Wildfire Path Spread Prediction System using Machine Learning

Use of ANN, Convolutional Autoencoder, and ConvLSTM ML model

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Abstract

Over the years, the frequency and intensity of wildfires have increased due to climate change, old fire management practices, and other environmental factors [1]. These wildfires pose a threat to ecosystems, infrastructure, property, and lives, particularly in highly susceptible Mediterranean regions, with suitable climatic conditions characterized by hot, dry summers and cool, humid winters [2]. Although fire is essential to maintaining such ecosystems' health, it can destroy long-term environmental sustainability and cause devastating destruction [1, 3].

Wildfire spread prediction from the ignition point to the surrounding area is a complex phenomenon affected by multiple variables such as weather, topography, and land-cover characteristics. Traditional systems used in wildfire spread prediction are often limited in accounting for the dynamic and complex factors influencing fire behaviour. To address this challenge, this research uses a multidisciplinary approach that combines Machine Learning techniques, remote sensing data, and wildfire science to develop an advanced wildfire prediction system.

This research performs a comprehensive investigation into the use of supervised classification Machine Learning(ML) models, specifically, Artificial Neural Networks(ANN), Convolutional Autoencoder, and Convolution Long Short-Term Memory(convLSTM), in predicting wildfire spread. The three ML models developed were based on domain knowledge of fire behaviour and utilised Google Earth Engine(GEE) weather data and Sentinel Hub burned scars satellite data to train a logistic method for simulating fire burn maps. The ML models were then trained, tested, and validated using this data.

An analysis of the models' capabilities in predicting the propagation of wildfire spread, as well as the driving factors that affect wildfire behaviour, was performed. The following evaluation matrices: loss, precision, recall, Area Under the Curve-Precision Recall(AUC_PR) and F1 score are used to assess the performance of the models in predicting the spatial and temporal properties of wildfire spread.

The results indicate that the convLSTM can predict both temporal and spatial properties of fire, while the Convolutional Autoencoder can predict only the spatial properties of fire with minimal loss. The ANN produced the least satisfying results in predicting fire's spatial properties.

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Nomenclature

1 Acronyms

A3C .... Asynchronous Advantage Actor-Critic

ANN .... Artificial Neural Networks

CA .... Cell Automaton

CAE .... Convolutioanl Autoencoder

convLSTM ..... Convolutional Long Short-Term Memory

GEE .... Google Earth Engine

MCTS .... Monte Carlo Tree Search

MDP .... Markov Decision Process

ML .... Machine Learning

MTC .... Mediterranean-type climate

ROS .... Rate of Spread

SDLC .... Software Development Life Cycle

WFDS .... Wildland Fire Dynamic Simulator

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Chapter 1

Introduction

1.1 Background

Wildfires, also commonly known as veld fires, bushfires, or forest fires, are unplanned fires that get out of control and can burn for days in forests, shrublands, and other ecosystems, destroying any damageable material in their path [2]. These inevitable and uncontrolled wildfires can cause extensive damage to the environment, damage property, and cause air and water pollution, resulting in the loss of biodiversity and the loss of the economy and posing a threat to human lives [2, 8]. Wildfires are a worldwide problem regarded as a common natural disaster in certain regions, particularly Mediterranean areas with suitable climate conditions and fire-prone vegetation.

Fig. 1.1. Vulnerable and endangered species impacted by wildfires in Australia

In Australia, severe and frequent wildfire attacks are experienced every year. According to Burgess et al. [9], the 2019-2020 Australian wildfire season, commonly known as the Black summer was one of the most devastating wildfire seasons, with approximately 24 million hectares of parks, bushes, and forests burned. These fires destroyed thousands of homes and infrastructure, claiming at least 33 lives and leaving many more people hospitalised [9].

Amongst the affected areas, widespread loss was experienced in Kangaroo Island, where one-third of the island and approximated 210000 hectares were burned by two fires that burned from December 20th to January 3rd [9]. As shown in figure 1.1, this island is home to endemic plant species and native wildlife such as the Queensland silver-headed antechinus, the Australian bittern, and the koalas. The Koala population experienced an extreme loss of life estimated at over 32 000, losing about half of its population due to wildfires [9].

Fig. 1.2. Wildfire destruction in California

Figure. 1.2 shows property damages and losses caused by these wildfires in California, in the United States. California has had more frequent and more destructive wildfires, with the 2020 fire season being recorded as the most destructive wildfire season in California's modern history. More than 9900 wildfires, which burned approximately 1.74 million hectares of land, were recorded over the year in this region [10]. These wildfires exposed people around California to prolonged, poor air quality, resulting in public health emergencies and the closure of businesses and schools [10].

Fig. 1.3. Cape Town 2021 wildfire

In Cape Town, South Africa, a devastating wildfire raged the Table Mountain on 19 April 2021 and lasted until the 20th April 2021. This fire burned approximately 650 hectares of land, including the Rhodes Memorial area and part of the University of Cape Town Campus. Additionally, the fire spread caused devastating damage to the Jagger Library and other UCT buildings, as shown in figure 1.3 [11]. The property and infrastructure loss of up to 1 billion Rands (approximately 60 million USD) was incurred by the University of Cape Town alone, along with irreplaceable historical collections in the Jagger Library that were destroyed [12].

1.1.1 Factors Affecting Increased Wildfire Frequency and Intensity

According to Bowman [13], the damage caused by wildfires is expected to worsen in the future. Various factors contribute to the increased severity and frequency of wildfires, such as climate change, old fire management practices, and human activity.

Climate change can increase the frequency and intensity of heatwaves experienced for prolonged periods, increasing the duration for which wildfires occur [10, 14]. The increased heat and longer drought sessions increase moisture loss in vegetation and soil. The drier the vegetation, the more flammable it is, hence increasing the chances of the start and rapid spread of wildfires. Additionally, the increased air pressure, caused by the enhanced difference between the land and sea temperatures, boosts the wind power in coastal regions [14]. The strong winds provide more oxygen for the wildfires to burn and spread rapidly.

Fire suppression as a means of fire management practised in the past centuries led to a higher density of trees and shrubs, which meant more fuel and resulted in more devastating wildfire occurrences [15]. In 1968, the prescribed burning policy replaced the fire suppression policy after emergent evidence of the necessity of fire in maintaining the health of fire-adapted vegetation, such as fynbos [15]. It was perceived that burning under controlled, safe conditions would reduce the occurrence and intensity of wildfires.

According to recent studies, prescribed burning, which had been encouraged for so long in fire management, could also contribute to the threat posed to the fire-dependent ecosystems by increasing the ignition sources, leading to increased fire frequency and a shorter return interval of fire[15]. The Fynbos fire regime is mostly affected by these frequent fires, causing a rapid spread and threatening the ecosystem. Additionally, frequent fires threaten the existence of plant species that take a longer time in between fires to mature, thus leading to weak plant coverage and increased soil erosion [15].

Although wildfires can occur from unplanned fire ignition sources such as lightning, they are caused mainly by human activities, intentionally or unintentionally. These activities include burning vegetation in preparation for fields, unattended campfires, disposal of lit cigarettes, and arson [16].

1.1.2 Wildfire Spread Prediction Modeling

The unpredictable behaviour and the potential for more frequent and intense wildfires present an urgent challenge to wildfire management, necessitating the development of wildfire spread predictive systems that capture the complexity of wildfire behaviour.

Wildfire spread models are predictive systems concerned with simulating wildfire spread to understand and predict fire behaviour [17]. The primary goal of all prediction systems is to allow end-users to make predictive forecasts about where the fire is most likely to spread, given the various parameters that influence the behaviour and spread of fire. By providing early predictions, these systems allow for the timely implementation of firefighting strategies, thus assisting in the mitigation of fire from spreading out of control and reducing or preventing catastrophic loss of biodiversity, life, and property [17].

Existing wildfire spread systems can be broadly categorized into physical, mathematical, and empirical. Physical models simulate wildfire behaviour using physics laws, specifically focusing on the conservation of energy, mass, and momentum [18]. These models are often too simplified and are limited in terms of capturing the complexities of wildfire spread. Additionally, once built, these models are difficult to change without reconstructing the model.

Mathematical models use mathematical equations to simulate wildfire spread. These models are overly designed for specific datasets and they perform well on known data, but poorly on unseen conditions. Therefore, advanced mathematical models involve extremely complex mathematical equations that require more computational power and specialised software to simulate [18].

The empirical models use historical data and statistical relationships to simulate the complex interactions between the fire and various environmental factors such as weather, terrain and fuel types [18]. These models solely rely on available data which may be incomplete, biased or noisy. Despite the significant contributions of these systems, they are developed based on specific regions' data; thus, they are often constrained by limited accuracy in predicting wildfire spread behaviour for unique environmental conditions, such as the Cape Floral Region.

1.1.3 Machine Learning Models in Wildfires Fire Spread Prediction

Researchers are exploring the use of Machine Learning (ML) models to overcome the limitations of the models discussed in 1.1.2. ML models process vast amounts of data from various sources to detect patterns and trends connected with the occurrence and spread of wildfires [19].

Satellite data has become a useful tool in wildfire spread prediction applications, offering vast, easily accessible, high-resolution key environmental, land-cover changes, and topographical data [19]. Large volumes of satellite data can be analyzed by ML models to detect patterns and trends connected with the occurrence and spread of wildfires, including the temporal and spatial distribution characteristics of factors that affect wildfire spread [19].

The integration of these freely available satellite data sources into Machine Learning techniques enables researchers in wildfire management to scale their systems beyond the traditional approaches, thus developing advanced wildfire spread systems, which can achieve improved accuracy and efficiency in monitoring ongoing fires [19, 20]. Accurate prediction of wildfire spread can assist fire management stakeholders in timely decision-making to suppress unwanted and unmanageable wildfires, thereby reducing the risk of catastrophic damages caused by these wildfires [19, 20]. This research leverages freely available satellite datasets and cutting-edge ML techniques to develop a data-driven wildfire spread prediction system tailored to the unique environmental conditions of the Mediterranean regions.

1.2 Study area: Mediterranean region, Cape Town, South Africa

Mediterranen-type climate(MTC) regions are indicated in figure 1.4, these regions include Western Chile, Southwestern Australia, California, the Mediterranean Basin, and the Western Cape of South Africa. These Mediterranean regions share similar climate and vegetation communities, with a climatic regime characterised by cold, wet winters and hot, dry summers, and with vegetation types mainly dominated by evergreen sclerophyllous-leaved shrublands and woodlands [1]. These suitable climatic conditions and highly flammable vegetation types make the MTC regions particularly vulnerable to frequent and intense wildfires.

While this research recognises the ecological and fire-prone characteristics of all MTC regions, it focuses particularly on Cape Town, South Africa, due to increasing wildfire frequencies, unique topography, and rapid wildland-urban expansion. Cape Town offers a localised study case within the broader context of MTC wildfire dynamics. By streamlining the focus to Cape Town while situating the discussion within the global MTC framework, the research avoids geographic bias and maintain relevance.

Fig. 1.4. The mediterranean climate regions in the world

1.2.1 Climate

The Cape region is considered a moist sub-humid to humid climatic region. Most wildfires occur in the dry summer months of November to March [21]. The average maximum temperature is 32 °C, and the minimum is 14 °C during the summer months. Total annual rainfall in the city averages between 500 and 600 mm, with most rainfall experienced during the winter season [22]. These conditions are characterised by the Mediterranean climate known for cold, wet winters and hot, dry summers.

Furthermore, a distinguishing characteristic of MTC regions is that during the rainy winter, precipitation exceeds potential evapotranspiration, leading to vegetation growth sufficient to build fuel loads that are extremely flammable during the dry summer seasons. The availability of highly flammable vegetation coupled with high temperatures in summer leads to frequently promoted wildfire events in summer [15, 1].

1.2.2 Vegetation

The Mediterranean regions are mostly dominated by evergreen sclerophyllous-leaved shrublands and woodlands [1]. Although the Cape region has the least landscape coverage compared to other Mediterranean regions, it is well known for its unique biodiversity and species richness. It is mostly dominated by shrubland vegetation, with the fynbos biome covering about 80% of all the vegetation in the Cape Floral Kingdom and containing over 9030 species, with about 69% endemic to this region [1, 23].

The Cape Florist biome's vegetation is not limited to fynbos shrublands; the other dominant types include the renosterveld shrublands found on relatively nutrient-rich shale substrates and granite-derived soils, and the stranded shrublands found mostly on coastal sandy soils and limestone substrates [24]. The fynbos and renosterveld vegetation are highly fire-adapted and fire-dependent for maintaining their health and regenerating new plants [15, 24, 25]. During the summer, the dry shrubs act as readily available fuel sources for fire, which results in the regular occurrence of wildfires in this region.

1.2.3 Topography

Maximum and minimum elevations in the Cape region are -1 and 1077 m respectively [26]. This shows that the Cape Region topography varies from very flat to steep slopes. The presence of mountainous terrain introduces more complexity in the prediction of wildfire spread due to elevation changes, and rapid changes in wind direction and speed [27]. In essence, all these mentioned factors affect wildfire frequency, intensity, and spread. Therefore, it is crucial that they are taken into consideration when developing a wildfire spread prediction system.

1.3 Problem Description

Wildfires are considered inevitable natural disasters that can quickly become uncontrollable and cause destruction and severe threats to human lives, biodiversity, infrastructure, and the economy. There is a rising concern about the increasing frequency and intensity of wildfires due to various factors such as climate change, past practices of fire management, and the expansion of urban development into high-risk wildfire areas. In MTC regions, these challenges are further exacerbated by the prolonged hot and dry climatic conditions experienced in the summer season and highly flammable vegetation cover, which provides an environment conducive to the rapid and unexpected spread of wildfires.

Understanding wildfire behaviour and its spread is a complex challenge that requires consideration of various factors such as topography, vegetation type, meteorology, and population. Currently, wildfire prediction models often fall short in accurately and timely predicting wildfire spread, which hinders an effective response in wildfire management. Additionally, traditional methods lack the spatial and temporal resolution required to monitor the dynamic nature of wildfires.

There is an increased need for advanced analytical and decision-making tools to assist with the efficient and effective management of wildfires. Moreover, developing these comprehensive and innovative tools that harness the potential of remote sensing data and ML techniques is essential to improving the ability to understand and predict the spread of wildfires.

Several ML techniques have been explored in wildfire spread modelling, each offering distinct strengths. ML models such as Random Forest, Support Vector Machines, and Decision Trees have been widely used for fire risk classification based on environmental data. However, models have a limited ability to model spatial and temporal dependencies. While advanced models such as Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) effectively handle temporal dependencies and Convolutional Neural Networks(CNN) handle spatial dependencies from the data, these models are often limited in independently predicting spatiotemporal complexities of wildfire spread behaviour.

1.4 Research Objectives

The objective of this dissertation is to develop a machine learning-based wildfire spread prediction system that models the spatiotemporal complexities of wildfire spread by leveraging satellite imagery, environmental and topographical data. This prediction system uses a variety of Machine Learning algorithms to investigate and explore the most effective approach for this purpose.

This research mainly focuses on:

- Developing and optimising the Artificial Neural Network, Convolutional Autoencoder and Convolutional LSTM Machine Learning algorithms for wildfire spread prediction.

- Incorporating satellite imagery, environmental and topographical features that affect wildfire spread as inputs to the system.

This system serves as a tool to assist in predicting the spatial and temporal properties of wildfires' progression from the ignition point to the surrounding areas over time. While, this project does not involve developing a Graphic User Interface(GUI), the need for one should be considered during the research and development of the wildfire spread prediction system.

1.5 Research Questions

This research aims to address the identified gaps in wildfire spread prediction models with a particular focus on the MTC's unique environmental and weather conditions that make it more favourable for frequent and more intense wildfires. The following key questions have been formulated to guide this research:

1. Which Machine Learning Models can accurately predict spatial and temporal patterns of wildfire spread?
2. What are the key factors that influence wildfire spread behaviour?
3. Which freely available satellite data sources with environmental, weather, and burn scar variables can be used to enhance the ML-based wildfire spread prediction performance?
4. How can the proposed ML models be used in fire management strategies for improved accuracy and reduced wildfire damages?

1.6 Significance of the Project

Firstly, this research investigates the efficiency and accuracy of various Machine Learning(ML) models in predicting wildfire spread's spatial and temporal properties. The best ML model with improved accuracy will contribute to improved evacuation planning and fire suppression strategies, thereby minimising the threat to human lives and reducing the ecological and economic risks associated with wildfires.

Secondly, wildfire spread is a complex phenomenon influenced by various factors. Recognising these complexities, the wildfire spread system designed in this dissertation incorporates various environmental and topographical factors, such as wind, temperature, and terrain. This not only enhances the reliability of wildfire predictions but also provides an understanding of how these factors affect wildfire spread to non-experts in wildfire science, such as volunteers and communities. This makes this system a useful tool in supporting collaborative efforts and improving community preparedness and response to wildfire threats.

Lastly, integrating freely available satellite data sources and Machine Learning techniques, together with the already existing wildfire spread models in wildfire science, can assist in improved systems that contribute to the preparedness and response capabilities of wildfire management services.

Below is an indication of some of the domains in which this wildfire spread system can be used:

- **Fire Management:** This system can be used in the planning and execution of firefighting strategies. By predicting fire progression over time, fire management teams can deploy resources effectively, ensuring that firefighting efforts are concentrated in the most critical areas.
- **Urban Planning:** The ability to predict wildfire spread is important in designing fire-resilient communities, especially for wildfire-prone areas like Cape Town.
- **Emergency Response:** incorporating fire spread's temporal properties is essential. By producing accurate and timely forecasts of wildfire behaviour, the system can inform, allocate resources and evacuation orders, and assist in effective response for various stakeholders such as firefighting teams, medical services, and law enforcement.

1.7 Scope and Limitations

1.7.1 Scope

Geographical Area: This research focuses on Cape Town, South Africa, a Mediterranean region, as a case study. It considers the Mediterranean region's distinctive climatic attributes and vegetation types, which make them suitable for frequent and intense wildfires.
Remote Sensing Data: This research used remote sensing data, particularly weather data from Google Earth Engine (GEE) and burn mask data from the Sentinel satellite.
Machine Learning Models: A supervised learning ML approach, namely, Artificial Neural Network (ANN), Convolutional Autoencoder, and convolutional-LSTM, is used for modelling wildfire spread prediction.
Season of the year: The research focuses on wildfires that occur during the summer seasons from December to March, which have a high likelihood of wildfires occurring.

1.7.2 Limitations

This research acknowledges the limitations that may affect the accuracy and generalisability of the wildfire spread prediction model. Each limitation along with its mitigation strategy and tools is outlined below.

1.7.2.1 Data resolution

Limitation: Achieving high temporal and spatial resolution in satellite data is a constraint. The primary satellite data sources, Sentinel-2 offer a maximum spatial resolution of 30 m x 30 m with a 5-day revisit time, while MODIS offers a maximum spatial resolution of 1km x 1km with a day revisit time. This limited the model's ability to support hourly fire progression predictions.

Strategy and tools: To address this, the data interpolation technique, which uses perlin noise algorithm to generate hourly landscape data is used. These generated landscapes act as interpolated temporal frames, filling the gaps between actual satellite captures, thus enabling the model to learn from hourly fire behaviour patterns.

1.7.2.2 Weather and topographical parameters

Limitation: The study includes weather and topography, with a major focus on wind speed and direction, temperature, and elevation. While this research is limited to these parameters, these parameters are among the most critical factors that influence wildfire spread particularly in MTC regions.

Strategy and tools: Given the significance of these parameters on wildfire spread behaviour, these key variables are prioritised to ensure the model's focus and computational efficiency.

1.7.2.3 Generalizability across MTC region

Limitation:
The development of robust ML models for wildfire spread predictions is essential. However, generalizing these models to geological regions with different environmental conditions could affect their accuracy and adaptation to other areas. It is mainly designed to suit areas with weather characteristics similar to MTC regions, particularly, Cape Town, South Africa.

Strategy and tools: A transfer learning approach can be adapted to train these models for different regions. In addition, data normalisation and regional calibration using location-specific datasets will help tailor the model to new geographies.

1.8 Document Outline

The rest of this document is outlined as follows:
Chapter 2 provides the literature review, which covers the fire behaviour and wildfire spread modelling and the technologies, theories, and techniques for wildfire spread predictions currently being used with a particular focus on Machine Learning approaches. It explores the different Machine Learning approaches and their application in wildfire spread prediction.

Chapter 3 details the research methodology employed and the Software Development Life Cycle(SDLC) approach used to develop the wildfire spread prediction system. The methodology outlines the project's phases: concept development, design, implementation, and testing. Each phase is closely aligned with the research objectives. Furthermore, the Iterative and Incremental SDLC model is adopted to ensure a systematic and adaptive approach is elaborated. This approach allowed for continuous system refinement through repeated development cycles, testing, and feedback. This chapter also covers the system analysis and real-world usability of the system.

Chapter 4 covers the design of the wildfire spread system. It begins by discussing the refined requirements and specifications and the high-level design of the entire system. It then explains satellite data downloads and the generation of data to form landscapes. Furthermore, it discusses the design choices made when developing the Artificial Neural Network, Convolutional Autoencoder, and ConvLSTM models, including the selection of hyperparameters, the structure of the neural networks, and how these models are integrated into the predictive system. Lastly, it explains the systems analysis tools used to evaluate and analyse the systems' performance.

Chapter 5 presents the results obtained in the testing and system analysis phase. This chapter showcases the performance of the ANN, Convolutional Autoencoder, and ConvLSTM models in predicting wildfire spread, including performance metrics like accuracy, precision, recall, and AUC_PR. This chapter will also showcase the system analysis results, including feature importance analysis and computational efficiency analysis, to demonstrate how well the system meets the objectives.

Chapter 6 presents the research's findings; it begins with a review of the research objectives and steps followed to achieve these objectives. followed by a discussion of the findings, including strengths and limitations of the ANN, Convolutional Autoencoder, and ConvLSTM models. It then discusses the insights gained from the results and any challenges encountered during testing. Then it concludes with a summary of the project's contributions and suggestions for future work.

Chapter 2

Literature Review

2.1 Introduction

Fire is an integral component in the functioning and structuring of ecosystems; it is one of the ecological disturbances that has driven the evolution of species over time. Exposure to fire in different ecosystems has led to adaptation techniques such as fire dependence and fire resistance. Fire-dependent ecosystems need fire to reproduce and maintain the health of such ecosystems, as these fires assist in critical processes such as seed dispersal, the cycling of nutrients, and the elimination of invasive species [28]. Fire-resistant ecosystems, on the other hand, have adapted to withstand fire by having thick protective barks [4, 2].

Large and intense wildfires can rapidly spread and become uncontrollable, leading to devastating impacts not only on those ecosystems but also on the surrounding communities [29, 30]. Thus, understanding fire behaviour characteristics and factors that affect fire behaviour is crucial in developing effective wildfire spread models. Fire behaviour refers to the overall release of heat energy when combustion occurs; it can be characterised by the fire front rate of spread, fire intensity, and fire severity discussed further.

Rate of spread(ROS):

The rate of spread is defined as the speed in m/s at which the fire perimeter expands from the ignition point to the surrounding areas. It is among the most important parameters used when analysing fire behaviour [31, 32, 33]. The wind, topography, fuel, and weather conditions affect the ROS, with wind and fuel aeration having the most instantaneous effects [32].
ROS can be expressed in many ways; equation 2.1 shows one of many ways to express ROS, which defines the technique for estimating the mean rate of spread for surface fires . The data obtained from recording the period of flame combustion, the burned area, and the mean length of the fire front are used in the equation [34].

$$\text{ROS} = \frac{A}{T} \times L \tag{2.1}$$

where:

$$\begin{aligned}
\text{ROS} &= \text{mean rate of spread (m/s)} \\
A &= \text{area burnt } (\text{m}^2) \\
T &= \text{period of flaming combustion (s)} \\
L &= \text{mean length of fire front (m)}
\end{aligned}$$

Fire intensity:
Fire intensity is expressed as the amount of heat energy per unit time per unit length (kJ/s/m) dissipated by fire. As depicted in equation 2.2, the fire intensity is a product of heat yield, fuel mass available, and ROS [34].

$$\text{I} = H \times W \times R \tag{2.2}$$

where:

$$\begin{aligned}
\text{I} &= \text{fire intensity (kJ/s/m)} \\
H &= \text{heat yield (kJ/kg)} \\
W &= \text{mass of available fuel } (\text{kg/m}^2) \\
ROS &= \text{rate of spread of the fire front(m/s)}
\end{aligned}$$

Fire severity:
The amount of biomass and surface soil organic matter burned is defined as fire severity. Dry, hot, windy conditions with large amounts of fuel yield more severe wildfires, resulting in severe burns that can damage re-sprouting plants [34].
ROS, fire intensity and fire severity provide a framework for how fire develops and impacts the surroundings. These fire characteristics are influenced by various factors such as topography, vegetation (fuel), weather conditions, and ignition sources. The next section will detail how these factors impact fire behaviour and, in turn, wildfire spread.

2.2 Factors Affecting Fire Behaviour

The impacts of fire over time can be classified into three categories: flame ignition, single wildfire, and fire regime [35]. A fire triangle illustrates the various factors influencing fire behaviour for each category. Temporal and spatial variations of the fire triangle provide a valuable framework for investigating controls of fire at different scales [4]. Fig. 2.1 illustrates the fire triangle in the form of dominating factors that affect fire at different scales.

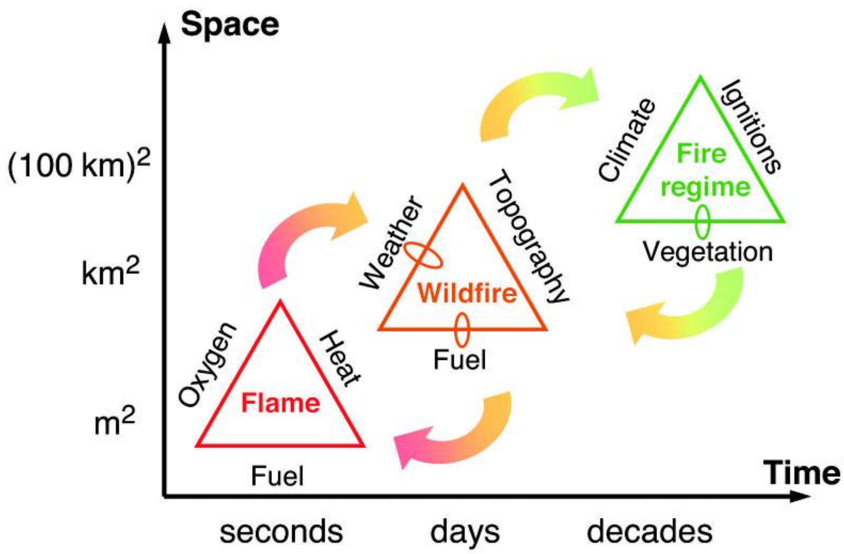


Fig. 2.1. Key factors that affect fire at different scales, namely, flame ignition, single wildfire and a fire regime [4]

2.2.1 Flame ignition

From fig. 2.1, the fire triangle illustrates the principles of fire combustion, where each side represents the three essential components necessary for a flame to ignite, namely: oxygen, heat, and fuel [32]. These three components influence the combustion rate. Oxygen is required for the chemical process of fire to burn, and fuel acts as a combustible material. When fuel burns, it reacts with the surrounding air (oxygen), releasing heat and generating combustion products [4]. Once a flame has started at the ignition point, heat is transferred to the surrounding areas through three mechanisms: conduction, radiation, and convection [36, 37]. These mechanisms contribute to fires' rapid spread and intensity.

- **Conduction** refers to the direct transfer of heat through a solid material such as the ground or vegetation.
- **Radiation** is the process in which heat is transferred through electromagnetic waves.
- **In convection**, as the fire burns and heats the air above it, this hot air rises and creates strong updrafts, which, in turn, causes the cooler air to transition to the base of the fire, fueling the flames.

Conduction mainly contributes to igniting fuels in contact with other burning materials, while radiation preheats and dries out the vegetation ahead of the flames. Although the combined effects of these three mechanisms drive the spread of wildfires, convection plays a significant role in fire spread as it is responsible for the rapid vertical and horizontal movement of flames [38].

2.2.2 Single Wildfire

Wildfires spread freely due to the limitless oxygen supply and availability of flammable materials in the forests, such as shrubs, grass, and trees. Interactions between the three essential components in the wildfire triangle, namely fuel, weather, and topography, determine wildfire behavior [4]. These factors influence wildfire spread characteristics such as fire rate of spread, intensity, and severity [4].

2.2.2.1 Fuel

Fuel is any flammable material that provides energy for wildfires. Fire behaviour is significantly related to the amount and type of fuel present for combustion. Different fuel characteristics, such as moisture, temperature, shape, and size, determine the ignition ability and spread of fire [39, 40].

Moisture
Moisture is the quantity of water in a fuel, represented as a percentage of the total oven-dry weight of that fuel. The moisture content of fuels has a significant impact on fire behaviour. It influences its combustibility and, subsequently, the fire rate of spread [40, 41]. As moisture content increases, the ROS decreases [42]

Temperature
The sun's heat energy warms the earth's surface, which heats the surrounding air and the fuels, reducing moisture content and bringing fuels closer to ignition temperature. In contrast, cooler temperatures have the opposite effect [40].

Shape and size
Fuel size and shape affect the heat transfer rate and the moisture content change. Fuel sizes are categorised into light, medium, and heavy. Light fuels produce higher ROS than medium and heavy fuels in similar atmospheric conditions [40].

2.2.2.2 Weather

The interaction of various weather elements, such as temperature, wind, relative humidity, and precipitation, results in weather conditions that affect wildfire behaviour [43].

Relative humidity
Relative humidity is the amount of air moisture that can add or remove fuel moisture. It is another factor that influences fire behaviour; more moisture in the air reduces the fuel's ignition probability [40].

Precipitation
Precipitation is the collection of solid water particles falling from the atmosphere to the earth's surface. The amount and duration of precipitation affect the fuel's moisture, and precipitation frequency increases moisture content and decreases the ROS [40].

Wind
The wind is the motion of air, measured in terms of direction, speed, and turbulence [32]. Wind and fuel moisture are the two most critical weather-related factors influencing wildfire behaviour.

The increase in wind spread causes an increased rate of drying fuels, while the wind direction determines the direction in which fire will spread [32].

Variation in wind speed and direction influences the shape of the fire perimeter [41]. The wind is more variable and unpredictable; it can unexpectedly change the spread and direction, resulting in sudden changes in the rate and direction of fire spread and the fire intensity [40, 32].

2.2.2.3 Topography

Holsinger [44] studied the influence of topography on wildfire spread. Topography describes the physical characteristics of the land surface, such as slope, aspect, and land cover. The impact of these characteristics on wildfire behaviour is discussed further.

Land cover
The different fire behaviours for different land covers show that wildfire susceptibility varies from ecosystem to ecosystem [27]. For example, shrublands commonly found in Mediterranean regions are more prone to wildfire than farmlands and agro-forestry areas [45]. Moreover, shrubs contain very flammable chemical content that can significantly increase the fire intensity [46].

Slope
The slope of the terrain influences the wildfire spread rate. The slope refers to the incline of any land mass, and the steeper the slope, the more susceptible the area is to wildfires [45]. Fire spreads more quickly uphill than downhill due to the upward movement of heat and flames and the preheating effect of ascending smoke [47, 45, 27]. With wind assistance, flames moving closer to the fuel on the uphill side dehydrate, preheat, and ignite them more quickly, increasing ROS [48].

$$R = R_o \cdot e^{b \cdot x} \tag{2.3}$$

where:

$$\begin{aligned}
R &= \text{rate of spread (m/s)} \\
R_o &= \text{rate of spread on level ground (m/s)} \\
e &= \text{exponential function} \\
b &= 0.0693 \\
x &= \text{angle of the slope (degrees)}
\end{aligned}$$

Equation 2.3 indicates the exponential relationship used to estimate slope effects on the surface head's ROS. This relationship is suitable for gradients less than 30° as the fuel at the surface for steeper slopes usually becomes discontinuous [32].

Aspect
The aspect of a slope impacts the effect of the sun's heat on the plants and trees on the slope, as well as the air temperature and moisture retention of the soil. By changing fuel moisture, solar radiant heating can influence fire behaviour. South-facing slopes are drier as they typically receive more sunlight, which promotes fire spread, than north-facing slopes, which may retain moisture. [44].

2.2.3 Fire Regime

Interactions between numerous weather conditions and ecological factors determine the range of fire sizes, fire spread rate, and day-to-day fluctuations in fire behaviour. This forms general patterns in which fires naturally occur in a particular ecosystem over an extended period, forming fire regimes [49]. Fire regimes are essential for understanding and interpreting the effects of changing climate on fire patterns and characterising their combined impacts on vegetation. Different fire regimes have evolved alongside various vegetation types that are adapted to, or resistant to wildfires [50]. The fire regime drivers, such as vegetation, climate, and ignition patterns, are shown in fig. 2.1 [4].

2.2.3.1 Vegetation

Vegetation is one of the significant elements that influence the natural fire regime patterns. It has been understood that vegetation influences the pattern of fire behaviour in wildfire science [51]. Studies on forest ecosystem wildfires focused on fuel moisture and fuel amount as the vegetation characteristics used to describe fire patterns [51].

2.2.3.2 Climate

Climate is well known to influence fire regions [39]. Meyn .et .al [51] state that long-term patterns in climate impact fuel moisture and fuel accumulation in an ecosystem. Climate change affects the primary productivity and decomposition of fuel globally by affecting the distribution of biomass moisture. Climate is another contributor that directly impacts wildfires' size, frequency, and intensity. [51, 52].

2.2.3.3 Ignitions

Fire ignitions are important in defining an area's fire regime and understanding the frequency of how often ignition events occur; their intensity and timing are crucial in fire behaviour prediction. Although lightning has been the primary non-human ignition source in African regions, most fire ignitions are caused by human activities through arson, accidental and prescribed burns [32].

In summary, this section discussed the factors that affect wildfires at different spatial and temporal scales. It detailed how each of these factors influences wildfire behaviour. These factors are vital in formulating fire spread models that predict how fire propagates through a landscape from the ignition point. The next section discusses wildfire spread modelling in detail.

2.3 Wildfire Spread Models

Modelling wildfire spread is a complex phenomenon affected by various factors, some of which are discussed in the above section. The fire-spread models investigate and predict the likelihood of fire propagating from the ignition point to the surrounding areas given the different parameters that affect fire spread [53]. Various wildfire spread simulation frameworks have been developed throughout history to predict temporal and spatial properties of fire propagation across the landscape. The early generation of wildfire spread models was categorised into physical, empirical, and mathematical frameworks explored further.

2.3.1 Physical Models

Physical-based models simulate fire behaviour based on the physical and chemical fundamentals of fire combustion and fire spread. They are, therefore, developed primarily for understanding the physical and chemical theoretical concepts that govern fire propagation [8, 54]. Fully physical models are based on the conservation of energy, mass, and momentum principles [55]. These principles are applied in a multiphased environment formed by vegetation fuel and atmospheric airflow. The solutions for such systems are formed using coupled non-linear partial differential equations in a 3D mesh grid [55]. Among other models, FIRETEC and WFDS are purely physical models.

2.3.1.1 FIRETEC

FIERETEC aims to model the typical behaviour of gases and fuels in wildfire presence. The model captures the physical processes primarily based on the principles of conservation of mass, energy, and momentum [54, 56]. Some of the physical processes that drive wildfires being investigated include the effect of non-homogeneous topography, transient wind conditions, non-uniform fuel beds with patchy distributions, and various vertical fuel structures [56].

This model represents interactions of the combustion, heat transfer, and fluid mechanics to study the effects of the atmosphere using a completely compressible gas transport concept [54]. The fully compressible gas transport formulations are used in conjunction with the HIGRAD (a hydrodynamics model to solve equations of high gradient flow) to simulate wildfire spread using a terrain-following three-dimensional grid with finite volume [56, 57, 58].

According to Sullivan [54], FIRETEC makes predictions about the propagation and behaviour of wildfires based simply on the formulations of the physics and chemistry involved rather than empirical interactions. Furthermore, the model has a high computational complexity, with a simplified FIRETEC simulation for a reasonable domain size running at one to two orders of magnitude slower than real time [54].

2.3.1.2 Wildland fire dynamic simulator

The Wildland Fire Dynamic Simulator (WFDS) is an extension of the Fire Dynamic Simulator (FDS) model, which was designed to predict fire spread within structures [54]. WFDS is a

3D computational model used to simulate the behaviour and spread of wildfires. It is based on formulations of motion equations for buoyant flow [54, 58]. These equations describe various physical attributes of wildfires such as fire combustion, heat transmission, and fluid dynamics [54, 57]. It predicts the rate of fire spread, the direction of fire spread, and the heat and smoke release of wildfires. To achieve this, the model considers various factors that affect the behaviour of fire, such as wind speed and direction, fuel type, fuel moisture content, and the slope and aspect of the terrain [54].

WFDS performs well; however, it is a computationally expensive model not suitable for real-time wildfire simulations [59]. These models require significantly more computational resources, and when dealing with large-scale wildfires, the resolution of the computational domain and the precision of the physical model are reduced significantly [54].

FIRETEC and WFDS models were validated using large-scale experimental grassland fires; hence, these models were initially not validated against actual wildfire observation data. Later, when validating against wildfire observation data, several deficiencies such as poor generalisation to complex topographies, sensitivity to input data, and reduced predictive accuracy under dynamic conditions were uncovered [54].

These limitations, therefore, highlight the necessity for data-driven or hybrid wildfire spread modelling approaches such as Machine Learning-based system that can learn complex fire behaviour patterns from historical wildfire data.

2.3.2 Mathematical Models

Mathematical analogue models are based on mathematical precepts to simulate fire spread over a landscape. These models often use a propagation algorithm mainly based on mathematical functions applied in wildfire spread [17]. Most of these approaches require computation resources to undertake the calculations required for implementing the mathematical concepts. The mathematical models discussed further are Rothermel Spread Model and FARSITE.

2.3.2.1 Rothermel spread model

Rothermel's spread model was developed by applying the conservation of energy principle to a unit of fuel ahead of a constantly approaching fire. The rate of spread is, therefore, defined as the ratio of the heat flux received from the source to the heat required for igniting by the potential fuel [38, 32].

This one-dimensional equation 2.4 is used to predict the crown and surface ROS. Although this model forms a basis for fire behaviour analysis used in various wildfire spread models, its limited dimensionality, static environmental inputs, and its inability to represent complex wildfire dynamics limit its suitability for wildfire prediction.

$$R = \frac{I_{\mathrm{R}} \cdot \xi \cdot (1 + \phi_{\mathrm{W}} + \phi_{\mathrm{S}})}{\rho_{\mathrm{b}} \cdot \varepsilon \cdot Q_{\mathrm{ig}}} \tag{2.4}$$

where:

$$\begin{aligned}
R &= \text{rate of spread (m/min)} \\
I_{\mathrm{R}} &= \text{intensity of flame reaction()kJ/min.m}^2) \\
\xi &= \text{coefficient of heat flux} \\
\phi_{\mathrm{W}} &= \text{ wind factor} \\
\phi_{\mathrm{S}} &= \text{slope factor} \\
\rho_{\mathrm{b}} &= \text{bulk density of the fuel (kg/m}^3) \\
\varepsilon &= \text{effective heating number} \\
Q_{\mathrm{ig}} &= \text{heat of pre-ignition (kJ/kg)}
\end{aligned}$$

2.3.2.2 FARSITE

FARSITE is described by the author Finney [60], as a two-dimensional deterministic model used to simulate fire growth across the landscape. It incorporates various fire behaviour models such as crown fire, surface fire, point-source acceleration, and spotting. These models were integrated using a vector propagation technique (Huygens' Principle) for simulating fire growth [60].

At specified time intervals, the model generates vector file perimeters (polygons) defined as two-dimensional points in (X,Y) coordinates [60]. These polygons' vertices consist of information about a fire's spread rate and intensity. The size of the fire polygon is calculated as a product of the spread rate and direction from each vertex by the timestep duration. As the fire grows over time, the number of polygons increases due to fire growth over a while, thus representing fire spread. This information is then interpolated to create raster maps of the fire behaviour [60].

The major constraints of this model are the static use of environmental inputs, which don't capture rapid changes in weather conditions and the extensive pre-processing required. In summary, mathematical models rely on fixed equations that often assume uniform conditions, thus limiting their flexibility and ability to learn complex wildfire behaviour patterns.

2.3.3 Empirical Models

In the past, the focus on empirical models has been the determination of the key characteristics that describe the fire behaviour, such as the Rate of Spread (ROS), flame height and flame depth at the head. The main aim of these models is to predict the fire propagation across a modelled 2-dimensional landscape. Wind direction is a key component used in empirical models; therefore, fire propagation is modelled in the direction of wind [18, 61].

Although these models are based directly on a statistical analysis of fire behaviour observations and do not incorporate any physical basis, there are quasi-empirical models, which incorporate some form of physical framework to support the chosen statistical model [18].

2.3.3.1 Heath

Heath is an empirical model developed in Australia by multiple research organisations. This model uses experimental and prescribed burn fire records for model fire development. It uses deterministic equations to simulate the rate and the direction of surface fire spread. The effects of multiple varying parameters such as fuel, terrain, and weather conditions on the Rate of Spread (ROS) of fire are modelled. [18].

Because of the highly pragmatic approach used in this model, its direct relation to real fires and their low computational complexity due to straightforward implementation, this model is the most predominantly used by wildfire authorities [53, 18, 61]. While this model follows a structured and computationally efficient approach, it is limited in capturing real-world data variability. Additionally, its simplification reduces the accuracy of wildfire prediction.

Previously discussed spread models formed a foundation for predicting fire behaviour through physical, mathematical, and empirical methods. These methods have shown limited assumptions of homogeneous fuels, static environmental conditions, and computational complexities. With technology advancements and increased access to open-source data, understanding and prediction of wildfire spread using Machine Learning techniques and remote sensing data are explored [58].

This research proposes a Machine Learning-based wildfire spread system to overcome the limitations of traditional wildfire spread systems. These ML systems leverage data-driven algorithms trained on satellite imagery and environmental and topographical data, hence enabling the capturing of complex, nonlinear patterns that affect wildfire spread. In the next chapter, we shall further explore the use of remote sensing data and machine learning techniques. This will assist in informing the decision-making of the models presented in the current study.

2.4 Machine Learning Algorithms in Wildfire Spread Modelling

This section explores the use of ML algorithms in wildfire spread modelling and the integration of remote sensing.

Remote sensing via the use of satellite data provides a global option for imaging wildfires, producing vast amounts of spatially and temporally consistent data which is publicly available [62]. There are a variety of large-scale multi-sensor satellites used for capturing and analysing the fire impacts by forest fire management [62]. These sensors include polar-orbiting and geostationary sensors such as the Moderate Resolution Imaging Spectroradiometer (MODIS), the Advanced Very High-Resolution Radiometer (AVHRR), the Landsat series, and the Visible Infrared Imaging Radiometer Suite (VIIRS) [63]. Polar-orbiting satellites have higher spatial resolution than geostationary satellites since they orbit at a lower altitude and eventually cover the whole Earth's surface. The VIIRS sensor on the Suomi NPP satellite collects wildfire-related signals with a 375m resolution. The MODIS instrument aboard the Terra and Aqua satellites collects wildfire-related data with a 1km resolution [63].

Having access to vast satellite data reduces spatial constraints in wildfire spread modelling as it provides continuous Earth's surface coverage. The imagery and data such as thermal anomalies, topographical data, weather data, and vegetation indices can be used as input data to the Machine Learning (ML) models. These ML algorithms identify patterns and explicitly learn their mappings from data, making them helpful in learning complex wildfire behaviour and enabling accurate prediction of wildfire spread. Such prediction models aid decision-making and reduce wildfire's adverse impacts [53, 5].

Various Machine Learning algorithms have been widely adopted to solve the diverse range of complex challenges in wildfire science and management as shown in fig. 2.2 [5]. This section mainly focuses on ML algorithms for predicting wildfire spread, among other vast applications in fire science and management. Machine Learning can be broadly categorised into supervised, unsupervised, and reinforcement learning discussed further.

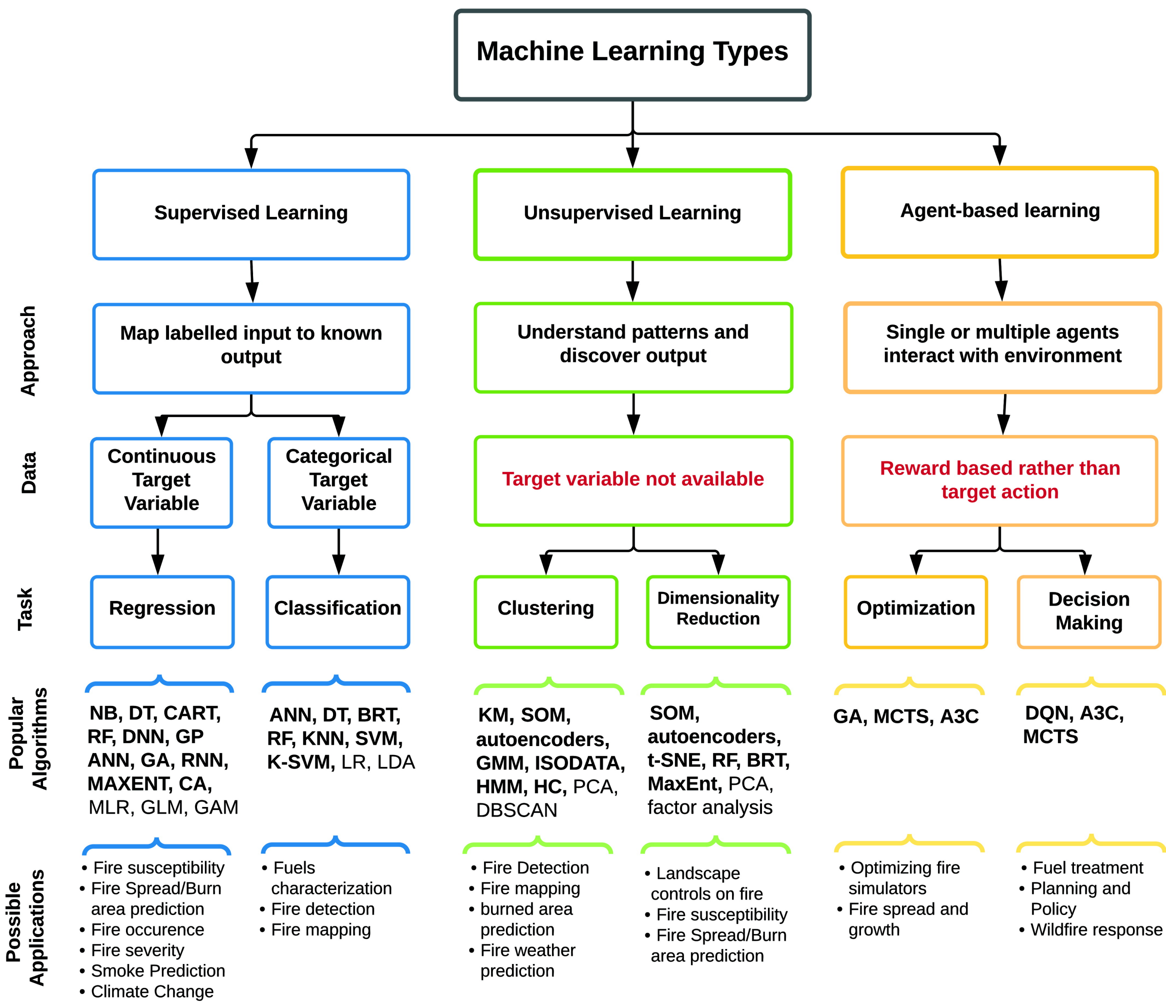


Fig. 2.2. Machine learning types and their potential application in wildfire science [5]

2.4.1 Supervised Learning

In supervised ML, a parameterised function is used to learn the mapping between known inputs and known outputs. The purpose of supervised learning is to use an algorithm to learn the parameters of a function from existing data. Algorithms used in supervised learning models to predict wildfire spread include, but are not limited to, Artificial Neural Networks, Convolutional Neural Networks, Convolutional Autoencoder, and Convolutional LSTM.

2.4.1.1 ANN, ConvAuto and ConvLSTM algorithms

Artificial Neural Networks

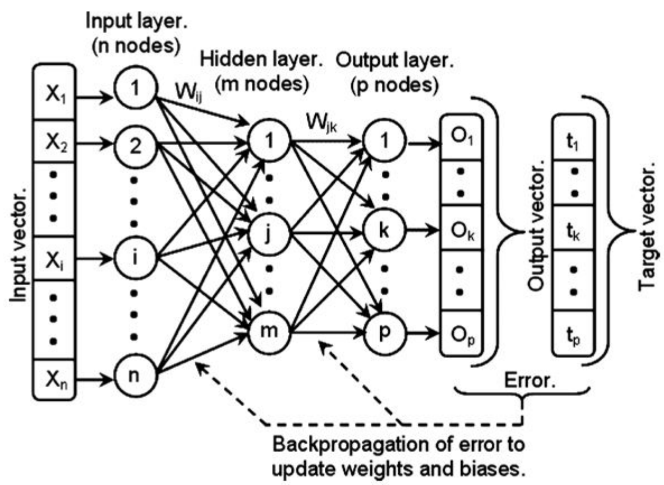


Fig. 2.3. Artificial Neural Network

An ANN Algorithm comprises interconnected multilayer neurons that process input to produce an output. The architecture has three layers: inputs, hidden layers, and output layers. The input layer receives and sends data to the neurons in the hidden layer. Each neuron applies a weight to an input signal, passing the result through an activation function to produce an output sent to the output layer [7]. A backpropagation is then used to update the weights and biases to reduce the error between the actual and predicted outputs, as shown in fig 2.3. ANN can accurately classify tasks by learning the data's complex patterns and non-linear relationships. Additionally, they allow for the integration of diverse data and can effectively learn from large datasets [7].

Convolutional Autoencoders

Convolutional Autoencoders are specialised neural networks optimised for processing 2D data structures such as images. Their basic structure consists of the following components: the encoder, bottleneck, and decoder. The Encoder compresses the input using convolutional and pooling layers. At the end of the encoder, a bottleneck is added to further compress the representation. From the bottleneck, the decoder is used to reconstruct the output via transposed convolution.

Convolutional LSTM

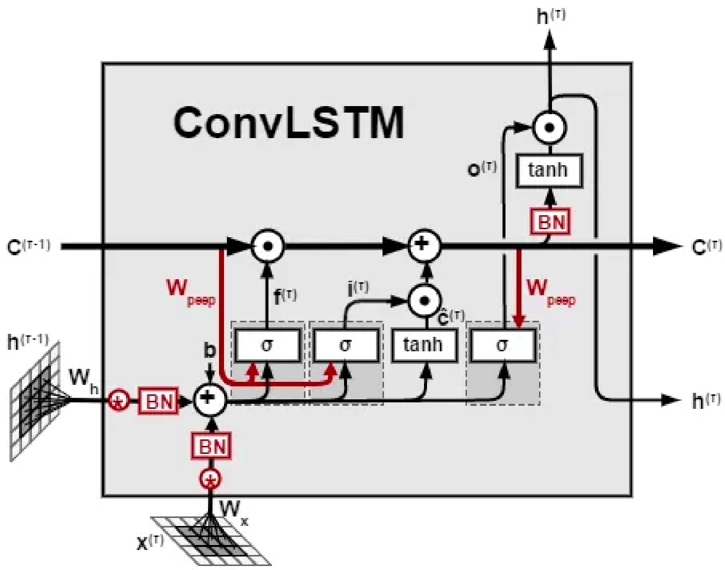


Fig. 2.4. ConvLSTM Cell

ConvLSTMs are specialised neural networks designed for processing spatiotemporal data structures such as video sequences. They incorporate convolutional layers for spatial feature extraction capabilities and LSTM units for temporal memory capacity. The convolutional processes within the LSTM gates allow the network to capture spatial dependencies in the input data; then, the recurrent connections allow it to model temporal dynamics.

LSTM is a Recurrent Neural Network architecture that adds a temporal dimension to the prediction by maintaining its state over time, allowing the network to have memory. ConvLSTM replaces matrix multiplications in typical LSTM cells with convolution operations, as shown in figure 2.4, making them especially useful for tasks requiring spatial and temporal correlations, such as wildfire spread prediction.

2.4.1.2 Supervised learning algorithms in wildfire spread prediction

FireCast model

The FireCast incorporates deep supervised machine-learning techniques. It uses 2D Convolutional Neural Networks(CNN) and data collection strategies from Geographic Information Systems (GIS) to predict areas surrounding a burning wildfire perimeter which have a high potential of burning in the next 24 hours of a fire ignition [64]. Geospatial inputs such as satellite imagery, weather data, elevation data, and historic fire perimeters are used to identify patterns associated with fire spread for certain environments to predict wildfire spread [64]. The Landsat8 satellite imagery is used as a visual input with its images taken on an interval of every few months, while the weather data parameters include the temperature, atmospheric pressure, dew point, wind speed, wind direction, precipitation, and relative humidity. The historic fire data perimeters are taken from the GeoMAC database, a USGS database.

The output of this model is an image of the area that displays the sampled POIs which are coloured in correspondence to their predicted values to burn, the images display areas that the model believes are locations of high risk for the fire spread [64]. FireCast is computationally inexpensive and can outperform currently used models in predicting the spread of fire, but because of limited training data, the model relied on data augmentation and weather interpolation to generate the required data needed to effectively train the model [64].

Next day wildfire spread model

The Authors Hout et.al [65] implemented a neural network model which takes advantage of the 2D spatial information and day in the prediction of wildfire spread. This model predicts the next day's fire spread using input data such as topography, vegetation, weather, drought index, population density, and historical wildfire burn area masks. It uses convolutional autoencoders, a specialised neural network to perform image segmentation on the data [65].

The Next Day Wildfire Spread (NDWS) and FireCast models both rely on the supervised learning ML algorithms. They both can capture the spatial features of wildfire spread, making them well suited for the dynamic fire spread prediction modelling. However, FireCast is limited in the temporal modelling of fire spread prediction, while the NDWS can predict future spread from the current state.

2.4.1.3 Unsupervised learning

In unsupervised learning, the models learn by dimensionality reduction and clustering, with patterns or relationships extracted from data without any guidance to the correct answer [5].

Self-organising Map (SOM) is an unsupervised learning ML algorithm that consists of a 2-dimensional array of nodes as an input layer [5]. SOM has been successfully used in situations where there was no expected outcome from the input data. Topography is preserved as nodes are arranged in a specified grid on the map when using the SOM algorithm. The Hidden Markov Model (HMM), compared to experimental results, showed good agreement with each other for real-time fire detection [66]. HMM-based flame detection models are robust and show high computational efficiency in detecting flames in colour video.

HMM also proved a reduction in false alarms due to the ordinary motion of flame-coloured moving objects. However, due to the strength of the wind having a direct influence on the spreading characteristics of the flame, it makes it impossible to model a periodic behaviour of flame boundaries within the same location and fixed time [67].

2.4.1.4 Reinforcement learning

Reinforcement Learning (RL) differs from supervised and unsupervised learning in that an agent learns the desired behaviour that maximises some reward by interacting with the environment [5]. In RL, the problem is modelled as a Markov Decision Process(MDP), whereby the transition probabilities are rather than explicitly known. Various RL algorithms include Value Iteration, Policy Iteration, Q-Learning, Monte Carlo Tree Search(MCTS) and Asynchronous Advantage Actor-Critic (A3C).

S Subramanian and M Crowley [68] introduce the approach of using reinforcement learning to investigate the wildfire spread dynamics by use of fire as an agent on the landscape, taking spatial actions as a response to various environmental factors. It also analyses the behaviour of spatially spreading process domains, which include wildfire spread prediction, using the five reinforcement algorithms stated above.

The wildfire spread prediction problem is represented as the Markov Decision Process with **S** as a set of states describing any position on the landscape and the agent as the fire which can spread in any surrounding cell of the landscape in any of the four cardinal directions or not spread [68, 69]. In the training phase of the model, the goal is to learn the policy that regenerates the spread of the fire by using a reward system whereby a positive reward is given to the agent for taking actions similar to the actual scenario. Otherwise, a negative reward is awarded. Satellite image data with a spatial resolution of 30m was used to validate the model predictions.

The performance comparison of these models was conducted to indicate which algorithms perform best in different situations. Among the five models simulated, the two algorithms that have shown the highest success rate in predicting the wildfire spread in the regions they were trained are the Monte Carlo Tree Search (MCTS) and A3C, and of the two algorithms, the A3C seemed to produce the best prediction due to having the most flexible state-action value function representation [68].

This model combines MCTS and A3C algorithms to predict spatial wildfire spread. The MCTS-A3C model uses satellite images along with deep reinforcement learning whereby the AI agent is the fire given the task of spreading over the surrounding areas [69]. This problem is formulated as an MDP with a set of states S defining any particular landscape location.

The agent's main goal is to learn a policy that regenerates the spread of fire by maximizing the discounted rewards meant to encourage high accuracy and precision of simulated images [69]. This model uses data from historical wildfire events and incorporates the largest fire spread factors: temperature, wind speed, wind direction, humidity, vegetation type, and water [69].

This literature review highlighted the evolution of wildfire spread prediction modelling from traditional physical, mathematical, and empirical models to more advanced data-driven approaches which use ML algorithms. While these early models provided a basis for understanding fire behaviour, they are limited mostly by assumptions of constant environmental conditions, uniform fuel distribution, and simplified terrain. Research has shifted toward ML models leveraging satellite data, weather, and topographical data to improve prediction accuracy and adaptability. Building on these advancements, the current study proposes a machine learning-based wildfire spread prediction system using the following ML algorithms: ANN, Convolutional Autoencoder, and Convolutional LSTM.

Chapter 3

Methodology

3.1 Introduction

Chapter 2 reviewed the literature on wildfire behaviour and the systems already in place for wildfire spread prediction. In this literature review-supported study, the literature heavily informed the concepts and techniques used in this research to achieve the objectives stated in the Introduction section 1.4. This methodology chapter explains the research process in modelling a predictive wildfire spread system.

An integrated mixed-method approach that combines a structured software engineering framework with qualitative and quantitative analysis is used to guide the research process and development of the wildfire spread system. At its core, this research follows the Iterative and Incremental Development (IID), Software Development Life Cycle (SDLC) model as shown in figure 3.1. This model provides a methodical framework for system development, while qualitative analysis and empirical evaluation ensure more contextual relevance and real-world applicability of the wildfire spread prediction system.

The IID model was chosen amongst other SDLC models, as it provides a flexible approach for handling complex and dynamic systems such as wildfire spread prediction. Unlike the waterfall model, which follows a linear approach, the spiral model, which focuses on risk assessment, or the Agile model, which focuses on adaptability and customer collaboration, this incremental and iterative approach focuses on structured gradual system enhancements through repeated cycles [6].

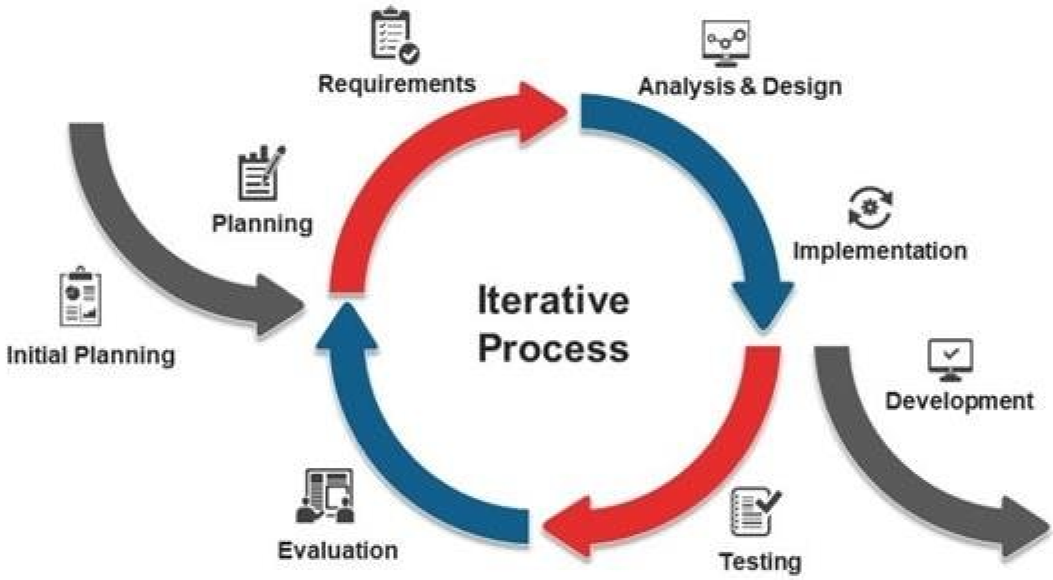


Fig. 3.1. Iterative and Incremental model [6]

The model involves going through the SDLC phases incrementally and iteratively, whereby the software is built in repeated cycles while at the same time enabling the incremental creations of improved solutions informed by feedback from end users and evaluation metrics regularly [70, 6]. These phases are divided into the Concept Development phase, the Design, Implementation and Testing phase and the System Analysis phase.

3.2 Concept Development Phase

The concept development phase established the foundation of the wildfire spread system. This initial planning phase involves the following steps: concept exploration, requirements development, literature review, and requirements analysis, as illustrated in figure 3.2.

Concept exploration involved refining the research process, which involved clearly defining the research topic, understanding the expected outcomes, and identifying and evaluating the potential approaches to follow. This was achieved by identifying the key challenges in the prediction of wildfire spread, formulating research questions and objectives, outlining the importance of the research, and determining its scope.

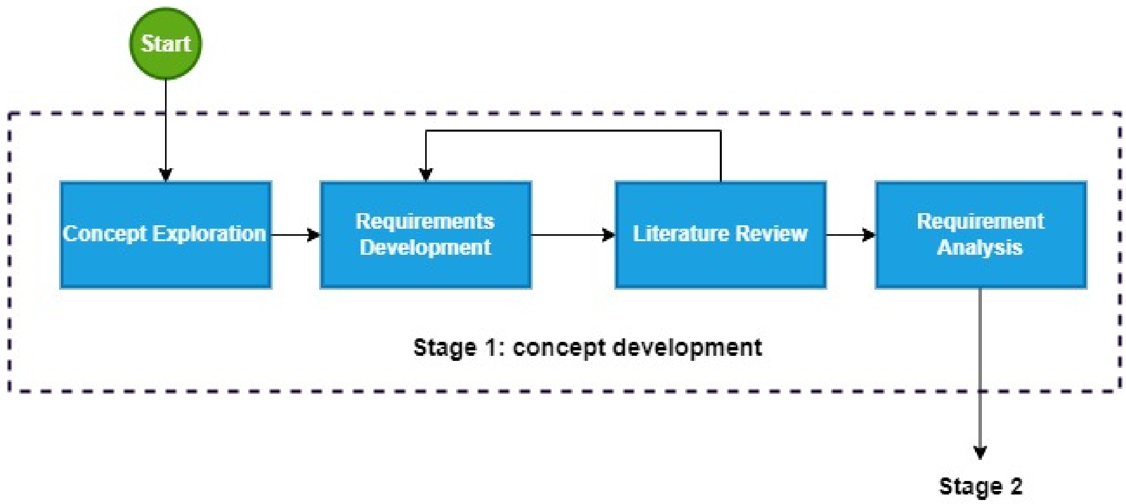


Fig. 3.2. Concept Development phase

The requirements development and literature review are the next steps in the initial planning phase. These steps involved developing the initial system requirements from the concept exploration findings. This was achieved by a qualitative review of the literature on existing models, which provided insights into their strengths and limitations and hence identified research gaps.

Finally, the requirement analysis involved a thorough examination of the system requirements to ensure they were well-defined and aligned to the research objectives. Since the iterative and incremental model is followed, the systems requirements were developed iteratively, meaning that the literature and expert knowledge was continuously revisited to refine the requirements.

The outcomes of the concept development phase are documented in Chapter 1 - Problem definition, Research Objective, significance of the project and scope and limitations, Chapter 2 - Literature review and Chapter 3 Section 4.1 - Refined requirements of the system.

3.3 Design, Implementation and Testing Phases

Figure 3.3 indicates the design, implementation and testing phase, which involves translating conceptual plans and system requirements into a working system. In the design phase, the first step is to derive the design specifications from the refined requirements. These specifications guide the selection of input data parameters, ML models, development frameworks and system architectures. These design specifications are detailed in design chapter, section 4.1.

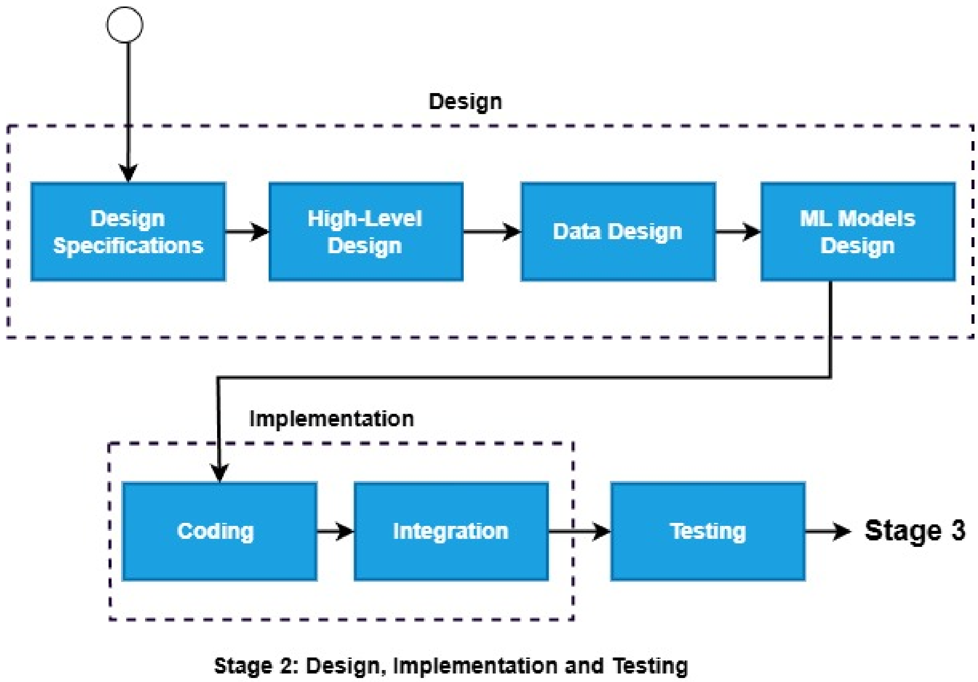


Fig. 3.3. Design, Implementation and Testing

The high-level system design follows the design specifications and provides a structured overview of the overall system architecture. It outlines the core system components, their functions and interactions between different modules. Guided by the high-level design, the detailed design which is split into the data design and ML models design follows. This further refines the system architecture by specifying data source selection, preprocessing techniques, feature engineering methods and model selection.

The selected data parameters include burn Maps downloaded from the sentinel 2 satellite package, and the wind speed, wind direction, temperature and elevation downloaded from MODIS packages. Preprocessing techniques such as feature scaling, outlier removal, and missing values handling were applied to standardise the data. This processed data together with the generated data combined into stacked layers to form generated landscapes, used as inputs to the ML models.

The ML model design involved selecting the appropriate model types, layers, and computational structures to handle the complexities of wildfire data. The following architecture: Artificial Neural Networks(ANN), Convolutional Autoencoders, and ConvLSTM, among others, were selected based on their ability to capture wildfire dynamics' spatial and temporal properties.

The implementation of these models was coded as modular development, using Python programming language and frameworks such TensorFlow, Keras, and NumPy. To accelerate training of large datasets the Google Colab GPU was used. The different modules were then integrated to ensure that all components functioned cohesively. Once the model's implementation was completed, they were trained, tested and validated using the generated landscapes.

For training optimisation and enhanced model performance techniques such as learning rate scheduling, batch normalisation and hyperparameter tuning are used. once trained, the models were tested and validated to assess their reliability and generalisation capabilities. The holdout validation and performance benchmarking testing strategies were applied to measure how well model performs on unseen data. In holdout validation, the dataset was split into 80:10:10 ratio, with accuracy, loss, precision, recall, Area Under the Precision-Recall Curve (AUC-PR) and F1-score used as performance metrics for model benchmarking

Additionally, an error map and a confusion matrix were generated. The error map shows the visual prediction discrepancies, while the confusion matrix indicates the correct and incorrect classifications. This varied testing approach allowed for fine-tuned model performance assessments and thorough evaluation of each model's strengths and limitations in accurately capturing the fire spread dynamics.

Once all the subsystems were designed, implemented, and tested, the next step was to integrate them into a whole wildfire spread prediction system. The next phase is performance analysis for the wildfire spread prediction system.

3.4 System Analysis Phase

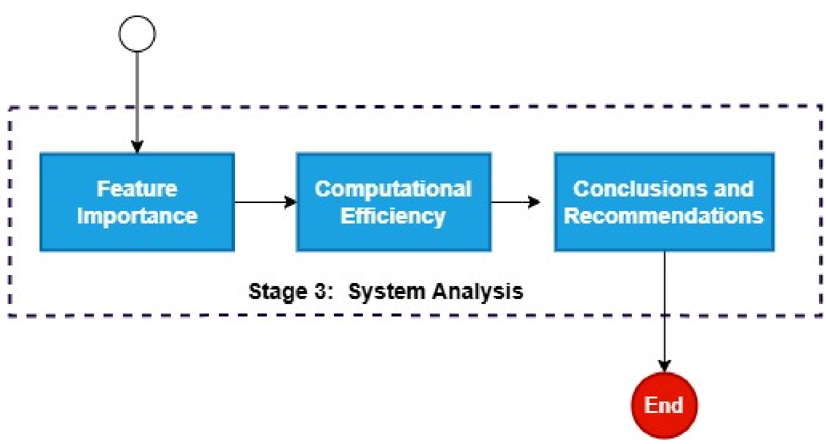


Fig. 3.4. Analysis of the system

The performance analysis phase focuses on the overall analysis of the system to ensure that the system meets the requirements and design specifications and that the research objectives are met. This phase includes feature importance analysis, computational efficiency, and conclusions and recommendations.

In the system analysis phase, a feature importance analysis testing how each parameter affects the system's prediction and how sensitive the system is to change in a specific parameter was performed by varying that one parameter and keeping the others constant. Additionally, a computational analysis of how the different models utilise the computational resources such as memory, CPU and disk usage and how this affects the system's performance was conducted. The system analysis results are documented in Chapter 5, and the conclusion and recommendation for future work are documented in Chapter 6

This chapter discussed the methodology used in developing the wildfire spread prediction system, applying the qualitative methodology through the literature review and conceptual analysis which informed the system requirements. The Iterative and Incremental Development SDLC model was applied to the software development, guiding the design, implementation and testing phases. The next chapter delves deeper into the system design focusing on the architectural framework and integration of ML models.

Chapter 4

Design

This chapter presents the wildfire spread system's detailed design guided by the Interactive and Incremental SDLC framework discussed in Chapter 3. The chapter begins by detailing the functional and non-functional requirements and formulating specifications. It then outlines the high-level system architecture, defining the key components of the system and their interactions. The data design specifying the data sources, preprocessing techniques, and forming of the landscape data for training the ML models is discussed. The ML model design follows, detailing the model selection, model architecture design, and training and validation techniques for the models. Finally, it details the integration of these models into the system architecture.

4.1 Refined Requirements and Specifications

The refined requirements and specifications of the system were formulated in alignment with the research objective of using ML algorithms together with topographical and environmental data to model wildfire spread behaviour discussed in the introduction 1. The IID process informed by the literature facilitated the continuous refinements of the requirements and the specifications after the planning and initial design phase.

4.1.1 Refined Requirements:

4.1.1.1 Non-functional requirements:

Table 4.1 lists the non-functional requirements that define how the system should behave; they define aspects such as performance, usability, and system constraints.

TABLE 4.1

Non-Functional Requirements of the System

ID	Non-Functional Requirements
NFR1	The system should provide hourly updates of fire spread for the ConvLSTM model
NFR2	It must be able to handle varying loads and computational requirements
NFR3	Ensure the system is accessible to users with different levels of technical expertise by designing a user-friendly interface.
NFR4	The system must be compatible with the Windows, Mac, and Linux operating systems

4.1.1.2 Functional requirements:

Table 4.2 lists the functional requirements that describe what the wildfire spread prediction system should do.

TABLE 4.2

Functional Requirements of the System

ID	Functional Requirements
FR1	The system must integrate various satellite data sources.
FR2	The wildfire spread prediction system must be open-source.
FR3	The system's software should be implemented in Python and use open-source libraries.
FR4	Generate burn maps to indicate the burn perimeter of the fire spread.
FR5	Utilize GPUs to accelerate training of the models, particularly for ConvLSTM.
FR6	Select and run a model to predict wildfire spread, taking into account the input variables
FR7	The system should use cloud-based infrastructure for storing data

4.1.2 Specifications

The designed system must meet the following specifications:

4.1.2.1 Environmental satellite data:

- **Burn Area Map:** Download Sentinel-2 burn Maps, with 10m-100m spatial resolution and 5-day temporal resolution.

- **Weather Parameters:** Download historical weather parameters, namely wind speed, wind direction, temperature, precipitation and elevation, with 1 - 10km from the European Centre for Medium-Range Weather Forecasts(ECMWF) ERA5-land hourly dataset.

4.1.2.2 Simulated data input:

- **Burn Map Frames:** Generate simulated burn map frames using the learned spread probability function and Cell Automaton.

- **Weather Parameters:** Generate weather parameter layers using the Perlin noise algorithm.
- **Generated Landscapes:** Combine the generated weather parameters and the simulated burn map frames as a TensorFlow matrix of shape (batch size, sequence length, height, width, channels). Each pixel in the dimension (height X width) should represent a (42m X 42m) grid size on the ground and a time step of 1-hour intervals.

4.1.2.3 ML algorithms:

Train and validate the following three supervised learning models using the generated landscapes.

- Artificial Neural Networks(ANN).
- Convolutional Autoencoder
- Convolutional LSTM

4.1.2.4 Output visualisations:

- Output probability burn map visualisations indicating the likelihood of fire spread to different areas, with red colour indicating burned areas and green colour indicating areas not burned.
- Include the wind and elevation information in this output visualisation

4.1.2.5 Model evaluation and validation:

- **Visual Comparison:** Have true and predicted burn Map for visual inspection.
- **Evaluation Metrics:** Use the evaluation metrics Precision, Recall, Area Under the Curve (AUC-PR) and F1-score to evaluate each model's performance.
- **Error Analysis:** Use a confusion matrix and Error Map to calculate the error of each model; the acceptable error should be in the range 0-15%.

4.2 System Overview

The previous section outlined the refined requirements and specifications of the wildfire spread prediction system. This section covers the proposed system overview as shown in figure 4.1. The first step is to download satellite data, which comprises weather data, topography data, and burn scar maps. This data is used in the second step, the data generation engine; the satellite data is used to learn the spread probability function for simulating wildfire spread and generating topographic and weather parameters.

The output of this step is a landscape with stacked layers of the weather parameters and frames of simulated burn Maps. These generated landscapes are split into the train, test, and validation (80:10:10) ratio in the third step: ML model development. The training dataset is used as input for the ML model's training, which learns hidden patterns from the data. Hyperparameter tuning is then performed using the validation dataset to optimise the model's hyperparameters. The optimised model is then tested on the testing dataset to evaluate the performance of the model, assessing the generalizability, reliability, and robustness. The last step involves the analysis of the system as a whole.

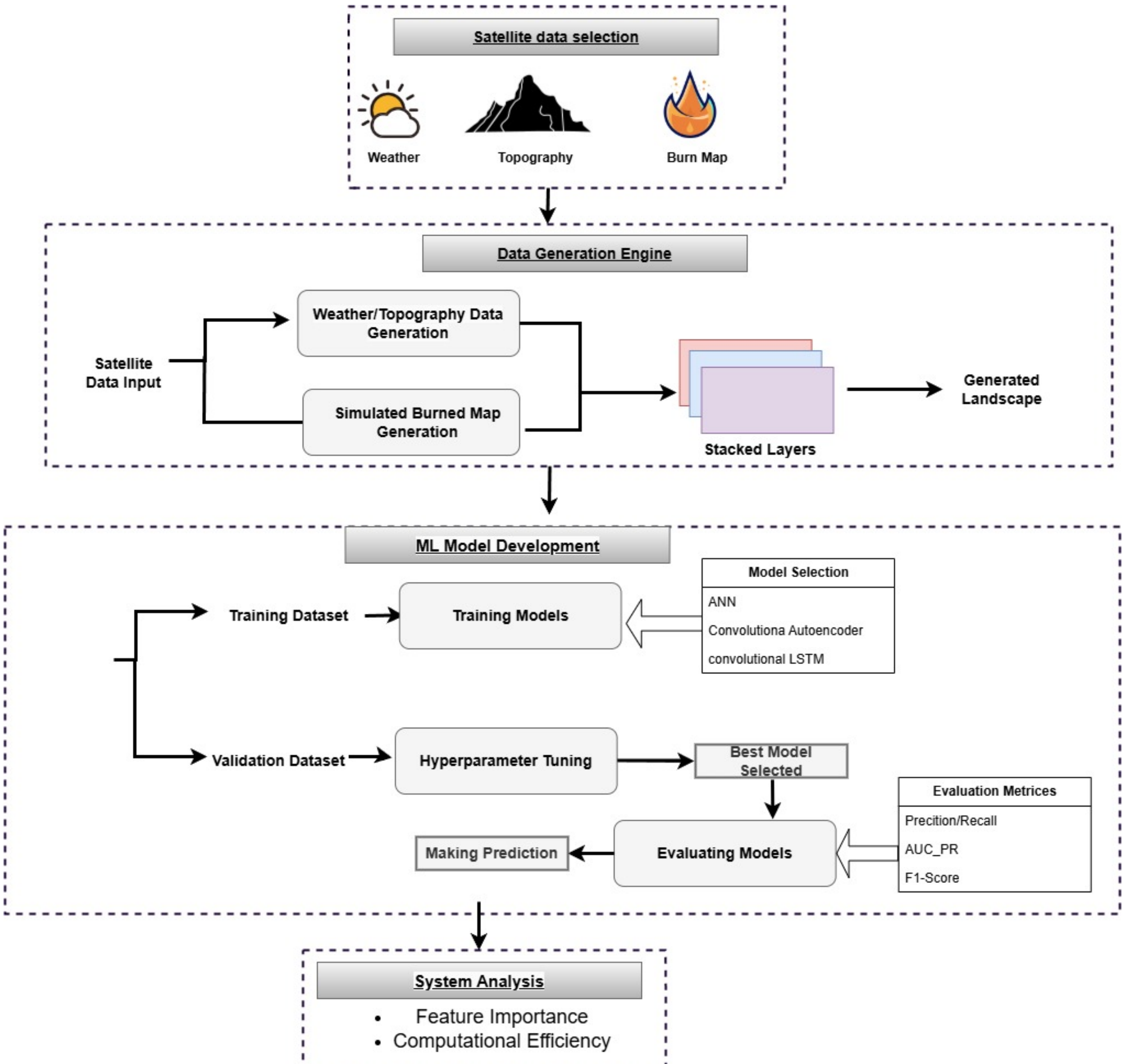


Fig. 4.1. System Overview

4.3 Satellite Data Collection

Historical satellite records of fire events that occurred between Feb 2022 and Feb 2023 in the Cape region discussed in the study area section 1.2 were downloaded. The downloaded satellite data included fire events in the western cape coastal regions such as Kalk Bay fire, Castle rock fire, Simon's town, Bella Vista fire, Overstrand,and BuffelJags fire among others. This data comprises the following parameters: wind speed, wind direction, elevation, temperature, and burn scar map of each fire event. Each fire event covers a $16km^2$ of area.

Weather and topography parameters
The weather and topography data is downloaded from the European Centre for Medium-Range Weather Forecasts(ECMWF) ERA5-Land hourly dataset. This dataset is a high-resolution dataset obtained from various satellites such as NOAA Polar Orbiting Environmental Satellites (POES), Moderate Resolution Imaging Spectroradiometer (MODIS), Geostationary Operational Environmental Satellites (GOES) and ESA's Sentinel series (e.g., Sentinel-1, Sentinel-2).

Wildfire Burn Map
The burned scar map, which shows the wildfire burned perimeter, is downloaded from the sentinel-2 satellite via the Copernicus sentinel hub website `https://www.sentinel-hub.com/`. This data has an effective spatial resolution of 20m.

4.4 Data Generation Engine

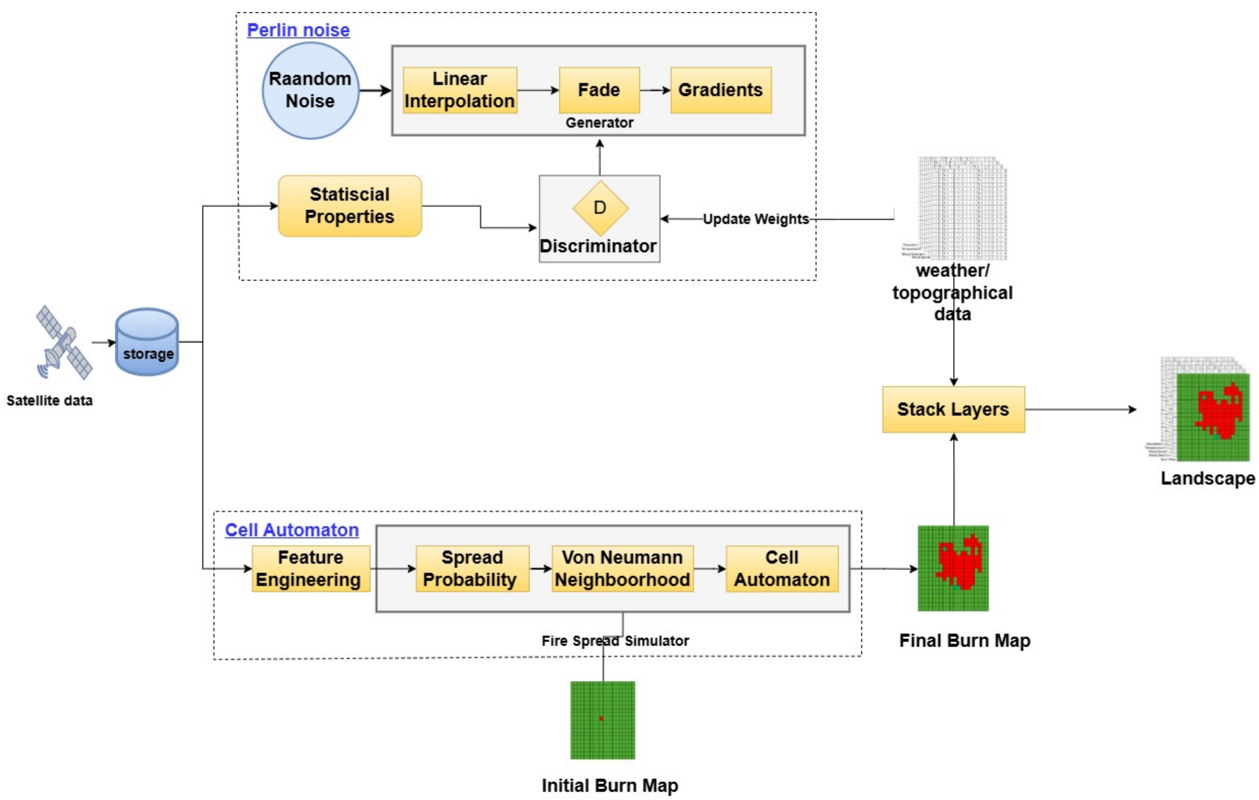


Fig. 4.2. Block Diagram of the data generation engine

Without adequate data, data-generation methods are used to generate data that mimics real-world fire data. The two techniques, Perlin noise and Cellular Automaton (CA) are used to generate the landscape layers as depicted in fig 4.2. The Perlin noise is used to generate the environmental layers: wind speed, wind direction, temperature, and elevation. Additionally, CA generates simulated fire burn maps using a spread probability function to spread fire from the initial start point to the surrounding areas. The generated layers from these two algorithms are stacked together to form landscapes that will be used as train, validation, and test datasets for the Machine Learning Models.

4.4.1 Perlin-noise

Perlin noise is a gradient noise function created by Ken Perlin to generate smooth, natural-looking textures widely used in computer graphics and simulations [71]. It achieves this by defining gradient vectors at each location in a grid and then interpolating between them to generate a smooth, continuous noise pattern. A polynomial smoothing function, such as the quintic function in 4.1, is used to ensure continuity and smoothness in the noise pattern [72].

$$f(t) = 6t^5 - 15t^4 + 10t^3 \tag{4.1}$$

This method eliminates the harsh, repetitive artefacts seen in simpler noise functions, making it useful in applications such as terrain generation [72]. This research generates more landscapes by creating random data on the layers that describe environmental factors, namely temperature, wind speed and direction, and elevation.
As shown in fig 4.2, the layers generated from the Perlin noise are passed through the discriminator, which compares the generated data with the real satellite data to ensure that the generated simulated data has similar statistical properties as the real data.

4.4.2 Cell Automaton

Cell Automaton(CA) is a collection of grid cells commonly used to simulate the spatio-temporal evolution of complex systems. It simulates the dynamics of fire spreading over a landscape to capture the temporal properties that change state in discrete time steps based on defined rules [73].

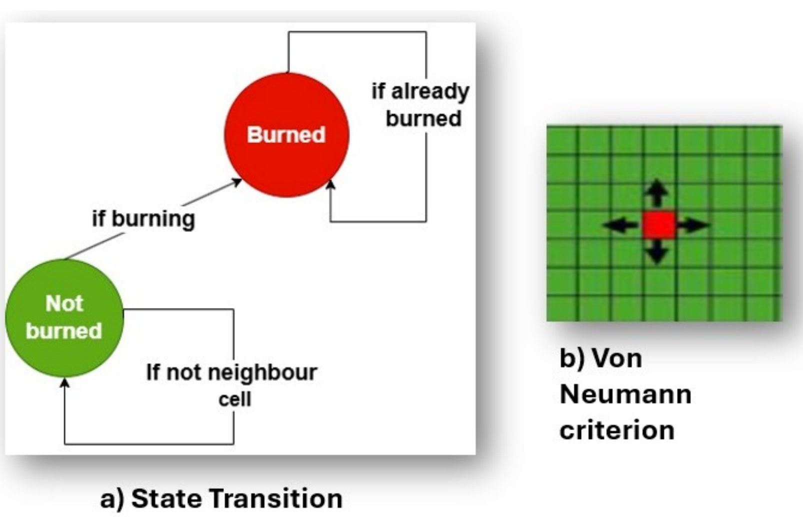


Fig. 4.3. The principle of CA: a) State transition b) The Von Neumann criterion

The Von Neumann criterion, which includes only the four adjacent cells touching the central cell, is used to classify the neighbourhood cells. As shown in fig 4.3, each cell has two states (cell burned, cell not burned) and evolves using the possible rules of transition from time (t) -> (t+1) as follows:

Algorithm 1: Cell Automaton algorithm for spreading fire

Input : initialBurnMap, maxTime
Output: finalBurnMap

```
for i ← 0 to maxTime do
    neighbourCells ← Neighbours(currentCell);
    spreadProbabilities ← SpreadProbability(neighbourCells);
    // state transition rules
    if cell == burned then
        if neighbourCells != burned then
            if speadProbabilities> threshold then
                neighbourCells ← burned
            else
                neighbourCells ← not burned
        else
            neighbourCells ← burned
    else
        neighbourCells ← not burned
return finalBurnMap;
```

Each cell has characteristics that define its particular state, and the fire spread behaviour is simulated across the grid as the cells change their state according to rules based on their neighbourhood cell states, as shown in Algorithm 1.

A logistic function is used to predict the spreading probability of the neighbouring cell, given that the cell is on fire, using the CA-defined state rules above. This logistic function is trained to learn the best parameters that fit the data; feature engineering on the input parameters of a landscape is performed.

Spread Probability

The logistic analysis is an interpretable linear model that gives a prediction accounting for the various influencing factors [74]. This function can cater to dataset imbalance by adjusting the decision threshold [74]

$$\text{Logistic Function: } \log m = \mu + \rho_0\omega + \rho_1\lambda + \rho_2\theta \text{ [74]} \tag{4.2}$$

4.4.3 Layered Data Visualisation

Figure 4.4 illustrates the landscape generation for the initial frame to the last frame depicted as frame n. The initial frame is formed by stacking 2D layers of wind speed, wind direction, elevation, temperature, and a burn map. Then, multiple other burn maps that depict fire spreading over time are captured as frames from the fire spread simulator.

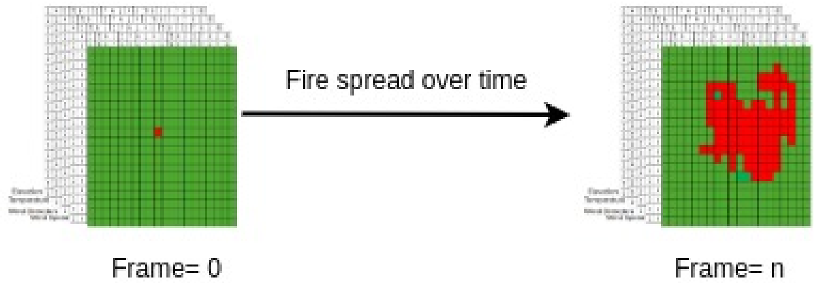


Fig. 4.4. Fire Spread on a 3D landscape visualisation.

4.4.3.1 Data restructuring:

The data restructuring follows a layered-based matrix approach, where the generated landscapes are structured to form a 5D matrix with shape (samples, frames, parameters, rows, columns).

Samples The total number of samples or fire incidents generated.

Frames The burn map frames indicate the time progression of fire spread.

Parameters 5 layers that represent a Landscape, with a 2D(rows, columns) matrix for each layer.

- layer 0 -> Burn Map
- layer 1 -> Wind Speed
- layer 2 -> Wind direction
- layer 3 ->Temperature
- layer 4 -> Elevation

Rows The row of each parameter

Columns The column of each parameter.

This data is used as input for the Machine Learning algorithms, which will be discussed further in the next section.

4.5 ML Models Design

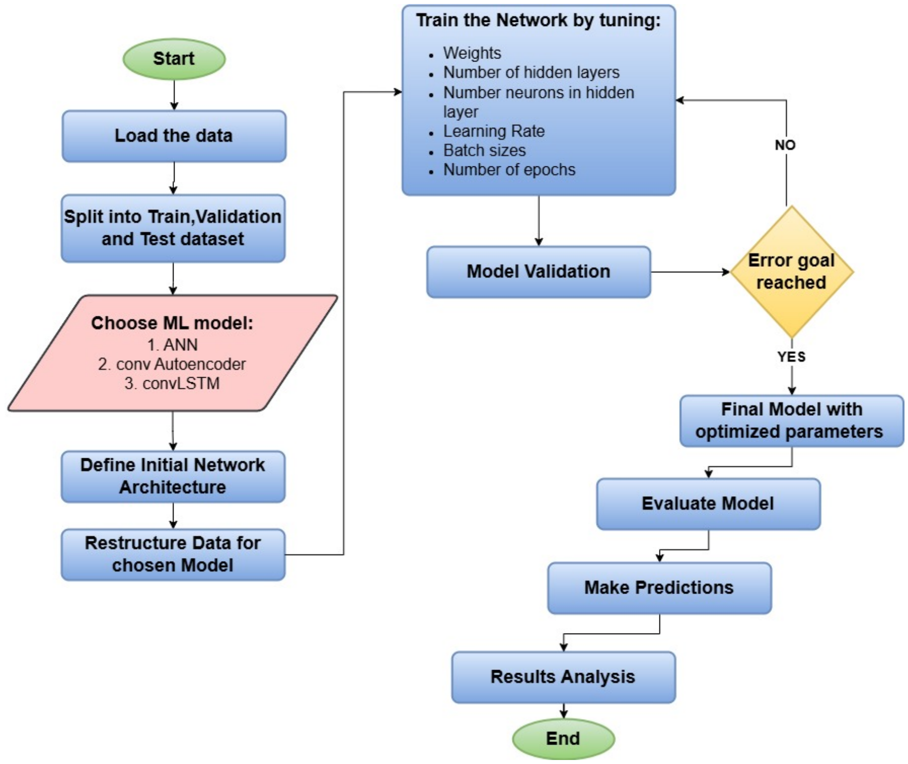


Fig. 4.5. Flowchart describes the ML design stages

Sections 4.3 and 4.4 illustrate detailed design concepts involved in generating and processing the data to form landscapes. Following the landscape generation process, the flowchart in fig. 4.5 demonstrates the progression of the ML model. It begins with loading the datasets and selecting the ML model. Followed by defining the chosen initial ML architecture and restructuring the dataset to meet the input dimensions of the selected model. Then, the initial architecture is trained by tuning the hyperparameters, such as the learning rate, batch size, epochs, and number of architecture layers, to find the final optimised model. The final model is evaluated, and predictions are made.

4.5.1 Machine Learning Algorithms Selection

This subsection focuses on the system's core predictive capabilities, specifically on developing and optimising the Artificial Neural Network (ANN), Convolutional Autoencoder, and Convolutional Long-Short-Term Memory (convLSTM) algorithms for predicting wildfire spread. The wildfire spread prediction problem is treated as a supervised learning classification problem, whereby each pixel in the burn map grid is classified as burned or unburned. This binary classification method allows for clearly defining the fire boundaries and tracking their progression over time.

4.5.1.1 Artificial neural network

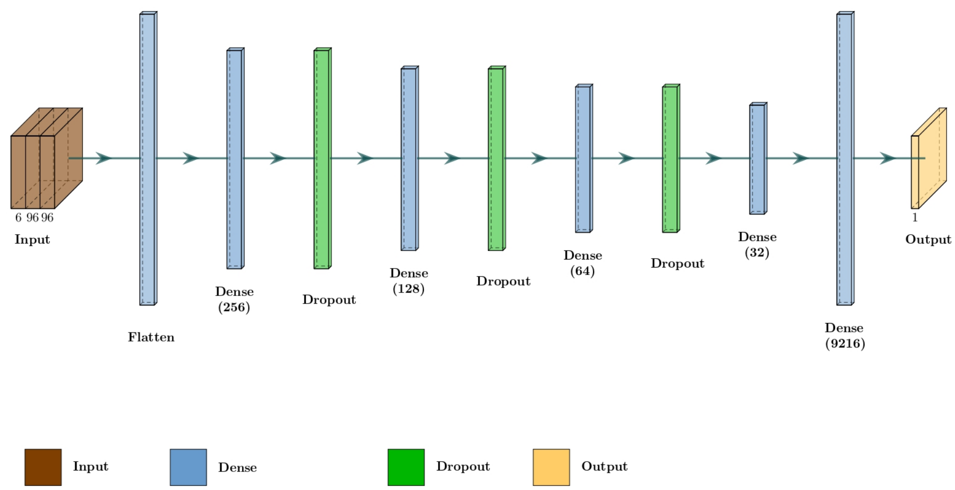


Fig. 4.6. Artificial Neural Network Architecture [7]

Fig 4.6 shows the initial ANN architecture overview, the input, output, and the hidden (dense and dropout) layers. The input data comprises six environmental and topographic features structured in a 96 x 96 x 6 grid. The first layer is the flatten layer, which converts the grid data into a 1D vector. Followed by 4 dense(fully) connected layers with 256, 128, 64, and 32 units, each using a ReLU activation function to introduce non-linearity. A dropout layer with a rate of 0.25 follows each dense layer to prevent overfitting. The final output layer has 96 x 96 sigmoid-activated neurons that represent the probability of each cell being burned. This is then reshaped back into a 96 x 96 2D grid to match the spatial resolution of the actual burn map.

The model is trained for 30 epochs, using a batch size of 64 with early stopping to prevent overfitting. During training, the predicted burn maps are compared with the actual burn maps, and the difference between the predicted and the actual outputs is quantified using the binary cross-entropy loss function.

4.5.1.2 Convolutional autoencoder

The initial convolutional autoencoder architecture follows a symmetric encoder-decoder structure shown in fig 4.7. This enables the model to compress the spatial features into a lower dimensional representation and then reconstruct them, thus preserving the key spatial features. The input consists of a 96 x 96 x 6 tensor, representing the 6 features per spatial grid. The encoder is constructed with multiple Conv2D layers using 64 and 512 filters and a 3 x 3 kernel size, all activated by the ReLU functions with the same padding to preserve spatial dimensions. The maxpooling2D layers are used to progressively downsample the feature maps and are followed by dropout layers with a rate of 0.25 to prevent overfitting and improve generalisation.

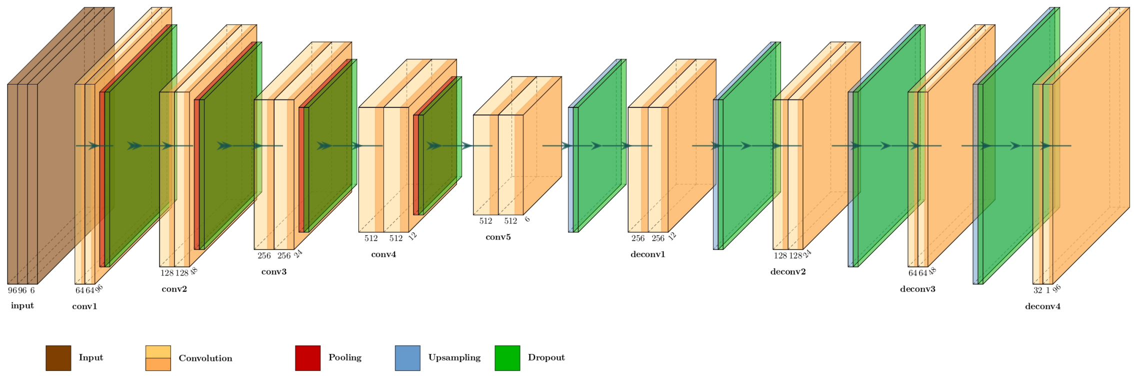


Fig. 4.7. Convolutional Autoencoder Architecture

The deepest layer encodes the compressed representation of the wildfire landscapes. This layer is then followed by the decoder which mirrors the encoder with conv2D and upsampling layers that gradually restore the original spatial resolution. The output is produced by a conv2D layer with a single filter and a sigmoid activation function. The model is compiled using the Adam optimizer , with a binary cross-entropy loss function to classify the burn and no-burn pixels.

4.5.1.3 Convolutional LSTM

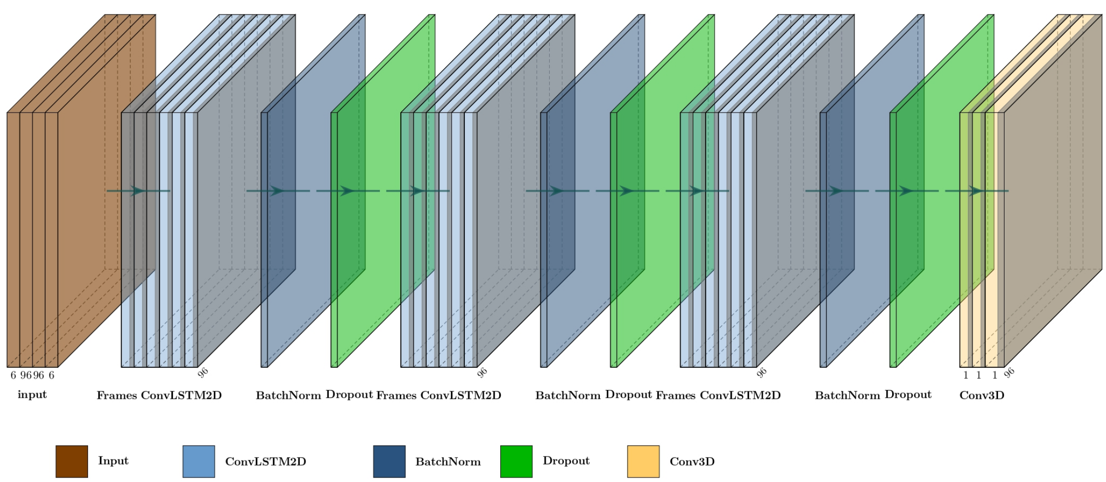


Fig. 4.8. ConvLSTM Architecture

Fig 4.8 shows the initial convolutional LSTM architecture design. The input to the model is a 5D tensor of shape (batch_size, time_step, 96, 96, 6), where each time frame consists of the six feature layers. The model begins with three stacked convLSTM2D layers, each with 64 filters and kernel sizes 5 x 5, 3 x 3, and 1 x 1, respectively. These layers are configured with ReLU activation, same padding and set to return sequences, preserving temporal resolution across all layers. Each layer is followed by BatchNormalization and Droupout of 0.3 to enhance stability and generalization.

The final temporal output is passed through a Conv3D layer with a sigmoid function and kernel size of 3 x 3 x 3, producing a probability map for each time step. The model is compiled using the Adam optimizer with a learning rate of 0.001, and a learning rate scheduler was introduced to gradually reduce the learning rate during training. The training was performed for 35 epochs with a batch-size of 24, time-step of 6. The binary cross-entropy loss function appropriate for pixel-level classification was used to classify pixels as burned or unburned.

4.5.2 Model Training and Validation

The ANN, convolutional autoencoder, and convolutional LSTM models illustrated in the subsection above are trained using the generated landscapes. The input data is split into (80:10:10) data split ratios for the training, validation, and test datasets. During training, the main objective is for the model to learn patterns from the training data by minimising the loss function. The validation dataset is used to tune hyperparameters and prevent overfitting, thus enabling the selection of the best-performing model.

The optimization process for these algorithms involved fine-tuning hyperparameters, adjusting network architectures, and implementing regularization techniques to prevent overfitting. This ensures the model generalizes well to new, unseen data while accurately identifying burned and unburned areas.
Multiple hyper-parameters varied to improve and optimise the performance of these models. In addition, alternate activation functions such as Adam, ReLU, and Leaky ReLu are used to improve the model's generalisation.

4.5.3 Metric Evaluation

Metric evaluation is performed to assess the model's performance and provide an unbiased estimate of the model's effectiveness. The optimal trained models are tested on the test set not seen during the training and validation. The performance metrics, such as Accuracy, Precision, Recall, and ROCAUC are calculated to evaluate the model's predictive performance.

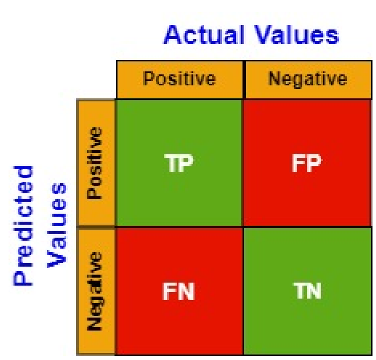


Fig. 4.9. confusion matrix

A confusion matrix with four terms, as shown in fig 4.9 is generated. This matrix summarises the number of correct and incorrect classifications into four categories named True Positives **(TP)**, True Negatives **(TN)**, False Positives **(FP)**, and False Negatives **(FN)**.

From this confusion matrix, the other evaluation metrics are computed.

$$\textbf{1. Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{4.3}$$

$$\textbf{2. Error} = \frac{\mathrm{FP} + \mathrm{FN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{4.4}$$

$$\textbf{3. Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{4.5}$$

$$\textbf{4. Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{4.6}$$

Once the validation is completed, the model validation outcomes, namely learning curves, confusion matrices, ROC curves, precision-recall curves, and feature importance, are visualised and analysed.

4.5.4 High-level Software Structure

A UML class diagram defines the project's software modules as shown in fig 4.10. Each module achieves a specific goal, as illustrated below.

For Data Generation, the following modules are used:
Satellite data: pre-process the downloaded satellite data.
Landscape: Generate and display landscapes with layers of burn map, wind speed, wind direction, temperature, and elevation.
Simulate fire: Simulates fire burning on the landscape to create the burn scar and display the final burn map.

For ML Modelling, the following modules are defined:
Wildfire Spread: Acts as a wrapper module for loading the data into the appropriate model and selecting the appropriate study case to be modelled.
Data Processing: To normalise the data and prepare it for the appropriate ML model.
ANN, Autoencoder and ConLSTM: Each model defines the model's architecture and the training and testing of the models.
Tensorboard: To display graphs and pictures of the model's performance matrix results.

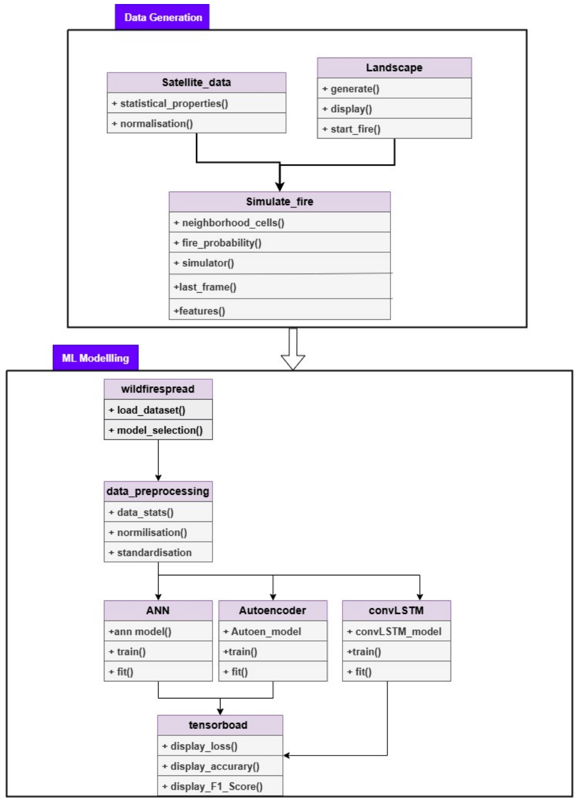


Fig. 4.10. UML class diagram for the ML models subsystem

4.6 System Implementation

4.6.1 Programming Language

Python was the selected programming language for data generation and constructing the ANN, Autoencoder, and ConvLSTM as it is the most popular programming language in the Machine Learning community. It is free, open-source software with packages like TensorFlow and Keras, designed specifically for neural network modelling.

4.6.2 Platform

This research uses Google Colab, a hosted Jupyter Notebook service. It allows free access to computational resources such as GPU and TPU, making it well-suited for machine learning, deep learning, and data science projects. Additionally, with Colab, multiple programmers can create and share notebooks with others and simultaneously work on the same notebook, enabling collaborative editing and real-time collaboration.
The hardware specifications of a Colab Notebook are:

CPU: Intel Xeon CPU with 2 vCPUs (virtual CPUs).

RAM: 13GB.

GPU: NVIDIA Tesla K80 with 12GB of VRAM (Video Random-Access Memory).

TPU v2 and TPU v3: 8 or 16GB of high-bandwidth memory (HBM).

4.6.3 Python Libraries

The following Python libraries and packages are used in the wildfire spread prediction system development stages, which include Satellite data download and processing, Data generation, and ML model development.

4.6.3.1 Satellite data

Table 4.3 illustrates the Python libraries required to download and process the satellite data.

TABLE 4.3

Satellite data download Python libraries

Library	Purpose
rasterio	provides Python API for easier interaction with geospatial raster datasets.
earthengine-api	provides Python API interacting with Google Earth Engine (GEE), a cloud -based platform designed for processing large-scale geospatial data.
requests	for making HTTP requests

4.6.3.2 Data generation

Table 4.4 illustrates the Python libraries required to generate and prepare the input datasets representing the landscapes.

TABLE 4.4

Data Generation Python libraries

Library	Purpose
scipy	Used for statistic and mathematical equations implementation
Numpy	Used for Matrix Manipulation
Matplotlib	For creating diagrams, graphs, animations and other visualisations

4.6.3.3 ML models development

To achieve the functionality for the subsystem: Machine Learning models as illustrated by the flowchart in fig. 4.5, the following python libraries illustrated in table 4.5 will be used.

TABLE 4.5

Machine Learning models Python libraries

Library	Purpose
Tfrecord	Used create and read tfrecord input files
Tensorflow data validation	Used to perform the inspection and visualisation of the dataset.
Tensorflow.keras	Used to create the Machine Learning models
Matplotlib	For creating diagrams, graphs and other visualisations
Tensorboard	visualisation tools for understanding, debugging and optimising Tensorflow for ML experimentation

4.7 System Performance Analysis

4.7.1 Feature Importance

Part of the literature review involved identifying weather and topography parameters to consider when designing the system. The subsections fuel 2.2.2.1, weather 2.2.2.2, and topography **??** of the literature review explain these parameters as critical to wildfire spread behaviour. Amongst others, the contribution of wind spread, direction, temperature, and elevation is investigated.

The following hypotheses are formulated to investigate the impacts of these parameters on wildfire spread.

Hypothesis 1 - Wildfire spreads faster uphill than downhill: to investigate how different elevations affect fire spread, the elevation values are varied while over variables are kept constant.

Hypothesis 2 - Wildfire spread direction is determined by the direction of wind: the wind speed and direction are varied while other variables are kept constant to consider how the wind speed and direction influence the likelihood of a cell burning in its direction.

Hypothesis 3 - Increase in temperature has a direct relationship with fire spread: the temperature is varied while other parameters are kept constant to examine the increase in temperature on the fire spread

TABLE 4.6

Investigating effect of environmental parameters on wildfire spread

Hypothesis	Temperature	Elevation	Wind
Hypothesis 1	Constant	Varied	Constant
Hypothesis 2	Constant	Constant	Varied
Hypothesis 3	Varied	Constant	Constant

To test each hypothesis, each case is evaluated separately by varying each parameter and keeping other parameters constant, as shown in table 4.6.

This chapter covered the design stages. First, it discussed the system's refined requirements and specifications, followed by a system overview. Then, detailed data generation and ML model design were performed. Finally, system implementation and performance analysis were conducted. The next section will discuss the results obtained.

Chapter 5

Results

This section describes the results of the three ML models trained to predict wildfire dynamics: ANN, Convolutional Autoencoder, and Convolutional LSTM. It emphasizes how the implemented model using the classification approach to detect burned and unburned pixels in a landscape contributes to the prediction of spatial and temporal fire dynamics. Additionally, it discusses how the model incorporates the identified key contributing factors of wildfire spread from the literature.

5.1 Data Results

Supervised classification ML models learn complex hidden relationships between data. This data is used for training, testing and validating the model.

5.1.1 Downloaded Satellite Data

5.1.1.1 Google earth engine

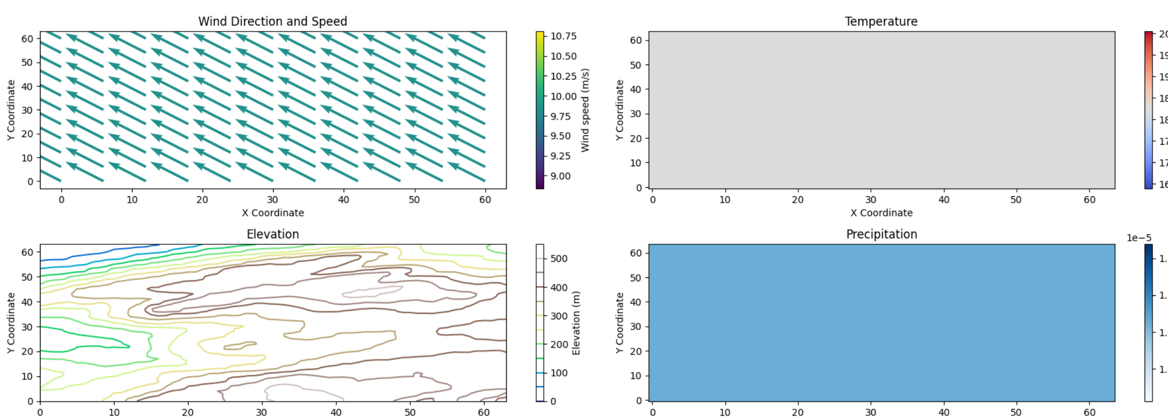


Fig. 5.1. Sample weather data from GEE

Figure 5.1 indicates sample wind and elevation data downloaded from the Google Earth engine. The downloaded data has parameters: wind speed, wind direction, temperature, and elevation, with each parameter having dimensions of (64 X 64). The dataset formed included 20 fire incidents around Cape Town.

5.1.1.2 Sentinel hub

Figure 5.2, indicates a sample record of how the fire masks were generated from the downloaded burn maps. The first image shows the downloaded burn scars with 3D color channels, while the second image is a 2D burn map that shows only the red and green color channels, and the third image is a 1D fire mask matrix with ones and zeros. This is to ensure that the predicted frames are correctly handled as single-channel (1D) mask values with 1 indicating fire and 0 indicating no fire, displayed as red and green, respectively.

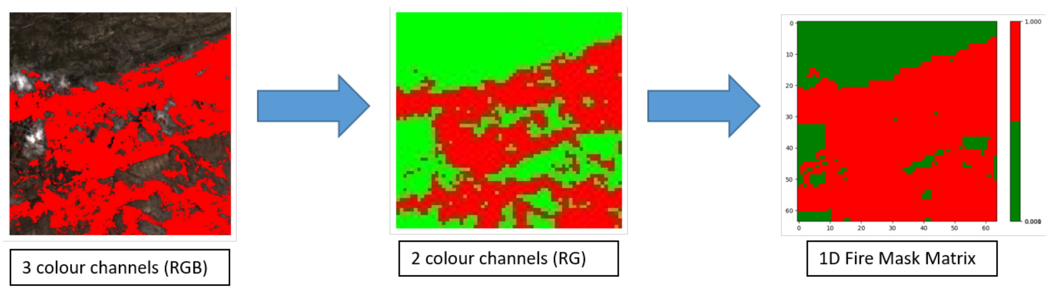


Fig. 5.2. Sample burn scars from sentinel hub

The weather, topographical data, and burn maps downloaded were used to learn the coefficients of the logit equation used to generate landscapes from equation 4.2.

5.1.2 Generated Landscape

5.1.2.1 Combined parameters that form a landscape

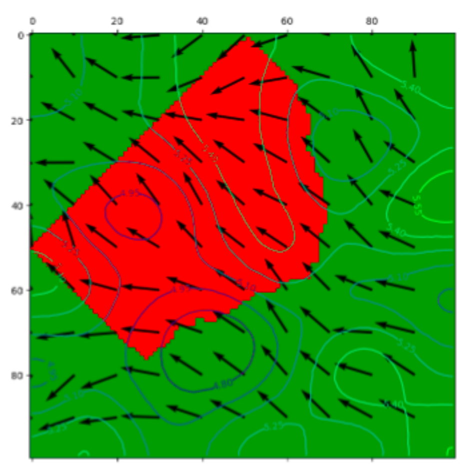


Fig. 5.3. Sample 3D landscape Visualisation.

A landscape represents a single fire event with parameters: elevation, temperature, wind speed,

wind direction, and final fire mask. The landscape is a 3-dimensional tensor of size (96,96,6). Figure 5.3 shows the landscape visualisation, which consists of a fire matrix, contour lines and wind direction.
A total of 500 landscapes are generated, making the input data to the ANN and Auto-encoder models a tensor of shape (500, 96, 96, 6) and labels shape (500, 96, 96, 1).

5.1.2.2 Fire spread simulation over a landscape

To incorporate temporal aspects of the fire spreading over a single landscape, multiple landscape frames which show the fire progression from frame 0, the ignition point, and frame 5, the fire spread pattern at t=5, are generated as shown in figure 5.4. This dataset was used as an input to the ConvLSTM model, which tensor shape (500,6, 96, 96, 6) and labels of tensor shape (500,6, 96, 96, 1).

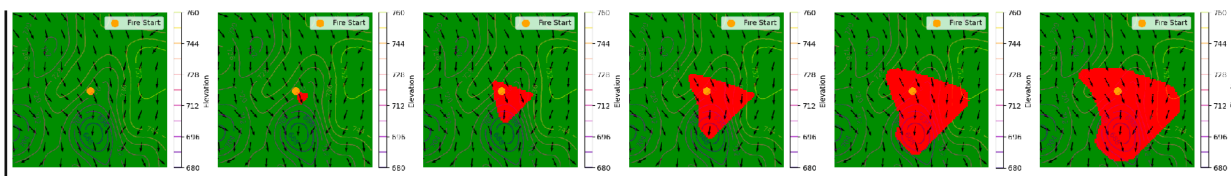


Fig. 5.4. Simulated fire spread frames

The ANN, convolutional Autoencoder, and ConvLSTM were trained and validated using the two generated landscape datasets. In the next section, we delve deeper into the results obtained for each model.

5.2 Model Performance

This section discusses the training results, including the performance metrics used to evaluate the models, a detailed analysis of the training and validation phases, and a comparative assessment of the models' effectiveness. The models were assessed using several evaluation metrics, including precision, recall, F1 score, and AUC_PR. These metrics offer a comprehensive view of each model's ability to predict landscape changes accurately and reliably.

5.2.1 ANN Model

5.2.1.1 Training process

The training and validation curves over epochs for the loss, precision, recall, and AUC_PR are indicated in figure 5.5, which observes the model's performance on both the training dataset and a separate validation dataset. The loss vs epoch curves recorded show no signs of overfitting and underfitting of the model, as both the training and validation loss decrease significantly over epochs.

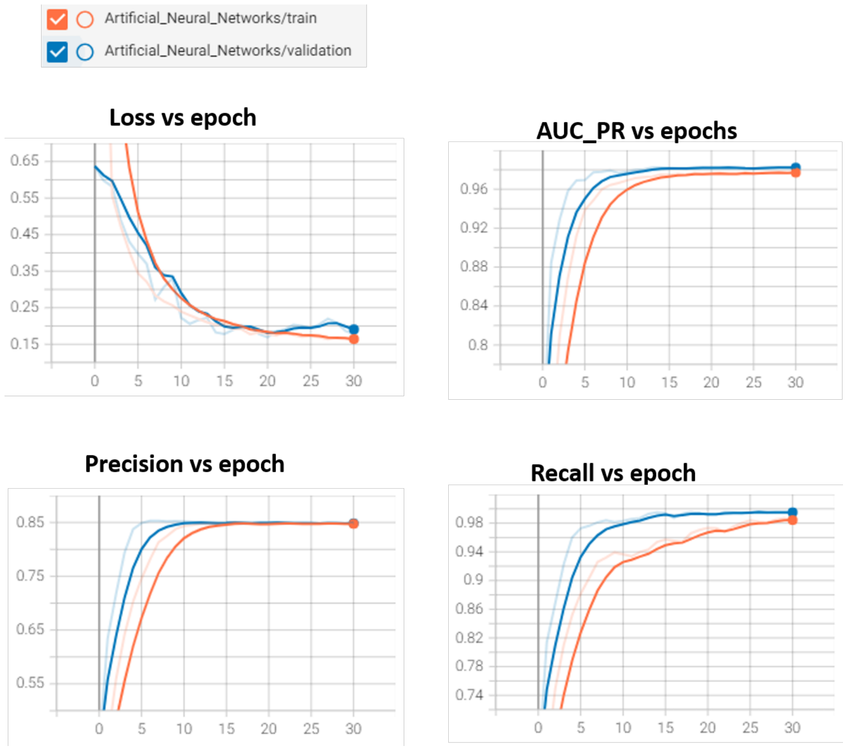


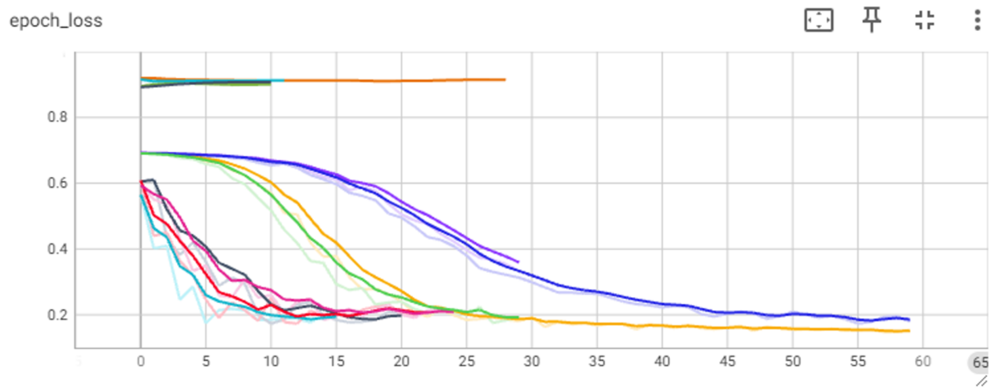
Fig. 5.5. Training loss over epochs

5.2.1.2 Hyperparameter tuning

Hyperparameter tuning is a critical step in optimizing the performance of the ANN model, which entails modifying hyperparameters such as the batch size, learning rate, and number of epochs. The Grid search technique was used to find the optimal values of the following hyperparameters:

- **Learning Rate**: [0.01, 0.001, 0.0001]
- **Batch Size**: [64, 128]
- **Number of epochs**: [30, 60]

The results of the grid search are shown in figure 5.6. From the figure, it can be seen that the model is the Artifical_Neural_Network-lr-0.0001-bs-64-epochs-30 is the optimal model, also an indication that the learning rate of 0.0001 and batch size 64 are the most important and give the optimal model. This optimal ANN model is then used for the prediction of results on unseen datasets; the results are indicated below.



Run ↑	Smoothed	Value	Step	Relative
Artificial_Neural_Networks-lr-0.0001-bs-128-epochs-30/validation	0.3595	0.3324	29	2.761 min
Artificial_Neural_Networks-lr-0.0001-bs-128-epochs-60/validation	0.1858	0.179	59	5.78 min
Artificial_Neural_Networks-lr-0.0001-bs-64-epochs-30/validation	0.1922	0.1913	29	3.311 min
Artificial_Neural_Networks-lr-0.0001-bs-64-epochs-60/validation	0.1517	0.1539	59	6.572 min
Artificial_Neural_Networks-lr-0.001-bs-128-epochs-30/validation	0.2088	0.2058	24	2.297 min
Artificial_Neural_Networks-lr-0.001-bs-128-epochs-60/validation	0.1978	0.2012	20	1.928 min
Artificial_Neural_Networks-lr-0.001-bs-64-epochs-30/validation	0.2071	0.2056	22	2.359 min
Artificial_Neural_Networks-lr-0.001-bs-64-epochs-60/validation	0.194	0.1985	15	1.605 min
Artificial_Neural_Networks-lr-0.01-bs-128-epochs-30/validation	0.9079	0.908	10	56.53 sec
Artificial_Neural_Networks-lr-0.01-bs-128-epochs-60/validation	0.9006	0.9015	10	56.87 sec
Artificial_Neural_Networks-lr-0.01-bs-64-epochs-30/validation	0.9131	0.9139	11	1.187 min
Artificial_Neural_Networks-lr-0.01-bs-64-epochs-60/validation	0.9149	0.9148	28	3.184 min

Fig. 5.6. best model training loss

5.2.1.3 Prediction quality

Side-by-side visualization of a true sample output and the model's predicted output is shown in 5.7. This visual comparison allows for an intuitive assessment of the model's performance. It can be seen that the fire does spread more in the direction of the wind. However, there are also a few false fire classifications. An error analysis was performed next to analyze the model's performance further.

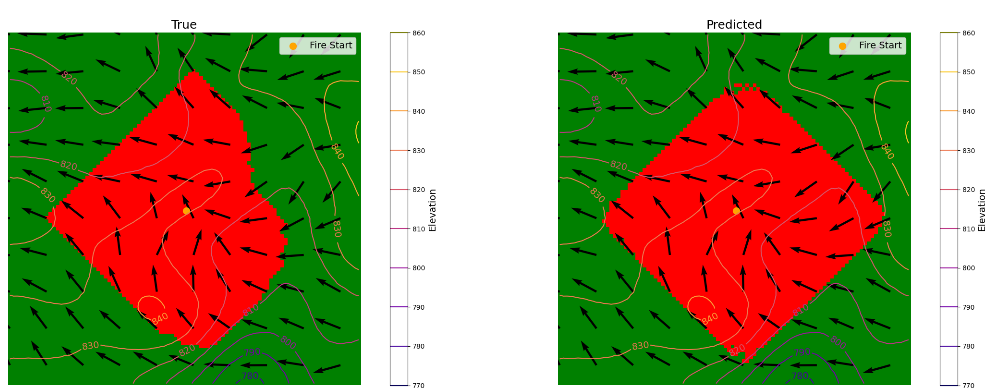
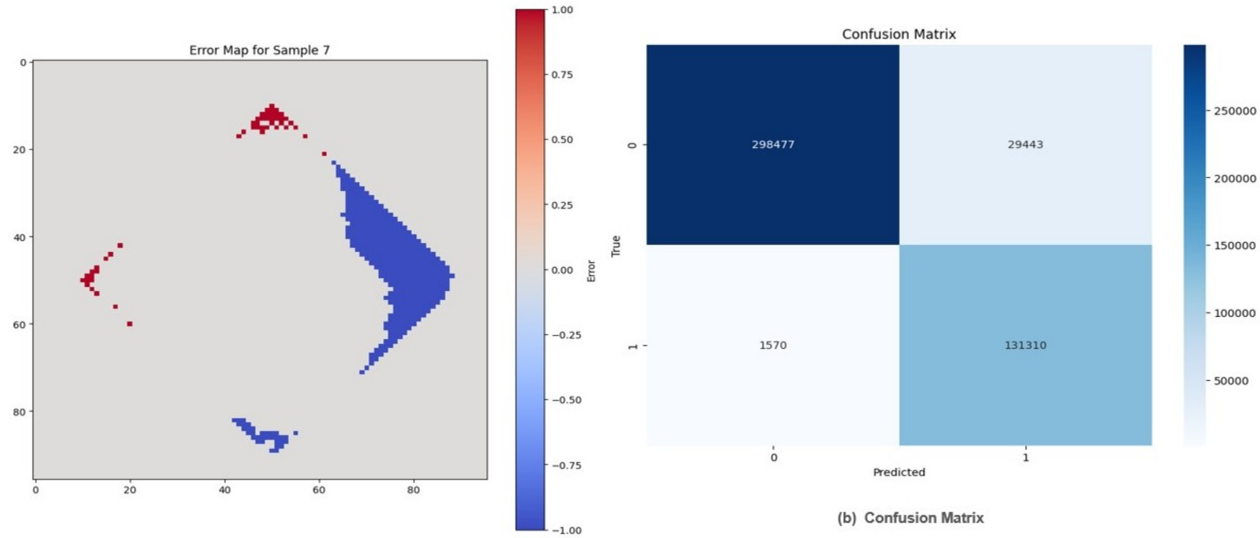


Fig. 5.7. True VS Predicted Outputs of the ANN model

5.2.1.4 Error analysis



(a) Error Map

(b) Confusion Matrix

Fig. 5.8. Confusion Matrix of the ANN model

The error map in figure 5.8 (a) indicates incorrectly classified pixels, with the blue pixels incorrectly classified as "Burned" and the red pixels incorrectly classified as "Not Burned". Using the values from the confusion matrix in 5.8 (b) and equation 4.4, the error rate for this model was calculated; therefore, the error rate of this model is 0.0674 or 6.74%.

5.2.1.5 Metric evaluation

The predicted classification report in table 5.1 is validated by calculating the evaluation metrics using the confusion matrix in figure 5.8 and equations in subsection 4.5.3 which yielded the same results.

TABLE 5.1

ANN Predicted Classification Report

	Precision	**Recall**	**F1-Score**
Not Burned	1.00	0.91	0.95
Burned	0.82	0.99	0.89
Accuracy			0.93

The "Not Burned" class has a precision of 1.00, indicating that all "Not burned" pixels were correctly classified; however, the "Burned" class has a precision of 0.82, which indicates some false positives, meaning the model incorrectly predicted some non-burned areas as burned. Additionally, the model has a high recall of 0.99 for the "Burned" classification, indicating its strong performance in detecting burned areas. However, as mentioned above, the model still predicts some false positives.

5.2.2 Convolutional AutoEncoder Model

A Convolutional Autoencoder that can learn 2D spatial properties was trained and analysed to address the shortcomings of the ANN model.

5.2.2.1 Training Process

Similar to the ANN model, the training and validation curves over epochs for the loss, precision, recall and AUC_PR are indicated in figure 5.9. The results show no indication of overfitting or underfitting the model.

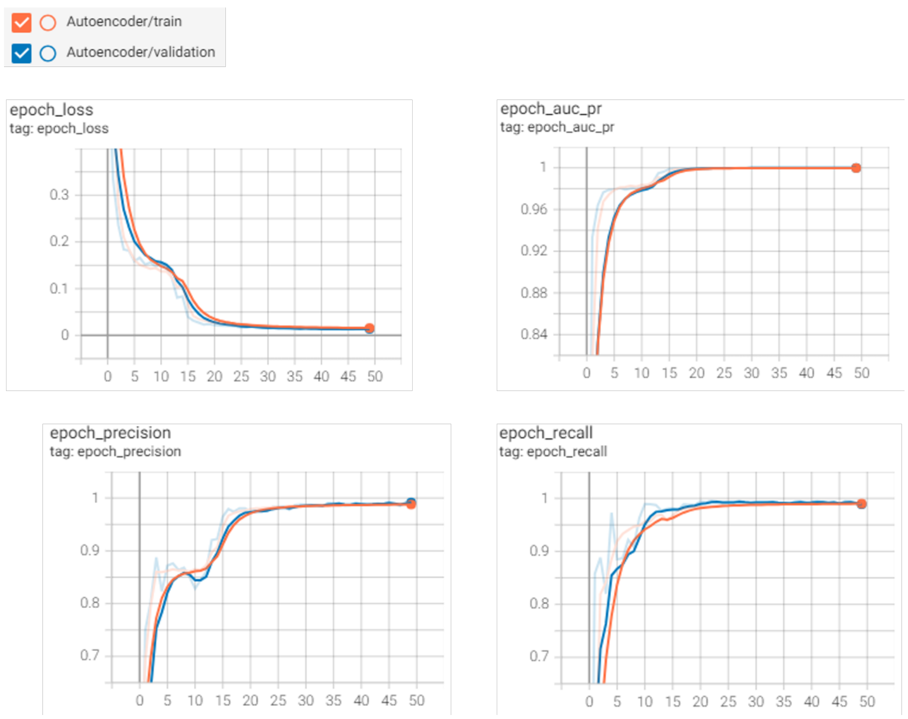


Fig. 5.9. Training loss, AUC PR, Precision, Recall over epochs

5.2.2.2 Hyperparameter tuning

Hyperparameter tuning was performed on the Autoencoder Encoder model by varying the following hyperparameters:

- **Learning Rate**: [0.001, 0.0001]
- **Batch Size**: [64, 128]
- **Number of epochs**: [20, 40]

The results obtained in figure 5.9 show that the optimal model is the Autoencoder-lr-0.001-bs-64-epochs-40, which means the learning rate of 0.001 and batch size 64 are the most important parameters and give the optimal model. This optimal convolutional autoencoder model was used to predict fire spread on unseen datasets and evaluate the model's performance.

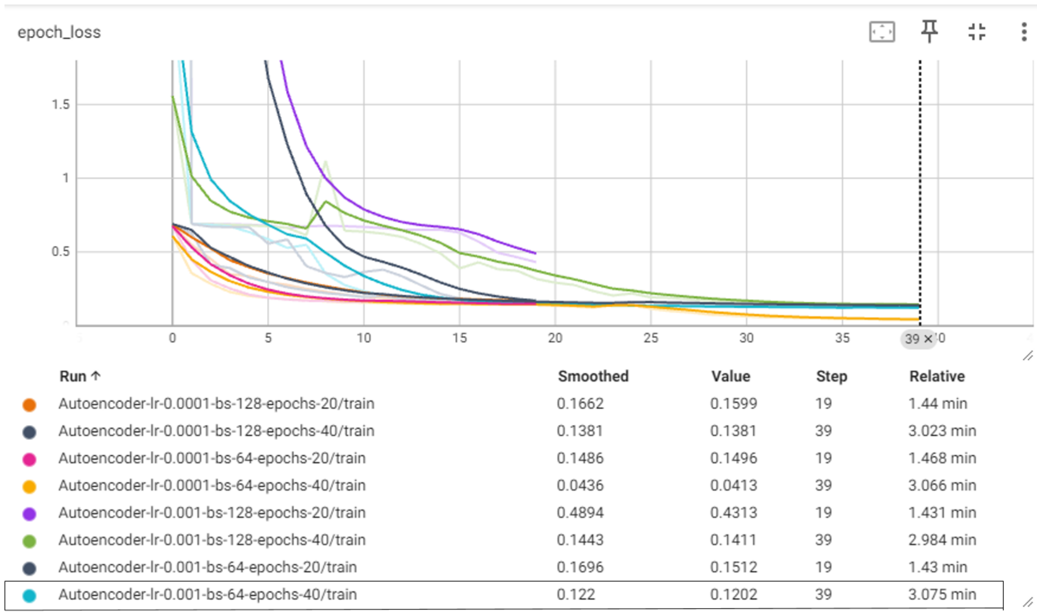


Fig. 5.10. best model training loss

5.2.2.3 Prediction quality

A side-by-side visualization of a true sample image and the model's predicted output is shown in figure 5.11. This visual comparison shows that the model can capture the spatial properties well and correctly classify the burned area. An error analysis was then performed to analyse the model's performance further.

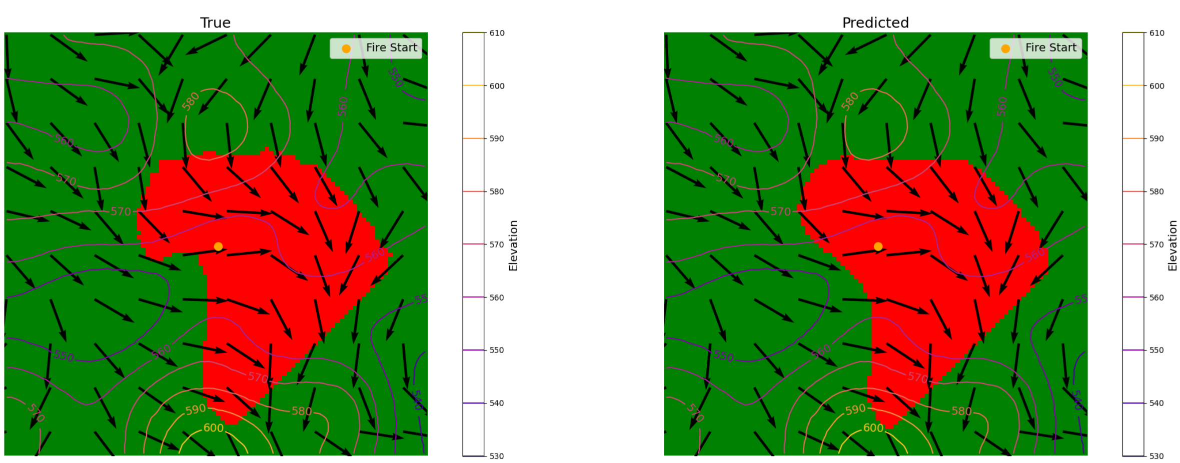
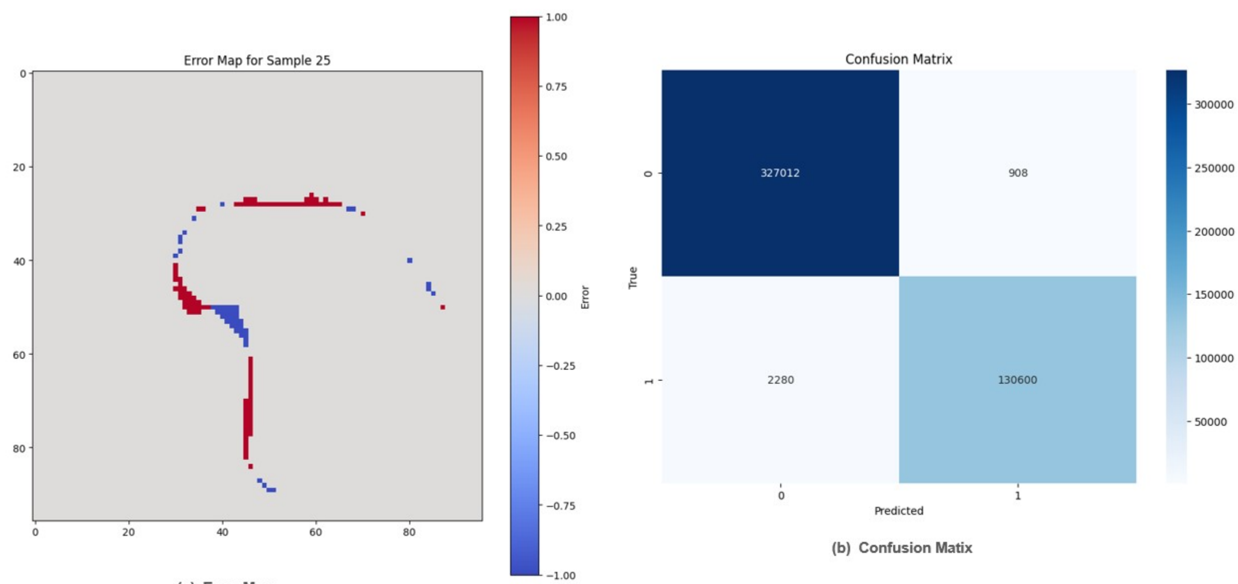


Fig. 5.11. True VS Predicted Outputs of the Autoencoder model

5.2.2.4 Error analysis



(a) Error Map

(b) Confusion Matix

Fig. 5.12. Confusion Matrix of the ANN model

The error map in figure 5.12 (a) indicates incorrectly classified pixels, with the blue pixels incorrectly classified as "Burned" and the red pixels incorrectly classified as "Not Burned". Using the values from the confusion matrix in 5.12 (b) and equation 4.4, the error rate for this model was calculated; therefore, the error of this model is 0.00691 or 0.691%. This error has significantly decreased when compared to that of the ANN.

5.2.2.5 Metric evaluation

The predicted classification report in table 5.2 is validated by calculating the evaluation metrics using the confusion matrix in figure 5.12 and equations in subsection 4.5.3, which yielded the same results.

The "Not Burned" class has a precision of 1.00, indicating that all "Not burned" pixels were correctly classified. Additionally, the "Burned" class has a precision of 0.99, indicating that this model correctly classifies burned areas. This is a significant improvement from an ANN model. The F-1 score of 0.99 is also high, reflecting the model's strong balance between precision and recall. However, the recall is slightly lower at 0.98 for the "Burned" classification, indicating that the model occasionally misses some burned areas.

TABLE 5.2

Autoencoder Predicted Classification Report

	Precision	**Recall**	**F1-Score**
Not Burned	0.99	1.00	1.00
Burned	0.99	0.98	0.99
Accuracy			0.99

Overall, the model's accuracy is 0.99. This high accuracy indicates that the model is more reliable than the ANN in classifying burned areas from unburned areas with minimal errors. However, this model does not incorporate the temporal properties of fire spread; a Conv-LSTM was investigated to achieve this.

5.2.3 Conv-LSTM Model

The convolutional layers in the Conv-LSTM are used for spatial feature extraction, and LSTM layers are used for temporal sequence processing.

5.2.3.1 Training process

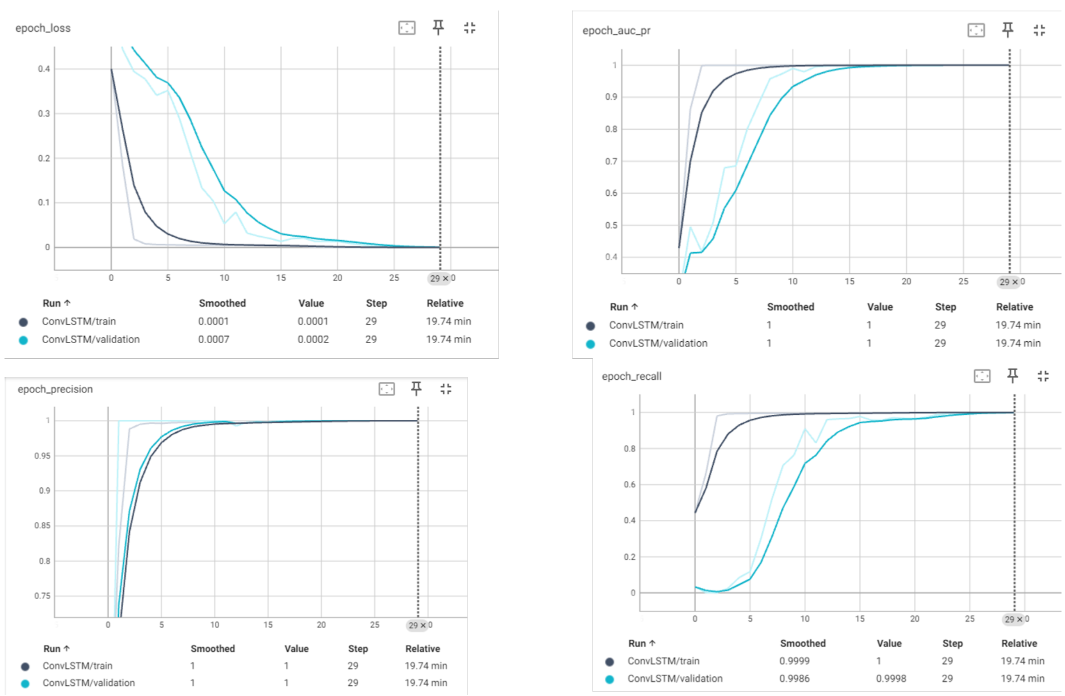


Fig. 5.13. Training loss, AUC PR, Precision, Recall over epochs

The training and validation of this model were performed, and the resulting curves over epochs for the loss, precision, recall, and AUC_PR are indicated in figure 5.13. These graphs show that the model is not overfitting to the training data, as the loss over epochs is very low, and the model's validation performance follows the training performance closely. Additionally, AUC-PR on the validation set increases significantly, which aligns with the training set performance, indicating the model generalizes well to unseen data.

5.2.3.2 Hyperparameter tuning

Hyperparameter tuning was performed by changing one hyperparameter and running the model. For the executed hyperparameters, the best model was found to have the following hyperparameters:

- batch size of 24
- learning rate of 0.0001
- number of epochs of 35

5.2.3.3 Prediction quality

To check the model's performance, a side-by-side visualization of true sample frames and the model's predicted output frames is depicted in 5.14. The 6 predicted frames depict how fire spreads from the start frame _0 to the end frame _5. The model produces predicted frames that have similar outputs to the expected results; this shows that the model can correctly classify where the fire will spread over six time steps from one frame to the next.

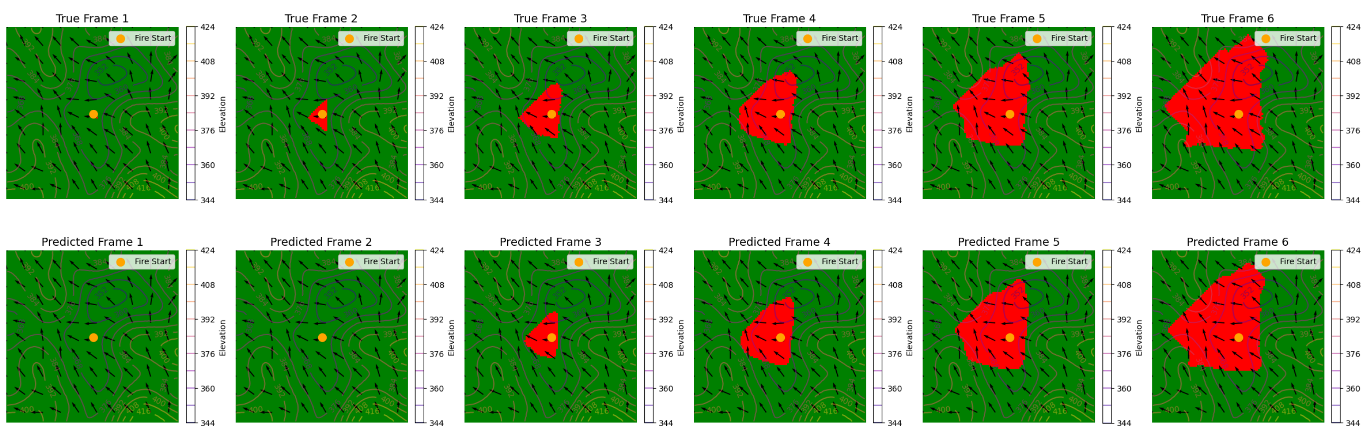


Fig. 5.14. True Vs Predicted Outputs of the Convolutional LSTM model

5.2.3.4 Error analysis

The error map in figure 5.15 (a) indicates incorrectly classified pixels when comparing the true and predicted pixels of frame 6, which is the last frame. The red pixels indicated show that these pixels were incorrectly classified as "Not Burned". Using the values from the confusion matrix in 5.15 (b) and equation 4.4, the error rate for this model was calculated; it was found that the error rate of this model is 0.0253 or 2.53%.

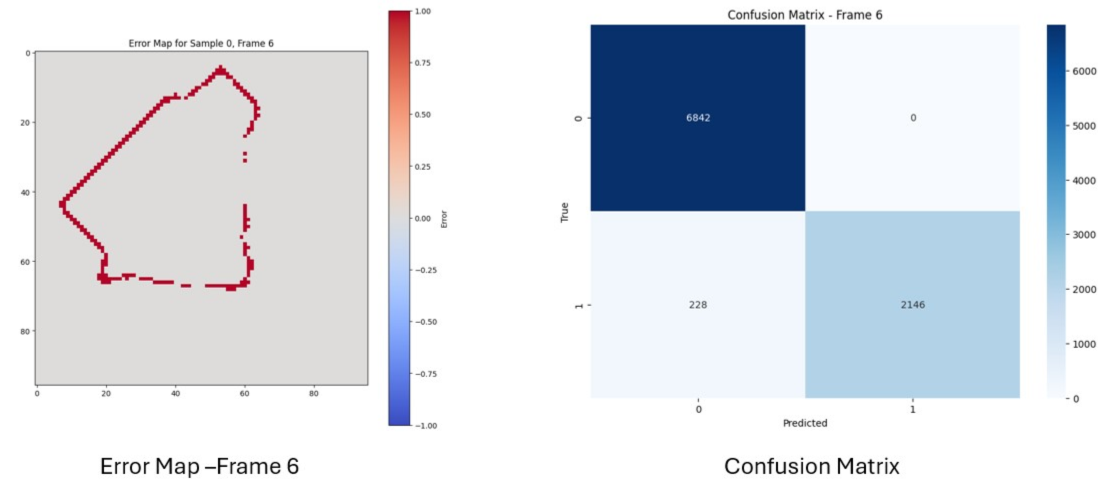


Fig. 5.15. Error Map and Confusion Matrix of the ConvLSTM

5.2.3.5 Metric evaluation

TABLE 5.3

ConvLSTM Predicted Classification Report

	Precision	Recall	F1-Score
Not Burned	0.97	1.00	0.98
Burned	1.00	0.90	0.95
Accuracy			0.98

From the predicted classification report in table 5.3, the F-1 score is high, reflecting the model's strong balance between precision and recall. The Accuracy is 0.99, indicating the model's ability to capture the spatial properties correctly, classifying the burned area. Most importantly, it captures the temporal properties of fire spread by accurately predicting where it spreads as it moves from the start point to the surrounding areas, as indicated in the multiple frame predictions, thus making potentially more accurate and robust predictions.

5.2.4 The Models Comparative Performance

Table 5.4 indicates the comparative evaluation of the three ML models ANN, Convolutional Autoencoder, and Convolutional LSTM, with the results of the three key evaluation metrics, accuracy, F1-score, and AUC-PR shown for each model.

TABLE 5.4

Comparative Performance of ANN, Autoencoder, and ConvLSTM Models

Model	**Accuracy**	**F1-Score**	**AUC-PR**
ANN	0.93	0.89	0.96
Autoencoder	**0.99**	**0.99**	**0.99**
ConvLSTM	0.98	0.95	0.99

The Autoencoder achieved the highest score of 0.99 across all metrics, indicating its ability to extract and reconstruct spatial features, while the ConvLSTM demonstrated the ability to capture spatiotemporal dependencies.

5.3 System Analysis

5.3.1 Feature Importance

To understand the feature's importance to the hypothesis formulated in the design, it is necessary to test how each feature affects the model's prediction and how sensitive the model is to changes in specific features. The results of varying one feature while keeping the others constant are discussed further.

5.3.1.1 Hypothesis 1: elevation effects

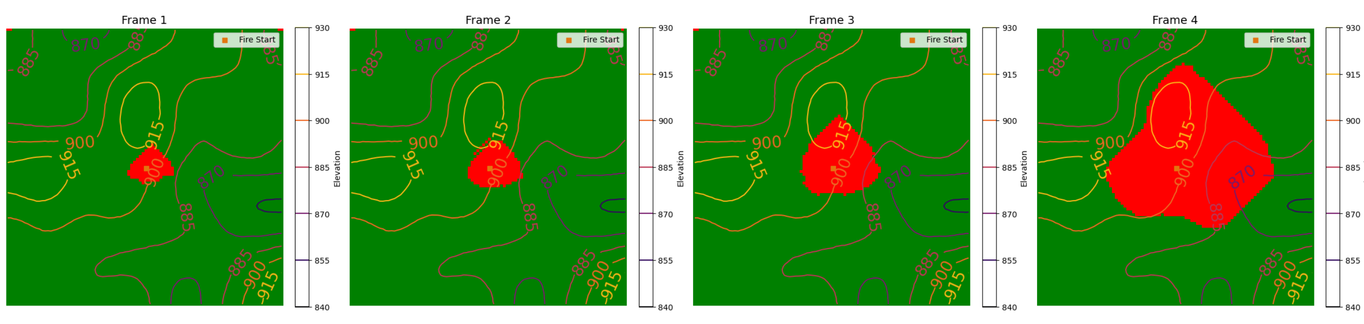


Fig. 5.16. Effects of elevation on Wildfire Spread

The elevation was varied while the other parameters were kept constant to investigate the effects of elevation on wildfire spread prediction. From frames 1 to 3 figure 5.16, it can be seen that the fire spread more towards the higher elevation values indicated by the contour lines. This highlights the importance of elevation in spreading wildfires.

5.3.1.2 Hypothesis 2: wind speed and direction effects

To investigate the effects of wind speed and wind direction on wildfire spread, the wind speed and direction are varied while other parameters are kept constant in the prediction. Figure 5.17 indicates that fire spreads more in the direction of the wind, as indicated by the black arrows. This highlights that the strong winds impact the direction of the fire and its speed.

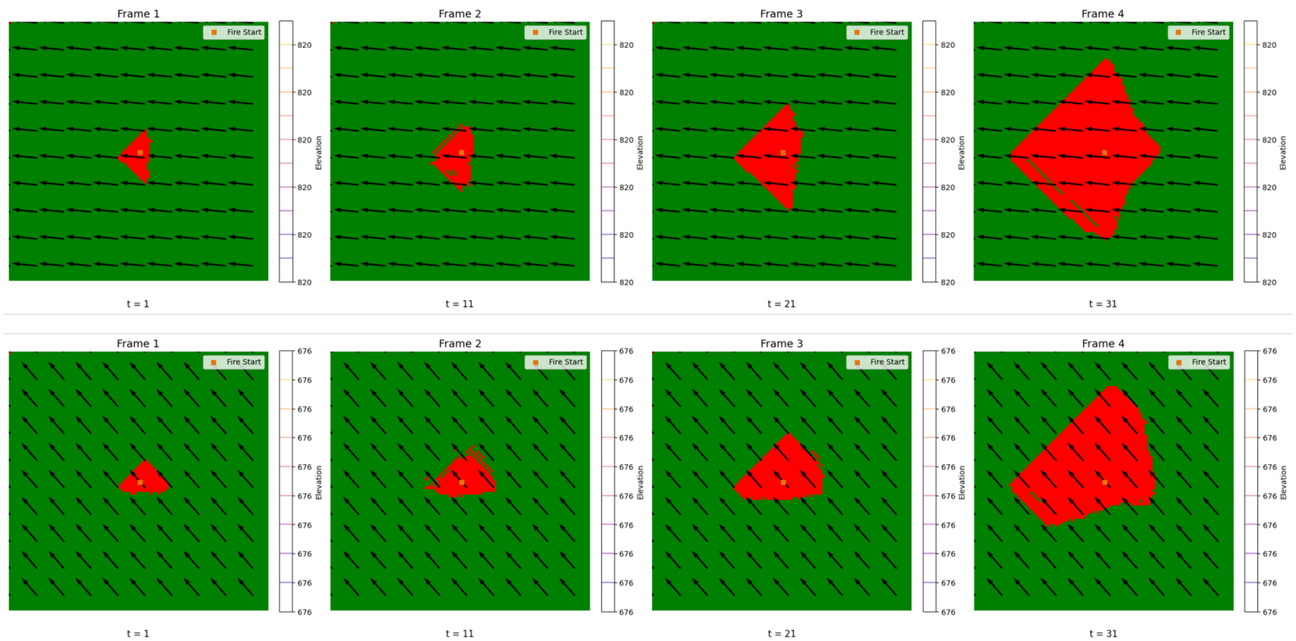


Fig. 5.17. Effect of wind on Wildfire Spread

5.3.1.3 Hypothesis 3: temperature effects

The relationship between temperature and how it affects fire spread is depicted in figure 5.18. The temperature colour map with higher values has burn scars, indicating that the fire is not only likely to occur at higher temperatures but also spreads around the surroundings with higher temperatures.

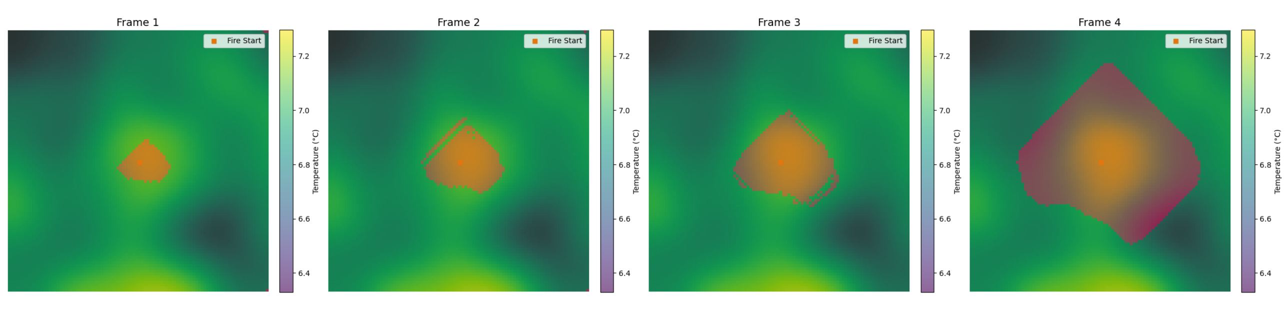


Fig. 5.18. Effects of temperature on wildfire spread

In summary, understanding the correlation of these features is crucial for creating accurate and reliable predictions of the spread of fire.

5.3.2 Computational Efficiency

```
!nvidia-smi

Sun Sep  1 11:35:31 2024
+---------------------------------------------------------------------------------------+
| NVIDIA-SMI 535.104.05             Driver Version: 535.104.05   CUDA Version: 12.2     |
|-----------------------------------------+----------------------+----------------------+
| GPU  Name                 Persistence-M | Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp   Perf          Pwr:Usage/Cap |         Memory-Usage | GPU-Util  Compute M. |
|                                         |                      |               MIG M. |
|=========================================+======================+======================|
|   0  Tesla T4                       Off | 00000000:00:04.0 Off |                    0 |
| N/A   56C    P8              10W /  70W |      0MiB / 15360MiB |      0%      Default |
|                                         |                      |                  N/A |
+-----------------------------------------+----------------------+----------------------+

+---------------------------------------------------------------------------------------+
| Processes:                                                                            |
|  GPU   GI   CI        PID   Type   Process name                            GPU Memory |
|        ID   ID                                                             Usage      |
|=======================================================================================|
|  No running processes found                                                           |
+---------------------------------------------------------------------------------------+
```

Fig. 5.19. The used GPU (TPU) specification

Figure 5.19 shows the GPU(TPU) utilised during the training of the models. The output shows that the Tesla T4 TPU with 15GB of memory was used.

5.3.2.1 Resource utilization on Google Compute Engine (GPU)

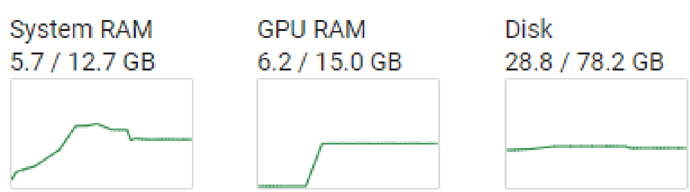


Fig. 5.20. Python 3 Google Compute Backend (GPU) resources

A Google Compute Engine (GCE) instance with a GPU backend's resource utilisation statistics offers information on how RAM, GPU memory, and disk space are currently used.

- **System RAM:** From figure 5.20, it can be seen that 5.4GB of the system's RAM was used for ConvLSTM model training and validation. ConvLSTM models can be memory-intensive, particularly when working with large datasets or deep architectures.
- **GPU RAM:** GPU memory is critical for accelerating the model's training and reducing the training time. Figure 5.20 shows that 6.2GB of GPU RAM is utilized for model training and validation, indicating that the model is leveraging the GPU resources efficiently.

- **Disk Usage:** From figure 5.20, it can be seen that 28.8GB of disk space is utilized, allowing for smooth data loading and checkpointing processes, which are critical for long training sessions.

5.3.2.2 Training and data loading times across models

TABLE 5.5

Time Comparison for Model Training and Data Loading

	ANN	Autoencoder	Conv LSTM
Training time GPU	1.84 min	3.07 min	19.74min
Data loading time CPU	1.38 min	1.38 min	21.65 min

The time it takes to load the data and train the three models is shown in 5.5. The ANN takes the least time, while the convLSTM takes longer to load data(21.65) and train the model (19.74) mins. However, these longer times in the convLSTM can be justified by its ability to handle more complex datasets. Thus, while the ConvLSTM is more computationally intensive, its efficiency lies in its ability to process and learn from more intricate data patterns, making it a superior choice when making sequence predictions.

5.4 Graphical User Interface

The wildfire spread system uses a Colab script to download satellite data, set up simulations and predictions, and visualize results. Although the Graphic User Interface (GUI) was not implemented as it was not part of the project's requirements, this section details the design of the proposed GUI.

Various parameters that the GUI would use have been identified from the experience gained when interacting with and developing the whole system. Additionally, after having done the experiments and produced results, the kind of components, adjustments, and settings that would need to be changed have also been identified. This knowledge informed the design of the proposed GUI as depicted in figure 5.21.

The different components shown in the GUI are outlined as follows:

- **Input panel:** For uploading the data in different formats or downloading data from satellite APIs.
- **Results Visualization Panel:** For displaying predicted results, the predicted burn maps can be overlaid on a Google Maps image to incorporate the terrain information of a location.
- **Output panel:** For outputting results on model performance analysis.
- **Get started:** Provides tutorials and FAQs.

- **Select model:** Select between Convolutional Autoencoder, which predicts one frame, or Convolutional LSTM, which predicts multiple time frames. Also includes using a trained model or retraining the model with different input data.

- **Select Parameters:** Select the following model parameters for each model.
  - **Convolutional autoencoder:** Learning rate, batch size.
  - **Convolutional LSTM:** Number of predicted time frames, learning rate, batch size.

- **Analysis tools:** Select model performance results of metrics such as precision, recall, AUC_PR, and F1 Score.

- **Reports:** Generate and export graphs as images or PDFs.

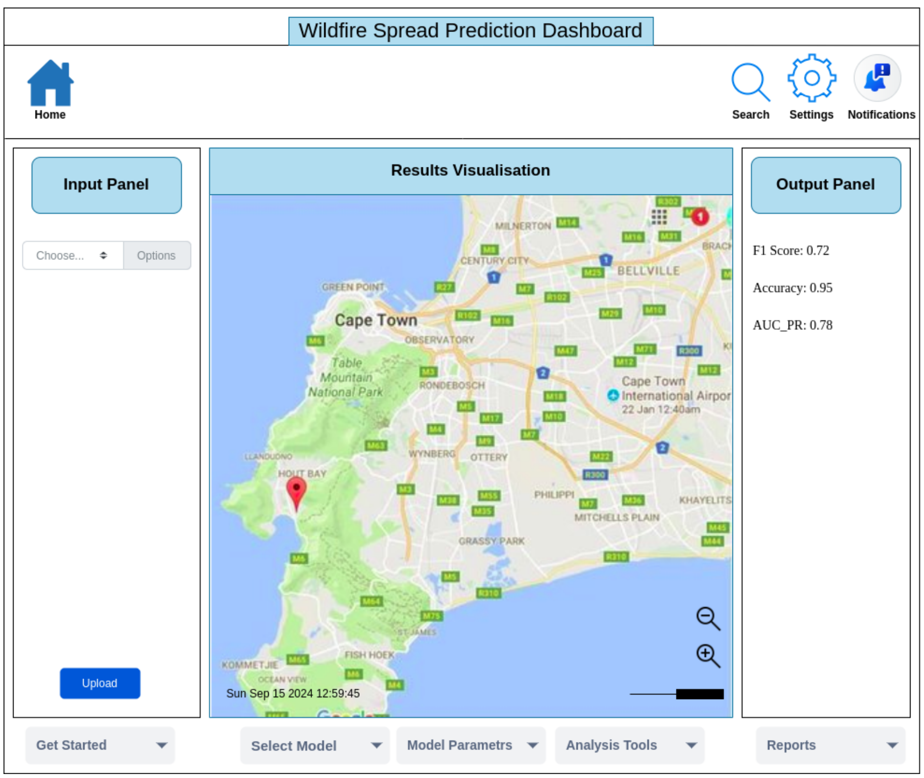


Fig. 5.21. Proposed Graphical User Interface

In summary, the results presented in this chapter demonstrate the effectiveness of the ANN, Convolutional Autoencoders, and ConvLSTM in capturing the spatiotemporal dynamics of the fire behaviour. Evaluation metrics such as F1 score, AURPR and confusion matrix analysis confirmed the model's ability to distinguish between burned and unburned areas with high reliability. The next chapter will draw broader conclusions for the study and present recommendations for future improvements for this work.

Chapter 6

Conclusion and Future Work

This chapter concludes the research and reflects on how the study has achieved its objectives outlined in chapter 1 section 1.4. It also outlines recommendations for future work, focusing on improving the current models and developing the graphical user interface.

6.1 Findings

The key findings that respond to the research questions outlined in chapter 1 section 1.5 are summarized in the subsections below. Each subsection highlights the findings of how the study addressed each research question.

6.1.1 Machine Learning Models:

In the design section 4.5, the following three supervised classification ML models were selected: ANN, Convolutional Autoencoders, and ConvLSTM. The models were fine-tuned through testing, validation, and hyperparameter tuning. Each model has shown strengths in different aspects of wildfire spread prediction, which are discussed in the following subsections.

ANN

The ANN demonstrated its capability to capture spatial patterns from the data with an accuracy loss of 6.74%, as shown in subsection 5.2.1.4. While noticeably significant, this loss did not greatly compromise the model's ability to make useful predictions. This performance is considered accurate as it falls within the stipulated specification of up to 10% loss for all models.

Additional metrics beyond accuracy loss, such as F1_score and AUC_PR, were considered to provide a more comprehensive evaluation of the ANN's performance. F1_score of 0.89 indicates that the model is good at identifying true positives(pixels correctly classified as pixels with fire) while minimising false negatives(pixels falsely classified as not fire) and false positives(pixels falsely classified as fire). Additionally, an AUC_PR of 0.96 shows the model's ability to correctly distinguish between positive(fire) and negative(no_fire) classes.

Despite the data complexity, the ANN model demonstrated the ability to capture complex non-linear relationships between the features. Although this model maintained a reasonable spatial predictive accuracy, thus meeting performance criteria as per the specifications, it struggled to capture the spatial dependencies from the data. Additionally, the ANN is limited in handling temporal sequences without major modifications to the model's architecture.

Convolutional Autoencoder

A Convolutional Autoencoder is excellent at feature extraction and dimensionality reduction; thus, it performed better than the ANN, achieving a much lower accuracy loss of 0.691%, as shown in subsection 5.2.2.4. This improvement in the model performance can be attributed to the model's ability to effectively incorporate and leverage the two-dimensional properties of the landscape data. In this model, the convolutional layers can learn the relevant features from the two-dimensional data, potentially capturing complex spatial patterns that the ANN might miss.

To provide a more comprehensive evaluation, the CAE achieved an F1-Score of 0.99, slightly higher than the ANN. The model also achieved an AUC_PR of 0.99, improving performance in correctly distinguishing between positive(fire) and negative(no_fire) classes. In achieving improved performance, this model also required fine-tuning of the model architecture to balance information compression and retention. The CAE's improved accuracy and other performance metrics highlight the importance of choosing an ML model that better suits the inherent structure of the analysed data.

The major limitation of this model was that, like a standard ANN, it also has limited capabilities in capturing the temporal dependencies.

ConvLSTM

To mitigate the limitation of ANN and Convolutional Autoencoder in capturing the temporal dynamics of fire spread, the ConvLSTM model was implemented. In the ConvLSTM, convolutional layers can extract the spatial features. At the same time, the LSTM units model the temporal sequence, making this model well-suited for capturing both the spatial and temporal dependencies from data. This model can provide short-term predictions by predicting a series of subsequent frames, thus making it powerful for predicting wildfire spreading over time.

This model achieved an accuracy loss of 2.53%, as shown in subsection 5.2.3.4. Since the ConvLSTM incorporates time series prediction, it is essential to note that this loss corresponds to the distant future prediction of the last frame (Frame 6). The slight loss increase compared to the Convolutional Autoencoder implies a trade-off between precise spatial reconstruction and the ability to predict future states.

Looking at other performance matrices, the model achieved an F1 Score of 0.95 and an AUC_PR of 0.99 for the last frame. This shows a robust performance across the fire and no fire classifications, even for distant future predictions. The ConLSTM model is recommended since it could efficiently predict both spatial and temporal dynamics of wildfire spread.

6.1.2 Satellite Data Sources:

In section 4.3 of the design, remote data from satellite sources was identified as an effective means of obtaining real-world data. The burn scars of fire incidents were downloaded from the Sentinel Hub, while the environment and weather of the same location and date of the fire incidents were downloaded from the Google Earth Engine.

The Environmental and weather data identified included the elevation, wind speed, wind direction and temperature data, and a sample of this is illustrated in the results section 5.1.1. Supplementary to that, more data with the same statistical characteristics as the satellite data was generated using the Perlin noise and spread probability function as discussed in the design section 4.4. A matrix-layered approach was used to restructure the data to form a 5D tensor, as illustrated in 5.1.2.

6.1.3 Identification of Key Factors Influencing Wildfire Spread Behavior:

From Chapter 5 subsection 5.3.1, which discusses the importance of each parameter on fire spreading, it can be concluded that wind speed and wind direction have a greater impact on the rate and direction in which the fire burns, as the image with longer arrows has more cells burned over the same timestamp.

Additionally, temperature and elevation effects were observed. The visualisation areas with higher temperatures seem more likely to burn than those with lower temperatures. As for the elevation, fire was observed to spread more towards higher contours, meaning higher elevations.

In summary, this research successfully achieved its objectives of developing an ML-based wildfire spread system that captures the spatial and temporal properties of wildfires, as well as using freely available satellite data to train, test, and validate the models.

6.2 Recommendations for Future Work

This section divides suggestions for further research into: incorporating more environmental and weather parameters 6.2.1, investigating alternative machine learning models and potential hybrid models 6.2.2, and implementing graphics user interfaces to facilitate easy use of the system 6.2.3.

6.2.1 Wildfire Spread Parameters

This research investigated the effects of wind speed, wind direction, temperature, and elevation on wildfire spread. Future work can explore the impact of other factors, such as fuel type and availability, atmospheric conditions, and terrain.

6.2.2 Potential of Hybrid Models

In this research, only three supervised learning ML models, ANN, Convolutional Autoencoders, and ConvLSTM were tested due to time limitations and the need to maintain reconfigurability. Future work can investigate more ML models, such as the Genetic Algorithm (GA) and Asynchronous Advantage Actor-Critic (A3C). Additionally, hybrid models between the different ML approaches and a combination of ML models with physical or empirical models can be explored to enhance the model's predictive capabilities.

6.2.3 Proposed Graphical User Interface

The implementation of the Graphic User Interface (GUI) design detailed in the results chapter 6.2.3 is proposed as part of future work that a Bachelor of Science degree final-year student can implement.

Final Words: Developing a reliable and effective wildfire spread prediction system is essential for mitigating wildfire impacts. With continued research and innovation, such systems can contribute to safeguarding lives, properties, and preserving natural beauty and biodiversity. Thus, ensuring the safety and sustainability of our communities and environment.

References

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Appendix A

First Appendix

A.1 Satellite Data Download and Preparation

This appendix provides the Google Colab code used to download and process the satellite data from GEE and Sentinel Hub. The processed data is stored directly on Google Drive in a TFRecord format.
This code can be accessed from this link

A.2 Data Generation Engine

The Data Generation code can be accessed from this link

A.3 ANN Model

The code for the ANN wildfire spread model can be accessed from this link

A.4 Convolutional Autoencoder Model

The code for the Convolutional Autoencoder wildfire spread model can be accessed from this link

A.5 Convolutional LSTM Model

The code for the Convolutional LSTM wildfire spread model can be accessed from this link