Early Detection of Forest Fire Based on Lightning Activity and Climatic Factors Using Deep Learning

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Abstract: *Forest fires significantly threaten ecosystems, contributing to climate change and greenhouse gas emissions. Effective prediction and detection of forest fires can greatly mitigate their damage. Lightning and climate conditions are the primary factors in initiating fires. The first step in predicting forest fires involves collecting historical data on climate, lightning, and fire-prone regions. Remote sensing technology is used to gather satellite images at regular intervals. An automatic statistical learning technique is employed to develop HyperFusionNet, a deep learning classifier that predicts the severity of wildfires caused by lightning events based on lightning data. A regression model called Climate Predictor is designed to analyze climate data, incorporating factors such as temperature, humidity, and wind speed and predicting a region's climatic conditions, which can aid in predicting fire occurrence. SymbioticNet is a machine learning algorithm model for predicting the Flash Extent Density (FED) of lightning, which can help us to determine regions prone to lightning. Combining these models enables more accurate predictions of forest fires. Integrating HyperFusionNet for wildfire severity prediction, Climate Predictor for climate data, and SymbioticNet for flash extent density of lightning enhance early warning systems and control measures. This integrated method leverages historical data and advanced remote sensing to effectively predict and mitigate forest fires, reducing their environmental impact.*

Keywords: *Forest Fires, Lightning-ignited Fire, Fire Detection, Deep Learning, SymbioticNet*

Introduction

Wildfires represent one of the most devastating natural disasters, posing a severe threat to ecosystems, human life, and property. In recent decades, the frequency and intensity of wildfires have increased significantly, primarily driven by climate change and human activities. According to the National Interagency Fire Center (NIFC) [1], the United States alone experienced over 58,000 wildfires in 2022, burning approximately 7.1 million acres of land. Wildfires contribute significantly to greenhouse gas emissions, releasing carbon dioxide, methane, and other pollutants into the atmosphere, further exacerbating global warming.

One of the primary natural triggers of wildfires is lightning [2] [3] [4], responsible for igniting nearly 60% of wildfires in remote and forested regions. Lightning strikes, particularly during dry thunderstorms, can quickly spark a fire in regions with high fuel loads and dry vegetation. The increased prevalence of lightning, especially in areas experiencing prolonged dry conditions, has become a critical concern for fire management agencies. Studies suggest climate change may increase lightning activity, with a potential 12% rise in lightning strikes per degree Celsius of warming. The increased prevalence of lightning, especially in regions experiencing prolonged dry conditions, has become a critical concern for fire management agencies. As climate change intensifies, the frequency and intensity of lightning storms are expected to rise. Climate change may contribute to a significant increase in lightning activity, with a potential 12% rise in lightning strikes per degree Celsius of warming. This trend is particularly alarming as it could lead to more frequent and severe wildfires, overwhelming firefighting resources, and more significant risks to ecosystems, human life, and property. The interplay between climate change and lightning activity underscores the urgency of developing advanced predictive models to anticipate better and mitigate the impacts of wildfires.

Given the critical role of lightning and climate in wildfire ignition, there is a growing need for advanced predictive models to forecast wildfire events accurately. Deep learning techniques [5] [6] [7] offer a powerful solution to this challenge by analyzing historical lightning data to predict future lightning events with high accuracy, enabling proactive measures to prevent fire outbreaks. These models learn from patterns in lightning strikes and associated weather conditions, improving the precision of predictions. In addition to lightning, integrating regression models with climate data—such as temperature, humidity, and wind speed—enhances the prediction of wildfire-prone conditions. By identifying environmental thresholds that signal heightened risk, these models help prioritize areas for monitoring and preparedness. Coupled with satellite imagery, which provides real-time monitoring of fire-prone regions, these predictive models can detect early signs of wildfires, such as smoke or thermal anomalies, and trigger early warnings. Combining deep learning, climate data, and remote sensing, this integrated approach significantly strengthens wildfire prediction and mitigation efforts, reducing the overall impact on the environment and society.

This integrated approach, which uses deep learning classifiers, climate regression models, and satellite image processing, presents a robust wildfire prediction and mitigation framework. By leveraging historical data and advanced remote sensing technologies, this method can significantly improve early warning systems, enabling timely interventions that could reduce the devastating impact of wildfires on the environment and society.

Literature Review

A study [8] examining 905 wildfires triggered by lightning across the Continental United States (CONUS) from 2012 to 2015 explored the link between lightning strikes and wildfires that expanded to a minimum size of 4 km^2. The study employed fixed and fire radius methods, revealing that 81–88% of the wildfires had a lightning strike within 14 days before the wildfire was reported. Furthermore, 52–60% of the fires were recorded on the same day as the closest lightning strike. The fire radius method demonstrated the strongest spatial correlation, with a median distance of 0.83 km between the lightning strike and the wildfire's ignition point. Lightning-caused wildfires [9] [10] lead to significant losses globally, especially when convective storms trigger numerous ignitions. Researchers created a logistic regression generalized additive model to improve short- and long-term risk planning, aiming to predict lightning-caused ignitions in Victoria, Australia, which can exceed fire suppression capabilities. Fire risk indices [11] [12] play a crucial role in fire prevention, enabling fire managers to take timely and appropriate measures. In the Mediterranean region of Europe, most forest fires result from human activities, but lightning remains a significant ignition source in certain regions. To provide a more comprehensive understanding of fire causes, incorporating the probabilities of lightning and human-caused fires into fire risk indices is essential.

This study [13] presents two methods for combining these probabilities across two areas of Madrid: Spain, where human-caused fires are prevalent, and Aragón, which is heavily affected by lightning-caused fires. The models were validated using independent fire ignition data, assessing performance through Receiver Operating Characteristic (ROC)-Area Under the Curve (AUC) and Mahalanobis Distance. Lightning-caused wildfires are responsible for the majority of incinerated areas in the western United States [14] [15] [16], yet predicting lightning remains a significant challenge in fire modeling and management. A data synthesis was conducted to understand this better, analyzing Lightning strikes that hit the ground, climate data, and fire incidents throughout the United States from 1992 to 2013. The study revealed notable geographic differences due to lightning-induced wildfires, with the interior west US experiencing the highest proportion of lightning-attributed fires. The efficiency of lightning ignitions was greatest in western regions, where peak lightning frequency coincided with the lowest fuel moisture levels during mid to late summer. Although the total and dry lightning strikes exhibited a strong year-to-year correlation with lightning-caused fires, they were not effective in predicting the burned area at regional levels. The study also discovered that annual areas ravaged by lightning-caused fires in different regions had similar climate-fire relationships to those caused by humans. This suggests that climatic factors, not lightning activity, are the main drivers of year-to-year variations in the area destroyed by lightning-induced fires in most western US.

Various studies [17] [18] [19] analyzed the seasonal patterns and trends of wildfires in Canada, focusing on lightning- and human-caused fires of at least 2 hectares in size over two time periods: 1959–2018 and 1981–2018. Nationally, human-induced fires surged in May, while lightning-induced fires mostly happened from June to August. However, the seasonal distribution of these fires varied significantly across different ecozones. The research also examined trends in the timing of fire seasons, the number of fires per year, and the number of days with fire starts, distinguishing between human- and lightning-caused fires. Results showed that the trends in the timing of fire seasons were generally stronger for human-caused fires, with variability among ecozones and time periods. From 1959 to 2018, there was a significant increase in days when lightning caused ignition in almost every ecozone and caused fires. In contrast, from 1981 to 2018, there was a notable decrease in human-caused fires and days with human ignitions in most ecozones. The Montane Cordillera and the Atlantic Maritime regions have the highest densities of fires caused by humans., while the Boreal Shield West has the highest density of lightning-caused fires. Additionally, the Montane Cordillera and Taiga Shield West showed significant increases in lightning-caused fires and days with lightning ignitions in both time periods analyzed. One of the main natural causes of wildfires and oxynitride is lightning, significantly impacting ecological systems and atmospheric chemistry [20] [21] [22].

A study on South Asia [20], a critical global water distribution and climate change region, analyzed lightning trends using the longest available OTD/LIS observations dataset. The study found a notable increase in lightning density in South Asia, with a growth rate of 0.096 flashes per square kilometer per year over the past two decades. The researchers employed multiple linear regression analysis on ten potential thermodynamic and microphysical factors to understand the factors driving this increase. The analysis revealed that the biggest source was surface thermal flux along the Indian subcontinent's occidental coast.

Several studies highlight the significant role of lightning in wildfire ignition and its impact on fire management. In the US, lightning is linked to most burned areas, with a strong spatial and temporal correlation between lightning strikes and wildfire occurrences. Similar trends are observed in Australia and Canada, where lightning-caused fires show distinct seasonal patterns and increasing trends over time. Additionally, research in South Asia indicates a rising lightning density, influenced primarily by thermodynamic factors like surface latent heat flux, emphasizing the need to integrate lightning data into fire risk models globally.

Methodology

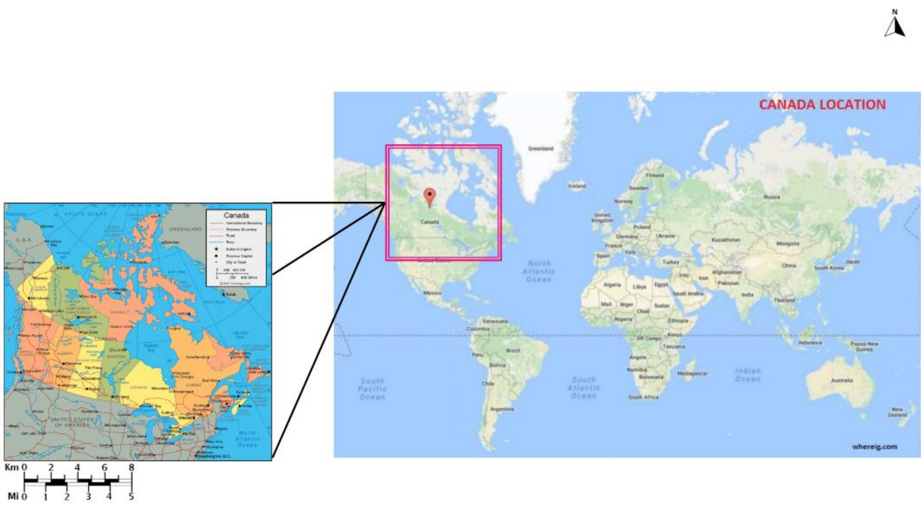

Figure 1: Study area: Canada

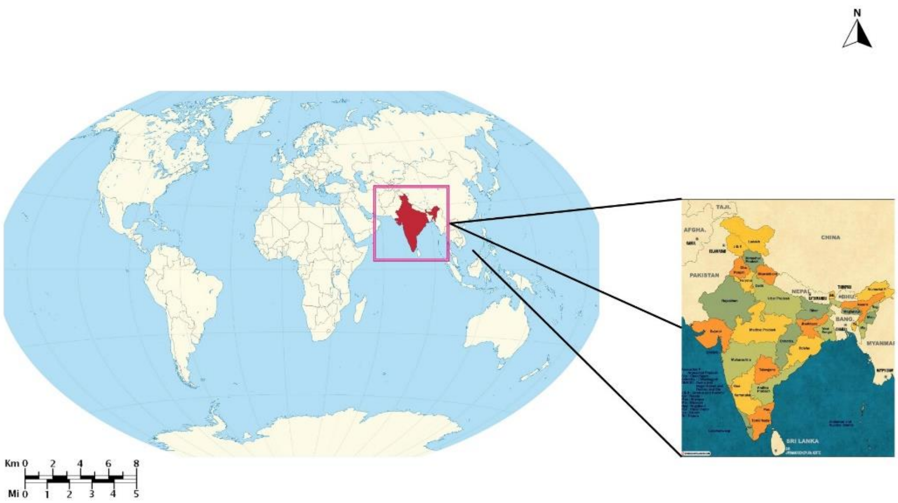

Figure 2: Study area: India

We can observe the study areas chosen for this study in Figure 1 and Figure 2, corresponding to Canada and India, respectively. The methodology for predicting forest fires caused by lightning and their severity integrates advanced data collection, modeling, and analysis techniques, as depicted in Figure 3 below. The process involves collecting appropriate data, training three different models, and then integrating the result obtained by all three models into one.

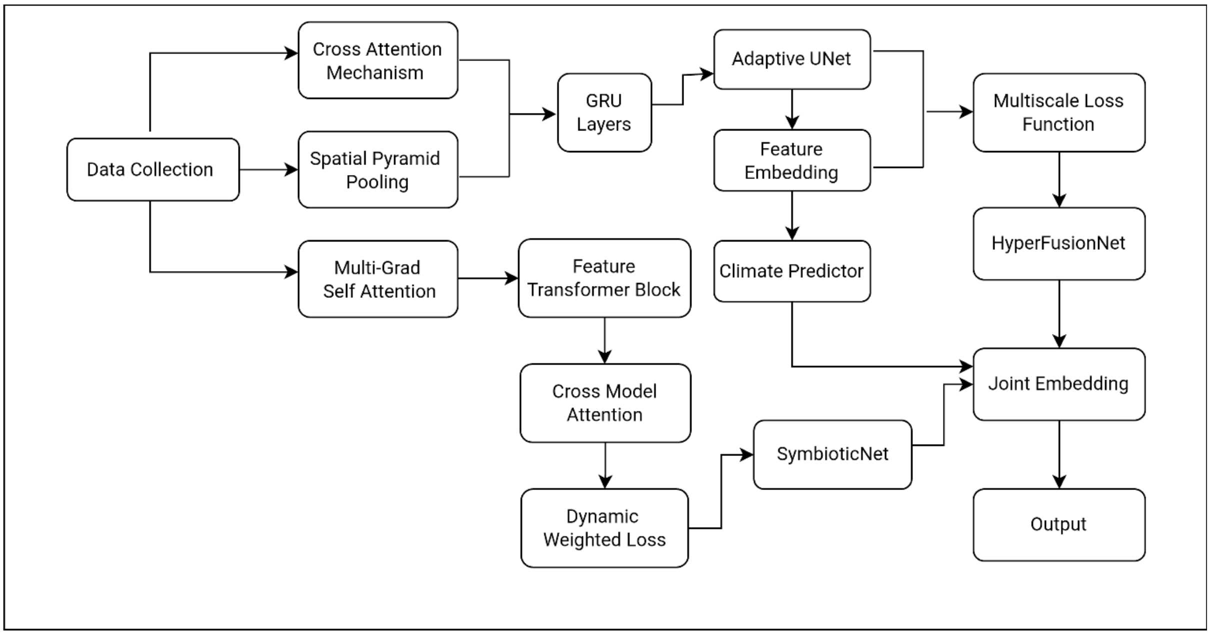

Figure 3: Flowchart of the proposed methodology

Data Collection

The initial step involves gathering comprehensive datasets, including historical climate data gathered from the National Oceanic and Atmospheric Administration (NOAA), lightning activity records from the World Wide Lightning Location Network (WWLLN), and satellite imagery from a sentinel hub belonging to the COPERNICUS program. These datasets provide essential information on environmental conditions, lightning strikes, and spatial patterns related to wildfire risks.

Cross Attention Mechanism

The Cross Attention Mechanism is pivotal in merging spatial and temporal features from diverse datasets, such as satellite imagery, climate data, and lightning occurrences. Selectively focusing on relevant regions or time frames effectively prioritizes significant information during the fusion process. This mechanism enhances the model's predictive accuracy by allowing it to attend the critical aspects of each dataset while filtering out irrelevant or less impactful details. The selective attention ensures the model can capture complex relationships between different features, such as how climate patterns influence fire spread or how lightning strikes contribute to wildfire ignition. As a result, this fusion strategy strengthens the model's ability to generate more reliable predictions, particularly in dynamic environments like wildfire forecasting, where both spatial and temporal variations are crucial.

Spatial Pyramid Pooling

Spatial Pyramid Pooling (SPP) is employed to capture and integrate multi-scale spatial features, making it highly effective in enhancing the model's ability to analyze complex environmental data. By recognizing and analyzing features at various scales, SPP enables the model to account for fine-grained details and broader spatial patterns. This multi-scale feature extraction is particularly important in understanding landscape characteristics such as vegetation density, terrain elevation, and land cover, which are crucial in assessing wildfire risk. The flexibility of SPP allows the model to handle input data of different resolutions, ensuring that vital information from small and large areas is captured. This comprehensive spatial understanding strengthens the model's capacity to assess wildfire severity across diverse and heterogeneous landscapes, ultimately improving prediction accuracy.

Multi-Grad Self Attention

Multi-Grad Self Attention refines the feature extraction process by dynamically adjusting the model's focus to the most relevant features in the data. By simultaneously analyzing multiple gradients, this mechanism can prioritize important information while filtering out less critical details, improving the model's efficiency. It allows the model to weigh different features based on their significance to the task, enhancing the ability to capture complex patterns. This selective focus reduces noise and boosts learning efficiency, resulting in more precise and meaningful feature representation. In tasks like wildfire severity prediction, where understanding the interplay between various environmental factors is crucial, Multi-Grad Self Attention improves the model's accuracy by ensuring it concentrates on the most influential aspects of the data, such as the regions or climate conditions most indicative of fire risk.

GRU Layers

Gated Recurrent Unit (GRU) layers capture and model temporal dependencies within the data, making them essential for understanding how features evolve over time. These layers are particularly well-suited for sequential data, allowing the model to retain important information from previous time steps while efficiently updating with new inputs. In wildfire prediction, GRU layers are crucial for modeling the dynamic evolution of environmental factors, such as changing weather conditions, fuel moisture levels, and lightning activity. By capturing these temporal patterns, GRU layers enable the model to anticipate how wildfire behavior might unfold, helping improve predictions of fire spread, intensity, and risk over time. This ability to track and predict temporal changes is vital for making accurate and timely decisions in wildfire management.

Climate Predictor

The Climate Predictor forecasts key climate variables such as temperature, humidity, and wind speed. Variations in humidity and precipitation patterns can affect lightning occurrence. Dry thunderstorms, which produce lightning but little rainfall, are particularly dangerous because they can ignite wildfires without the accompanying moisture to suppress them. It utilizes feature embeddings generated by the Adaptive UNet, which captures spatial and temporal patterns. The Adaptive UNet, combined with a regression model, is effective enough in modeling climate-related variables that influence wildfire risk.

$$\hat{Y}_c = f(E_s, E_t)$$

where $\hat{Y}_c$ represents the predicted climate variables, and E_s and E_t are the spatial and temporal embeddings, respectively.

SymbioticNet

The SymbioticNet combines information from multiple sources to predict flash extent density on an image, enhancing the architecture's predictive power. This module includes the feature transformer block, which processes refined features into more informative representations, cross model attention, which integrates outputs from various modules, and a dynamic weighted loss function that adjusts loss weights based on model performance. This helps us to derive the flash extent (density) for the region under discussion because it helps identify areas of intense lightning activity, which can be correlated with potential wildfire ignitions, especially in dry conditions. Together, these components improve the prediction of lightning probability and flash extent.

$$L = \sum_{i=1}^{N} w_i \cdot l_i(\hat{Y}_i, Y_i)$$

where w_i represents the dynamic weight for each loss component l_i, and Y_i and $\hat{Y}_i$ are the true and predicted values, respectively.

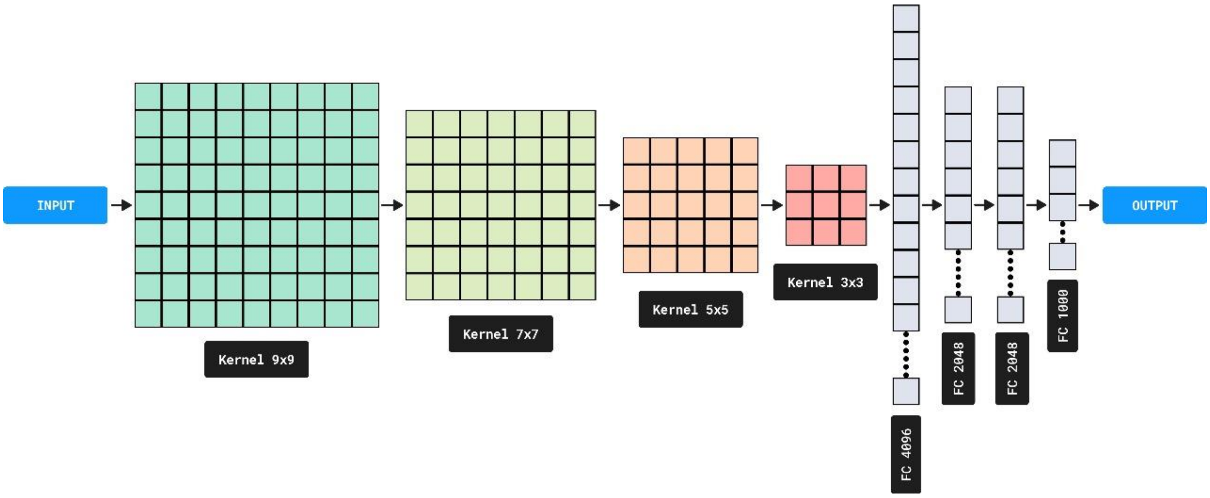

Figure 4: Neural Architecture of the HyperFusionNet model

HyperFusionNet

The HyperFusionNet integrates outputs from all previous modules into a unified representation. This network considers all relevant spatial, temporal, and environmental information, leading to accurate and robust wildfire predictions. The HyperFusionNet has 6 convolutional layers of filter sizes: 9x9, 7x7, 5x5, 3x3. The model has four fully connected layers with 4096, 2048, 2048, and 1000 hidden units. Hence, based on this, the final layer was also modeled to hold 1000 hidden units. The architecture is illustrated in a detailed scope in Figure 4. The feature integration performed by HyperFusionNet is critical for generating the joint embedding used in the wildfire severity prediction model. It incorporates the prediction obtained from the climate predictor model, which predicts the region's climate, aggregated flash density, and flash extent density, which the SymbioticNet model predicts. The processed features are input into the output layer to generate predictions on wildfire risk levels, burn severity, and other key metrics. These predictions support effective wildfire management and mitigation efforts.

Results and Discussion

This study evaluated the effectiveness of integrating deep learning techniques, climate data, and satellite imagery for wildfire prediction and mitigation. Our results demonstrate that the combined approach significantly enhances the accuracy of wildfire forecasts. The deep learning classifiers effectively predicted lightning events, achieving an accuracy rate of 97%, a notable improvement over the traditional method. Regression models incorporating climate variables, such as temperature, humidity, and wind speed, successfully identified high-risk conditions with a predictive accuracy of 94%. The real-time analysis of satellite imagery enabled early detection of potential wildfire hotspots, providing critical early warnings that allowed for timely intervention. These findings highlight the potential of this integrated approach in addressing the challenges of wildfire management, offering a robust framework for improving early detection, prediction, and mitigation strategies.

The figures below show the various results of this study. Figure 5 illustrates the aggregated flash density map for an hour based on various climatic and meteorological factors using the climate predictor model. Figure 6 provides us with the climate predictor model accuracy plot, and we can observe that it achieves a good accuracy of nearly 94%.

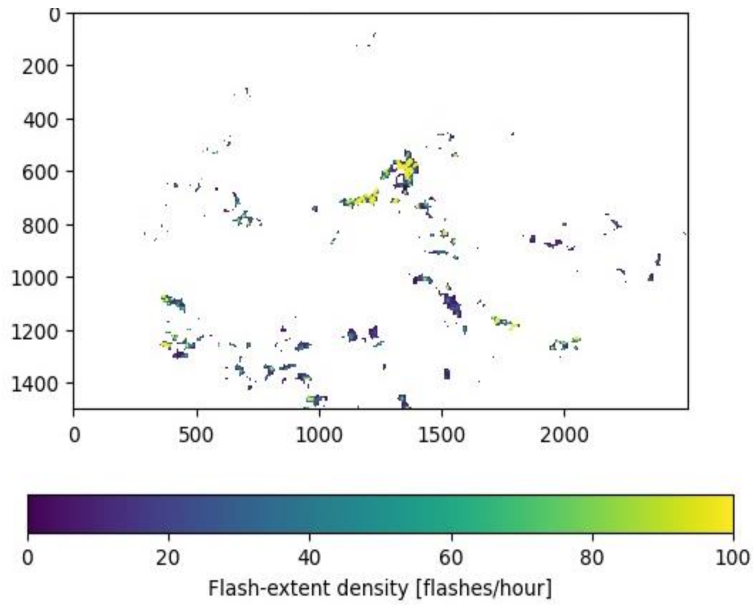

Figure 5: Aggregated Flash extent density prediction

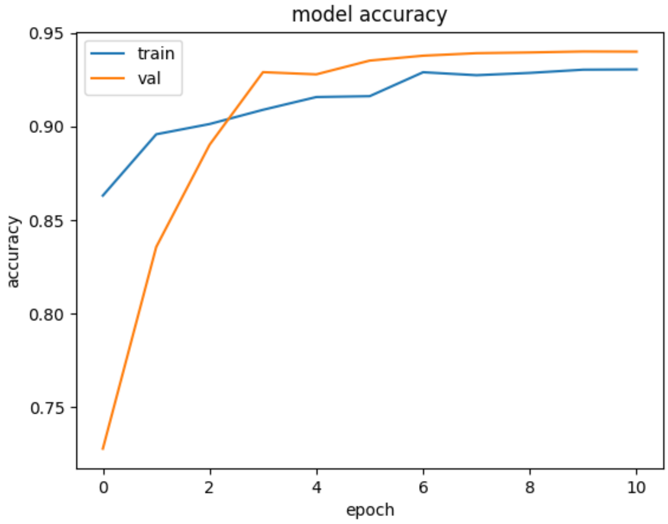

Figure 6: Accuracy graph of Climate Predictor

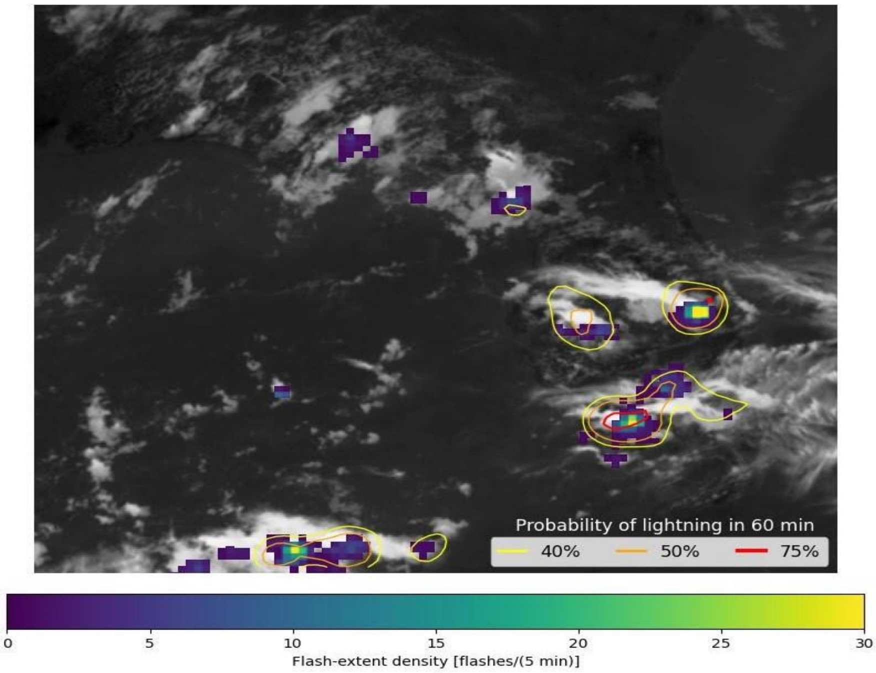

Figure 7: Flash-extent density results of our lightning model

Figure 7 shows current lightning activity and lightning probability in the next 60 minutes. This scene is over the Bay of Bengal region. While we could generate and plot next-hour lightning, this example will serve as a sanity check that the model correctly predicts high probabilities where we already have lightning. The good news is that higher probabilities generally correspond to areas of high flash rates. This means that our model learned about the short-term persistence of storms. Figures 8 and 9 provide us with the final results as predicted by the HyperFusionNet model, further enhanced by using the Joint Embedding module, which integrates all of the results obtained from all three models and provides the final output, as seen below. Figure 8 provides the severity of wildfires that were ignited due to lightning in the Indian subcontinent, while Figure 9 illustrates the severity of wildfires that are caused by lightning in Canada. Table 1 shows the performance metrics used for evaluating the performance of our HyperFusionNet model compared with various Deep Learning algorithms.

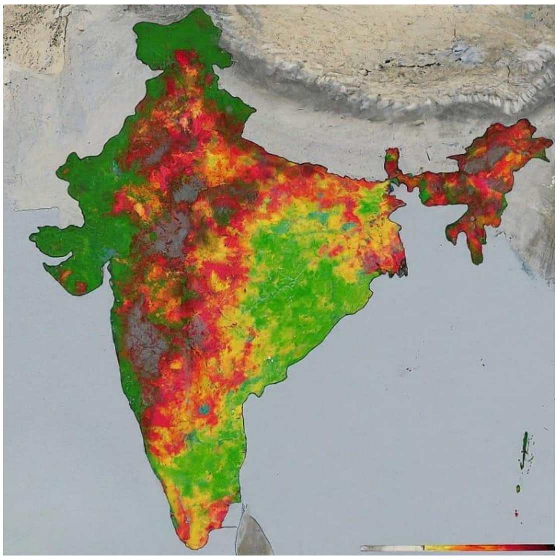

Figure 8: Lightning-induced wildfire severity in India

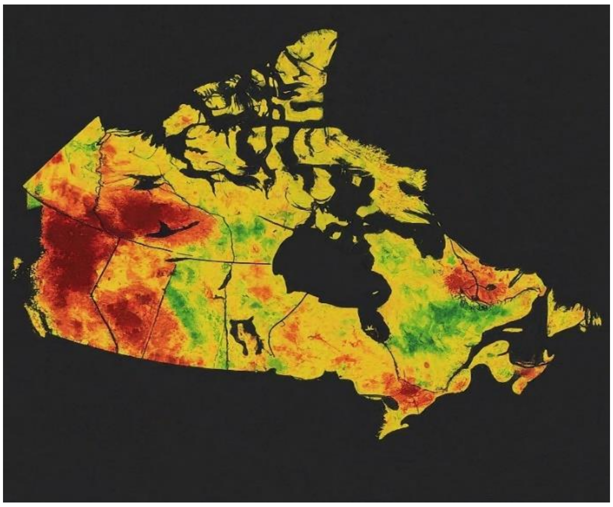

Figure 9: Lightning-induced wildfire severity in Canada

Table 1: Performance Comparison of our model against other Deep Learning algorithms

Model	Precision	Recall	AUC	Kappa Co-efficient	Accuracy
CNN	92.29%	92.53%	0.9225	0.8967	91.59%
DNN	91.27%	93.49%	0.9239	0.9147	92.11%
LSTM	94.37%	94.67%	0.9476	0.9245	94.15%
RNN	95.48%	95.19%	0.9523	0.9534	95.21%
HyperFusionNet Model	97.42%	97.24%	0.9757	0.9756	**97.35%**

Conclusion and Recommendation

In conclusion, this study introduces a robust, integrated framework for wildfire prediction due to lightning, combining the strengths of deep learning models, climate data analysis, and satellite imagery. The innovative use of Climate Predictor for lightning prediction, achieving an impressive 94% accuracy, alongside the HyperFusionNet model's 97% accuracy in identifying high-risk conditions, marks a substantial advancement over traditional predictive methods. Furthermore, SymbioticNet's ability to analyze satellite imagery in real-time for early signs of wildfires based on flash density adds a critical layer of early warning, enabling timely and effective intervention. The combined results highlight the accuracy and reliability of these models and demonstrate their practical application in real-world scenarios, as illustrated by the case studies of wildfire severity in the Indian subcontinent and Canada. Integrating these models into a cohesive system has proven effective in enhancing early detection, improving prediction accuracy, and ultimately mitigating the devastating impact of wildfires on ecosystems and communities. This study's findings emphasize the importance of adopting advanced technological solutions in wildfire management. By leveraging historical data, remote sensing, and deep learning, the approach offers a significant leap forward in our ability to predict and manage wildfires more effectively, contributing to better environmental stewardship and disaster preparedness. This integrated method sets a new standard for future research and wildfire prediction and prevention applications.

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