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An Intelligent Warning System Helping To Predict And Prevent Fire

Defined By

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Abstract

Forest fires have devastating consequences, causing extensive damage to natural resources and posing a significant threat to the ecological environment. The destruction caused by these fires is often difficult to compensate for. To mitigate the impact of forest fires, it is crucial to develop effective prediction systems. In this study, we focus on using weather data as a key factor in predicting forest fires. We prove that by analyzing weather patterns and conditions, we can gain valuable insights into the likelihood of fire incidents. For that, we employ supervisory learning algorithms, specifically Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). Our research involved comparing the performance of these three algorithms in predicting forest fires based on weather data. After conducting extensive experiments and analysis, we found that the Random Forest algorithm (RF) outperformed the other two algorithms, SVM and ANN, in terms of predictive accuracy. To address the urgent issue of forest fires, we developed an intelligent fire warning system called ”Predict and Prevent (IFWS)”. This system combines the power of artificial intelligence algorithms and the Internet of Things (IoT) to create an effective and efficient solution for predicting and preventing forest fires. By using advanced AI techniques and real-time data from IoT sensors, IFWS aims to provide timely and accurate warnings, enabling Early action to be taken.

Keywords: Forest Fire, Machine Learning, Fire Application, Weather Conditions, Predicting Fire, Risk , Data analysis.

ملخص

حرائق الغابات لها عواقب وخيمة ، تسبب أضرارًا جسيمة للموارد الطبيعية وتشكل تهديدًا كبيرًا للبيئة البيئية. غالبًا ما يصعب تعويض الدمار الناجم عن هذه الحرائق. للتخفيف من تأثير حرائق الغابات ، من الضروري تطوير أنظمة تنبؤ فعالة.

في هذه الدراسة ، نركز على استخدام بيانات الطقس كعامل رئيسي في التنبؤ بحرائق الغابات. نثبت أنه من خلال تحليل أنماط الطقس وظروفه ، يمكننا الحصول على رؤى قيمة حول احتمالية وقوع حوادث حريق. لذلك ، نستخدم خوارزميات التعلم الإشرافي ، دعم آلات المتجهات (SVM) و Random Forest (RF) والشبكات العصبية الاصطناعية (ANN) على وجه التحديد.

تضمن بحثنا مقارنة أداء هذه الخوارزميات الثلاثة في التنبؤ بحرائق الغابات بناءً على بيانات الطقس. بعد إجراء تجارب وتحليلات مكثفة ، وجدنا أن خوارزمية Random Forest (RF) تفوقت على الخوارزميتين الأخريين ، SVM و ANN ، من حيث الدقة التنبئية.

لمعالجة القضية الملحة المتمثلة في حرائق الغابات ، قمنا بتطوير نظام إنذار ذكي للحرائق يسمى التنبؤ والوقاية (IFWS) آ. يجمع هذا النظام بين قوة خوارزميات الذكاء الاصطناعي وإنترنت الأشياء (IoT) لإنشاء خوارزميات فعالة وحل فعال للتنبؤ بحرائق الغابات ومنعها. من خلال استخدام تقنيات الذكاء الاصطناعي المتقدمة والبيانات في الوقت الفعلي من مستشعرات إنترنت الأشياء ، تهدف ايذوا إلى توفير تحذيرات دقيقة وفي الوقت المناسب ، مما يتيح اتخاذ إجراءات مبكرة.

الكلمات الرئيسية : حرائق الغابات ، التعلم الآلي ، تطبيق الحرائق ، الأحوال الجوية ، التنبؤ بالحرائق ، المخاطر ، تحليل البيانات.

Acknowledgement

In all humility we bow before the Most Merciful Allah who has given us the heart to feel and the mind to think, so that we may know what not to do.

All respect and praise to the Holy Prophet, Hazrat Muhammad (may God bless him and grant him peace), who came as the light of knowledge for all researchers and a true model for all mankind.

We are grateful to my supervisor, Dr. Brahim Belgroun, for his patience, inspiring guidance, kind attitude, and cooperation throughout my research and for his keen interest as well as the editorial corrections that he made during thesis writing.

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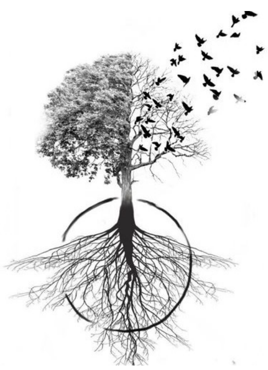
May Allah bless all of us. Amen



Dedication

I dedicate my dissertation work to my family and my friends. A special feeling of gratitude to my loving parents, Achour who has been nicely my supporter until my research was fully finished, and my beloved mother Mounia who, for months past has encouraged me attentively with her fullest and truest attention.

I dedicate this work and give special thanks to my little brother Nadji for being there for me throughout the entire master's degree. You guys were my best supporters.

Merdaci Anfel

I am dedicating this thesis to beloved people who have meant to me. First and foremost, to my paternal grandfather Moussa whose love for me knew no bounds, he has gone forever away from our loving eyes, I will never forget you, My Allah bless you. And my maternal grandmother Hafssiya who raised me, loves me, May Allah prolong your life.

I also I'd want to dedicate this to my parents, Abed el-Ouaheb and Ismahan, who have always loved me without condition and whose good examples have inspired me to work hard for the things I want in life.

Last but not least I am dedicating this to my little sisters Malak and Hadjer and My best friend Amel who encouraged me to pursue my dreams and finish my dissertation.

Khammar Houayda

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Chapter I

Introduction, research problem, and methodology

The world is currently experiencing a surge in natural disasters due to ongoing climate change, with forest fires being one of the most widespread occurrences.

The prediction, detection, and control of forest fires have become a global concern, with many countries seeking to develop advanced techniques to manage this problem.

In Algeria, we will use artificial intelligence techniques are being employed to predict forest fires using weather data. Weather is considered one of the most significant factors influencing the prediction of fires. The nonlinear relationship between these variables makes it difficult to accurately predict the likelihood of forest fires based solely on weather parameters. For instance, high temperatures, and low humidity may not necessarily lead to fire due to the nonlinear nature of their interaction, which cannot be adequately described using simple linear correlations.

Several machine learning algorithms are being used to discover patterns in the big data required to accurately predict forest fires. These algorithms are divided into two categories: **supervised and unsupervised learning**. Supervised learning is the most widely used category, with algorithms learning what conclusions they should draw from the data. It needs prior knowledge of the algorithm's potential outcomes, and employed training data must be annotated with accurate responses. Classification and regression constitute the primary categories of supervised learning.

In this study, we developpe an Intelligent Fire Warning System **(IFWS)**[1], a critical system that can save lives and prevent property damage by detecting and warning about fire hazards early.

On the one hand, this system can predict and prevent fire using advanced algorithms such as **RF**[2], **SVM** [3] and **ANN**[4].

[1]Name of our system
[2]Random Forest
[3]Support and Vector machine
[4]Artificial Neural Network

On the other hand, we will use the **IoT**[5] tools to implement an electronic part of this study. It will use the model that resulted from the training part using an **Arduino**[6]

Tracking past events that can identify trends and patterns, and predictive models can be built to forecast future fires. This approach helps identify high-risk areas and allocate resources for prevention and mitigation efforts.

I.1 Problematic

Predicting and preventing forest fires is critical for minimizing their impact, but it can be challenged due to their complex and dynamic nature.

This study aims to develop an **IFWS** that faces several challenges, such as selecting the appropriate sensors to detect fire hazards accurately, designing the algorithms to predict and prevent fire, and integrating the system with the Arduino microcontroller.

The fire can be triggered by many factors related mainly to weather conditions. Many questions can be posed before treating this problem.

- Which indicators (features) can play a role in catching fire?
- Is there any relationship (linear and/ or nonlinear) between these indicators?
- Which algorithms of AI can be used to extract this relationship?

I.2 Objective

The main objective of this study is to design and implement an intelligent fire warning system**(IFWS)** using **(RF), (SVM), and ANN** algorithms, along with an Arduino microcontroller.

the main objective of this study is to train an intelligent model that can predict fire starting from the weather information (temperature, humidity,..). The new model will be, implemented on the Arduino to make alerts and prevent automatically whenever the risk exceeds a given threshold. The prevention aims to change the weather conditions to decrease the risk.

Finally, the system must be robust, reliable, and able to operate in various environments, including high temperatures. The study will address these challenges and propose an **IFWS** solution that can effectively predict and prevent fire.

[5] Internet of Thing

[6] microcontroller can make the system cost-effective and easy to implement. Data mining technique. are also employed to extract valuable insights from historical data on forest fires.

I.3 Brief Methodology

In this study, we aim to propose a forest fire warning system using machine learning algorithms and Arduino to achieve this objective, we will follow the following steps:

1. **Determine the coverage area**: Identify the area that needs to be monitored for forest fires and determine the number of wireless sensor networks required to cover the area(Given the data available to us, we will cover the Bejaia region in Algeria).

2. **Select the sensors**: Choose the appropriate sensors for detecting forest fires, such as temperature sensors, humidity sensors, and smoke sensors.

3. **Collect data**: Collect data from the sensors and store it in a database.

4. **Train the machine learning model**: Use the collected data to train a machine learning model, such as a decision tree or a random forest, to detect forest fires. since further experimentation may be needed to confirm the findings. One frequently encountered conclusion is the need for further experimentation. Most statistical, and hence machine learning or data mining, studies are iterative.

5. **Deploy the model**: Deploy the trained model on an Arduino board to enable real- time detection of forest fires.

6. **Alert system**: Set up an alert system to notify authorities and nearby residents in case of a forest fire.

I.4 Thesis Architecture

To treat our problematic, the thesis will be divided into four chapters:

Chapter One: Introduction, problem, and methodology This chapter introduces our study, defines its objective, and highlights the methodology, and the content of this thesis.

Chapter Two: Causes and behavior of forest fires Exploring the multifaceted nature of forest fires, including their definitions, causes, behavior, and different types, along with statistical insights, as well as ways to combat them using artificial intelligence, in addition to new techniques to fight the fires using artificial intelligence.

Chapter Three: State-of-the-art" forest fire and artificial intelligence algorithms" In the chapter on AI and ML and DL, we explore forest fire applications. We also discuss the related work in this field and will see the challenges associated with accurate and timely forest fire detection.

Chapter Four: An Intelligent Fire Warning System Predict And Prevent (IFWS) The study focused on the development and evaluation of an Intelligent Fire Warning System (IFWS) for using "Predict and Prevent". The study presented the general architecture of IFWS, which encompassed data collection, data processing, prediction model development, and performance evaluation. Three different classifiers were employed and compared for the classification task. Performance evaluation was carried out using metrics such as accuracy, precision, recall, and F1-score. The study also considered the execution time as a performance measure and proposed an IoT architecture with various devices and sensors for efficient data collection. Additionally, the hardware connections of the system were tested to ensure proper functionality.

Chapter II

Forest fire: Causes and Behavior

II.1 Introduction

Forests play essential roles in nature such as soil fertilization, nutrient cycling, climate regulation, water and air purification, carbon storage, and supporting biodiversity. Additionally, the forest products industry generates numerous jobs and contributes significantly to a country's economy.[**1**]

Sadly, forest fires damage millions of hectares of forest every year, and considerable resources are spent on extinguishing them. These fires pose a severe threat to ecological systems, economic properties, infrastructure, and human lives.[**1**]

Over the past 50 years, a lot of the world's natural forests have been destroyed due to forest fires and poor forest management. Currently, almost all forests face natural and human-made environmental risks, global warming, and extreme climate change.[**2**],[**3**]

Detecting forest fires early is crucial to minimize their destructive impact.[**3**],[**4**] There is an urgent need to develop new tools for efficient decision-making and forest management through fast and cost-effective data acquisition, measurement, and monitoring of forest fires and inventories. Such methods could be a promising alternative to traditional forest fire detection approaches. [**5**]

In this chapter, we will define some terminology related to the field of forest fire and its behaviors. We will also determine which conditions affect fires (ignition, spread, suppression,...) to consider them in our study as features of the database will be used in this study.

II.2 What is The Fire

Fire is a chemical reaction of fuel[1] with the required amount of heat [2], and oxygen to raise the fuel to what's known as its ignition point which is where it Decomposes into the burnable mixture, and during this reaction, heat light is produced.[**6**]

II.3 Definition of Forest Fire

Forest fires are naturally occurring uncontrolled flames that are usually aggravated by weather conditions, Dry conditions increase the chance of forest fires sparking. [**7**]

A forest fire is distinguished from other types of flames by its large size, rapid spread, and ability to cross gaps such as highways and rivers. A forest fire can last for a very long time can be days weeks or even a few months before it can be put out now before proceeding further.[**8**]

II.4 Forest Fire Behavior

Spreading forest fires involves a process where the front of the fire heats and ignites unburned woody and herbaceous materials. This process involves the evaporation of moisture within the fuel (fuel temperatures > 100 °C), at that point the cellulose is thermally broken down and its breakdown items volatilized (> 200 °C) and at long last, the volatiles is lighted to create an obvious fire (300-400 °C).[**9**]

Heat is primarily transferred through convection [3] and radiation in forest fires, while conduction is not significant due to the poor heat conductivity of wood and soil. The fire must constantly move to consume more fuel, and once most of the volatiles have been burned, the remaining carbon may undergo glowing combustion. Flaming and glowing combustion are not distinct events in forest fires, as they involve a complex mixture of fuel sizes, moistures, and arrangements. Gases dominate the flaming front, while glowing combustion occurs primarily after the flaming front has passed.[**9**]

An Idealized flaming front with modes of heat transfer As shown in **FigureII.1**,**FigureII.2**,**FigureII.3**.

[1] is a flammable substance that ignites easily and burns rapidly with the flame this can be a solid liquid or a gas
[2] this heat source can be lightening the sun volcanoes or others .
[3] convection is the process by which heat rises from the fire and warms the air around it.

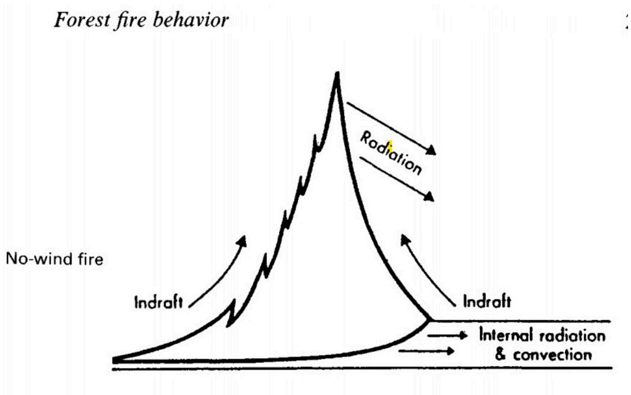

Figure II.1: No-Wind Fire [9]

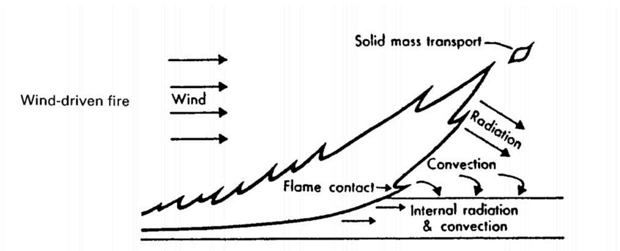

Figure II.2: Wind-Driven Fire [9]

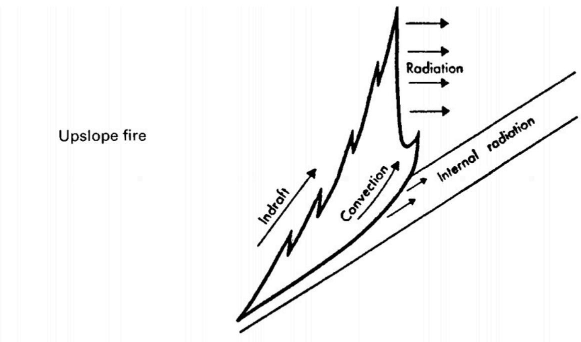

Figure II.3: Upslope Fire [9]

II.5 Mechanism of Fire Spread

The environment plays a major role in influencing the behavior and spread of forest fire weather, fuel, and topography It is divided into several branches **FigureII.4**.

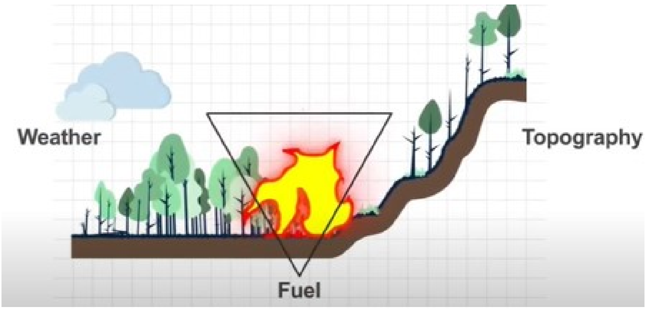

Figure II.4: Fire Behavior of Related to the Fire Environment [**99**]

II.5.1 Fuel characteristic

Forest fuel is essential for providing heat and can serve multiple functions including as a heat source, sink, and transportation. It plays a vital role in starting, spreading, and consolidating crown fires. Forest fuel is made up of various small particles, both living and dead, such as duff, litter, slash, grass, shrubs, and trees.[**10**]

Bulk density, which includes air, is an important factor to consider when assessing fuel. Packed fuels, despite their large surface-to-volume ratio, do not allow for efficient air and gas transport, making them function as a denser heat sink. Additionally, the mineral content, waxes, and oils are relevant parameters to take into account when considering fuel.[**10**]

II.5.2 Topography of The Land

The existence of hills and mountains impacts how a fire starts and moves. The incline of the land has a bearing on how quickly the fire spreads, as it tends to spread more easily uphill than downhill. Additionally, the angle and orientation of the land influence how much sunlight the vegetation receives, which affects its dryness and flammability. These variables are commonly included as input parameters in many fire models.[**10**]

II.5.3 Weather Conditions

More than 90% of forest fire behavior can be attributed to meteorological conditions. The dryness of fuel is closely linked to its ability to catch fire and burn, which in turn affects the likelihood and behavior of fires. The role of wind is widely acknowledged as crucial in the spread of flames through the forest.[**10**]

II.6 Types of Forest Fire

Depending on the conditions of the fire event, one or multiple types of fires can occur at a time. The types of Forest fires are described as follows **FigureII.5**.

Figure II.5: Types of forest fires [11]

II.6.1 Ground Fire

A type of forest fire known as a Ground fire initiates underground due to the combustion of materials such as debris. Depending on the circumstances, Ground fires may progress to become surface flames by burning through the ground surface. Unlike surface fires, these fires have a slower rate of spread and may continue burning for several months.[**11**],[**12**]

II.6.2 Surface Fire

Surface fires' intensity depends on the circumstances and are typically fueled by low-lying vegetation, ignited by ground fires that breach the surface. Despite scorching tree canopies, surface fires lack the energy to cause tree burning which would result in a fire. Surface fires usually spread slowly, but steep slopes or windy conditions can accelerate them.[**11**],[**12**]

Most surface fires do not develop into severe ”crown fires” and eventually extinguish on their own.[**11**],[**12**]

II.6.3 Crown Fire

A unique type of forest fire is a Crown fire, where the fire spreads from the topmost layer of the trees, known as the canopy, to the next. These fires can swiftly spread, moving much faster than fires that start from lower levels. The height of the fire from the ground makes it vulnerable to the wind, resulting in fast and intense burning. Crown fires have the potential to become severe due to their rapid progression.[**11**],[**12**]

II.7 Causes of Forest Fires

1. **Caused by negligence**: They are often caused by residents near forests, pastoralists, or passers-by. Like throwing cigarette butts. [**13**]

2. **Arson**: Humans may rely on illegal forest fires to expand agricultural land. Or produce charcoal from burning trees to cause a natural disaster in Algeria[**13**]
3. **Natural fires**: caused by high temperatures, with transparent materials such as glass, Or materials reflecting sunlight.[**13**]

II.7.1 Natural Causes of Forest Fires

1. **Volcanic Eruption**: Burning lava eruptions have the potential to set fields on fire up to a distance of 1 kilometer.[**14**]
2. **Lightning**: Forest fires can be triggered by lightning, particularly a type known as ”hot lightning”. These fires, sparked by hot lightning, tend to persist for a relatively extended period. If hot lightning strikes the ground, it has the potential to generate a spark that may ignite a fire in a forest or field.[**14**]
3. **Dry Climates**: Arid regions or dry climates are characterized by very little water, which makes it difficult for plants and animals to survive. The absence of moisture in these areas promotes forest fires.[**14**]
4. **Extremely Hot Weather**: Forest fires have been attributed to excessively hot weather in certain situations. The ongoing and most fatal Australian Bushfire, for instance, was caused in part by unprecedented high temperatures in Australia.[**14**]
5. **Wind**: Although the wind itself does not start forest fires, it is certainly a significant factor in causing small fires to escalate into larger forest fires.[**14**]

II.8 Forest Fire: some statistics

II.8.1 Forest Fire in The World

The Brazilian Amazon is currently experiencing the highest level of forest fires in 12 years, which have devastating consequences on ecosystems, economies, property, and livelihoods, and also release millions of additional tons of carbon.[**15**]

In 2020, California’s forest fires released 25% more carbon dioxide into the atmosphere than the state’s annual emissions from fossil fuels.[**15**]

Forest fires in the EU and UK during the summer of 2022 released the highest level of carbon emissions since 2007 .

Between 2001 and 2019, fires caused the loss of 119 million hectares of tree cover globally, which is 27% of all tree cover loss, while other causes of loss resulted in 318 million hectares of tree cover loss.[**16**]

Russia experienced the highest loss of tree cover (50 million hectares) due to fires between 2001 and 2019 **FigureII.6**. In 2016, the highest loss of tree cover (9.61 million hectares) due to fire was also recorded.[**16**]

The largest individual forest fire of the past decade occurred in the Australian region, burning approximately 24 million hectares **FigureII.7**.[**16**]

India reported 345,989 forest fire events between November 2020 and June 2021, with the highest number of events recorded in Odisha (51,968), followed by Madhya Pradesh (47,795), Chhattisgarh (38,106), Maharashtra (34,025), Jharkhand (21,713), and Uttarakhand (21,487).[**16**]

Rank	Name	Country	Area burned (Km^2)
1	2019-2020 Australian bushfire season	Australia	240,000
2	2021 Russia wildfires	Russia	200,000
3	2019 Siberia wildfires	Russia	43,000
4	2014 Northwest Territories fires	Canada	34,000
5	2009 Black Saturday bushfires	Australia	21,000
6	2020 California wildfires	United States	18,000
7	2010 Bolivia forest fires	Bolivia	15,000
8	2011-2012 Australian bushfire season	Australia	14,000
9	2006-2007 Australian bushfire season	Australia	13,000
10	2017 British Columbia wildfires	Canada	12,000

Figure II.6: A table shows prominent forest fires in the world from the past decade (Source: Anon 2021) [**16**]

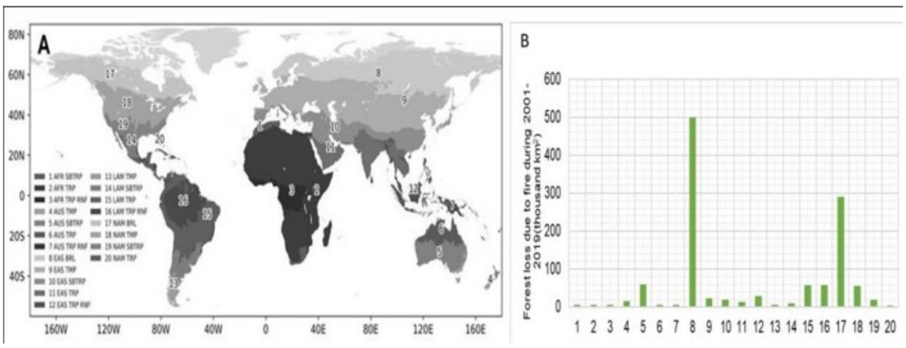

Figure II.7: Forest loss due to fire between 2001 and 2019 (modified from Tyukavina 2022) [**16**]

II.8.2 Algeria Forest Fire

Climate change is causing an increase in the frequency of forest fires in Algeria during summer, leading to a higher rate of being affected.[**17**]

Forest fires in Algeria have resulted in the annual destruction of over 36,000 hectares of forests and economic losses exceeding 113 billion Algerian dinars between 1985 and 2006. This cost calculation does not include yearly expenses for firefighting and the long-term impact on biodiversity and forest ecosystem balance.[**17**]

Prevention and early detection are the only effective strategies to reduce the damage caused by forest fires in Algeria. [**17**]

Climate, soil, and plant species should be considered to identify the causes of fires and find appropriate solutions. Research is being conducted in Algeria to understand the types of forest fires and the underlying issues, which will enable us to devise solutions and make predictions about potential fires.

1. **Fire Risk (RI):** The response of vegetation to fires relies on its characteristics such as type, appearance, components, and arrangement.[**18**]
   Compared to hardwoods, softwoods are highly susceptible to catching fire. Marquis and scrubland comprising of several aromatic herbs like thyme, rosemary, lavender, and heather are prone to fire outbreaks. Grasslands and meadows that contain annual species and tend to dry out rapidly can also serve as potential fuels. In contrast, low steppe formations with scant coverage pose a relatively low risk of fires.[**18**]

2. **Drought Resistance (RS):** The significance of water requirements for plant growth is valued through a parameter that is derived from the bibliographical compilation. The plants are classified into different vegetation types based on their shared traits and characteristics, which are used to estimate their ability to withstand drought.[**18**]

3. **Erosion Protection (EP):** The density of biosensors is connected to a certain parameter, which is evaluated and adjusted based on its relation to other factors. Typically, soils that are covered by thriving and dense forests or crops possess a greater water infiltration coefficient and better erosion protection. Conversely, soils that are partially covered (such as scrublands or steppes) or bare tends to promote heavy runoff. Table I is a summary of the ratings of various parameters chosen for vegetation.[**18**]

4. **Choice of Parameters:** Many climatic and vegetative parameters contribute fundamentally to affecting forest fires in Algeria. The research approach focused only on a few of the Parameters that were found in some studies, such as the research paper on desertification conducted by Mostefa Salamani, Halima Kadi Hanifi, Aziz Hirche, and Dalila Nedjraoui entitled ASSESSMENT OF DESERTIFICATION SENSITIVITY IN ALGERIA in 2012.

Trainings	resume	IR	RS	PE
Coniferous forests	1	2	1	1
Deciduous forests	1	1.5	1	1
maquis	1.66	1.5	1.33	1.5
Lawns	1.66	2	1.66	1
Steppes	2	1	1.66	2
Pseudo steppes	2	1	2	2
Irrigated crops	1	1	1	1
Dry crops	2	1	2	2

Figure II.8: A table shows Scores of the Different Vegetation Parameters [18]

IQV	Description	Color
0	Unclassified	Blue
< 1.2	Good quality	Dark green
1.2< IQS< 1.4	Medium quality	Light green
1.4< IQS< 1.6	Bad quality	Yellow
IQS >1.6	Really bad quality	Red

Figure II.9: A table shows Class bearing vegetation quality index (IQV) [18]

II.9 Forest Fire Fighting Techniques

Forest firefighting techniques refer to the various strategies and methods employed to suppress and extinguish forest fires in forested areas. These techniques aim to control the spread of fire, protect lives, preserve property, and mitigate the environmental impact of forest fires. Here is a description of some commonly used forest firefighting techniques:

II.9.1 Mapping Software

Fuel mapping is a crucial activity in forest fire risk management[19]. It is based on remote-sensing image processing methodologies that use Analytic Hierarchy Process (AHP) and Frequency Ratio (FR) to determine weights from remote sensing (RS) data and geographic information system (GIS) techniques and approaches.[19]

Fuel types are complex and highly heterogeneous spatial entities, and there are four types of complexity associated with remote sensing-based mapping. These include purely spectral complexity [4], spatial heterogeneity of fuel types; spectral signatures, spatial horizontal structures of fuel types, and fuel types; vertical structure heterogeneity. To address these complexities, various methods have been developed, such as pixel-based spectral methods, texture analysis-based methods, object-based methods, and 3D analysis methods.[20]

While it is impossible to control nature, mapping forest fire risk zones and minimizing the frequency of fire through fuel mapping is possible.[21]

[4] Purely spectral complexity refers to the challenges of accurately identifying objects based on their spectral characteristics, including overlapping profiles and noise.

II.9.2 Fire Urgency Estimator in Geosynchronous Orbit

The Fire Urgency Estimator in Geosynchronous Orbit is a futuristic technology that involves drones and satellites equipped with infrared sensors **FigureII.10**.[**22**]

It is currently in the conceptual stage and aims to detect the initial signs of forest fires from space.[**22**]

The system, created by astrophysicist Carlton Pennypacker, will use multiple platforms at different altitudes, including Earth-orbiting satellites. Although untested, FUEGO is a promising example of the innovative technologies being developed to combat forest fires and tackle climate change.[**22**]

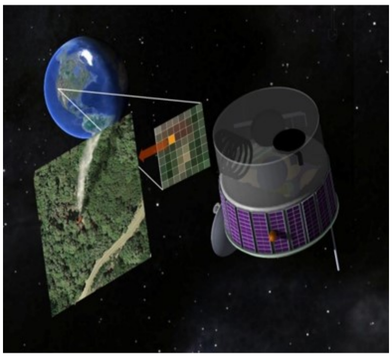

Figure II.10: Artist's Concept of FUEGO on Orbit during a fire alert (FUEGO Concept Art by R. E. Lafever, LBNL) [22]

II.9.3 Drones to Identify Fire Spread

Drones are a new technology that is increasingly being used, and they have been suggested as a possible solution to address climate change. They are capable of flying for up to eight hours at a time and can carry equipment for monitoring wildfires, which can be communicated directly to forest service teams.[**23**]

Drones are particularly useful for monitoring forest fires in situations where it is unsafe for manned aircraft to fly, such as at night or in thick smoke or high winds.[**23**]

According to Justin Baxter, the Forest Service National UAS Operations Specialist, drones are not effective in providing solutions for forest fires at the early stages. Although they are useful in protecting lives and monitoring the spread of forest fires, drones have limitations **FigureII.11**.[**23**]

A new platform is available that uses Unmanned Aerial Vehicles (UAVs) to constantly patrol areas that may be at risk of fires. These UAVs use Artificial Intelligence (AI) and have onboard processing capabilities, enabling them to recognize and detect smoke or fire using computer vision methods based on images or video from their cameras.[**24**]

The platform offers various scenarios for using UAVs in detecting forest fires, including a solution that combines fixed and rotary-wing drones.[24]

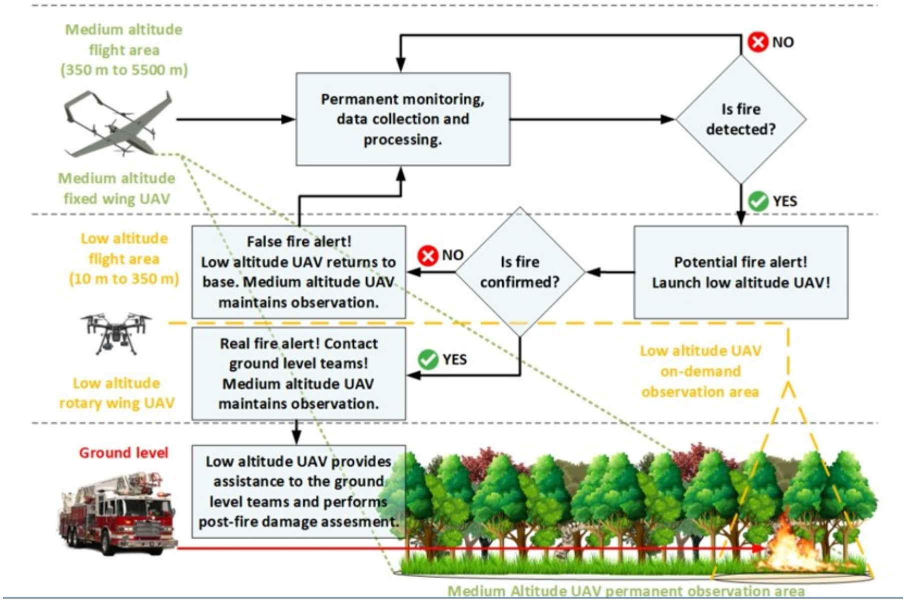

Figure II.11: Conceptual model of the early forest fire detection system with the use of fixed wing and rotary wing UAVs [24]

II.9.4 Infrared Cameras

A research paper addresses the challenge of detecting and monitoring fires at night using regular cameras. It suggests using cameras equipped with infrared lighting to capture infrared filters[5], allowing the detection of active fires through the presence of sunlight, light, and smoke plumes. [25]

Low-resolution satellite imagery and color models like RGB and YCbCr can enhance images and differentiate fire and non-fire regions. The paper presents a formula implemented in MATLAB, using color intensity and four rules (I, II, III, and IV) to analyze images and detect fire regions and centers. Rules I and II filter fire regions and identify the brightest area, while Rules III and IV detect cloud and smoke presence and concentration between luminance.[25]

Wavelet Analysis, specifically Haar analysis[6], can decompose images into smaller parts, detecting small fires and smoke through changes in total wavelet energy.[25]

II.9.5 Instant Foam

Water has been the primary substance for extinguishing forest fires for many years and is still widely used today. However, in addition to water, various chemicals have been studied and commercially

[5]Infrared filters are optical filters specifically designed to allow only infrared light to pass through while blocking or attenuating other wavelengths of light, such as visible light or ultraviolet light. These filters are commonly used in various applications, including photography, remote sensing, scientific research, and industrial imaging.

[6]Haar analysis is a mathematical technique for signal and image processing, decomposing data into wavelet coefficients to capture local and global features efficiently. It has applications in compression, denoising, and feature extraction.

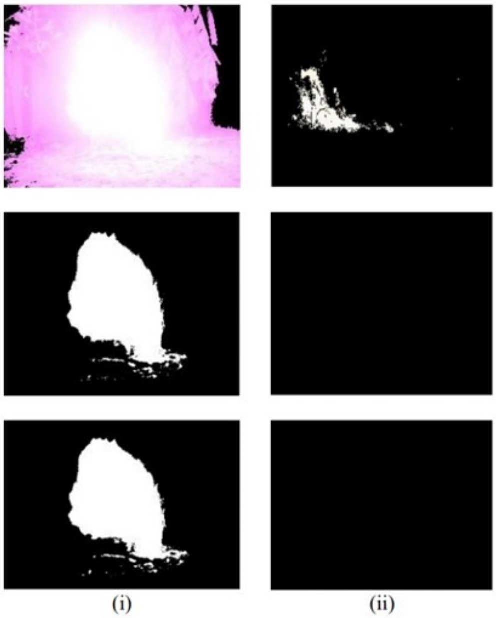

Figure II.12: (i) Raw image, Segmented fire region by satisfying Rule III, Segmented fire region satisfying Rule IV, Segmented fire region by adding Rule III and Rule IV by using an infrared camera (ii) Raw image, Segmented fire region by satisfying Rule III, Segmented fire region satisfying Rule IV, Segmented fire region by adding Rule III and Rule IV from internet source [**25**]

produced for fire-fighting purposes. [**26**]

Class A foams for fighting solid fires play a significant role among these chemical products. Unlike water, which has a high surface tension and cannot remain on fuel surfaces, class A foams reduce the surface tension of water, covering the fuel surfaces and breaking the edges of all three fire triangle components, including oxygen, heat, and fuel.[**26**]

In forest fire-fighting, both direct and indirect attack techniques are employed, and the characteristics of class A foams, such as expansion ratio, density, draining characteristics, and surface tension, need to be taken into account to use them effectively.[**26**]

Firefighting can become more efficient by identifying fighting strategies and selecting the most suitable foam type according to the intervention type.[**26**]

II.9.6 Firefighting Robots

Robots have been created to provide support to firefighters or to engage in firefighting operations using independent navigation and remote control. Bigger robots have been built to combat large-scale fires like those in fuel tankers and forests, while smaller robots have been designed for indoor fire-fighting purposes **FigureII.13**. [**27**]

The SAFFiR program is working on developing an autonomous firefighting robot with a humanoid form, which would be the first of its kind in the United States.[**27**]

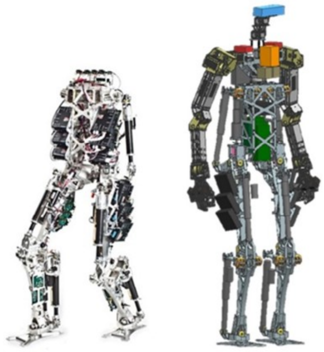

Figure II.13: Currently the state of completion of SAFFiR on the left and proposed final CAD model [27]

II.9.7 WirelessSensor Networks

The Internet of Things (IoT) plays a pivotal role in technological advancements globally, following the computer, Internet, and mobile communication industries. One of its information technologies is the Wireless Sensor Network (WSN), which comprises small sensors that consume low power while collecting and transmitting data. These sensors can communicate with each other efficiently and have low cost and long battery life. [28]

Each node can be structured or unstructured and has multiple sensors and transceivers that can detect gaseous and solid materials like CO2, CO, and petroleum. There are various methodologies for sensing and transmitting collected data, such as using mesh topology to collect data in a topological structure. [28]

We need to examine the dynamics and causes of forest fires regularly to predict fires accurately. WSNs, composed of hundreds or thousands of sensors, can sense environmental measures like temperature, pressure, and movement and transmit the data wirelessly to a central base station, making it ideal for environmental monitoring. A multifaceted and comprehensive approach is necessary for continuous situational awareness and prompt responsiveness. WSN technology is a promising green technology for efficiently detecting forest fires in the future. [28]

II.9.8 Augmented Reality

Augmented reality involves the capability to perceive one's surroundings in obstructed environments such as smoke. The C-Thru system deploys a thermal camera to create a live map of the area ahead of a firefighter, even in dense smoke. Subsequently, an onboard computer transforms this information into a visual representation of the surrounding terrain and individuals within it, which is then transmitted to the display on the firefighter's mask.[29]

II.10 Conclusion

In this chapter, we have represented the basic notions of forest fire fields. The behavior of the fire, and the reasons why it can burn extinguished. Fire is a chemical reaction of fuel with heat and oxygen that produces heat, light, and gases. A good understanding of how fires occur, how they spread and their behavior leads to determining the essence of the problem. This, in turn, has led us to the need to understand the topography and weather of the study area, which has recently become exposed to fires like all other countries due to climate change. The solutions applied in various fields can be developed and used as reference work to find the best possible solutions.

Chapter III

State of the art: forest fire and artificial intelligence algorithms

III.1 Introduction

Various methods are used to forecast forest fires and create a model that can be implemented in practical scenarios.[**30**]

Since the 1990s, artificial intelligence has been used in the forest fire sector, with initial uses including neural networks and expert systems. With the widespread adoption of machine learning (ML) techniques in the environmental sciences, the sector has made significant strides.[**30**]

Forest fires are a complex phenomenon, influenced by numerous interrelated factors such as the ignition source, fuel composition, weather, and topography. Additionally, fire activity can be analyzed and observed on a broad range of scales, from ignition and combustion procedures that occur on a centimeter scale over seconds to fire propagation and expansion over minutes to days, ranging from meters to kilometers.[**30**]

In this chapter, we will focus on the mechanism of machine learning and its techniques in the field of predicting forest fires, including a study of the research conducted in this field, and the development of a supported problem that affects the progress of applying a good prediction.

III.2 Artificial intelligence (AI)

AI is an interdisciplinary field that encompasses various professions such as computer science, neuroscience, and psychology. [**31**]

Different scholars have provided various definitions of AI, with **Poole** describing it as "computational agents that act intelligently," **Russell** defining it as a cognitive system that shares human characteristics, and **Kaplan's** definition being influenced by big data and the Internet of things technologies.[**31**]

However, the primary concept of AI remains constant, which is the use of machines to perform specific tasks and activities that enhance or replace manual labor.[**31**]

III.3 Machine Learning(ML)

Machine learning is a branch of artificial intelligence that enables computers to learn from data without being explicitly programmed.[**32**]

It aims to train machines using algorithms and data, allowing them to make decisions based on processed information. Machine learning is a dynamic process that can adjust itself when exposed to new data.[**32**]

The algorithms used in machine learning aim to minimize errors and increase the accuracy of predictions. Essentially, machine learning is a technique for implementing AI.[**33**]

There are different types of machine learning systems, we can divide them into categories, depending on whether :

III.3.1 Supervised Learning(Classification)

Supervised Learning is the most common type of machine learning, where algorithms learn to conclude labeled data and pre-determined potential outputs, the training data is labeled with accurate answers **FigureIII.1**.[**34**]

Predictive models in Supervised Learning use classification and regression techniques to predict categorical or continuous responses, respectively. Linear and logistic regression, Artificial Neural Networks, and Support Vector Machines are commonly used algorithms in Supervised Learning.[**34**]

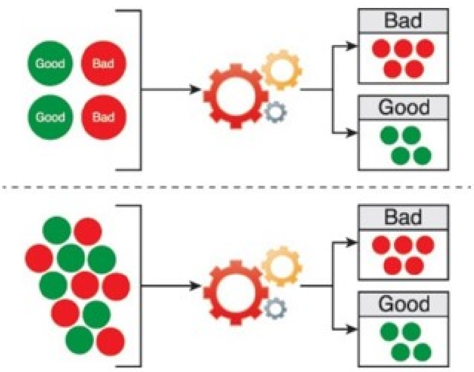

Figure III.1: Machine learning can be used to automatically classify datasets [**100**].

A. **Support Vector Machines(SVM)**

The concept of SVMs originated from Vapnik's Estimation of Dependence Based on Empirical

Data, to find optimal hyper-planes for linearly separable classes.[**35**]

SVM models and neural networks share a connection, where employing a sigmoid kernel function within an SVM model corresponds to a two-layer perceptron neural network.[**36**]

The SVM algorithm addresses sample complexity by searching for ”large margin” separators, which separate a training set with a large margin if all examples are on the correct side of the separating hyperplane and far away from it. Restricting the algorithm to generate a wide-margin separator can reduce the sample complexity, even when dealing with feature spaces of high dimensions. The concept of margin is linked to the regularized loss minimization paradigm and the convergence rate of the Perception algorithm.[**37**]

- **Advantage:**
  (a) It performs well in spaces with many dimensions.[**38**]
  (b) It remains effective even if there are more dimensions than samples.[**38**]
  (c) It is memory efficient as it only uses some training points called support vectors in the decision function.[**38**]
  (d) It is flexible as various kernel functions can be used in the decision function. While it comes with common kernels, it is also possible to use customized ones.[**38**]
- **Disadvantage:**
  (a) When there are more features than samples, it’s essential to select kernel functions and regularization terms carefully to prevent overfitting.[**38**]
  (b) Probability estimates cannot be directly obtained from SVMs and require a costly five-fold cross-validation process.[**38**]

B. **Random Forest (RF)**

The random forest classifier uses multiple decision trees to train and predict samples. The goal is to create a strongly integrated classifier by training several weak classifiers based on a random selection method.[**39**]

This approach involves two types of randomness: selecting training samples with replacement and randomly selecting features when building decision trees. This randomness reduces the correlation between decision trees and creates uncorrelated trees, resulting in a more accurate model. [**39**]

When a new input sample is processed, each decision tree in the forest independently determines the class of the sample, and the final result is the category that is most frequently predicted by the decision trees.[**39**]

- **Advantage:**
  (a) Random forests are a highly accurate and reliable method for both classification and regression problems.[**40**]
  (b) They do not suffer from overfitting due to averaging out all predictions.[**40**]
  (c) They can handle missing values through median substitution or proximity-weighted averages.[**40**]
  (d) Random forests also provide information on feature importance, which can aid in selecting the most significant features for the classifier.[**40**]
- **Disadvantage:**
  (a) Random forests are slow in generating predictions due to multiple decision trees and the time-consuming process of predicting and voting.[**40**]
  (b) The interpretability of random forest models is difficult compared to decision trees, which allow for easy decision-making by following the path in the tree.[**40**]

C. **k Nearest Neighbors (kNN)**

The K nearest neighbor classification was created as an alternative to discriminant analysis when reliable parametric estimates of probability densities are unknown or difficult to determine.[**41**]

The k nearest neighbor (or kNN) rule is a simple algorithm that classifies a test point based on the voting of the k nearest neighbors, where 'nearest' can be measured in terms of various distance functions.[**42**]

The kNN algorithm has a fast training time and is easy to implement, but it requires large memory and is easily influenced by irrelevant attributes.[**42**]

The classification results of the kNN rule are dependent on the structure of the data set and the selection of the parameter k.[**42**]

- **Advantage:**
  (a) The K-Nearest Neighbor (KNN) algorithm has several advantages such as simplicity, comprehensibility, and scalability, with high predictive power. [**43**]
  (b) The algorithm uses basic concepts like Euclidean distance calculation, making it useful for analyzing non-linear data.[**43**]
- **Disadvantage:**
  (a) KNN can be computationally expensive when determining K for large datasets.[**43**]
  (b) Requires more storage than an efficient classifier.[**43**]
  (c) Selecting appropriate K value, distance measure, and feature selection can be a significant challenge.[**43**]

III.3.2 Unsupervised Learning (Clustering)

Algorithms are commonly employed in exploratory data analysis to identify concealed patterns within unlabeled input data. Among unsupervised learning methods, clustering is the most prevalent, involving the grouping of data sets into clusters of similar sizes. Unsupervised learning algorithms, such as k-means clustering and association rules, are some examples of this **FigureIII.2**.[**34**]

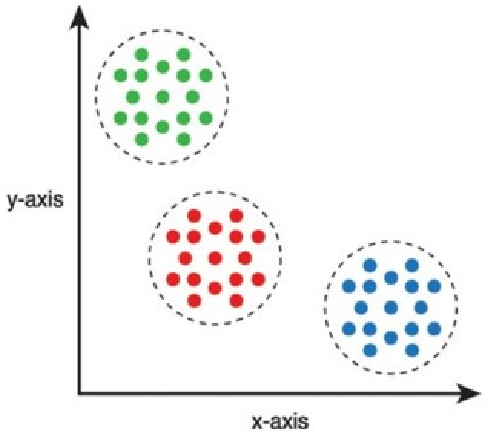

Figure III.2: A scatter graph summarizes the results of clustering [**100**].

A. **Maximum Entropy (MaxEnt)**

Phillips introduced the Maximum Entropy (MaxEnt), which is a framework that uses presence-only data to fit a spatial probability distribution by maximizing entropy and staying consistent with prior knowledge.[**44**]

MaxEnt follows the Bayesian method, which means that it aligns with the application of the Bayes Theorem by using existing knowledge as a prior distribution.[**45**]

Landscape ecology species distribution modeling often makes use of MaxEnt due to its ability to incorporate prior knowledge, specifically occurrence observations for the species being studied.[**45**]

- **Advantage:**
  (a) When it comes to predictive accuracy, MaxEnt typically performs better than other methods.[**46**]
  (b) MaxEnt software is user-friendly, but users need to make decisions regarding input data selection and settings to create models.[**46**]
  (c) MaxEnt is ideal for solving complex problems rather than simple exploratory analyses.[**46**]

- **Disadvantage:**
    (a) To accurately model the distribution of events or species, MaxEnt requires a large training data set. Obtaining data can be challenging in some cases where data is limited or difficult to obtain.[**46**]
    (b) Comparing MaxEnt output with other algorithms can be challenging as the output indicates environmental suitability rather than predicted probability of occurrence.[**47**]
    (c) MaxEnt's logistic output assumes prevalence instead of estimating it, which is a limitation.[**47**]

III.3.3 Semi-Supervised Learning

Semi-supervised learning uses both labeled and unlabeled data for training to improve the accuracy of machine learning models. It employs a blend of supervised and unsupervised learning methods.[**48**]

A. **Fuzzy Logic (FL)**
Fuzzy logic is a theory that studies human reasoning principles and methods[**49**].

It was introduced by Professor Lofty Zadeh in 1965 and consists of numerous probabilities or valuable logic. FL variables have a genuine value ranging from zero to one and aim to obtain their actual value, which can range from completely true to entirely false.[**50**]

FL uses special functions to regulate the values of linguistic variables and obtain the real value from the rate of development. The membership function is a fuzzy set, and its extension is an enhancement over the classic complex.[**50**]

- **Advantage**
    (a) Advantages of the fuzzy logic system include its similarity to human reasoning, its linguistic model, its use of simple mathematics for complex systems, and its high precision and rapid operation.[**51**]
    (b) It can be efficiently used for HVAC systems and incorporates human knowledge through membership rules and functions.[**51**]
- **Disadvantage**
    (a) the need for more fuzzy grades for greater accuracy, which can result in an exponentially increasing number of rules. [**51**]
    (b) It also has lower speed and longer run time, lacks real-time response, cannot easily receive feedback for learning, and has a limited number of input variables.[**51**]
    (c) It cannot straightforwardly determine the optimal number of fuzzy rules and membership function parameters.[**51**]

III.4 Deep Learning (DL)

Deep Learning (DL) is an advanced form of Machine Learning that enhances the complexity of the model by incorporating various functions that enable data representation through several levels of abstraction.[**52**],[**53**]

This allows for automatic feature extraction from raw data, where higher-level features are composed of lower-level features.[**54**]

DL excels in solving complex problems due to its highly complex models that allow for massive parallelization. With adequately large datasets, DL can increase classification accuracy or reduce errors in regression problems.[**55**]

DL comprises various components, such as convolutions, pooling layers, fully connected layers, gates, memory cells, activation functions, encode/decode schemes, etc., depending on the network architecture used. [**55**]

DL is highly adaptable to a wide variety of complex challenges and can be applied to any form of data, such as audio, speech, and natural language, or continuous or point data such as weather data, soil chemistry, and population data.[**55**]

III.4.1 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) imitates the information processing system of biological nervous systems such as the human brain.[**56**]

Neural Networks are composed of many nodes which process information and provide output signals. The process is parallel and distributed. Data mining involves data acquisition, preprocessing, exploration, model building, interpretation, and evaluation.[**57**]

Neural Networks use interconnected nodes and links with variable weights to compute output. They can explore multiple hypotheses simultaneously and are commonly used for data classification and prediction **FigureIII.3**.[**58**]

Researchers use neural networks in various fields, including document classification and solar radiation prediction, and have achieved good results and high performance.[**59**]

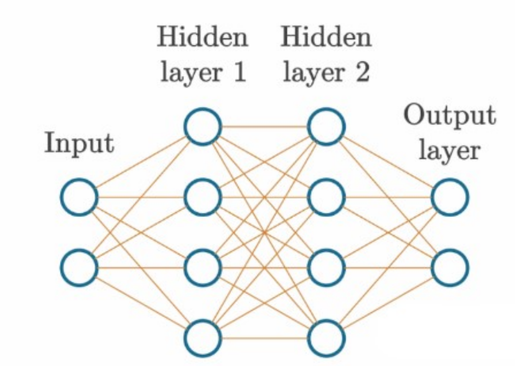

Figure III.3: Artificial neural network.(ANN) [**101**].

- **Advantage:**
  (a) Parallel processing capability allows for performing multiple tasks simultaneously.[**60**]
  (b) Data is stored across the entire network rather than being centralized in a single database.[**60**]
  (c) Data is distributed across the entire network rather than being centralized in a single database.[**60**]
  (d) Fault-tolerant and can still generate output even with corrupted cells.[**60**]
  (e) Distributed memory for learning from examples and teaching according to the desired output.[**60**]
- **Disadvantage:**
  (a) Hardware-dependent and require processors with parallel processing power.[**60**]
  (b) Unexplained behavior reduces trust in the network.[**60**]
  (c) No specific rules for determining the network structure.[**60**]
  (d) Unknown duration of training.[**60**]

III.5 Forest Fire applications

Types of data and modeling tasks concerning popular algorithms and potential applications in Forest Fire science and management. Note that the algorithms shown in bolded are core ML methods whereas non-bolded algorithms are often not considered ML as shown in **FigureIII.4**.[**61**]

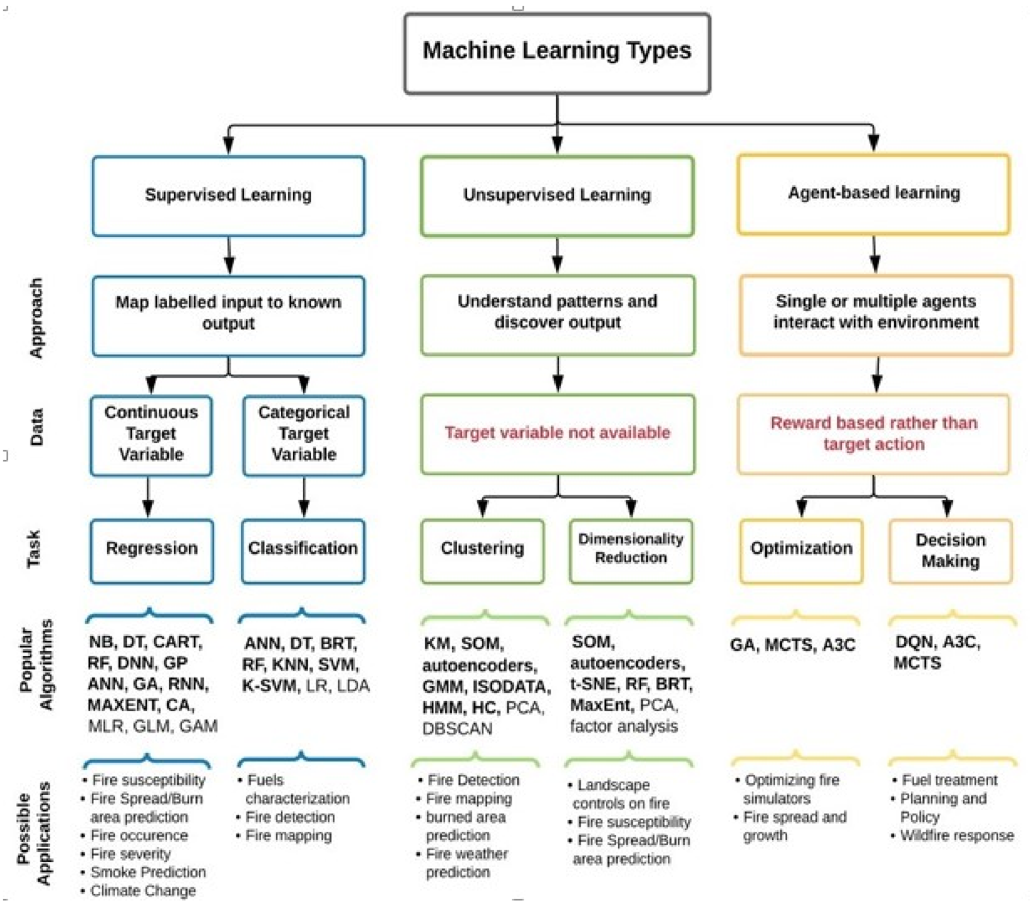

Figure III.4: A diagram showing the main machine learning types [61]

III.5.1 Fuels Characterization, Fire Detection, and Mapping

A. **Fuels characterization**

Forest fuel is a combination of living or dead plant matter present in an ecosystem that can ignite and burn when exposed to a heat source. It is created naturally through leaf and branch fall, as well as hummus formation, but human activities like forest harvesting also contribute to it.[62]
Forest fuel can be classified based on factors like weight, size, state of decomposition, or location, but the most commonly used classification is based on its delay time, which describes the duration required for a deceased plant material fuel to experience a two-thirds change between its original moisture content and its equilibrium moisture content, either by gaining or losing moisture. and its equilibrium moisture content concerning the surrounding environment.[62]

B. **Fire detection**

Detecting forest fires quickly is crucial because delays in identifying the location of the initial ignition can result in more severe fire outbreaks.[63]
The conventional method of using sensors and alarms that detect smoke, heat, or flames to alert people of danger is employed in this process. Detecting the original ignition of a fire quickly is critical to effective first response, and early fire detection systems can help prevent large areas from being burned. Therefore, integrating intelligent algorithms into decision support systems for firefighting and civil protection could have a significant impact.[63]

C. **Fire perimeter and Severity Mapping**
Fire maps serve two purposes in management:

- Precise mapping of the active fire perimeter is essential for planning daily suppression operations and/or evacuations, and for forecasting the spread of the fire.[**64**]
- Mapping the final burn perimeter and the severity of the fire is crucial for evaluating and anticipating the economic and ecological consequences of a forest fire, as well as for planning the recovery process.[**64**]

These maps can be created using various methods such as aerial or ground sketch mapping, or aerial GPS.[**64**]

III.5.2 Fire Weather and Climate Change

At a small time scale, weather and climate are fundamentally distinct phenomena and were regarded as independent of each other.[**65**]

A. **Fire Weather Prediction**
The forecast is heavily influenced by weather, and information is gathered from sources like a meteorological station or NASA's Prediction Of Worldwide Energy Resources website. The data collected typically includes factors such as temperature, humidity, wind, precipitation, and lightning.

B. **Climate Change**
The models showed a pattern of more extensive burning as the climate changed from cooler and wetter to warmer and drier conditions. When using machine learning techniques to predict quantities affected by environmental changes, such as climate change, it is important to consider the transferability of the model.[**65**]
Transfer modeling involves extrapolating beyond the training data, and previous research has suggested that machine learning approaches can be effective for transfer modeling in scenarios of future climate change, based on studies in species distribution modeling.[**61**]

III.5.3 Fire Occurrence, Susceptibility, and Risk

A. **Fire occurrence prediction**
There are two main categories of methods for predicting forest fires: systems/indices and artificial intelligence. Many of these methods rely on weather prediction and monitoring various features. [**66**]
Predicting forest fires is important for resource allocation, mitigation, and recovery efforts.[**66**]
Developing countries can benefit from a simplified and cost-effective system that uses a limited number of easily measurable features that are highly correlated with fire risk. Another area of interest is predicting the burned area on a landscape scale.[**66**]

B. **Forest Fire Risk Mapping and Fire Monitoring**
A risk map is useful for identifying vulnerable areas and creating a pre-management plan to prevent risks.[**67**] Quantitative data on forest fires is crucial for managing and understanding them.[**68**]

Detecting fires in real time and monitoring them can provide important information for resource managers, helping them prioritize prevention and suppression strategies. Forest fire management relies heavily on methods such as MCDA, FR, AHP, and machine learning, which are often integrated with GIS to develop risk maps. These methods have been successfully used around the world.[**69**],[**70**]

III.5.4 Fire Behavior Prediction

The primary purpose of developing fire behavior models is to enhance our comprehension of the factors responsible for the spread of fire and the amount of energy released, thereby providing decision-making support tools for fire management.[**71**]

1. **Fire Spread and Growth**
   The focus of fire behavior is on how fuel burns, which is crucial for predicting the growth of forest fires in the future. To do this, we use simulation models and machine learning, along with wind speed measurements.

2. **Burned area and fire severity prediction**
   Predicting the extent of a forest fire can aid in managing it effectively. This is a complex task that requires powerful computational tools to estimate the amount of land that will be burned, based on data from the forest and meteorological information.[**72**]

III.5.5 Fire Effects

Regression-based methods have been predominantly used in studies predicting the effects of fire. These studies establish a relationship between physical measures of fire severity and exposure with associated costs, losses, and other impacts such as post-fire ecology, forest fire, socioeconomic factors, and soil erosion.[**61**]

The category of fire effects prediction also encompasses modeling of forest fire smoke and particulate levels. However, smoke detection has already been discussed in the fire detection section.[**61**]

The impacts of fire on soil erosion and deposits, post-fire regeneration, succession, and ecology are also included in this category.[**61**]

- **Smoke and Particulate Levels**

To quickly detect forest fires, it's important to have smoke detection capabilities. The video-based cognition algorithm designed for detecting forest fires uses intelligent algorithms to analyze video and extract smoke features. This allows for more accurate and earlier identification of fire smoke.[**73**],[**74**] A crucial component of these algorithms is the moving target detection algorithm.[**75**]

III.5.6 Fire Management

Fire management aims to maximize the benefits of fire while minimizing associated costs and losses.[**76**]

To effectively manage forest fires, it is crucial to predict and detect their incidence, spread, intensity, and potential damage. The monetary value of damage helps authorities decide how much to spend on firefighting, but the valuation process poses its challenges. Choosing the best resource combination for local firefighting, in terms of productivity and cost-effectiveness, is also important.[**77**]

Fire management models can be either predictive or prescriptive. While ML techniques have been applied in forest fire management, there are relatively few studies in this area compared to other forest fire domains. This suggests great potential for ML to be applied in the future to improve planning and policy, fuel treatment, fire preparedness and response, and social factors.[**61**]

III.6 Related Work

III.6.1 Portugal Area

Study Area and Data Resources

The study conducted by **Samaher Al Janabi, Ibrahim Al Shourbaji, and Mahdi A. Salman** aimed to identify the best predictor for detecting forest fires in **Montesino Natural Park in Portugal**. They analyzed 517 different entries gathered at different times.[**78**]

Analysis

The researchers used the principle component analysis (PCA) to identify patterns and the particle swarm optimization (PSO) technique to segment fire regions.[**78**]

Results(better accuracy SVM)

Five soft computing (SC) techniques based on the neural network were used to identify the best technique for predicting forest fires.[**78**]

The results showed that the support vector machine (SVM) was the most effective and efficient predictor, providing more precise predictions than other predictors with small estimation errors. [**78**]

The SVM technique is suitable for predicting forest fires and improves prediction accuracy compared to other methods, according to the obtained results based on five quality measures including root mean squared error (RMSE), mean squared error (MSE), relative absolute error (RAE), mean absolute error (MAE), and information gain (IG).[**78**]

III.6.2 China Area

Study Area and Data Resources

The research was conducted on **13th September 2022** by a group of researchers comprising **Yongqi Pang, Yudong Li, Zhongke Feng, Zemin Feng, Ziyu Zhao, Shilin Chen, and Hanyue Zhang**. The study used various sources of data collected between 2003 to 2016, including fire hot spots, meteorological conditions, terrain, vegetation, and socioeconomic data, to determine the primary factors driving forest fires in **China**. The models were evaluated based on five performance indicators, namely accuracy, precision, recall, f1 value, and area under the curve.[**79**]

Results(better accuracy RF)

Four forest fire prediction models were built using different machine learning algorithms (ANN, RBFNN, SVM, and RF).[**79**]

The evaluation results showed that all models had an accuracy level of above 75%, indicating their potential in forest fire prediction. Among the four models, the RF model had the highest comprehensive predictive ability with an accuracy level of 89.25%, making it the optimal choice for forest fire prediction models in China.[**79**]

The RF model was used to predict the probability of forest fires in China, and based on these predictions, a map was drawn to show the probability of forest fire occurrence by season (spring, summer, autumn, and winter). [**79**]
This research helped identify high-incidence areas and areas at risk of forest fires, enabling the researchers to suggest fire prevention recommendations for specific regions and seasons.[**79**]

Overall, this study provides useful insights into the main driving factors of forest fires in China and can serve as a reference for selecting high-precision forest fire prediction models.[**79**]

III.6.3 Indonesia Area

Study Area and Data Resource

In this study, **Dedi Rosadi, Widyastuti Andriyani, Deasy Arisanty, and Dina Agustina** used multiple machine learning methods to predict the likelihood of forest fires in **Indonesia's peatlands**. The researchers collected data on various variables, including time of data collection, Land Surface Temperature, Wind Speed, Humidity, Height, and Normalized Vegetation Index (NDVI). The data was collected in 2018 and comprised 202 cases.[**80**]

Results

In this study, various traditional classification methods, including SVM, KNN, log reg, DT, and NB, were examined for their effectiveness in detecting fire occurrences in peat lands. The empirical results are presented in **FigureIII.5**, and the performance of each method was evaluated using different sample sizes for training and testing data.[**80**]

The accuracy of the AdaBoost method was found to outperform the other methods in the in-sample data. However, in the out-sample study, where boosting was used over the DT approach, it only improved the weaker learning method (i.e. DT), and kNN outperformed AMD in classification. Overall, the study concluded that both traditional and advanced machine learning methods can be used for fire occurrence detection in peat lands.[**80**]

Algorithms	Ratio data testing and training	Accuracy Training	Accuracy Testing
SVM	9:1	91,76%	95,00%
	8:2	90,74%	92,5%
	7:3	90.78%	91,8%
kNN	9:1 (k=3)	-	100%
	8:2 (k=3)	-	95,00%
	7:3 (k=7)	-	91,80%
Logistic Regression (logreg)	9:1	76,37%	90,00%
	8:2	75,92%	85,00%
	7:3	74,46%	83,60%
Decision Tree (DT)	9:1	91,00%	95,00%
	8:2	91,00%	92,00%
	7:3	91,00%	90,00%
Naïve Bayes (NB)	9:1	82,40%	90,00%
	8:2	82,1%	87,5%
	7:3	83,00%	86,9%
Adaboost (DT Based)	9:1	100%	95,00%
	8:2	100%	92,50%
	7:3	100%	91,80%

Figure III.5: Table summary of the performance Classification Methods [**80**]

III.6.4 Canada Area

Study Area and Data Resource

The research was conducted by **Vega Garcia in January 1996**, in the White Court Provincial Forest located in **Alberta, Canada**. The forest was divided into two areas - 5 km from a road and areas greater than 5 km from a road, resulting in eight fire occurrence prediction units. The study used a data set of 314 fire and no-fire occurrences between 1986-1990 for training.[**81**],[**82**]

Analysis

The analysis revealed that various geographic and temporal factors are closely associated with forest fires. These factors include distance to the nearest road, town, and campsite, topographical elevation, fuels, forest commerciality, forest district, and weather-related codes and indices, among others. For the general model, the input variables of FWI, ISI, FFMC, and ROAD were found to be the most consistent contributors to good-performing networks. DMC, BUI, and MONTH were also significant but less so. Only one out of 15 networks identified DISTRICT as the main contributor. Logistic regression analysis was also used to identify important input variables.[**81**],[**82**]

Results

The results showed that by using artificial neural networks and geographic information system (ARC/INFO) technology, the model was able to predict no-fire observations with an 85% accuracy and fire observations with a 78% accuracy, demonstrating better accuracy than the previous model.[**81**],[**82**]

III.7 The algorithms applied ML in Forest Fire science

The study conducted by **Iyush Jain, Sean C P Coogan, Sriram Ganapathi Subramanian, Mark Crowley, Steve Taylor, and Mike D Flannigan** analyzed 300 relevant publications that used machine learning (ML) in forest fire science until the end of 2019. The study found that commonly used ML methods for forest fire problems included **random forests, MaxEnt, artificial neural networks, decision trees, support vector machines, and genetic algorithms**. The authors suggest that there are opportunities to incorporate newer ML methods like **deep learning and agent-based learning in forest fire science**, particularly in cases involving large and complex datasets **FigureIII.6**.[**61**]

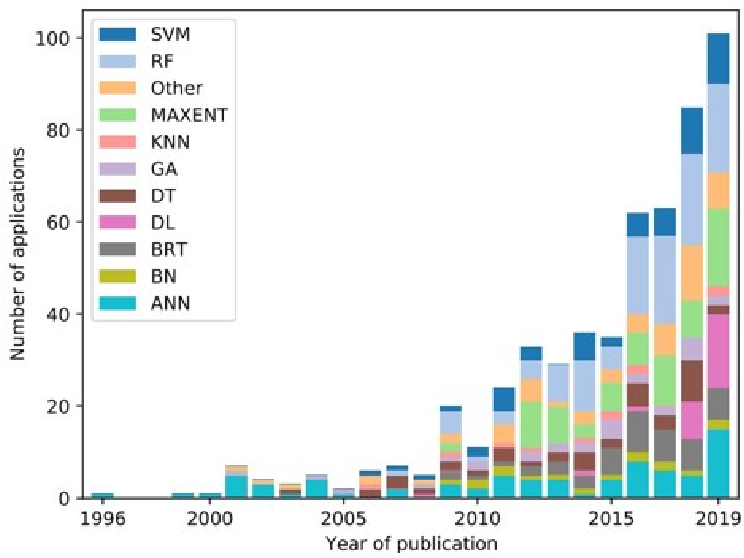

Figure III.6: Number of ML applications by category and by year for 300 publications on the topic of ML and Forest Fire science and management as identified in this review [**61**]

III.8 Challenges and constraints in CV for Forest Fire detection

III.8.1 Scarcity in Data

Forest fire detection is limited primarily by the lack of data. Even open-source datasets may not contain sufficient forest fire data.[**83**]

III.8.2 Difficulty in feature-tracking

Obtaining features like flame height, flame inclination angle, and firebase width from forest fires using CV is very challenging. If these measures are not predicted accurately, it can lead to a poorly performing model.[**83**]

III.8.3 Uncontrollable or sudden changes in the environment

A frequent limitation in industries that incorporate computer vision is external factors, which also apply to forests or wildlife. The environment cannot be fully controlled, and events such as animal migration or unexpected disasters like forest fires may occur, which differ from the conditions the model was trained on. This can lead to calibration issues that are difficult to avoid.[**83**]

III.8.4 Improved Prediction Models

At present, forecasting models rely on previous data and current weather conditions, but their precision and dependability can be enhanced. Advanced prediction models using machine learning and artificial intelligence methods have the potential to achieve higher accuracy.[**84**],[**85**]

III.9 Conclusion

In recent years, the use of artificial intelligence (AI) has become increasingly prominent, particularly in the realm of unsupervised algorithms.

Through our research, we have witnessed this growing trend, driven by the exceptional efficiency and accuracy demonstrated by these algorithms. Furthermore, the current era is characterized by an abundance of data, enabling the optimal employment of this transformative technology. Taking these observations into account, we have chosen to employ algorithms such as artificial neural networks (ANN), random forest (RF), and support vector machines (SVM) in our investigations.

Nevertheless, the persistent challenge lies in the scarcity of data, which can be overcome through proactive measures such as seeking assistance from specialized agencies like the meteorological station.

Chapter IV

Contribution: An Intelligent Fire Warning System: Predict And Prevent (IFWS)

IV.1 Introduction

In this thesis, we aim to propose an intelligent system that uses the history of fire to predict it early in the future. When the last level of risk is reached, the system issues a warning and then intervenes automatically to change the conditions (feature values) that affect that risk.

Three algorithms will be implemented in this study: **the SVM**, **the RF**, and **the ANN**. A comparative table will be drawn up at the end of this chapter to evaluate the performance of each one.

In this chapter, we will present our study area we will present the general architecture of our approach by highlighting their components and their steps. finally, we will present the results (models) that have been obtained by applying this approach.

IV.2 Study Area

The Bejaia region, covering an area of 3268 square kilometers ($36° 15' - 36° 54'$ north latitude, and $4° 27' - 5° 33'$ east longitude) in northeastern coastal Algeria, served as the research location due to its significance in representing remote rural and urbanized regions in northeastern Algeria.[**86**]

Bejaia is recognized as a significant fire-prone area in Algeria, particularly in the year 2014. This can be back to various environmental and human factors, including extensive forest and shrubland coverage, high agropastoral activity, elevated fire weather risk, and significant human impact on fire ignitions. Bejaia boasts a diverse forest heritage, encompassing 122,500 hectares of forests, accounting for 38% of the total forest area in Algeria and hosting various key species.[**86**]

Part One : General architecture of IFWS

IV.3 General Architecture of IFWS

To build our new approach (IFWS), we pass by three steps look at **FigureIV.1** :

1. We start by collecting data which includes information about the fire phenomenon such as temperature, humidity, and other relevant factors.
2. We process the collected data to ensure it is ready to be split into training and testing parts. The testing part will be trained and used by the selected algorithms.
3. We test the testing category in the prediction model we built to obtain a result that either indicates a fire or no fire.

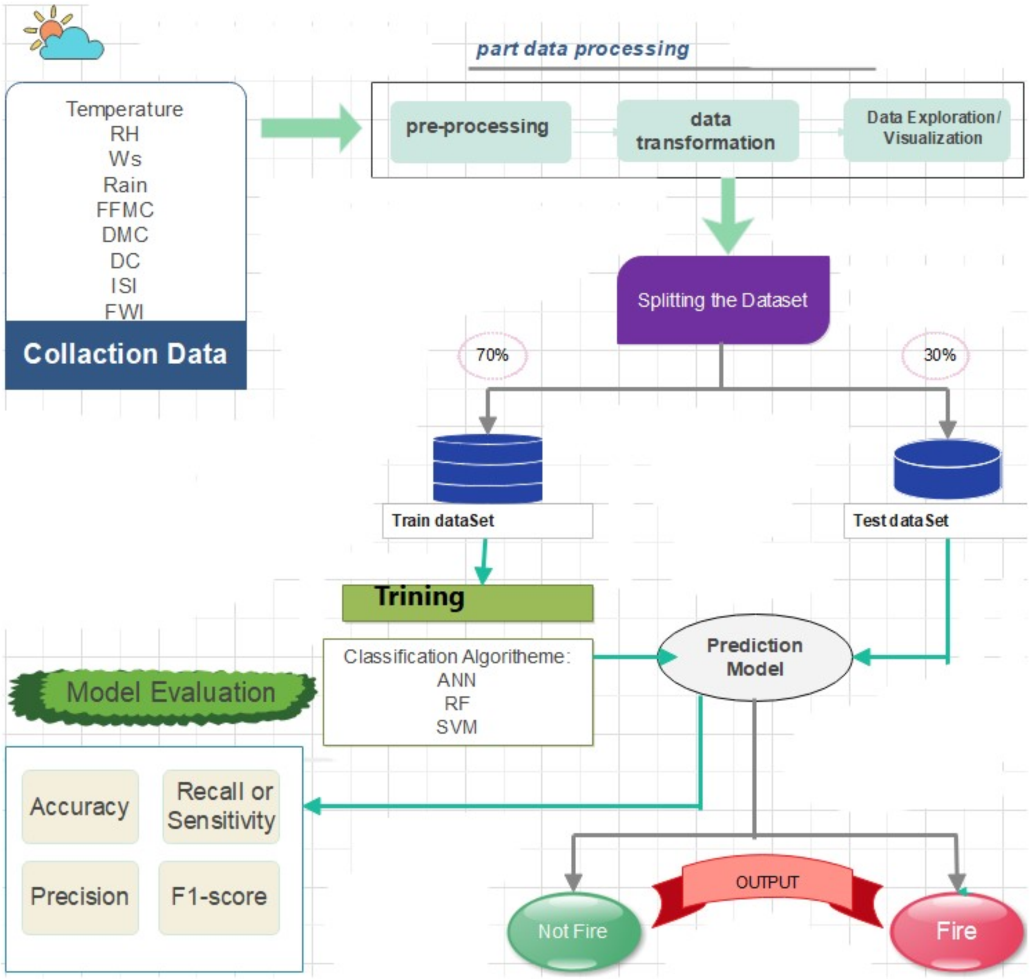

Figure IV.1: Presents The General Architecture of The IFWS

IV.3.1 Data Collection

Our initial step involves providing a thorough description of the data used in this study, which was obtained from the UCI Dataset Repository[1]. Specifically, we used data from the year 2012, spanning from July to September.[**87**]

The data consists of four primary attributes, which include noon temperature (Temp), relative humidity (RH), wind speed (Ws), and rainfall (Rain). In addition, we also used composite variables derived from the global system FWI (Fine Fuel Moisture Code), including Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Buildup Index (BUI), and Fire Weather Index.[**87**]

[1]The UCI Network Data Repository is an effort to facilitate the scientific study of networks.

The Normalized system FWI

The Fire Weather Index (FWI) system is used to estimate the risk of forest fire in Canada. It consists of six components,[**88**] three of which are the Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), and Drought Code (DC)**FigureIV.2**. [**89**]

The **FFMC** is a numeric rating of the moisture content of litter and other cured fine fuels, representing moisture conditions for shaded litter fuels. [**89**]

The **DMC** is a numeric rating of the average moisture content of loosely compacted organic layers of moderate depth, representing moisture conditions for decomposed organic material underneath the litter.[**89**]

The **DC** represents a numerical assessment of the average moisture level found in deep, densely packed organic layers. It provides an approximation of the soil's moisture conditions at a significant depth, indicating the potential for moisture to evaporate from deeper layers.[**89**]

The **FFMC** ranges from 0-101, while the DMC and DC are unitless and open-ended, with maximum values of 1000. Subtracting the FFMC value from 100 can provide an estimate for the equivalent fuel moisture content. [**89**]

The FWI system provides important information on fuel moisture and fire danger, aiding in forest fire prevention and management.[**89**]

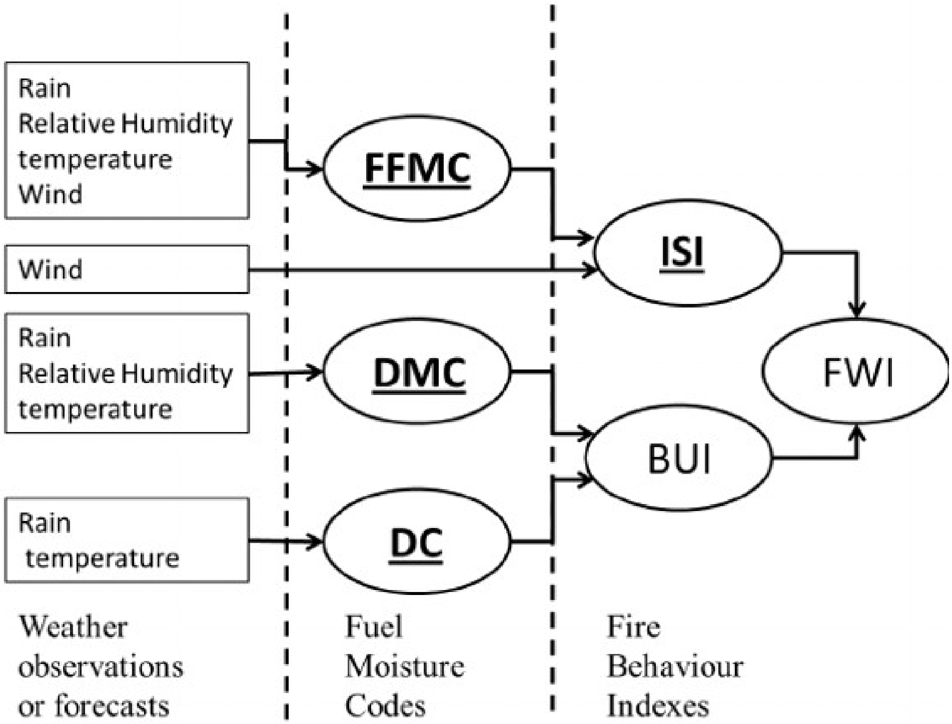

Figure IV.2: The structure of the Fire Weather Index (FWI) System [88]

IV.3.2 Data Processing

Data processing involves employing computer-based techniques and algorithms to transform, analyze, and decipher data. It is a crucial aspect of numerous applications, such as business intelligence, data mining, and machine learning. [90]

The systematic conversion of data into valuable information is the primary goal of data processing The use of computer-based tools and techniques is mandatory to ensure the accuracy, consistency, and efficiency of the entire data processing operation. [90]

1. **Pre-processing**
   Before conducting any analysis or modeling, it is important to preprocess the data to ensure its suitability for use.

   In the context of predicting forest fires, this involves selecting variables that are relevant to the research question, and in this case, 10 variables were selected from the real dataset, namely FFMC, BUI, DMC, DC, ISI, FWI, RH, wind, rain, and temperature. These variables were chosen as they were deemed to be suitable inputs for the prediction model. Since the dataset only contains 122 data records, the data values were designated to a range of fire -not fire to facilitate the calculation process in the training phase.

   After the designation of the data, the input and output data were determined. The training and testing data were determined from the existing dataset of 122 records. Preprocessing the data in this manner ensures that the data is suitable for use in the prediction model and helps to improve the accuracy of the analysis. Data pre-processing is a crucial step in preparing raw data for analysis or modeling. It involves a variety of techniques for cleaning, transforming, and organizing data to make it suitable for use in algorithms and machine learning.

(a) **Missing Data:** Missing data occurs when observations are not available for analysis, either because they were not collected or because they were lost or damaged during data collection or processing. This can lead to either completely missing data, where no information is available for a particular note, or partially missing data, where some information is available but other data points are missing.[**91**]

- When we tested our data, we did not find a missing value.

(b) **Outliers:** In the field of data science, outliers are a common occurrence. The process of recording data can be complex and errors can occur, leading to nonsensical measurements. Additionally, human error can also lead to outliers, particularly when data entry is done manually.[**92**]
One common method for identifying outliers is through the use of boxplots, which show the distribution of the data and any outliers **FigureIV.3**. [**92**]

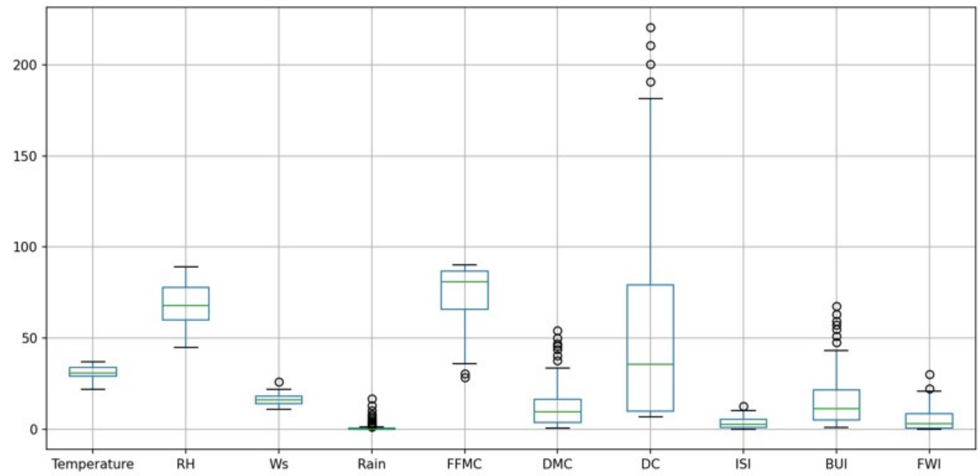

Figure IV.3: Boxplot showing outliers

We find the outliers outside the domain of the square and replace them with the mean value and in others, we replace it with a median.

2. **Data Transformation**
   The process of data transformation refers to converting raw data into a format that is suitable for analysis or model training.[**93**]

   - Overall, the conversion of categorical values into numerical values is a necessary step in the data preparation process. Thus, we have converted the categories into numerical values of fire (1) and not fire (0). This conversion will enable us to perform mathematical operations on the data and input it into our machine-learning algorithms effectively.to compare the differences between groups concerning the variance within the group.

   As we note, the number of fires during 122 days is 63, that is since 2012 was the most difficult period that Algeria went through concerning the period of burning, which gives us a suitable sample for the study, despite the scarcity of data.

3. **Data Exploration/Visualization**
   Understanding the patterns and relationships in the data depends heavily on data exploration and visualization. Exploring the data is a process of uncovering hidden patterns or trends, and gaining an overall understanding of the data. By using graphs, charts, and other visual aids, By analyzing the raw data, we can recognize and uncover patterns and trends that might not be readily noticeable at first glance **FigureIV.4**.[**94**]

   - The prediction of forest fires is influenced by a variety of factors, and the relationship between these factors and forest fires is complex. Therefore, it is important to carefully select the factors that are included in the prediction model. Redundant or highly correlated factors can increase the complexity of the model and reduce its performance.

   One way to address the issue of redundancy is to use a correlation matrix to identify which factors are most strongly related to each other. By removing redundant factors from the model, it is possible to reduce its complexity and improve its accuracy.

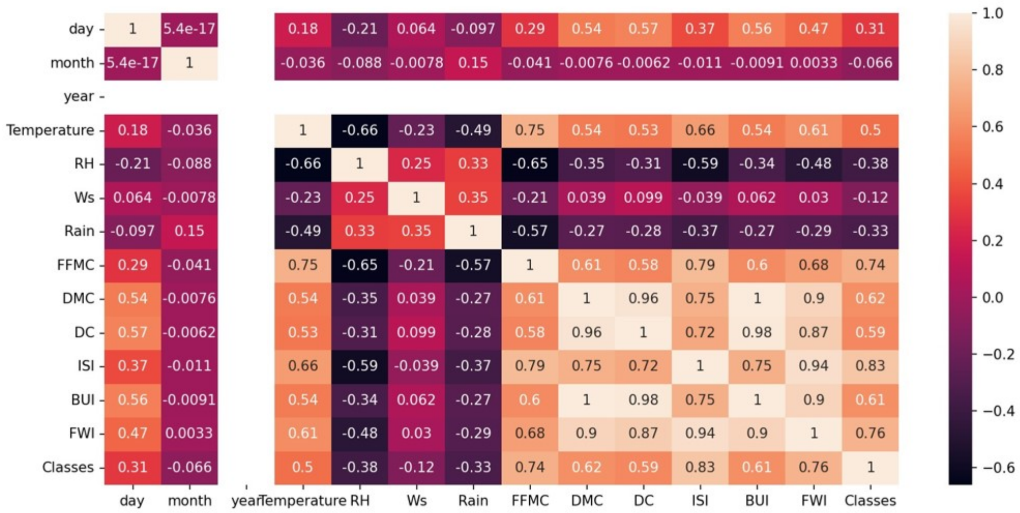

Figure IV.4: Heat map of variables with relationship coefficient

Upon examining the correlation matrix, it was observed that there is a strong association between BUI and DMC, as well as ISI. The Build-Up Index (BUI) is a measure of the potential fuel availability for a forest fire, while Drought Code (DMC) and Initial Spread Index (ISI) are indicators of fire behavior. BUI has a more positive correlation with the DMC and ISI.

To visually represent the correlation between BUI and another variable, you can use the seaborn (**jointplot**) library in Python to create a graph. This graph will provide a clear picture of the relationship between the two variables, including the strength and direction of the correlation **FigureIV.5**.

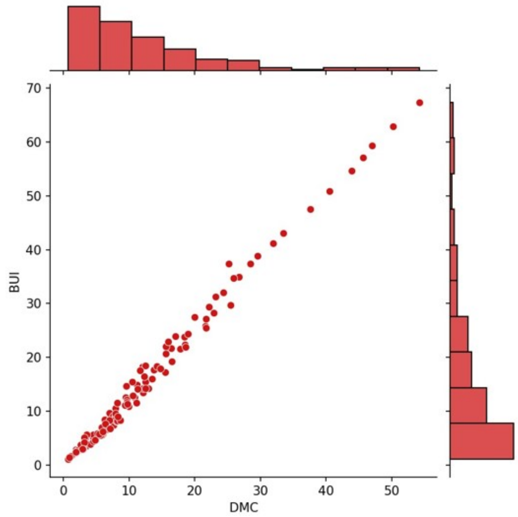

Figure IV.5: Representation BUI and DMC

Multicollinearity refers to strong correlations in the relationships among the explanatory variables in the regression, We will have to drop the feature BUI.

- Generally speaking, high temperatures and low humidity create dry conditions that increase the risk of fires, while cooler temperatures and higher humidity can help reduce the risk **FigureIV.6**.

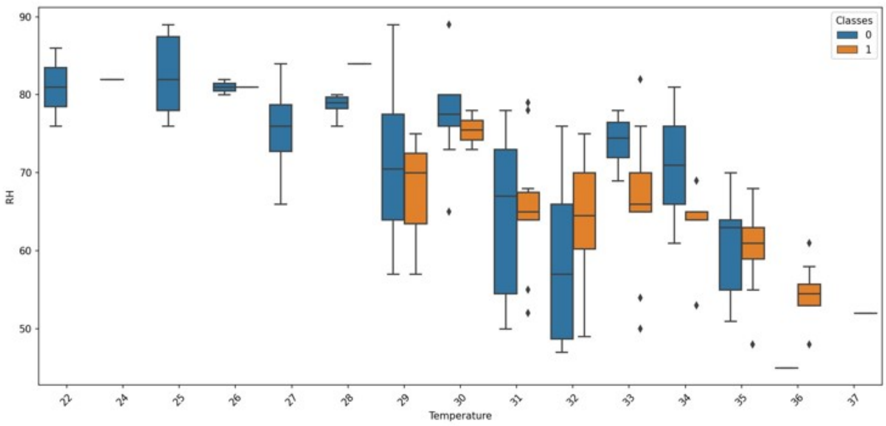

Figure IV.6: The continuous real-valued feature of Bejaia.

The level at which forest fires occur is determined by an average of greater than 29 accompanied by a decrease in moisture. As the temperature increases, the moisture content of the vegetation decreases, making it more susceptible to catching fire.

4. **Splitting the Dataset**

The goal of splitting the initial data into partitions is to make predicting the target outcome easier. This is achieved by creating partitions that have a different and more favorable distribution of classes or values than the original sample.[**95**]

After finishing the data processing, we first selected the labeled dataset (Classes)or the classes of data that we want to predict. This label dataset will be used as the target variable(**'Temperature',**

’RH’,’ Ws’, ’Rain’, ’FFMC’, ’DMC’, ’DC’,’ ISI’, ’FWI’) in our machine learning model. we proceeded to split the dataset into training and test sets, with a ratio of 70% for the former and 30% for the latter. This allows us to use the training set to build a predictive model for forest fires, and then evaluate its performance on the test set.

IV.3.3 Predction Model (Training)

1. **Feature Selection** During the training phase, the prediction model is trained using various algorithms or techniques. The model learns the patterns and relationships present in the input data by iteratively adjusting its internal parameters to minimize the difference between the predicted outcomes and the actual target variables in the training dataset.

   Feature selection is a critical step in improving accuracy and performance while eliminating irrelevant or disadvantageous features in a model or analysis.

   It involves reducing data dimensionality while preserving essential information. The selected features enhance accuracy, minimize complexity, and improve explanatory power.

   Feature selection is essential for developing efficient and effective models or analyses in various fields.

Temperature	RH	Ws	Rain
7.59080609	1.8277374	1.26305329	6.12530925

FFMC	DMC	DC	ISI	danger_fire
1.65929871	2.2436215	1.20763494	1.34382621	3.18889266

Table IV.1: Univariate Feature Selection for Forest Fire Prediction

2. **Introduction of Core Parameters And Model Equation**

   (a) **RF Prediction Algorithm**: This part mainly uses the Random Forest Classifier method in Python's construct the model, where the important parameters are described as follows FigureIV.7.

   i. **n_estimators**: 100
   ii. **random_state**:42
   iii. **min_samples_split, (the minimum number of samples of the node, which means the minimum)**:4

   Some transactions can be used:

   i. **max_depth**: the maximum depth of the tree.
   ii. **min_samples_split**: the minimum number of samples of the node, which means the minimum.
   iii. **number of samples** : that can be further cut by the current tree node.
   iv. **criterion**: cutting strategy, gini or entropy.
   v. **min_impurity_decrease**: set the stopping condition.
   vi. **class_weight**: set the weight of different classes of samples in the dataset, the default is None, that is, the weight of all classes of samples is 1.

```
from sklearn.ensemble import RandomForestClassifier
RF = RandomForestClassifier(n_estimators=100,min_samples_split=4, random_state=42)
RF.fit(X_train, y_train)
# Evaluate the model
y_pred2 = RF.predict(X_test)
```

Figure IV.7: Code python RF

   (b) **ANN Prediction Algorithm**:

   - The main parameters of this predictor include: the number of Multilayer perceptron NN
   - The main parameters of this predictor include the number of inputs = 9.
   - the number of layers = 4 (2 hidden).
   - The hidden layer 1 neuron: the hidden layer activation function is ReLU.
   - The hidden layer 2 neurons: the hidden layer activation function is ReLU.

- The output layer activation function is Sigmoid, output : 0 ou 1.
- we've got a binary classification problem: **loss='binary_crossentropy'**

```
import tensorflow as tf
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

model = tf.keras.models.Sequential([
  tf.keras.layers.Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
  tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(8, activation='relu'),
  tf.keras.layers.Dense(1, activation='sigmoid')

])

model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
# fit the model to the training data
history = model.fit(X_train, y_train, validation_data = (X_test, y_test), batch_size = 10, epochs = 10)

print(model.summary())

y_pred3 = model.predict(X_test)
y_pred3 = (y_pred3 > 0.5)
```

Figure IV.8: Code python ANN

(c) **Support Vector Machine (SVM)**:The main parameters of this predictor include:
a NuSVC (support vector classification) model is instantiated with the polynomial kernel and a degree of 2.
The probability parameter is set to True, allowing the model to generate class probability estimates in addition to class predictions **FigureIV.9**.

```
from sklearn import svm
SVM =svm.NuSVC(kernel='poly',degree=2,probability=True)
SVM.fit(X_train,y_train)
#Make predictions on the test data:
y_pred1= SVM.predict(X_test)
```

Figure IV.9: Code python SVM

3. **Model Evaluation** To assess the accuracy of a classification model on a given dataset, we need to quantify its performance. This quantification is useful for various purposes such as evaluating the effectiveness of the classifier, comparing different models, selecting the best model for a specific dataset, parameter tuning, and ensemble analysis.

There are two main challenges in quantifying the accuracy of a classification model:

(a) **Methodological Issues**:
These issues arise from dividing the labeled data into appropriate training and test segments for evaluation. The choice of methodology has a direct impact on the evaluation

process, leading to potential underestimation or overestimation of classifier accuracy. Several methodologies are possible, including holdout, bootstrap, and cross-validation.[96]

(b) **Quantification Issues** :
When evaluating the accuracy of a classifier, several measures can be used depending on the nature of the classifier output.[96]

In the first case, the output is predicted as a label associated with the test instance, and the accuracy is calculated by comparing the predicted label with the ground-truth label of the test instance. This approach is used in most classifiers.[96]

In the second case, the output is presented as a numerical score for each possible label. In this scenario, a threshold is used to convert the scores into predicted labels, and the accuracy is then calculated using the same method as in the first case. This approach is used in some classifiers, such as probabilistic classifiers.[96]

4. **Model Test**
We will test a hypothetical set of meteorological data with the same inputs that we used for a month in our forecast model, which will be used to test the accuracy and effectiveness of the forecast model. It is part of our concern to improve weather forecasting methods and techniques FigureIV.11.[97]

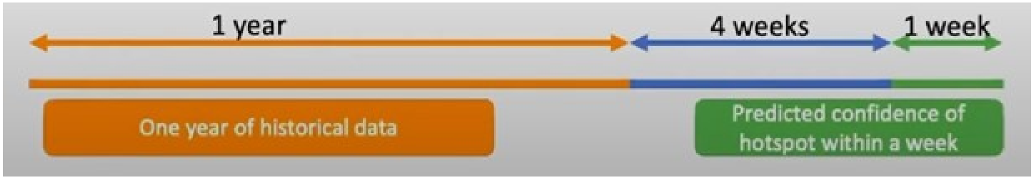

Figure IV.10: Testing Accuracy and Effectiveness of Forecast Model Using Historical Data

We have introduced a new forecast format for fire occurrences at our destination. The format offers enhanced accuracy by using advanced algorithms and considering various factors. The forecast provides a weekly overview, displaying the likelihood of fires each day. Default values serve as a baseline but can be adjusted based on specific circumstances. The format includes an interactive interface, recommendations, and safety tips. It aims to help users plan, mitigate risks, and ensure safety.

Forecasts are subject to change based on evolving conditions, and we will continue to improve our system for more reliable information We also refer to the data that will be displayed for the state of Bejaia only.

IV.4 Performance Evaluation

The performance indicators used in this study come from the confusion matrix. detailed The discussion on the confusion matrix x can be used to calculate a variety of performance metrics for the

Figure IV.11: Interface

classifier, including accuracy, precision, recall, and F1 score, which can provide insights into the strengths and weaknesses of the classifier and guide its further development and refinement.[**98**]

Overall, the confusion matrix is a powerful tool for evaluating and improving the performance of supervised learning classification **Table IV.2**.

1. **True positives (TP)**: The number of times the model correctly predicted a positive class (actual positive and predicted positive).

2. **False positives (FP)**: The number of times the model incorrectly predicted a positive class (actual negative but predicted positive).

3. **True negatives (TN)**: The number of times the model correctly predicted a negative class (actual negative and predicted negative).

4. **False negatives (FN)**: The number of times the model incorrectly predicted a negative class (actual positive but predicted negative).

	Not fire	Fire
Not fire	True Negative	False Negative
Fire	False Positive	True Positive

Table IV.2: Visual representation of confusion matrix

IV.4.1 Accuracy

The ratio of the correct number of samples classified by the classifier to the total number of samples.

Accuracy = (TP + TN) / (TP + FP + TN + FN) (1)

IV.4.2 Precision

The ratio of the total number of positive samples correctly classified by the classifier to the total number of samples identified as positive samples by the classifier.

Precision = TP / (TP + FP) (2)

IV.4.3 Recall or Sensitivity

The ratio of the total number of correct positive samples classified by the classifier to the total number of real positive samples.

Recall = TP / (TP + FN) (3)

IV.4.4 F1-score

As the harmonic mean of recall and precision, it is better than independent precision or recall indicators, which is an important indicator for evaluating classification models [20]. Precision and recall have their shortcomings. When the threshold is set to a high value, it results in a high level of precision but leads to significant data loss. Conversely, a low threshold yields a high level of recall., but the prediction will be very inaccurate. Hence, the adoption of the F1-score provides a comprehensive evaluation of the classifier, effectively balancing the impact of precision and recall.

F1 = 2 precision × recall precision + recall algorithms (4)

IV.5 Tow Different Classifiers for the Classification

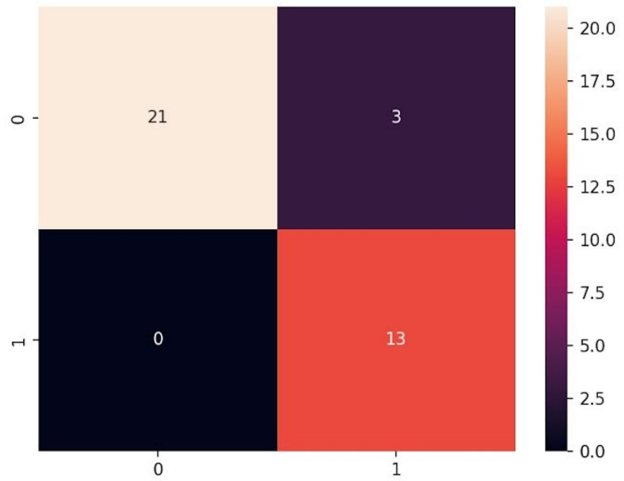

Figure IV.12: Confusion matrix for SVM classifier

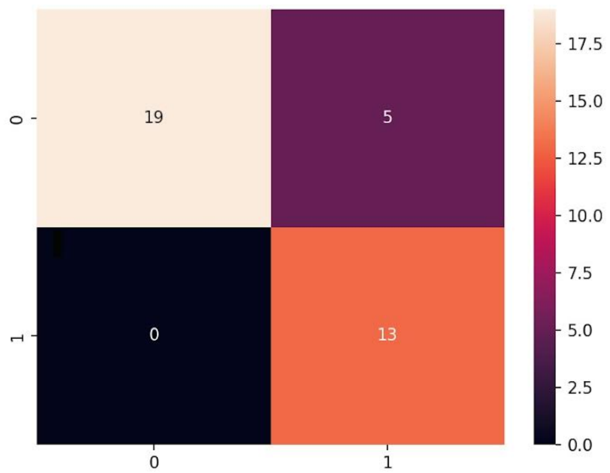

Figure IV.13: Confusion matrix for SVM classifier

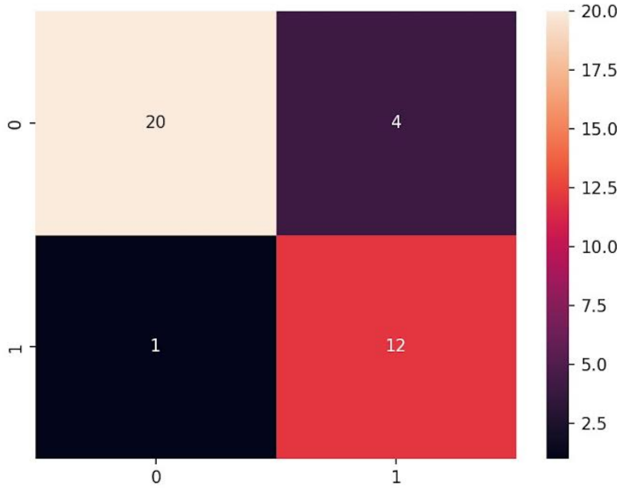

Figure IV.14: Confusion matrix for ANN classifier

	Accuracy	Precision	Recall	f1_score
SVMs	0.7567567567567568	0.8947368421052632	0.7083333333333334	0.7906976744186046
RF	0.918918918918919	1.0	0.875	0.9333333333333333
ANN	0.8918918918918919	0.9545454545454546	0.875	0.9130434782608695

Table IV.3: Result analysis of 30% split ratio with statistical accuracy-based parameters

IV.5.1 Model Comparison

The study evaluated three models - Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN) - for their predictive performance. The models were evaluated using various performance metrics including accuracy, precision, recall, and F1-score.

The results showed that Random Forest achieved the highest accuracy of approximately 91.89% and perfect precision of 100%, indicating it correctly classified all instances and made zero false positive predictions. SVM achieved an accuracy of approximately 75.67% and maintained. ANN also showed good performance with an accuracy of approximately 89.19% and a high precision score of approximately 95.45% look at **FigureIV.15**, **FigureIV.16** , **FigureIV.17**.

RF shows the highest performance across all metrics, with a high accuracy, precision, recall, and F1 score. SVMs and ANN also demonstrate reasonable performance but with slightly lower metrics compared to RF. These results suggest that RF may be the most effective model for the prediction of forest fires, providing accurate predictions with high precision and recall.

The performance evaluation suggests that RF is a promising model for predictive fire warning systems, while other models like SVM and ANN also have potential applications for predicting fire risks based on collected data.

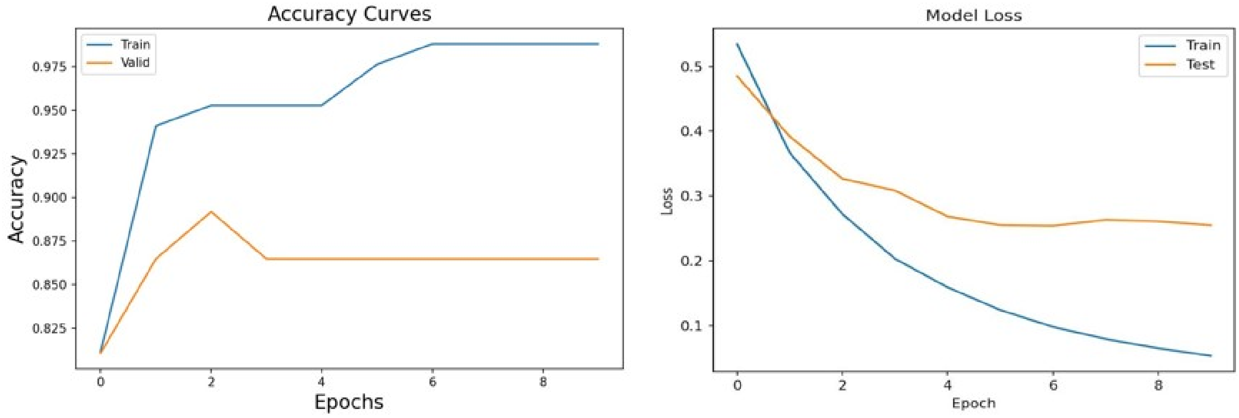

Figure IV.15: Accuracy/Loss Support Vector Machine (SVMs)

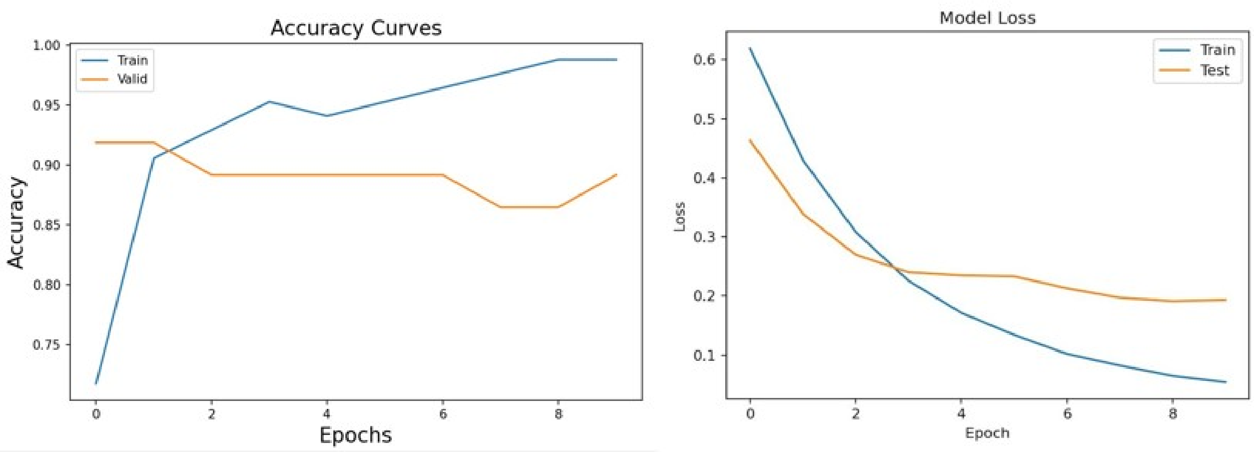

Figure IV.16: Accuracy/Loss Random Forest (RF)

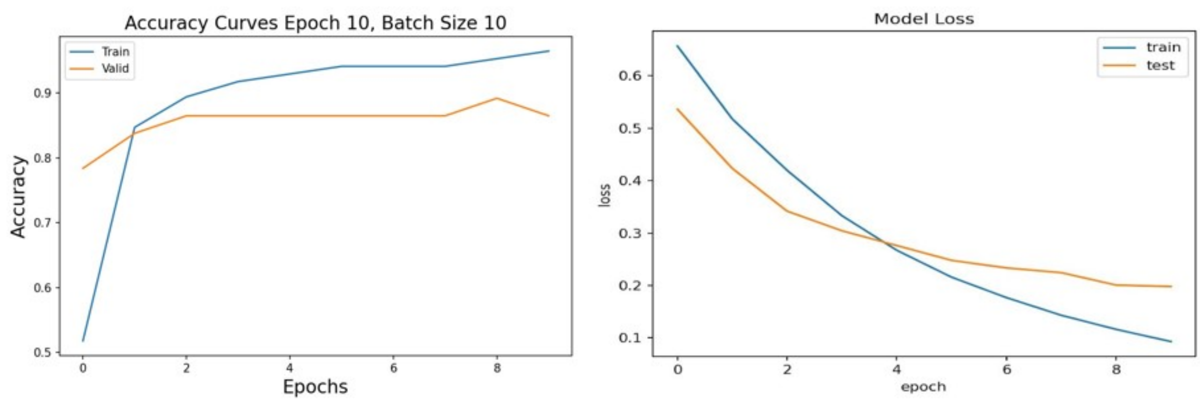

Figure IV.17: Accuracy/Loss Artificial Neural Network

In the matter of the magnitude of the modeling error three models: SVM, RF, and ANN. The SVM model showed divergent results between training and testing, indicating a potential overfitting issue. The RF model achieved acceptable results, suggesting better generalization and a lower modeling error. Remarkably, the ANN model performed the best despite the lack of training data, highlighting its ability to minimize errors and generalize effectively.

IV.6 Evaluation of Performance Based on Execution Time

In this scenario, the execution times of three algorithms are compared: Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). The execution times for SVM (0.2 seconds), RF (0.01 seconds), and ANN Larger(2.5 seconds) represent approximate values **FigureIV.19**.

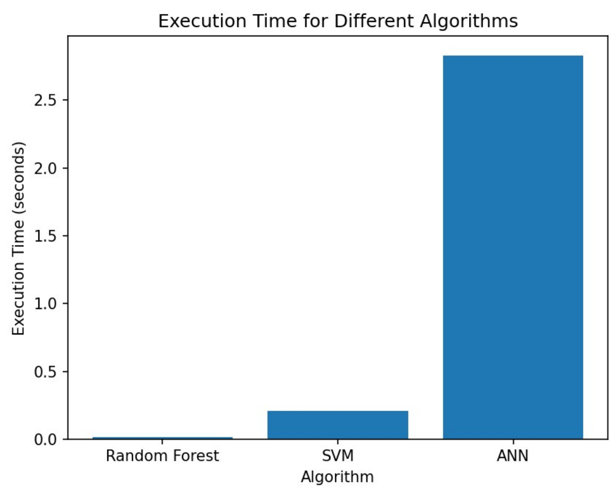

Figure IV.18: Evaluation of Performance Based on Execution Time for Different time.

1. **Support Vector Machines (SVM)**

   (a) Execution Time: 0.2 seconds.

(b) SVM is considered relatively fast in this scenario, as indicated by its execution time of 0.2 seconds. It can efficiently process data and generate results within a short timeframe.

2. **Random Forest (RF)**

   (a) Execution Time: 0.01 seconds.

   (b) RF stands out as exceptionally fast compared to both SVM and ANN, with an execution time of only 0.01 seconds. This suggests that RF can swiftly process data and generate results with great efficiency.

3. **Artificial Neural Networks (ANN)**

   (a) Execution Time: 2.5 seconds.

   (b) The execution time of 2.5 seconds for ANN indicates that it is relatively slower compared to SVM and RF in this scenario. Training and evaluating a neural network can be computationally intensive, especially when dealing with large and complex datasets.

In summary, based on the provided execution times, Random Forest (RF) emerges as the fastest algorithm, followed by Support Vector Machines (SVM), while Artificial Neural Networks (ANN) exhibit the slowest execution time. It is worth noting that RF not only demonstrates superior speed but is also considered the best in terms of accuracy and implementation efficiency.

Part Two: IFWS Implementing Using IoT Tools

In this part, the objective is to provide an electronic practical framework implementing an intelligent system based on the model that is created in the previous part. An IoT architecture will be used to collect some indicators using specific sensors (temperature, humidity,...). Then the Arduino UNO (microcontroller) will use this weather indicator and apply our model (the result of the previous part) to compute the risk level. Finally, the system commands a water pump to modify the weather conditions (temperature and humidity) to decrease this risk if it poses a danger **FigureIV.21**.

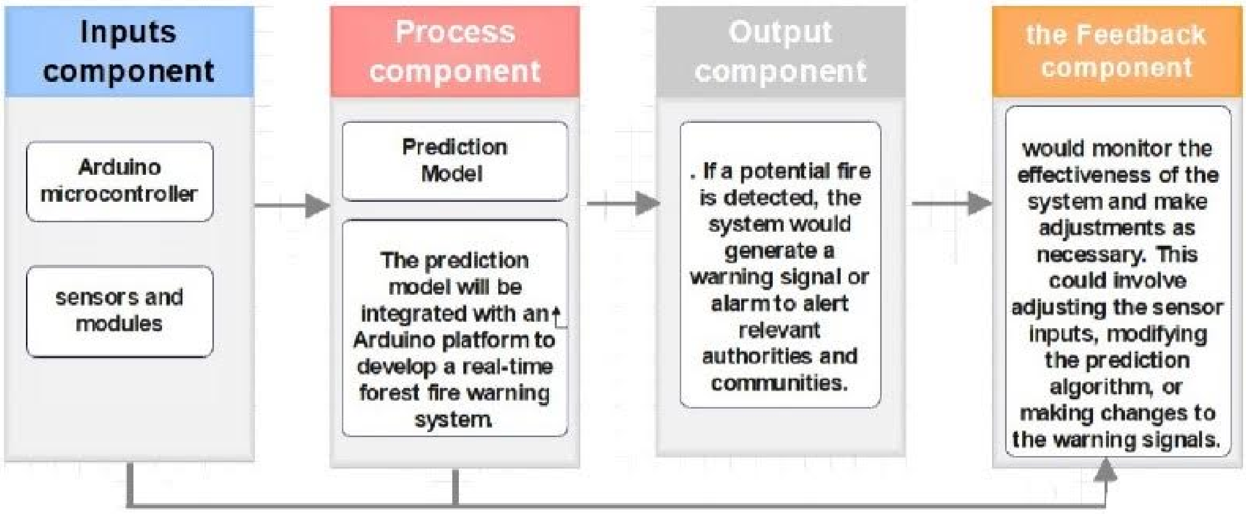

Figure IV.19: An Architecture System for IFWS

IV.7 IoT Architecture

In this part, we provide a practical electronic frame for our model. we will design an IoT implementation of our model. **FigureIV.18** represent the general architecture of our IoT.

IV.7.1 Devices and Sensors

in this project, we use the following components (modules):

1. **Microcontroller :** we use the Arduino Uno.
2. **Humidity ,Temperature :** we use the sensor DHT11.
3. **potentionmeter.**
4. **Actuators :** we use the Pumpe (VandPumpe)
5. **Resistor :** we use the resistor 220 ohm Carbon film 1/4 W.
6. **LEDs .**

IV.7.2 Inputs / outputs :

- 4 analog inputs.
- 6 discrete digital outputs.

IV.7.3 Designing The Hardware Prototype

involves gathering the hardware components mentioned earlier and commencing the construction of the system. The circuit diagram for the project, created using **Fritzing**[2], is depicted in the following **FigureIV.18**.

[2]Fritzing is an open-source initiative to develop amateur or hobby CAD software for the design of electronics hardware (http://fritzing.org/)

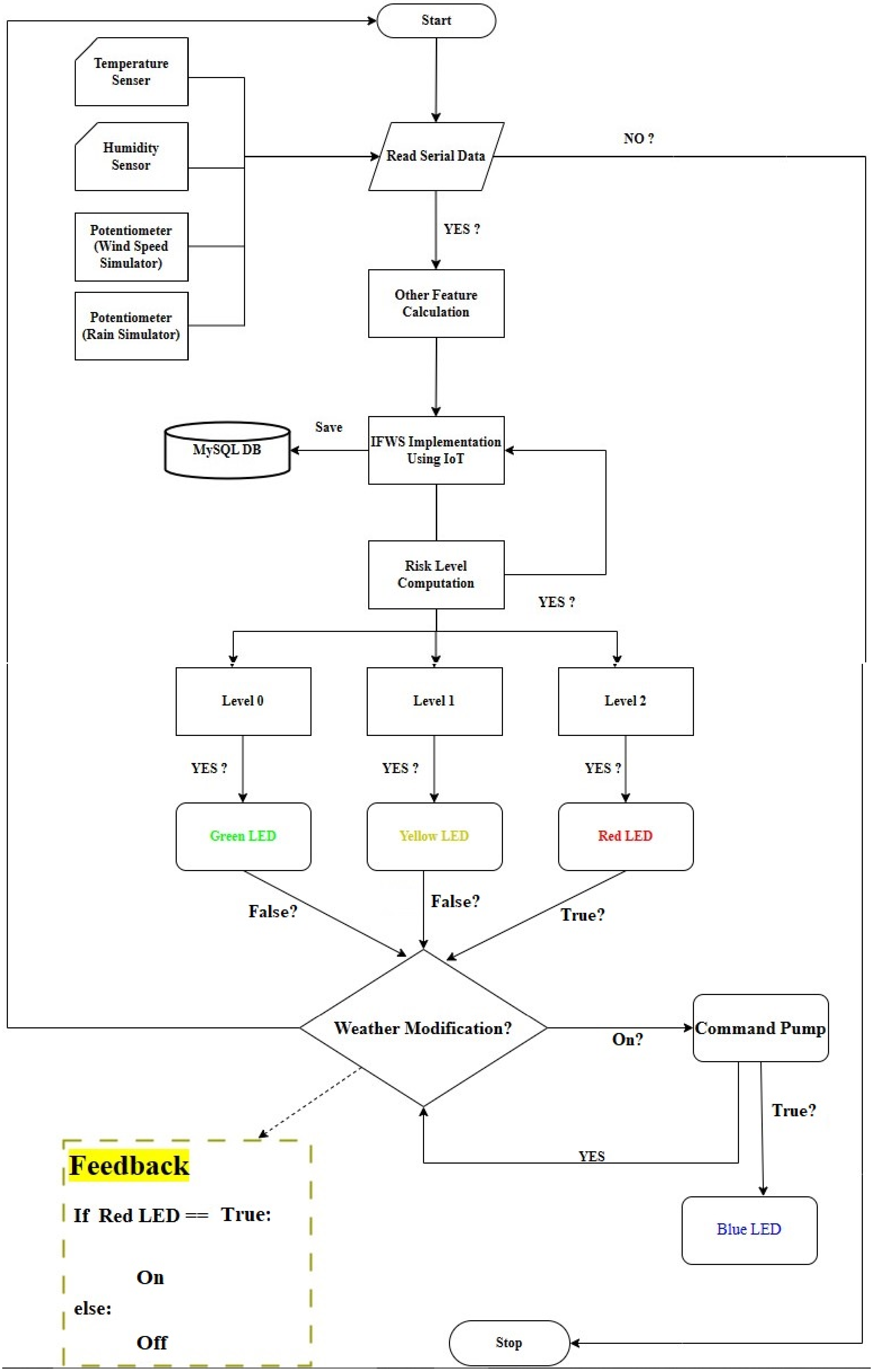

Figure IV.20: Architcture of IoT system

IV.7.4 Hardware Requirements

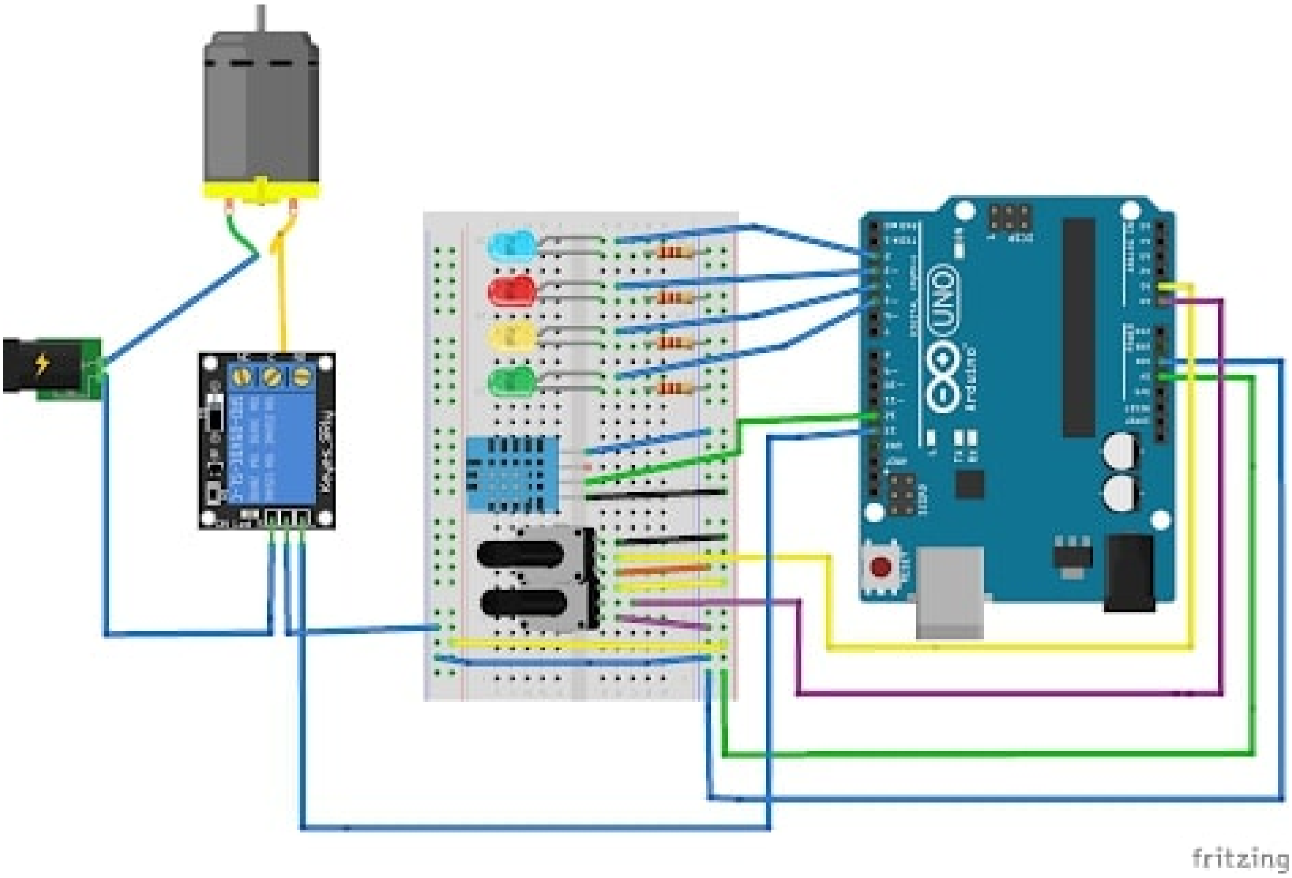

Figure IV.21: breadboard schematics for Arduino UNO in forest fire prediction task, Arduino schematic was developed using the Fritzing software.

To create an Arduino project with the following functionalities:

1. Reading temperature and humidity from a DHT11 sensor.
2. Monitoring two potentiometers representing rain and wind speed.
3. Controlling four LEDs, a pump, and a power plug using a model.

For that we followed the following steps:

1. **Hardware Setup:**
   (a) Connecting the DHT11 sensor to the Arduino board following the provided circuit diagram. Make sure to connect the pin to a suitable voltage source (3-5VDC), GND to the ground pin, and DATA to a digital pin (e.g., pin 2).
   (b) Connect the four LEDs to digital pins on the Arduino board (pins 3, 4, 5, and 6). Connect each LED's longer pin (anode) to the respective digital pin.
   (c) Connecting the two potentiometers to analog pins on the Arduino board (pins A0 and A1). Connect the outer pins of each potentiometer to power and ground, and the middle pin to the analog pins.

(d) We Connect the pump by connecting the negative side of the pump to the positive side of the power socket. Additionally, we connect the positive side of the pump to the negative side of the tongling device.

(e) We connect the negative side of the power socket to the positive side of the tongling device.

(f) We establish a connection between the tongling device and the Arduino board to control the flow of electric current. This is achieved by connecting the tongling device to pin 13 and GND on the Arduino board.

2. **Arduino Code:**

(a) Writing the Arduino code to read temperature and humidity from the DHT11 sensor using the DHT library.

(b) Use the analogRead() function to read the values from the two potentiometers representing rain and wind speed.

(c) Use the analogWrite() function to control the intensity of the LEDs based on the potentiometer readings.

(d) Implement suitable control logic to activate/deactivate the pump and power plug based on certain conditions (e.g., thresholds, user inputs, etc.).

(e) **Circuit Compilation and Upload:** Once the circuit is properly connected and the Arduino code is written, compile the code and upload it to the Arduino board using a USB cable.

After completing these steps, your Arduino project will be capable of reading temperature and humidity from the DHT11 sensor, monitoring rain and wind speed through the potentiometers, and controlling the four LEDs, pump, and power plug based on the implemented logic.

IV.7.5 The Software Architecture

The software architecture of the project consists of three components: hardware, the sketch, and Python pyserial. Data is collected from sensors and potentiometers, then processed by Arduino, and the values are passed to Python pyserial for prediction in model evaluation. Here are some relevant concepts related to software architecture:

1. **The Sketch**
   The sketch refers to the Arduino code that is written to interface with the hardware components, read data from the sensors and potentiometers, and control the output devices. The Arduino sketch will process the data and send it to the Python pyserial module.

   To initiate our sketch, we will input the following code into the Integrated Development Environment (IDE). By doing so, we will set the foundation for our program:

2. **Python Pyserial**
   This library is responsible for receiving the data from the Arduino board through the serial port and processing it. It also includes the machine learning model that predicts the incidence of fire hazards in the forest, which is testing on the collected dataThe Pyserial module receives the data and applies a machine learning model for prediction.

   The result of the prediction is used to further control the output devices, such as adjusting the intensity of the LEDs or activating/deactivating the pump.

   The sketch refers to the Arduino code that is written to interface with the hardware components, read data from the sensors and potentiometers, and control the output devices. The Arduino sketch will process the data and send it to the Python pyserial module.

IV.8 Interference System

The output of the microcontroller is the main input of the whole interference system, a water pump to deliver water. The water pump is used to spray the area where the expected rate of fire is high to control the basic parameters, reduce the temperature and increase the humidity.

IV.9 Informing System

The proposed system incorporates LEDs to provide visual indications of different fire occurrence levels.

The LEDs are used to indicate three cases: low, medium, and high-level risk .

Each case is represented by a specific LED that lights up accordingly.

This visual feedback allows users to quickly assess the current fire risk level based on the illuminated LED.

IV.10 Testing hardware connections

The test is conducted by placing a heat source directly in front of the sensor receiver, simulating a fire scenario.

The sensor used in this test is connected to the Arduino Uno.

The user interface will enable us to display the variations in climatic values that trigger the activation of the monitoring program model.

IV.11 Conclusion

In this chapter, we proposed an intelligent fire warning system (IFWS) for forest fire, which aims to develop a predictive model using weather conditions to predict and control fire-fighting actions. The project is motivated by the need to minimize losses costs in terms of human life and the loss of natural resources caused by forest fires.

The results of the study indicate that the Random Forest classifier had higher accuracy in overall classification compared to the neural network (NN) and support vector machine (SVM) classifiers. To test the model, we used sensors that are compatible with the inputs used in the prediction model. The sensors were connected to an Arduino microcontroller, then the collected data were used to apply our new intelligent model to predict and prevent the fire according to the risk that is estimated by the model.

Overall, the proposed (IFWS) has the potential to improve the effectiveness of forest fire prevention and control. By using predictive models based on weather conditions and sensor data, the system can provide early warnings of potential fires and enable faster and more accurate fire-fighting responses.

Conclusion

In this study, we proposed a new Intelligent system to pridect and prevent the forest fire using the weather conditions (temperature, humidity...)

For that, we started by exploring the causes and the behavior of forest fires (Chapter II), as well as the various types of forest fires and their effects.

We also discussed the different methods of fighting forest fires, including chemical flame retardants, drones, and artificial intelligence.

Next, we explored some methods and approaches that are used in this field (Chapter III), using artificial intelligence algorithms and then we choose the best one for the prediction forest fire and we also saw some related work to forest fire and other some challenges that they encountered on their studies

Finally, our contribution (IFWS) was presented through three steps:

1. First, we collect relevant data about the fire phenomenon, including temperature, humidity, and other pertinent factors.

2. Then, we process the collected data to prepare it for training and testing. The testing subset is then used to train the selected algorithms.

3. Finally , we employ the testing subset in our prediction model to obtain results indicating the presence or absence of a fire. where we focus on the inputs/outputs of our system (weather conditions (inputs)), fire state (output), also we present how to use some machine learning algorithms .

Furthermore, we introduce an IoT implementation of our model, which offers a practical electronic framework. The IoT architecture enhances the operationalization of our model, improving its effectiveness and practicality in real-world scenarios.

As a result, our approach indicate that when evaluating accuracy, precision, recall, and f1 score, the RF algorithm outperformed the SVM and ANN algorithms. Additionally, we developed a prototype using Arduino, which effectively connected and simulated the data to provide a realistic representation. This prototype has the potential to be scaled up and used in the future as a means of forest fire prevention and loss reduction.

In the future ,the Intelligent Fire Warning System (IFWS) will be enhanced incorporating more environmental data, investigating advanced machine learning techniques, employing satellite images, and improving real-time data updates to increase fire prediction and prevention capabilities. Furthermore, incorporating GIS technology, encouraging data sharing, and undertaking field testing and constant monitoring would improve the IFWS's effectiveness and usefulness.

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