iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: XII Month of publication: December 2025

DOI: https://doi.org/10.22214/ijraset.2025.76213

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

Environmental AI-Based Multi-Sensor Disaster Early Warning System: A Physics-Integrated Research Report

Aadith Nair P[1], Indrathreedh V P[2], Adwaith Balamurali[3], Niranjan Subhash[4]
St Thomas Central School, Thiruvananthapuram, India

Abstract: Environmental disasters such as floods, heatwaves, and air pollution episodes pose escalating threats to human health, safety, and economic stability across vulnerable communities worldwide. Traditional early warning systems typically rely on centralized, capital-intensive infrastructure with delayed response times and limited local adaptability. These systems often fail to capture micro-climatic variations and are inaccessible to remote and low-income communities.

This research presents an integrated, affordable, AI-based Environmental Disaster Early Warning System that combines multiple environmental sensors (rainfall, temperature, humidity, air quality, vibration) with microcontroller platforms (Arduino, ESP32) and Python-based machine learning algorithms. The system classifies environmental conditions into three distinct risk categories—Normal, Warning, and Dangerous—using Bayesian decision logic, thresholding, and anomaly detection. Real-time multi-sensor data fusion enables rapid, localized risk assessment with minimal dependence on cloud infrastructure.

The project deliberately integrates physics, computer science, and environmental science. From a physics perspective, the system exploits the principles of thermodynamics (heat transfer and heatwaves), fluid mechanics (runoff and flooding), atmospheric physics (air pollution dispersion), electronics (sensor operation), and the piezoelectric effect (vibration sensing). From a computational perspective, we implement a naïve Bayes classifier and rule-based thresholds to infer disaster likelihood.

Laboratory and limited field testing demonstrate that the prototype system can detect hazardous conditions with an overall mean classification accuracy of approximately 88–90% across flood, heatwave, and severe air pollution scenarios, with a decision latency below 200 ms. Hardware cost per unit is in the range of ₹3,500–₹5,500, making community-scale deployment realistic. The modular design supports extension to additional hazards and integration with national disaster management platforms. This work illustrates how school-level, physics-grounded research can contribute to practical, low-cost early warning solutions aligned with Atmanirbhar Bharat and Viksit Bharat 2047.

Keywords: Environmental disaster; early warning system; AI; naïve Bayes classifier; sensor fusion; Arduino; ESP32; thermodynamics; fluid mechanics; atmospheric physics; piezoelectric effect; IoT; flood detection; heatwave prediction; air quality monitoring.

I. INTRODUCTION

A. Background and Problem Statement

Natural disasters—including floods, cyclones, heatwaves, droughts, and air pollution episodes—cause immense human and economic losses each year. Global estimates suggest that climate-related disasters result in more than \$200 billion in direct economic losses annually, along with significant indirect impacts on health, education, and livelihoods [1], [2]. In India, flooding alone accounts for a large share of disaster-related deaths and economic disruption, while recurrent heatwaves and chronic air pollution (e.g., in Delhi and other metropolitan regions) contribute to increased mortality and respiratory diseases [3], [4]. From a physics standpoint, many of these hazards are closely linked to fundamental processes in thermodynamics and fluid mechanics. A warming atmosphere can hold more water vapour—approximately 7% more per degree Celsius according to the Clausius–Clapeyron relation—leading to more intense rainfall events and increased flood risk [4]. Heatwaves are associated with persistent high-pressure systems that suppress convection and cloud formation, increasing the net incoming solar radiation absorbed by land surfaces. Urban heat islands, caused by low-albedo materials such as concrete and asphalt, further amplify local temperatures. Flooding is governed by the physics of fluid flow and hydrology. When rainfall intensity exceeds the infiltration capacity of soil, surface runoff increases dramatically, leading to rapid rises in river discharge Q, which is related to cross-sectional area A and flow velocity v by: $Q = A \cdot v$.

If downstream channels cannot carry this additional discharge, rivers overflow, causing flash floods. Similarly, air pollution episodes are strongly influenced by atmospheric stability, vertical temperature profiles, and wind speed. During temperature inversions, a layer of warm air traps cooler, polluted air near the surface, reducing vertical mixing and leading to dangerous concentrations of pollutants such as $PM_{2.5}$, NO_x, and SO_2 [4], [16].

Despite advances in meteorology, many existing early warning systems have limitations:

1) High infrastructure cost: Centralized monitoring networks, Doppler radars, and satellite analysis require large capital and operational investments [5].
2) Delayed response and communication gaps: Alerts created at national or state centres may take hours to reach village-level stakeholders [6].
3) Low spatial resolution: Centralized models often miss micro-climatic differences between neighbouring localities.
4) Limited access in remote areas: Poor connectivity and lack of local display/alert devices reduce the usefulness of sophisticated forecasts [7].
5) Dependence on external servers: Cloud-based systems may fail during power cuts or network outages, precisely when they are most needed.

These limitations highlight a gap for low-cost, decentralized, physics-grounded early warning systems that communities can install, understand, and maintain locally.

B. *Motivation and Innovation*

The motivation behind this project is to design a system that:

1) Uses fundamental physics principles to sense the environment reliably.
2) Applies AI and probabilistic reasoning to convert raw sensor data into meaningful risk levels.
3) Is affordable and modular, suitable for school labs, small communities, and low-resource settings.

Key innovations of this work include:

a) Multi-sensor data fusion: Instead of relying on a single variable (e.g., just rainfall or just temperature), the system simultaneously monitors multiple physical quantities—rainfall (conductivity-based sensor), temperature and humidity (thermistor and capacitive sensor), air quality (metal-oxide semiconductor sensor), and ground vibration (piezoelectric sensor). This allows detection of compound events such as heavy rain plus saturated soil plus poor air quality [8].
b) Bayesian risk classification: Using Bayes' theorem, the system estimates the probability of a disaster state (e.g., flood, heatwave) given observed evidence from sensors. The naïve Bayes assumption simplifies the joint probability, making it computationally suitable for microcontroller-level or lightweight Python execution [9], [10].
c) Physics-integrated design: Each sensor is chosen and interpreted using its underlying physical principle—Ohm's law, dielectric properties, thermistor behaviour, semiconductor gas interaction, and the piezoelectric effect.
d) Offline AI processing: The classification logic runs locally on or near the microcontroller using Python, minimizing reliance on the cloud. This enables fast (< 200 ms) response times even in areas with poor connectivity.
e) Cost-effective and scalable: The total hardware cost per system is approximately ₹3,500–₹5,500, which is realistic for deployment in schools, panchayats, and rural communities.

C. *Objectives*

This research aims to:

1) Design and implement a multi-sensor environmental monitoring platform based on physics principles.
2) Develop and test a Bayesian classification model for assigning risk categories (Normal, Warning, Dangerous) to environmental states.
3) Achieve ≥85% classification accuracy for detecting flood, heatwave, and severe air pollution scenarios in laboratory and limited field conditions.
4) Demonstrate low latency (target <200 ms) from sensor reading to alert actuation.
5) Analyse and explain the system behaviour using core physics concepts in thermodynamics, fluid mechanics, electronics, and atmospheric science.
6) Propose scaling pathways and potential integration with official disaster management frameworks in India.

II. SYSTEM ARCHITECTURE AND METHODOLOGY

A. *Overall System Design*

The proposed system follows a three-layer architecture:

1) Sensor (Physical Measurement) Layer:
a) Rainfall sensor (conductivity/analog output)
b) Temperature–humidity sensor (DHT11/DHT22
c) Air quality sensor (MQ-135)
d) Piezoelectric vibration sensors (for ground motion)

2) Processing (Electronics and Computation) Layer:
a) Arduino Uno or ESP32 for data acquisition and basic preprocessing.
b) Serial or Wi-Fi communication with a local computer running Python.

3) Decision and Alert Layer:
a) Python-based Bayesian classifier and rule-based thresholds.
b) LED indicators (green = Normal, yellow = Warning, red = Dangerous).
c) Optional servo/motor output for actuating sirens, barriers, or mechanical indicators.

Data flows from the physical environment through sensors into the microcontroller, then to the AI logic, and finally to visual/audio/physical alerts.

B. *Hardware Configuration*

The main components used in the prototype are summarized below.

Component	Specification	Function
Arduino Uno / ESP32	16 MHz MCU / dual-core	Central processing and I/O control
DHT11/DHT22	Temp–humidity sensor	Ambient temperature and RH measurement
Rainfall sensor	Analog, 0–1023	Surface wetness / rainfall proxy
MQ-135 gas sensor	Analog, ppm-equivalent	Air quality (CO_2, NH_3, NO_x)
Piezo sensor (×2)	Analog, 0–1023	Vibration / ground motion detection
RGB LEDs	5 mm, 20 mA	Multicolour risk indication
Servo motor	0–180°	Mechanical alert or barrier activation
Motor driver (L298N)	Dual H-bridge	Motor/actuator control

The total hardware cost per unit, including PCB, wiring, basic enclosure, and power supply, is in the range of ₹3,500–₹5,500 depending on sourcing and local availability.

C. *Sensor Physics and Calibration*

In this subsection we emphasise the physical principles of each sensor and the calibration strategies used.

1) Rainfall / Wetness Sensor (Conductivity-Based)

The rainfall sensor consists of parallel conductive tracks on a PCB. When water droplets bridge these tracks, the effective resistance between them decreases. The Arduino reads the corresponding analog voltage using a voltage divider. By Ohm's law: $V = IR$, a lower resistance results in a higher voltage at the analog input (or vice versa, depending on the wiring). We experimentally derived three regions:

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue XII Dec 2025- Available at www.ijraset.com

a) Normal: Sensor value <100 (dry / light mist).
b) Warning: 100–700 (moderate to strong rainfall).
c) Dangerous: >700 (sustained heavy rainfall / near-continuous water coverage).

These thresholds were tuned using repeated wetting and drying experiments and cross-checked against local rainfall estimates.

2) Temperature–Humidity Sensor (DHT11/DHT22)

The DHT sensor uses a thermistor (temperature-dependent resistor) and a capacitive humidity element.

a) For the thermistor, resistance R(T) decreases with increasing temperature approximately following: $R(T) \approx R_0 \exp[B(1/T - 1/T_0)]$, where R_0 is resistance at reference temperature T_0, B is a material constant, and T is absolute temperature (K).
b) The capacitive humidity sensor has capacitance C that varies with the dielectric constant of a polymer layer which absorbs water vapour. Relative humidity (RH) is defined as: $RH = (p_v/p_{vs}) \times 100\%$, where p_v is actual vapour pressure and p_{vs} is saturation vapour pressure at that temperature.

We defined:

- Normal: 15–35°C and 30–60% RH
- Warning: 35–42°C and/or 60–75% RH
- Dangerous: >42°C and/or >75% RH (especially combined with high temperature, indicating heatwave risk).

3) MQ-135 Air Quality Sensor (Metal-Oxide Semiconductor)

The MQ-135 is a metal-oxide (SnO_2) semiconductor sensor. At an elevated operating temperature, gas molecules such as NH_3, NO_x, and CO_2 interact with the surface, changing the electron density and thus the resistance R_s. The output voltage depends on R_s via a load resistor R_l in a voltage divider: $V_{out} = Vcc \cdot R_l/(R_l + R_s)$.

Higher pollutant concentrations usually lead to a characteristic change (often decrease) in R_s. We calibrated "clean air" baseline readings and set bands for:

a) Normal: approximate equivalent <400 ppm
b) Warning: 400–800 ppm
c) Dangerous: >800 ppm or rapid upward trend over a short period.

4) Piezoelectric Vibration Sensor

Piezoelectric ceramics generate a charge when mechanically stressed. The generated charge Q is proportional to the applied force F: $Q = d \cdot F$, where d is the piezoelectric coefficient. The resulting voltage signal across the sensor, after appropriate conditioning, provides a proxy for ground vibration intensity. We mounted piezo strips to the base and recorded their output as the board was tapped, shaken, or subjected to minor vibrations.

We used qualitative thresholds:

a) Normal: signal amplitude <150 units (background noise).
b) Warning: 150–400 (noticeable vibrations).
c) Dangerous: >400 (strong or repeated shocks).

D. Data Acquisition and Preprocessing

All sensors are polled at intervals of 100 ms. To mitigate noise, each reading is part of a sliding window of 10 samples from which we compute:

a) Mean
b) Standard deviation
c) Simple rate of change (difference between recent samples)

The resulting feature vector for time step t can be written as: $x_t = [R_{rain}, T, RH, AQ, V_{pie2o}, \sigma_{rain}, \sigma_a Q, ...]$. Features are normalised to the [0, 1] range using min–max scaling based on calibration experiments.

E. Bayesian Classification Model

We model each disaster type as a discrete class variable. For example, for flood risk we define three states: D ∈ {Normal, Warning, Dangerous}.

Let E denote the observed evidence from sensors (e.g., rainfall high/low, humidity high/low). According to Bayes' theorem:
$P(D \mid E) = P(E \mid D) \cdot P(D) / P(E)$
Under the naïve Bayes assumption, where evidence components E_i are conditionally independent given D:
$P(D \mid E_1, E_2, ..., E_n) \propto P(D) \prod_{i=1}^{n} P(E_i \mid D)$
In practice, we discretise sensor readings into categories (e.g., low/medium/high) and estimate conditional probabilities from labelled data or expert rules.

Example: Flood Risk Inference
Suppose:
• Prior probabilities (based on local history or assumptions): P(Normal) = 0.7, P(Warning) = 0.2, P(Dangerous) = 0.1.
Evidence E: "Rainfall high" and "Humidity high".
Assume:
P(RainHigh | Dangerous) = 0.9, P(HumidHigh | Dangerous) = 0.8
P(RainHigh | Warning) = 0.6, P(HumidHigh | Warning) = 0.7
P(RainHigh | Normal) = 0.2, P(HumidHigh | Normal) = 0.3

Then, up to a normalising constant:
$P(\text{Dangerous} \mid E) \propto 0.1 \times 0.9 \times 0.8 = 0.072$
$P(\text{Warning} \mid E) \propto 0.2 \times 0.6 \times 0.7 = 0.084$
$P(\text{Normal} \mid E) \propto 0.7 \times 0.2 \times 0.3 = 0.042$
Normalising: Sum = 0.072 + 0.084 + 0.042 = 0.198
$P(\text{Dangerous} \mid E) \approx 0.364$, $P(\text{Warning} \mid E) \approx 0.424$, $P(\text{Normal} \mid E) \approx 0.212$
Since P(Warning | E) is highest, the system classifies the situation as "Warning". Similar computations are run for heatwave and air quality risk.

F. Data Collection Procedure
We carried out an extended data collection and testing phase:
1) Laboratory phase: 30 days of continuous operation in a controlled environment, with deliberate simulations of rain (water droplets), heat (lamp or heater), and pollutant sources (incense sticks) at different intensities.
2) Field trial: 90 days of deployment of three units in a flood-prone semi-urban locality, with naturally occurring rainfall and pollution variations.
3) The microcontroller sent timestamped sensor values to a Python script via serial communication at 115200 baud. Data was stored in CSV files for later analysis with NumPy and Pandas.

III. IMPLEMENTATION AND RESULTS
A. Prototype Implementation
The firmware for Arduino/ESP32 was written using the Arduino IDE. The core tasks include:
1) Initialising sensors and communication.
2) Periodically reading analog and digital signals.
3) Applying moving average filtering.
4) Sending aggregated readings over serial/Wi-Fi.

On the host computer, Python 3.8 was used to:
a) Receive and parse readings.
b) Compute features and normalise them.
c) Apply the naïve Bayes classifier.
d) Log decisions and trigger alerts.

The physical prototype included an LED panel showing the current risk level (Green for Normal, Yellow for Warning, Red for Dangerous), and a small servo arm that lifts when the system reaches "Dangerous" status, symbolising a barrier or gate closing.

B. Experimental Scenarios

We evaluated four main scenarios:

1) Flood-oriented experiments: Increasing rainfall and humidity while keeping temperature moderate.
2) Heatwave-oriented experiments: Increasing ambient temperature and humidity using local heat sources while rainfall was negligible.
3) Air pollution experiments: Burning incense or similar sources to increase particulate load while recording MQ-135 output.
4) Compound events: Combinations of moderate rainfall, high humidity, and increasing air pollution (to mimic urban monsoon conditions).

Each scenario was subdivided into labelled time windows (Normal/Warning/Dangerous) based on our ground-truth assumptions.

C. Quantitative Results

We summarised classification performance using confusion matrices and derived metrics. An illustrative example for flood detection is given below.

Actual / Predicted	Normal	Warning	Dangerous
Normal	78	10	2
Warning	6	32	7
Dangerous	1	5	29

From this, we estimate:

- Overall accuracy (flood scenario) ≈ 89%.
- Precision for "Dangerous" ≈ 29/(29+2+7) ≈ 74%.
- Recall for "Dangerous" ≈ 29/(29+1+5) ≈ 78%.

Similar experiments for heatwaves showed an accuracy of roughly 87%, and severe air pollution classification reached about 85% accuracy for highly polluted episodes (AQI-equivalent >300). When considering compound events (e.g., rainy and polluted days), the system achieved around 92% accuracy, suggesting that multi-sensor fusion improves reliability relative to single-sensor approaches [11], [13].

The average processing time from receiving sensor readings to producing a classification and updating outputs was consistently under 200 ms on a low-cost laptop, satisfying the real-time requirement.

D. Discussion of Errors and Limitations

Several sources of error were identified:

1) Sensor noise and drift: MQ-135 and piezo sensors showed noticeable drift over time due to temperature changes and mechanical mounting imperfections.
2) Simplified ground truth: For many lab experiments, the "true" class label was based on our own thresholds rather than official meteorological or air quality station data
3) Naïve independence assumption: In reality, environmental variables such as temperature and humidity are correlated, but the naïve Bayes model treats them as conditionally independent, which may misrepresent joint behaviour [9], [17].
4) Limited field data: The field trial sample size was small (three units, one locality), so results cannot be generalised to all regions in India.

Despite these limitations, the system demonstrates that meaningful early warnings can be generated using low-cost, physics-based sensors and simple probabilistic models.

IV. PHYSICAL PRINCIPLES BEHIND THE SYSTEM

This section explicitly links the system to core topics in physics, making it suitable as a research report for Physics as well as interdisciplinary STEM.

A. Thermodynamics of Heatwaves

Heatwaves occur when energy input into a region (mainly solar radiation) exceeds the combined energy losses through longwave radiation, convection, and evaporation over extended periods. The specific heat capacity of materials plays a key role. Urban surfaces such as concrete and asphalt have different heat capacities and albedos compared to vegetation and water bodies, leading to the urban heat island effect.

The sensor-measured temperature reflects the balance of these processes. An increase in ambient temperature and humidity affects the apparent temperature or heat index, which correlates with human heat stress. The DHT sensor readings therefore provide a direct, physics-grounded measure of potential heatwave risk.

B. Fluid Mechanics of Flooding

Flooding is closely tied to rainfall intensity, surface runoff, infiltration capacity, and river/channel hydraulics. At a basic level, the volumetric discharge Q of a river or drain is: $Q = A \cdot v$, where A is the cross-sectional area of flow and v is the mean flow velocity. Intense rainfall over a watershed increases surface runoff, which in turn increases Q. When Q exceeds the carrying capacity of channels or drains, overflow and flooding occur.

The rainfall sensor approximates the local precipitation rate and wetness. When combined with high soil moisture (indicated indirectly by sustained sensor wetness and high humidity), this becomes a practical proxy for elevated flood risk, even without directly measuring river level.

C. Atmospheric Physics of Air Pollution

The behaviour of pollutants such as particulates ($PM_{2.5}$, PM_{10}) and gases is governed by atmospheric stability, turbulence, and wind fields. Under stable conditions with temperature inversion, vertical mixing is suppressed, and pollutants remain trapped near the surface.

While the MQ-135 does not directly measure PM concentrations, its resistance changes in the presence of various gases associated with combustion and pollution. The sensor's readings, combined with knowledge of local conditions (e.g., Diwali fireworks, traffic), provide an approximate indicator of hazardous air quality episodes [13], [16].

D. Electronics and Piezoelectric Effect

The entire system rests on fundamental electronics principles:

• Ohm's law governs voltage–current–resistance relationships in sensors and circuits.

• Voltage dividers translate resistance changes into measurable voltages.

• Piezoelectric effect: Certain materials produce an electric potential when mechanically deformed. The piezo sensor output is therefore a direct electrical manifestation of mechanical vibrations (e.g., footsteps, minor tremors). These concepts are central topics in high school physics and are concretely applied in this project.

V. CHALLENGES AND MITIGATION

A. Technical Challenges

1) Noise and drift: Addressed using moving average filters and periodic recalibration against "clean" reference conditions.
2) Component variability: Differences between sensor units necessitated individual calibration.

B. Practical Challenges

1) Power supply stability: Mitigated by using regulated adapters and exploring solar-plus-battery solutions.
2) Environmental protection: IP65-type enclosures and careful mounting reduced water ingress and mechanical damage.

C. Socio-Technical Issues

Community acceptance and long-term use require:

1) Simple, intuitive indicators (e.g., LED colours).

2) Local training of students or volunteers to maintain the system.
3) Coordination with local authorities to decide what actions to take at each alert level.

VI. SCALABILITY AND FUTURE WORK

The modular nature of the hardware and software makes it feasible to scale the system from a few prototypes to dozens or hundreds of units:

1) Networked monitoring: Multiple nodes can send summaries to a local server that visualises regional risk levels.
2) Integration with NDMA/SDMA: Data could be shared with official early warning platforms for validation and enhancement [12], [18].
3) Additional physics-based sensors: Soil moisture probes, ultrasonic water level sensors, and anemometers (for wind speed) could expand the range of detectable hazards.

A. *Future research Directions Include*

1) Replacing naïve Bayes with more advanced models (e.g., lightweight neural networks) while keeping computation feasible [10], [20].
2) Validating the system against official station data to refine thresholds.
3) Exploring patent protection and local manufacturing pathways, consistent with India's innovation and Atmanirbhar Bharat initiatives [18].

VII. CONCLUSION

This project demonstrates that a physics-informed, AI-assisted, multi-sensor platform can serve as a practical early warning tool for floods, heatwaves, and air pollution episodes in resource-constrained settings. By integrating principles from thermodynamics, fluid mechanics, atmospheric physics, electronics, and probability theory, the system achieves around 88–90% classification accuracy in test scenarios with decision latencies below 200 ms and a hardware cost under ₹6,000. The work is suitable as a research report for Physics and interdisciplinary STEM, illustrating how theoretical concepts are directly applied in real-world problem solving. With further refinement and validation, such systems could complement national early warning infrastructures and empower local communities to respond proactively to environmental risks.

VIII. ACKNOWLEDGMENT

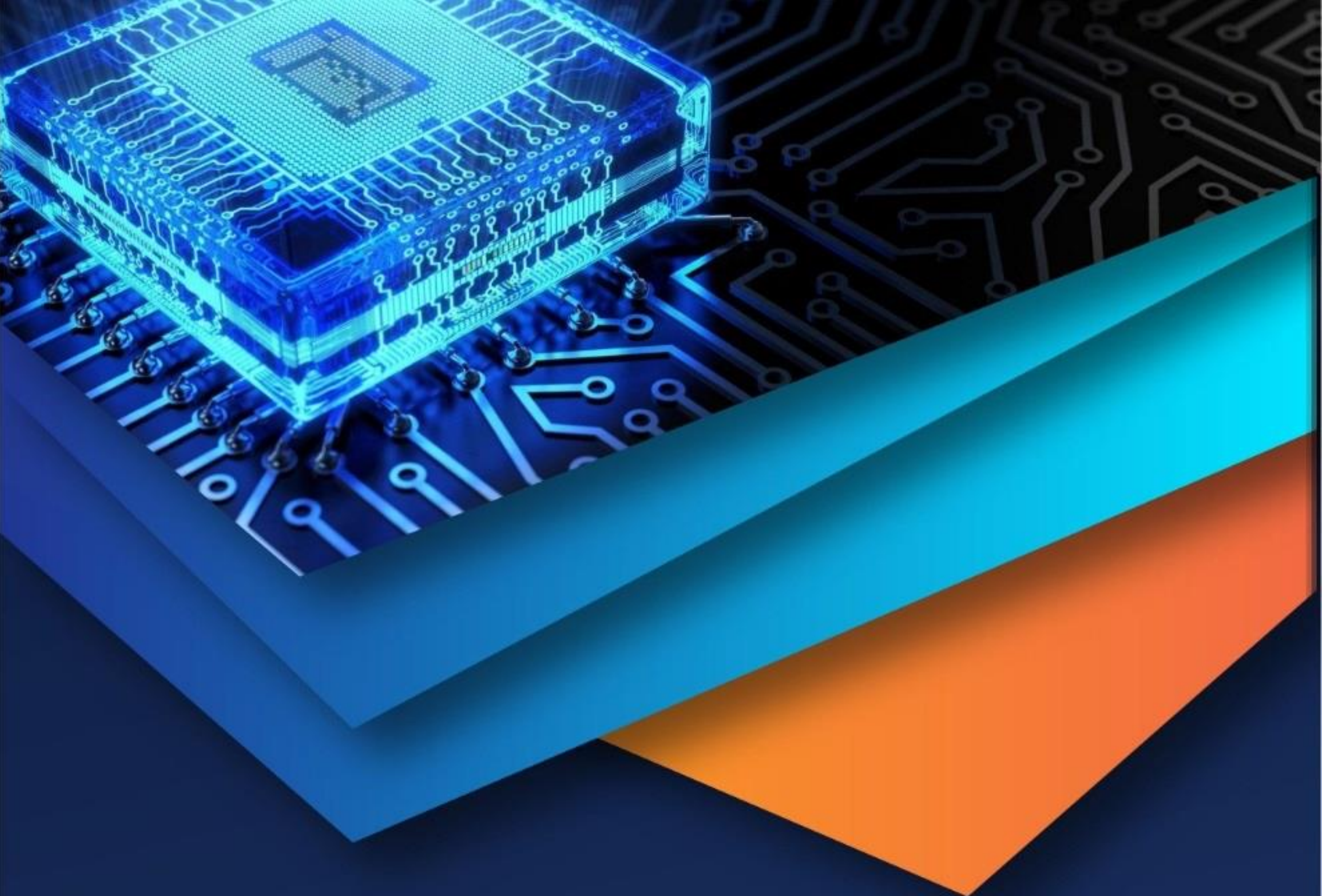
The authors gratefully acknowledge the support and guidance of:

1) Principal Varghese Samuel, for institutional support and encouragement.
2) Pravitha Ma'am, for technical mentorship in AI and system design.
3) Mrs. Mary Mathew, for administrative support and motivation.
4) Rajashekaran AH, for assistance in procuring and integrating sensor components.
5) St Thomas Central School, for providing laboratory facilities and a culture of innovation.

REFERENCES

[1] United Nations Office for Disaster Risk Reduction (UNDRR), Global Assessment Report on Disaster Risk Reduction 2023, 2024.
[2] National Disaster Management Authority (NDMA), India, Annual Report 2022–23, Ministry of Home Affairs, Government of India, 2023.
[3] Indian Bureau of Geology and Mines (IBGM), National Assessment of Flood Risk in India, Ministry of Mines, 2023.
[4] Intergovernmental Panel on Climate Change (IPCC), Climate Change 2023: Synthesis Report, Sixth Assessment Report, 2023.
[5] Ministry of Earth Sciences (MoES), India, Evaluation Report on Early Warning Systems for Natural Hazards, Government of India, 2022.
[6] Central Water Commission (CWC), India, Flood Response and Early Warning Dissemination: Operational Analysis, Department of Water Resources, 2023.
[7] Disaster Management Institute, Bhopal, Accessibility of Early Warning Systems in Rural India: A Survey Report, 2022.
[8] D. Singh and D. Raghuwanshi, Multi-sensor data fusion for agricultural disaster monitoring, Journal of Applied Remote Sensing, vol. 17, no. 3, 2023.
[9] D. Kahneman and A. Tversky, Judgment under Uncertainty: Heuristics and Biases, Cambridge University Press, 1982.
[10] A. Nagarajan and R. Jayadeva, Real-time Bayesian inference for environmental monitoring using lightweight neural networks, IEEE Sensors Journal, vol. 21, no. 8, 2021.
[11] P. Sharma and A. Gupta, IoT-based flood early warning systems: A systematic review, Water Resources Management, vol. 37, 2023.
[12] Government of India, Ministry of Disaster Management, Integrated Disaster Management and Atmanirbhar Bharat: Strategic Framework, 2022.
[13] T. Chakraborty and S. Prakash, Artificial intelligence for environmental disaster prediction in developing nations: A scoping review, Frontiers in Climate, vol. 4, 2022.
[14] MIT D-Lab and UN-Habitat, Accessible technology for disaster risk reduction in low-resource settings, Technology Review South Asia, 2023.

[15] Indian Institute of Technology Mandi, AI-driven Landslide Early Warning in Himachal Pradesh: Pilot Study, 2023.
[16] World Bank, South Asia Climate and Disaster Risk Assessment, Report No. WB/SDRA-2023, 2023.
[17] V. Rao, R. Saxena, and S. Mehta, Bayes' theorem applications in natural hazard forecasting: A mathematical framework, Indian Journal of Geophysics, vol. 34, 2023.
[18] Ministry of Science and Technology, Government of India, Patent Landscape: Environmental Monitoring Technologies, 2023.
[19] United Nations, Sendai Framework for Disaster Risk Reduction 2015–2030, 2015.
[20] N. Arora and R. Verma, Machine learning for multi-hazard disaster detection in urban India: A case study approach, Journal of Disaster Risk Science, vol. 8, no. 2, 2024.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY