Forest Guard: An Integrated Sensor cum AI-based Fire-prone Area Mapping and Early Forest Fire Detection System

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Abstract

Ever-increasing global warming and human disruptions have resulted in unprecedented frequency, spread and intensity of destructive wildfires across continents. Thus, effective systems to tackle this are the need of the hour. "Forest Guard" is an integrated dispersed multi-variable sensor network cum AI-based system that promises pre-emptive prediction of fire-prone areas and proactive detection of wildfires. A deep learning AI model classifies the forest area on the basis of a numerical % probability of forest fire occurrence, calculated according to value intensity and degree of correlation between moving averages of parameters like Atmospheric. Temperature, Humidity and Soil Moisture gathered from sensors and other static variables. It then plots a color encoded percentage risk assessment map after extrapolating individual sensor node results to an area of 0.031km2. As this is a novel approach, the model was trained on reinforcement learning and tested on 3 simulations of 10000 data points each. It received accuracy of 98% + 2%. Forest Guard detects distinctive wildfire and bird (distress-callings) sounds through analyzing and differentiating sounds recorded every 2 minutes by running them through a short Fast-Fourier-Transformation Deep Learning model and then raises a preliminary alarm. A confirmatory fire alarm is raised after the algorithm detects simultaneous sudden deviations with respect to the calibrated baseline in continuously monitored parameters (Atmospheric. Temperature, Humidity, Smoke, Soil Temperature and Moisture). As tested in 3 different control burns, of 2500m2 each(avg.), the fire was detected within 2-3minutes (Minimum-time recorded- Preliminary-Alarm- 2:23 minutes, Confirmatory-Alarm- 3:58 minutes from ignition). All simulations/ experiments proved the hypothesis of using localized/ on-ground parameters for detection/prediction.

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Introduction

Wildfires come unplanned and unannounced and pose a great threat to the ecological system. Due to several environmental factors, the occurrence of these unwanted surprises has only increased over the years. The increased fire frequency in ordinarily fire-dependent areas has upset natural cycles and damaged native plant communities. This increase can be attributed mainly to the increase in atmospheric temperatures, change in weather patterns, prolonged drought due to increase in global warming and increase in human interventions in previously pristine ecological environments. (put vicious cycle figure). To bring the issue severity into perspective, Forest fires in the US have burnt through 4.2 million acres in 2021 alone [21]. In the year 2021, the amazon forests, regarded as the lungs of the earth, shifted from being a net carbon reducer to a net carbon producer. Wildfires release large amounts of carbon dioxide, Carbon Monoxide, and ozone precursors into the atmosphere. In addition, the financial mark it leaves on the country's economy is only increasing. US spent more than $2.9 billion in combating fires (12 times of that in 1985). Several techniques and devices have been developed, with varying degree of success, for early detection of forest fires, however it continues to poses a great challenge. **Forest Guard** has been designed as an early warning and real time forest fire detection system. The proposed system is a cost- effective and practical system that works in conjunction with the existing devices and natural cues like bird callings for real time monitoring and predicting the fire prone areas based on inputs from its sensors and pre-programed algorithms.

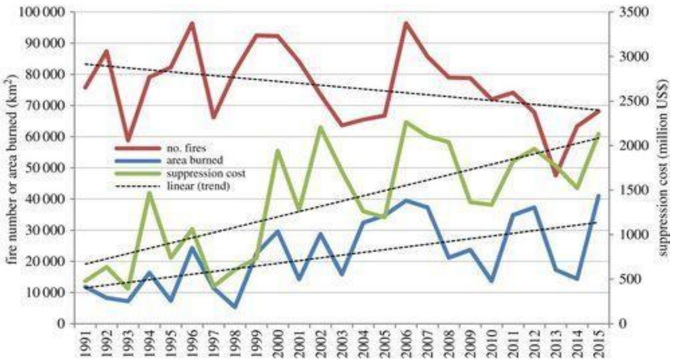


Figure 1: Wildfire Statistics from 2007-2020* I *Royal Society Publishing

Review Of Literature

Existing Methods of Forest- Fire Risk Assessment

Forest Fire risk mapping is used to predict place of occurrence of ignition events [18,19,20]. To assess fire risk, variables which increase the probability of fire occurrence are used to map fire hazard/danger. One method of creating such maps is using point-wise meteorological data-based operating systems using meteorological data such as temperature, precipitation, humidity, and wind speed to assess fire danger over large geographic regions. However, these systems suffer from several limitations including input data being limited to the point distribution of data collection stations and the need for interpolation to generate fire danger map leading to creation of blind spots. The other is by creating maps created by the use of remote sensing technologies and geographic information systems (GIS) and can be further broken into two broad categories: long-term and short-term. Long-term (seasonal) fire risk maps generally map risk using inputs which do not vary greatly over time such as vegetation/ land over type using indices such as the Normalized Difference Moisture Index (NDMI) and Normalized Difference Vegetation Index (NDVI), canopy cover/ height/ bulk density), human settlements, and topography (elevation, slope, aspect) [14]. Short-term fire risk maps (accurate to days- weeks after creation) use many of the same inputs as long-term fire risk maps but also include variables that are continuously changing such as fuel moisture content, weather conditions like min/max temperatures, humidity, precipitation, windspeed, wind direction, and vegetation conditions. But using satellites like MODIS with a temporal resolution of 2 days and a spatial resolution of > 500m created data latency and blind spots (for a forest fire to ignite, an area of 5m2 is sufficient enough).Therefore, though satellites are most accurate to map static variables, they fail in providing updated dynamic variables for creating short term maps. As made evident by the failure of humans to curb the increase in the number of forest fires, satellite data is not suitable for fire risk mapping.

Existing Systems of Early Forest- Fire Detection

Detection system can be broadly classified into 3 types which are discussed below-

2.1.1. Optical Sensors/ Digital Cameras- Video Cameras are programmed to detect a visible spectrum of smoke recognisable during day and fire blazes during night. Infrared, thermal imaging cameras detect heat flow/ signature of the fire, IR spectrometers identify spectral characteristics of smoke particles, Light Detection and Ranging

Systems (LIDAR) measure laser rays reflected back from smoke particles. But these systems have a high rate of false alarm which can mainly be attributed to climatic conditions (fog, shadows, smoke), dust produced by farmers, pollen, fog, smoke, water plumes produced by power plants, etc. (examples are shown in Fig.2). Other drawbacks include light of sight vision which creates blind spots, high costs and low range (15- 80km). There is a long delay from ignition to produce noticeable smoke that can be detected by sensor cameras.

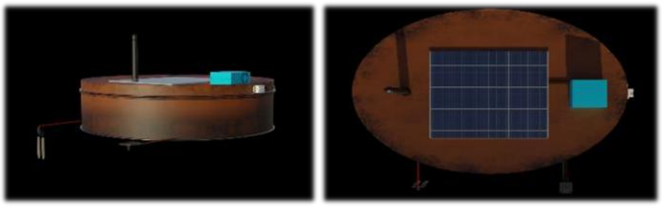
2.1.2. Satellites- Satellites make use of High Determination Radiometer (AVHRR) to detect the optical and the infrared (heat) radiation emitted by flames but the intensity may be too feeble in the early stages to be detected by a satellite. The intensity decreases as the inverse square of the distance. The position and orientation of satellite might not be optimal for detecting a forest fire at an early stage. The low temporal resolution of satellites (1-2 days for MODIS satellites) creates huge time gaps between monitoring and detection might be hindered by weather conditions like mist.

2.1.3. Wireless Sensor Network- Such systems make use of costly sensors to collect on- ground data like smoke levels and temperature and run on site analysis/ compare to threshold values to determine possible fires. It provides 24/7 monitoring and is capable of detecting surface fires at the point of ignition. But the current WSN systems have high per sensor node cost and face the problem of data relay. Systems like FireWXNet and South Korea's FFSS use MCF (minimum cost path forwarding) as a routing protocol, which required a routing table for each node to find the minimum path to the sink and hence are prone to breaking under node failures.

Parameter	Satellites	Camera	Sensor System
Effective detection	× Huge gaps b/w monitoring/ Delay	× Delayed detection	✓ Instantaneous sensing and relay
Practical/ Feasible	× Gives estimates	× Line of Sight vision	✓ Easy installation and monitoring
Maximum Range	× Intermittent	× 15-50 km range	× Low range on individual level
Cost effectiveness	× Costly	× Costly (> $30,000)	✓ Low Cost (Varies)
Accuracy	✓ Mostly accurate	× False Alarms	✓ On ground data

SYSTEM ARCHITECTURE OF FOREST GUARD

Forest Guard is an AI based wireless sensor network that promises pre-emptive prediction of fire-prone areas and proactive detection of wildfires. The system comprises of 4 multi- variable sensors actively monitoring parameters such atmospheric temperature and humidity, soil temperature, soil moisture and carbon monoxide level which transmit data every minute to a micro- processor Node MCU for on- site automated AI analysis. All of the hardware is encased in an aluminum cylindrical casing (Dimensions- Height- 7cm, Diameter- 27 cm) due to the material's high heat resistance.



The micro- processor runs 3 deep learning models on the collected data in different time frames-

- A sensor reading augmentation AI model adjusts every reading for the variable error limits of their respective sensors. (3.2)

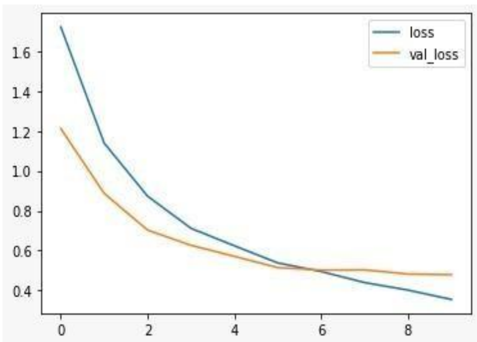
- A short fast Fourier transformation model which analyses sounds recorded by a high sensitivity micro- phone for characteristic wildfire and wildlife sounds for preliminary early detection every 2 minutes, along with a simple model which compares sensor readings with a dynamic baseline constructed by calculating moving averages of parameter values to detect deviations indicative of a forest fires for confirmatory detection in infancy. Any anomaly detected is sent to the forest guard app for alert generation.

- A DL model which classifies forest fire prone areas on the basis of a numerical percentage probability of forest fire occurrence, calculated according to value intensity and self- learned patterns in all related factors according to value intensity and modulus of degree of correlation. The risk percentage is then sent to the app for the generation of a colour encoded percentage forest-fire risk assessment map.

The whole system is based on individual sensor nodes/ modules strategically placed in a 250 * 250 m square grid on the vertices and diagonal intersection. Each module covers an area of 40000 m^2 and costs about $15. The module is power by a 12V solar panel and may be connected to a bio- energy harvesting charger in thick canopy areas. Data relay can be achieved through using remote geo- stationary satellite connectivity systems like Star-link and Range extender.

Enhancing the sensor readings through a neural network-

To maintain low cost of individual nodes, low cost sensors were installed making a trade off with reading accuracy. But in order to simultaneously maintain system accuracy and prevent false alarms, a Deep Learning AI Model was trained to augment sensor readings and adjust the data for their respective error limits. All 5 sensors were tested at 15 different points across their measuring range and were found have a variable error limit as we moved from one extreme of the range to another. Hence a linear relation could not be determined between the measured and actual readings. A self-learning model was then trained on a dataset of 5000 data points provided by IIT BHU, India which could account for the variability and augment data accordingly. The model faired with an accuracy of 98.6% and loss value of 0.0121.



COMPONENTS OF THE SYSTEM

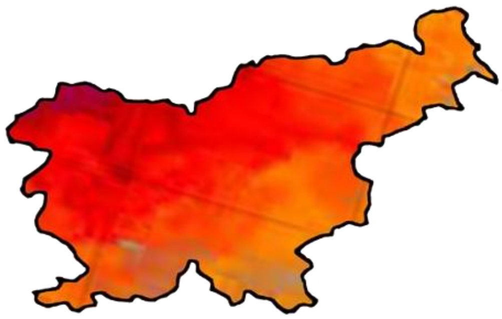
Fire- Prone Area Mapping DL Model-

Forests are a dynamic ecosystem where dry areas continuously emerge and disappear in time periods as short as 4 days. Increasing rate of forest fires are a testament to the fact that the current systems of forest fire prone area classification are a dismal failure. Though long-term classification maps are fairly accurate and helpful, the short-term classification maps, which account for dynamic variables alongside static variables are highly in-accurate due to large scale spatial and time gaps. Satellite data, currently used, has low spatial resolution due to which data of extremely localized variables like fuel moisture content, min/max temperatures, humidity, precipitation, wind speed and wind direction is extrapolated to a large area (>500m) which masks variability within the extrapolated area. Due to low temporal resolution, data is monitored once every few days and hence does not take into account the changes between the time intervals. The data taken at the isolated time intervals may be affected by point fluctuations in weather conditions at the time of collection and is not representative of the whole time period between readings which renders the map un representative and in-accurate.

Forest Guard's fire prone area mapping system makes use of on- ground data collected by its sensors on dynamic variables like atmospheric temperature and humidity, soil temperature and moisture and transmit it to the database to perform a weekly analysis and create a more representative and accurate short-term classification map basis intensity and correlation between parameters. A Bidirectional encoder representational transformer Deep learning model was trained to perform the analysis and assign corresponding risk values. The model was pre-trained on SQUAD question answering dataset for NLP tasking.

As the range or scale of the parameters is different, the deep learning model first performs pre- processing steps like standard scalar, normalization and removing outliers on the 10,080 data points collected for each parameter through the week. Through pre- processing, the data values are scaled up or down into a uniform scale without distorting the numerical equivalence between individual values measured in different units. In our case, all values were brought between a common scale of 0 to 1. This facilitates future calculations and comparisons between different parameters. Removing outliers helped us remove any stand-alone parameter spikes or single day weather events. This is not possible in the case of satellite data because of absence of data before and after the outlying values to compare them to.

The model calculates the rolling averages of the normalized values of each parameter to reduce the dataset of each sensor node to a single line/row. It then adds columns of sensor geo- location specific static variables like foliage ignition temperature, canopy cover/ height/ bulk density, and topography (elevation, slope, aspect) taken from satellites to the single data rows of each node. Each data row is then assigned a risk value on the numerical intensity of parameters and self-learned gradients. The model is looking for an area with high positive correlation between atmospheric temperature and soil temperature, atmospheric humidity and soil moisture and a high negative correlation between atmospheric temperature and humidity, soil temperature and moisture to be classified as a high-risk area. Every sensor module is assigned a risk value using the above procedure and classification. All analyses till this step is done at the module itself after which the calculated percentage is transmitted to the app. The risk percentage is then extrapolated to an area of 0.03145 km^2 around the coordinates of each sensor node and plotted on the map according to the color codes pre assigned to the risk values to generate a color encoded percentage risk assessment map.



Training the model –

As this is a novel approach and hence no ready dataset was available, we trained the model through reinforcement learning. Basis the understood knowledge on the employed parameters and identified correlations between the parameters and dry/fire- prone areas through data collection from known dry/ high risk areas, we defined parameter values for ideal conditions of 0 and 100% fire risk given below and inserted the conditions in a dataset containing all parameters curated by combining different 3 datasets. We, then, trained a simple artificial neural network on the above dataset with mean squared error loss since this task is similar to the regression task. After training the model for 50 epochs its training accuracy was 98 percent and validation accuracy was 96 percent.

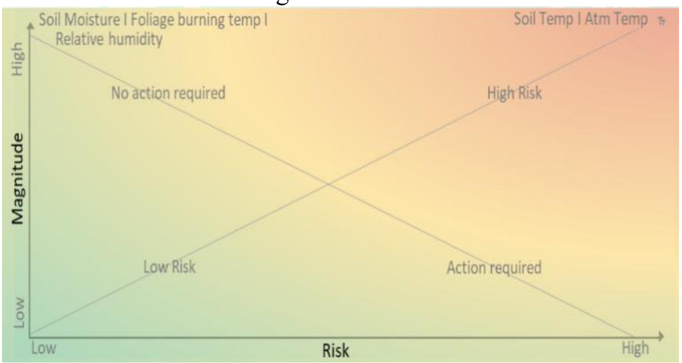
In the second iteration, we took a dataset of 100 values again and applied random values from the range given by the Fire Weather Index in the target column. Right now, these were just random values from the range with no rational basis, but the same ANN is trained again on this dataset in the next iteration. After training it for 50 epochs these random values became fixed for that deep learning model for a given set of values of the parameters.

In the third iteration, a set of 100 samples was taken again and run through the model to arrive at prediction target values. After the prediction, both the datasets are combined to make 200 samples in total, and the deep learning model is then trained on this dataset. Repeating this cycle makes the model accurate and the random values become more fixed and prediction accurate. This approach is inspired by Monte Carlo simulation and reinforcement learning.

A color encoded risk assessment map is then created as per the color code of each percentage value wherein the percentage and hence the color of each individual module is generalized to a surrounding area of 0.031 km2.

Conditions for the two extreme risk values (0 and 100) were defined and as we were dealing with highly non-linear data, a satellite dataset was used to train the model on assigning risk values on the basis of different combinations of variable and static parameters' values. Dataset was divided in the ratio of 80:20 in which 80 percent of the data was used for training purposes and 20 percent of data was used for validation purpose. Instead of using standard PCA procedure through graph visualization, we used RESNET model which is based on transfer learning for feature extraction. The dataset was given to the Resnet model after removing its last two fully connected DENSE layers which were used for classification with SOFTMAX ACTIVATION Function. We used this model with the pooling layer form obtained an array of (728,728, None) and this array was directly given to the BERT MODEL for training.

The color graph generated by the model on the right shows its self- learned patterns on the basis of which it assigns risk values.

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_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_3 (Dense)              (None, 100)               1200
_________________________________________________________________
activation_3 (Activation)    (None, 100)               0
_________________________________________________________________
dropout_3 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_4 (Dense)              (None, 200)               20200
_________________________________________________________________
activation_4 (Activation)    (None, 200)               0
_________________________________________________________________
dropout_4 (Dropout)          (None, 200)               0
_________________________________________________________________
dense_5 (Dense)              (None, 100)               20100
_________________________________________________________________
activation_5 (Activation)    (None, 100)               0
_________________________________________________________________
dropout_5 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_6 (Dense)              (None, 1)                 101
_________________________________________________________________
activation_6 (Activation)    (None, 1)                 0
=================================================================
Total params: 41,601
Trainable params: 41,601
Non-trainable params: 0
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The rationale behind the self-learned patterns-

Constant high atmospheric temperature may or may- not lead to low humidity in a forest ecosystem. If the soil has high moisture content, relative humidity would not drop down at the expected rate as the trees would continue to increase the relative humidity through transpiration of water absorbed through the soil. Hence there would not be a strong negative correlation between temperature and humidity or a high positive between humidity and moisture. This would indicate towards a relatively low risk area despite the high temperature. On the other hand, if the soil is dry/ has less moisture content, relative humidity would drop drastically as expected by the trend with high temperatures because the trees won't have water to lose through transpiration. In such conditions, a high positive between humidity and moisture and a high negative between atmospheric temperature and humidity which is characteristic of high-risk areas with a high chance of static charge developing and leaves drying out or shedding. A high positive correlation between the high atmospheric temperature and soil temperature on the other hand reaffirms other correlations as soil moisture is responsible for regulating soil temperature (there exists a negative correlation between the two variables). So, the positive correlations show high soil temperatures with high atmospheric temperatures which would occur only with low soil moisture which would in turn cause low humidity, thereby indicating the perfect dry conditions.

Early Forest Fire Detection System-

Early detection of forest fires can help curb spread before they become uncontrollable. The International Association of Fire and Rescue Services estimates that the fire may be contained if containment efforts begin within 100- 250 acres of burnt area which takes 70- 150 minutes from the time of ignition to burn through *(estimate subject to on ground weather variables like wind speed, vegetation, etc.).
Wireless Sensor Network (WSN) systems have proven to be the most effective, reliable and accurate for 24/7 long monitoring. But current systems employ/ plan to employ high grade sensors which increase the per sensor node cost, hence making the whole system unpractical. The cost only translates to increase in accuracy and precision of readings and not a substantial increase in the sensing environment range, i.e. all sensors only sense their immediate environment.

Forest Guard is programmed to raise an alarm if it senses a fire within its vicinity by analyzing data from its 4 sensors and microphone. It employs low-cost sensors which reduce per sensor node cost and hence allows us to reduce the distance between consecutive nodes and increase the frequency of sensor nodes to minimize unmonitored area. The system uses a Deep Learning Model to augment sensor readings and compensate for the inaccuracies of the low-cost sensors. The system makes use of 4 sensors and 1 microphone to provide warning in two-time frames to enhance alert times.

Preliminary Alarm-

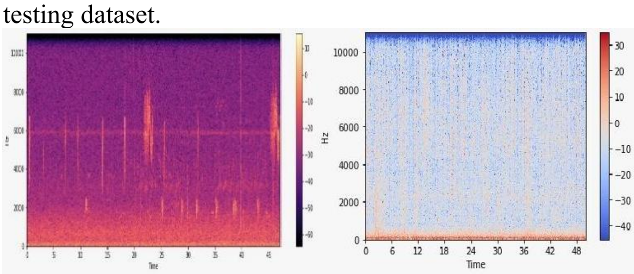
A preliminary warning is given on the basis of wildfire and bird sounds captured by the microphone of each sensor node. We hypothesized that as Infrared or illumination cameras suffered from LOS related problems and any change in atmospheric and soil conditions to be detected by our sensors would require the fire to come under 5m which would take maximum of 32- 45 minutes (in accordance with the grid design and FROS as 0.06 m/s), using natural auditory cues the characteristic crackling sound of wildfires and birds would be best suited for early detection as sound waves can traverse through any obstruction and are detectable even from a distance. As tested in an experiment, wildfire sounds were audible till 107m 5:23 minutes after ignition. But this audible distance may be affected by the type and amount of vegetation and dampening with distance. To combat this, bird sounds are also taken into consideration. Volant birds are responsive to even the smallest change in their environment due to their quick reflexes to auditory and visual stimuli. As leaves ignite to produce smoke, sound and light, birds send out an auditory alarm which is responded to by another set of beckoning by other birds, combining to achieve resonance. A Deep Learning model was trained to distinguish the characteristic sounds of wildfires and bird callings. To minimize false alarms caused by birds sounds for other than wildfires stimuli, the system was trained to only raise an alarm if bird sounds are simultaneously detected by more than 5-6 modules. This feature was designed basis the assumption that a cumulative sound will be produced by all the birds in the vicinity in case of a fire.

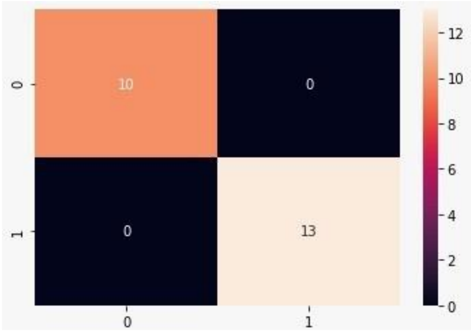
The model was trained on 280 audio clips of different types of vegetation of 50 seconds each sourced from Kaggle. Random sounds were also inserted in the dataset to train the classification model to differentiate target sounds from other noises. This resulted in a binary dataset for binary classification.

After analysing the data, we found that the frequency of the wildfire sounds reached up to 8192 Hz and that of bird sounds ranged between 1000 Hz to 8000 Hz. To avoid false alarms due to alarms made due to other small disturbances, the wildlife sounds must be detected by at least 5 adjacent modules to raise an alarm

To make the dataset's feature vectors to be fed into the neural network for classification, we used the Short Fourier transformation technique. Since this is an Audio classification task, we used a transformer network instead of a normal RNN or LSTM to avoid Vanishing/ Exploding Gradients. The Multi Head Attention layer will apply attention to those feature vectors which are necessary to be considered to get the desired output. This will also give us a higher computing speed.

After Training the model for 100 Epochs we got a training accuracy of 99 percent and validation accuracy of 98 percent. Following is the confusion matrix which tells true positives and negatives, false positives and negatives given by the model on the testing dataset.





Confirmatory Alarm-

To minimize the chance of any false alarms, Forest Guard will only confirm the wildfire after the sensors report change in their environments. The system employs 5 parameters- smoke, atmospheric temperature and humidity, and soil moisture and temperature. As tested in an experiment, we confirmed our hypothesis that if the fire is 3-4 feet from the sensor node, the temperature increases and humidity decreases drastically with a simultaneous rise in soil temperatures and a drop in soil moisture. These changes can be recorded before the module burns out as they are a result of the heat cloud which is created around the fire in the direction of spread, i.e. direction of wind. These data variations are compared against a localized baseline specific to each node only. The node MCU forms a dynamic baseline for every different parameter by first removing outliers and then averaging the parameter values from the previous week stored in the SD card. The micro- controller is programmed to raise an alarm if the parameter values exceed the respective tolerance deviations, factoring in safety limits to account for point deflections, from the dynamic baseline. The baseline is calibrated every week.

+ 8% $\pm$ 2- Atmospheric Humidity
+ 5 C $\pm$ 3 C- Atmospheric Temperature
+ 3 C $\pm$ 2.7 C- Soil Temperature
+ 15 % $\pm$ 3 %- Soil Moisture

If parameters exceed the tolerance levels and simultaneous changes are observed w.r.t baseline, a confirmatory alarm is raised.

Why install 4 sensors

Many of the sensor detector modules like FireWxNet, currently in testing, employ 1-2 parameters and are costly as well. We have tried to adopt a different thought process and approach here. Instead of relying on two costly sensors considering only 2 parameters, we have used 4 low-cost small sensors which were already employed for data collection for prediction.

EXPERIMENTS

Experiment 1-

Multiple small open fires were lit in uncontrolled environmental conditions at the Indian Institute of Technology, Varanasi (ignited by ethyl alcohol) to test the hypothesis on which early detection was based. Straw, hay, oven-dried leaves, pine needles and small branches were used as fuel.

Results and Interpretation-

The 1st set of fires were set in a 6*5m plot and took 1 minutes 26 seconds (avg.) to travel 6m (speed of fire as 0.06 m/s). The fire was inhibited at 3 feet from the module to measure the time taken to detect a fire from that distance because we estimate that if the forest fire comes under 3 feet of the module, the sensors may melt and malfunction. It took the node 58 seconds (avg.) to detect the fire 3 feet away. Viewing the data collected, we confirmed the hypothesized trends in changes in parameter values in case of a fire. When we cross referenced the data with the baseline in a time- series graph, we found that the parameter value lines were taking longer than expected to cross the baseline thresholds.

To test why, we lit a 2nd fire 3 feet from the node. Burning material was dry wood and hay grass kept in a pile. Upon comparing our sensor readings with other instruments, we found that the sensors had a high variability at extreme readings and the readings weren't crossing the baseline when they should have. Our solution- train an AI model to correct the data input from the sensors (3.2.)

To cut time delay in detection due to the fire having to come within the sensing range, we trained a sound analysis DL model (4.2.1.)

To test our improvements, we set up a 3rd fire in a 15m by 8m open dry grass plot with no middle object interference. The preliminary alarm was raised within 49 seconds by successful sound analysis achieved at a distance of 12 m which cut down the delay due to limited sensing range significantly. As the fire came within 4 feet of the node, the confirmatory alarm was raised at 1:53 seconds

Experiment 2-
To test the final prototype in real conditions, we tested our device in a prescribed control burn scheduled in a dry 50m by 25m plot in Oklakanda Range, Nainital, Uttarakhand (Permit granted by Forest Authority of Uttarakhand, India). The site was an open dry wild grass plot with cleared vegetation on all sides to isolate the fire site. The Forest Guard Module was placed opposite to the point of ignition.

Results and Interpretation-
The data trends have been summarized in the graph below which confirm the hypothesized correlations. The device was able to detect the fire with the help of the wildfire sounds within 2 minutes 3 seconds, way before the fire could travel 48m till the node. When the fire reached within 2.7 feet of the node at 5 minutes 38 seconds, the node detected the deviation from the baseline within 49 seconds. The smoke was detected with 90% more efficiency with the PM 2.5 sensor. The app notified the authorities and people within 10km range at 5 minutes 42 seconds.

Conclusion
With the emergence of sensor systems as the most efficient and reliable, Forest Guard builds up on that to provide more than just early forest fire detection. When compared with other sensor-based systems in testing, ours is the only system which has both detection and prediction capabilities. Both features combined outweigh the advantages of any single system currently in use both cost and technology wise. Our system’s approach is simple- remove fuel not heat to break the fire triangle. It’s both easier and cheaper. Provide accurate fire prone area mapping, eliminate high risk areas through measures like artificial rain, control burns, control belts. If fire occurs, give the warning under 3 minutes, guide the fire- fighters on the movement and direction of the fire in the early hour and set up transparency and communication channel. Forest guard, today is and tomorrow will be the one stop 2 forked solution to wildfires globally.

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