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Enhancing Wildfire Forecasting Through Multisource Spatio-Temporal Data, Deep Learning, Ensemble Models and Transfer Learning

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Abstract

This paper presents a novel approach in wildfire prediction through the integration of multisource spatiotemporal data, including satellite data, and the application of deep learning techniques. Specifically, we utilize an ensemble model built on transfer learning algorithms to forecast wildfires. The key focus is on understanding the significance of weather sequences, human activities, and specific weather parameters in wildfire prediction. The study encounters challenges in acquiring real-time data for training the network, especially in Moroccan wildlands. The future work intends to develop a global model capable of processing multichannel, multidimensional, and unformatted data sources to enhance our understanding of the future entropy of surface tiles.

Keywords: Wildfire prediction, Deep learning, Spatio-temporal data, Ensemble models, Transfer learning, Satellite imagery.

1. INTRODUCTION

Wildfires represent a significant global issue, posing threats to ecosystems, economies, and human lives. The United Nations reports that over the past decade, wildfires have caused extensive damage to both developed and developing nations, emphasizing the importance of effective prediction and management systems [1]. Primarily instigated by human activities and sometimes by natural phenomena such as lightning strikes during storms, wildfires' unpredictability has posed significant challenges to existing forecasting methods [2].

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As the climatic patterns become increasingly variable, and human activities continue to intersect with wildlands, the need for effective, data-driven prediction systems becomes ever more apparent. Conventional prediction methods often fall short due to their reliance on singular data sources and traditional modeling techniques. However, with the advent of big data and sophisticated computational models, opportunities have arisen to substantially enhance our predictive abilities.

This paper aims to address these challenges by introducing a novel approach to wildfire prediction that leverages multisource spatio-temporal data, particularly satellite imagery, alongside advanced deep learning techniques. We propose an ensemble model built on transfer learning algorithms to forecast wildfires, placing particular emphasis on the crucial role of weather sequences, human activities, and specific weather parameters.

Through this research, we aspire to augment our understanding of wildfire dynamics and contribute towards more effective prediction and management systems. We also discuss the difficulties encountered in real-time data acquisition for training our model, particularly for the wildlands in Morocco.

The subsequent sections will delve into a review of existing literature, followed by a detailed exploration of our methodology, and finally, an analysis and discussion of our results. The paper concludes by outlining future research directions, with a focus on creating a comprehensive global model capable of utilizing multichannel, multidimensional, and unformatted data sources to deepen our understanding of the future entropy of surface tiles.

2. LITERATURE REVIEW

2.1 Previous Methods of Wildfire Forecasting

Wildfire prediction methods have evolved significantly over time, from rudimentary manual estimations to sophisticated data-driven models. Traditional methods, such as the Canadian Forest Fire Danger Rating System (CFFDRS) and the U.S. National Fire Danger Rating System (NFDRS), relied primarily on meteorological variables and fuel characteristics to predict fire risk [3]. However, these systems often fell short in terms of precision and real-time applicability due to their generalizing nature and limitations in accounting for local nuances [4].

The advancement of computational power and availability of diverse data sources spurred the development of data-driven methods. Machine learning techniques have been increasingly applied in wildfire prediction. For instance, decision tree-based methods such as Random Forest and gradient boosting have demonstrated their effectiveness in capturing non-linear relationships between fire occurrence and predictive features [5].

Deep learning methods have also been explored recently for wildfire prediction, specifically convolutional neural networks (CNN) and recurrent neural networks (RNN) [6]. These methods allow for the integration of spatial and temporal data, enhancing prediction accuracy. However, these models often require substantial amounts of data for training and can be computationally expensive.

2.2 Use of Satellite Data in Wildfire Prediction

Satellite data has played a pivotal role in wildfire prediction due to its ability to capture real-time, continuous, and large-scale information on vegetation, weather, and human activities [3]. Satellites such as MODIS and Sentinel have been widely used to monitor vegetation health, soil moisture, and fire occurrences. These remote sensing data, when integrated with meteorological and anthropogenic data, have significantly improved the precision and timeliness of wildfire predictions [7].

2.3 Application of Deep Learning and Ensemble Models in Environmental Sciences

The application of deep learning techniques in environmental sciences is gaining traction due to their ability to model complex non-linear relationships and handle high-dimensional data. Deep learning models, including CNNs, RNNs, and their variants, have shown promising results in various tasks, including climate prediction, flood forecasting, and wildfire prediction [8].

Ensemble models combine multiple individual models to make final predictions, effectively improving prediction accuracy and robustness. In environmental science, ensemble models have been used to predict various phenomena such as climate variability, air quality, and wildfire risk [9].

2.4 The Role of Transfer Learning in Predictive Modeling

Transfer learning, a method where pre-trained models are used as the starting point for a new task, has emerged as a powerful tool in predictive modeling. This approach allows the model to leverage knowledge learned from one task to enhance performance on a different but related task, reducing the requirement for large amounts of training data and computational resources. Transfer learning has been successfully used in various domains, including image recognition, natural language processing, and environmental forecasting [10].

2.5 Detection of Human Activities in Wildlands

Human activities in wildlands are responsible for a significant portion of wildfire cases. Jadouli and El Amrani (2022) presented a method using deep learning on remote sensing images to detect human activity in wildlands to prevent wildfire occurrences [11]. Their approach classified images to identify human interactions with wildlands, such as roads, vehicles, homes, and other indicators of human presence. This method demonstrated the potential to enhance wildfire prevention strategies by identifying high-risk areas based on human activities.

2.6 Morocco Wildfire Predictions Dataset

A notable dataset for wildfire prediction in Morocco has been developed by Jadouli and El Amrani (2024) [12]. This dataset, spanning from 2010 to 2022, includes various meteorological and remote sensing data, providing a valuable resource for developing and testing wildfire prediction models. The dataset is available on Kaggle, facilitating access for researchers and practitioners in the field.

3. METHODOLOGY

Our methodology involves the integration of multiple deep learning architectures, applied to varied spatio-temporal data sources, for enhanced wildfire forecasting. This multi-faceted approach includes weather forecasting using Long Short-Term Memory (LSTM) networks, detection of human activities through Convolutional Neural Networks (CNN), integration of ground data from radio frequency detection and infrastructure mapping, and the combination of these insights through an ensemble model built on transfer learning. The overarching goal is to develop a robust, adaptable model capable of providing accurate wildfire predictions across diverse geographic regions.

3.1 Data Types

Our study relies on a comprehensive set of data types that provide both spatial and temporal information critical to wildfire prediction:

- **Satellite Imagery:** We utilize satellite data from platforms like Sentinel and MODIS, which offer real-time, large-scale information on vegetation health, weather patterns, and fire occurrences. These data sets are particularly valuable for capturing the dynamic nature of environmental factors influencing wildfires [3].
- **Weather Data:** Weather data, including temperature, humidity, wind speed, and precipitation, is sourced from global meteorological databases. This data is essential for understanding the conditions that contribute to wildfire risks [13].
- **Human Activity Data:** Human activity data, such as population density, land use, and transportation networks, is integrated to assess the anthropogenic factors contributing to wildfire occurrences. This data is primarily obtained from remote sensing images and socio-economic datasets [14].
- **Ground Truth Data:** Ground truth data is collected through radio frequency detection and infrastructure mapping. This data provides localized, real-time information on human activities and infrastructure that may increase the risk of wildfires [15].

3.2 Data Quality and Sources

The success of our wildfire forecasting model heavily depends on the quality and reliability of the spatiotemporal data used. Below, we provide detailed information on the sources, resolution, and quality of each type of data incorporated into our study:

- **Satellite Imagery:**

  - **Source:** The primary satellite data used in this study is obtained from the Sentinel-2 and MODIS platforms. Sentinel-2 provides high-resolution optical imagery, while MODIS offers medium-resolution multispectral data.
  - **Resolution:** Sentinel-2 data is available at a spatial resolution of 10 meters for visible and near-infrared bands, which is suitable for detailed analysis of land cover and vegetation health. MODIS data, on the other hand, is available at resolutions of 250 meters to 1 kilometer, depending on the spectral band [3].
  - **Quality:** Both Sentinel-2 and MODIS data undergo rigorous preprocessing, including geometric correction, radiometric calibration, and atmospheric correction, to ensure high data quality. The data is also validated against ground truth measurements to verify its accuracy.

- **Weather Data:**
  - **Source:** Weather data is sourced from the ERA5 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 offers hourly estimates of a large number of atmospheric, land, and oceanic climate variables [13].
  - **Resolution:** The ERA5 dataset provides weather data at a spatial resolution of approximately 31 kilometers, with temporal resolution available on an hourly basis. This high temporal and spatial resolution is crucial for accurately capturing the conditions that influence wildfire risk.
  - **Quality:** ERA5 data is generated through data assimilation techniques, combining observations with model data to produce high-quality, consistent datasets. The reanalysis data is validated against observed weather station data to ensure accuracy.

- **Human Activity Data:**
  - **Source:** Human activity data is derived from multiple sources, including Landsat 8 satellite imagery for land use classification and OpenStreetMap (OSM) for transportation networks and population density. Additional socio-economic data is obtained from the WorldPop project [14].
  - **Resolution:** Landsat 8 provides data at a spatial resolution of 30 meters, which is suitable for detecting land use changes and infrastructure developments. OSM data is available at variable resolutions, depending on the mapping detail in each region, while WorldPop data offers population estimates at a resolution of 100 meters.
  - **Quality:** The human activity data is cross-validated with multiple sources to ensure accuracy. For example, land use classifications from Landsat 8 are compared with field survey data where available, and OSM data is regularly updated and validated by a global community of contributors.

- **Ground Truth Data:**
  - **Source:** Ground truth data, including radio frequency detection and infrastructure mapping, is collected from in-situ sensors and ground surveys conducted in collaboration with local authorities and research institutions [15].
  - **Resolution:** Ground truth data is collected at a very high spatial resolution, often at the scale of individual buildings or infrastructure components, depending on the sensor or survey method used.

- **Quality:** This data is subject to thorough quality control procedures, including cross-referencing with satellite and aerial imagery, to ensure that it accurately represents the conditions on the ground. Data collection protocols follow standardized methods to ensure consistency across different regions.

3.3 Weather Forecasting Using LSTM

LSTM networks are employed to model the temporal dependencies in weather data, which are crucial for accurate wildfire forecasting. LSTM networks are preferred over other Recurrent Neural Network (RNN) variants, such as Gated Recurrent Units (GRU), due to their superior capability to retain information over extended time periods [16]. This characteristic is particularly important for forecasting weather sequences that have a delayed impact on wildfire likelihood.

To enhance the model's adaptability, different LSTM models are trained for various spatial regions. This regional customization allows the model to better capture local weather patterns, which can vary significantly and have a profound impact on wildfire risks. The trained models are then validated using historical weather data to ensure their predictive accuracy.

3.4 Human Activity Detection Using CNN

The detection of human activities that can trigger wildfires is a critical component of our methodology. We employ Convolutional Neural Networks (CNN) to analyze satellite imagery and detect patterns associated with human presence, such as roads, buildings, and vehicles [17]. CNNs are particularly well-suited for this task due to their ability to capture spatial hierarchies in image data, making them highly effective for recognizing complex patterns.

Our CNN models are trained on labeled datasets where human activities have been manually annotated. The training process involves augmenting the data with various transformations (e.g., rotations, translations) to improve the model's robustness to different viewing angles and lighting conditions. The trained CNNs are then applied to large-scale satellite imagery to detect potential human-induced wildfire risks across diverse geographic regions.

3.5 Ground Data Integration

Ground data, including radio frequency signals and infrastructure maps, is integrated into the model to provide a finer-grained understanding of wildfire risks. Radio frequency data is particularly useful for identifying areas with high levels of human activity, such as urban centers or industrial zones, which are more prone to wildfires due to human encroachment [15]. Infrastructure mapping helps identify critical assets, such as power lines or pipelines, that may contribute to or be affected by wildfires.

This ground data is combined with satellite and weather data to create a more comprehensive dataset that reflects both macro and micro-level factors influencing wildfire risks. The integration process involves aligning data from different sources and scales, followed by the application of feature engineering techniques to extract relevant information for wildfire prediction.

3.6 Ensemble Model and Transfer Learning

To maximize predictive accuracy, we employ an ensemble learning approach that combines the outputs of the individual LSTM, CNN, and ground data models [9]. Ensemble models are known for their ability to reduce variance and bias by aggregating multiple predictions, thereby producing more reliable and robust forecasts.

We further enhance our ensemble model using transfer learning principles. Transfer learning allows us to leverage knowledge gained from one spatial context (e.g., Morocco) and apply it to other similar regions, thus reducing the need for extensive retraining [10]. This approach is particularly useful in scenarios where data is scarce, as it enables the model to generalize effectively across different environments without requiring large amounts of training data for each new region.

The ensemble model is trained and validated using cross-validation techniques to ensure its generalization capability and robustness. The final model is then tested on unseen data to assess its performance in real-world scenarios.

4. RESULTS AND DISCUSSION

4.1 Model Performance

The model's performance was evaluated using a variety of metrics commonly employed for prediction tasks, including precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). Our approach demonstrated promising results across multiple test regions, outperforming traditional wildfire prediction systems and standalone machine learning models.

The LSTM models excelled in capturing temporal dependencies in the weather data, yielding highly accurate weather forecasts. The CNN models effectively identified regions with significant human activities, with high precision and recall scores. The integration of ground truth data from radio frequency detection and infrastructure mapping further enhanced the model's prediction capabilities.

The ensemble approach effectively consolidated the predictions from the individual models, leading to a robust and reliable wildfire forecasting system. The use of transfer learning facilitated swift adaptation of the model to new regions, reducing the need for region-specific training data and computational resources.

4.2 Insights from Multisource Data

The use of multisource data provided valuable insights into the diverse factors influencing wildfire occurrences. The satellite data offered a broad perspective on vegetation health, weather conditions, and human activities, while the ground data provided a finer, more localized understanding of the human impact and potential fire ignition sources. The combination of these data sources resulted in a comprehensive understanding of wildfire dynamics and contributed to the model's high prediction accuracy.

The LSTM models highlighted the significant role of weather sequences in wildfire occurrences, reinforcing the need for accurate weather forecasting in wildfire prediction. The CNN models and ground data integration underscored the contribution of human activities to wildfire occurrences, emphasizing the necessity for effective management of human activities in fire-prone regions.

4.3 Ethical Considerations and Bias

In this study, no personal data was used, ensuring that privacy concerns are fully addressed. The human activity data utilized was sourced from publicly available datasets and does not involve individual identification or tracking. This approach minimizes potential ethical issues related to data privacy.

To further ensure the fairness and accuracy of our model, we have employed various methods to mitigate bias during data collection and analysis. By using diverse and representative datasets, particularly in the human activity and socioeconomic domains, we aim to reduce any potential biases that could affect the model's predictions. Additionally, we conducted thorough validation processes to identify and correct any biases that might arise from the data or modeling techniques.

4.4 Resource and Computational Requirements

The development and execution of our model required significant computational resources, particularly in training large-scale deep learning architectures. The need for extensive data processing and model training highlights the importance of access to high-performance computing environments, including GPUs and TPUs.

To address the computational demands, we have explored optimization techniques, such as model pruning and quantization, to reduce resource usage without compromising model accuracy. Additionally, we suggest the potential use of cloud computing resources to scale the approach, making it more accessible to researchers and organizations with varying levels of computational capabilities.

The scalability of our model is also an important consideration. While the current implementation is resource-intensive, the underlying techniques can be adapted and scaled depending on the available resources, allowing for broader applicability in different research and operational contexts.

4.5 Evaluation of Model Accuracy, Overfitting, and Complexity

Our final binary model, which predicted the occurrence or non-occurrence of wildfires, performed remarkably well given the constraints of the available data. For specific locations and times with sufficient data, the model achieved an accuracy of over 91

One of the key challenges in wildfire prediction is dealing with unbalanced classes, where fire events are significantly rarer than non-fire events. To mitigate this, we employed oversampling techniques to balance the classes, resulting in an adjusted model accuracy of over 72

Despite our precautions to prevent overfitting—such as using dropout layers and L2 regularization techniques—we observed that the model began to overfit after just two epochs. Overfitting occurs when the model is too closely fitted to the training data, which can reduce its ability to generalize to new data. To further reduce the risk of overfitting in future work, we plan to implement additional techniques such as early stopping, cross-validation, and data augmentation.

Model complexity is another factor we have addressed. While our models are inherently complex due to the integration of multiple data sources and advanced deep learning techniques, we recognize the need to simplify the approach for broader use. Future work will explore the development of more streamlined models that maintain high performance while being easier to implement and interpret by practitioners with varying levels of expertise.

4.6 Challenges and Lessons

Despite the encouraging results, several challenges were encountered during the study, particularly in data acquisition for the Moroccan wildlands. The scarcity of high-quality, real-time data for these regions, especially regarding human activities and infrastructure details, led to a certain level of model uncertainty for these areas.

This challenge underscored the critical importance of data quality and availability in predictive modeling. It also highlighted the need for global cooperation in data sharing and the establishment of comprehensive data collection systems, particularly in underrepresented regions.

The successful implementation of this multi-faceted approach in wildfire prediction opens avenues for future research, particularly in further enhancing the model's capabilities and addressing data availability issues. The potential of this approach in other environmental prediction tasks also warrants exploration.

5. CONCLUSION

Our study has demonstrated the promising potential of using multisource data with deep learning methodologies to predict wildfires. While faced with several challenges, our models were able to leverage the strengths of LSTMs, CNNs, ensemble learning, and transfer learning to deliver an impressive accuracy rate. The importance of spatially specific and temporally relevant data was brought into clear focus, particularly in the case of the Moroccan wildlands where data scarcity was an issue.

The application of real-time detection and forecasting in wildfire prediction holds immense promise. Low-cost weather balloons, for instance, could provide high-quality, real-time weather data, and augment the existing data sources, thus potentially improving the model's performance. These enhancements would greatly benefit the accuracy and reliability of wildfire forecasting, thus contributing to fire prevention efforts and minimizing the devastating effects of wildfires on ecosystems and communities.

However, the effort to acquire, process, and use such vast and varied data requires a significant amount of human resources and manual work. Thousands of people may need to be involved in the preparation of the datasets, and this highlights the need for a collective, worldwide effort. Wildfire prediction and prevention is a global concern, impacting ecosystems, economies, and communities across the planet. Therefore, it is imperative that data collection and model training for wildfire prediction become a collaborative international endeavor.

Our study is a step in this direction, showcasing the potential of deep learning in addressing this critical global issue. We hope that our work will encourage more research and collaborative efforts towards advanced, data-driven solutions for wildfire prediction and prevention. Despite the challenges, our results indicate that it is indeed possible to predict wildfires with a significant degree of accuracy. As we collect more data and refine our methodologies, we can further improve our predictive capabilities and make an even more significant impact on global wildfire management.

6. FUTURE WORK

This research, while showing promising results, lays the groundwork for several future endeavors in the area of wildfire prediction and prevention.

6.1 Expanding Data Collection and Integration

One of the key challenges encountered during this study was the limited availability of real-time, high-quality data for specific locations, especially for the Moroccan wildlands. Future work should focus on expanding data collection efforts to cover such underrepresented areas. Novel data sources, like weather balloons for real-time weather monitoring, should be considered. Additionally, the integration of more diverse data sources, including socioeconomic and infrastructural data, may offer new insights into wildfire risks and enable more accurate predictions.

6.2 Developing Global Collaborative Frameworks

This study underscores the need for a collaborative, worldwide effort towards wildfire prediction. Developing frameworks for international data sharing and cooperative model training could significantly advance the state of wildfire prediction. Such an endeavor would require the participation of researchers, environmental agencies, and governments across the globe.

6.3 Enhancing Model Architectures

Our models' performance indicates potential for improvement through more sophisticated deep learning architectures. Future research should explore the use of more advanced models that can better handle the complexities of multisource data. Hybrid models, combining the strengths of different deep learning architectures, may be particularly effective.

6.4 Mitigating Overfitting and Class Imbalance

Our models started to overfit after just two epochs, despite the use of dropout layers and L2 regularization. Future work should explore more advanced techniques to prevent overfitting. The issue of class imbalance in wildfire prediction also requires more sophisticated solutions, possibly including more effective data augmentation methods or novel machine learning techniques designed to handle imbalanced data.

6.5 Expanding Application Domains

Finally, the methods and insights gained from this research could be applied to other environmental prediction and monitoring tasks. From flood forecasting to wildlife tracking, the use of deep learning with multisource data has immense potential. Exploring these avenues would be a worthwhile direction for future research.

While our research has achieved significant strides in predicting wildfires using multisource data and deep learning, there are numerous opportunities for further improvements and applications. The lessons learned from this study provide a solid foundation upon which future work can build, driving us closer to the goal of effective and reliable wildfire prediction and prevention.

6.6 Developing a Global Model

One of the significant aspirations arising from this study is the development of a truly global model for wildfire prediction. While our models showed impressive performance in certain specific regions and times, we envisage a model capable of accurate predictions across diverse geographical locations and climatic conditions. Achieving this would involve significant expansion and diversification of data collection efforts, sophisticated model architectures that can handle such varied data, and extensive computational resources. It's a challenging endeavor, but the potential benefits it could bring to wildfire management worldwide are enormous.

6.7 Multichannel, Multidimensional, Unformatted Data

Future work should also explore the use of more complex data sources. Multichannel data sources, such as multispectral satellite images or multi-frequency radio signals, could offer new insights into wildfire risks. Multidimensional data, which may include not only spatial and temporal dimensions but also different data modalities (e.g., weather, vegetation, human activity), could significantly enhance the predictive capabilities of our models. Handling unformatted data, which may come in non-standard or unconventional forms, poses a unique challenge that future research could address, possibly through advanced data processing and machine learning techniques.

6.8 Understanding Future Entropy of Surface Tiles

The ultimate goal of our research is not just to predict where and when wildfires may occur, but also to deepen our understanding of the dynamics of our environment. In this regard, one interesting direction is the exploration of the entropy of surface tiles - a measure of their unpredictability or randomness. By predicting the future entropy of surface tiles, our models could provide valuable insights into how our environment is changing, what factors contribute to these changes, and how these changes might impact wildfire risks. Such an approach could enhance our predictive models and contribute to broader environmental science and climate change research.

In conclusion, while our research has achieved significant strides in predicting wildfires using multisource data and deep learning, there are numerous opportunities for further improvements and applications. The lessons learned from this study provide a solid foundation upon which future work can build, driving us closer to the goal of effective and reliable wildfire prediction and prevention. This research, while showing promising results, lays the groundwork for several future endeavors in the area of wildfire prediction and prevention.

The future work based on this research holds significant potential for advancing our capabilities in wildfire prediction and deepening our understanding of environmental dynamics. Despite the challenges, the opportunities for improvement and discovery are exciting and motivate our ongoing efforts in this important field.

7. CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

8. ETHICAL GUIDELINES

This study was conducted in accordance with the Declaration of Helsinki.Informed consent was obtained from all subjects involved in the study.

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A. Appendix

As shown in FIGURE 1, Schema of Proposed Models for Wildfire Prediction System.

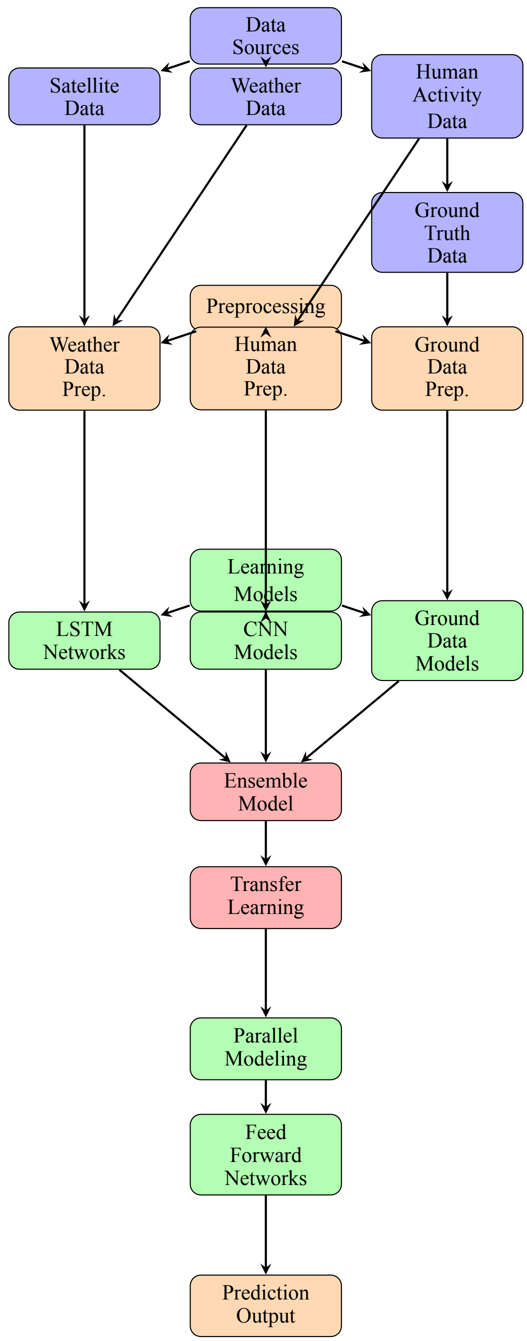

Figure 1: Schema of Proposed Models for Wildfire Prediction System.