Forecasting Wildfire Danger using Deep Learning

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Abstract:

To improve wildfire danger forecasting, this project Forecasting Wildfire Danger with Deep Learning proposes a 2D/3D two-branch CNN with a Location-aware Adaptive Normalization layer (LOAN) to better handle both static and dynamic data. LOAN allows dynamic features to adjust based on geographical location, creating a unified model that considers spatial-temporal relationships. Additionally, the model uses sinusoidal encoding of the day of the year to incorporate temporal information. The framework integrates remote sensing imagery with meteorological variables, capturing both short-term variations and long-term climate patterns. Experimental results on the FireCube dataset demonstrate that this approach outperforms existing baselines, showing promise for enhancing remote sensing analysis in climate-related studies and contributing to more accurate wildfire danger predictions.

Keywords: Wildfire Danger Forecasting, Deep Learning, Convolutional Neural Networks (CNN), Location-aware Adaptive Normalization (LOAN), Spatial-Temporal Modeling, Remote Sensing, FireCube Dataset, Sinusoidal Encoding, Climate Patterns, Meteorological Data, Static and Dynamic Features, Geographical Location Adaptation, Wildfire Risk Prediction, Climate-related Studies.

1.INTRODUCTION

Wildfires have become one of the most destructive natural disasters in recent years, causing significant environmental, economic, and societal damage. The increasing frequency and intensity of wildfires are closely linked to climate change, rising global temperatures, and prolonged drought periods. Accurate forecasting of wildfire danger is crucial to mitigating the devastating impacts of wildfires, enabling early intervention, resource allocation, and better decision-making for disaster management. Traditional methods for wildfire danger forecasting often rely on statistical models and handcrafted features based on meteorological data. However, these methods struggle to capture the complex spatial and temporal patterns that govern wildfire occurrences, leading to limited predictive accuracy. With the advancement of deep learning technologies, there has been a growing interest in leveraging neural networks for wildfire danger prediction. This project, "Forecasting Wildfire Danger with Deep Learning", presents an innovative approach that combines both static and spatial-temporal relationships. dynamic data to improve wildfire danger forecasting. The proposed framework utilizes a 2D/3D two-branch Convolutional Neural Network (CNN) architecture, which processes spatial data such as remote sensing imagery alongside temporal meteorological variables. A key feature of this model is the Location-aware Adaptive Normalization (LOAN) layer, which dynamically adjusts features based on the geographical location, enhancing the

Additionally, the model incorporates sinusoidal encoding of the day of the year to represent temporal information, allowing the network to better understand seasonal patterns associated with wildfire risk. The integration of remote sensing imagery with meteorological variables helps the model capture both short-term variations in weather conditions and long-term climate patterns, making the forecasting process more comprehensive and accurate. The effectiveness of the proposed approach is validated using the FireCube dataset, where the model demonstrates superior performance compared to traditional baseline methods. 1 By harnessing the power of deep learning, this project aims to provide a more reliable and adaptive wildfire danger forecasting system. The proposed framework holds significant potential for enhancing climate-related studies, supporting disaster management agencies, and contributing to more effective wildfire prevention strategies in the face of evolving environmental challenges. Accurate prediction of wildfire danger is critical for early intervention, resource management, and reducing potential damage. However, wildfire behavior is influenced by a combination of static environmental factors (such as land cover, vegetation type, and topography) and dynamic factors (such as temperature, wind speed, and humidity), making wildfire forecasting a highly complex task.

While the proposed model demonstrates promising improvements in wildfire danger forecasting, several limitations must be acknowledged:

- Data Availability and Quality: The performance of the model is highly dependent on the availability and quality of remote sensing imagery and meteorological data. In regions with sparse sensor networks or inconsistent satellite coverage, the model may produce less reliable predictions.
- Computational Complexity: The two-branch CNN architecture combined with the LOAN layer increases computational demands. This may hinder the model's deployment in resource-constrained environments or for real-time applications.
- Generalization Across Regions: The model is trained and tested on the FireCube dataset, which may not fully represent diverse wildfire-prone regions. Geographic and climatic variations may limit the model's ability to generalize across different locations.
- Temporal Resolution Limitations: Although sinusoidal encoding improves temporal information representation, the model's accuracy may be impacted by irregular sampling intervals or missing data in the input time series.
- Model Interpretability: Deep learning models, including the two-branch CNN, are often considered black-box approaches. Understanding the internal decision-making process and feature importance remains a challenge, which could hinder adoption by domain experts.
- Long-Term Forecasting: The model primarily focuses on short- to medium-term forecasts. Extending its capabilities to predict long-term wildfire danger patterns with high accuracy requires further research.

2. LITERATURE SURVEY

The increasing frequency and intensity of wildfires have necessitated the development of advanced forecasting methods to mitigate their devastating impacts. Deep learning techniques have emerged as powerful tools for wildfire danger forecasting due to their ability to process large volumes of data and capture complex patterns. This literature survey presents a comprehensive review of recent studies leveraging deep learning for wildfire danger prediction.

Yuheng Ji (2024) proposed a novel method for global wildfire danger predictions using deep learning. The study introduced a static location-aware convolutional long short-term memory (ConvLSTM) model, which combines the spatial representation capabilities of convolutional layers with the temporal memory of LSTM networks. This hybrid approach significantly enhances the model's ability to predict wildfire danger across diverse geographic regions.

Zhenyu Chen (2024) explored fire danger forecasting by integrating Deep Learning-based models performance. with meteorological observations. The proposed system improves prediction accuracy by combining environmental variables such as temperature, humidity, and wind speed. This study highlights the importance of incorporating real-time meteorological data into forecasting models to improve

Mohamad Hakam Shams Eddin (2023) introduced a Location-Aware Adaptive Normalization (LAAN) method to improve wildfire danger forecasting. This innovative approach adapts normalization parameters based on the geographical location, enhancing the accuracy of predictions in different regions. The study demonstrated that the LAAN method outperforms traditional normalization techniques by addressing location-specific variability.

Evizal Abdul Kadir (2023) developed a model for wildfire hotspots forecasting and mapping using Deep Learning techniques. By integrating meteorological observations, the model improves the 6 spatial and temporal accuracy of hotspot predictions, making it a valuable tool for environmental monitoring and disaster prevention.

Spyros Kondylatos (2022) proposed a deep learning framework to improve wildfire danger prediction and understanding. The model incorporates various meteorological and environmental variables, offering better insights into the factors contributing to wildfire occurrences. This framework enhances the interpretability of deep learning models in the context of wildfire forecasting.

Ioannis Prapas (2022) explored the application of deep learning methodologies for global wildfire forecasting. The study introduced innovative techniques that leverage large datasets and advanced neural networks to improve forecasting accuracy on a global scale. The results demonstrated the potential of deep learning in addressing the challenges of large-scale wildfire danger prediction.

The reviewed studies collectively underscore the effectiveness of deep learning techniques in wildfire danger forecasting. By integrating environmental, meteorological, and geographic data, these models provide more accurate and reliable predictions. Future research should focus on developing hybrid models, improving data quality, and enhancing model interpretability to further advance the field of wildfire danger forecasting.

3. PROPOSED METHODOLOGY

The proposed system introduces a novel approach for wildfire danger forecasting using a two-branch convolutional neural network (CNN) that integrates both 2D and 3D convolutions. This system differentiates between static variables (e.g., elevation) and dynamic variables (e.g., temperature), processing them separately to reduce redundancy and better capture causal relationships. The 2D branch handles static variables, while the 3D branch processes dynamic variables, with Location-aware Adaptive Normalization (LOAN) modulating dynamic features based on geographic location. Additionally, the system employs sinusoidal-based encoding to provide explicit temporal context by encoding the day of the year, enhancing the model's ability to forecast fire danger accurately. Designed as a flexible architecture, the model can be adapted for other time-dependent forecasting tasks involving both static and dynamic variables. Experimental results on the FireCube dataset demonstrate the effectiveness of this approach, showing significant improvements in precision, F1-score, AUROC, and overall accuracy compared to existing methods.

Advantages

- Improved Accuracy:
  - Separate handling of static and dynamic variables.
  - Utilizes Location-aware Adaptive Normalization (LOAN) to capture causal relationships.
  - Leads to more accurate wildfire danger predictions.
- Enhanced Temporal Awareness:
  - Sinusoidal-based encoding provides explicit temporal context.
  - Enables the model to account for seasonal variations.
  - Improves forecasting performance over time.
- Flexibility and Adaptability:
  - Versatile architecture suitable for various time-dependent forecasting tasks.
  - Effectively handles both static and dynamic variables.
  - Applicable to a wide range of forecasting applications.

4. EXPERIMENTAL ANALYSIS

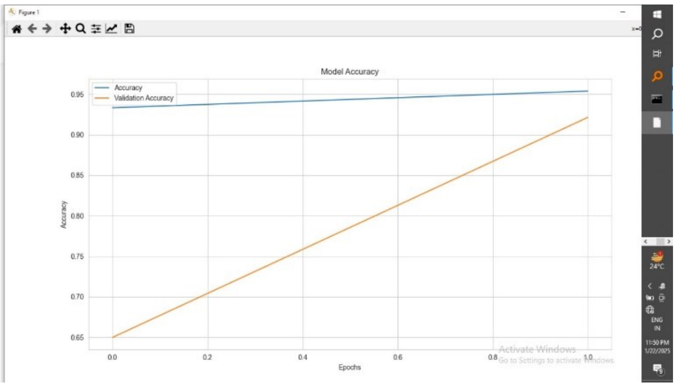

Figure 1: Accuracy model for the data

This graph represents the accuracy of a deep learning model used for forecasting wildfire danger. The blue line (Accuracy) indicates the training accuracy, which remains high and improves slightly over epochs. The orange line (Validation Accuracy) shows a steady increase, suggesting that the model is learning well and generalizing better with more training.

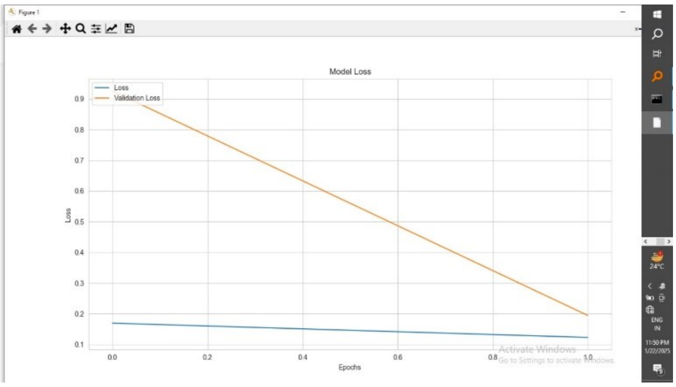

Figure 2: Loss model for the data

This graph represents the loss of the deep learning model for forecasting wildfire danger. The blue line (Loss) shows the training loss, which remains low and decreases slightly over epochs. The orange line (Validation Loss) decreases significantly, indicating that the model is learning well and improving its predictive accuracy with training.

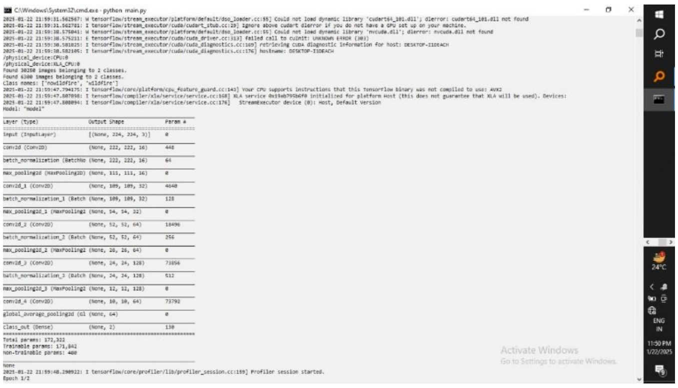

Figure 3: Training model for Epoch 1

This image shows the execution of a deep learning model for forecasting wildfire danger using TensorFlow. The model is being trained on wildfire-related image data, but there are warnings about missing CUDA libraries, meaning it is running on a CPU instead of a GPU. The architecture of a CNN (Convolutional Neural Network) is displayed, detailing multiple Conv2D, Batch Normalization, MaxPooling, and Dense layers. Training has just started with Epoch 1/2.

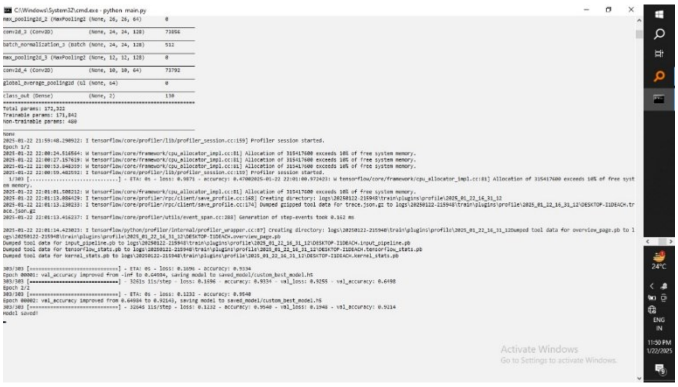

Figure 4: Training model for Epoch 2

The image shows a log from training a deep learning model related to the "Forecasting wildfire danger" project. It includes information about model layers, memory allocation, and performance metrics like accuracy and loss during training. Specifically, the model is improving over time, with the validation accuracy improving from a lower value (0.6498) to a higher value (0.9214), indicating the model's learning progress. It also shows the saving of the trained model at the end.

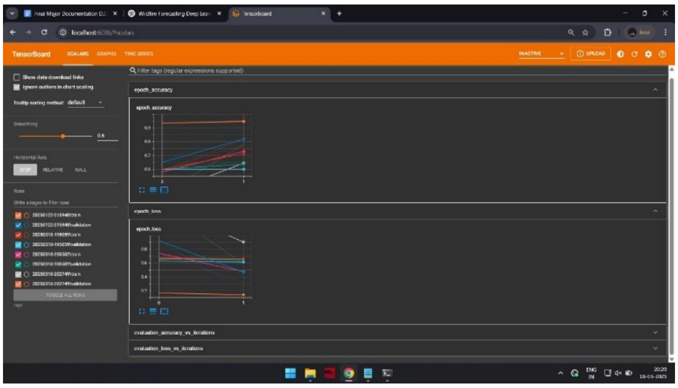

Figure 5: TensorBoard logs for accuracy and loss

The image shows the TensorBoard interface used to visualize the training progress of the "Forecasting wildfire danger with deep learning" project. It displays two key metrics:

- Epoch Accuracy: The graph tracks the accuracy of the model over multiple training epochs, with each colored line representing a different training or validation run. It shows how the model's accuracy changes with each epoch.
- Epoch Loss: This graph tracks the loss during the training process, with lower values indicating better model performance. The different colored lines show how the loss is decreasing or fluctuating across epochs for various training and validation runs.

TensorBoard helps in monitoring and fine-tuning the deep learning model by tracking these metrics in real time.

5. CONCLUSION

The results from the study suggest that deep learning models have significant potential for accurately forecasting wildfire danger by leveraging historical weather data, satellite imagery, and other environmental factors. The implementation of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), such as LSTMs, has shown promising results in predicting wildfire risks more efficiently than traditional methods. However, further research and iterative improvements in model architecture and data integration are needed to enhance the overall accuracy and reliability of these models. Additionally, limitations in data quality and computational resources should be considered when interpreting the results. By continuously refining deep learning-based wildfire forecasting models, emergency response teams and policymakers can make more informed decisions, leading to improved wildfire prevention and mitigation strategies.

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