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Integrating Remote Sensing and U-Nets for Wildfire Detection

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Dedication

"To all the people I know in my life, who have helped me and been there for me."

Sabrina BOUMAIZA

"To my parents, whose sacrifices and prayers have been my foundation throughout my studies. To my lovely sisters for their encouragement and moral support. To my partner, Sabrina, who always believed in me and ensured the success of this work. To all those around me who have never ceased to support me."

Nour El Houda BRAHIMI

Acknowledgement

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Sabrina BOUMAIZA
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Abstract

Wildfires pose a significant threat to ecosystems and communities worldwide. Early and accurate detection is crucial for effective response and mitigation strategies, making monitoring systems essential for tracking and managing these disasters. Our proposed system utilizes satellites as a remote sensing source to monitor the Earth for real-time wildfire detection. We explore the effectiveness of the U-Net deep learning architecture using three different fire masks—Intersection Masks, Voting Masks, and Murphy Masks—on Landsat-8 satellite data. This allows alerting the relevant emergency services and facilitating a rapid response. Additionally, we conducted a comparative study evaluating the performance of U-Net against other commonly used techniques: image classification (InceptionV3), object detection (YOLOv3-tiny), and image segmentation (Fire-Net). The results demonstrate that U-Net is highly effective in wildfire detection, achieving significant performance metrics.

Keywords: Wildfires, Image Segmentation, U-Net, Early Detection, Remote Sensing, Satellite Imagery.

Résumé

Les incendies de forêt représentent une menace significative pour les écosystèmes et les communautés du monde entier. La détection précoce et précise est cruciale pour une réponse et des stratégies de mitigation efficaces, rendant les systèmes de surveillance essentiels pour suivre et gérer ces catastrophes. Notre système proposé utilise des satellites comme source de télédétection pour surveiller la Terre et détecter les incendies de forêt en temps réel. Nous explorons l'efficacité de l'architecture d'apprentissage profond U-Net en utilisant trois masques de feu différents—masques d'intersection, masques de vote et masques de Murphy—sur les données satellites de Landsat-8. Cela permet d'alerter les services d'urgence concernés et de faciliter une réponse rapide. De plus, nous avons mené une étude comparative évaluant la performance de U-Net par rapport à d'autres techniques couramment utilisées : la classification d'images (InceptionV3), la détection d'objets (YOLOv3-tiny), et la segmentation d'images (Fire-Net). Les résultats démontrent que U-Net est très efficace pour la détection des incendies de forêt, atteignant des métriques de performance significatives.

Mots Clée: Incendies, Segmentation d'Images, U-Net, Détection Précoce, Télédétection, Imagerie Satellitaire.

ملخص

تشكل حرائق الغابات تهديدا كبيرا للنظم البيئية والمجتمعات في جميع أنحاء العالم. إن الكشف المبكر والدقيق أمر حيوي للاستجابة الفعالة واستراتيجيات التخفيف، مما يجعل أنظمة المراقبة ضرورية لتتبع وإدارة هذه الكوارث. يستخدم نظامنا المقترح الأقمار الصناعية كمصدر للاستشعار عن بعد لمراقبة الأرض واكتشاف حرائق الغابات في الوقت الفعلي. نستكشف فعالية بنية التعلم العميق شبكة الU-Net باستخدام ثلاثة أقنعة حرائق مختلفة—أقنعة التقاطع، أقنعة التصويت، وأقنعة مورفي—على بيانات الأقمار الصناعية لاندسات-8. يتيح ذلك تنبيه خدمات الطوارئ المعنية وتسهيل استجابة سريعة. بالإضافة إلى ذلك، أجرينا دراسة مقارنة لتقييم أداء شبكة الU-Net مقارنة بالتقنيات الأخرى المستخدمة بشكل شائع: تصنيف الصور (InceptionV3)، واكتشاف الأجسام (YOLOv3-tiny)، وتجزئة الصور (Fire-Net). تظهر النتائج أن شبكة الU-Net فعالة للغاية في الكشف عن حرائق الغابات، محققة مقاييس أداء جيدة.

الكلمات المفتاحية :حرائق الغابات، تجزئة الصور، شبكة الU-Net، الكشف المبكر، الاستشعار عن بعد، صور الأقمار الصناعية.

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List of Acronyms

- **AI** : Artificial Intelligence
- **ANN** : Artificial Neural Network
- **CNN** : Convolutional Neural Network
- **CUDA** : Compute Unified Device Architecture
- **DL** : Deep Learning
- **GPU** : Graphic Processor Unit
- **IoU** : Intersection over Union
- **IR** : Infra-Red
- **ML** : Machine Learning
- **MODIS** : Moderate Resolution Imaging Spectroradiometer
- **NASA** : National Aeronautics and Space Administration
- **ReLU** : Rectified Linear Unit
- **RGB** : Red Green Blue
- **TIFF** : Tag Image File Format
- **UAV** : Unmanned Aerial Vehicle
- **WSN** : Wireless Sensor Network
- **YOLO** : You Only Look Once

Introduction

Forests, as they are often referred to as "The Earth's lungs," keep our planet breathable by taking in carbon dioxide and releasing oxygen, providing the resources of life for both humans and wildlife. They supply homes for countless species and ensure biodiversity between the creatures. Exceeding their extraordinary ecological role, forests offer a wealth of other resources, such as timber, fuel, food, and even medicine, that humans benefit from in different ways. Sadly, this fortune is now in danger of being damaged by the consistent occurrence of wildfires due to global warming and human activities.

It is becoming a huge concern that wildfires are ruining our main resources of life and causing other disasters related to our environment, economy, and even the biodiversity on the planet by destroying and demolishing vast areas of wild lands. Their increasing number of disasters in recent years has even resulted in the loss of lives. Algeria witnessed in both 2021 and 2022 some of the worst wildfires in its history. Losing around 127 people and burning more than 25000 hectares [1]. In addition, the Australian bushfires of 2019 and 2020 burned 42 million hectares and killed 3 billion animals and 30 people [2]. Many statistics state that human activities are one of the main causes of wildfires, aside from natural causes such as climate change, which brings us to highlighting the crucial role of humans in wildfires and having some serious governmental regulations regarding that.

For this, urgent and serious action is required to prevent their devastating impact. Traditional methods, reliant on human surveillance or specialized sensors, may fall short due to limited coverage, reliability, and timeliness. This inadequacy emphasizes the need for more advanced solutions. Advanced remote sensing technologies, including satellites, drones, and surveillance cameras, coupled with deep learning techniques for data analysis, facilitate the automated detection of wildfires at an early stage, minimizing false alarms. Satellites like MODIS provide real-time data for fire detection systems like Firelight [3]. These systems use deep learning techniques like Convolutional Neural Networks to analyze the data and identify fires anywhere on Earth in real-time.

Usually, to achieve an accurate system when tackling wildfire detection using computer vision techniques, three main approaches emerge: classification, object detection, and segmentation. While classification and object detection identify fire, they lack the detail needed for informed management. In contrast, segmentation excels at classifying each image pixel, allowing us to differentiate burning zones, vegetation, smoke, and other land cover types. This fine-grained analysis is crucial for accurate fire perimeter estimation and resource allocation during firefighting, and this is why the chosen approach for this research is segmentation. In addition, while various remote sensing technologies exist for wildfire detection, this research leverages satellite imagery (specifically Landsat-8 satellite data) for its large-scale coverage, real-time data provision, and the ability to pierce through difficult weather conditions. Furthermore, the detection of wildfires is critical for effective mitigation and containment efforts. Thus, to identify the most effective approach for wildfire detection using satellite data, this research will conduct a comparative study evaluating the U-Net architecture's performance against other models of commonly used methods (classification and object detection), as it excels at segmentation tasks.

This thesis tackles the wildfire issue and solutions in three chapters. The first one is devoted to the literature review, where we delve into the dangers of wildfires and global warming, exploring statistics that illuminate their destructive impact, moving to exploring remote sensing for wildfire detection and discovering the different methods used in this concept, and finally having an overview of the implementation of Deep Learning for wildfire detection.

The second chapter unpacks the methodology followed to implement this solution effectively by giving an idea of the U-Net architecture we adopted in our study as well as the satellite data we worked on and key evaluation criteria used to measure its performance.

Lastly, the third chapter unveils the results of our study and discusses potential future directions for this research.

Chapter 1

Literature Review

1.1 Introduction

Wildfires play a crucial role in unbalancing our planet's ecosystem, often leaving lasting effects on forests for years before regeneration occurs. Researchers emphasize the need to identify wildfire origins and develop strategies to reduce their impact. Regardless of the cause, the emphasis remains on finding solutions to manage these crises and limit their damage.

Cutting-edge technologies, mainly deep learning and remote sensing techniques, are an effective solution for swiftly and accurately detecting wildfires in real or near-real-time.

This chapter provides a broad interpretation of wildfire threats in Africa, including a representation of wildfire detection and different techniques used for remote sensing (satellites, drones, etc.), and related works in this area of study, aiming for a comprehensive understanding of the issue.

1.2 Wildfires and Global Warming

Most wildfires ignite from human activities such as arson, improperly burning debris, or simple negligence. But what fuels these initial fires and spreads them are persistent droughts and high global temperatures, as shown in Figure 1.1, highlighting a concerning correlation between fire frequency and climate variables.

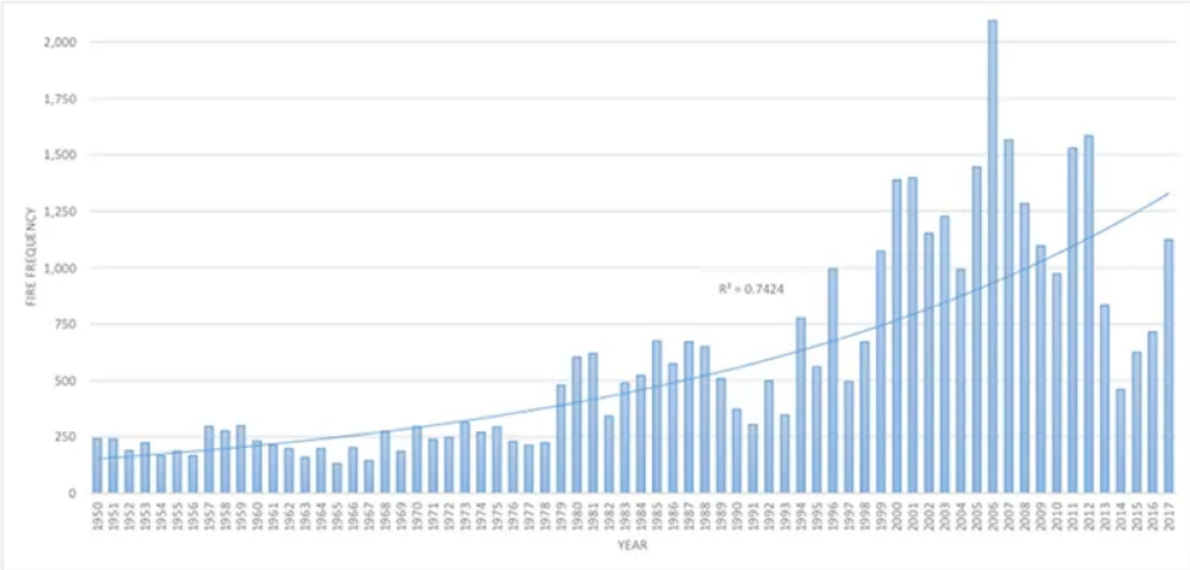


Figure 1.1: Fire frequency from 1950 to 2020 [4].

According to NASA's Goddard Institute for Space Studies (GISS), global temperatures have risen by at least 1.1°C since 1880, accelerating after 1975 at a rate of 0.15-0.20°C per decade. This suggests a direct correlation between increasing global temperatures and fire frequency [5], as depicted in Figure 1.2.

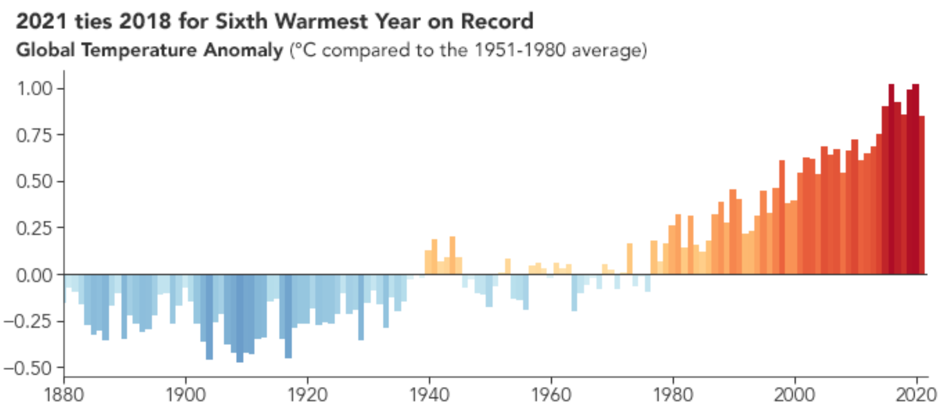


Figure 1.2: Global temperatures from 1880 to 2020 [5].

Global warming's impact on wildfires varies by region and understanding how different regions are affected is crucial for developing effective mitigation strategies. To explore these disparities, we'll take a closer look at wildfires in Africa and Algeria in the following subsections.

1.2.1 Wildfires in Africa

Africa boasts a quarter of the world's biodiversity and hosts the largest populations of large mammals. Its diverse biomes range from mangroves and deserts to rain-forests, temperate grasslands, and even ice-capped mountains [6] (Figure 1.3).

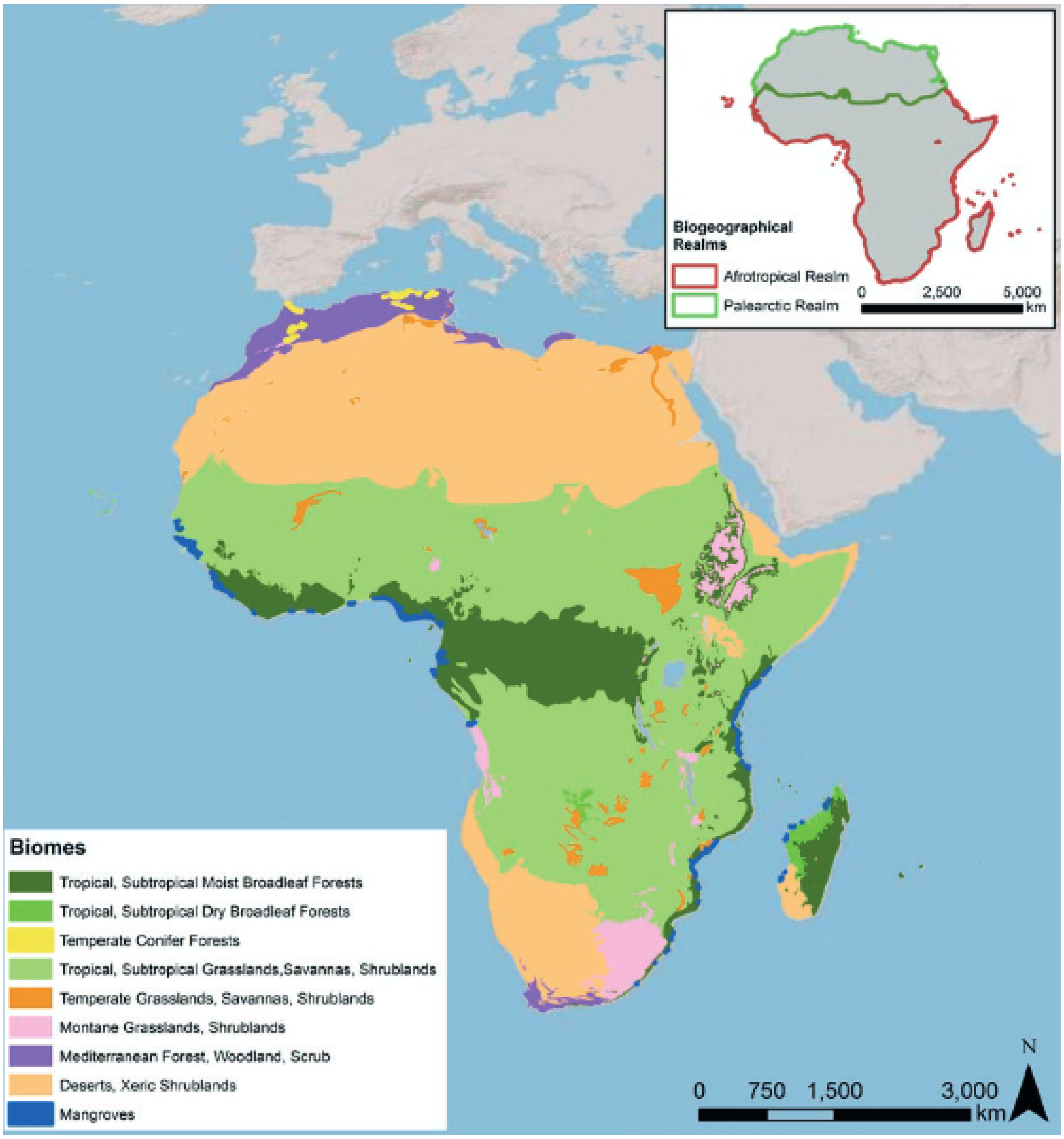


Figure 1.3: Distribution of main biomes and bio-geographical realms on land in the Africa region (map produced by UNEP-WCMC using data from Olson et al. 2001) [6].

Africa's incredible biodiversity is under threat from recurring wildfires. These are not new events, unfortunately. Places like Algeria's once-lush mountains in Tizi-Ouzou bear the scars of over 100 fires in recent times [7].

The damage is not limited to one country. South Africa also faces severe wildfires, such as those in the Garden Route in 2017. Knysna suffered greatly, with 7 deaths, over 1,000 buildings razed, and numerous evacuations due to a mix of dry winds and accumulated flammable debris [8].

1.2.2 Wildfires in Algeria

The Mediterranean forest, covering about 65 million hectares, is crucial but fragile, threatened by climate change and human activities [9]. Algeria's forests, totaling 4 million hectares, consist mainly of bush and shrubland, with forest rates of 11% in the north and 1.7% overall, as shown in Figure 1.4, highlighting the scarcity of forest cover [9].

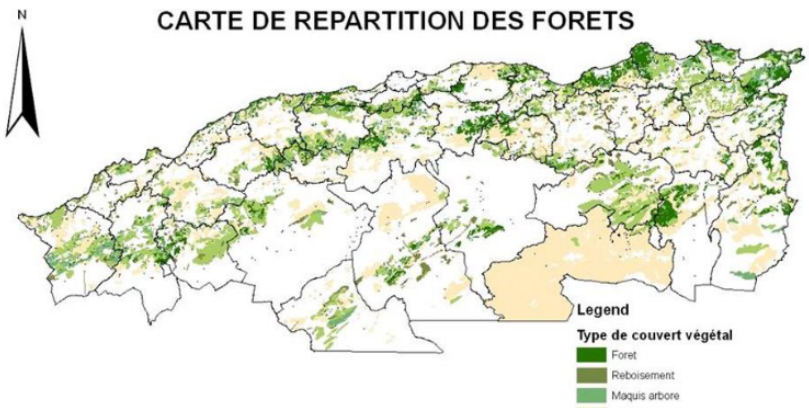


Figure 1.4: Forests distribution in Algeria [10].

Unfortunately, wildfires are the biggest threat to these forests, causing around 90% of the degradation. On average, 45,000 to 50,000 hectares of forest are lost annually. Data from 1985 to 2010 reveals a concerning trend in northern Algeria (Figure 1.5) with over 42,000 fires burning 910,640 hectares of land. The number of fires has been increasing yearly [9, 11].

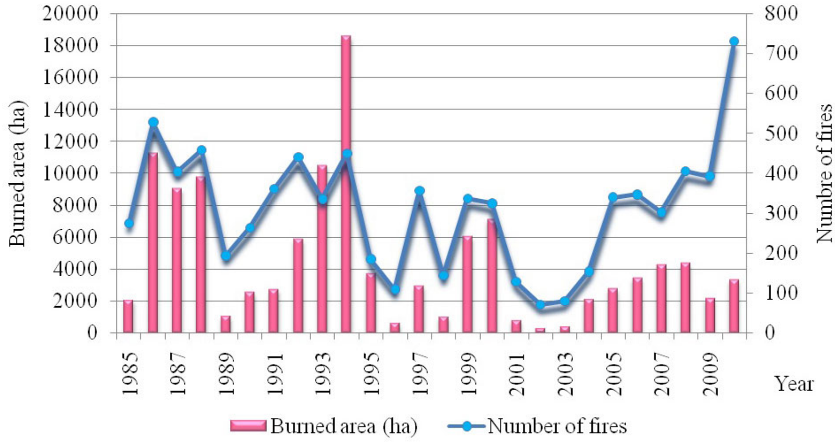
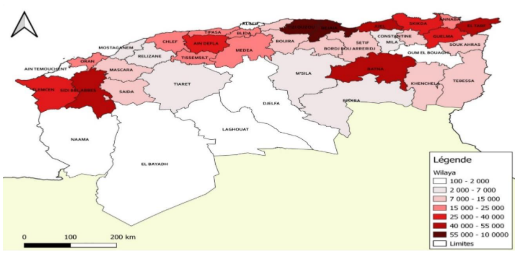


Figure 1.5: Fire Activity and Burned Area in Algeria (1985-2010) [11].

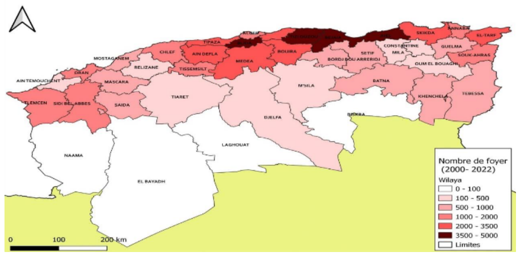
- **Wildfires statistics in Algeria**

  Looking geographically (Figure 1.6a), Tizi-Ouzou and Bejaia have borne the brunt of wildfires, with 55,000 to 100,000 hectares burned over the past two decades. El Tarf, Batna, and Sidi Bel-Abbes follow closely behind, with 40,000 to 55,000 hectares affected.

  In terms of fire frequency (Figure 1.6b), Tizi-Ouzou, Bejaia, Jijel, and Blida have witnessed the highest number of outbreaks, each with 3,500 to 5,000 fires and still face significant damage due to their forest-rich environments.



(a) Map of total burned areas (2000-2022).

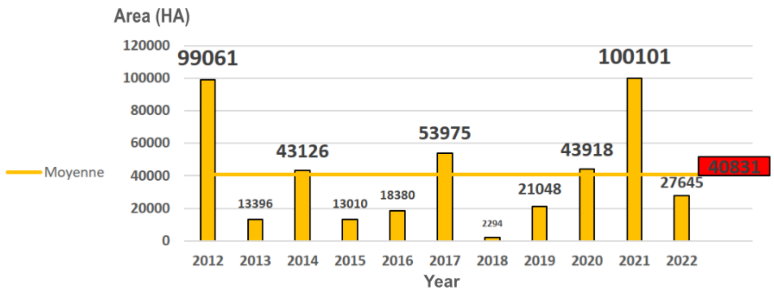


(b) Map of total wildfire disruptions.

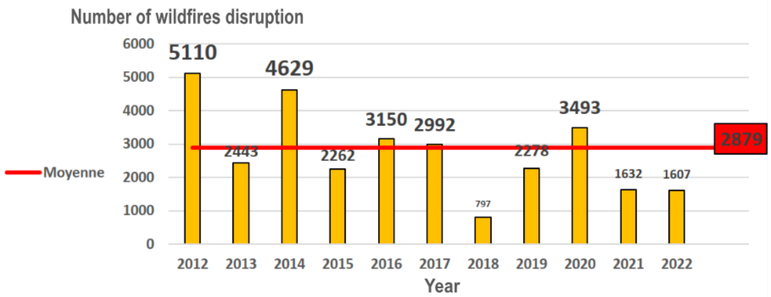
Figure 1.6: Wildfires comparative study between the Algerian Wilayas [12].

While the total burned area in 2022 (Figure 1.7a) was below the decade's average of 40,831 ha, 2021 witnessed the most severe fire damage, with 100,101 ha burned, followed closely by 2012 at 99,061 ha. This is more than double the average annual burned area over the past decade.

The number of fires follows a similar pattern (Figure 1.7b). On average, there have been 2,879 fires annually, with peaks in 2012 and 2014 at 5,110 and 4,629 fires, respectively.



(a) Burned areas.



(b) Number of wildfires disruptions.

Figure 1.7: Wildfires comparative study in Algeria over the last decade [12].

The fluctuating trends in wildfire frequency and intensity over time in Algeria underscore the importance of employing advanced detection methods like remote sensing for accurate wildfire detection and monitoring, as explored in the subsequent section of this chapter.

1.3 Remote Sensing for Wildfires Detection

Remote sensing encompasses the acquisition of information about Earth's surface features without direct physical contact [13]. This technology utilizes various platforms, such as satellites, surveillance cameras, and drones, to capture data across the electromagnetic spectrum, which includes visible light, infrared, and microwave wavelengths, offering valuable insights beyond the limitations of human vision.

Figure 1.8 illustrates the remote sensing pipeline and process using satellites, wherein the study of reflected and emitted radiation from Earth's surface and atmosphere helps monitor and analyze environmental changes, including the crucial aspect of detecting wildfires using deep learning algorithms to take the necessary measures, which we are going to conduct in the next sections of this chapter.

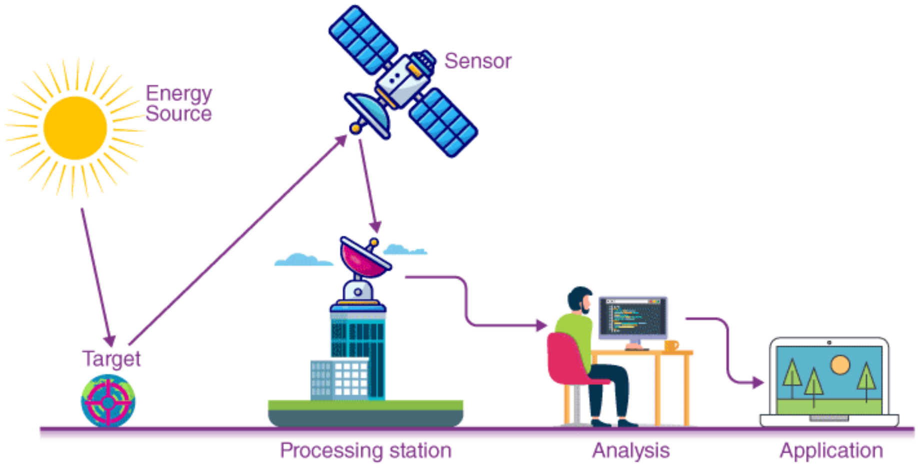


Figure 1.8: Remote Sensing pipeline [14].

Remote sensing data collection methods are divided into two primary types, active and passive. The difference between these two types lies in how they gather data and the type of energy they use.

1.3.1 Active Remote Sensing

Active remote sensing systems function by emitting their own energy source to illuminate a target and subsequently measure the reflected energy as depicted in Figure 1.9. For example:

- **RADAR (Radio Detection and Ranging)**
  This technology emits radio waves and detects their return to determine an object's position, speed, and direction. It is utilized in weather forecasting, aviation for obstacle avoidance, and by law enforcement for speed detection [15].

- **LiDAR (Light Detection and Ranging)**
  This system utilizes laser light pulses to generate 3D images and to measure distances. It is employed in tasks such as crafting precise maps, land surveys for construction, and enabling autonomous vehicle navigation [16].

1.3.2 Passive Remote Sensing

Contrary to active remote sensors, passive remote sensing involves observing natural radiation emitted or reflected by the Earth without actively emitting any signals, as depicted in Figure 1.9. This natural radiation, originating from the sun, covers various wavelengths including visible light, infrared, and radio waves. For example:

- **Radiometer**
  An instrument that measures the intensity of electromagnetic radiation across different spectrum bands, like visible light, infrared, ultraviolet, or microwaves. It is widely employed in tasks such as remote sensing, weather forecasting, and studying Earths atmosphere [17].

- **Sounder**
  A device that analyzes vertical atmospheric conditions by measuring temperature, pressure, and composition using multi-spectral data. It is vital in meteorology, environmental monitoring, weather forecasting, climate research, and air quality studies [17].

There are remote sensing sources like satellites that can play role in both active and passive remote sensing (Figure 1.9) depending on their main use they are built for.

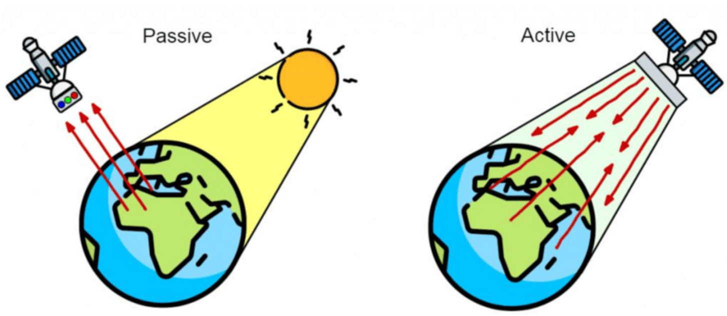


Figure 1.9: Passive and Active Remote Sensing [18].

These types of remote sensing methods are all implemented in different remote sensing technologies that are responsible for the data collection, like surveillance cameras, drones, and satellites.

1.3.3 Wildfires Detection Technologies

Detection technologies for wildfires are essential components of early warning systems, crucial for spotting and lessening the damaging effects of these events. They range from traditional methods to advanced cutting-edge systems.

A. Surveillance Cameras

Surveillance cameras, including optical and thermal (infrared - or IR) varieties, which can play passive or active remote sensing role, are commonly used in forests for early fire detection. Optical cameras capture visible light, offering detailed, high-resolution colored images, as shown in Figures 1.10a and 1.10b, while thermal cameras detect thermal radiation emitted by objects in the scene as shown in Figures 1.11a and 1.11b.

They are strategically positioned for comprehensive coverage and employ various aspects of flame and smoke detection. However, they have limitations such as vulnerability to obstructions, weather conditions, and high costs, especially in remote areas.

(a) An optical camera [19]. **(b)** A wildfire captured by an optical camera [20].

Figure 1.10: Images taken by optical cameras.

(a) An IR camera [21]. **(b)** Thermal image of a forest fire at night [22].

Figure 1.11: Images taken by IR cameras.

B. Wireless Sensor Networks (WSN)

These networks consist of independent sensor nodes spread across an area, as illustrated in Figure 1.12, each equipped with sensors to detect environmental parameters like temperature, pressure, and chemical levels. These nodes collect data continuously, communicate wirelessly, and send it to a central base station (BS) [23].

WSNs are a cost-effective and scalable solution for forest fire detection, offering real-time data from high-risk areas to enable swift response. Their modular design facilitates straightforward network expansion as required.

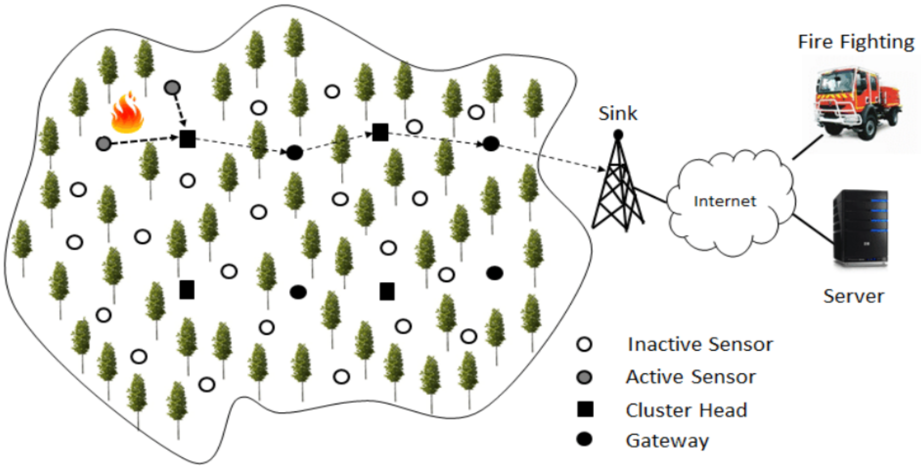


Figure 1.12: WSN illustration in forest fire detection systems [24].

C. Aerial Photography

Aerial photography, conducted from aircraft, drones, helicopters, or balloons equipped with cameras that conduct passive remote sensing, is essential for wildfire detection. It provides high-resolution images covering large areas efficiently, providing a bird's-eye view for better situational awareness, as depicted in Figure 1.13a, and aiding in pinpointing fire locations, intensity and direction. It also assists in initial response efforts and post-fire activities such as mapping burned areas, assessing damage, and planning recovery efforts, as shown in Figure 1.13b.

(a) Aerial View of a Wildfire [25].

(b) Aerial View of Post-fire Devastation [?].

Figure 1.13: Aerial Photography.

D. Satellite Imagery

Satellites have emerged as a vital tool for near-real-time wildfire detection, monitoring, and mapping using advanced sensors that capture data across various spectral bands to identify thermal anomalies and smoke plumes.

Their comprehensive coverage shown in Figure 1.14 facilitates the identification of potential fire hazards and offers essential data on fire location, size, intensity, and behavior, aiding firefighting and forest management. However, there is a trade-off between image resolution and coverage: **higher resolution offers detailed analysis but covers smaller areas, while lower resolution covers larger expanses but sacrifices precision.**

Figure 1.14: Satellite image of a wildfire [26].

- **The Role of Satellite Imagery in Wildfire Monitoring**

  Satellite imagery plays a crucial role in forest fire detection and monitoring across three key stages:

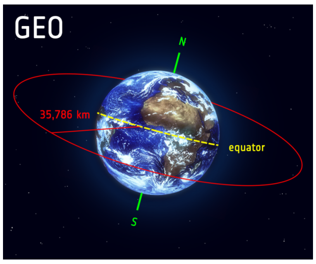
  1. **Pre-fire Stage**
     Satellite imagery enables early detection and monitoring of fire-prone areas by analyzing vegetation conditions like temperature and moisture stress [27].
  2. **Active Fire Stage**
     Thermal sensors on satellites detect active fires by capturing infrared radiation, allowing for the determination of the approximate location of wildfires as well as their movements and progression.
  3. **Post-fire Stage**
     After a fire, satellite imagery provides precise assessments of burn severity, vegetation loss, and soil damage. It aids in monitoring forest recovery, tracking regrowth, erosion, and ecosystem resilience.

Satellites help with large-scale coverage of the Earth's surface, real-time data provision, and the ability to pierce through difficult weather conditions, which will play a key role in monitoring forests and detecting fire at the three stages. This is the main motivation behind choosing satellite imagery for wildfire detection in this research.

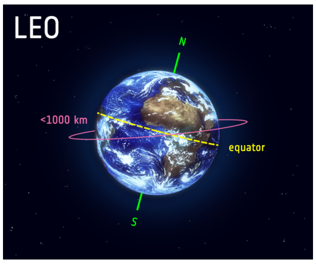
- **Satellite Systems Categories**

  Based on their orbit, satellite systems used for wildfire detection can be divided into three main categories:

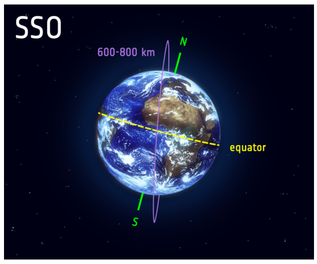
  1. **Geo-stationary orbit (GEO)**
     These satellites orbit Earth at high altitude (36,000 km) [28] (Figure 1.15a), and over a period of 24-hours, identical to the Earths rotation period, this provides continuous weather monitoring of a specific Earth region by matching Earth's rotation and remaining fixed overhead. This offers crucial wind data for wildfire assessment [28, 29]. However, they may have low spatial resolution and long revisit times.
  2. **Low-earth orbit (LEO)**
     Centered on the Earth and not exceeding 1,000 kilometers in altitude (Figure 1.15b), LEO orbits are approximately equivalent to one-third of Earths radius and have an orbital period of less than one day. These orbits, such as SpaceXs Swarm [30], are well-suited for remote sensing missions due to their close proximity to the Earths surface. They offer high-resolution imagery and faster data transmission but their lower altitude results in shorter lifespans [31].
  3. **Polar sun-synchronous orbit (SSO)**
     Satellites in SSO are synchronized with the path of the sun and maintain a steady altitude of 200 to 1000 kilometers [28] (Figure 1.15c), allowing continuous daily coverage of a specific area at the same time. These satellites, such as AVHRR (Advanced Very-High-Resolution Radiometer), provide detailed views of wildfires globally, assisting firefighting strategies with precise information on size, location, and intensity [32].



(a) Geo-stationary orbit (GEO).



(b) Low-earth orbit (LEO).



(c) Polar sun-synchronous orbit (SSO).

Figure 1.15: Satellite System Categories [28].

- **Types of Satellite Image Representations**
  Satellite images for wildfire detection are commonly represented in digital formats, offering valuable insights into the Earth's surface that can be processed and analyzed by computer algorithms. The most common representations include:

  1. **Multi-spectral Imagery**
     Images captured across multiple spectral bands, typically in the visible and infrared regions of the electromagnetic spectrum, reveal details on urban areas, vegetation health, land cover, and fire characteristics.
  2. **Hyper-spectral Imagery**
     Hyper-spectral satellites capture data across numerous spectral bands, offering more accurate and detailed information on the chemical composition of the Earth's surface, including features such as smoke, burned vegetation, or heat.
  3. **Thermal Infrared Imagery**
     These images are sensitive to heat radiation in the thermal infrared spectrum, revealing temperature variations. This data helps identify heat sources, hotspots, and active fire fronts, even in obscured conditions like smoke or cloud cover [33].

Understanding the different remote sensing data types available for wildfire detection is a crucial part for choosing the suitable one for this research. Remote sensing data processed with deep learning algorithms helps in the detection and identification of forest fires, a topic we will delve into in the upcoming section.

1.4 Deep Learning

Early detection of wildfires is critical for effective mitigation and containment efforts. Traditional methods, reliant on human surveillance, satellite data, or specialized sensors, may fall short due to limited coverage, reliability, and timeliness.

Deep Learning (DL) offers a promising solution due to its capacity to efficiently leverage extensive datasets and identify complex patterns, improving wildfire detection accuracy across different environmental conditions and geographical regions.

1.4.1 Deep Learning for Fire Risks

Artificial intelligence (AI) encompasses various techniques for tackling real-world challenges, and wildfire detection is a prime example. Machine learning (ML), a sub-field of AI, trains machines to learn from data without explicit programming. ML algorithms analyze past fire data, enabling them to predict future outbreaks, assess fire risk, and even identify existing fires based on new information. Two key approaches exist within ML: supervised learning and unsupervised learning [34, 35]. Supervised learning employs labeled data when training, while unsupervised learning employs unlabeled data. These two approaches can achieve the goal of fire detection, potentially revealing hidden indicators of wildfires.

DL, on the other hand, a subset of ML, leverages Artificial Neural Networks (ANNs) inspired by the human brain's structure and function used for complex computational tasks such as image processing. Unlike conventional ML algorithms, DL algorithms are less linear, more complex, and hierarchical, capable of learning from enormous amounts of data, and able to produce highly accurate results [34,35] driving many computer vision technologies like wildfires detection.

ANNs consist of interconnected layers (input layers, hidden layers, and output layers) containing neurons that perform mathematical operations on data (Figure 1.16). These neurons work together, adjusting weights and connections throughout the network to learn and identify complex patterns in images such as fires.

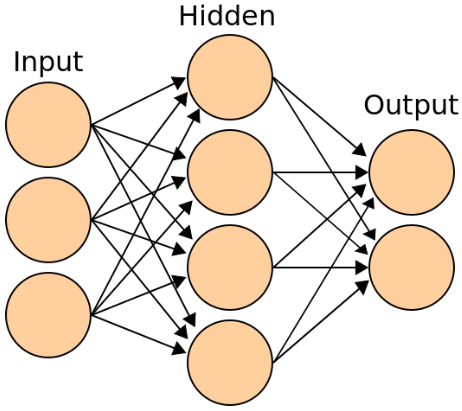


Figure 1.16: Artificial Neural Networks [36].

Wildfire detection can be formulated as classification, detection, and image segmentation tasks, specifically:

A. Image Classification

This is the primary domain in which DL plays the most important role in classifying images into a class based on what is contained in the image by assigning a label to the input image (Figure 1.17) [37]. In wildfire detection, deep learning analyzes satellite or drone imagery, classifying them as containing fire or not based on predefined categories like smoke, burned vegetation, or heat signatures. An example of a wildfire detection technique in image classification is InceptionV3 model [38].

B. Object Detection

Object detection surpasses classification by not only identifying and classifying objects but also pinpointing them with rectangular bounding boxes (Figure 1.17) [39]. This precise localization capability is crucial for wildfire detection, allowing for targeted response efforts. Unlike image classification, which gives a general "fire" or "no fire" for the whole image, object detection helps identify and locate specific fire signatures within the image. One example of a technique for wildfire detection using object detection is YOLOv3-tiny [40].

C. Image Segmentation

Image segmentation, another powerful computer vision approach, delves deeper by meticulously partitioning the image into meaningful and distinguishable segments or regions by grouping pixels sharing certain features (Figure 1.17) [41]. This detailed analysis allows for a more precise understanding of the fire's shape and size, including characteristics like burning intensity based on variations in color or texture, by creating a pixel-wise mask that isolates the fire from the background. An example of an image segmentation technique used for wildfire detection is Fire-Net [42].

- **Pixel-Wise Mask**

  In the context of image segmentation, a pixel-wise mask refers to a detailed segmentation map that assigns each pixel in an image to a specific label or class [43]. It identifies which pixels belong to which objects or regions of interest, effectively outlining their shapes within the image [44]. For instance, in Figure 1.17, the mask categorizes pixels into one of three classes: Class 1 (pixels belonging to the pets), Class 2 (pixels bordering the pets), and Class 3 (pixels that are neither / surrounding pixels).

  These masks are crucial in applications such as wildfire detection, enabling accurate mapping and monitoring of fire spread.

Figure 1.17: Difference between Image Classification, Object Detection and Image Segmentation [45].

To truly unlock deep learning's potential for wildfire detection, a profound comprehension of Convolutional Neural Networks (CNNs) is essential, as they are central to its effectiveness.

1.4.2 Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) have emerged as the most adopted deep learning architecture for computer vision tasks as they have achieved expert-level performance in image recognition, object detection, and image segmentation [46].

CNNs consist of three main layers: convolution, pooling, and fully connected layers, facilitating the analysis of gridded data such as images and the automatic acquisition of spatial hierarchies of features from low to high-level patterns, as depicted in Figure 1.18.

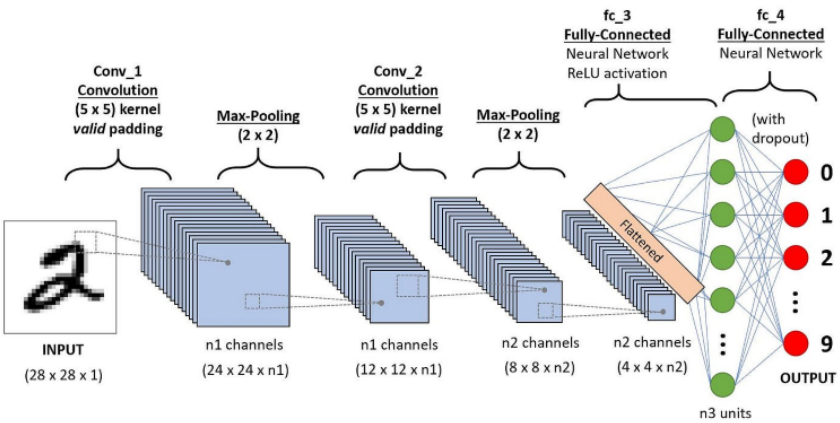


Figure 1.18: Basic CNN Architecture [47].

A. Convolutional Layer

This layer is responsible for feature extraction using a combination of linear and nonlinear operations and activation functions.

These layers use kernels (small numerical arrays) to perform convolutions, essentially sliding filters across the image and capturing local patterns (Figure 1.19). Activation functions, like ReLU, are then applied to introduce non-linearity. By using multiple kernels and convolutions, CNNs can generate a hierarchy of increasingly complex feature maps, representing distinct aspects of the input image.

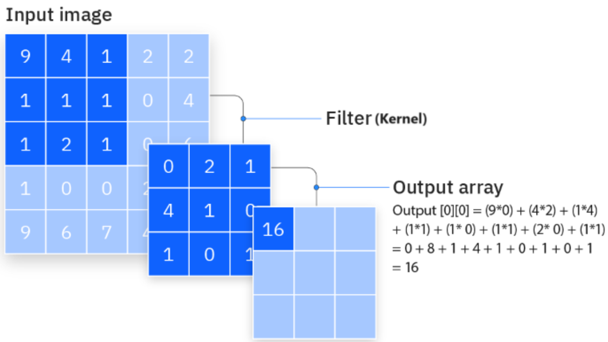


Figure 1.19: In depth of the Convolutional Layer [48].

B. Pooling Layer

After the convolution layer, pooling layers offer a crucial step in managing network complexity. These layers down-sample the data by applying a filter (without learnable weights) across the input [46]. This process reduces the dimensionality of the data, leading to benefits like reduced memory usage, lower computational demands, and ultimately, a decreased risk of over-fitting.

There are different types of pooling operations (Figure 1.20), such as:

- **Max pooling:** Selects the maximum value within a defined window, emphasizing the most prominent features.
- **Average pooling:** Computes the average activation within the filter region, capturing the overall presence of features.

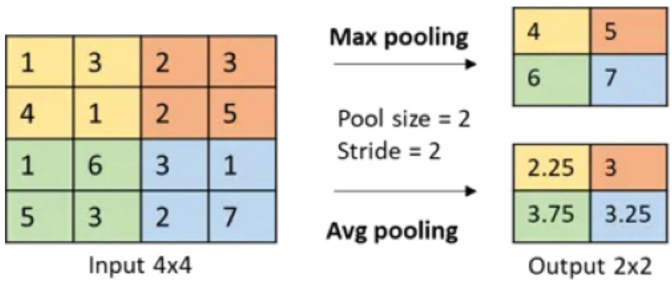


Figure 1.20: Types of Pooling Operations [49].

C. Fully Connected Layer

The output feature maps of the final convolution or the pooling layer are typically flattened, i.e., transformed into a one-dimensional (1D) array or vector, and at the end, they pass through the fully connected layers to make the final prediction.

In the fully connected layers, each neuron is connected to all the neurons in the previous layer, and each fully connected layer is followed by a nonlinear function, such as ReLU [50], to classify inputs appropriately, producing a probability from 0 to 1 [48].

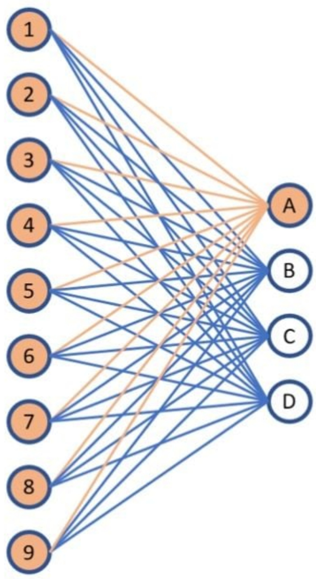


Figure 1.21: Illustration of a Fully Connected Layer [51].

Leveraging the foundation established by deep learning, the assessment of deep learning models requires robust performance metrics to measure their effectiveness in practical contexts. These metrics act as quantifiable benchmarks to judge how well a model performs in real-world scenarios. The upcoming section will delve deeper into the role of these performance metrics, exploring how they help us evaluate the overall usefulness of deep learning models for wildfire detection. By carefully choosing and analyzing these metrics, we can ensure our models are not only detecting fires but doing so with the necessary accuracy and detail to inform critical firefighting decisions.

1.5 Performance Metrics for Object Detection

The evaluation of deep learning models for wildfire detection is crucial to assessing their efficacy in real-world scenarios. This section discusses the key performance metrics used to evaluate deep learning models for wildfire detection: precision, recall, F1-Score, IoU, and dice score.

A. Precision and Recall

Precision reflects the model's ability to avoid false positives by assessing the ratio of correctly identified objects to all detected positives. Meanwhile, recall, or sensitivity, focuses on the model's ability to detect all relevant objects by calculating the ratio of true positives to all actual positives in the ground truth data [52].
Mathematically, precision and recall are represented by Equations 1.1 and 1.2, respectively.

$$Precision = \frac{TP}{TP + FP} \tag{1.1}$$

$$Recall = \frac{TP}{TP + FN} \tag{1.2}$$

B. F1-Score

F1-Score is derived from precision and recall, offering a balanced view of a models performance by calculating their harmonic mean (Equation 1.3). In the context of wildfire detection, a high F1-Score indicates the models capacity to accurately detect wildfire pixels while reducing false positives and missed detection [52].

$$F1 - Score = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{1.3}$$

C. Intersection over Union (IoU)

The IoU metric plays a vital role in object detection tasks, measuring the overlap between a detected bounding box and the ground truth annotation (Figure 1.22). Scores range from 0 (no overlap) to 1 (perfect overlap), with higher values indicating better object localization [53].

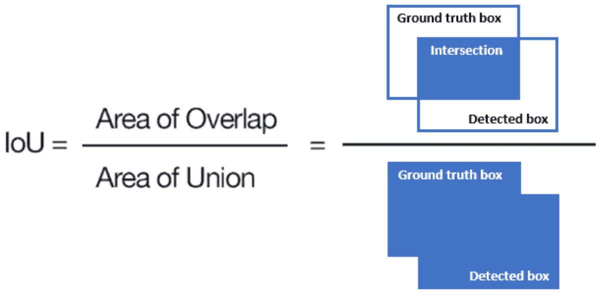


Figure 1.22: Graphical view of the IoU Equation [54].

D. Dice Coefficient Score

The Dice coefficient score is pivotal in image segmentation, assessing model performance by measuring overlap between predicted and ground truth segmentation (Figure 1.23). It ranges from 0 to 1, with higher values indicating better alignment between predicted and actual segmentation [55].

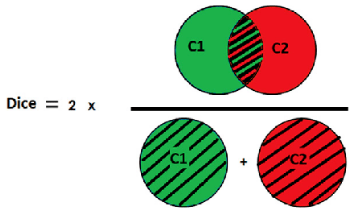


Figure 1.23: Graphical view of the Dice Coefficient Score Equation [55].

While performance metrics offer a crucial basis for evaluating deep learning models, practical application necessitates delving into established techniques. The following section explores a selection of prominent deep learning models specifically designed to tackle the challenges of wildfire detection.

1.6 Related Works

Wildfires pose a serious environmental threat. To combat this, researchers are leveraging deep learning for early detection. These models analyze real-time data from satellites and drones and tackle them using deep learning techniques, classification, object detection, and segmentation.

For instance, Priya et al. [38] explored InceptionV3, a Convolutional Neural Network (CNN) architecture, to classify forest fires in satellite images of a dataset consisting of 534 images. It achieved high accuracy in distinguishing fire from non-fire regions, giving a weighted average precision of both classes of 97.50%. Jiao et al. [40] employed

YOLOv3-tiny, trained on aerial UAV imagery for wildfire detection by precisely locating fire signatures. Their training process was extensive, involving 60,000 epochs with batches of 64 images each and giving relatively good results, precision of 82.00% and recall of 79%. Seydi et al. [42] proposed Fire-Net, a novel segmentation model that utilizes both RGB and thermal data from satellites. Training it on a dataset of 722 image patches of 256*256 pixels. Fire-Net effectively segments active fire areas, offering a detailed pixel-wise analysis of fire extent and intensity. It achieved an impressive overall accuracy of 97.35%, even for detecting small fires.

These studies can be summarized in the following table:

Table 1.1: Related Works Summary.

Model	Dataset Size	Dataset Type	Approach
InceptionV3	534	Satellite	Classification
YOLOv3-tiny	/	UAV	Object Detection
Fire-Net	722	Satellite	Segmentation

The results from these studies guided our decision to adopt a segmentation approach for wildfire detection in satellite imagery. Unlike classification and object detection, segmentation provides a more granular analysis. It allows us to exactly differentiate between burning zones, healthy vegetation, smoke, and other land cover types within the satellite image. This detailed information regarding fire footprint and potential variations in fire intensity is critical for effective fire management strategies and resource allocation during firefighting efforts.

These studies and techniques play a crucial role in the advancement of the research in the wildfire detection area, contributing in finding better and faster solutions to avoid disaster on the planet.

1.7 Conclusion

This chapter has provided a comprehensive overview of the wildfire threat, highlighting its correlation with global warming, particularly in Africa and Algeria. The literature review has also explored the use of remote sensing data and deep learning processing methods for wildfire detection and monitoring.

In the next chapter, we will outline our methodology for studying the efficacy of the U-Net architecture for the wildfire detection task, covering key aspects including the implementation of the architecture, data collection, and preparation.

Chapter 2

Methodology

2.1 Introduction

In response to increasing wildfire risks, recent years have seen a surge in wildfire research focusing on prediction, utilizing machine learning algorithms for comprehensive data analysis with accessible computing resources.

This chapter delves into the specific methodology adopted for this project, particularly focusing on our system's pipeline and U-Net segmentation, a well-suited deep learning architecture for accurately identifying wildfire boundaries in images. It outlines the U-Net model configuration, data preparation process, and training details for a better model's performance in wildfire detection.

2.2 Our System's Pipeline

The implementation pipeline functions as a constantly running system that devours real-time Landsat-8 satellite imagery data as soon as it becomes available. This data typically captures information in various spectral bands, which can be sensitive to heat signatures. This data is then fed into the detection model that analyzes each image. By examining these spectral bands, the model can identify pixels with characteristics that deviate significantly from the norm, potentially indicating the presence of fire. The model then employs segmentation on the image, essentially partitioning the image into fire pixels and no fire pixels. Following segmentation, the fire intensity is calculated, and the core principle lies in the proportion of white pixels within the segmented fire area. A higher percentage of white pixels directly correlates to a more extensive burning area, indicative of a more intense fire releasing greater heat energy. Conversely, a lower proportion of white pixels suggests a less severe fire with a lower heat output, as illustrated in Figure

2.1. Therefore, by leveraging image segmentation and automatically computing the white pixel percentage within the fire mask, we obtain a quantitative measure of fire intensity.

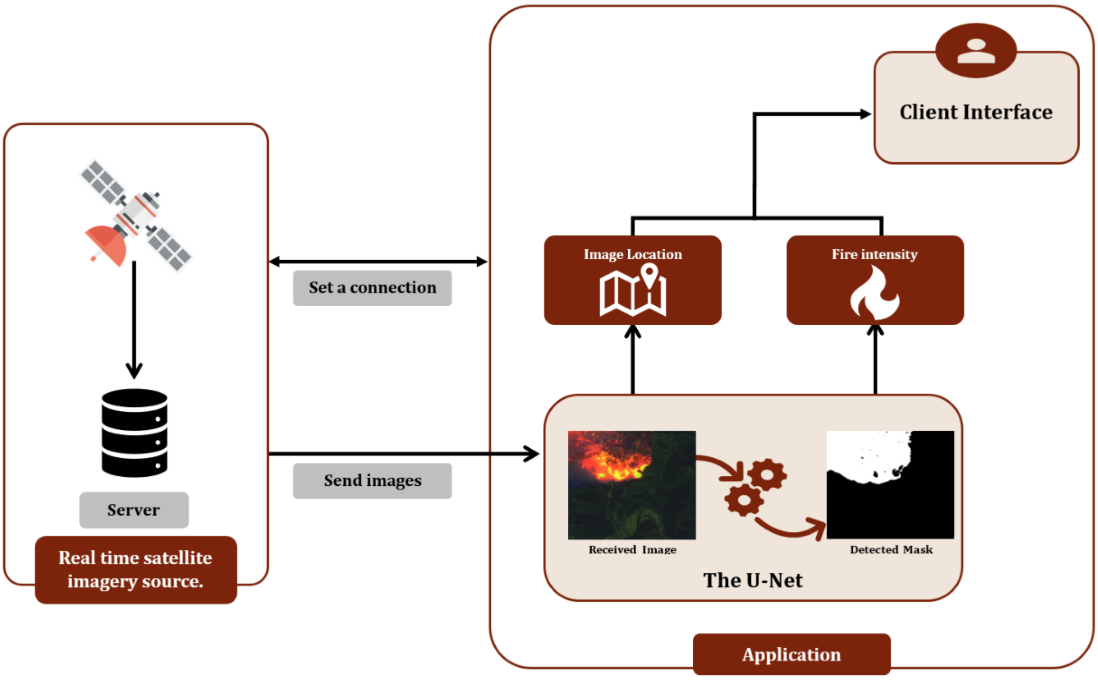


Figure 2.1: Our System's pipeline.

This approach leverages a critical aspect of wildfire detection: real-time data acquisition from the Landsat-8 satellite. By incorporating this real-time data stream, the system gains the ability to detect wildfires as soon as they emerge. Furthermore, the extent of the detected fire pixels within the satellite imagery allows for an initial assessment of the fire's intensity, providing valuable information for prioritizing firefighting efforts.

Since the U-Net architecture is the main method used in our system, we will discover in the next section this architecture and the main modifications we made for a good model training.

2.3 The U-Net Architecture

U-Net, a type of CNN, is specifically designed for image segmentation tasks. It has gained popularity for its ability to precisely delineate objects in images, making it ideal for tasks such as wildfire detection, where the exact location and extent of fires need to be identified. Developed by Ronneberger et al. [56], U-Net's unique U-shaped structure excels at segmenting intricate features, making it ideal for identifying wildfires in complex environments. This U-shaped structure is key to U-Net's success. It consists of two main pathways: an encoding path and a decoding path [56], where the encoding path resembles standard Convolutional Networks; it progressively extracts high-level features from the image by iteratively applying convolutional operations while reducing the image size with a max pooling operation. The decoder path is what makes this architecture unique. This path, unlike the encoder that shrinks the image, utilizes transposed convolutions to expand the information from lower-level, increasing the resolution of the feature map, and incorporating skip connections that directly transmit detailed spatial information from the corresponding level of the encoder to the decoder, ensuring the decoder retains crucial location data. This allows the decoder to make pictures with high resolution and precise localization, highlighting areas with wildfires in the final segmentation map.

After several tests and to leverage the strengths of U-Net for wildfire detection in this research, we adopted the original U-shaped architecture with slight modifications since the tests conducted with the original architecture did not achieve good results due to the complexity of the satellite images. The modifications include batch normalization after each convolution to improve training efficiency by normalizing data in small batches, and dropouts (rate of 0.4) after each max pooling operation to prevent over-fitting and improve generalization. The overall architecture is an encoding path that employs four iterations of double convolution, followed by max pooling operations. The decoder path also mirrored the original architecture, utilizing four iterations of transposed convolutions with double convolution operations within each iteration. The utilized architecture for this research is summarized in Figure 2.2.

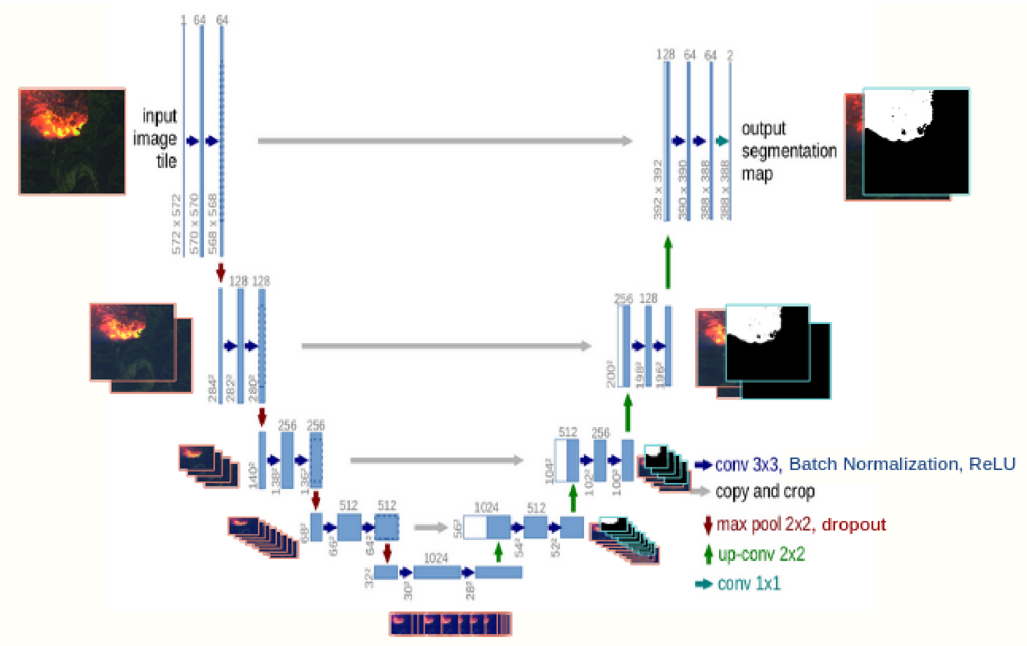


Figure 2.2: The utilized U-Net architecture.

2.3.1 Motivation

Our decision to utilize the U-Net architecture for wildfire detection in satellite imagery stems from its strengths in several key areas. Unlike object detection architectures and models, U-Net excels at precise pixel-level classification, which is crucial for delineating the exact fire boundaries needed for accurate perimeter estimation. Additionally, U-Net's skip connections effectively preserve spatial information during processing, ensuring that critical details for fire delineation are not lost. Furthermore, U-Net's success in handling complex backgrounds (such as complex backgrounds in satellite imagery), similar to those encountered in medical image segmentation tasks, makes it well-suited for this application. These combined advantages make U-Net a compelling choice for our deep learning approach to wildfire detection.

Although the U-Net architecture is powerful for segmentation tasks, a good dataset for training is important to achieve excellent results. The process of collecting and preparing the data is presented in the following section.

2.4 Data Collection and Preparation

Forest fire detection using U-Net relies on robust and sufficient datasets to enhance model accuracy and generalization. Our model utilizes the "Active Fire Detection in Landsat-8 imagery" dataset, a large-scale dataset referenced in a deep-learning study [57]. This selection was made after carefully evaluating several publicly available wildfire detection datasets, including the "Wildfire Prediction Dataset (Satellite Images)" [58].

The chosen dataset offers 146,214 pre-labeled 256 x 256 pixel image patches from all continents. These images, captured by Landsat-8, are available in 10-band imagery in 16-bit TIFF format, totaling 192 GB. These 10-channel (from c_1 to c_{10}) images provide rich spectral information crucial for fire detection, significantly surpassing the other dataset, which has a lower data volume (approximately 2 GB) in JPEG format and exhibits unclear fire signatures and even instances lacking fire presence entirely.

Furthermore, the "Wildfire Prediction Dataset (Satellite Images)" lacked pre-labeled segmentation masks, which are essential for training deep learning models. The absence of these masks would have required manual creation, a time-consuming and potentially error-prone process. In contrast, the "Active Fire Detection" dataset includes pre-labeled segmentation masks generated using algorithms based on the criteria proposed by Schroeder et al. [59], Murphy et al. [60], and Kumar & Roy [61], making it a suitable choice for training our U-Net model.

- **Schroeder et al.** [59]
  Schroeder et al.'s approach uses seven Landsat-8 channels, c_1 to c_7, to create hierarchical segmentations at different scales based on both spectral and spatial characteristics [57].
  Fires are detected through a two-step process: initially, pixels are classified as fire if they satisfy the condition 2.1 or the condition 2.2.

$$(R_{75} > 2.5) \text{ And } (\rho_7 - \rho_5 > 0.3) \text{ And } (\rho_7 > 0.5) \tag{2.1}$$

Or

$$(\rho_6 > 0.8) \text{ And } (\rho_1 < 0.2) \text{ And } ((\rho_5 > 0.4) \text{ Or } (\rho_7 < 0.1)) \tag{2.2}$$

  Where R_{ij} is the ratio between the reflectance in channels c_i and c_j (ρ_i/ρ_j). And ρ_i is the reflectance in channel c_i [57].
  Then, reflectance thresholds are adjusted based on surrounding conditions, and water pixels are excluded from the analysis to ensure more accurate fire detection.

- **Murphy et al.** [60]
  In contrast, Murphy et al. utilize CNN-based machine learning to detect thermal anomalies, producing highly sensitive segmentation masks.
  They established criteria to identify saturated pixels using data from channels c_5, c_6, and c_7 [57]. A pixel is identified as an active fire by the threshold condition 2.3.

$$(R_{76} \geq 1.4) \text{ And } (\rho_7 \geq 0.15) \tag{2.3}$$

  Additionally, surrounding pixels are classified as potential fires if they meet the condition 2.4.

$$(R_{65} \geq 2) \text{ And } (\rho_6 \geq 0.5) \tag{2.4}$$

- **Kumar & Roy** [61]
  Meanwhile, Kumar & Roy employ various spectral indicators to identify fire pixels, based on channels c_2 to c_7 [57]. Unambiguous fire pixels are identified as those that satisfy the condition 2.5.

$$(\rho_4 \leq 0.53 * \rho_7 - 0.214) \tag{2.5}$$

  And pixels respecting one of the thresholds expressed in condition 2.6 are considered potential fire pixels.

$$(\rho_4 \leq 0.53 * \rho_7 - 0.125) \text{ Or } (\rho_6 \leq 1.08 * \rho_7 - 0.048) \tag{2.6}$$

Figure 2.3 compares the segmentation masks generated by the three algorithms from an input image from the adopted dataset.

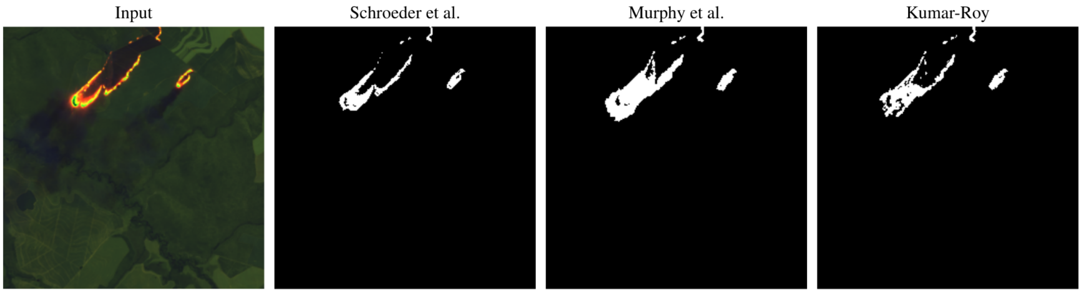


Figure 2.3: Comparison of wildfire segmentation masks generated by Schroeder et al., Murphy et al., and Kumar & Roy [57].

The dataset also includes intersection masks, requiring agreement on fire pixels from all three algorithms, and best-of-three voting masks, necessitating agreement from at least two algorithms.

Focusing on African wildfires and the intersection and voting masks, we filtered the dataset to retain only images and masks for the African continent. However, we noted an imbalance among the number of masks generated by the three different algorithms: some image patches had all three types of masks, others had only Kumar and Murphy masks, and still others had only one type of mask. This imbalance significantly impacted the creation of combination masks (intersection and voting). To rectify this, we performed a secondary filtering step, resulting in a final dataset comprising 17,638 images with their respective intersection and voting masks (total of 35,276 of both images and their masks), totaling approximately 23 GB of storage.

We also established another filtering of the "Active Fire Detection in Landsat-8 imagery" dataset in the African region and got 22,688 images, each paired with its respective Murphy masks (totaling 45,376 images and their masks). These masks were chosen for their heightened sensitivity in detecting color changes in pixels, especially in wildfire satellite imagery. This subset, totaling 29 GB, provides substantial value for individual evaluation.

The resulting sub-datasets utilized in this research are summarized in Figure 2.4.

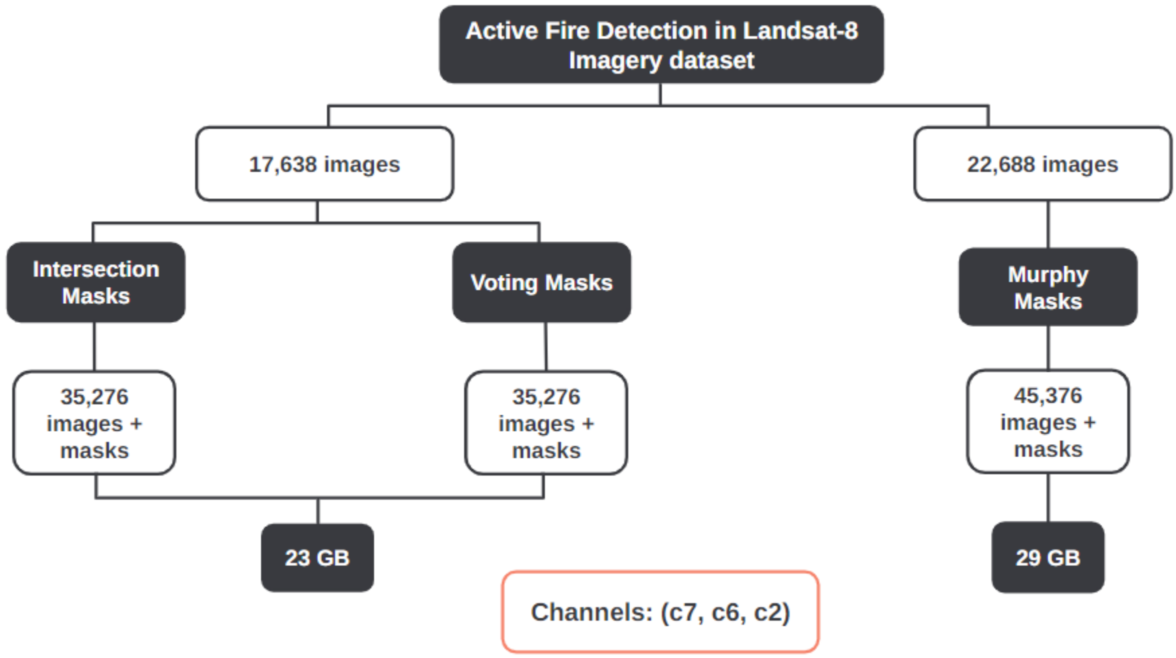


Figure 2.4: The utilized sub-datasets.

The strategy of our work with our dataset before starting the training is to perform some pre-processing techniques and split the data in balance to avoid any over-fitting or under-fitting during the training.

- **Data Augmentation:** For the pre-process of our data, we performed data augmentation to enhance the model's robustness and improve detection accuracy since there is an unbalance in the dataset. This technique helps generate diverse data variations, which is crucial in addressing the limited diversity of the original dataset. We employed several augmentation methods, including rotation, horizontal and vertical flips, random brightness and contrast adjustments, random cropping, elastic deformation, and image normalization. These transformations simulate real-world variations and help the model generalize better, especially in challenging scenarios like different lighting conditions or viewing angles.
- **Data Split:** The split of the dataset is important to ensure the balance of data during the training and plays a key role in avoiding over-fitting and under-fitting. The proposed split was set on a seed random state of 42, with 70% for the training set and 30% for the validation set.

In transitioning to wildfire detection, specialized training and optimization strategies become essential, complementing the intricate structure of the U-Net architecture and the dataset preparation for this research.

2.5 Model Training and Optimization Strategies

Wildfire detection with machine learning models needs special training and optimizing methods to ensure their high accuracy, efficiency, and generalization.

2.5.1 Optimizer: Adaptive Moment Estimation (Adam)

Optimizers serve as an essential component for training deep learning models as they update the network's weights, or parameters, to minimize a chosen loss function, allowing the model to learn from the training data and progressively improve its performance. One widely used optimizer in deep learning is Adam, which is an extension of Stochastic Gradient Descent (SGD). It is a widely used optimizer that dynamically adjusts learning rates for each parameter, enhancing convergence speed and performance with fewer computational resources [62]. For this research, we adopted Adam optimizer to achieve better convergence during training for our model.

2.5.2 Loss Function: Binary Cross-Entropy (BCE)

A loss function, or cost function, measures the discrepancy between predicted outputs and actual labels, guiding the model's learning process. In our research on segmenting fires in satellite images, we adopted the Binary Cross-Entropy (BCE) loss function, which is widely used for binary classification tasks [63].

BCE calculates the loss by comparing predicted probabilities with actual binary labels (0 or 1). The function penalizes the model based on the accuracy of its predictions:

- If the true label y_i is 1, the loss increases by $\log(\hat{y}_i)$.
- If y_i is 0, the loss increases by $\log(1 - \hat{y}_i)$.

The BCE formula, shown in Equation 2.7

$$BCE = -\frac{1}{N} \sum_{i=1}^{N} \left[y_i \cdot \log(\hat{y}_i) + (1 - y_i) \cdot \log(1 - \hat{y}_i) \right] \tag{2.7}$$

Here, N is the total number of samples, y_i is the actual label, and $\hat{y}_i$ is the predicted probability. This loss function helps the model minimize errors and improve classification accuracy.

2.5.3 Activation Function: Rectified Linear Unit (ReLU)

Activation functions decide if a neuron should be activated in an ANN based on its inputs, weights, and bias. They introduce non-linearity, allowing the network to learn complex patterns by determining if the neuron's output exceeds a predefined threshold, thus either activating or deactivating the neuron for further signal propagation [64].

For this research, since we maintained the original architecture of U-Net, we adopted ReLU as the activation function.The input to the ReLU function is the weighted sum of inputs to the neuron, also known as the linear combination of the inputs and weights, plus a bias term. ReLU selectively activates neurons by outputting the input value if it is positive; otherwise, it outputs zero. This prevents gradients from vanishing and speeds up computation with simpler mathematical operations, as defined in Equation 2.8 where x is the input of the neuron.

$$\mathrm{ReLU} = \max(0, x) \tag{2.8}$$

Adjusting these training metrics for the model before and during the training is important to get a good performance of the model, which we performed several times before fixing these proposed taining metrics.

2.6 Conclusion

In this chapter, we have described the methodology adopted for our wildfire detection system using U-Net segmentation, covering data collection and preparation processes, including the specifics of the wildfire dataset we used. We have also explained the suitability of the U-Net architecture for wildfire boundary detection in satellite imagery and the training metrics for training the model. The next chapter will present the experimental results and discuss the system's strengths and limitations.

Chapter 3

Experiments and Results

3.1 Introduction

This chapter presents the results of our experiments evaluating the effectiveness of combining remote sensing data and U-nets for wildfire detection. First, it describes the development environment we used, providing an overview of the technologies behind our approach. Next, it details the experimental procedures, ensuring transparency and reproducibility. Then, it discusses and analyzes the results in terms of their significance, implications, and limitations. Finally, it present the interface that was built for our system.

3.2 Setup

To effectively integrate remote sensing data with U-nets for wildfire detection, we established a robust development environment. This environment centered around:

- **PyTorch:** PyTorch, a powerful open-source deep learning framework based on the Python programming language and the Torch library [65], is known for its flexibility and efficiency in building neural network architectures. Its rich library ecosystem and ability to handle large image sizes, coupled with its ease of use, made it ideal for our research.

- **Kaggle:** Kaggle, a data science platform equipped with vast datasets and cloud computing resources [66], facilitated the efficient execution of our experiments with its CUDA GPU support and enabled us to effectively scale them to handle extensive remote sensing data, consequently enhancing the robustness and generalization of our wildfire detection model.

- **Visual Studio Code (VS Code):** Visual Studio Code is a code editor redefined and optimized for building and debugging modern web and cloud applications developed by Microsoft [67]. It is highly popular among developers due to its extensive features, customizability, and wide range of extensions. This code editor helped us in the process of building our application interface, making the building process smooth and seamless.

- **Streamlit:** Streamlit, a free and open-source Python framework, empowers machine learning engineers and data scientists to effortlessly build and deploy dynamic data apps with minimal coding, simplifying data display and parameter collection for modeling [68]. Its integration significantly streamlined our development process while enhancing the user interface of our final application.

- **Neptune Ai:** Neptune is a machine learning platform that helps track, compare, store, and collaborate on models [69]. It provides a Python API for saving model's metadata and for exploring, comparing, and monitoring experiments. Its PyTorch integration allowed us to easily track model metrics, visualize training curves, and smooth the results in order to optimize and improve the performance of our model.

These powerful tools made the process of this research easy and of good quality. Their integration into this work was seamless and efficient, which helped us experiment three models, as presented in the next chapter.

3.3 Experiments

To demonstrate the validity and effectiveness of U-Net for forest fire detection using satellite images, we conducted three experiments. The experiments are based on the three masks chosen for the dataset (intersection, voting, and Murphy) to see the best method or algorithm used in the masks. Each model of the experiments utilized a composition of three channels (c_7, c_6 and c_2) to enhance fire visibility in images. The training was conducted on Kaggle platform [66] and the training parameters set for the three models are:

- **Learning rate:** The learning rate was set to 0.001 for the three experiments. We also implemented a learning rate scheduler to update it when the training does not improve well.

- **Batch size:** The batch size was set to 64, as it is recommended as a starting point since the dataset contained an overall total of 35,276 images and masks for experiment 1 (intersection masks) and experiment 2 (voting masks), as well as 45,376 images and masks for experiment 3 (Murphy masks).

- **Epochs:** In our research, we initialized the number of epochs to 50 since our satellite images contain a lot of information and it is recommended to improve the performance of the models in this case.

The three experiments conducted in this research are summarized in Figure 3.1.

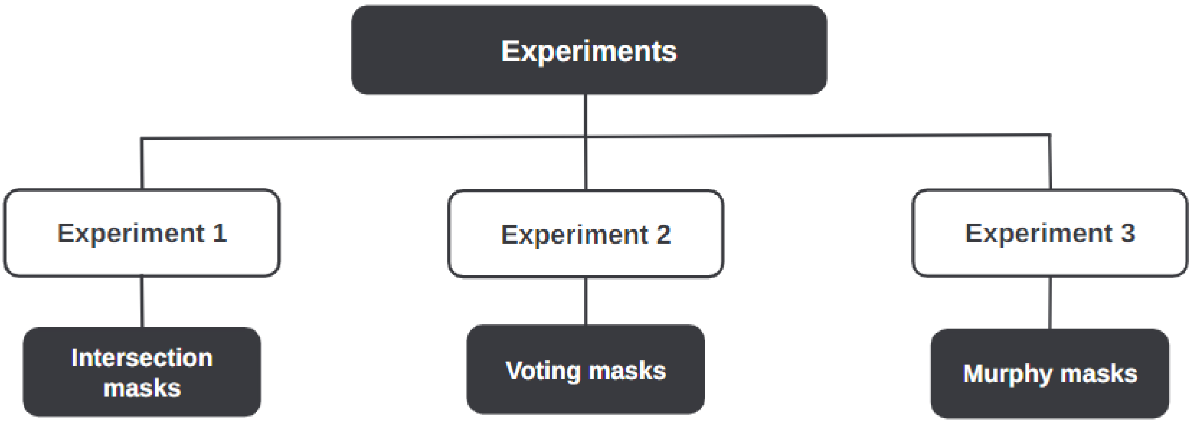


Figure 3.1: The Three Experiments.

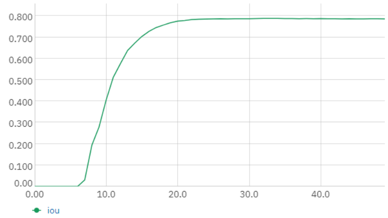
These experiments play a key role in finding the best model for wildfire detection in this research. The next section will present the results achieved from the three experiments.

3.4 Results of The Experiments

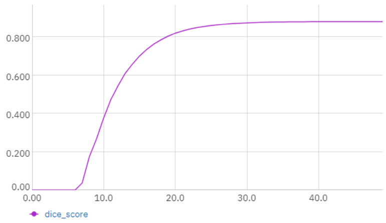
The models of the three experiments were evaluated on the validation data (30% of the dataset) by calculating metrics such as: IoU, Dice score, Precision, Recall, and F1-score for each epoch. These results were visualized using Neptune.ai [69] for better clarity.

A. U-net Intersection Masks Model

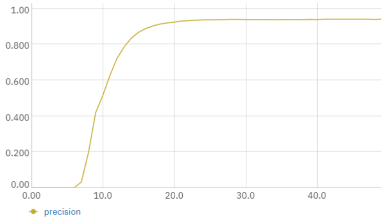
The first model utilized satellite images of the African continent along with their intersection masks from the first dataset (35,276 images and intersection masks). The results of the evaluation of the model are depicted in Figure 3.2.



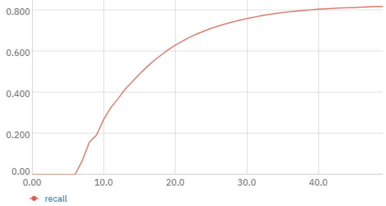
(a) IoU Plot.



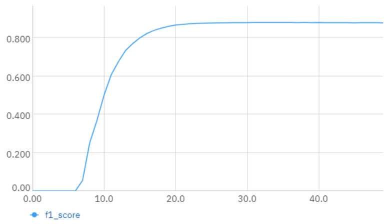
(b) Dice Score Plot.



(c) Precision Plot.



(d) Recall Plot.



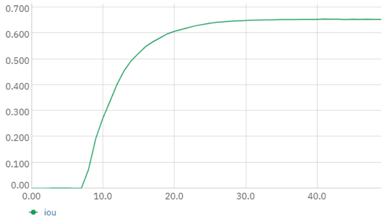
(e) F1-Score Plot.

Figure 3.2: U-Net Intersection Masks Model Performance

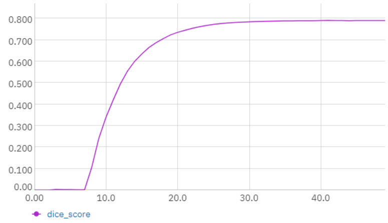
The results shown on the graphs indicate that the Intersection model achieved 0.79% for the IoU (Figure 3.2a), 0.88% for the Dice Score (Figure 3.2b), a Precision of 0.93% (Figure 3.2c), a Recall of 0.84% (Figure 3.2d), and 0.88% for the F1-Score (Figure 3.2e).

B. U-net Voting Masks Model

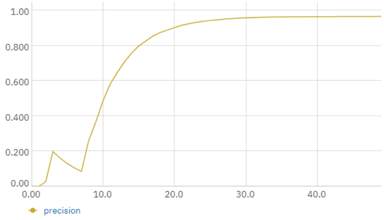
The second model employed the same dataset but used voting masks (35,276 images and voting masks). The results of its evaluation plots are represented in Figure 3.3.



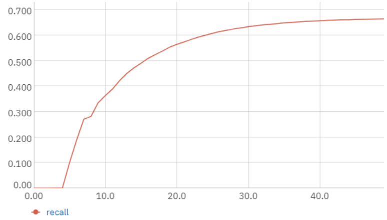
(a) IoU Plot.



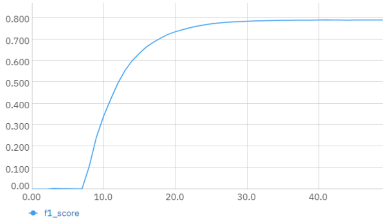
(b) Dice Score Plot.



(c) Precision Plot.



(d) Recall Plot.



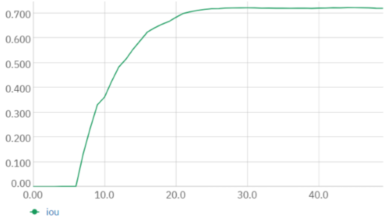
(e) F1-Score Plot.

Figure 3.3: U-Net Voting Masks Model Performance

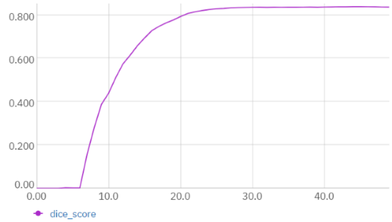
The Voting model achieved good results as well. Scoring with 0.78% for the IoU (Figure 3.3a), 0.87% for the Dice Score (Figure 3.3b), a Precision of 0.94% (Figure 3.3c), as well as a Recall of 0.82% (Figure 3.3d), and 0.87% for the F1-Score (Figure 3.3e).

C. U-net Murphy Masks Model

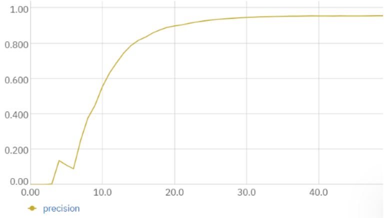
The third model, used Murphy masks, was trained on the second dataset (45,376 images and Murphy masks). The evaluation results are displayed in Figure 3.4.



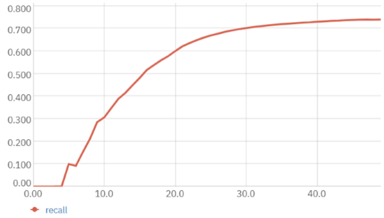
(a) IoU Plot.



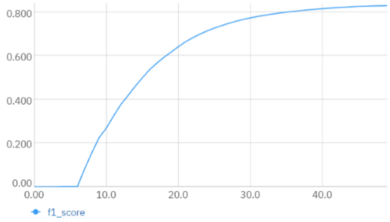
(b) Dice Score Plot.



(c) Precision Plot.



(d) Recall Plot.

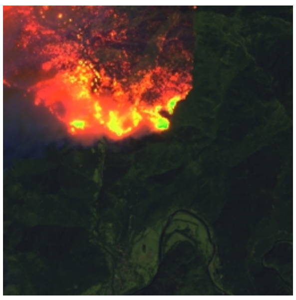


(e) F1-Score Plot.

Figure 3.4: U-Net Murphy Masks Model Performance

The Murphy model surprisingly achieved lower results compared to the Intersection and Voting models, with 0.71% for the IoU (Figure 3.4a), 0.83% for the Dice Score (Figure 3.4b), a Precision of 0.95% (Figure 3.4c), a Recall of 0.74% (Figure 3.4d), and 0.83% for the F1-Score (Figure 3.4e).

The resulting three models were tested on 100 images from the "Wildfire Prediction Dataset (Satellite Images)" of the European region [57]. An example of this test is shown in Figure 3.5.




(a) The Input Image. **(b)** Intersection Model Mask. **(c)** Voting Model Mask. **(d)** Murphy Model Mask.

Figure 3.5: Comparison of the detected masks from our U-Net models.

Although the plots indicate a good performance of the three models, we can see a remarkable difference when testing them on unseen images (Figure 3.5).

- **The Models' Performance Against Related Works**
  This part delves into a comparative presentation of our U-Net models' performance against other prevalent techniques in the domain that were previously mentioned in chapter 1. Table 3.1 summarizes the performance of the models:

Table 3.1: The Models' Performance Against Related Works.

Model	Precision	Recall	F1-Score
InceptionV3	97.50%	98.50%	98.00%
YOLOv3-tiny	82.00%	79.00%	81.00%
Fire-Net	93.49%	92.63%	93.08%
U-Net Intersection	93.13%	84.42%	88.54%
U-Net Voting	94.52%	82.14%	87.88%
U-Net Murphy	95.75%	74.31%	83.64%

The high performance of InceptionV3 and Fire-Net compared to our models can be justified with the high complexity of these two models. The InceptionV3 [38] having 48 deep convolutions can extract very small information from the images, furthermore, the Fire-Net [42] having a double extracting path helps with detecting small details in the images as well.

These solid results were achieved through precise hyper-parameters that played a key role in these experiments. The analysis of the results achieved by our models is presented in the next section.

3.5 Analysis

Following the experiments and their results, the subsequent analysis delves deeper into the results to assess the effectiveness of U-Nets for wildfire detection. A detailed examination of the training metrics revealed interesting patterns, highlighting the strengths and weaknesses of each model.

Comparing the three models, the voting and intersection models achieved a well-rounded performance across all evaluation metrics with high Dice scores (0.87 and 0.885, respectively) and IoU scores (0.78 and 0.79, respectively), indicating a strong overlap between detected fire masks and ground truth as well as effective fire boundary predictions.

Additionally, these two models demonstrated high precision (0.93 and 0.94, respectively) and respectable recall scores (0.82 and 0.844, respectively) and high F1-scores (0.87 and 0.885, respectively), suggesting a low rate of false positives and good wildfire detection ability. These findings are reflected in Figures 3.5b and 3.5c of the previous section.

Conversely, the Murphy model, despite high training metrics (Dice score: 0.83, Precision: 0.95, F1-score: 0.83), showed a significant decline in test performance (IoU: 0.71, Recall: 0.74) indicative of over-fitting. The model's high precision (0.95) but lower recall (0.74) during testing implies a high rate of false positives and missed fire detection (Figure 3.5d of the previous section). This behavior likely stems from the model's high sensitivity, causing it to misclassify non-fire pixels as fire.

Therefore, based on these evaluation metrics and visual inspection of the test results, we selected the voting model for our final application due to its balanced high performance, accuracy of the results, and fire detection capability. While the intersection model performed similarly, the voting model's slightly higher recall makes it more suitable for real-world wildfire detection, where missing fires could have significant consequences. This suggests the voting model's effectiveness in detecting wildfires using satellite imagery.

3.6 Application Interface

This section details the development and construction of our final application. We leverage the power of remote sensing data and U-Nets to create a user-friendly web application tool that simulates real-world wildfire detection scenarios using satellite imagery. Since most real-time platforms that provide real-time satellite data are not free and the free platforms do not provide real-time data (some take hours and some take days), we proposed to simulate the real-time process using real-world satellite images from the Landsat-8 satellite on different continents (excluding Africa, which we used as our dataset). This application will mimic the real-time process by employing sockets, a well-established communication technology within network architectures, which act as virtual pathways enabling data exchange between devices on a network.

In our application, one computer acts as a server, housing the satellite images and continuously transmitting images through the sockets to another computer acting as the client, which hosts the web application. The client-side web application receives the streamed images via sockets. Upon receiving an image, the application leverages the U-Net model to perform wildfire detection (as illustrated in Figure 3.6).

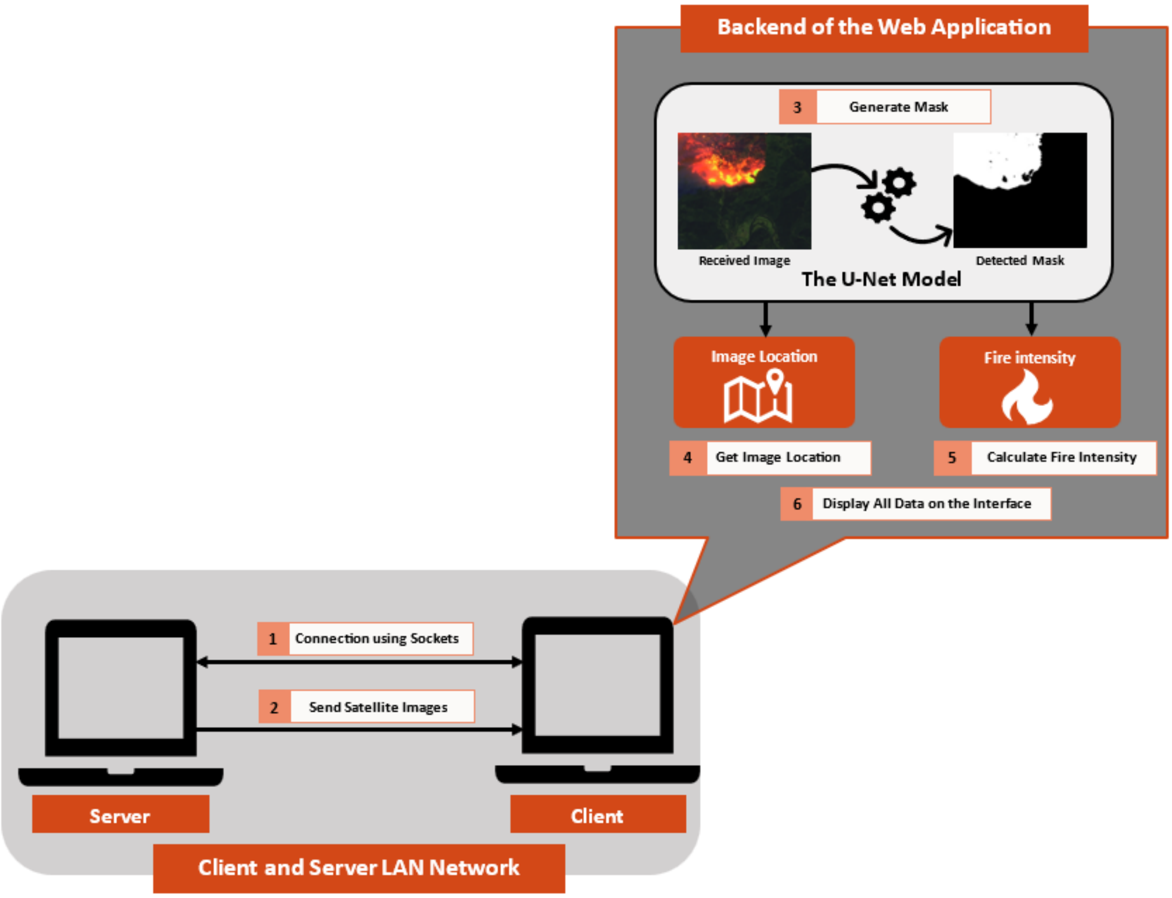


Figure 3.6: Final Application Architecture.

The server-side application is responsible for managing image data and ensuring the continuous transmission of images to the client. A screenshot of the running server-side is provided in Figure 3.7.

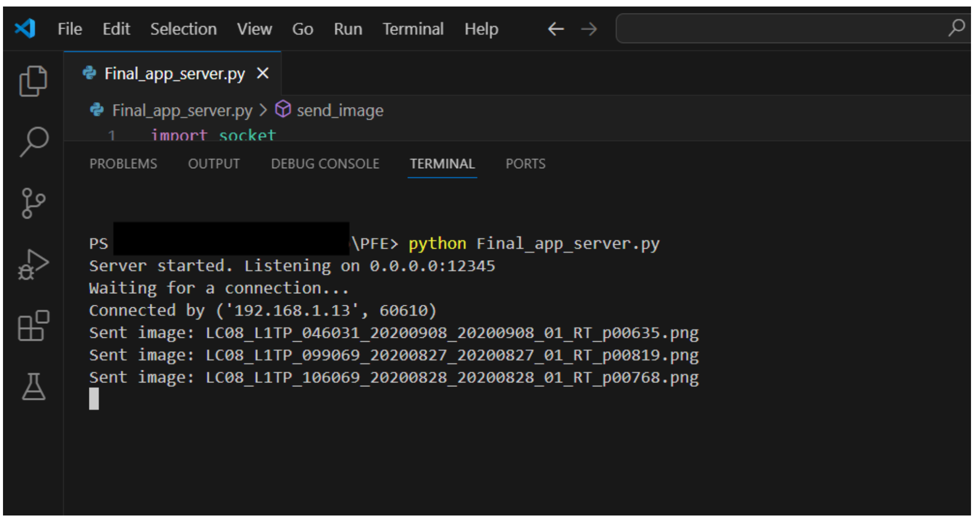


Figure 3.7: Final Application Server.

The client-side application will display the received images and their detected masks in the sidebar, along with their location and fire intensity (Figure 3.8).

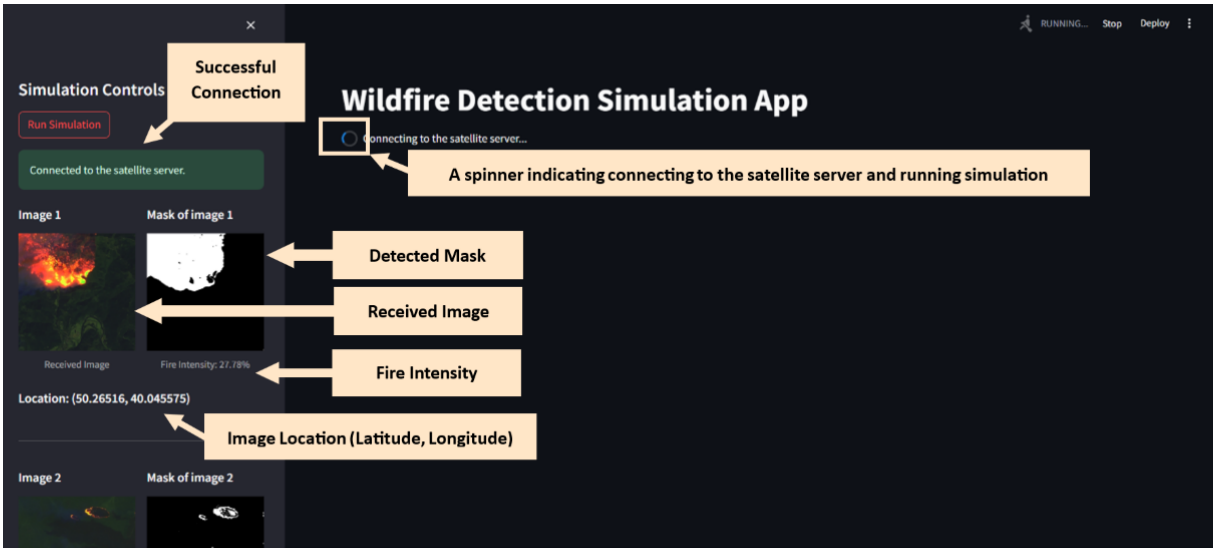


Figure 3.8: Final Application Interface.

Additionally, the application will output a scatter map for fire intensity at each location (Figure 3.9). Hovering over a scatter point reveals additional information about image numbering and fire intensity at that location (Figure 3.10).

Figure 3.9: Scatter Map on the Final Application Interface.

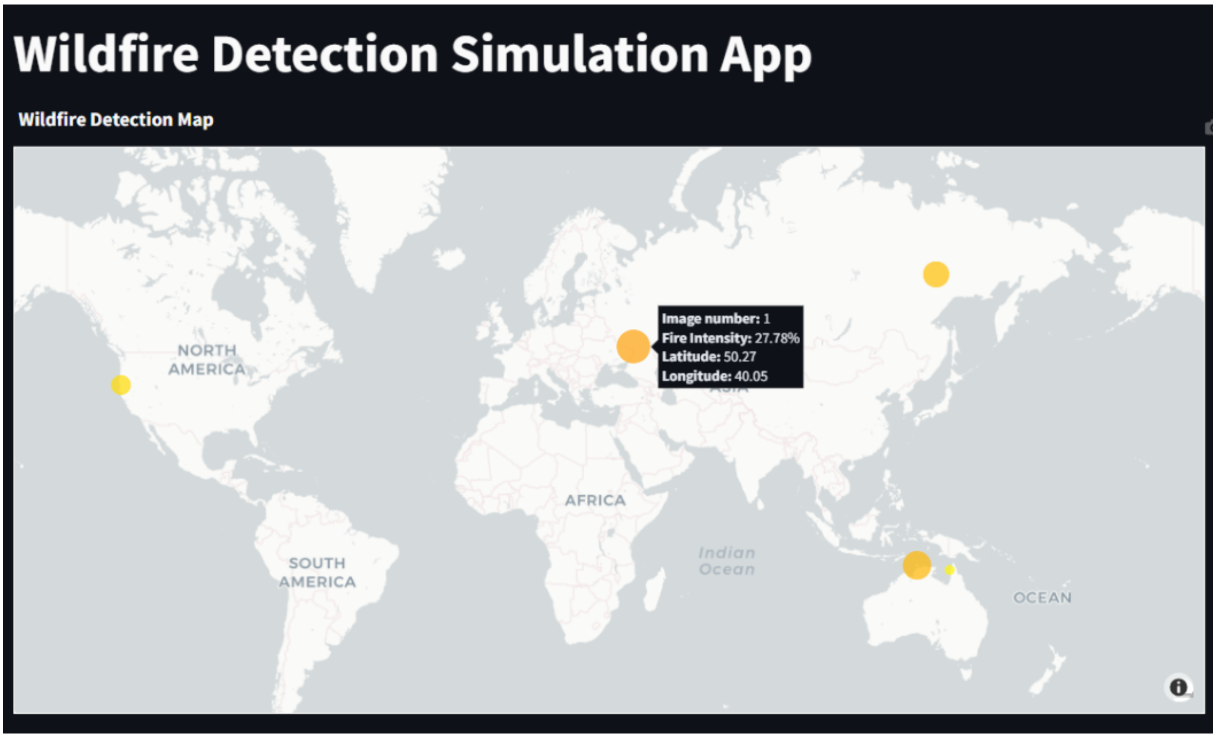


Figure 3.10: The data box provided by hovering over a scatter plot on the map.

The building process of the model and the application interface of our system are the end products of this research, in which application interface visualizes the performance of our system in the most seamless way possible.

3.7 Conclusion

This chapter has presented the different tools and development setups that were adopted during the research, the experiments proposed in this research, and the results of each of them. The Murphy masking technique, although known for its high sensitivity, gave poor results compared to the intersection and voting approaches. These results led to choosing the best-performing model (the voting model) to integrate into the application interface.

Conclusion

Wildfires pose a growing threat to our planet's ecosystems, communities, and infrastructure. Fueled by climate change, prolonged droughts, and land-use practices, these blazes can erupt with terrifying speed, devouring landscapes and displacing populations. Early detection is crucial for mitigating wildfire damage, allowing for faster response times and more effective containment efforts.

This thesis investigated the potential of the U-Net architecture for wildfire detection using remote sensing data from satellites and experimenting with three types of masks in our dataset (Intersection, Voting, and Murphy masks). Our research demonstrates that U-Net offers a powerful tool in this fight. The investigation using the three experiments revealed that U-Net achieved high accuracy in identifying fire pixels and details within satellite imagery for both Intersection and Voting masks, while the Murphy masks resulted in over-detection due to their high sensitivity. These findings highlight the effectiveness of U-Net in recognizing the complex spectral signatures associated with wildfires.

The utilization of U-Net for wildfire detection presents significant advantages. Unlike traditional methods, U-Net's deep learning capabilities allow it to learn intricate patterns from vast amounts of data, enabling pixel-level segmentation for precise fire identification. This offers a substantial benefit for early-stage wildfire detection, where rapid and accurate information is paramount.

However, it is essential to acknowledge the limitations of this approach. Challenges such as closed real-time satellite data sources and the dependence on very high-quality training data require further exploration. Future research should investigate methods to address these limitations, potentially through exploring the performance of the model in real-time instead of simulations. Incorporating techniques or sources for high-quality training data is a suggested solution for better model performance in detecting wildfires. This research can also be improved and helpful for the environment when integrating techniques to estimate the total CO2 emitted from the burnt areas through exploring the different types of trees, their biomass (living and dead plant material), and other indicators.

Processing and analyzing real-time data, including latency and data quality, as well as exploring methods to optimize the resulting model of this research through the U-Net architecture's variations for real-time applications, is another topic of future research, potentially involving model compression techniques.

Looking ahead, this research paves the way for significant advancements in wildfire detection using deep learning techniques. We envision a future where real-time monitoring applications powered by U-Net or similar architectures can provide crucial information to firefighters and first responders. Additionally, the integration of this technology with forest management practices can lead to improved preventative measures and controlled burns, ultimately minimizing the risks associated with wildfires. By continuing to refine and develop these technologies, we can move closer to a future where early wildfire detection becomes the norm, safeguarding our communities and ecosystems from the devastating impacts of these natural disasters.

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