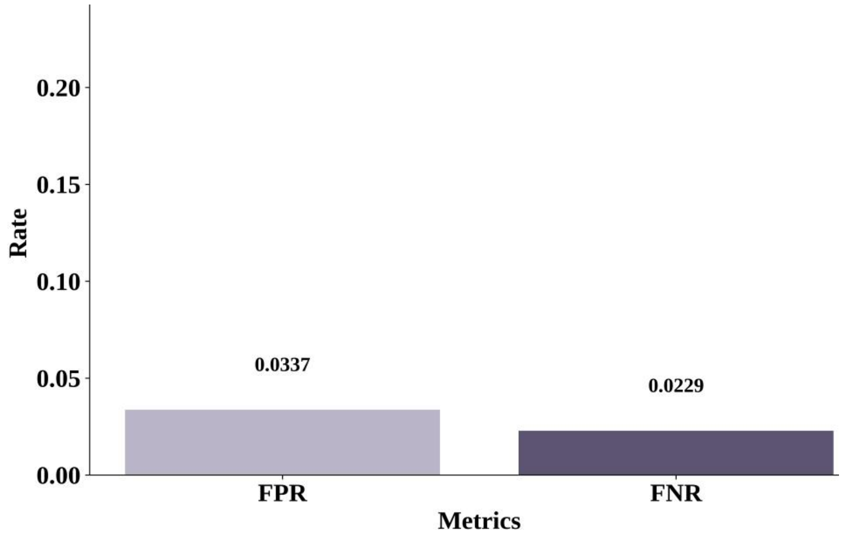

Figure 6: Error Distribution for Wildfire Classification

Figure 6 depicts the distribution of the errors, and the figure illustrates the mistakes made by the DL model in terms of false positive rate against false negative rate (FPR-FNR). These factors determine the consistency of early warning systems, where a false positive can result in unwarranted alerts, and a false negative can lead to undetected fire outbreaks. The model had an FPR of 0.0337 and an FNR of 0.0229, indicating a high bias towards true fire events, but with a low false alarm rate. In this way, it proves the accuracy of the model in discriminating the situation of wildfire to support its applicability in proactive forest fire monitoring and risk reduction.

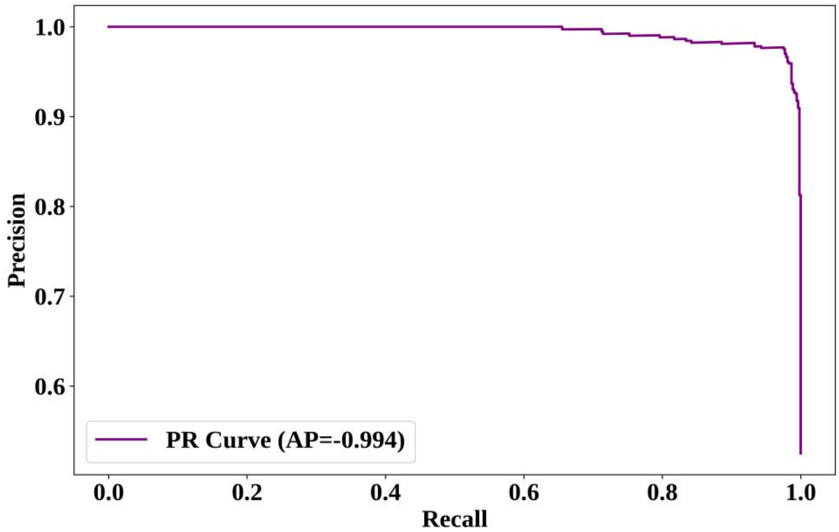

Figure 7: Precision–Recall Curve for Wildfire Classification Robustness

Figure 7 shows the precision-recall (PR) curve of wildfire classification, which determines the discriminatory performance of the AI model during imbalanced data conditions. The curve shows the accuracy against the recall at different classification thresholds, which reveals a trade-off between the ability to detect an occurrence of wildfires correctly and the reduction of the false alarms. The model achieves a high average precision score of 99.4, indicating perfect departure between fire and no-fire classes. This confirms the CNN model's reliability in prioritising true wildfire detections while maintaining minimal false positives for disaster mitigation.

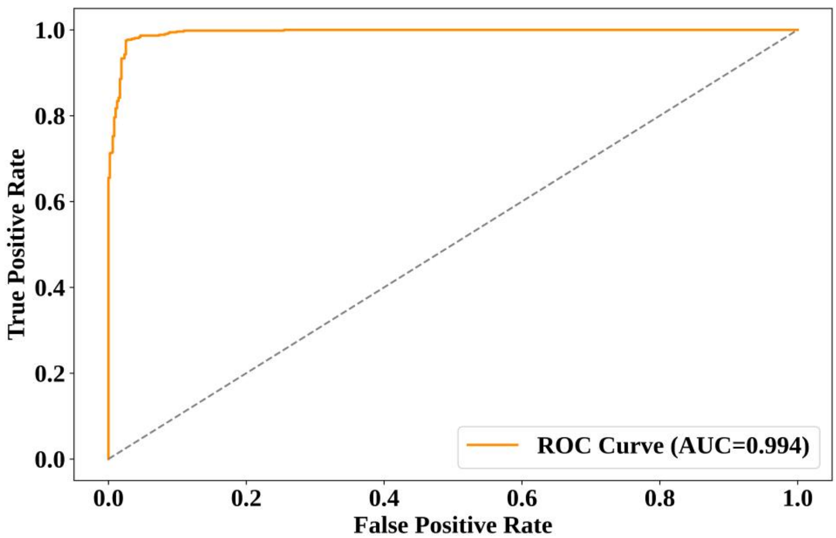

Figure 8: ROC Curve for Wildfire Detection Sensitivity

Figure 8 presents the ROC curve for wildfire detection, which evaluates the classification performance of the CNN–Triplet Loss model by plotting the TPR against the FPR across varying decision thresholds. The curve indicates strong discriminative capability, with the model achieving an Area Under the Curve (AUC) of 99.4, signifying near-perfect classification. This assesses the model's sensitivity and specificity, confirming its ability to accurately detect wildfire events while minimising false alarms, an indispensable trait for reliable early warning systems in forest fire management.

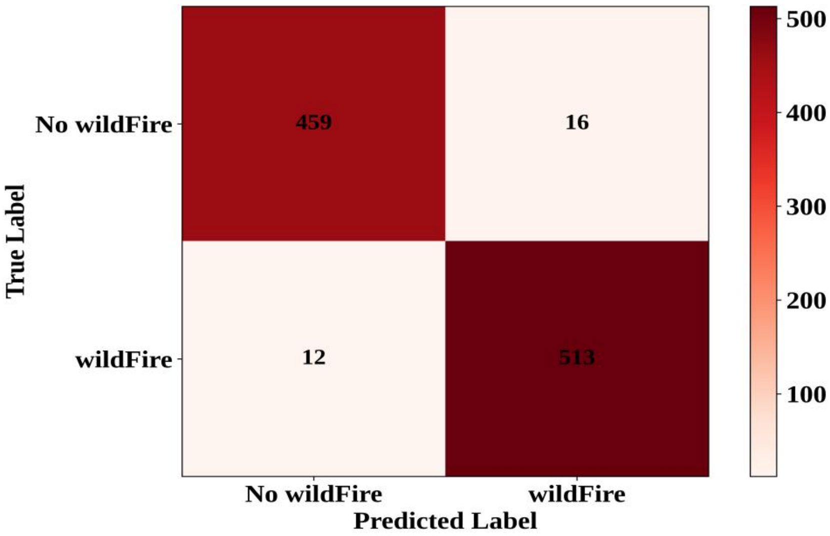

Figure 9: Confusion Matrix for Wildfire Classification Precision

Figure 9 shows the heatmap of the confusion matrix of wildfire classification, which measures the percentage of the prediction of the wildfire classes (actual and predicted) by the DL model. This is shown in the matrix of 513 True Positives (wildfire correctly predicted), 459 True Negatives (no wildfire correctly predicted), 16 False Positives (no wildfire misclassified as wildfire) and 12 False Negatives (wildfire missed). This will measure the stability of the model in practice by highlighting detection success and error margins. The low false rates and high true classification numbers verify the quality and accuracy of the model in differentiating the wildfire events and hence can be used in proactive forest fire early warning systems.

4.2. Comparative Analysis

The section will compare the functionality of the DL Model with the existing fire detection model to demonstrate that it is superior. It also showcases the use of multi-modal data fusion and Triplet Loss optimisation as superior relative to conventional single-source and image-only methods. In this comparison, the work demonstrates the efficiency and early-warning capacity of the proposed system in real-time forest fire monitoring.

Table 1: Comparative Performance Analysis of Forest Fire Classification Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
VGG 19 [36]	95	95.7	94.2	94.96
InceptionV3 [37]	92.25	84.5	84.5	84.5
YOLO [38]	-	93.91	88.87	88.35
Proposed CNN–Triplet Loss	**97.20**	**96.98**	**97.71**	**97.34**

The results of the proposed CNN-Triplet Loss hybrid model are compared with the state-of-the-art models, including VGG19, InceptionV3 and YOLO, on the forest fire classification task in Table 1. The proposed model had the highest accuracy, with a total of 97.20, which is higher in all the main indicators of precision, recall, and F1-score. Such an increase in performance is primarily associated with the incorporation of multi-modal IoT and remote sensing data, as well as the application of triplet loss optimisation, which has contributed to improved feature discrimination and lower false detection. The model, therefore, demonstrates greater strength and early warning capabilities in real-time monitoring of forest fires and threat prediction.

4.3. Discussion

As the experimental outcomes of the suggested hybrid forest fire monitoring and early warning system indicate, combining data from IoT-based ground sensors with satellite-based remote sensing imagery significantly increases the accuracy and timeliness of fire hazard predictions. The accuracy (97.20%), precision (96.98%), recall (97.71%) and F1-score (97.34%) of the DL model allow inferring that the system is capable of learning spatial as well as temporal relationships between forest fire ignition and particular characteristics. Contextually, these findings indicate that ground-level IoT sensors provide fine-scale microclimatic data, whereas remote sensing imagery is an indicator of macro-scale spatial patterns. This combination enabled the CNN architecture to identify the complicated interdependencies. In comparison to the works, the current article presents a DL-based fusion paradigm and data-driven early warning models that can provide real-time predictions of risks.

These discoveries, in a more generalised manner, add to the new field of AI-driven environmental intelligence. This work, through sensor networks combined with remote sensing analytics, illustrates how interdisciplinary integration can defeat the conventional constraints of temporal resolution and spatial coverage of fire detection. The framework not only enhances the technical edge of forest fire prediction but also provides a model that can be reproduced in multi-modal early warning systems for other environmental areas, e.g., flood prediction or air quality monitoring. All these innovations have created a new standard in forest fire risk analytics, proving that smart integration of heterogeneous sources of data can lead to significant improvements in the accuracy of predictions, false alarms, and timely and active mitigation of disasters.

5. Conclusion

In this study, a hybrid fine-scale forest fire monitoring and early warning framework was successfully developed by integrating IoT-based ground sensor data with satellite-derived remote sensing imagery for accurate and timely forest fire risk prediction. An end-to-end pipeline was used that featured a multi-modal feature fusion layer to combine heterogeneous data into one analytical form. The integrated data was processed with a CNN trained with triplet loss, which enables the creation of strong distinctions between areas at risk of wildfires and those not at risk. Experimental testing showed the best performance with an accuracy of 97.20%, a precision of 96.98%, a recall of 97.71%, and an F1-score of 97.34%, which is much higher than benchmark models. These findings confirm the strength of the model, its convergence stability and its ability to generalise its results to a wide range of forests. Fine-grained and real-time fire prediction with a low false alarm rate (FPR: 0.0337, FNR: 0.0229) can be achieved by integrating IoT and remote sensing data, providing a consistent early-warning tool for active control of forest works and disaster prevention. Overall, this work presents a brilliant solution that can turn the traditional fire monitoring frameworks into dynamic early warning systems that would make forest ecosystems more resilient to the risks of wildfires caused by climate change. Nevertheless, the use of IoT and satellite data fusion is mainly used in this work, which can be a limitation in situations when the data acquisition is compromised by sensor malfunctioning, cloud cover, or signal interference, which breaks the continuity of real-time monitoring.

5.1. Future work

This framework should be extended in the future to incorporate Unmanned Aerial Vehicle (UAV) data, meteorological variables, and social sensing inputs to make it more robust and situation-aware. The addition of edge intelligence and the federated learning paradigm could also enable on-device processing and collaboration with distributed forest stations in a privacy-preserving manner. This creates a multi-modal environmental watch, which plays an important part in the pre-emptive disaster prevention, ecological resilience, and advancing sustainable forestry practices to adapt to worsening climate conditions

Data Availability

The datasets were obtained publicly in this study. The data on IoT were collected from the Forest Fire Detection Management System published on GitHub, and the data on remote sensing were taken from the Wildfire Prediction Dataset published on Kaggle.

- IoT data: Forest Fire Detection Management System – GitHub
- Remote sensing data: https://www.kaggle.com/datasets/abdelghaniaaba/wildfire-prediction-dataset

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