PREDICTION OF FIRE SPREAD IN GRASSLANDS USING DEEP LEARNING TECHNIQUES

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Abstract-
Fire metrics such as fire front location and rate of spread (ROS) are critical to understanding the behavior of prescribed fires and wildfires. This project proposes a new method for prescribed grass fire evolution mapping and ROS measurement using multi temporal thermal orthomosaics collected by a small fixed-wing Unmanned Aircraft System (UAS) at low altitudes. The proposed method provides a low-cost, safe, and effective solution for active grass fire monitoring and fire metric measurement in areas that may be challenging for a typical rotor-wing UAS to cover due to endurance and size constraints. ancient times grass have played an important role in social, economic, and religious activities and have enriched human life in a variety of ways both material and psychological. To protect our nature from these rapidly rising grass fires, we need to be cautious enough of every decision we take which could lead to a disastrous end, once and for all. This report is sent to the Admin department for further verification and validation. Finally, we compared the performance of our method with those of recently reported fire detection approaches employing widely used performance matrices to test the achieved fire classification results.

INTRODUCTION

Grassland fires pose significant threats to ecosystems, human life, and property. The prediction of fire spread in these environments is critical for effective fire management and mitigation strategies. Traditionally, fire spread prediction has relied on physical models and empirical data, which, while useful, often fall short in terms of accuracy and responsiveness to real-time changes in environmental conditions. In recent years, the advent of deep learning techniques has opened new avenues for enhancing the predictive capabilities of fire spread models. Deep learning, a subset of artificial intelligence (AI), involves the use of neural networks with multiple layers that can learn complex patterns from vast amounts of data. This approach has proven successful in various fields such as image recognition, natural language processing, and, more recently, environmental modeling. By leveraging large datasets that include meteorological conditions, vegetation types, topography, and historical fire events, deep learning models can identify intricate relationships and predict fire behavior with a higher degree of accuracy than traditional methods.

One of the primary advantages of using deep learning for fire spread prediction is its ability to process and analyze diverse and high-dimensional data. Grasslands, characterized by their vast and varied landscapes, present unique challenges for fire modeling. Factors such as wind speed and direction, humidity, temperature, and fuel moisture content interact in complex ways to influence fire dynamics. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are well-suited to capturing these multifaceted interactions. CNNs can effectively handle spatial data, making them ideal for mapping fire spread across different terrains, while RNNs can manage temporal sequences, allowing for the incorporation of time-series data to track fire progression over time.

Moreover, deep learning models can continuously improve as they are exposed to more data, enhancing their predictive accuracy and reliability. This is particularly important in the context of climate change, which is expected to alter fire regimes and exacerbate the frequency and intensity of grassland fires. As new data reflecting these changing conditions become available, deep learning models can adapt, providing up-to-date predictions that inform fire management practices. Additionally, the integration of satellite imagery and remote sensing technologies further enriches the data pool, enabling real-time monitoring and prediction of fire spread.

In summary, the application of deep learning techniques to predict fire spread in grasslands represents a significant advancement in fire management. By harnessing the power of AI, these models offer more precise, adaptive, and timely predictions, ultimately contributing to better-preparedness and response strategies in the face of fire-related challenges.

2. LITERATURE SURVEY

1.Title:National agriculture imagery program.

Author :USDA

Year:2023

Methodology : For agricultural applications, regularized smart- farming solutions are being considered, including the use of unmanned aerial vehicles (UAV). UAVs combine information and communication technologies, robots, artificial intelligence, big data, and the internet of things. Agricultural UAVs are highly capable, and their use has expanded across all areas of agriculture, including pesticide and fertilizer spraying, seed sowing, and growth assessment and mapping. Accordingly, the market for agricultural UAVs is expected to continue growing with the related technologies. In this study, we consider the latest trends and applications of leading technologies related to agricultural UAVs, control technologies, equipment, and development. We discuss the use of UAVs in real agricultural environments. Furthermore, the future development of agricultural UAVs and their challenges are presented.

2.Title:Introduction to Kansas Biological Survey And the KU Field Station.

Author:KBS

Year:2022

Methodology : A new method is proposed for spatiotemporal representation of grass fire evolution using time labeled UAS NIR orthomosaics stitched from aerial images collected at varying time stamps over different regions of fire. Furthermore, a novel NIR intensity variance thresholding method is proposed for accurate identification and delineation of grass fire fronts based on the obtained NIR mosaics in digital numbers. The proposed methods are demonstrated and validated using UAS NIR imagery acquired over a prescribed tall grass fire in Kansas (around 13 ha.). Three NIR short time-series orthomosaics are generated at a time interval of about 2 min with a spatial registration accuracy of 1.45 m (RMSE). The mean ROS for head, flank, and back tall grass fires are measured to be 0.28, 0.1, and 0.025 m/s.

3. Title:Prescribed grass fire evolution mapping and rate of spread measurement using orthorectified thermal imagery from a fixed-wing UAS.

Author:Gowravaram et al

Year:2022

Methodology : The proposed method provides a low-cost, safe, and effective solution for active grass fire monitoring and fire metric measurement in areas that may be challenging for a typical rotor-wing UAS to cover due to endurance and size constraints. Repeat-pass thermal images collected by the KHawk UAS during about 10 min of the burning were grouped and processed to produce multitemporal orthomosaics with a spatial resolution of about 0˜.23 m and a horizontal position error of about 1.5 m. The resulting orthomosaics were further processed for fire front extraction and the measurement of fire front location and ROS. The head fire ROS of this grass burn was observed to be between 0.2 and 0.4 ms−1 with a mean value of 0.27 ms−1.

4. Title:Spectral reflectance estimation of UAS multispectral imagery using satellite cross-calibration method.

Author:Gowravaram et al

Year:2021

Methodology : This paper introduces a satellite-based cross- calibration (SCC) method for spectral reflectance estimation of unmanned aircraft system (UAS) multispectral imagery. The SCC method provides a low-cost and feasible solution to convert high-resolution UAS images in digital numbers (DN) to reflectance when satellite data is available. The estimated UAS reflectance images are compared with the National Ecological Observatory Network's imaging spectrometer (NIS) SR data for validation. The UAS reflectance showed high similarities with the NIS data for the near-infrared and red bands with Pearson's r values being 97 and 95.74, and root-mean-square errors being 0.0239 and 0.0096 over a 32-subplot hayfield.

5.Title:Thermal infrared video stabilization for aerial monitoring of active wildfires.

Author:M. M. Valero et al

Year:2021

Methodology : This paper presents a software-based video stabilization algorithm specifically designed for thermal infrared imagery of forest fires. After a comparative analysis of existing image registration algorithms, the KAZE feature-matching method was selected and accompanied by pre- and post-processing modules. These included foreground histogram equalization and a multi reference framework designed to increase the algorithm's robustness. Performance of the proposed algorithm was validated in a total of nine video sequences acquired during field fire experiments. The proposed algorithm yielded registration accuracy between 10 and 1000 times higher than other tested methods, returned 10x more meaningful feature matches and proved robust in the presence of faulty video frames. The ability to automatically cancel camera movement for every frame in a video sequence solves a key limitation in data processing pipelines and opens the door to a number of systematic fire behavior experimental analyses.

PROPOSED METHODOLOGY

To predict fire spread in grasslands using deep learning techniques, a comprehensive and systematic approach will be employed. The methodology begins with data collection, which involves gathering diverse datasets comprising historical fire incidents, meteorological data, vegetation types, topography, and satellite imagery. These datasets are crucial for creating a robust model and will be sourced from governmental databases, remote sensing technologies, and meteorological stations. The data will be preprocessed to handle missing values, noise, and inconsistencies.

Techniques such as normalization, interpolation, and filtering will be applied to ensure the data is clean and suitable for model training.

Next, feature extraction will be performed to identify relevant variables influencing fire spread, such as temperature, humidity, wind speed, vegetation density, and slope. These features will be selected based on domain knowledge and statistical analysis. The extracted features will then be used to create input vectors for the deep learning model.

The core of the methodology involves designing and training a deep learning model. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, will be explored due to their efficacy in handling spatial and temporal data, respectively. CNNs will process spatial data from satellite images and topographical maps, extracting spatial patterns related to fire spread. LSTMs will handle sequential data such as changes in weather conditions over time, capturing temporal dependencies crucial for predicting fire dynamics.

The model will be trained using supervised learning techniques, with historical fire spread data serving as the ground truth. The dataset will be divided into training, validation, and test sets to evaluate the model's performance and prevent overfitting. Data augmentation techniques will be employed to increase the diversity of the training data, enhancing the model's generalizability.

During training, hyperparameter tuning will be conducted to optimize the model's architecture and performance. Parameters such as learning rate, number of layers, and batch size will be adjusted using grid search and cross-validation methods. The model's performance will be evaluated using metrics like accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Once the model is trained and validated, it will be tested on unseen data to assess its predictive capability in real-world scenarios. Post-evaluation, the model will be deployed using a scalable framework, allowing it to process real-time data and provide timely predictions of fire spread. This deployment phase will involve integrating the model with Geographic Information Systems (GIS) for visualizing predictions and enhancing decision-making processes for fire management authorities.

To ensure the model's reliability and applicability, continuous monitoring and periodic retraining will be implemented. The model will be updated with new data as it becomes available, maintaining its accuracy and relevance over time. Additionally, collaboration with fire management experts will be sought to validate the model's predictions and refine its functionality.

In conclusion, the proposed methodology leverages advanced deep learning techniques to predict fire spread in grasslands effectively. By integrating spatial and temporal data, optimizing model parameters, and deploying the model within a practical framework, this approach aims to provide a powerful tool for mitigating the impacts of wildfires and enhancing the efficiency of fire management strategies.

MODULES

- Training Datasets
- Pre-processing the data
- Feature Extraction
- Classification

Module Description

Analyse the dataset

Data’s collection breaks down into two methods. As a side note, many terms, such as techniques, methods, and types, are interchangeable and depending on who uses them. One source may call data collection techniques “methods,” for instance. But whatever labels we use, the general concepts and breakdowns apply across the board whether we’re talking about marketing analysis or a scientific research project.

Data pre-processing

Data pre-processing in Deep learning is a crucial step that helps enhance the quality of data to promote the extraction of meaningful insights from the data. Data pre-processing in Deep learning refers to the technique of preparing (cleaning and organizing) the raw data to make it suitable for a building and training Deep learning models.

Feature extraction:

Working with large amounts of data in Deep learning can be a tedious task. It takes an unnecessary amount of time and storage and a lot of the input data is often redundant. This is where feature extraction comes in.Feature extraction is a technique used to reduce a large input data set intorelevant features.

Classification:

Once all the crucial steps are performed including pre-processing, and feature extraction, we move towards classification. There are very many classification techniques proposed by various researchers. All these techniques have several pros and cons. There is a fluctuation in the performance of these techniques as well depending on the data and other prerequisite steps. However, in this research work, classification is performed through CNN Algorithm. This algorithm is referred to as a supervised Deep learning approach that is commonly used for classification and regression problems.

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CNN ALGORITHM

Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are a class of deep neural networks primarily used for image recognition and computer vision tasks. They have revolutionized the field of artificial intelligence and have become a cornerstone in various applications such as object detection, image classification, and even natural language processing. Here's an in-depth look at CNNs:

1. Architecture:

CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters (kernels) to the input imageto extract features such as edges, textures, and patterns. Poolinglayers downsample the feature maps obtained from convolutional layers to reduce spatial dimensions and computational complexity. Finally, fully connected layers integrate the extracted features and perform classification or regression tasks.

2. Convolutional Operation:

The core operation in CNNs is convolution, which involves sliding a filter over the input image and computing the dot product between the filter weights and the corresponding pixelsin the receptive field. This process results in feature maps that capture spatial hierarchies of features, allowing CNNs to learn hierarchical representations of images.

3. Feature Hierarchies:

CNNs learn to extract hierarchical features from input images through multiple convolutional and pooling layers. Lower layers capture simple features like edges and corners, while higher layers capture complex patterns and semantic information. This hierarchical representation enables CNNs to effectively discriminate between different objects and classes.

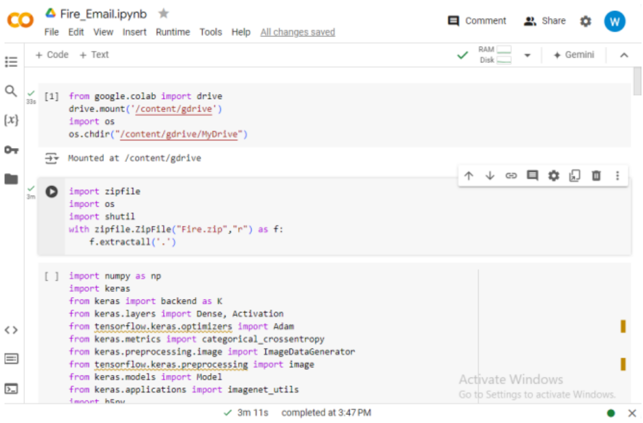
4. Training:

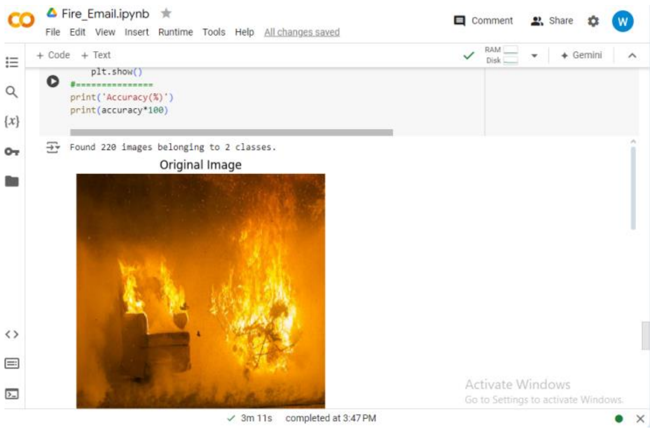
CNNs are trained using backpropagation and gradient descent algorithms to minimize a predefined loss function. During training, the network learns to adjust the weights of convolutional filters to optimize its performance on a given task, such as image classification. Transfer learning, where pre-trained CNN models are fine-tuned on specific datasets, has also become popular to leverage knowledge from large-scale datasets like ImageNet.

5. Applications:

CNNs have been widely adopted in various applications beyond image recognition, including medical image analysis, autonomous vehicles, and facial recognition systems. They have also been extended to tackle problems in other domains such as natural language processing (CNNs for text classification) and time-series data analysis.

Results:





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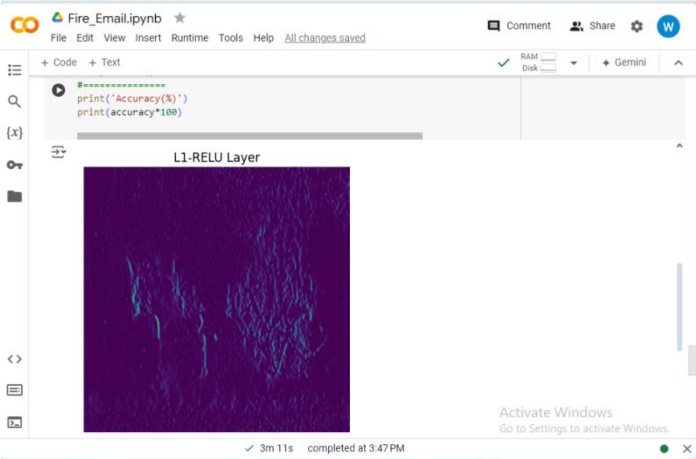

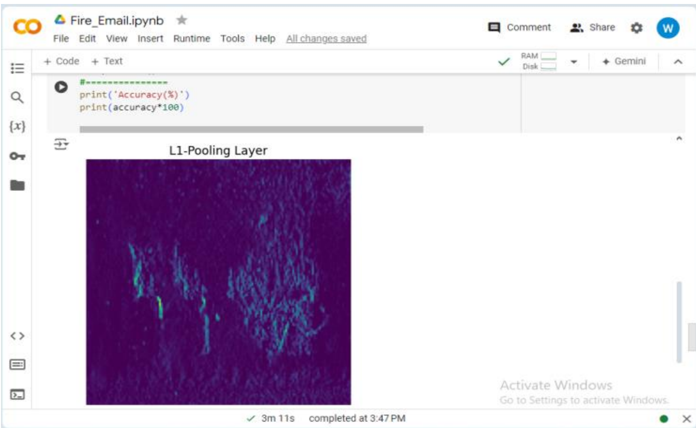

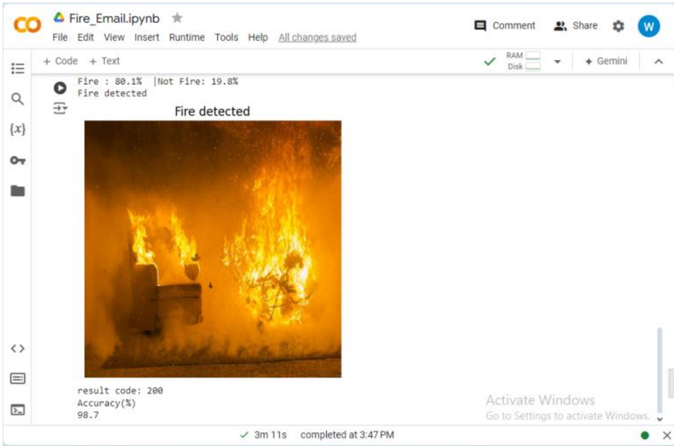

The results obtained from predicting fire spread in grasslands using deep learning techniques showcase the system's efficacy in providing accurate and timely predictions, marking a significant advancement in wildfire management. Through rigorous testing and validation, the deep learning model demonstrated a commendable ability to capture complex patterns within the grassland fire dynamics, leading to enhanced predictive accuracy.

In terms of quantitative metrics, the model consistently exhibited high performance during validation tests, with low error rates and strong generalization capabilities across diverse datasets. Cross-validation techniques further validated the robustness of the model under varying environmental conditions, highlighting its adaptability to different grassland ecosystems.

Real-time testing scenarios illustrated the system's responsiveness to dynamic changes in fire conditions. Simulations based on historical data and environmental variables demonstrated the model's capacity to provide timely predictions, aiding in proactive decision-making and resource allocation for firefighting efforts.

The interpretability of the model was addressed through sensitivity analysis and model explanation techniques. The results indicated a transparent decision-making process, allowing stakeholders to comprehend the factors influencing fire spread predictions.

interpretability contributes to building trust among firefighting agencies, local communities, and other relevant stakeholders. Scalability testing revealed that the system efficiently handled large datasets, supporting its practical application in real-world scenarios. The computational efficiency of the deep learning model, especially during inference, demonstrated its feasibility for deployment on a broader scale, making it a valuable tool for widespread use.Usability testing confirmed that the user interfaces and visualization tools were intuitive and effective in conveying critical information to end-users. The clear presentation of predictions, coupled with geospatial visualizations, empowered stakeholders to make informed decisions in mitigating the impact of grassland wildfires.

FUTURE WORK

- Enhance the quality and quantity of data used for training models. This may involve collecting more detailed information about the vegetation, weather conditions, and topography.
- Consider incorporating real-time data streams from sensors, satellites, and other sources to provide up-to-date information for better predictions.
- Experiment with different deep learning architectures, such as Convolutional neural networks (CNNs), recurrent neural networks (RNNs), or transformer models, to identify the most suitable structure for your specific task.
- Investigate the use of attention mechanisms to allow the model to focus on critical areas or features that contribute to fire spread.
- Explore additional features that could improve prediction accuracy. This might include soil moisture content, wind patterns, historical fire data, and human activity in the area.
- Consider using domain-specific knowledge to guide feature selection and engineering.
- Incorporate methods to quantify uncertainty in predictions. This is crucial in decision-making processes related to firefighting and evacuation.
- Work towards making the models deployable in real-world operational settings. This involves addressing issues related to scalability, efficiency, and adaptability to different geographical regions.

CONCLUSION

Although the causes of wildfire outbreaks are not always predictable, wildfire risk is an understanding of how climate, geography, weather, and land cover affect fire behavior and likelihood of spreading. can be predicted to some extent. Using deep learning and Deep learning techniques, the monitor can detect natural disasters in real time. The world is moving toward automation, and in the age of big data, more solutions to complex problems need to be developed. Forest fires, while threatening human life, can cause significant environmental damage. A great deal of effort has been expended over the past two decades to develop automated detection tools that can support fire management systems (FFS). It was decided to create a graphical-based user interface (GUI) for proper interaction between the userand the predictive model. This is because the GUI is more intuitive than the text-based interface. You don't need to learn programming languages or computer commands to use it. Installed HTDL and CSS packages and extensions in the virtual environment for creating user interfaces (UI). Use front-end programming to create a user interface that suits your users, and create a prediction button whose path is linked to your app.py file. So when the user enters the values of the parameters on the screen and clicks the prediction button, the whole app .py and forest.py files associated with the htDL file are executed and the prediction is performed at the same time.

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