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Data-Driven Forest Fire Risk Prediction

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***Abstract*—Data-driven Forest fire Prediction system addresses the pressing issue of forest fire risk assessment by leveraging two different machine learning models which excel in their own tasks. The challenge lies in predicting and preventing potential fires, crucial for minimizing the devastating consequences of uncontrolled wildfires. By leveraging the power of XGBoost classifier for classification and Random Forest Regressor for regression, the project aims to provide accurate predictions for forest fire danger and fuel moisture code indices. Data retrieval from a MongoDB database ensures that the models are well-informed by current and relevant information. The implementation of a Flask web application offers a user-friendly interface for easy interaction with the predictive models. The societal impact is significant, as timely interventions enabled by accurate predictions can safeguard ecosystems and human lives from the catastrophic effects of wildfires.**

Keywords—Random Forest, XGBoost, MongoDB, Flask web app, Wildfires, Accurate.

I. INTRODUCTION

The Forest Fire Risk Assessment System represents a comprehensive solution leveraging data science and machine learning to predict and evaluate the risk of forest fires. In this interdisciplinary project, we combine meteorological data, historical fire observations, and real-time environmental input to provide users with timely and accurate information. The heart of our system lies in two key components: a classification model and a regression model. The classification model, powered by XGBoost, assesses the risk of forest fires based on a range of features. Simultaneously, the regression model, employing the Random Forest Regressor, focuses on predicting fuel moisture indices, a critical factor in understanding fire susceptibility. To ensure the system's accessibility and relevance, we've integrated user-friendly interfaces using Flask, enabling seamless interaction. Users can not only access risk assessments but also input real-time environmental data, contributing to the refinement and adaptability of the models. The project's foundation rests on a MongoDB database, housing historical fire data retrieved through a dedicated module. Real-time meteorological data is dynamically integrated from the Open Weather API, enhancing the models' accuracy. Our system embraces an iterative approach, incorporating user feedback to continuously refine the classification and regression models. This iterative process ensures the adaptability and precision of the system in responding to evolving environmental conditions.

In summary, the Forest Fire Risk Assessment System is a robust and user-centric platform that amalgamates cutting-edge machine learning techniques, real-time data integration, and intuitive interfaces. By predicting fire risks and fuel moisture indices, the system not only aids in proactive decision-making for forest management but also serves as a valuable tool for environmental protection. The inclusive design, with features like speech-to-text conversion, broadens its applicability, making it an essential resource for both experts and the public. The project stands as an example to the efficient data-driven prediction practices in addressing critical problems and fostering a more developed, resilient, and informed society.

II. RELATED WORK

The literature related work indicates that our proposed model with XGBoost and Random Forest algorithm gives highest accuracy and precision. The methodology proposed is achieved by thorough research and it is illustrated below.

Singh et al. [1] Proposes a parallel Support Vector Machine (SVM) model for forest fire prediction. It utilizes Spark and PySpark for data segmentation and feature selection. This paper employs Forecast Weather Index (FWI) and weather parameters for prediction. It may not be effective in forecasting large-scale wildfires because it is limited to minor flames. depends on FWI, which in complex situations might not be able to capture all fire-related elements. Black-box nature of SVM makes model's decision-making and interpretability process difficult. Lee [2] It introduces the Canopy Stress Index (CSI) which is derived from Soil

Moisture Active Passive (SMAP) data for large-scale wildfire prediction. CSI integrates vegetation water content and temperature information. Also evaluates the model's performance on historical wildfire occurrences in California. It relies on SMAP data availability, which might be limited in certain regions. CSI might not be sensitive to specific fire ignition factors like lightning strikes or human activities and Limited evaluation on diverse wildfire scenarios and geographic regions. Rashkovetsky etal.[3] It Employs deep semantic segmentation on multisensory satellite imagery for wildfire detection and utilizes convolutional neural networks (CNNs) trained on labelled wildfire data. It achieves high accuracy in detecting active fire pixels from satellite images. Requires huge labeled dataset for training, which cannot be cost efficient and time efficient to acquire. High computational cost associated with training and running deep learning models. It might struggle with generalizability to unseen fire scenarios or different sensor types. Wood [4] It develops an optimized data matching and mining algorithm for predicting burned areas of forest fires and leverages historical fire data and spatial relationships between burned areas. Aims to provide valuable insights into fire spread patterns and risk assessment. It relies on accurate historical data, which might not be readily available for all regions. It assumes spatial relationships between past fires hold true for future events, which might not always be the case. Limited focus on real-time prediction and early warning capabilities. Xu et al. [5] It Proposes a similarity-based geographical sampling method for selecting fire safe points for spatial prediction of forest fire and also utilizes a regression model weighted geographically to account for space variations in fire risk factors. Aims to improve prediction accuracy by addressing the issue of imbalanced data in non-fire and fire locations. Requires detailed spatial data and computational resources for geospatial analysis. The effectiveness of the geographical similarity-based method might depend on the specific fire risk factors and study area and limited evaluation on different fire risk scenarios and prediction horizons.

Hong et al. [6] proposed a novel methodology called SBT-Fire Net for near real-time monitoring of fire spots using Himawari-8 satellite images. The proposed method uses a deep learning-based approach that combines the spatial binary tree (SBT) and Fire Net models to detect fire spots. The SBT extracts satellite images features, and the Fire Net model classifies the features extracted as fire or non-fire. The weakness of this method is that it requires huge labeled dataset for training the deep learning models, which may not be time-efficient and cost efficient. Ahmad et al. [7] proposed a machine learning-based approach for forest fire prediction. The proposed method uses multiple machine learning algorithms such as SVM, random forests, and decision tree for the prediction of forest fires. The weakness of this method is that it only makes predictions based on historical data, which may be inaccurate in the case of sudden changes in weather or other environmental factors. Wu et al. [8] proposed a simulation-based approach for forest fire spread prediction using artificial intelligence. The proposed method uses a combined cellular automata and ANN approach to simulate the spread of forest fires. The weakness of this approach is that it requires the input data like wind speed, temperature, and humidity to be accurate, which may not always be available in real-time. Rubí et al. [9] proposed a behavioral study for Brazilian Federal District region forest fires by using a machine learning-based approach. The proposed a model which uses multiple machine learning models such as SVM, random forest, and decision tree to analyze the behavior of forest fires. The weakness of this system is that it only makes predictions based on historical data, which may be inaccurate in the case of sudden changes in weather or other environmental factors. Mahaveer Kannan et al. [10] proposed a cat swarm with LSTM model integrated IOT based forest fire detection system. The proposed method uses a combination of IoT sensors and machine learning models to detect forest fires. The weakness of this system is that it requires an abundant number of IoT sensors to cover a huge forest area, which can be expensive and difficult to maintain.

Reis and Turk [11] proposed a system for forest fire detection using deep CNN with a transfer learning approach. They used a pre-trained CNN model and fine-tuned it on their dataset. However, the method used in this study requires a huge labeled dataset for training, which can be an issue obtaining. Pham et al. [12] used remote sensing and machine learning to classify forest cover and map forest fire susceptibility in Dak Nong province, Vietnam. They used a Random Forest classifier. However, their method relies heavily on the quality of the remote sensing data, which can be affected by weather conditions and other factors. Saleh et al. [13] conducted a review of deep learning methods for forest fire surveillance systems. They discussed various Deep learning models, which includes CNNs, RNNs, and GANs. They highlighted the potential of these models in improving the accuracy of forest fire detection and prediction. However, they also noted that deep learning methods require a large amount of data and computational resources. Xu et al. [14] proposed a geographical similarity-based sampling method for spatial prediction of forest fires. They used a kriging interpolation method to estimate the probability of fire occurrence in a given area. But their method assumes that the probability of fire occurrence is spatially correlated, which may not always be the case. Anandaram et al. [15] proposed a forest fire management system using machine learning techniques. They used a decision tree classifier to predict the severity of a fire based on various environmental factors. This method relies on the availability and accuracy of the environmental data, which can be easily influenced by various factors like sensor malfunction and data processing errors.

Lim et al. [16] proposed a ordinary least squares regression analysis based prediction model for fire at the urban planning stage. The analysis is based on data of the South Korean urban area land use and fire damage. The authors used a dataset of 1,000 fire incidents that occurred between 2015 and 2019 in South Korea. The study found that the area of urban land use is a significant predictor of fire damage. However, the study did not consider other important factors that could affect fire damage, such as building materials, population density, and fire prevention measures. Júnior et al. [17] proposed an automated calibration system for assessing forest fire risk levels using clustering techniques for regionally differentiable classification of fire risk. The authors used a dataset of meteorological and fuel moisture data from the Brazilian National Institute of Meteorology. The study found that the proposed method can improve the accuracy of forest fire danger rating. However, this paper did not consider the influence of other factors, such as topography and vegetation type, on forest fire danger. Deng and Zhang [18] proposed an improved forest fire monitoring algorithm using three-dimensional Otsu. The authors used a dataset of satellite images from the MODIS sensor. The study found that the proposed algorithm can improve the accuracy of forest fire detection and monitoring. However, the research did not consider the influence of cloud coverage and atmospheric conditions on the accuracy of the algorithm. Carrillo et al. [19] proposed a data-driven framework for prediction of fire spread in forest. The authors used a dataset of forest fire spread data from the Spanish Forest Fire Fighting Service. The study found that the choice of error function can significantly impact the accuracy of forest fire spread prediction. However, the paper did not consider the impact of weather-related factors, such as wind direction and speed, on fire spread. Chen et al. [20] proposed a detection system for wildfire and uses a RGB/IR drone image dataset monitoring method. The authors used a dataset of drone-collected images from the University of California, Berkeley. The study found that the proposed method can improve the accuracy of wildland fire detection and monitoring. However, this paper did not consider the impacts that may happen over weather changes, such as Direction of the wind speed, on the accuracy of the method.

In summary, each of the papers proposed a unique methodology for fire prediction, forest fire danger rating, forest fire monitoring, forest fire spread prediction, and wildland fire detection and monitoring. However, each study had its limitations, such as not considering all the factors that could affect fire behavior and not accounting for the impact of weather conditions on the accuracy of their proposed methods. Our proposed approach overcomes this limitation attaining higher accuracy.

III. Proposed Methodology

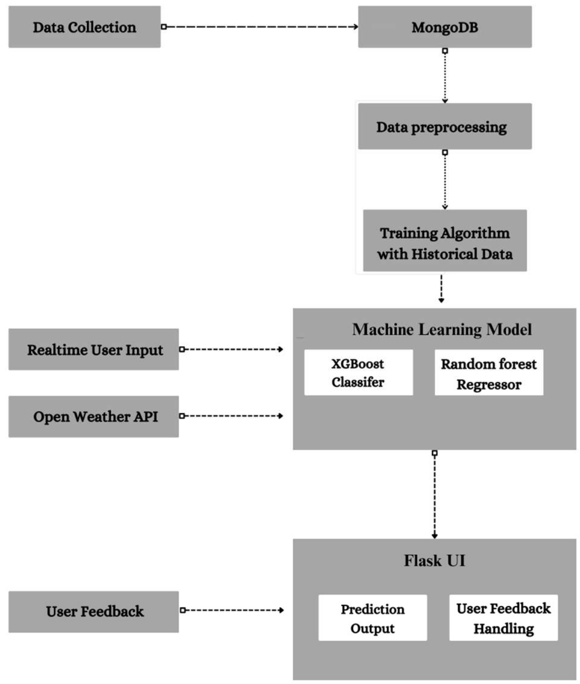

Fig. 1. Architecture Diagram of Data Driven Forest Fire Risk Prediction

Our research proposes a methodology for Data driven forest fire prediction System that uses XGBoost classifier and Random Forest regressor which produces enormous information in the prediction of the answer. This section talks about the procedures and algorithms that are used for the system. Fig. 1 depicts the workflow of the proposed methodology. The XGBoost Classifier is employed for the classification task, specifically to assess whether a forest is at risk of a fire or is deemed safe. The Random Forest Regressor is utilized for regression, specifically predicting fuel moisture indices, a critical factor in assessing fire risk. By integrating these models, your system can provide a nuanced and accurate understanding of forest fire risks, enabling proactive decision-making and resource allocation for effective forest management.

A. Data Collection:

In the development of the Forest Fire Risk Assessment System, the data collection phase is crucial for acquiring diverse and comprehensive information essential for model training and validation. The following outlines the type of inputs to our model.

- Historic Data - Historical data related to forest fires, meteorological conditions, and relevant features will be extracted from the MongoDB database. We utilized a dataset of “Algerian forest fires” sourced from UCI, specifically focusing on Forest Fires in two Unique Algerian regions, which are the Sidi Bel-Abbes region and the Bejaia region. Our dataset encapsulates a comprehensive timeline of data Spanning from June 2012 to September 2012.

- Real-time Meteorological Data - Integration with the Open Weather API to collect real-time weather metrics which includes relative humidity, temperature, rainfall and other environmental factors. This real-time data enhances the system's adaptability to current conditions.
- User-Provided Data - The system allows users to input real-time environmental data directly through the Flask web interface. This user-provided data contributes to the model's adaptability and enables personalized risk assessments for specific locations.

B. *Mongodb For Handling:*

MongoDB is a source for retrieving historical data during the model training phase. The system leverages the stored information to train the machine learning models effectively. MongoDB-stored data undergoes preprocessing steps to ensure its suitability for model training. The database also supports data quality checks, helping identify and handle anomalies or outliers within the stored information. MongoDB's scalability features make it well-suited for handling large datasets and evolving data requirements.

C. *XGBoost classifier for classification:*

The eXtreme Gradient Boosting, also known as XGBoost is a significant and flexible machine learning algorithm which is one of an efficient gradient boosting algorithm. It is an ensemble learning algorithm that builds a series of decision trees to make predictions. XGBoost is renowned for its efficiency, speed, and ability to handle complex relationships within data. In our System, it is employed for the classification task. It is designed to predict whether a forest is in danger or safe based on input features such as meteorological conditions and derived indices. The model learns from historical data to identify patterns that correlate with different classes (danger or safe). By leveraging the strengths of boosting, XGBoost creates a robust ensemble of decision trees, each correcting the errors of the previous ones, leading to a highly accurate classification model. it is trained using the selected and standardized features.

D. *RandomForest regressor for regression:*

Random Forest is an ensemble learning algorithm that constructs a multitude of decision trees during training and outputs the mean prediction for regression tasks. Each tree in the forest is trained on a different subset of the data, and the randomness introduced during the process enhances the model's robustness and generalization. In our System, it is employed for the regression task. Its role is to predict the Fuel Moisture Code (FWI) index, a critical factor in assessing the risk of forest fires. By considering meteorological features and historical patterns, the model captures the intricate relationships influencing the FWI index. The ensemble of decision trees in the Random Forest allows for a comprehensive understanding of the complex dependencies in the data, contributing to accurate predictions of FWI. The regression task is specifically employed to handle FWI parameters.

The Fire Weather Index (FWI) is a comprehensive system used for Forest fire risk assessment. The fire weather index system was developed to provide a quantitative measure of fire behavior in a specific forest or wood fuel type. It consists of several indices, those are.

- Fine Fuel Moisture Code (FFMC): It describes Fine fuel moisture content. The calculation is done based on temperature, relative humidity, wind speed, and precipitation.
- Duff Moisture Code (DMC): It explains the content of moisture in a decomposed organic material beneath the soil litter layer. It is influenced by temperature, rainfall, and time since the last rain.
- Drought Code (DC): It describes the content of moisture in the deeper soil layers which has organic materials. It considers long-term drying effects and is influenced by temperature, precipitation, and DMC.
- Initial Spread Index (ISI): Estimates the fire spread rate by depending on the Fine Fuel Moisture Code and Wind speed.
- Buildup Index (BUI): It describes the total fuel amount that will be available for combustion. It is influenced by the Duff Moisture Code and Drought Code indices.
- Fire Weather Index (FWI) Calculation: It is calculated by combining the ISI and BUI indices:

$$FWI = \frac{ISI + BUI}{2}$$

The FWI provides valuable information for assessing the current fire danger and implementing appropriate fire management strategies. The higher the FWI, higher the risk and spread of fire.

E. *Open weather API for Real time integration:*

The Open Weather API is a service that provides weather data and forecasts, allowing developers to access forecasts, historical and current weather condition data for various locations worldwide. It can provide a wide range of weather parameters like Relative humidity (Rh), temperature, Rainfall, and more. In our system, Open weather API is queried to obtain up-to-date weather information for the specific geographic region where the forest fire risk is being assessed. Historical weather data retrieved from the Open Weather API can contribute to long-term planning and risk assessment.

F. *User interface:*

The user interface (Fig. 2.) of the Forest Fire Risk Assessment System is designed to provide a user-friendly and intuitive experience for interacting with the application. Flask framework integrates with the classification and regression models the predictions are dynamically presented to users based on the submitted meteorological data and will be displayed on the prediction dashboard. Flask is also can be used to create an API endpoint that communicates with the

Open Weather API to fetch real-time meteorological data. Flask handles the submission and processing of user feedback through dedicated forms. It captures user comments, suggestions, or issues, enabling an interactive feedback loop.

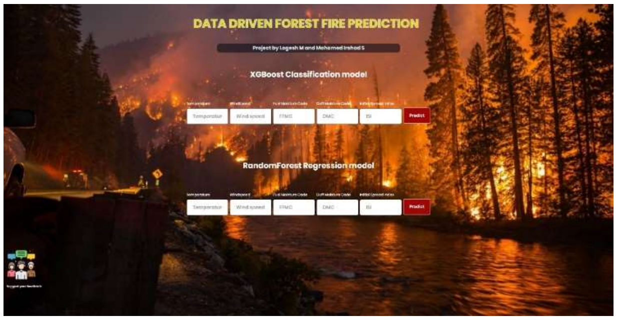

Fig. 2. User Interface

IV. Experimental Results

The experiment was setup using the proposed methodology and certain results were obtained. while to attain higher accuracy, analysis was conducted to determine the best classification and regression model for our system and its results will be listed below. Also, the proposed system was compared with existing forest fire prediction systems to analyze the accuracy rate of the predicted results.

A. Dataset Analysis:

The Algerian Forest dataset contains information from two regions, such as Bejaia and Sidi Bel-Abbes, it adds geographical diversity to the dataset. This diversity can be beneficial for training a model that aims to predict forest fire risk, as it considers variations in environmental conditions and characteristics between different regions.

TABLE I. Results on Datasets

Dataset	Accuracy Rate
Bejaia Region	85%
Sidi Bel-Abbes Region	80%

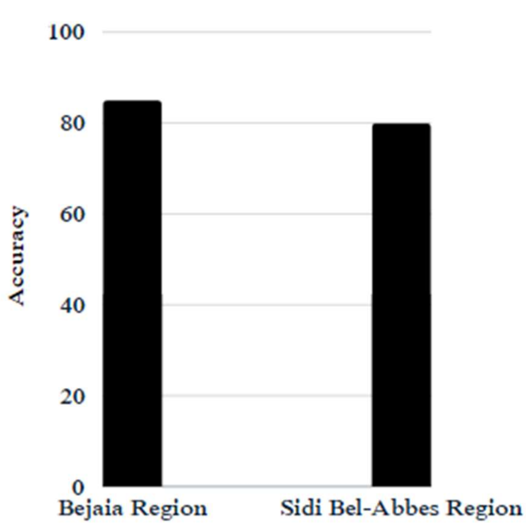

Fig. 3. Graph Illustration of Dataset Accuracy Rate

Fig. 3. illustrates the graphical representation of the dataset accuracy rate that has been tested by the proposed system. This shows that the accuracy rate of the predicted results with respect to the test images in the bejaia dataset is around 85% in average while Sidi Bel-Abbes is around 80%. This shows the ability of the system to predict the context of the risk accurately. Each dataset's Records are stored with classes. Within the trained dataset lies the solution to the pertinent input. This historic Algerian forest fire dataset is now fed into the system that was proposed. The anticipated response was nearly identical to the actual response. This shows the efficiency of the proposed system. The model will analyze the user provided parameters in all perspectives and produces the results as Alert and Alarm.

B. Comparison with Existing Systems:

Numerous forest fire prediction systems with various machine learning and deep learning models are currently in use. Every system has its own features, way and means of predicting risk of the forest fire. However, there is a progressive variation in the correctness of the information supplied by the system. In this sense, the reliability of the information offered makes the system we propose stand out remarkably well.

TABLE II. Comparison between Proposed and Existing Sytems

Models	Accuracy Rate
Parallel SVM	94%
RBF	75.85%
MPNN	81%
CCN	75%
Proposed Model	97.6%

The accuracy rates of existing and proposed system were compared. Table II shows the efficiency of the Data-driven Forest fire Prediction system. The accuracy rate of the suggested model is 97.6%, whereas the accuracy rates of the current models are 94%, 75.8%, 81%and 75%, respectively. This indicates that the suggested model performs better when predicting with classification and regression process for risk assessment. The system is able to predict the risk accurately considering every parameter with most important features for each region of the dataset utilizing XGBoost and Random Forest algorithms.

V. CONCLUSION

The Forest Fire Risk Prediction System is the optimal solution at the intersection of data science and environmental protection. By integrating machine learning models, including XGBoost for classification and Random Forest Regressor for regression, the system achieves a holistic understanding of forest fire risks and fuel moisture indices. Its user-friendly interfaces, developed with Flask, empower users to not only access risk assessments but also contribute real-time environmental data, fostering a dynamic and adaptive ecosystem. The iterative refinement process, driven by user feedback, underscores the commitment to continuous improvement and adaptability. Leveraging historical data from MongoDB and real-time meteorological insights from the open Weather API, the system ensures a comprehensive approach to risk assessment. The Forest Fire Risk Assessment System is more than a predictive tool; it's a proactive measure for informed decision-making in forest management. The inclusive features, such as speech-to-text conversion, broaden its accessibility, making it a valuable resource for diverse user groups. As we conclude, this project represents a significant stride toward leveraging technology for environmental sustainability. The fusion of data-driven insights, real-time inputs, and user engagement positions the system as a pivotal tool in mitigating the impact of forest fires. Looking ahead, the potential expansion into live streaming and video data integration opens avenues for further advancements and wider applicability in the realm of environmental monitoring and protection.

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