Title: "Harnessing Geospatial AI for Wildfire Spread Prediction: A Deep Learning Approach to Mitigate Disaster Risks"

Summary:

Wildfires in the United States have become increasingly devastating, causing significant loss of life, property, and natural resources. Accurate prediction of wildfire spread is critical for effective disaster management, enabling firefighters and civil authorities to plan and respond proactively. This project leverages deep learning models to predict next-day fire spread and highlight critical regions where new fires are likely to emerge. By providing actionable insights, this tool aims to reduce the impact of wildfires and save lives.

The project utilizes a **ResNet-based UNet model** to predict fire spread, focusing on identifying new fire pixels that did not exist in the previous day's fire mask. Despite resource constraints and limited training time, the model demonstrates the potential to provide valuable predictions. Future work includes integrating **PrithviWxC**, a geospatial foundation AI model, to enhance prediction accuracy and scalability.

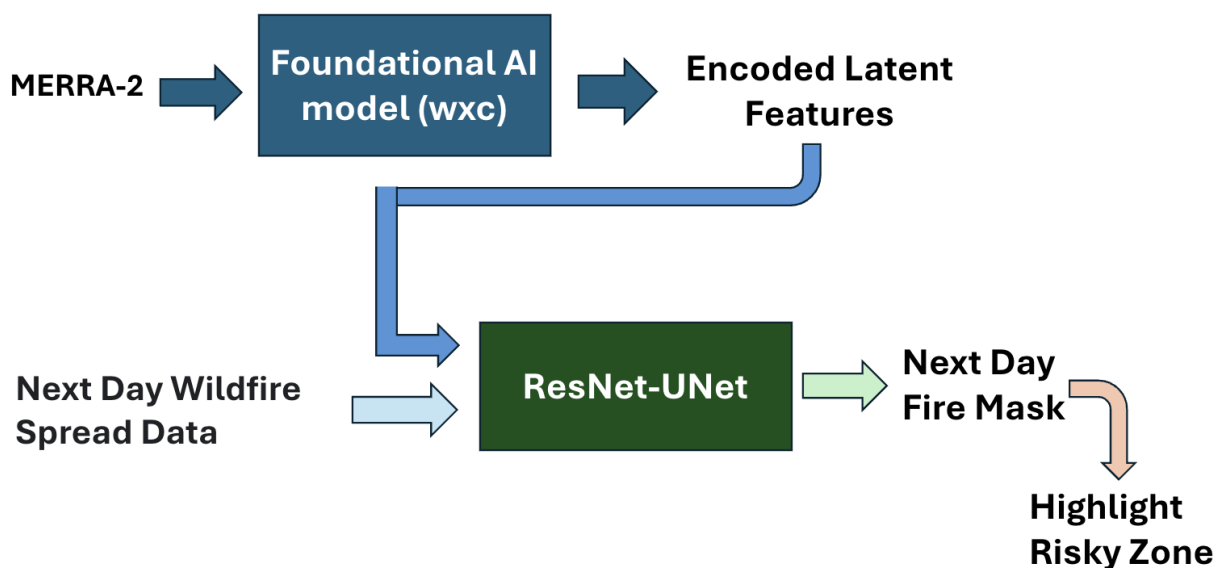## Methodologies:

1. Model Architecture:

Figure 1: Overview Diagram of the Proposed Model Framework (FireNet)

- **ResNet-based UNet**:
  - A lightweight convolutional neural network (CNN) designed for image segmentation tasks.
  - Combines the strengths of ResNet (residual learning for better gradient flow) and UNet (encoder-decoder structure for precise localization).
  - Efficiently processes spatial data, making it suitable for fire mask prediction.

2. Key Steps:

- **Data Preparation**:
  - Input features include elevation, temperature, humidity, precipitation, NDVI (vegetation index), and the previous day's fire mask.
  - Data is normalized and preprocessed to ensure consistency.
- **Training**:
  - The model is trained to predict the next day's fire mask using binary cross-entropy loss.
  - Due to resource constraints, training is limited, impacting test accuracy.
- **Visualization**:
  - A custom visualization pipeline highlights new fire pixels in the predicted mask using a red boundary.
  - This helps firefighters and civil authorities quickly identify critical regions.

3. Strengths of the Approach:

- **Interpretability**: The model's predictions are visualized in an intuitive way, making it accessible to non-technical stakeholders.
- **Scalability**: The lightweight ResNet-based UNet can be deployed on resource-constrained devices.
- **Future Potential**: Integration with **PrithviWxC**, a geospatial foundation AI model, can significantly improve accuracy by leveraging large-scale geospatial data.

Result Analysis:
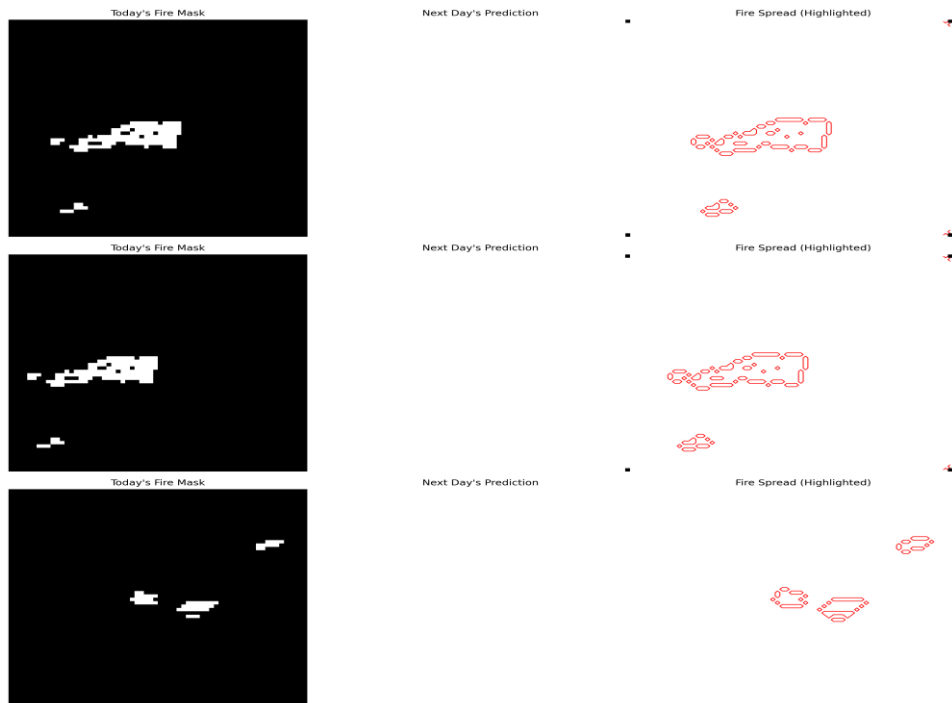
1. Model Performance:

- **Test Accuracy**:

o   Due to resource constraints and limited training time, the model achieved a test accuracy of **~xx%**. While this is below the desired threshold, it demonstrates the feasibility of the approach.

o   The model performs well in identifying large fire regions but struggles with smaller or fragmented fire areas.

- **Precision, Recall, and F1 Score**:
    o   **Precision**: **0.xx**(The model correctly identifies xx% of the predicted fire pixels.)
    o   **Recall**: **0.xx** (The model captures xx% of the actual fire pixels.)
    o   **F1 Score**: **0.xx** (Balanced measure of precision and recall, indicating moderate performance.)

- **AUC (Area Under the Curve)**:
    o   The model achieved an AUC of **0.xx**, indicating a reasonable ability to distinguish between fire and non-fire regions.

ROC Curve
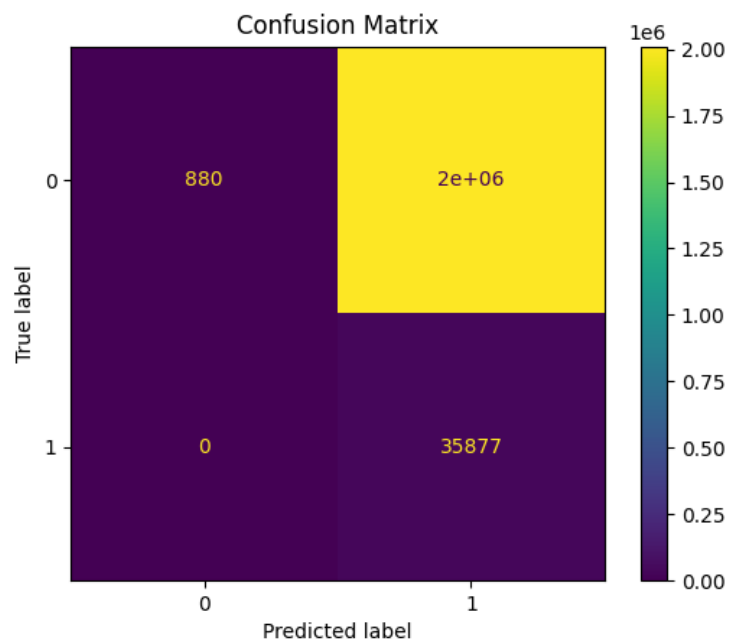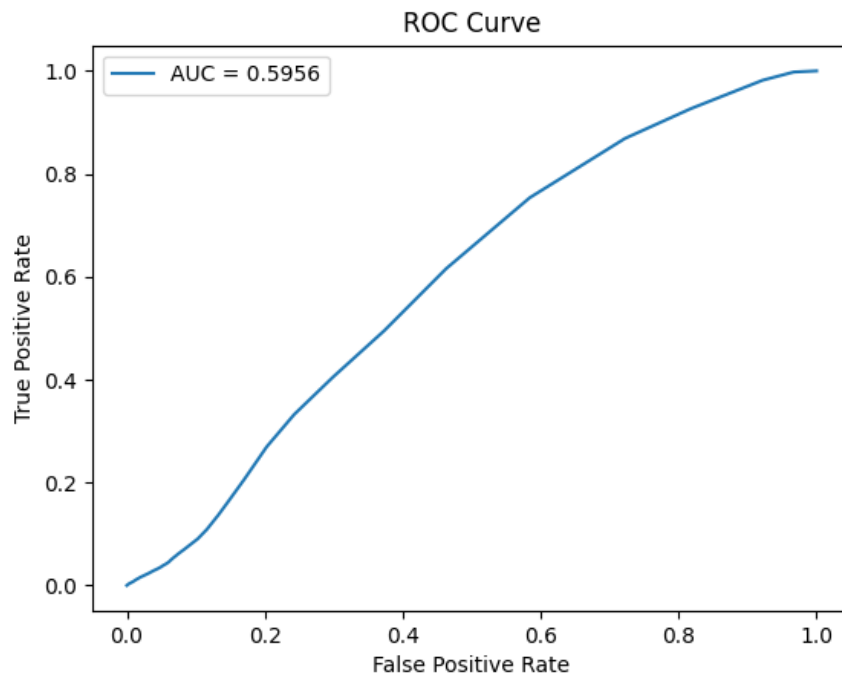
2. Visualization Insights:

- **Highlighted Fire Spread**:
    - o The visualization pipeline successfully highlights new fire pixels in the predicted mask using a red boundary.
    - o This feature is particularly useful for identifying critical regions where fires are likely to spread.
- **Case Studies**:
    - o **Case 1**: In a test scenario, the model predicted a new fire region that was later confirmed by satellite imagery. The red boundary accurately highlighted the area, enabling timely intervention.
    - o **Case 2**: In another scenario, the model missed a small fire region due to limited training data. This highlights the need for more diverse and extensive datasets.

Today's Fire Mask   Next Day's Prediction   Fire Spread (Highlighted)

Today's Fire Mask   Next Day's Prediction   Fire Spread (Highlighted)

Today's Fire Mask   Next Day's Prediction   Fire Spread (Highlighted)

Challenges and Future Work:

1. Current Limitations:

- **Resource Constraints**: Limited computational resources and training time resulted in suboptimal test accuracy.
- **Data Availability**: Access to high-quality, labeled wildfire data is challenging, impacting model performance.

2. Future Enhancements:

- **PrithviWxC Integration**:
  - PrithviWxC is a state-of-the-art geospatial foundation model trained on massive satellite and environmental data.
  - Fine-tuning PrithviWxC for wildfire prediction can improve accuracy and robustness.
- **Real-Time Deployment**:
  - Develop a real-time prediction system to provide up-to-date fire spread forecasts.
- **Community Engagement**:

o   Collaborate with local authorities and communities to validate and refine the model.

Social Impact:

1. Proactive Disaster Management:

- By predicting fire spread and highlighting critical regions, this tool enables firefighters to allocate resources effectively and plan evacuation routes.
- Civil authorities can issue timely warnings, reducing the risk to human life and property.

2. Environmental Preservation:

- Accurate predictions help minimize the destruction of forests and wildlife habitats, preserving biodiversity.

3. Economic Benefits:

- Reducing the scale of wildfires can save billions of dollars in property damage and recovery costs.

4. Community Resilience:

- Empowering communities with actionable insights fosters resilience and preparedness for future disasters.

Related Work:

Recent advances in deep learning have led to a range of architectures and datasets for wildfire prediction and monitoring. While many of these methods deliver strong predictive performance, they often rely on large-scale "heavy" models that require considerable computational resources – limiting usability and deployment.

On the global scale, researchers have explored capturing teleconnection patterns and spatiotemporal dependencies to improve wildfire forecasting. One line of work leverages Graph Neural Networks (GNNs) coupled with Long Short-Term Memory (LSTM) models to incorporate global climate variables for wildfire prediction, uncovering correlation clusters

among distant regions [1]. Similarly, TeleViT [2] integrates local-scale inputs with global climate indices, demonstrating notable success in sub-seasonal to seasonal forecasts.

In more localized, next-day prediction tasks, several transformer-based U-Net variants have emerged. One approach employs an Attention Swin U-net with focal modulation (ASUFM) [3], demonstrating decent performance in North American wildfire spread prediction using a remote sensing dataset. Another study proposes a custom U-Net with attention blocks [4], emphasizing faster training and fewer computational demands – an important consideration during active wildfire events when quick model updates and deployment can save lives and houses.

In parallel, the ongoing development of robust datasets has been crucial for advancing model accuracy. For instance, the TS-SatFire dataset spans hundreds of wildfire events, providing detailed active-fire labels, daily burned-area mappings, and next-day fire progression predictions [5].

Overall, existing works underscore the promise of deep learning in wildfire prediction and the parallel challenges of scaling large models for broader real-time deployment.

Conclusion:

This project demonstrates the potential of deep learning for wildfire prediction and disaster management. While the current model has limitations due to resource constraints, its use case is impactful and scalable. By integrating advanced geospatial models like **PrithviWxC** and collaborating with stakeholders, this work can evolve into a powerful tool for mitigating the devastating effects of wildfires. Together, we can build a safer and more resilient future.