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GEOSPATIAL WILDFIRE RISK PREDICTION USING DEEP LEARNING

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GEOSPATIAL WILDFIRE RISK PREDICTION USING DEEP LEARNING

A Project

Presented to the

Faculty of

California State University,

San Bernardino

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

in

Computer Science

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by

Abner Benavides

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ABSTRACT

This report introduces a thorough analysis of wildfire prediction using satellite imagery by applying deep learning techniques. To find wildfire-prone geographical data, we use U-Net, a convolutional neural network known for its effectiveness in biomedical image segmentation. The input to the model is the Sentinel-2 multispectral images to supply a complete view of the terrain features.

We evaluated the wildfire risk prediction model's performance using several metrics. The model showed high accuracy, with a weighted average F1 score of 0.91 and an AUC-ROC score of 0.972. These results suggest that the model is exceptionally good at predicting the location of wildfire risks and distinguishing between wildfires and non-wildfires.

The model generally demonstrated solid performance but encountered difficulties in certain aspects. There were instances where its risk level predictions diverged from the ground truth data. This discrepancy could stem from the multifaceted factors of wildfire risk prediction, an area impacted by numerous variables. Therefore, to enhance precision and accuracy, the model necessitates additional fine-tuning.

The report also explores using a class imbalance strategy to address the disparities in data distribution among the different classes. We discuss the inherent challenges in predicting wildfire-prone regions, which provides insights into the complexities of wildfire prediction and management.

This study found that deep learning techniques have resulted in a highly accurate prediction of the risk of wildfires. Despite some shortcomings, the model's predictions aligned closely with the ground truth data. Therefore, this study suggests that deep learning models could effectively manage and prevent wildfires on a large scale.

ACKNOWLEDGEMENTS

I want to express my most profound appreciation to my graduate project committee for their unwavering support and guidance throughout this project. Each member has been invaluable in their unique way.

To Dr. Ronald Salloum, thank you for your tireless efforts and encouragement and for consistently pushing me to think critically and explore new perspectives. Your insight and expertise have been instrumental in shaping this work.

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CHAPTER ONE

INTRODUCTION

Background

The impact and prevalence of wildfires are escalating due to shifts in climate affecting air temperature, humidity, and vegetation. Wildfires burn an estimated five hundred million hectares of land yearly. Climate change and human land use activities have significantly influenced these fires' spatial distribution, frequency, and intensity [1, 3, 4].

In the United States alone, wildfires account for billions of dollars in expenses annually [5], a sizable part dedicated to prevention and mitigation efforts. To optimize these expenditures and ensure the safety of at-risk communities, we must understand and accurately pinpoint areas with heightened wildfire risk.

The USDA Forest Service periodically updates its Wildfire Hazard Potential, the most recent in 2020. However, given the rapidly changing climate conditions and the increasingly unpredictable nature of wildfires, there is a growing need for more frequent and precise information to guide decision-making.

Existing methodologies for wildfire risk prediction rely heavily on historical fire data and only partially use the vast amounts of real-time geospatial data now available. Additionally, these models may not consider the intricate and nonlinear relationships between various environmental factors contributing to wildfire risk.

To address the challenges related to wildfire risk assessment, we have developed a framework that utilizes deep learning techniques to generate accurate and up-to-date fire hazard maps. Our approach involves innovative image processing techniques and comprehensive geospatial datasets to provide a timely and more precise evaluation of wildfire risk in the United States.

Problem Statement

Wildfires significantly threaten ecosystems and communities, causing extensive damage and billions of dollars each year spent on response and recovery efforts. To effectively plan and allocate resources for mitigation efforts, it is critical to have accurate and prompt wildfire risk predictions. However, existing wildfire risk assessment methods often rely too heavily on historical fire data and do not fully exploit the vast amount of geospatial data available today.

Furthermore, more modern conventional methods should consider the intricate and nonlinear interplay among multiple environmental factors contributing to wildfires’ likelihood. This results in an inadequate and obsolete comprehension of wildfire risk, leading to inefficient planning and response strategies. Therefore, an urgent and improved approach to wildfire risk prediction is necessary, utilizing advanced machine learning techniques and extensive geospatial datasets to deliver precise, timely, and high-resolution risk assessments.

Purpose and Objectives

Our project aims to utilize the geospatial datasets found on Google Earth Engine and employ a U-Net machine learning model to create a detailed, current map that precisely identifies wildfire risks and hazard levels throughout the United States. By attaining an 85% model accuracy and providing weekly updates, our project aims to offer essential and timely data that can aid in strategic planning and rapid responses, ultimately reducing the harmful effects of wildfires.

CHAPTER TWO

LITERATURE REVIEW

Introduction

Wildfire risk assessment is a crucial study area with considerable implications for natural ecosystems and human societies. Over time, methodologies for risk assessment have significantly evolved, with recent advances in geospatial data analysis and machine learning offering new possibilities. Two pivotal studies have contributed significantly to this field of study.

Geospatial Data-Driven Solutions

An essential study in this field, “Developing a geospatial data-driven solution for rapid natural wildfire risk assessment,” by Adhikari et al., highlighted the efficiency of geospatial data in expediting wildfire risk assessment processes [2].

Summary of Findings

Their proposed geospatial data-driven solution not only proved effective in predicting wildfire risk, but it also outperformed traditional methods. The model successfully showed areas with high wildfire risk, with an overall accuracy of 82%.

Critique

Despite the promising findings, their research mainly focused on the central and northern sections of the study area. Therefore, the applicability of their model to other regions with differing geographical and climatic conditions may be limited.

Relevance to Our Research

This study underpins using geospatial data for risk assessment, a notion we further cultivate in our project. We focus on implementing a deep learning-based system for generating up-to-date fire hazard maps across the United States.

Machine Learning Approaches

A significant contribution in this field is “Spatial Prediction of Wildfire Susceptibility Using Field Survey GPS Data and Machine Learning Approaches” by Ghorbanzadeh et al. Their research highlights the potential benefits of integrating machine learning with geospatial data [3].

Summary of Findings

Their machine learning-based spatial prediction model effectively predicted wildfire susceptibility and surpassed conventional methods. The model found regions with varying susceptibility levels, achieving an overall accuracy of 84.4%. Factors such as slope, proximity to rivers, and proximity to roads make an area more vulnerable to wildfires.

Critique

The model, though effective, was primarily based on field survey GPS data. How the model would perform when dealing with larger, more diverse datasets still needs to be determined.

Relevance to Our Research

Furthermore, our project employs machine learning, specifically the U-Net model, in conjunction with the expansive geospatial datasets on Google Earth Engine.

Conclusion

These two pivotal works play a crucial role in the evolution of wildfire risk assessment methodologies, proving the powerful potential of geospatial data and machine learning. They also suggest further research to address potential limitations and apply these methods on a broader scale. Our study aims to contribute to this expanding field by combining deep learning and geospatial data to create an up-to-date map presenting wildfire risk and hazard levels across the United States.

CHAPTER THREE

METHODS / METHODOLOGY

This chapter presents the data collection, preprocessing, and modeling techniques used in this study. It aims to provide a comprehensive description of the steps followed in this project to ensure replicability.

Data Collection

2020 Geospatial Datasets

The geospatial datasets used in this study were gathered from the year 2020 and are from three sources:

- Sentinel-2 Harmonized dataset.
- Fire Information for Resources Management System (FIRMS)
- GridMET meteorological dataset

The datasets selected for 2020 were chosen based on their extensive coverage, relevance to predicting wildfire risk, and availability during the specified year. Per the project's requirements, we extracted specific bands from each dataset based on the collection timeframe 2020.

Wildfire Hazard Potential (WHP) Data

We retrieved the WHP raster data used as the target label in our model from the USDA Forest Service website. The raster data was then uploaded to Google Earth Engine to ease easy access and uniformity in the data processing.

The selected WHP data represents the wildfire risk and hazard levels across the United States for 2020.Dataset Description

Sentinel-2 Harmonized. We used the Sentinel-2 dataset to gather multispectral imagery. The dataset, provided by the European Space Agency, offers comprehensive coverage with a high revisit rate, making it ideal for monitoring and prediction tasks. We selected critical bands such as B2 (Blue), B3 (Green), B4 (Red), B8 (Near Infrared), B11 (Shortwave Infrared), and B12 (Shortwave Infrared) for this study. Figure 1 displays an example of imagery from the Sentinel-2 dataset.

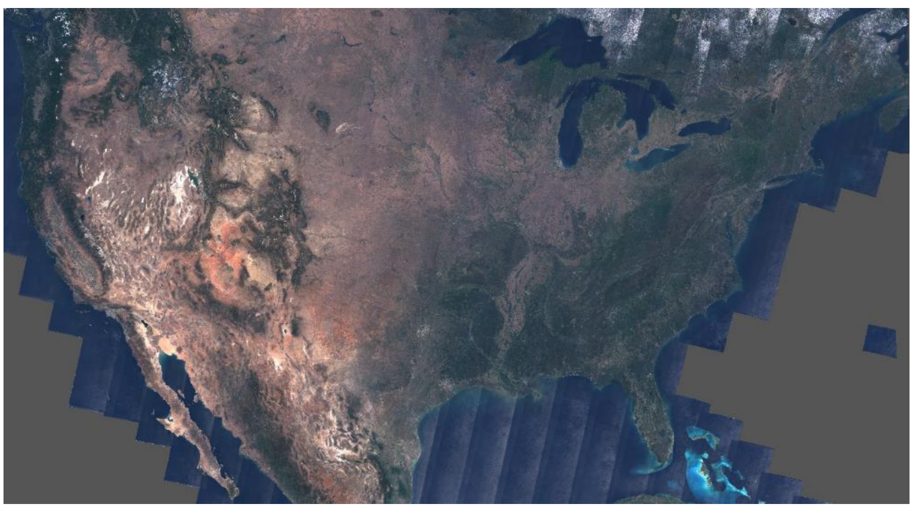

Figure 1. Sentinel-2

FIRMS. The Fire Information for Resource Management System (FIRMS) dataset supplied fire occurrence data. Specifically, we used the brightness temperature band (T21), which represents the temperature of the fire. Figure 2 illustrates an example of imagery from the FIRMS dataset.

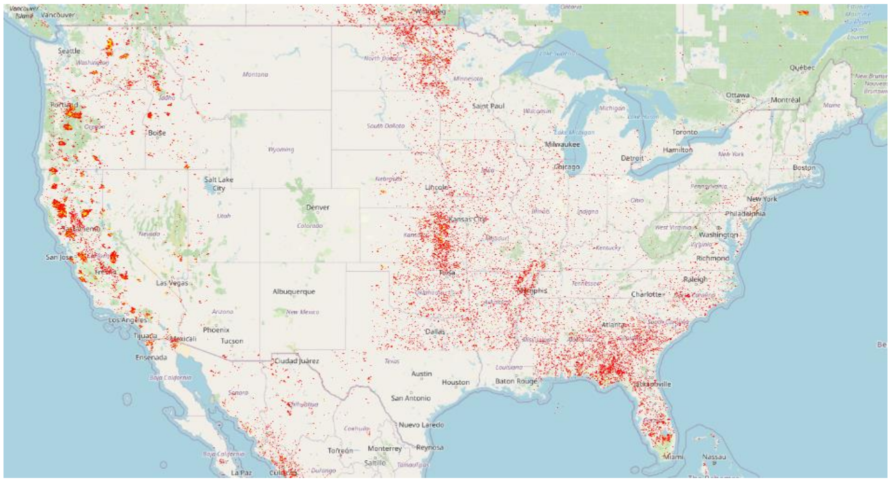

Figure 2. FIRMS

<u>GridMET.</u> The GridMET dataset supplied meteorological data, including maximum and minimum temperature (tmmx, tmmn), precipitation (pr), wind speed (vs), and specific humidity (sph). Figure 3 provides an example of imagery from the GridMET dataset.

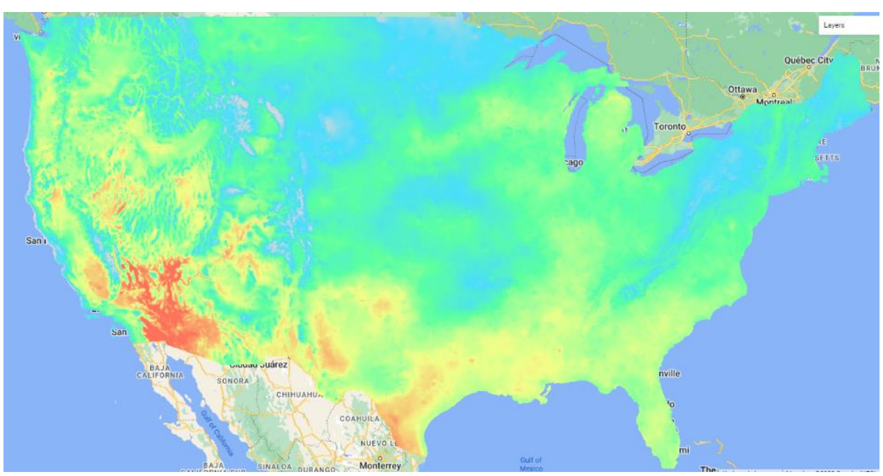

Figure 3. GridMET

SRTM. The Shuttle Radar Topography Mission (SRTM) dataset from NASA supplied elevation data. Figure 4 demonstrates an example of imagery from the SRTM dataset.

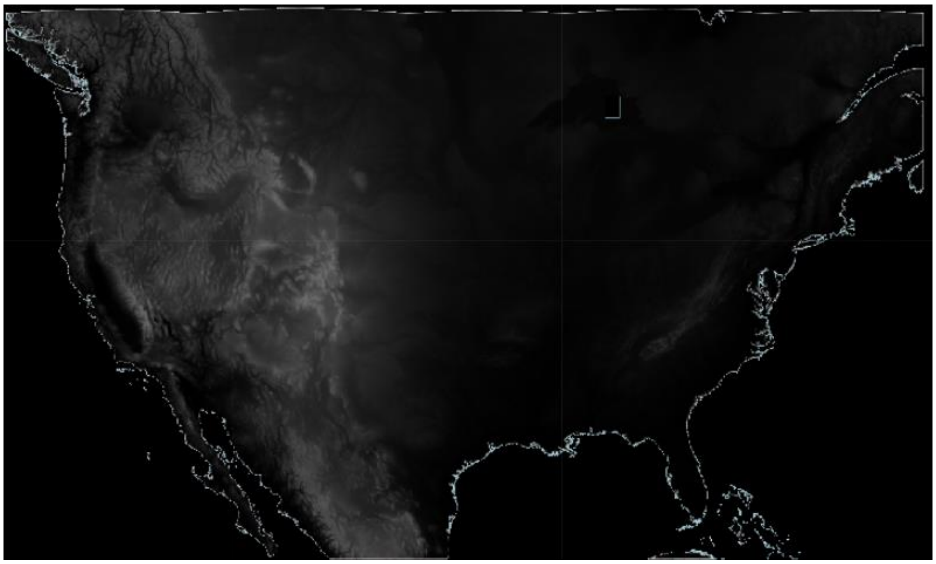

Figure 4. SRTM

Wildfire Hazard Potential (WHP). The Wildfire Hazard Potential dataset, obtained from the USDA Forest Service, was used as the label for model training. Figure 5 exhibits an example of imagery from the 2020 WHP dataset.

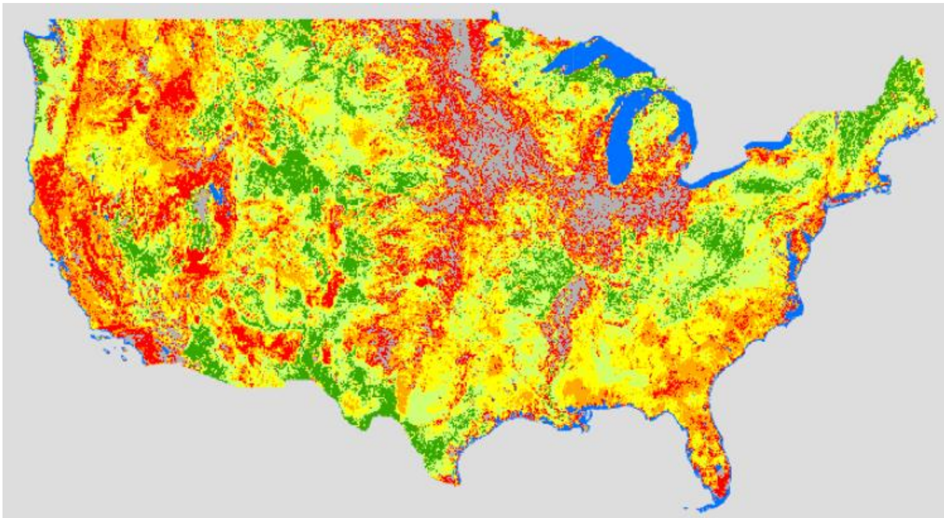

Figure 5. USDA 2020 Wildfire Hazard Potential

Data Preprocessing

Data preprocessing involved multiple steps to ensure compatibility with the machine learning model.

Image Normalization

For the Sentinel-2 and other geospatial datasets for analysis, we normalized the images to lie between 0 and 1. The normalization process involves subtracting the minimum value of each band and dividing it by the range of the band values. This process helps reduce skewness and improves the model's ability to learn from the data.

Cloud Masking

Images from the Sentinel-2 dataset were subjected to cloud masking to remove cloud-covered areas that could obscure underlying features relevant to wildfire risk prediction.

Calculation of Indices

From the Sentinel-2 images, we calculated three different indices: the Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), and Normalized Difference Water Index (NDWI). These indices were chosen due to their relevance in assessing vegetation health, burn severity, and water content, respectively, which are all factors that can influence wildfire risk.

Reprojection and Resampling

The data were reprojected and resampled to ensure all images shared the exact Coordinate Reference System (CRS) and had the same pixel resolution.

Machine Learning Model

The machine learning model employed in this study is the U-Net, a convolutional neural network (CNN) initially designed for biomedical image segmentation. U-Net's architecture makes it suitable for predicting wildfire risk levels from geospatial datasets.

Model Preparation

The U-Net model was prepared using the ResNet152 backbone. The backbone was chosen due to its robust feature extraction capabilities, making it suitable for high-dimensional input data such as the one used in this study. The

ResNet152 weights were not preloaded, allowing the model to learn unique patterns in the wildfire datasets from scratch. We compiled the model using an optimizer and the Binary Cross-Entropy Dice Loss as the loss function. We chose this specific loss function due to its ability to manage class imbalance, a common issue in image segmentation tasks. The model was set up to output a softmax activation function, mapping the outputs to a probability distribution over the predicted output class.

Data Split

For model training and evaluation, the collected data, making up 3500 samples, was split into three subsets: training, validation, and testing.

The data was divided as follows:

- Training set: 80% of the total data (2800 samples)
- Validation set: 10% of the total data (350 samples)
- Testing set: 10% of the total data (350 samples)

The distribution of data across these subsets is displayed in Table 1.

Table 1. Distribution of Data across Training, Validation, and Testing Subsets

Dataset	Number of Samples	Percentages
Training	2800	80%
Validation	350	10%
Testing	350	10%

Model Selection and Justification

This study utilized the U-Net machine learning model, a convolutional neural network (CNN) initially developed for biomedical image segmentation. The U-Net's unique architecture features a symmetric, expansive path that assists in accurately localizing and classifying pixels, making it an ideal choice for image segmentation tasks.

The architecture consists of two main components: a contracting (downsampling) path and an expansive (upsampling) path. The downsampling path captures the scene's context, while the upsampling path helps to localize and combine features from the downsampling path. This feature enables the U-Net to handle various image analysis tasks without additional manual feature engineering.

Using the U-Net model on geospatial datasets for wildfire risk prediction is especially advantageous due to its ability to manage variability in the data. Wildfire-affected areas vary significantly in size and shape and may not always adhere to predictable patterns. The U-Net's architecture effectively allows it to learn these variations and nuances from the data.

Moreover, because of the U-Net efficiency with data augmentation techniques, U-Net can operate well utilizing smaller datasets. This feature is handy in our study, where labeled wildfire data may be limited.

In conclusion, the U-Net's architecture and ability to manage high-dimensional data make it an apt choice for predicting wildfire risk levels from geospatial datasets. Figure 6 shows an example of a U-Net model diagram, highlighting the correspondence between the layers of the expansive and contracting path.

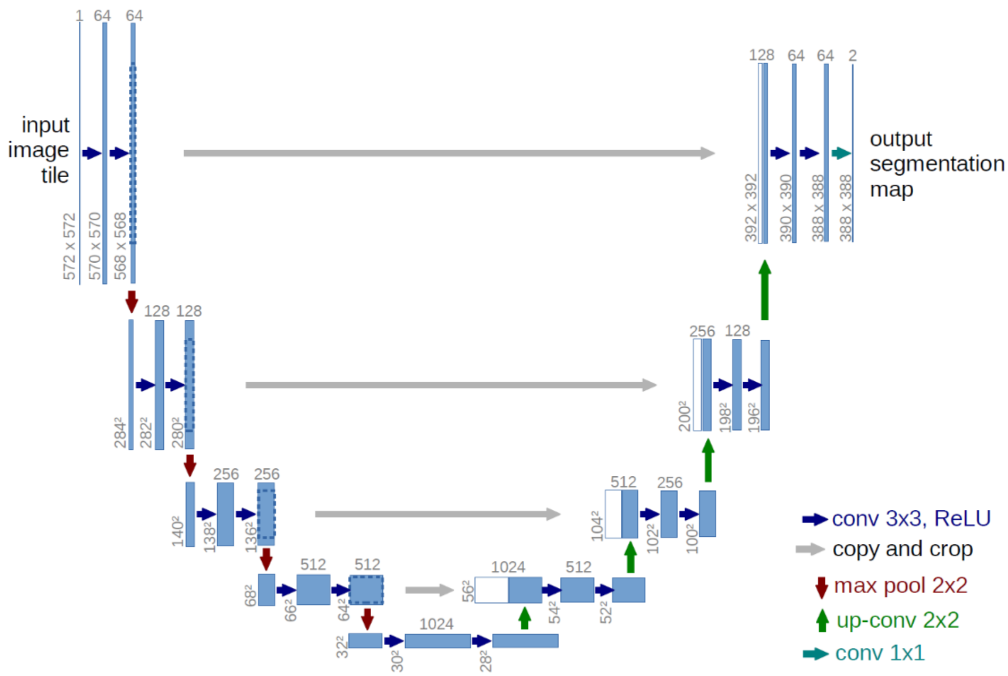

Figure 6. U-Net architecture [7]

Model Training

The model was trained with input data in 128 over 933 epochs batches. To assess the model's effectiveness, we measured its intersection over union (IoU) score and Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The IoU score shows how well the model predicts the segmentation compared to the actual image, while the AUC-ROC indicates the model's ability to differentiate between different classes.

Throughout the training process, the model state was exclusively saved when there was a noticeable improvement in the validation loss. This technique, referred to as model checkpointing, guarantees that the optimal model state is maintained, even if the model's performance declines in subsequent epochs.

Model Evaluation

We used the test dataset not utilized during the training phase to assess the model's performance. The crucial metrics to evaluate the model's performance were the Intersection over Union (IoU) score and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Evaluation Metrics. The Intersection over Union (IoU) or Jaccard Index is a widely used metric to evaluate image segmentation tasks. It measures the overlap between the predicted and actual output by calculating the ratio of the size of their intersection to the size of their union. This ratio can be mathematically represented as IoU = (Area of Overlap) / (Area of Union).

The IoU score is precious in this scenario since it measures the degree of overlap between the anticipated and real-world wildfire-prone areas. A higher IoU score indicates better performance, with a score of 1 indicating complete overlap.

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) is a way to measure how well a model can classify different groups based on varying thresholds. The ROC is a curve representing probabilities, and the AUC indicates how well the model can distinguish between these probabilities. The higher the AUC, the better the model is at identifying areas at risk for wildfires compared to those not.

We chose AUC-ROC as the metric because it is resistant to imbalanced datasets. In our situation, the number of pixels depicting non-fire regions is generally much more significant than those representing fire areas, making AUC-ROC an appropriate performance indicator.

When we use both IoU and AUC-ROC together, we can assess the model's effectiveness in binary classification (using AUC-ROC) and its ability to accurately predict the exact regions where wildfires may occur (using IoU).

The metrics' outcomes measure the model's accuracy in predicting wildfire risk levels in a quantifiable way.

CHAPTER FOUR

RESULTS / FINDINGS

In this chapter, we will discuss the outcomes of applying the U-Net model to predict the risk of wildfires. We use the Intersection over Union (IoU) and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) metrics to evaluate the model's performance. Additionally, we visually inspect the model's predictions to ensure that it accurately predicts high-risk wildfire areas.

Performance Metrics

Table 2 displays the model's average precision, recall, and F1 score of 0.91. These metrics are computed for classes 1 to 7, indicating that the model successfully distinguished between these classes.

Table 2. Metrics Score

Precision	Recall	F1 Score
0.91	0.91	0.91

After analyzing the comprehensive metrics for each wildfire risk class in Table 3, we can evaluate the model's performance for each category.

Table 3. Detailed Metrics of the Wildfire Prediction Model by Class

Class	Precision	Recall	F1-Score
1. Very Low	0.91	0.90	0.90
2. Low	0.90	0.88	0.89
3. Moderate	0.86	0.90	0.88

4. High	0.90	0.89	0.90
5. Very High	0.92	0.93	0.92
6. non-burnable	0.92	0.92	0.92
7. Water	0.98	0.98	0.98
Accuracy			0.91
Macro avg	0.91	0.91	0.91
Weighted Avg	0.91	0.91	0.91

According to the results, the model could accurately predict the risk of wildfires for 91% of the cases in the test dataset. Table 4 shows the accuracy scores for each category, indicating the percentage of correctly classified cases.

Table 4. Accuracy for Each Class in the Wildfire Prediction Model

Class	Accuracy	Instances Correctly Classified
1. Very Low	90.31%	1055855 / 1169085
2. Low	88.05%	769939 / 874450
3. Moderate	90.46%	729663 / 806613
4. High	88.86%	632677 / 712019
5. Very High	92.83%	570875 / 614941
6. non-burnable	91.54%	834903 / 912064
7. Water	97.52%	629220 / 645228

AUC-ROC Score

The Area Under the Receiver Operating Characteristic Curve (AUC-ROC) score was 0.972. The model effectively differentiates between classes based on the high score, even when the dataset is not evenly balanced.

Average Intersection Over Union (IoU)

The average IoU score was 0.867. This score calculates the degree of overlap between the regions with predicted wildfire risks and those historically impacted by wildfire. Thus, a score of 1 indicates a substantial overlap, suggesting that the model effectively predicted the spatial distribution of wildfire risk.

Confusion Matrix

From the confusion matrix, it is evident that our model is generally accurate in predicting classes. However, there are instances where the model may not make the most precise prediction. These instances include the Very Low, Low, Moderate, and High classes. For a visual representation of our model's performance, please refer to Figure 7.

Figure 7. Raw Confusion Matrix of the Wildfire Risk Prediction Model

Normalized Confusion Matrix

Let’s consider the normalized confusion matrix in Figure 7 to identify better how well our model performs in different classes.

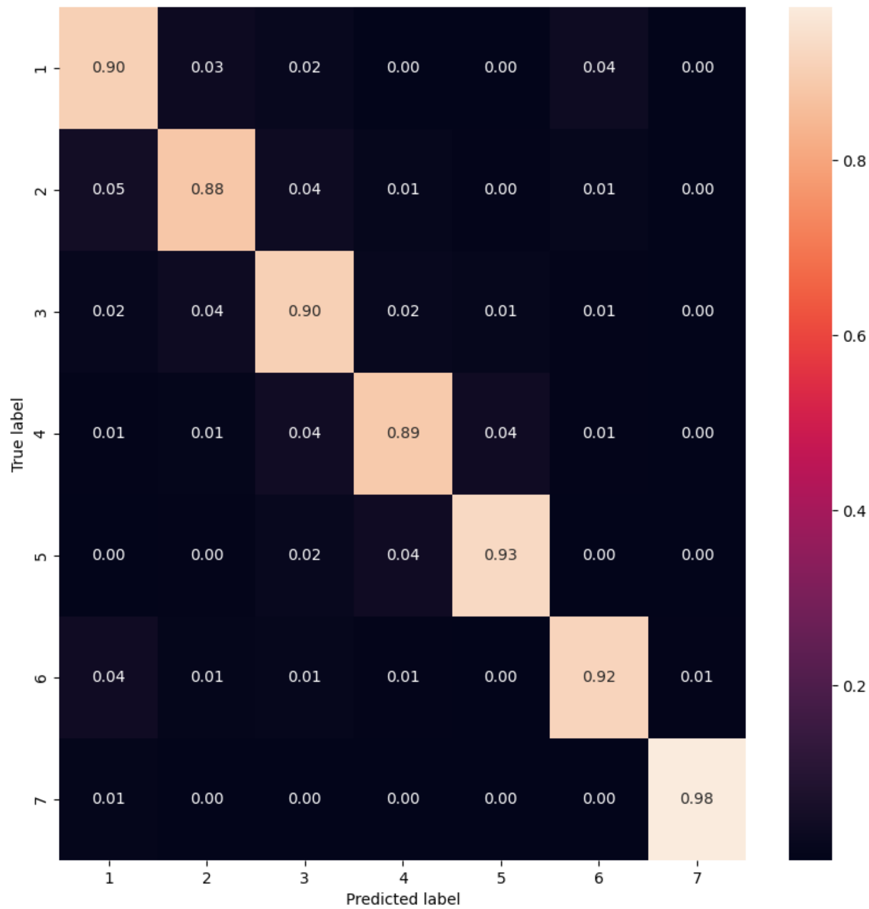

Figure 8. Normalized Confusion Matrix of the Wildfire Risk Prediction Model

Based on the normalized confusion matrix, the model has a high level of accuracy in predicting most classes. For instance, it accurately predicted 88.04% of the Low cases and 90.46% of the Moderate ones. However, there were some misclassifications between classes, indicating that some classes are more likely to be incorrectly classified than others.

Classification Color Coding

To correctly interpret the wildfire risk prediction images, it is essential to comprehend the classification system being employed. The predictions are divided into eight categories: Very Low, Low, Moderate, High, Very High, Non-burnable, and Water. Each class is assigned a specific color code to simplify visual differentiation. Table 5 displays the classification system alongside its corresponding color codes.

Table 5. Classification for Each Label in the Wildfire Prediction Model

Class	Color code	
Very Low	38A800	
Low	D1FF73	
Moderate	FFFF00	
High	FFAA00	
Very High	FF0000	
Non-burnable	B2B2B2	
Water	0070FF	

Table 5 provides a color-coded system for comprehending wildfire risk forecasts. It offers both qualitative and quantitative insights into the model's accuracy.

Visual Inspection of State-level Wildfire Risk Predictions

We utilized a unique approach to evaluate the model's ability to predict the risk of wildfires at a state level. The method involved extracting 256x256 patches from the 2020 geospatial data for California and Nevada. We then compiled these data to create a complete wildfire risk prediction for each state. This technique made it possible to examine the wildfire risk throughout the entire state closely. As a result, it provided a detailed view of how risk levels differ across various regions.

We compared the model's predictions with the 2020 Wildfire Hazard Potential (WHP) ground truth data, which benchmarked the model's predictive accuracy.

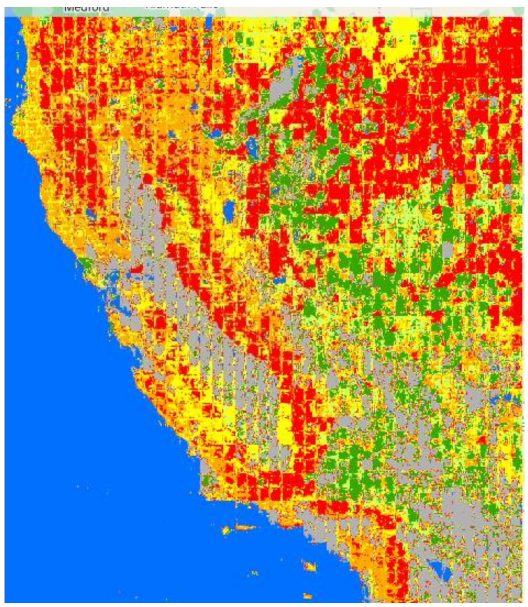

Figure 9. 2020 Assembled Wildfire Risk Prediction for California and Nevada

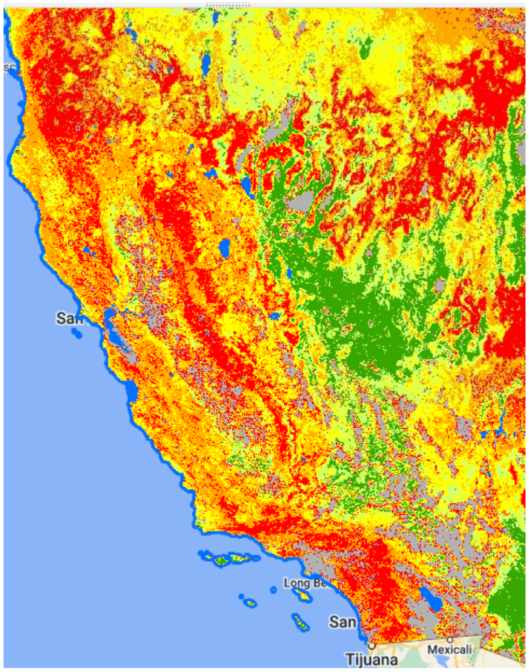

Figure 10. 2020 WHP for California and Nevada

Analysis: The model's state-level predictions for California and Nevada strongly align with the 2020 WHP ground truth data. The correlation demonstrates that the model can predict wildfire risk accurately at a detailed and broader level. This correlation also suggests that the patch assembly approach is practical.

In Central California, the model classified a larger area as 'Non-burnable' (Class 6) compared to the ground truth data. This discrepancy could be attributed to specific features in the 2020 geospatial data, which led the model to identify these regions as non-burnable.

Additionally, a few regions displayed a one-class deviation in the predicted risk level compared to the 2020 WHP ground truth. Such discrepancies might arise from different interpretations of the 2020 data or contrasting model structures. While our model is trained with a distinct set of data compared to the 2020 WHP ground truth, these discrepancies may occur due to variations in methodology and variable weighting, leading to slight divergences in predicted wildfire risk. These variances underline the complex nature of wildfire risk prediction and highlight the importance of continual model refinement for improved precision.

In addition, incorporating geospatial data brings another level of intricacy. Geospatial data captures the dynamic nature of environmental and human factors, which may cause variations between our model's forecasts and the actual 2020 WHP ground truth. This emphasizes the importance of having models that can learn from current data, adjust to changes in these factors, and precisely anticipate the risk of wildfires in an ever-evolving setting.

In conclusion, although there are some differences, the predictions made by the model closely match the 2020 WHP ground truth data. This correlation indicates that the model can potentially be a valuable tool for predicting wildfire risk on a large scale. The slight variations also highlight the importance of continuously refining the model and integrating the latest geospatial data to ensure accurate predictions of wildfire risk.

Looking Ahead: Incorporating 2022 Data into Future Analysis

We utilized the model to produce wildfire risk forecasts for the 2022 and 2020 data. However, since no WHP ground truth was available for 2022, a direct comparison could not be made. Nevertheless, the 2022 predictions serve as a valuable data point for future model performance evaluation.

Upon the availability of the 2022 WHP ground truth data, these predictions can be contrasted to assess the model's predictive accuracy in a different temporal context. This will further confirm the model's capabilities and highlight areas of refinement, particularly concerning evolving environmental changes that can impact wildfire risk.

As such, the 2022 predictions pave the way for continuous model improvements. They exemplify the model's adaptability in handling new data and underscore its potential for forecasting future wildfire risks based on recent geospatial data. By integrating the most up-to-date data into the model, we aim to maintain and improve its accuracy in predicting wildfire risk.

Figure 11 below displays our model's assembled wildfire risk prediction for California and Nevada in 2022. Even without the 2022 WHP ground truth data for a direct comparison, this prediction offers a visual insight into the model's ability to manage and interpret recent data and its adaptability to changes over time.

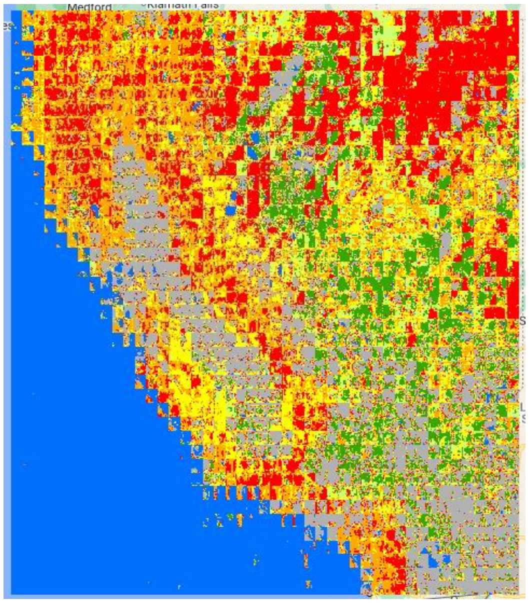

Figure 11. 2022 Assembled Wildfire Risk Prediction for California and Nevada

CHAPTER FIVE

CONCLUSION

This research aimed to predict wildfires using a U-Net deep learning model and geospatial data. The results showed high performance with an F1 score of 0.91, proving that deep learning models are practical tools for this task.

The potential ramifications of this study are substantial. Given the increasing frequency and severity of wildfires, likely exacerbated by climate change, reliable prediction models like the one developed in this study can be integral to planning and mitigation strategies. They can offer valuable insights for decision-makers to develop effective forest management plans, distribute resources wisely, and enact proper public safety measures, thereby minimizing the damaging impacts of wildfires.

Future research on wildfire prediction could explore various avenues to improve models' accuracy and reliability. One possibility is using different deep learning architectures, which better capture the complex relationships between distinct factors contributing to wildfire risk. Another option is incorporating other data types, such as weather patterns or more granular land use data. These modifications could give the model a complete picture of the wildfire risk landscape, leading to more accurate predictions.

In addition to improving the accuracy of models, it is also essential to ensure that they are scalable and can be used in real-world scenarios. This improvement means addressing any identified shortcomings in the models, such as their ability to manage large datasets or their performance in different geographic areas. It is also vital to ensure that models are updated regularly with new data to keep pace with changing wildfire risk conditions.

Despite the challenges, this research has successfully proved the application of a deep learning model for predicting wildfire risk, contributing to a vital area of study with extensive real-world implications. The research is a promising step towards improving prediction models and, by extension, contributing to more effective wildfire management strategies. The continued refinement and advancement in this field have the potential to lead to fewer wildfire incidents and a safer environment.

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