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Wildfire Detection Using Machine Learning

Vaishanavi Hedaoo, Priyanka Gupta, Omkar Tajane, Chinmay Navale
Department of Computer
Savitribai Phule Pune University, Pune, Maharashtra, India
vhedaoo1012@gmail.com, priyag8600@gmail.com omkartajane511@gmail.com chinmaynavle26@gmail.com

Abstract: *Due to climate change globally Forest fire disasters are recently getting lots of attention. Because climate changes are rapidly changing the fire patterns on Earth. Prediction of fire activities in the forest guides the authorities to make optimal, efficient, and sound decisions in fire management. This paper aims to summarize recent trends in the forest fire events prediction, detection, spread rate, and mapping of the burned areas. Furthermore, fire emissions in terms of smoke also put the Earth's public health and ecological system at greater risk. Hence, future policy making can be more accurate in saving billions of dollars, improving the healthy environment and ecological cycle for the inhabitants of this Earth. This paper provides a comprehensive review of the usage of different machine learning algorithms in forest fire or wildfire management.*

Keywords: Machine Learning, Wildfire, Forest Fires, Fire Susceptibility, Forecasting

I. Introduction

We face many severe crises such as economic, ecological, and environmental ways due to wildfire. Due to this many people living in the forest areas lose their lives in the incidents occur without even realising or any prediction. To decrease this type of calamity we have researched on this and going to conclude with name i.e., "WILDFIRE DETECTION USING MACHINE LEARNING".

In this paper, they are covering all the advantages regarding economical, ecological as well as environment related problems. As we know forests are situated outside the cities due to which the help, we want to provide at the time of incidence is not possible because of distance between the forest and cities is too large to reach the destination at a certain time.

The technique in this paper is used to detect fire with wireless sensor networks (WSNs) which are self-configured, infrastructure-free wireless networks that help monitor physical or environmental variables and transfer data via the network to chosen location or sink where it may be viewed and analysed main benefit of WSN are its efficiency and low power usage.

Here we are using microprocessor, transceiver module, and power components, which deploys wireless sensor nodes in a design with cellular manner to cover the entire space with sensors to monitor relative humidity, temperature, carbon monoxide (CO), and light intensity level. The power is provided to the sensors is through batteries as the major source and also through solar panels but at the secondary power source.

Additionally, the ratio generated from the sensor's node is transferred to the base station for analytical processing. The tree topology is used for this transmission, because it is beneficial as it takes low power consumption, low latency, and low complexity. In this network, data is collected and send to a base station.

II. Related Work

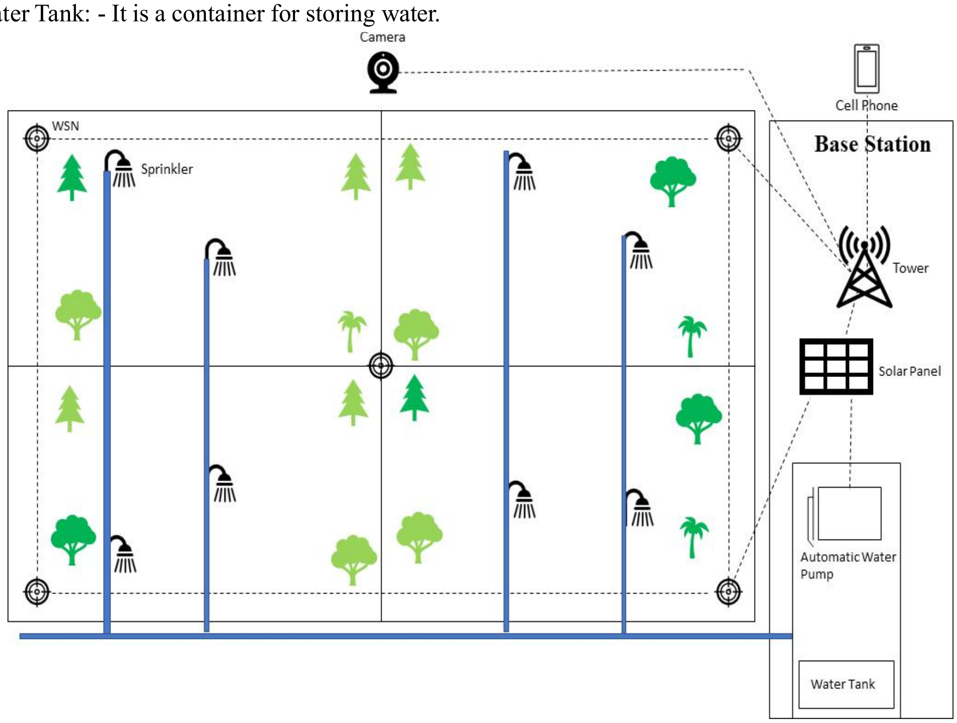
Fuel moisture content (FMC) estimation is critical part of any fire danger rating system. FMC alone does not provide a comprehensive assessment of fire danger. A simple method to convert FMC values to danger ratings is proposed. The method has been tested for the Madrid region (central Spain)[1].

This study presents an analysis of the influence of general landscape-level indicators on wildfire and its spatial susceptibility across a fire-prone landscape in China. Multi- class landscape indicators (i.e., slope, aspect, altitude, NDVI, annual rainfall, wind speed, land use, and proximity to rivers, roads, and human settlements) are weighted by the integrated WOE-AHP model[2]. Landslide susceptibility prediction (LSP) has been widely and effectively implemented by machine learning (ML) models based on remote sensing (RS) images and Geographic Information System (GIS) comparisons of ML models for LSP have not been explored. Ningdu County with 446 recorded landslides obtained through field investigations is introduced as case study[3].

Climate change has increased the probability of the occurrence of catastrophes like wildfires, floods, and storms. Wildfires ravage forest areas, as recently seen in the Amazon, the United States, and more recently in Australia. The availability of remotely sensed data has vastly improved, and enables us to precisely locate wildfires[4].

III. Architecture

1. **Sprinkler**: - A fire sprinkler which is also called as sprinkler head is the component which discharge water when the fire has been detected or we can say that when the temperature has been exceeded.
2. **Water Tank**: - It is a container for storing water.



3. Base Station: - Is the control system of entire structure and provides the interface between the cell sites and the mobile switching centre. The following are the components of base station: -
   a. Tower
   b. Water Tank
   c. CCTV camera
   d. Automatic Water Pump
   e. Solar Panel
4. Wireless Sensor Network (WSNs): - It is used to monitor the system, physical or environmental conditions. It is connected to the base station through the internet to share data.
5. Microprocessor: -A Microprocessor is a computer processor where the data processing logic and control is included on a single integrated circuit.

IV. Conclusion

Forest fires are a common occurrence in the flora and fauna of the world. Thousands of hectares are destroyed every year throughout the world. As we all know forest fire is very harmful for human as well as animals. For decreasing forest fire here we are using a system for predicting the forest fire. A system for forest fire detection using wireless sensor networks and machine learning was found to be an effective method for fire detection in forests. The analysis takes place within both the sensor node and at the base station. Because of the primary power supply provided by rechargeable batteries with a secondary solar power supply, a solution is readily implementable as a standalone system. Here we completed our research and created a system that predicts the risk of flames using weather data provided by the user, such as temperature, oxygen and humidity.

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