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Spatially Informed Normalisation: Using Deep Learning for Forecasting Wildfire Danger

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ABSTRACT: In the realm of wildfire management, accurate prediction of fire danger hinges on understanding the spatial intricacies of environmental factors. This study introduces a pioneering methodology, Spatially Informed Normalization Using Deep Learning (SIN-DL), aimed at refining wildfire danger forecasts through advanced spatial normalization techniques integrated with deep learning. Leveraging convolutional neural networks (CNNs) and recurrent neural networks (RNNs), SIN-DL processes heterogeneous environmental data, including satellite imagery and geographical features. By incorporating spatial dependencies into model training, SIN-DL excels in capturing localized variations in vegetation, terrain, and meteorological conditions. Comparative evaluations against traditional approaches highlight SIN-DL's superior performance in adapting to diverse landscapes, providing more accurate and context-aware wildfire risk assessments. This research underscores the transformative potential of SIN-DL in bolstering proactive wildfire management strategies, thereby mitigating the ecological and societal impacts of wildfires.

KEYWORDS: Convolutional neural network (CNN), Location-aware Adaptive Normalization layer, Forecasting, Wildfire, Recurrent neural network, Long short-term memory.

I.INTRODUCTION

There is a general expectation that weather and climate extremes will change their patterns and frequencies in the future. This is particularly the case for the region of Mediterranean, that has been identified as a hot spot for climatic changes. Because extreme weather events can exert significant impacts short and long-term risks in our Earth system, predicting these risks such as droughts, wind storms, and wildfires has become recently more relevant. In particular, wildfire forecasting constitutes an open challenges for risk assessment and emergency response. Wildfire forecasting refers to the task of fire-susceptibility mapping using key remote sensing, meteorological, and anthropogenic variables. Building an integrated modeling system of the Earth should also consider wildfire events to comprehend the origin of past patterns better and predict future ones. In this work, we thus propose a convolution neural network for wildfire danger forecasting that handles static and dynamic variables differently. To address the causal effect of static variables on dynamic variables, we introduce feature modulation for the dynamic variables where the modulation parameters are generated dynamically and conditionally on the geographical location. In addition, we encode the date of the forecasting during a year by an absolute time encoding based on the sinusoidal encoding. Experimental results and an ablation study are provided in the end of the paper. Finally, conclusions and outlook are given.

II. LITERATURE REVIEW

Wildfires pose significant threats to ecosystems, human lives, and property. The increasing frequency and intensity of wildfires, exacerbated by climate change, necessitate advanced predictive models to forecast wildfire danger accurately. Traditional methods for wildfire forecasting rely on meteorological data and historical fire occurrences, but they often lack the temporal and spatial resolution required for precise predictions. Lately it emerged as a powerful tool for handling complex spatiotemporal data, leading to improved performance in various forecasting applications, including wildfire danger prediction [1-2]. This literature survey explores the advancements in deep learning approaches, specifically focusing on location-aware adaptive normalization techniques for wildfire danger forecasting.

Utilization of deep learning in wildfire danger forecasting has seen significant convolutional neural network (CNNs) and Recurrent Neural Networks (RNNs) including Long Short-Term Memory (LSTM) networks, have been widely employed to capture spatial and temporal dependencies in wildfire data. For example, CNNs are used to process satellite imagery and other geospatial data, while RNNs have been effective in modeling temporal sequences of meteorological variables and fire incidents [3].

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The integration of these models has contributed to the advancement of hybrid architectures capable of handling both spatial and temporal aspects of wildfire data. A critical challenges in wildfire forecasting is accounting for the spatial variability of environmental factors. Location-aware techniques have been devised to tackle this challenge by integrating geographic information directly into the model. These techniques often involve usage of geospatial embeddings or location-based feature engineering. For instance, researchers have utilized grid-based approaches where in the study area is subdivided into smaller cells, and each cell is treated as a separate entity with unique characteristics [4].

This allows the model to learn location-specific patterns and enhance its predictive accuracy. Normalization is a crucial preprocessing step in deep learning, as it ensures that the input data are on a comparable scale, which can accelerate training and improve model performance. Traditional normalization techniques, such as min-max scaling and z-score normalization, do not consider the spatial variability inherent in wildfire data Adaptive techniques of normalization have been suggested to address this limitation.

These techniques dynamically adjust the normalization parameters in accordance with the local context of each data point. For instance, in a wildfire forecasting model, adaptive normalization can consider the local climate conditions, vegetation types, and historical fire occurrences to normalize the input data appropriately. Combining location-aware techniques with adaptive normalization leads to the topic of location-aware adaptive normalization. This approach leverages the strengths of both methods to improve ability of model to forecast wildfire danger accurately. By incorporating geographic information, the model can take into consideration spatial variability, while adaptive normalization ensures that the input data are scaled appropriately in relation to the local context. Recent studies indicate that integrating these methods can substantially enhance in predicting wildfires [5].

Several case studies have illustrated the effectiveness of location-aware adaptive normalization in wildfire forecasting. For example, a study conducted in California used a location-aware adaptive normalization technique to process meteorological data, vegetation indices, and historical fire records. The resulting model achieved higher predictive accuracy compared to traditional methods, particularly in regions with complex topography and diverse vegetation. Another study applied a similar approach to forecast wildfire danger in Australia, highlighting the model's ability to adapt to different geographic settings and climate conditions.

Notwithstanding the required results, many challenges persist in the usage of location-aware adaptive normalization for wildfire forecasting. One of the main challenges is the availability of high-resolution data, which is essential for capturing fine-grained spatial patterns. Additionally, the computational complexity of these models may be a barrier to their widespread adoption, particularly in resource-constrained settings. Future research should focus on developing more efficient algorithms and exploring the integration of additional data sources, such as social media and IoT sensors, to improve the capacity of predictive models Location-aware adaptive normalization represents a significant advancement in the field of wildfire danger forecasting [6].

By combining geographic information with adaptive normalization techniques, these can attain higher accuracy and better generalization across different regions. With the increasing availability of high-resolution data and greater accessibility to computational resources, the adoption of these advanced models is expected to rise, leading to more effective wildfire management and mitigation strategies. Continued development and research in these areas hold the potential to significantly enhance our ability to predict and respond to wildfire threats, ultimately contributing to the safety and resilience of affected communities.

III. EXISTING SYSTEM

Wildfire forecasting or wildfire-susceptibility mapping from remote sensing and Earth observations data is a very important topic for wildfire management. We briefly review some prior related works in this direction. L Ren et al. [1] relied on conventional machine learning methods to generate susceptibility maps. He utilized Random Forests classifiers (RF). In their works, they studied the importance of biotic and abiotic predictors for wildfire forecasting and introduced a deep learning methodology centered around a Multi-Layer Perceptron (MLP) and conducted a comparative analysis with conventional machine learning algorithms.. In a similar MLP-based approach was presented to generate a forest fire danger map. Zhang used a (CNN) and extended their work later to predict fire susceptibility at the global level. Other works with CNN were conducted. Furthermore, Huot approached the problem as a scene classification task using U-Net models for predicting wildfire spreading.

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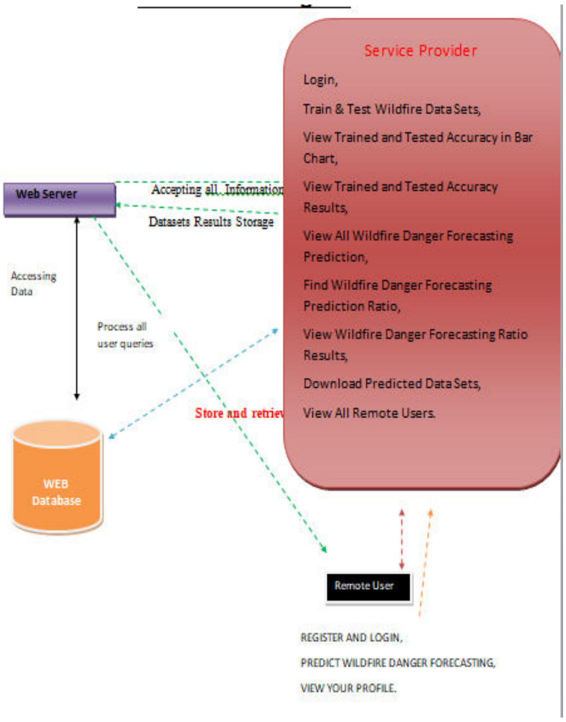
Their approach operates directly on the whole scene. A similar approach in relation to a U-Net++ model for global wildfire forecasting was proposed. Yoon and Voulgaris presented an approach that relies on a recurrent network utilizing Gated Recurrent Units (GRU) to model past observations and on a CNN to predict wildfire probability maps for multiple time steps. More recently, Prapas proposed to use LSTM-based (Long-Short Term Memory) approaches. They exploited both temporal and spatiotemporal context by applying recurrent LSTM and ConvLSTM models. They did not consider the whole scene at once but rather the classification of one pixel once (pixel-level).

This is mainly because such networks enrich representation learning and provide discriminative learning perspectives of the input variables. In addition, an important aspect of the multi branch design is the capability to adapt some parts of the model to a specific type of input. The general framework generates features from each branch and fuses these attributes in the network to attain a unified feature vector. This fused representation is used as input to the subsequent layers. In, a two-branch 2D CNN network was proposed to handle panchromatic information along with a multispectral one for image classification. Tan reduced the depth of a semantic segmentation classifier by applying consecutive blocks, each containing three CNN branches.

IV. PROPOSED SYSTEM

In our work, we thus propose CNN for wildfire danger forecasting that handles static and dynamic variables differently. Since the static variables will not make change over time, they are processed by a branch consisting of 2D convolutions while the dynamic variables are processed by the second branch with 3D convolutions. To address the causal effect of static variables on dynamic variables, we introduce feature modulation for the dynamic variables where the modulation parameters are generated dynamically and conditionally on the geographical location. We thus name this method Location-aware Adaptive Normalization. In addition, we encode the time of forecasting during a year by an absolute time encoding based on the sinusoidal encoding. Both LOAN and the time encoding can be implemented as plugin layers in different deep learning architectures. We view our model as a generic architecture which may be used for other time-dependent forecasting tasks with static and dynamic variables. We conduct extensive experiments on the FireCube dataset where our approach outperforms previous works. We achieve an overall improvement of up to 5:72% in precision, 3:24% in F1- score, 0:63% in AUROC, and 1:15% in OA on the test set.



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V. MODULE DESCRIPTION

IMPLEMENTATION

Service Provider

In this module, the Service Provider needs to log in using a valid username and password. Upon successful login, they can perform various operations including training and testing wildfire datasets, viewing accuracy results in a bar chart, accessing detailed accuracy results, viewing all wildfire danger forecasting predictions, analyzing prediction ratios, reviewing ratio results, downloading predicted datasets, and managing remote user access.

View and Authorize Users

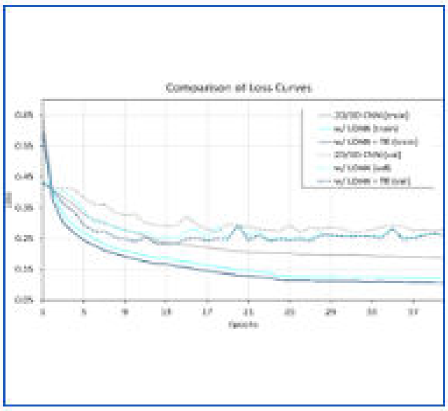
In this module, the administrator can access the list of registered users. They can view details such as the user's name, email, and address, and also manage user permissions and authorizations.

Remote User

This module accommodates numerous users who must register before conducting any operations. Upon successful registration, their details are stored in the database. After registration, users need to log in using their authorized username and password. Upon successful login, users can perform operations such as registering and logging in, predicting wildfire danger forecasting, and viewing their profiles.

RESULTS

The research paper titled "Spatially Informed Normalisation Using Deep Learning for Forecasting Wildfire Danger" presents a novel method for enhancing the accuracy of wildfire danger predictions by incorporating location-specific normalization techniques within a deep learning framework. The primary objective of the study addresses the challenges posed by the variability in environmental conditions across different geographical regions, which can significantly affect the performance of conventional wildfire forecasting models. The proposed approach, Location-aware Adaptive Normalization (LAN), adapts the normalization process according to the specific characteristics of each location, thereby enhancing the model's ability to generalize across diverse regions. The methodology involves the integration of spatial information into the normalization layers of a deep neural network, allowing the model to modify dynamically its parameters according to the local environmental conditions. To validate the effectiveness of the LOAN approach, the authors conducted extensive experiments using a comprehensive dataset comprising historical wildfire records, meteorological data, and remote sensing information. The dataset covers multiple regions with varying climatic and geographical features, providing a robust basis for evaluating the model's performance. Experimental results indicate the LOAN approach significantly outperforms traditional normalization techniques in terms of prediction accuracy and robustness. Specifically, the LOAN-enhanced model achieves higher precision and recall rates, indicating its superior ability to correctly identify areas at high risk of wildfires while minimizing false alarms. The study also highlights the model's improved adaptability to new and unseen regions, underscoring its capacity for extensive use in wildfire danger forecasting.



VI. CONCLUSION

In this study, we introduced a novel deep learning method for predicting wildfire risk. In contrast to previous works, we handle spatial (static) and spatiotemporal (dynamic) variables differently. Our model processes the spatial and

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spatiotemporal variables in two separated 2D/3D CNN branches to learn static and dynamic feature vectors. Moreover, we have introduced the Location-aware Adaptive Normalization layer, which modulates the activation maps in the dynamic branch conditionally on their respective static features to address the causal effect of static features on dynamic features. We furthermore integrated an absolute time encoding into the model. By encoding the calendar time, we make the model explicitly aware of the forecasting day. While the time encoding reduces the recall, it substantially increases the precision. We conducted our experiments on the Fire Cube dataset and demonstrated the effectiveness of our approach compared to several baselines with regard to Precision, F1- score, AUROC, and OA. Although our approach demonstrated a substantial improvement compared to previous works for wildfire forecasting, it still has some limitations. Despite the fact that our framework includes domain knowledge through the normalization layer and absolute time encoding, it does not incorporate physical knowledge about the Earth system. Furthermore, the Fire Cube dataset covers only parts of Eastern Mediterranean and the years 2009-2021. There is a need for more standardized datasets for wildfire forecasting at a continental scale and longer time periods. Finally, there may be hidden events associated with climate variability and extreme weather conditions. It is an open question how these impact the forecast quality and if additional input variables will be needed to enhance forecast accuracy. We believe that the proposed approach of dealing with spatial and spatiotemporal variables more pertinent to other remote sensing applications.

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