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Fire prediction monitoring system based on a spatial interpolation algorithm

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ABSTRACT

Fires endanger not only the environment's wealth but also the entire fauna and flora, drastically disrupting a region's biodiversity and ecology. This article monitors the spread of a fire in a specific area, determines its approximate direction, attempts to extinguish it in an organized manner, and identifies the safest solutions. A new system has been developed, consisting of two parts: embedded and reconfigurable. This system comprises four accurate flame sensors, a buzzer, an Arduino, and a field-programmable gate array (FPGA) DEV board. The Arduino and FPGA collect data from these sensors and send it to MATLAB, which processes and displays the results. This paper also uses a two-stage prediction based on a spatial interpolation algorithm. The results showed that the speed and direction of fire spread could be predicted quickly and accurately using a spatial interpolation algorithm, achieving the lowest predictive error (mean absolute error (MAE) ≈0.33 and root mean square error (RMSE) ≈0.48) at approximately epoch 70. Moreover, the proposed method achieved a 92% success rate in detecting flames and fire flashes, indicating that the sensors respond to fires within under 1 minute of occurrence.

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1. INTRODUCTION

Forest fires are natural disasters that pose significant challenges to society due to their substantial human and financial costs [1], [2]. Firefighting simulations can be used to forecast fire behaviour and assist in more effective and safer fire extinguishment. This approach aims to reduce the costs associated with this natural disaster and improve fire management [3], [4]. When projecting the spread of a forest, two key factors should be considered: accuracy and the time required for projection [5].

In the case of natural disasters, it is well understood that the emulator's input data may contain some uncertainty, which influences a portion of the forecast error [6], [7]. Because of this, several calibration techniques have been developed by the scientific community to lower input data uncertainty and thereby improve prediction error [8], [9].

Fire management organizations assess fire weather conditions and issue public alerts utilizing fire hazard indices [10]. The McArthur Fire Forest Hazard Index and the Grassland Fire Danger Index are the two most popular fire danger indices in Australia [11]. These indices are computed at meteorological stations using data on fuel and weather variable readings [12]. Understanding the geographical distribution of fire weather indicators, especially the extreme ends of the scale, is essential for a vast country like Australia in assessing the risk of catastrophic fire weather events [13].

This research study will present a new method for monitoring the speed at which fire spreads in a specific area. Additionally, it will estimate potential ignition paths and explore strategies for systematically and effectively extinguishing the fire. It will also identify the safest solutions to extinguish any fire automatically without delay.

The following sections will be structured as follows: section 2 will examine the literary works discussed by researchers in earlier studies relevant to this work. Section 3 will detail the proposed design methodology for this paper. It will include a comprehensive explanation of the essential design components related to predicting fire occurrences, as well as an extensive discussion of the interpolation technique. Section 4 will outline the methodology for designing a circuit to forecast fire flames. While section 5 will provide an analysis and discussion of the results obtained, whether from MATLAB and Proteus programs or from practical experiments and real tests. Section 6 will provide conclusions and suggest potential for future work.

2. RELATED RECENT LITERATURE

A research team of scientists from the National Institute of Standards and Technology, or "NIST," in the United States, has developed an electronic method to forecast this perilous phenomenon. This system primarily relies on temperature readings from heat sensor units located within the burning building. It is designed to continue operating even as the building's sensors start to fail one by one as the fire spreads. The research team found that this method has an 86% success rate in predicting fire incidents and can forecast flames a full minute in advance [14].

Another research team [15], [16] displayed FirePro systems that were made with the most recent iteration of the proprietary FirePro steel composition. The solid substance used by FirePro transforms into a condensed aerosol that quickly expands and extinguishes fires with exceptional effectiveness. During the transformation process, the aerosol is dispersed and evenly distributed throughout the cap. Compared to gas materials, the overall immersion enhancement is achieved without increasing the pressure within the protected area. Rather than using traditional methods suggested by the fire triangle, such as oxygen depletion or cooling, the fire is extinguished by interrupting the exothermic chemical reactions occurring in the flame. FirePro technology puts out a fire by impeding, at the molecular scale, the chemical chain reactions occurring in the flame without decreasing its oxygen supply. The research team found that this method has an 88% success rate in predicting flashing fire, which can happen up to a minute before it occurs.

This research study monitors the speed of fire spread in a specific area, estimates its direction, attempts systematic extinguishment, and identifies the safest alternative routes. The project includes four real flame sensors and one virtual flame sensor. MATLAB processes data from Arduino sensors and displays the results in a diagram that illustrates how interpolation can forecast the direction and speed of fire spread. This paper uses a two-stage prediction algorithm. Since a unique approach is employed to obtain the optimal input data for the simulation, this calibration method requires extensive computations and takes longer to complete. It is necessary to consider the time constraints imposed by the fire prediction system. To deliver a decent time, it is essential to maintain a reasonable balance between precision and user account time. This study found that the proposed method has a success rate of 92% in predicting fires and fire flashes. The sensors respond quickly, detecting fires less than one minute before they occur.

3. DESIGN METHOD

This section introduces two subsections. In the first subsection, the paper proposes the basic components of the project idea. The second subsection presents the interpolation methodology.

3.1. Proposed design components

This subsection explains the most important components used to design and implement the idea proposed in this research paper.

3.1.1. Arduino Nano

The Arduino Nano is a small electronic board that features a microcontroller, similar to those found in computers. It has lower power requirements and offers various input and output pins for both digital and analogue signals, as well as a USB port for programming and communication [17]. By entering commands into a simple programming interface, you can control an electric motor by sending signals through outputs. This can involve using keys to connect or disconnect the electrical current, communicating with another panel, or reading data from an input that provides information—such as the current distance between a painting and an obstacle directly in front of it—using a sensor like a laser or ultrasound [18], [19]. All the input and output pins for the Arduino Nano are illustrated in Figure 1.

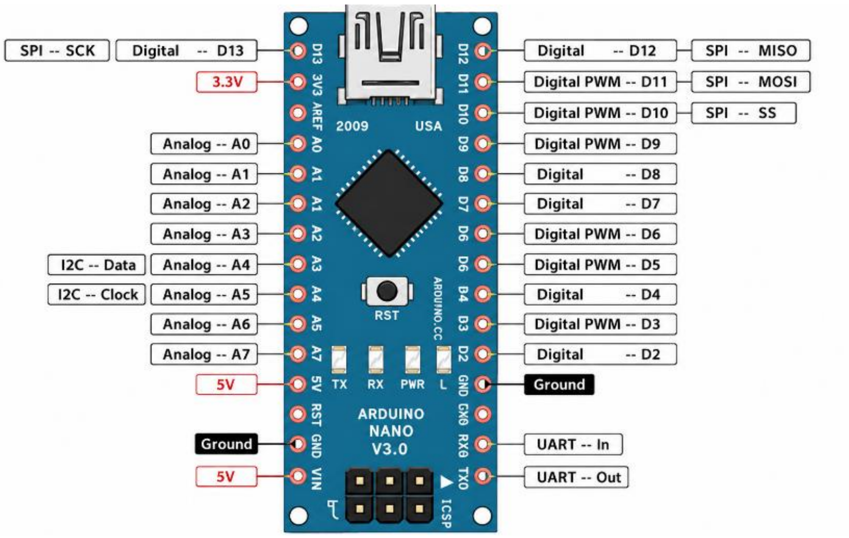

Figure 1. Pins inputs and outputs of Arduino Nano breadboard [18]

3.1.2. Flame sensor

It can detect light sources with wavelengths ranging from 760 to 1100 nm, including fire sources. With this sensor, a 360-degree detection angle allows flames to be detected from a distance of 100 cm. This sensor outputs a digital or analogue signal [20]. These sensors are employed in firefighting robotics, such as flame alarms. This sensor can detect fire at temperatures up to 60 °C; however, as the distance increases, its effectiveness diminishes. Although the flame sensor is extremely sensitive to the flame, it responds normally to light in waveform [21]. The input and output pins for this sensor are shown in Figure 2.

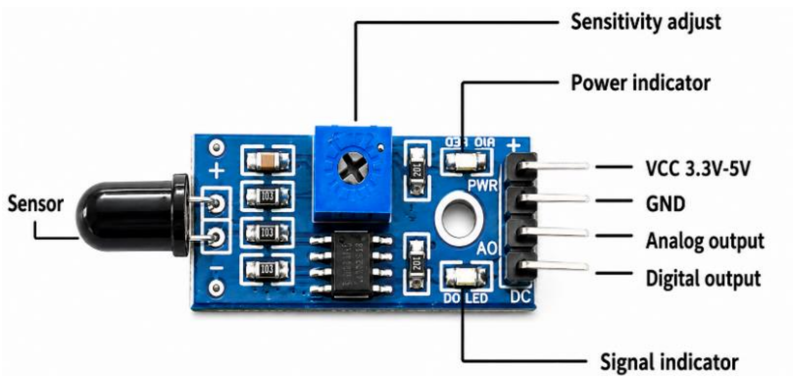

Figure 2. The output and input pins for the flame sensor [21]

3.1.3. Buzzer

A device converts electrical energy into audible alarms used in microphones, ovens, audio notification devices, and more. The buzzer's tannin model has electrodes that range in voltage from 6 V to 12 V. Figure 3 shows the arrangement of the buzzer's pins, which include a positive pin and a negative pin. The "+" sign or a longer terminus indicates a positive terminal. The short terminal, known as the negative terminal, is linked to the GND terminal and is denoted by the sign "-" [22].

Figure 3. Configuration of the buzzer pin [22]

3.2. Spatial interpolation algorithm methodology

It is a mathematical method for estimating new data points from a given set of graphic points [23]. The outcomes of experiments in applied sciences and engineering typically consist of data points gathered through statistical analysis or conducted in controlled environments [24]. Data points are used to create a mathematical equation that closely resembles them, using interpolation methods [23], [24]. Interpolation is a sort of estimation used in the mathematical discipline of numerical analysis. It is a technique for creating new points of information within the bounds of a discrete collection of existing data points [25].

In science and engineering, one frequently possesses several information points that, by sampling or testing, indicate the values of the function for a finite set of independent variable values. It is frequently necessary to interpolate or determine the value of that function for an intermediary value of an independent variable [23]–[25]. The steps of the spatial interpolation algorithm methodology adopted in this study are summarized.

3.2.1. Data collection and preprocessing

The first step is collecting spatial and environmental data from monitoring stations, such as temperature, humidity, wind speed, vegetation index, and soil moisture. Each station has known coordinates $(x_i,\ y_i)$ and a measured value $Z(x_i)$. Before interpolation, the data must be cleaned by removing outliers, handling missing values, and normalising variables as needed [23]–[26]. A common normalization formula is used, as in (1):

$$Z_{norm} = \frac{Z - Z_{min}}{Z_{max} - Z_{min}} \tag{1}$$

3.2.2. Spatial distance calculation

To estimate fire risk at an unknown location x_0, we calculate the spatial distance between x_0 and all known data points x_i. The most common method is the Euclidean distance based on (2) [23], [26]:

$$d_i = \sqrt{(x_0 - x_i)^2 + (y_0 - y_i)^{\,2}} \tag{2}$$

Distance plays a critical role in spatial interpolation because points that are closer together exert a stronger influence on predictions than those that are farther apart. This idea is consistent with Tobler's First Law of Geography, which states, "Everything is related to everything else, but nearby things are more closely related than distant ones."

3.2.3. Selection of interpolation method

Several spatial interpolation algorithms can be used in fire prediction systems. The most common ones are:

- Inverse distance weighting (IDW),
- Kriging,
- Spline interpolation.

The choice depends on data characteristics. For environmental fire monitoring, IDW is simple and fast, while Kriging is more accurate because it models spatial autocorrelation [25], [26].

3.2.4. Inverse distance weighting algorithm

In IDW, the predicted fire risk value at location x_0 is calculated as a weighted average of nearby observations using (3) [25], [26]:

$$Z(x_0) = \frac{\sum_{i=1}^{n} w_i Z(x_i)}{\sum_{i=1}^{n} w_i} \tag{3}$$

where wi are the weights, it can be calculated as in (4) [24]–[26]:

$$w_i = \frac{1}{d_i^p} \tag{4}$$

Here, d_i denotes the distance between the unknown point and the i-th known point, while p represents the power parameter (usually between 1 and 3). A higher p-value gives more influence on closer stations. This method is computationally efficient and suitable for real-time fire monitoring systems.

3.2.5. Kriging algorithm

It is a geostatistical interpolation method that accounts for spatial autocorrelation, and the predicted value is based on (5) [24], [26]:

$$Z(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{5}$$

where λ_i is the weight. The weights are calculated using the semivariogram model, the semivariogram function is defined as shown in (6) [24], [25]:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + H)]^2 \tag{6}$$

where h is the separation distance.

Kriging reduces estimation variance and offers both predicted values and errors, making it a reliable method for mapping fire risk.

3.2.6. Fire risk index calculation

After interpolating environmental variables (temperature, humidity, wind speed, and vegetation dryness), a fire risk index (FRI) can be calculated using a weighted linear combination as shown in (7) [25], [26]:

$$FRI = aT + bH + cW + dV \tag{7}$$

where T is the interpolated temperature, H is the humidity, W is the wind speed, V is the vegetation dryness index, and a, b, c, d are weighting coefficients. These coefficients are determined using statistical regression or expert knowledge.

3.2.7. Fire risk mapping and monitoring

The interpolated fire risk values are visualized as a continuous spatial surface (risk map). Areas are classified as follows:
– Low risk,
– Moderate risk,
– High risk,
– Extreme risk.

Threshold classification can be defined as:

$$\text{Risk Level} = \begin{cases} \text{Low} & \text{FRI} < 0.25 \\ \text{Moderate} & 0.25 \leq \text{FRI} < 0.5 \\ \text{High} & 0.5 \leq \text{FRI} < 0.75 \\ \text{Extreme} & \text{FRI} \geq 0.75 \end{cases}$$

This final step allows decision-makers to monitor and respond to potential fire outbreaks in real time.

3.2.8. Validation and error measurement

To evaluate model accuracy, cross-validation is performed. Common error metrics include:
– Mean absolute error (MAE) is calculated by (8) [27]:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^{n} \left| Z(x_i) - \hat{Z}(x_i) \right| \tag{8}$$

– Root mean square error (RMSE) is calculated based on (9) [27]:

$$\text{RMSE} = \sqrt{\frac{1}{n} \quad \sum_{i=1}^{n}\left(Z(x_i) - \hat{Z}(x_i)\right)^2} \tag{9}$$

All steps of the proposed spatial interpolation algorithm methodology are summarized in a flowchart, as illustrated in Figure 4.

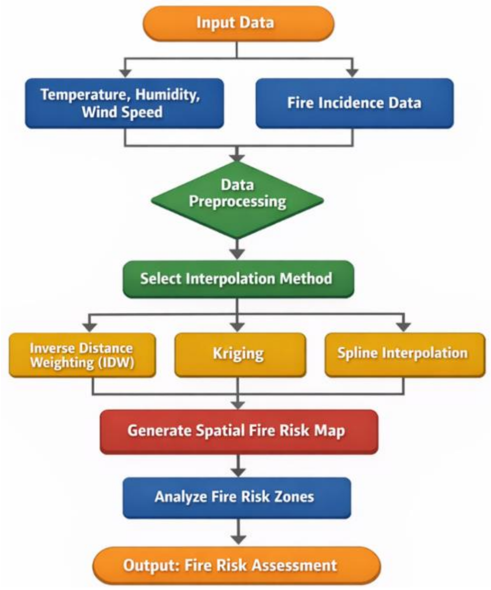

Figure 4. The processes and programming steps for extinguishing and controlling fires using the spatial interpolation algorithm

4. PROPOSED DESIGN DIAGRAM METHODOLOGY

For the project, the following components were collected: an Arduino board, a buzzer, four flame sensors, and a set of jumper wires. Each flame sensor has four pins: one signal pin, and one power supply pin (5 V), and one ground pin (0 V). These pins are linked to the input terminals on the Arduino board. The Arduino has 12 input pins, as shown in Figure 5. The project focuses on the Arduino, which has been completed after extensive research. The Arduino was connected to the fire sensors using jumper wires and linked to the computer via a USB cable. Initially, a basic Arduino program was implemented, and additional programming was added as necessary. The design of the fire extinguishing circuit, illustrated in Figure 5, was developed using Proteus software. Figure 6 illustrates the applied circuit, which shows the system as consisting of two parts: embedded and reconfigurable.

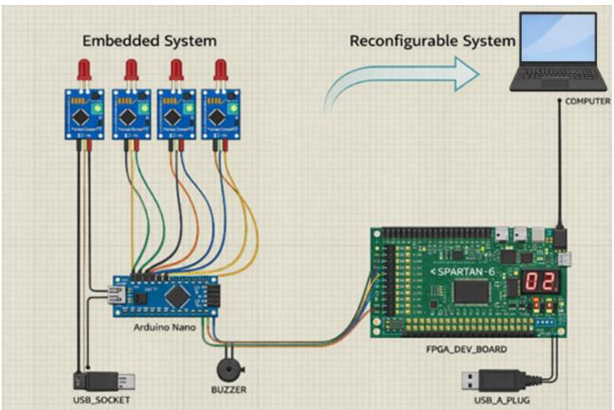

Figure 5. Flame-sensing circuit designed using Proteus software

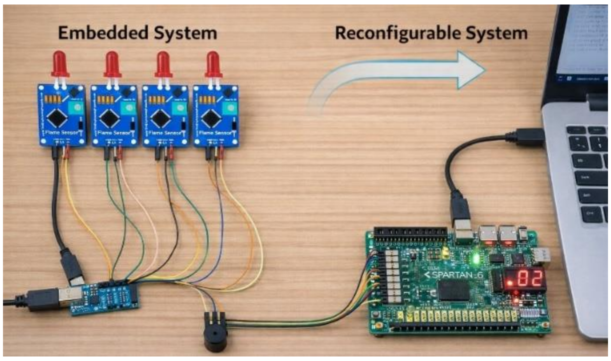

Figure 6. The applied circuit design for an embedded and reconfigurable fire monitoring system

Additionally, Figure 7 depicts the practical design of this circuit after it has been organized and housed in an external environment that simulates a forest, making it ideally suited for advanced projects. Additionally, Figure 7 displays all the project accessories and components. The flame sensors are positioned in all directions to detect flames from every angle. Furthermore, Figure 8 shows the flowchart detailing the steps involved in designing the project idea proposed in this article, which is based on the internet of things (IoT).

Figure 7. The flame fire sensing project was designed using practical components

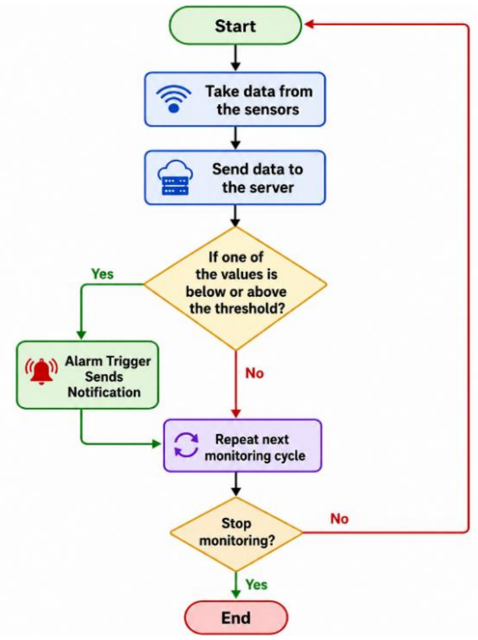

Figure 8. A flowchart of the steps involved in designing the proposed project idea

5. RESULTS ANALYSIS AND DISCUSSION

Figure 9 illustrates the time required for one sensor to reach another, as shown by the values displayed in the boxes generated by MATLAB. The final of the four squares in the half of the figure yields a value of zero, indicating that the fire has completely engulfed it. The four squares at the center represent real sensors, while the other squares in MATLAB represent virtual sensors. The distances between the squares vary arbitrarily due to various environmental factors. The following squares display ascending numbers, indicating the gradual arrival of the fire; both scenarios involve significant combustion.

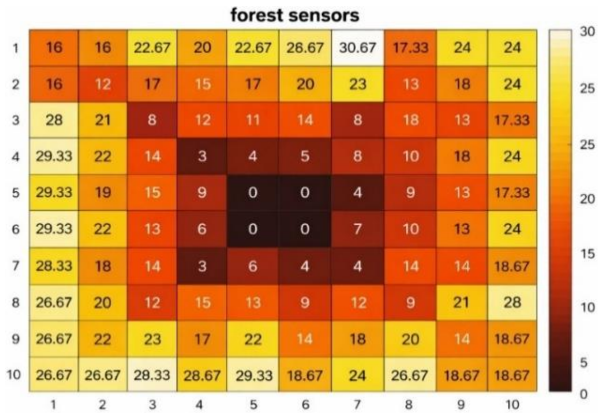

Figure 9. Fire flame intensity data was produced through MATLAB

The fire system was used to identify fires that spread recklessly and inaccurately, and the conclusion reached is that the fire spreads unevenly, moving randomly in some squares and taking between 0 and 4 seconds or between 0 and 5 seconds to do so. This uneven distribution is affected by environmental factors, and fires present major challenges to society due to their high economic costs. Firefighting simulations can predict fire behaviour, enabling more effective and safer extinguishing methods while also reducing costs associated with natural disasters.

The receiver operating characteristic (ROC) curve shown in Figure 10 demonstrates the strong performance of the proposed fire prediction monitoring system. The curve rises sharply toward the top-left corner, indicating a high true positive rate with a very low false positive rate. The reported area under the curve (AUC)=0.92 reflects optimal discriminative capability, meaning the system can effectively distinguish between fire and non-fire events. Compared to a baseline of random guessing (AUC=0.5), the proposed method significantly outperforms chance-level detection. Achieving a 92% accuracy rate in detecting flames and fire flashes further confirms the model's reliability. Additionally, the system can detect fire in under a minute, demonstrating its rapid sensor responsiveness and effectiveness for real-time early-warning applications.

Figure 11 illustrates the MAE and RMSE curves versus the number of epochs for a proposed spatial interpolation algorithm for fire prediction monitoring. As the number of epochs increases, both error metrics decrease sharply at first and then gradually stabilize, indicating that the model is learning effectively and converging towards a minimum error. The consistently higher RMSE values reflect their greater sensitivity to larger errors, which is crucial in fire prediction, where extreme deviations can have serious implications. The flattening of both curves suggests that further training yields diminishing returns, and the model has reached a stable performance level suitable for spatial interpolation tasks in fire monitoring.

Table 1 presents a comprehensive comparison between the study proposed in this article and the latest studies conducted by other researchers. This comparison focused on seven key components: proposed method, study type (applied/simulation), target environment, algorithm/model, sensors used, data source (database), and fire suppression response rate. The study's statistics indicate that the proposed method achieved a 92% accuracy and response rate in detecting flames and fire flashes within the target environment, surpassing many other studies. This is a result that many academics interested in controlling sudden fires aspire to. Furthermore, the proposed methodology is applied to a real-world environment, providing an accurate impression of the results and a rapid, realistic response time. Fires were detected less than a minute before they started, making it ideal for real-world process studies in diverse environments. Unlike other studies, which have not been practically implemented and whose results are mostly simulations, this leads to inaccurate results in terms of accuracy and response time in real-world scenarios.

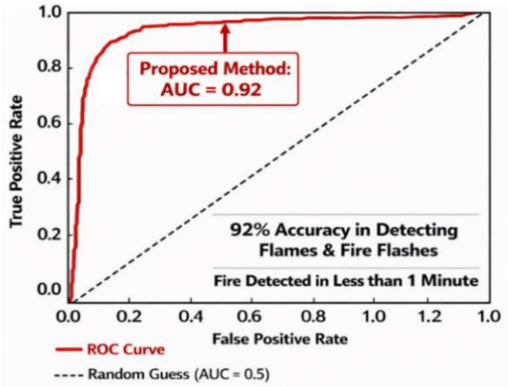

Figure 10. Efficiency and response curves of the proposed fire prediction system

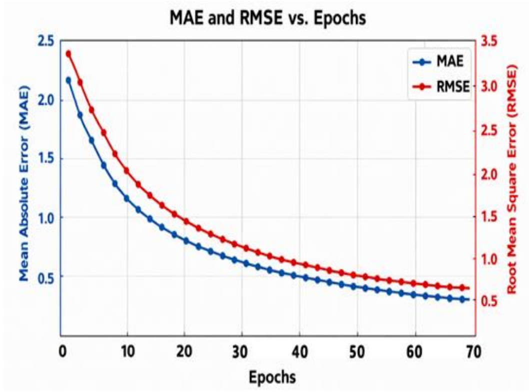

Figure 11. The MAE and RMSE curves versus the number of epochs for the proposed spatial interpolation algorithm

Table 1. A comprehensive comparison of this study's work with recent scientific articles

Ref.	Proposed method	Study type (applied/ simulation)	Target environment	Algorithm/model	Sensors used	Data source (database)	Fire suppression response rate
[28]	Indoor fire threat field detection	Simulation-based generated dataset from PyroSim	Indoor fire environment	Long short-term memory (LSTM) + Kriging (improved)	Multiple sensor time series (fire sensor temporal data)	Fire scenarios simulated (PyroSim + sensor output)	Not directly applicable (focuses on detection accuracy)
[29]	Fire detection using spatial reconstruction of surface temperature	Simulation (real fire satellite data usage)	Outdoor/forest environment	Spatial feature reconstruction +machine learning (ML)+contextual spatial algorithm	Remote-sensed satellite data (spatial pixels)	Himawari-8/9 imagery + SRTM DEM data	Not directly measured suppression – improves detection sensitivity
[30]	Prediction of fire occurrence using spatial ML	Simulation (model trained on historical fire and environmental data)	Outdoor/forest fire risk areas	ML/neural network models	No fixed physical sensors—uses multi-source input variables	Historical forest fire + environmental datasets	Not explicit suppression rate (prediction focus)
[31]	Fire risk prediction model with spatial interpolation of meteorological data	Simulation (statistical + interpolation used on historical data)	Outdoor/large-area fire risk	Stacking ensemble + spatial interpolation of meteorological data	Indirect spatial data interpolation from weather stations	China Meteorological Station data (multi-year)	Not the suppression rate
[32]	Fire probability mapping with spatial interpolation	Simulation (real historical data + interpolation mapping)	Outdoor/forest fire risk	Kriging for spatial fire risk estimation	Uses spatial variables derived via kriging/IDW	Historical spatial fire occurrence + environmental variables	Probability of fire occurrence (not suppression)
This work	Outdoor fire threat field detection	Applied (model trained on real environmental data)	Outdoor fire environment	Spatial Interpolation Algorithm (IDW, Kriging, Spline interpolation)	Multiple fire sensors (special specifications and a fast response time)	Data from applied and produced fire scenarios in the targeted work environment	92% accuracy rate and response in detecting flames and fire flashes

6. CONCLUSION

This paper helps the community by monitoring the fire's speed and direction. It detects signals from fire sensors, transmits them to the computer, and activates the fire alarm. Once the rescue personnel are aware of the fire's speed and direction, they may act to best benefit the situation. The project's advantage is to conserve forests and significant locations as quickly as possible while safeguarding humans from harm. This study found that the suggested technique has a 92% success rate in predicting fires and fire flashes; the sensors responded quickly, detecting fires less than a minute before they happened. In the future, this system is being developed and applied to the smallest parks and gardens to protect people from sudden fires, as well as expand this idea and apply it to mobile devices that allow everyone to monitor their surroundings and alert the relevant authorities when a fire occurs at maximum speed without causing any damage.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state there is no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

DATA AVAILABILITY

Data availability does not apply to this paper, as no new data were created or analyzed in this study.

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