# MACHINE LEARNING-BASED FOREST FIRE PREDICTION MODEL UTILIZING UAV VIDEOS

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**ABSTRACT**-Forest fires represent a pervasive and significant natural calamity, yearly devastating millions of hectares of forest and presenting a grave danger to human life and property. Precise quantitative forecasting of forest fire propagation is crucial for formulating prompt risk management plans and executing efficient firefighting methods. This work presents a Forest Fire Spread Behavior Prediction (FFSBP) model, which has two essential components: the Forest Fire Spread Process Prediction (FFSPP) model and the Forest Fire Spread Results Prediction (FSRP) model. The FFSPP model predicts the direction and velocity of forest fire propagation by integrating the Cellular Automata model with the Wang Zhengfei model. The FFSRP model, instead, emphasizes predicting the magnitude of the burnt area by using machine learning techniques. A genuine case study using the "3.29 Forest Fire" disaster in China is conducted to assess the usefulness of the presented models. The FFSPP model is verified for this example, while the FFSRP model is evaluated using a real fire dataset sourced from Montesinho National Forest Park in Portugal. The validation procedure indicates that during the natural growth phase of the "3.29 Forest Fire," the FFSPP model forecasts a burnt area of 286.81 hm², with a relative error of 28.94%. This relative inaccuracy is much less than those recorded in the Farsite and Prometheus fire behavior simulation models. The FFSRP model has notable prediction efficacy, especially with small and medium-sized fire situations. The results highlight the FFSBP model's potential as an effective instrument for improving forest fire forecast accuracy and enabling more effective risk reduction and firefighting techniques

**1.INTRODUCTION**: The increasing incidence and intensity of worldwide forest fires, intensified by global warming and extreme weather events, present significant hazards to human life, property, and ecosystems [1], [2]. Each year, millions of hectares of woods are consumed by fire, resulting in significant economic losses and fatalities. The precise forecasting of forest fires is crucial in preventing many disasters. Forest fire prediction is often categorized into three types: fire risk weather forecasting, forest fire occurrence forecasting, and forest fire behavior forecasting. The aforementioned categories account for distinct factors: (i) fire risk weather prediction emphasizes meteorological elements [3], [4]; (ii) forest fire occurrence prediction encompasses meteorological factors, combustibles, and ignition sources [5], [6], [7]; (iii) forest fire behavior prediction integrates meteorological factors, combustibles, and topographical conditions [8], [9], [10]. Weather and occurrence forecasts evaluate the possibility for forest fires, while behavior prediction, which includes weather, combustibles, and topography, examines the direction, speed of spread, and burnt area—essential for efficient firefighting [11], [12]. This research focuses on predicting forest fire behavior, including both the processes and results of forest fire events. The forecasted data for the occurrence process include the direction and velocity of fire propagation, given graphically. Outcome projections include the expected burnt area. The spread of a forest fire, an aspect of its behavior, refers to the properties shown by combustibles from ignition until extinction. The forest fire spread model utilizes mathematical approaches under simplified settings to establish quantifiable correlations between essential components (e.g., fuel characteristics, topography, climatic variables) and forest fire behavior, including propagation velocity [13]. These linkages enable the forecasting of imminent or current forest fire behavior, informing firefighting efforts and everyday forest management practices. Since W.R. Fons presented a mathematical model in 1946, researchers globally have suggested several models predicated on diverse assumptions about flammable materials. Prominent models include the Canadian forest fire spread model [14], the Australian McArthur model [15], the American Rothermel model [16], [17], the Chinese Wang Zhengfei forest fire spread model [18], and the modified iterations derived from these models [18], [19], [20]. Notwithstanding its value, each model has limitations, particularly in the absence of assumptions, resulting in significant inaccuracies. Consequently, comprehending the applicability, criteria, and advantages and disadvantages of a model is essential prior to its implementation. These models are categorized into empirical, physical, and semi-empirical/semi-physical depending on their underlying concepts. Empirical models depend on statistical analysis of real data, disregarding physical processes. Physical models rely on the principles of energy conservation and heat conduction; yet, they may encounter difficulties in obtaining input values. Semiempirical or semi-physical models, such as the Wang Zhengfei and Rothermel models, integrate experimental data informed by particular physical processes. The eleven input variables of the Rothermel model, characterized by intricate interrelations and demanding acquisition prerequisites, provide hurdles to its implementation. Conventional forest fire propagation models, often based on mathematical or physical principles, do not possess intrinsic self-organizing capabilities. As system complexity increases or disruptions arise, the difficulty of solving differential equations or estimating numerical values escalates [21], [22]. The use of Cellular Automata (CA) mitigates this shortcoming by remedying the lack of self-organization in traditional models and presenting a more dynamic representation of forest fire propagation [13], [23], [24]. This research combines the Wang Zhengfei model with the Cellular Automata (CA) paradigm to provide a user-friendly and self-organizing framework. This comprehensive method seeks to forecast the trajectory and velocity of forest fire propagation, eventually resulting in a visually comprehensible depiction. Moreover, with the advancement of computational power and the evolution of Machine Learning (ML), ML has attracted attention for its capacity to identify nonlinear correlations among various input parameters. Researchers have used machine learning for forest fire prediction, including techniques such as backpropagation neural networks, random forests, deep learning, and ensemble learning. Although several machine learning algorithms have shown enhanced efficacy in predicting fire risk relative to probabilistic and statistical methods, the focus has mostly been on forecasting the chance of forest fire occurrence rather than the extent of the burnt area. In recent decades, ensemble learning has gained significance in the machine learning domain because to its effectiveness in tackling practical application issues [26], [27], [28]. Therefore, this paper use ensemble learning to predict the results of forest fire incidents, particularly the region affected by the fire. This decision seeks to improve the forecasting of fire conditions and enable prompt reaction actions. This research aims to examine the prediction of the forest fire spread process and its consequences, culminating in the development of a Forest Fire Spread Behavior Prediction (FFSBP) model. This model consists of two essential components: the Forest Fire Spread Process Prediction (FFSPP) model and the Forest Fire Spread Results Prediction (FFSRP) model. The FFSPP model integrates the Wang Zhengfei model with the Cellular Automata (CA) model to forecast the direction and velocity of forest fire propagation, while the FFSRP model use ensemble learning techniques to estimate the burnt area. The "3.29" forest fire in Anning, Southwest China, exemplifies the validation of the forest fire spread prediction model. The burnt area prediction model is validated using an actual fire dataset from January 2000 to December 2003, sourced from Montesinho National Forest Park in Portugal. The research findings possess considerable practical ramifications for forest fire management: (i) forecasting and visualizing the trajectory and velocity of fire propagation yields critical insights for the allocation of firefighting assets; (ii) estimating the extent of the burned area informs the consolidation of comprehensive firefighting resources; (iii) the proposed methodology's uncomplicated calculation process, along with its versatility across various datasets, enables straightforward application and enhancement of the model.

## 2.LITERATURE SURVEY

**M. Flannigan, B. Stocks, M. Turetsky, and M. Wotton, ''Impacts of climate change on fire activity and fire management in the circumboreal forest,'' Global Change Biol., vol. 15, no. 3, pp. 549–560, Mar. 2009**

Forest fires are a substantial and inherent component of the circumboreal forest. Fire activity is closely associated with meteorological conditions, and heightened fire activity resulting from climate change is expected or has likely already occurred.

Recent estimates indicate a twofold increase in the area burnt and a 50% rise in fire incidents in some regions of the circumboreal by the century's end. The capacity of fire management agencies to address the rising fire activity is constrained, as these organizations function within a slim margin of success and failure. Consequently, a disproportionate number of fires may evade initial suppression efforts in a warmer climate, leading to a significantly greater increase in burned area than the corresponding rise in fire weather severity. In a decade or two, heightened fire activity may render fire management agencies incapable of sustaining their existing efficacy.

**M. R. Turetsky, E. S. Kane, J. W. Harden, R. D. Ottmar, K. L. Manies, E. Hoy, and E. S. Kasischke, ''Recent acceleration of biomass burning and carbon losses in Alaskan forests and peatlands,'' Nature Geosci., vol. 4, no. 1, pp. 27–31, Jan. 2011.** Climate change has expanded the region impacted by forest fires annually in boreal North America1,2. Anticipated increases in burnt area and fire frequency are projected to exacerbate carbon losses in boreal regions. The intensity of burning also influences the effect of wildfires on carbon emissions. The impact of climate change on the intensity of biomass burning has been challenging to evaluate. We investigated the extent of ground-layer combustion across 178 locations mostly including black spruce in Alaska, using data from 31 fire incidents occurring between 1983 and 2005. The depth of burning grew as the fire season advanced while the yearly area burnt was little. Nevertheless, extensive combustion transpired during the fire season when the yearly area incinerated was substantial. The intensity of combustion heightened towards the conclusion of the fire season in upland forests, but it remained unchanged in peatland and permafrost locations. Simulations of carbon losses from Alaskan black spruce stands due to wildfires during the last 60 years indicate that ground-layer combustion has intensified regional carbon losses in the last decade, attributed to an expansion in burn area and late-season burning. Consequently, soils in these black spruce stands have transformed into a net carbon source for the atmosphere, with carbon releases significantly surpassing decadal absorption. Prior modeling results indicate that heightened fire frequency in boreal areas influences forest composition, escalates greenhouse gas emissions, and acts as a primary factor in the boreal carbon balance. The overall impact of combustion on boreal carbon stocks is influenced by both the frequency and intensity of fires, and the implications of climate-induced alterations in the fire regime for biomass consumption rates remain unknown. Despite advancements in remote sensing yielding more precise data on the yearly area burnt in the boreal biome, quantifying the susceptibility of boreal biomass to intense burning continues to pose challenges. A significant fraction of the boreal carbon pool is sequestered in moss, litter, and peat layers that are partly or wholly incinerated during fires. The combustion of this ground-layer biomass was predicted to account for almost 85% of the total fuels burned in Canadian forest fires. The intensity of ground-layer biomass combustion influences C emissions and governs several ecological processes, such as soil temperature regulation, respiration, permafrost preservation, and forest succession.

**N. Ntinopoulos, M. Spiliotopoulos, L. Vasiliades, and N. Mylopoulos, ''Contribution to the study of forest fires in semi-arid regions with the use of Canadian fire weather index application in Greece,'' Climate, vol. 10, no. 10, p. 143, Sep. 2022** Forest fires have significant relevance in the Mediterranean area. Fire weather indices are meteorological metrics designed to provide insights into the effects and features of fire events within ecosystems. This research examines the spatiotemporal patterns of the FWI system within the geographical confines of the Greek state. The Fire Weather Index (FWI) has been computed and analyzed for both present and prospective periods utilizing data from the Climate Forecast System Reanalysis (CFSR) model by the National Centers for Environmental Prediction (NCEP), alongside information from NASA satellite initiatives and the European Centre for Medium-Range Weather Forecasts (ECMWF) in netCDF file format. The computation and analysis of the results were executed using the Python programming language, and supplementary drought- and fire-related indices were derived, including the standardized precipitation index (SPI), the count of consecutive 50-day dry periods (Dry50), the Fosberg fire weather index (FFWI), and the number of days when the FWI surpasses values of 40 and 50 (FWI > 40) and (days FWI > 50). Comparable trends are readily observable across all indices, which seem to exhibit elevated values mostly in the southeastern region of the nation, attributable to increased temperatures and a greater incidence of drought episodes influencing the indices' dynamics in both present and future contexts.

## 3.EXISTING SYSTEM

The spread of a forest fire, a component of its behavior, refers to the properties shown by combustibles from ignition until extinction. The forest fire spread model utilizes mathematical approaches under simplified settings to establish quantifiable correlations between essential components (e.g., fuel characteristics, topography, climatic variables) and forest fire behavior, including propagation velocity [13]. These linkages enable the forecasting of imminent or current forest fire behavior, informing firefighting efforts and everyday forest management practices. Since W.R. Fons published a mathematical model in 1946, researchers globally have suggested several models predicated on diverse assumptions about flammable materials. Prominent models include the Canadian forest fire spread model [14], the Australian McArthur model [15], the American Rothermel model [16], [17], the Chinese Wang Zhengfei forest fire spread model [18], and the modified iterations derived from these models [18], [19], [20]. Notwithstanding its value, each model has limitations, particularly in the absence of assumptions, resulting in significant inaccuracies. Consequently, comprehending the applicability, circumstances, and advantages and disadvantages of a model is essential prior to its use. These models are categorized into empirical, physical, and semi-empirical/semi-physical depending on their underlying concepts. Empirical models depend on statistical analysis of real data, disregarding physical processes. Physical models rely on the principles of energy conservation and heat conduction; yet, they may encounter difficulties in obtaining input values. Semiempirical or semi-physical models, such as the Wang Zhengfei and Rothermel models, integrate experimental data informed by particular physical processes. The eleven input variables of the Rothermel model, characterized by intricate interrelations and demanding acquisition prerequisites, provide problems for its implementation.

## 3.1.PROPOSED SYSTEM:

The project has been completed using machine learning methods, namely Convolutional Neural Networks (CNN), to detect forest fires in real-time. It accepts images as input, with further picture preprocessing conducted appropriately. This research examined an automated forest fire monitoring system using photos taken by unmanned aerial vehicles (UAVs) to anticipate fire movement and identify affected areas. The primary limitation of this project is its reliance solely on image input, necessitating additional time and effort to detect forest fires. By the time fire detection occurs through images, a significant portion of the forest may already be consumed by flames, leaving little opportunity for intervention. To address this issue, we have developed alternative deep learning models for forest fire detection. The proposed system utilizing wireless sensor networks and machine learning has proven to be an effective approach for forest fire detection, yielding more accurate results. The automated fire detection system using thermal analysis is the most effective option in combating forest fires. This system facilitates the early detection, localization, and monitoring of forest fires. We will employ Convolutional Neural Networks (CNN) alongside You Only Look Once (YOLO) for fire detection. The primary advantage of utilizing YOLO is its pre-trained and validated methodology, which is expected to yield superior accuracy compared to CNN. The system will process both video and image inputs, thereby enhancing its accuracy relative to existing systems.

## 4.IMPLEMENTATION

### 4.1. SYSTEM ARCHITECTURE

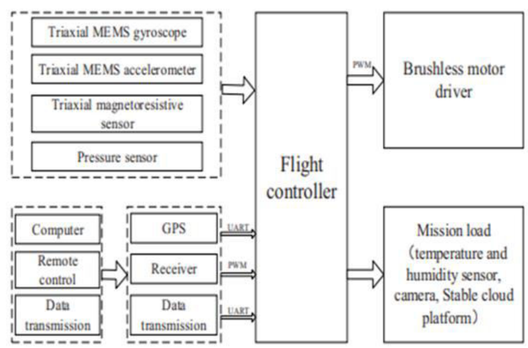
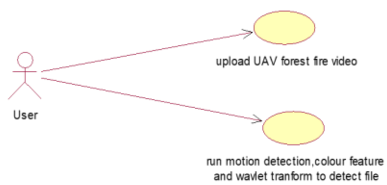



**Fig: System Architecture**

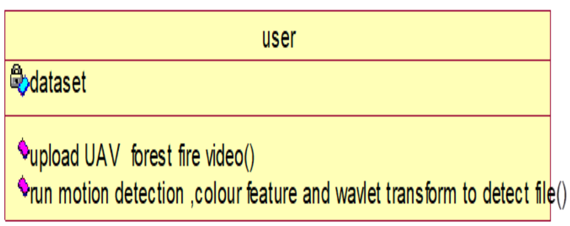
### USE CASE DIAGRAM:

A use case diagram in the Unified Modeling Language (UML) is a behavioral diagram developed by a use-case study. The objective is to create a graphical representation of a system's functioning, illustrating actors, their objectives (depicted as use cases), and the interdependencies among those use cases. The primary objective of a use case diagram is to illustrate the system functions executed for each actor. The roles of the players inside the system may be shown.




## CLASS DIAGRAM:

A class diagram in the Unified Modeling Language (UML) is a static structural diagram that delineates the architecture of a system by illustrating its classes, attributes, operations (or methods), and the interrelations among the classes. It delineates the class that encompasses the information.

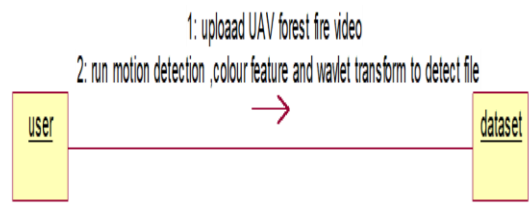



## SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is an interaction diagram that illustrates the interactions between processes and their chronological order. It is a representation of a Message Sequence Chart. Sequence diagrams are also referred to as event diagrams, event situations, and timing diagrams.


## COLLABORATION DIAGRAM:

Activity diagrams are visual representations of workflows including sequential activities and actions, accommodating options, repetition, and simultaneous processes. Activity diagrams in the Unified Modeling Language are used to delineate the sequential workflows of components inside a system, including both business and operational processes. An activity diagram illustrates the comprehensive flow of control.




## 4.2.MODULES

GUI Setup

- Purpose: Create the graphical user interface (GUI) to allow user interaction.
- Tools: Use Tkinter for buttons and text areas.

Video Upload

- Purpose: Provide functionality for users to upload a video file for analysis.
- Tools: Use tkinter filedialog for file selection.

Video Processing

- Purpose: Extract frames from the uploaded video for fire detection.
- Tools: Use OpenCV to handle video frames.

Fire Detection

- Purpose: Implement the fire detection algorithm using machine learning or rule-based logic.
- Tools: Use OpenCV for color-based detection and optionally integrate machine learning models like CNN.

## 5.SCREENSHOTS


**Fig: UI Of Forest Fire Predcition**


Fig: Uploading Data Set

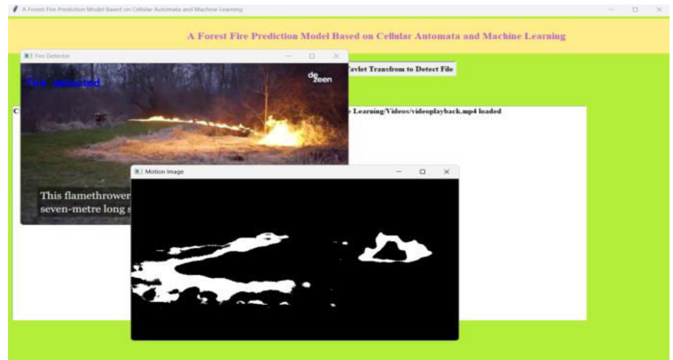



Fig: Forest Fire Predicted

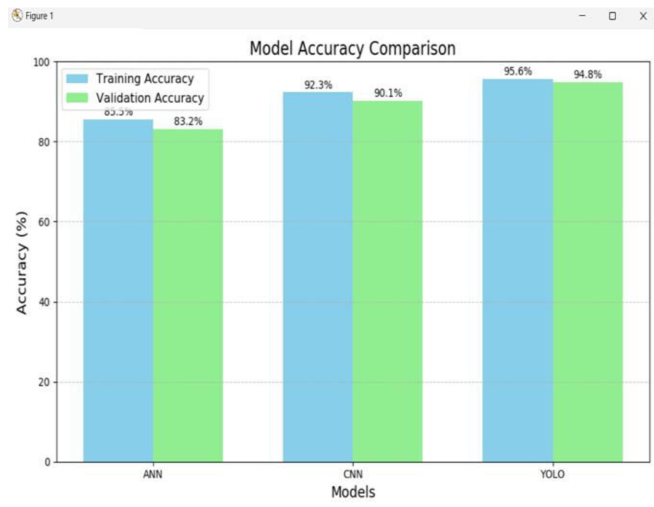



Fig: Displaying accuracy

## CONCLUSION

This study introduces an FFSRP model after an unintentional forest fire event. Initially, drawing from relevant literature and real-world scenarios, the components affecting forest fires that are readily accessible during the practical application of the models have been identified: combustible materials, climatic circumstances, and topographical features. The FFSPP model is formulated by integrating the CA model with the Wang Zhengfei model. The FFSRP model is designed to forecast the burnt area using machine learning approaches. The "3.29 Forest Fire" in China and the actual fire dataset from Montesinho National Forest Park in Portugal are used as examples to validate the suggested model and methodology. The relative inaccuracy of the suggested FFSPP model is less than that of the Farsite and Prometheus fire behavior simulation models. The suggested FFSRP model has commendable forecasting ability in small to medium-sized fire scenarios. The primary study findings are as follows: (1) The determinants of forest fire are identified. The primary elements influencing forest fires are flammability, climatic circumstances, and topographical features. The combustible state primarily pertains to vegetation type, while meteorological factors encompass temperature, humidity, wind speed, wind direction, and the Fire Weather Index (FWI). Topographical conditions include geographical location and slope, all of which are readily accessible during practical model application. The proposed Fire Spread Prediction Model (FFSPP) effectively delineates the process of fire propagation. The FFSPP model is formulated by integrating the CA model with the Wang Zhengfei model to forecast the trajectory and velocity of forest fire propagation and facilitate visualization. The findings indicate that the proposed model surpasses the Farsite and Prometheus fire behavior simulation models typically used in the US and Canadian sectors. The suggested FSRP model effectively characterizes the impact of fire. The FFSRP model is constructed on the Anaconda ML platform by merging XGB, LGB, and GBoost learners via stacking. The model's final MAE score on the training dataset is 16.50, indicating effective predictions, particularly for small and medium-sized fire scenarios.

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