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ML Model to Tackle Forest Fire Problem Using Forest Flare in Uttarakhand

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Abstract
This project aims to detect forest fires early in Uttarakhand using machine learning and real-time weather data. Environmental parameters like temperature, humidity, pressure, and soil moisture are collected and analyzed using five algorithms: CatBoost, Random Forest, LightGBM, XGBoost, and Decision Tree. CatBoost achieved the highest accuracy at 96.23%. The system enables reliable fire risk prediction, supporting early warnings and proactive response. It offers a practical solution to assist forest departments in preventing and managing wildfire incidents effectively.

Keywords: Forest Fire, Early Detection, ML model, Fire, Alert, Temperature, Humidity, Pressure, Soil Moisture, MQ-5, FFMC, DMC, DC, ISI, BUI, FWI, CatBoost, Random Forest, Decision Tree, LightGBM, Uttarakhand

1. INTRODUCTION

A forest is a natural area characterized by a dense concentration of trees. Forests are among the most precious natural resources and are vital to human life and the environment. People who live in hilly areas are socially and ecologically linked to woods, which are essential to the prosperity and economic development of the area. Uttarakhand is known for its unique biodiversity. Different forest types can be found throughout the state, due to the topographical and climatic diversity of the various regions. [1] Because of the state's biodiversity, protected areas make up 13.68% of its total land area. Four conservation reserves, six National Parks, and wildlife sanctuaries are part of the state's biodiversity.
An uncontrolled fire that quickly spreads throughout vegetation in forested areas is referred to as a forest fire, wildfire, or bushfire. Forest fires, a major environmental concern, can arise from either natural events or human activities. They pose significant threats to human life, disrupt ecosystems, and cause substantial financial losses.
Uttarakhand's unique forest cover—dominated mainly by oak and deodar trees, which account for around 45% of the forested area—combined with its climatic patterns, makes the region especially susceptible to forest fires. The peak fire season in Uttarakhand typically falls between March and June, a period marked by dry weather and high temperatures, creating ideal conditions for the ignition and spread of fires.
Uttarakhand, a state in the northern Himalayas, is especially susceptible to forest fires because of its high forest cover and distinct climate. The main environmental, economic, and social problem in the Uttarakhand region is forest fires. [2] The major species in the forest of Uttarakhand are pine, oak and deodar that cover 45% of the forest. Most forest fires occur in the period of (March-June) when the forests are dry.

Figure 1Political Division of Uttarakhand

[2]The 2016 forest fire, which peaked in intensity in late April and early May, was one of the most destructive wildfires in Uttarakhand's history. It caused significant damage to the local population, business, and nature, raising severe concerns about the region's preparedness to face similar calamities. During that time, about 1,600 fire occurrences were reported. Over 4,500 hectares of forest area were destroyed in 13 districts of Uttarakhand. The districts most severely affected were Nainital, Almora, Pithoragarh, Pauri, Chamoli, and Rudraprayag.

1.1 Region-Wise Distribution of Forest Land

Uttarakhand state has a total of thirteen districts. The Forest Department of Uttarakhand divided the forests into different regions based on their geographical behavior. These regions are Garhwal region, Kumaon regions and Wildlife regions.

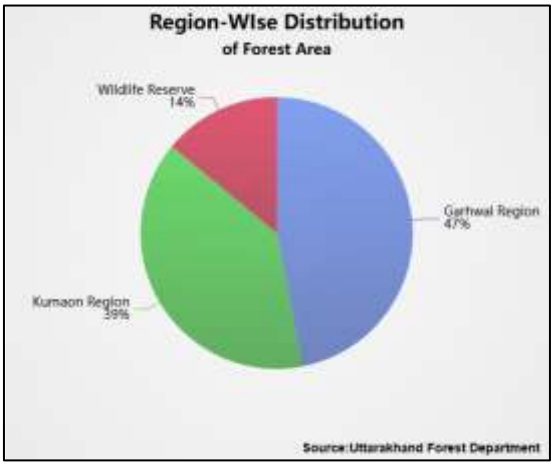

Figure 2:Region-Wise Distribution

1.Garhwal Region

Garhwal region covers the western part of the Uttarakhand state.[3] It covers 47% of the forest area of Uttarakhand state. The Forest Region of Garhwal is covered by seven districts that are Chamoli, Dehradun, Haridwar, Pauri, Rudraprayag, Tehri and Uttarkashi

2.Kumaon Region

Kumaon Region covers the eastern part of the Uttarakhand state. [3] It covers 39% of the forest area of

Uttarakhand state. The Forest Region of Kumaon is covered by six districts that are Almora, Bageshwar, Champawat, Nainital, Pithoragarh, Udham Singh Nagar.

3.Wildlife Region

These regions intersect with the Garhwal and Kumaon areas, yet they are managed independently for conservation purposes.[3] It covers 14% of the forest area of Uttarakhand state. The Forest Region of Wildlife Region is covered by National parks, wildlife sanctuaries and tiger reserves that are Rajaji Tiger Reserve.

Garhwal Region	• Chamoli District • Dehradun District • Haridwar District • Pauri District • Rudraprayag District • Tehri District • Uttarkashi District
Kumaon Region	• Almora District • Bageshwar District • Champawat District • Nainital District • Pithoragarh • Udham Singh Nagar
Wildlife	• Wildlife Circle ❖ Rajaji Tiger Reserve Circle ❖ Corbett Tiger Reserve Circle ❖ Kedarnath Wildlife Sanctuary Circle ❖ Binsar Wildlife Sanctuary Circle • National Parks and Sanctuaries ❖ Valley of Flowers National Park ❖ Nanda Devi National Park ❖ Binsar Wildlife Sanctuary

Table 1:Region Division List

1.2 Causes of Forest Fire in Uttarakhand

In Uttarakhand, a mixture of natural and man-made factors triggers forest fires. The state is highly prone to these incidents due to its unique topography, climate, and dense woods, especially during the dry season. For a long-time dry spells, particularly during the summer, reduce the moisture content of the soil and vegetation in Uttarakhand. This makes the ideal atmosphere for flames to start and spread swiftly. The geographical region's high-velocity winds often act as a catalyst, turning small fires into larger, uncontrollable fires by transporting ashes across great distances. While they are rare, forest fires can be started by lightning during pre-monsoon thunderstorms, especially in places with a lot of vegetation. The number and extent of forest fires in Uttarakhand have increased due to rising global temperatures. Forests are far more exposed to fire outbreaks now that the winter's rainfall has decreased, and summer dry spells have begun earlier.

In forested areas, fires often get started by careless activities like trekking or picnics, leaving campfires left alone, and not properly disposing of ignited cigarettes. To provide an area for cultivation, farmers often burn crop waste, dried leaves, and grass. Large-scale fires often occur by uncontrolled burning those spreads to surrounding forests. Sometimes locals purposefully create fires to promote the development of grass for livestock consumption. Uttarakhand has a long tradition of gathering forest products, such as pine tree resin. This may accidentally start fires, particularly if the surroundings are not properly maintained.

1.3 Effects

In Uttarakhand, forest fires have an immense effect on society, the economy, and the environment. The loss of biodiversity is one of the most important effects since fires destroy natural habitats, which causes animals to be moved and eventually die. They also upset the natural balance of the environment by seriously damaging plants. By increasing carbon emissions, the smoke and toxic substances released during fires contribute to air pollution and worsen climate change. Due to the destruction of forest resources, decreased tourism, and the cost of firefighting and rebuilding, forest fires cause significant financial losses. Additionally, they influence nearby populations by affecting livelihoods that depend on forest resources and generating health problems because of extended exposure to pollutants and smoke. Furthermore, fires reduce the topsoil of nutrients, which results in erosion and lower agricultural output in the surrounding areas. The fertility of the soil is negatively impacted by this.

The overall consequences of Uttarakhand's forest fires highlight the pressing need for efficient management techniques to reduce their negative effects on the state's economy, environment, and public health.

2. LITERATURE SURVEY

There have been minimal studies on fire detection, compared to generic classification and detection systems. Wireless technologies for detection have been proposed for forest fires.

Sensor networks [1]. This is a classic solution to the issue. While the results are true, scaling up will be challenging.

Using YOLOv3, a small-scale CNN achieves an 83% detection rate in tests [2]. The algorithm is sensitive to big forest tracts and performs poorly in less likely fire-prone locations.

A much faster R-CNN model has been suggested to identify forest fires [3]. To reduce uncertainties in data used to train, non-real smoke pictures were created by incorporating actual or simulated smoke onto a forest background. However, this detection method is prone to simulating forest smoke, requiring additional updates for real-time discovering fires performance.

Wildfire's combustion detection system is a quick, sensible in price, and dependable way to monitor fire-prone locations [4]. The suggested strategy utilizes image processing algorithms to extract features and computer-aided intelligence algorithms for categorization. The preparation process involves sub samples picture sequences, detecting flow zones, and extracting relevant smoking zones. The potential locations are analyzed using a smoke color analysis method, a sharp point detector, and detection algorithms for expanding and rising areas. Neural classifiers are used to assess smoking regions across various circumstances. This strategy proved effective even under challenging settings.

Real-time smog detection may be achieved by accumulation foreground photos and analyzing visual flow

[5]. This approach identifies the passage of smoke and flames based on color disruptions. Their technology effectively reduces noise in subsequent frames. Its constraints were confined to light-sensitive items. For example, lights may be switched on and off. However, their approach was able to discern between various fire-like things.

An The Internet of Things (IoT) structure driven by cloud and fog-based computing was released in this study [6] for quick safety precautions, loss reduction, and wildfire detection. We used the X-bee sharing module to send data to various nodes using the device known as the Raspberry Pi CPU and WiSense nodes, which are made up of a range of monitoring the environment sensors. An AI neural network is used to assess a forest zone's softness based on characteristics that cause wildfires. The accuracy of the model, when evaluated on the WCPs dataset, was 95.32 percent.

A different study [7] suggested a prior fire-detecting approach that makes use of a Raspberry Pi computer and a number of sensors, including temperature, gas, and sparks sensors. To send the location of that particular area, the alarm message was combined with the GPS tracker. The model used the Global Mobile System (GSM) module to provide message warnings to the end user. Employ neural networks With an accuracy of 96.7 percent, the model was evaluated for estimate on the Kaggle forest fire dataset.

The author of this research [8] presented a network based on LoRa satellite technology that can determine whether a wildfire is present in rural areas and the risk of a fire. The system is made up of several nodes with sensors that measure the humidity, speed of the wind, temperature, and the greenhouse gas levels in the surrounding air. The Network of Things server stores and analyzes the contract data.

The authors of this research [9] suggested a method based on autonomous drones for identifying and putting out forest fires. Subnetworks of various sensors are positioned throughout the grounds, trees, and animals to identify fires and communicate data to the control room. The control center is connected to all subnetworks by gateway nodes. Alerts are used to inform people. Drones are trained in the control room for firefighters and visualization.

In order to identify fires, [10] combines a number of IoT sensors, including temp. and pollutants sensors, cloud computing tools like ThingSpeak via Bluetooth and WiFi, and unmanned aerial vehicles. To improve system accuracy, this system made use of image processing techniques. Comparing the

.Title / Objective	Algorithm Used	Features	Pros
Forest fire detection using sensor networks	Sensor-based	Temp, smoke, humidity sensors	Traditional method, practical for small areas
Forest fire detection using YOLOv3	YOLOv3 (CNN)	Image-based	83% accuracy in large forest tracts
Forest fire detection using Faster R-CNN	Faster R-CNN	Synthetic smoke images	Enhanced detection with synthetic data

Combustion detection system using image processing	Image Processing + Neural Classifiers	Smoke color, motion flow	Fast, cost-effective, accurate under different settings
Real-time smog detection using visual flow	Visual Flow + Foreground Extraction	Motion, color disruptions	Noise reduction, good fire-like object differentiation
IoT-based wildfire detection using cloud and fog computing	IoT + Neural Networks	Temp, humidity, wind, gas	95.32% accuracy, fast and efficient response
Prior fire detection using Raspberry Pi and sensors	Neural Networks + GSM + GPS	Temp, gas, spark sensors	96.7% accuracy, alerts with location info
Wildfire detection using LoRa and satellite nodes	LoRa + Sensor Nodes	Temp, humidity, wind, gas	Long-range, rural applicability
Autonomous drone-based wildfire detection and suppression	Sensor Networks + Drones	Temp, motion, aerial imagery	Automated response, good for large coverage
Fire detection using UAVs, IoT sensors, cloud processing	IoT + UAV + Image Processing	Temp, gas, images	Up to 98% accuracy, real-time processing

Table 2 Comparative Study of All Model

proposed approach to previous models, test and simulation findings show that it increased the rate of fire detection by up to 98%.

The authors of this study [11] put forth a straightforward algorithm that relies on humidity and the weather. They created two basic functions using regression analysis, using time as an independent variable and climate and moisture as dependent factors. The basic functions were used to illustrate how the dependent variables behaved during a fire event. To ascertain whether a fire has broken out, the sensor nodes' data may thereafter be compared to these base functions

3. PROPOSED MODEL

To address the challenges of early forest fire detection and prediction in Uttarakhand, the proposed model integrates IoT-based environmental data collection with machine learning algorithms. Real-time data such as temperature, humidity, air pressure, smoke density, and soil moisture are gathered using low-power sensors. These inputs are processed to compute fire indices and predict fire occurrence and spread using Machine Learning algorithms like XGBoost, Random Forest, Decision Tree, Logistic Regression, LightGBM. The model aims to deliver high accuracy, quick response time, and adaptability to regional conditions. This system will support proactive firefighting strategies and help minimize ecological and economic damage caused by forest fires.

III.I Develop an Efficient and Reliable Fire Prediction Model

Forest fires have increasingly become a recurring and destructive phenomenon in various parts of India, especially in ecologically sensitive regions like Uttarakhand. These fires pose a severe threat to biodiversity, human settlements, and natural resources. One of the primary reasons for the extensive damage caused by forest fires is the delay in detection and the lack of predictive systems that can anticipate fire outbreaks before they occur. To mitigate this issue, the proposed project aims to develop a highly efficient and reliable fire prediction model that can accurately assess the likelihood of forest fires using real-time data and machine learning techniques.

The core objective of this model is to move from reactive to proactive fire management by predicting potential fire incidents before they start. The model will leverage environmental variables such as temperature, humidity, air pressure, smoke density, and soil moisture—collected through a network of IoT-based sensors deployed across vulnerable forest regions. This real-time data will be analysed in combination with historical fire incident records to train machine learning models like XGBoost, Random Forest, Decision Tree, Logistic Regression, LightGBM, which are known for their high accuracy and robustness in handling nonlinear and high-dimensional data.

Additionally, geographical data such as terrain type, vegetation cover, and elevation will be integrated into the model to enhance spatial awareness and improve predictive performance. The model will use derived indices such as the Fire Weather Index (FWI), Fine Fuel Moisture Code (FFMC), and Initial Spread Index (ISI) to quantify fire risk more effectively. These fire indices are essential for interpreting the relationship between environmental conditions and the behaviour of fires, thus making predictions more actionable for on-ground authorities.

One of the key features of this model is its adaptability and continuous learning capability. As more data is collected over time, the system will automatically retrain itself to improve accuracy and responsiveness. This makes the prediction system not only dynamic but also scalable for wider applications in different regions with varying climate and forest density.

Early warnings generated by the model will be transmitted to forest officials, disaster management authorities, and local communities through alert systems. This will allow for timely deployment of resources such as firefighting teams, aerial water bombers, and evacuation protocols, thus reducing the potential for large-scale disasters. Moreover, the model's forecasts can support strategic planning in resource allocation, helping authorities to focus efforts on high-risk zones during vulnerable seasons.

In a region like Uttarakhand, where forest fires are common during the dry months, such a model can be a game-changer. It promises to bridge the gap between environmental monitoring and actionable intelligence. Ultimately, the goal is to minimize ecological destruction, safeguard human lives and property, and promote a culture of data-driven forest fire prevention and management.

III.II Utilize Iot Devices for Real-Time Environmental Data Collection

In the effort to predict and prevent forest fires, access to real-time, accurate, and location-specific environmental data is of paramount importance. Traditional fire monitoring methods—such as satellite imaging, manual patrolling, and post-event analysis—are often delayed, lack precision, and are reactive rather than proactive. To overcome these limitations, this project proposes the use of Internet of Things (IoT) devices as a robust solution for real-time data collection in vulnerable forest areas, especially in regions like Uttarakhand where forest fires are a seasonal hazard.

IoT-based sensor networks will be strategically deployed throughout fire-prone zones to continuously monitor critical environmental parameters that contribute to the ignition and spread of forest fires. These parameters include air temperature, relative humidity, soil moisture, wind speed, atmospheric pressure, and smoke density. Each IoT node will be equipped with a variety of sensors capable of capturing these metrics and transmitting them wirelessly to a centralized data processing unit through technologies like LoRa, Wi-Fi, or GSM, depending on the terrain and connectivity requirements.

One of the key advantages of utilizing IoT devices is their ability to operate autonomously and relay data at frequent intervals. Unlike satellite data, which may be updated only a few times a day and can be hindered by cloud cover, IoT sensors offer continuous ground-level data acquisition, enabling micro-level environmental monitoring. Moreover, these devices can be powered through solar panels or battery systems, allowing them to function effectively in remote forest areas without the need for constant human intervention.

The collected data will feed directly into a cloud-based or edge computing platform where machine learning models are trained to analyse patterns and detect early signs of potential fire hazards. This allows for immediate alerts to be generated if environmental conditions reach a threshold that indicates high fire risk. Alerts can be sent to forest officials, disaster response teams, and local authorities through SMS, emails, or app notifications, ensuring timely and coordinated responses.

Furthermore, the integration of real-time IoT data greatly improves the accuracy of fire prediction models by minimizing the lag between environmental changes and their detection. This real-time capability is crucial for identifying rapid weather shifts or detecting the first signs of smoke before it escalates into a full-blown wildfire. Over time, the accumulated sensor data will also help refine prediction models by contributing to historical datasets used for training machine learning algorithms.

By adopting IoT technology for fire risk monitoring, the proposed system offers a transformative approach to forest management. It enables a shift from traditional, reactive firefighting methods to a modern, data-driven strategy aimed at early detection and prevention. Ultimately, this will lead to better protection of natural resources, reduced ecological and economic losses, and safer communities living near forest regions.

III.III Analyze Critical Environmental Parameters Affecting Forest Fires

Forest fires are complex natural disasters influenced by a combination of environmental, meteorological, and geographical factors. For any fire prediction model to be truly effective, it must be rooted in a thorough understanding of the key parameters that contribute to fire ignition and spread. This project aims to identify and analyse these critical environmental parameters, using real-time data from sensor networks to assess fire risks with high accuracy and reliability.

The most significant factor contributing to forest fires is temperature. Elevated temperatures reduce the moisture content in vegetation and soil, creating conditions that are more susceptible to combustion. Extended periods of high temperature, particularly during the dry seasons, are strong indicators of increased fire risk. Alongside temperature, relative humidity plays a vital role. When the air has low humidity, it draws moisture from surrounding vegetation, making leaves, twigs, and underbrush highly flammable. A drop in humidity is often an early warning sign of worsening fire conditions.

Another crucial parameter is wind speed. Winds not only supply oxygen that fuels combustion but also help spread fire across large areas in a short time. Rapid gusts of wind can carry embers over long distances, igniting new fires far from the original source. Therefore, real-time wind data is essential for both predicting and tracking the spread of wildfires.

Fuel moisture content is another indicator of fire vulnerability. It refers to the amount of water present in vegetation, such as leaves, grass, and shrubs. When this moisture content is low, fuel becomes dry and ignitable. Monitoring this parameter helps determine how easily a fire might start and how intensely it could burn.

Smoke density is also a critical parameter. Early-stage fires embers release smoke before visible flames are observed. Sensors that detect elevated levels of particulate matter (PM2.5, PM10) and gases like carbon monoxide (CO) can serve as early indicators of combustion activity, especially in densely vegetated or remote regions where visual confirmation is delayed.

By continuously analysing these environmental parameters, the proposed model will not only predict the likelihood of a fire but also detect its early onset. Furthermore, the combination of these parameters allows the model to identify spatial and temporal patterns—such as recurring fire-prone periods or high-risk areas—which is crucial for long-term fire management planning and policymaking.

This data-driven approach enables proactive strategies, allowing forest departments to allocate resources effectively, plan controlled burns in advance, and take precautionary steps before a fire becomes unmanageable. By integrating these environmental insights with machine learning algorithms, the project seeks to establish a comprehensive and reliable forest fire prediction and prevention system, especially critical for regions like Uttarakhand that are prone to seasonal wildfires.

III.IV Implement Machine Learning Algorithms For Accurate Predictions

Machine Learning (ML) is at the heart of modern forest fire prediction systems. By leveraging historical fire data, real-time sensor readings, and weather patterns, ML algorithms can significantly enhance the accuracy and reliability of predictions. In this project, machine learning is not just a tool but a critical component in interpreting complex environmental data and translating it into actionable insights. This intelligent system enables early warnings and facilitates strategic resource deployment to mitigate the risks and damages caused by forest fires.

Several powerful machine learning techniques will be utilized, including Random Forest, XGBoost, Decision Tree, CatBoost, and LightGBM. These algorithms are well-suited for structured datasets with a mix of continuous and categorical variables and are capable of handling noisy and non-linear data, which is often the case with environmental conditions. Each algorithm contributes uniquely Random Forest and Decision Tree provide robustness and interpretability, XGBoost and LightGBM deliver high performance in large-scale predictive tasks, while CatBoost handles categorical variables efficiently with minimal preprocessing.

These algorithms will be trained using a combination of historical fire data and continuously updated sensor inputs, such as temperature, humidity, air pressure, smoke density, and wind speed. By identifying patterns and correlations within this data, the model will be able to predict not only the likelihood of a forest fire but also the potential severity, direction of spread, and affected zones. Unlike static rule-based systems, the machine learning model improves over time, refining its predictions as more data becomes available through real-time monitoring.

One of the standout features of ML-based systems is their ability to handle non-linear relationships—something traditional statistical models often struggle with. For example, a sudden drop in humidity coupled with a spike in temperature and specific wind conditions might not independently raise concern, but collectively they could indicate a high fire risk. Machine learning models excel in identifying such subtle and complex interdependencies.

The system will also integrate cross-validation techniques to evaluate model accuracy and prevent overfitting, ensuring that predictions remain reliable across different seasonal and geographical conditions. Additionally, feature importance analysis will help highlight which parameters are most critical in predicting fires, allowing for better sensor placement and resource prioritization.

Overall, this approach allows for a predictive, preventive, and adaptive fire management system—a major leap forward from traditional reactive methods. Authorities will be equipped not just with alerts but with detailed insights into risk levels and potential fire behavior, enabling quicker decision-making and more efficient deployment of firefighting teams and equipment.

In a wildfire-prone region like Uttarakhand, this can be a game-changing advancement. The combination of real-time IoT data and intelligent ML algorithms ensures a proactive approach to forest fire management, significantly reducing environmental damage, property loss, and human risk.

III.V Develop a Robust Alert System to Inform Authorities and Stakeholders

An essential component of an effective forest fire management system is a robust, real-time alert mechanism that ensures rapid communication between the prediction model and key decision-makers. While accurate predictions are the foundation of prevention, timely alerts and swift responses can be the difference between a contained fire and a devastating wildfire. This project aims to implement a fully automated, intelligent alert system that will immediately notify relevant authorities and stakeholders when a high risk of fire is detected.

The alert system will be tightly integrated with the machine learning prediction model and IoT sensor network. As soon as the system registers environmental conditions indicative of a potential fire outbreak—such as high temperature, low humidity, increased smoke density, or rapid changes in wind speed—it will trigger an alert. These alerts will be sent via SMS, email, and dashboard notifications to forest officials, disaster response teams, firefighting units, and other concerned agencies.

To ensure real-time responsiveness, the system will be designed with minimal latency, using cloud-based messaging services and secure communication protocols. The interface will also include a centralized dashboard, where live fire risk updates, sensor data, and prediction confidence levels can be monitored continuously. This dashboard will provide geospatial visualization, allowing responders to identify and localize potential fire zones with high precision.

A key advantage of this system is its scalability and multi-tiered communication structure. Alerts can be customized based on severity—low, medium, high or extreme risk—ensuring that authorities are not overwhelmed with minor notifications while still being informed of critical developments. For high-risk scenarios, the system can automatically escalate alerts to emergency response units and even pre-deploy firefighting resources if integrated with resource management tools.

Moreover, the system will consider public safety by incorporating a community alert mechanism. Local populations living in or near forested regions—especially in fire-prone areas of Uttarakhand—can be alerted via regional SMS broadcasts or mobile app notifications. These alerts will include precautionary instructions, evacuation guidelines, and contact numbers for emergency services. This community-level engagement ensures that the people most affected by forest fires are not left out of the information loop.

Additionally, all alert activity will be logged and time-stamped, providing valuable data for future analysis and system improvement. Authorities can assess how quickly alerts were acted upon and how effective responses were, thereby refining operational protocols and disaster readiness.

In conclusion, this alert system acts as the final, crucial link between advanced prediction technologies and real-world action. By ensuring timely, accurate, and localized communication, it empowers stakeholders to take swift preventive measures, significantly reducing the damage caused by wildfires and protecting both ecosystems and human lives.

III.VI Provide Data-Driven Insights for Proactive Firefighting and Preventive Measures

In addition to accurate fire prediction and timely alerts, one of the most transformative aspects of this project lies in its ability to provide data-driven insights that enable long-term, strategic decision-making. Forest fire management is not only about responding to immediate threats but also about proactively reducing the likelihood of fires through planning, resource optimization, and ecosystem management. By systematically collecting and analysing large volumes of environmental and historical fire data, this model will empower authorities with the intelligence needed for informed, proactive intervention.

The integration of IoT-based real-time data with historical records of wildfire occurrences allows the system to identify high-risk areas—zones that have historically witnessed frequent or severe fire events due to environmental or human-related factors. These patterns can then be visualized using geospatial mapping tools, enabling zone-specific preventive planning. For example, areas prone to recurring fires during summer seasons can be prioritized for afforestation with fire-resistant species, while others may benefit from the creation of firebreaks or implementation of controlled burns to manage dry biomass.

Additionally, the insights derived from this data will help in forecasting seasonal fire trends, allowing forest departments to allocate manpower, firefighting tools, and emergency services more effectively. Rather than reacting to fires as they happen, resources can be pre-positioned in high-alert zones before peak fire seasons, dramatically improving response times and reducing losses. This is especially crucial in regions like Uttarakhand, where steep terrain and remote forested areas can delay manual detection and accessibility.

The system will also support long-term forest management initiatives. By studying variables such as changing wind patterns, shifting vegetation zones, and the impact of climate change on humidity and temperature, policymakers can adopt adaptive management practices. Data-driven evaluations can help refine existing policies or introduce new regulations aimed at fire prevention, such as restricting human activity in certain zones during peak risk periods or incentivizing community-based forest protection initiatives.

Furthermore, the compiled and processed data can serve as a valuable research asset for environmental scientists, conservationists, and academic institutions. It can contribute to studies on climate impact, forest health, wildlife displacement due to fires, and the effectiveness of various mitigation strategies. This will

lead to a sustainable knowledge loop, where data informs policy, which in turn improves data collection strategies, further enhancing model accuracy and decision-making.
Ultimately, these insights will transform Uttarakhand's Forest fire management from a reactive system to a resilient, proactive, and adaptive framework. Not only will it protect natural ecosystems and biodiversity, but it will also safeguard human lives and livelihoods, ensuring that future generations inherit a safer and healthier forest environment.

4. METHODOLOGY

Weather and environmental indices are essential tools that help interpret sensor data to assess atmospheric and ground conditions for agriculture, forestry, disaster management, and health. The indices you mentioned—related to temperature, humidity, pressure, gases, soil moisture, and fire danger—serve distinct but interconnected purposes.
Temperature, humidity, and pressure are fundamental weather parameters. Temperature influences plant growth, evaporation, and fire risk. Humidity determines moisture content in the air, affecting human comfort and vegetation dryness. Atmospheric pressure indicates weather patterns—falling pressure often signals storms, while rising pressure indicates fair weather.
Soil Moisture is a critical index in agriculture and hydrology. It reflects the amount of water available for crops and vegetation. Low soil moisture increases drought and fire risks, while high levels may lead to waterlogging.
MQ-5 and MQ-7 are gas sensor-based indices. MQ-5 detects combustible gases (LPG, natural gas, methane), and MQ-7 detects carbon monoxide (CO). These sensors are vital in environmental monitoring and safety systems to detect gas leaks or combustion-related pollutants—key indicators during forest fires or industrial emissions.
Fire danger is assessed using specialized indices developed as part of the Canadian Forest Fire Weather Index (FWI) System:
FFMC (Fine Fuel Moisture Code): Reflects moisture content in fine surface fuels (leaves, twigs). A low FFMC means damp fuels, while high values indicate dry, flammable conditions.
DMC (Duff Moisture Code): Represents moisture in loosely compacted organic layers beneath the surface. It reacts more slowly to weather and is useful for predicting the ignition of deeper fuel layers.
DC (Drought Code): Measures moisture in deep, compact organic layers. It responds to long-term drying and is crucial for assessing smoldering fire risk.
ISI (Initial Spread Index): Combines FFMC and wind speed to estimate how fast a fire would initially spread. High ISI means rapid fire spread potential.
BUI (Build-Up Index): Combines DMC and DC to reflect the total fuel available for combustion. It indicates how intensely a fire could burn once started.
Together, these indices provide a comprehensive picture of fire danger and weather impact on ecosystems. Monitoring these values with sensors allows for real-time risk analysis, enabling proactive responses in wildfire management, agriculture, and environmental safety.

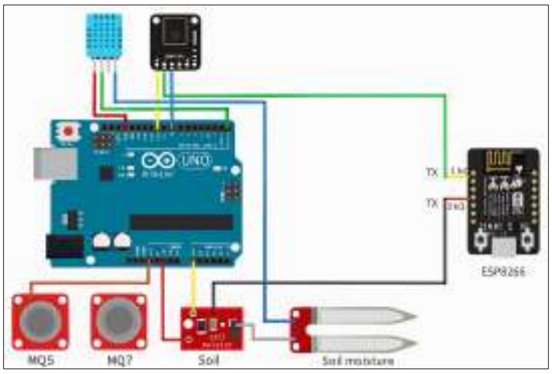

Figure 3 Circuit Diagram

In predictive analytics, building efficient machine learning systems is crucial for turning raw data into actionable insights. This project presents a comprehensive workflow to classify environmental risk levels—such as forest fire hazards—using various machine learning models. It employs powerful algorithms including CatBoost, XGBoost, LightGBM, Decision Tree, and Random Forest.

The process begins with importing essential Python libraries like Pandas, Seaborn, Scikit-learn, and gradient boosting frameworks. The dataset, containing multiple environmental features and a target column "Risk," is loaded and preprocessed. Since the target labels are categorical (e.g., Low, Medium, High, Extreme), they are encoded into numeric values using a dictionary for model compatibility.

The data is split into input features (X) and labels (y), and further divided into training and test sets using an 80-20 ratio. This ensures robust model evaluation. Each classifier is trained on the training set and evaluated on the test set using accuracy as the performance metric. Predictions are converted back to human-readable labels for interpretability.

The workflow compares multiple models to identify the best-performing one for the specific risk prediction task—crucial in sensitive areas like forest fire forecasting. Finally, all trained models are serialized using Joblib and saved as .pkl files (e.g., catboost_model.pkl, fire_risk_xgb.pkl). This model persistence step supports efficient reuse and deployment in real-world applications, including real-time inference and IoT integration, without retraining.

Overall, this pipeline offers a scalable, accurate, and interpretable solution for classifying environmental risks using advanced machine learning techniques.

Model	**Accuracy (%)**
Random Forest	94.67
Decision Tree	89.87
CatBoost	96.23
LightGBM	94.83
XGBoost	93.91

Table 2 Model Accuracy Table

Figure 3 Real-Time Monitoring Dashboard

RESULT

The state of Uttarakhand is highly vulnerable to forest fires, especially during the dry season when environmental conditions become favorable for ignition and rapid fire spread. To address this critical issue, our project focuses on the early detection of forest fires using predictive analytics. By collecting real-time weather data—such as temperature, humidity, pressure, and soil moisture—our system utilizes advanced machine learning algorithms to predict the likelihood of fire outbreaks. The models employed include Random Forest, Decision Tree, CatBoost, LightGBM, and XGBoost. Each model was trained and tested on labeled environmental data, achieving high accuracy in predicting risk levels. Among the models, CatBoost emerged as the most accurate with an impressive 96.23% accuracy, followed by LightGBM at 94.83%, Random Forest at 94.67%, XGBoost at 93.91%, and Decision Tree at 89.87%. This multi-model approach ensures robust and reliable predictions, aiding in early warnings and timely action. The integration of this system can significantly support forest departments in Uttarakhand by enabling data-driven decision-making and minimizing fire-related damages.

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