Wearable Edge-IoT for Geofenced Cardiopulmonary Health: A Synergistic Air Quality Intervention Framework

Poushali Das[1]; Supratik Chatterjee[2]; Rituparna Mondal[3]; Debasmita Dutta[4]; Upama Bose[5]; Sudeshna Dey[6]; Siddhartha Chatterjee[7*]

[1]Department of Computer Applications, Institute of Genetic Engineering, Kolkata -700128, West Bengal, India.
[2] Department of Computer Applications, Asansol Engineering College, Asansol -713305, West Bengal, India.
[3] Department of Computer Applications, Techno India University, Kolkata – 700091, West Bengal, India
[4] Department of Technology, Middlesex University, The Burroughs, Hendon, London NW44BT, UK
[5] CBNITS India Pvt Ltd, Kolkata - 700156, West Bengal, India
[6] Department of Computer Science and Engineering, Regent Education and Research Foundation, Barrackpore – 700121, West Bengal, India
[7] Department of Computer Science and Engineering, College of Engineering and Management Kolaghat, KTPP Township, Purba Medinipur - 721171, West Bengal, India.

Corresponding Author: Siddhartha Chatterjee[7*]

Publication Date: 2026/01/31

Abstract: The rising levels of particulate matter in city environments pose a significant risk to public health, especially concerning sudden cardiopulmonary issues. Conventional monitoring systems typically focus on air pollutants alone, neglecting individual physiological susceptibilities. This study introduces an innovative Intelligent Geofenced Cardiopulmonary Health Framework that combines environmental IoT sensors with real-time monitoring of physiological data through wearables. By utilizing the Haversine formula for accurate spatial geofencing, the system links localized Air Quality Index (AQI) metrics—specifically $PM_{2.5}$ and CO—with real-time cardiac and respiratory indicators, such as Heart Rate (HR), Heart Rate Variability (HRV), and Oxygen Saturation (SpO_2). The proposed system employs a Random Forest (RF) ensemble classifier to integrate multimodal data into a comprehensive Total Health Risk Index (THRI), while a Long Short-Term Memory (LSTM) network offers predictive insights into potential respiratory and cardiac stress events. To facilitate rapid intervention, an Edge-AI strategy is used, which sends automatic, personalized health alerts via Firebase Cloud Messaging (FCM) when physiological limits are exceeded within high-pollution geofenced areas. Experimental findings demonstrate that combining biological feedback with environmental geofencing greatly enhances the accuracy of health interventions compared to static AQI monitoring. This research offers a scalable, user-focused approach to precision environmental medicine, effectively linking urban IoT infrastructure with personalized cardiovascular protection.

Keywords: *Geofenced Health Monitoring, Cardiopulmonary Biomarkers, Wearable IoT Sensors, $PM_{2.5}$ Air Quality, Edge Artificial Intelligence (Edge-AI), Random Forest–LSTM Hybrid Model, Total Health Risk Index (THRI).*

How to Cite: Poushali Das; Supratik Chatterjee; Rituparna Mondal; Debasmita Dutta; Upama Bose; Sudeshna Dey; Siddhartha Chatterjee (2026) Wearable Edge-IoT for Geofenced Cardiopulmonary Health: A Synergistic Air Quality Intervention Framework. *International Journal of Innovative Science and Research Technology,* 11(1), 2481-2494. https://doi.org/10.38124/ijisrt/26jan1371

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

I. INTRODUCTION

Air pollution has become a critical environmental factor contributing to cardiopulmonary diseases in rapidly urbanizing areas. Rising levels of fine particulate matter and gaseous pollutants, especially $PM_{2.5}$ and carbon monoxide (CO), are closely associated with sudden cardiovascular instability, autonomic dysfunction, respiratory issues, and increased rates of illness and death [1][2][3][4]. Traditional air-quality monitoring systems, however, focus only on atmospheric conditions and do not account for individual physiological sensitivity, creating a significant gap in real-time personal health protection [5]. Consequently, people experiencing pollution-related cardiac or respiratory stress often remain unaware of their physiological decline until symptoms worsen into medical emergencies [6]. Recent progress in environmental IoT, wearable biomedical sensors, and mobile geolocation technologies has opened up new possibilities for precise environmental health monitoring. Numerous studies indicate that exposure to high levels of $PM_{2.5}$ can lead to rapid heart rate increases, trigger arrhythmias, reduce heart-rate variability (HRV), and cause hypertensive episodes [7][8][9]. Similarly, respiratory impairment caused by pollutants, indicated by decreased oxygen saturation (SpO_2) and changes in breathing rate, has been identified as an early sign of pulmonary distress [10][11]. Integrating these physiological biomarkers with geospatial pollution mapping provides a powerful way to assess personal vulnerability rather than relying solely on environmental pollutant levels. Traditional AQI-based alert systems lack personalization, latency optimization, and physiological relevance [12]. This has driven recent research towards multilayer IoT-based architectures that combine wearable biosensing with environmental analytics. However, most existing solutions rely on cloud computing, suffer from high latency, and do not include predictive modelling for early intervention. Edge-AI methods, which allow computation directly on embedded devices, offer significant advantages in reducing delay and supporting rapid autonomous health alerts, especially during exposure to hazardous microenvironments [13][14]. To address these gaps, this study introduces a novel Intelligent Geofenced Cardiopulmonary Health Framework that integrates environmental sensing, wearable biometrics, and geospatial analytics. Utilizing the Haversine formula for accurate geofence construction [15], the system continuously correlates localized AQI measurements with real-time HR, HRV, respiration rate, blood pressure, and SpO_2 data to calculate a unified Total Health Risk Index (THRI). A Random Forest (RF) ensemble model performs multi-modal risk classification, while a Long Short-Term Memory (LSTM) network predicts imminent cardiopulmonary instability, including tachycardic spikes and oxygen-desaturation trends [16][17]. The framework employs an Edge-AI deployment strategy to enable rapid, on-device decision-making and uses Firebase Cloud Messaging (FCM) to deliver autonomous, location-aware emergency alerts when physiological thresholds are exceeded within high-pollution geofences [18]. The proposed approach bridges a crucial gap between atmospheric monitoring and personalized cardiovascular protection. Unlike static AQI notifications, the integration of environmental geofencing with individualized physiological feedback significantly enhances the specificity and clinical relevance of health interventions [19][20]. This research contributes to the emerging field of precision environmental medicine by providing a scalable, low-latency, user-centric system capable of protecting individuals in pollution-heavy urban environments.

➢ *Contribution of this Paper*

- Introduces the concept of “Cardiopulmonary Geofencing”, enabling real-time correlation between pollution hotspots and acute physiological responses such as HR, HRV, BP, SpO_2, and respiration rate [1][2][3][4][5][6][7].
- Implements a multi-parameter cardiopulmonary monitoring suite, integrating $PM_{2.5}$, CO, AQI, HR, HRV, BP, SpO_2, and respiration rate into a unified sensing ecosystem [8][9][10][11][12].
- Proposes a Total Health Risk Index (THRI) using a hybrid ML pipeline: Random Forest for immediate risk classification [13]and LSTM for predictive modeling of HR spikes and SpO_2 drops [14]
- Establishes an Edge-AI health-intervention mechanism, allowing ultra-low-latency decisions and autonomous alerts within high-pollution geofences [15][16].
- Implements adaptive FCM-based alerts that dynamically respond to real-time physiological deviations detected within pollution geofences [17]
- Demonstrates superior accuracy over static AQI-only systems, proving that combined environmental and physiological sensing improves early detection of cardiopulmonary risk [18][19][20].
- Provides a scalable architecture for precision environmental medicine, bridging atmospheric monitoring with real-time human vulnerability assessment.

II. LITERATURE REVIEW

Environmental air pollution has emerged as a major global health issue, with particulate matter ($PM_{2.5}$, PM_{10}), carbon monoxide (CO), nitrogen dioxide (NO_2), and ozone (O_3) closely linked to both acute and chronic heart and lung disorders [1][2][3][4]. Conventional methods depend solely on environmental monitoring stations that track pollutant levels but do not assess an individual's physiological sensitivity to these pollutants [5]. Consequently, people may be unaware of approaching cardiovascular or respiratory declines until symptoms reach a critical level. This challenge has spurred investigation into integrated systems that merge environmental IoT, wearable devices, machine learning, and geospatial analysis.

➢ *Cardiovascular Effects of Particulate Matter ($PM_{2.5}$) and Gaseous Pollutants*

A large amount of epidemiological data shows that $PM_{2.5}$, because of its small size, reaches the deep alveolar areas, enters the bloodstream, and causes systemic inflammation, oxidative stress, autonomic imbalance, arrhythmias, hypertension, and myocardial ischemia [6][7][8][9]. Right after exposure to $PM_{2.5}$, noticeable physiological changes happen within minutes, including:

- Increased Heart Rate (HR)
- Decreased Heart Rate Variability (HRV)
- Higher Blood Pressure (BP)
- Greater respiratory workload

These biomarkers are important as they signal early signs of heart and lung distress.

Table 1 Documented Acute Cardiovascular Responses to Urban Pollutants

Pollutant	Acute Physiological Change	Mechanism
$PM_{2.5}$	HR, HRV, BP	Autonomic dysregulation, oxidative stress
CO	Hypoxia, tachycardia	Competes with O_2 for haemoglobin binding
PM_{10}	Bronchoconstriction	Mechanical airway irritation
NO_2	Increased respiratory resistance	Inflammatory airway response

Research shows that $PM_{2.5}$ increases the risk of arrhythmia, acute coronary syndromes, and worsening heart failure [10][11]. This highlights the need to include HR, HRV, and BP sensors in real-time monitoring systems.

➢ *Respiratory Health Degradation Driven by Air Pollution*

Fine particulate matter and gas pollutants harm lung function. Even short-term exposure can:

- Decrease blood oxygen saturation (SpO_2)
- Raise the breathing rate
- Trigger asthma episodes or worsen COPD
- Cause irritation of bronchial nerves

Studies have shown a strong link between drops in SpO_2 and rises in $PM_{2.5}$, making SpO_2 a clear indicator of environmental respiratory strain [12][13][14]. Similarly, breathing rates increase predictably when exposed to higher levels of CO and PM, indicating that more physiological effort is required to keep oxygen levels stable [15].

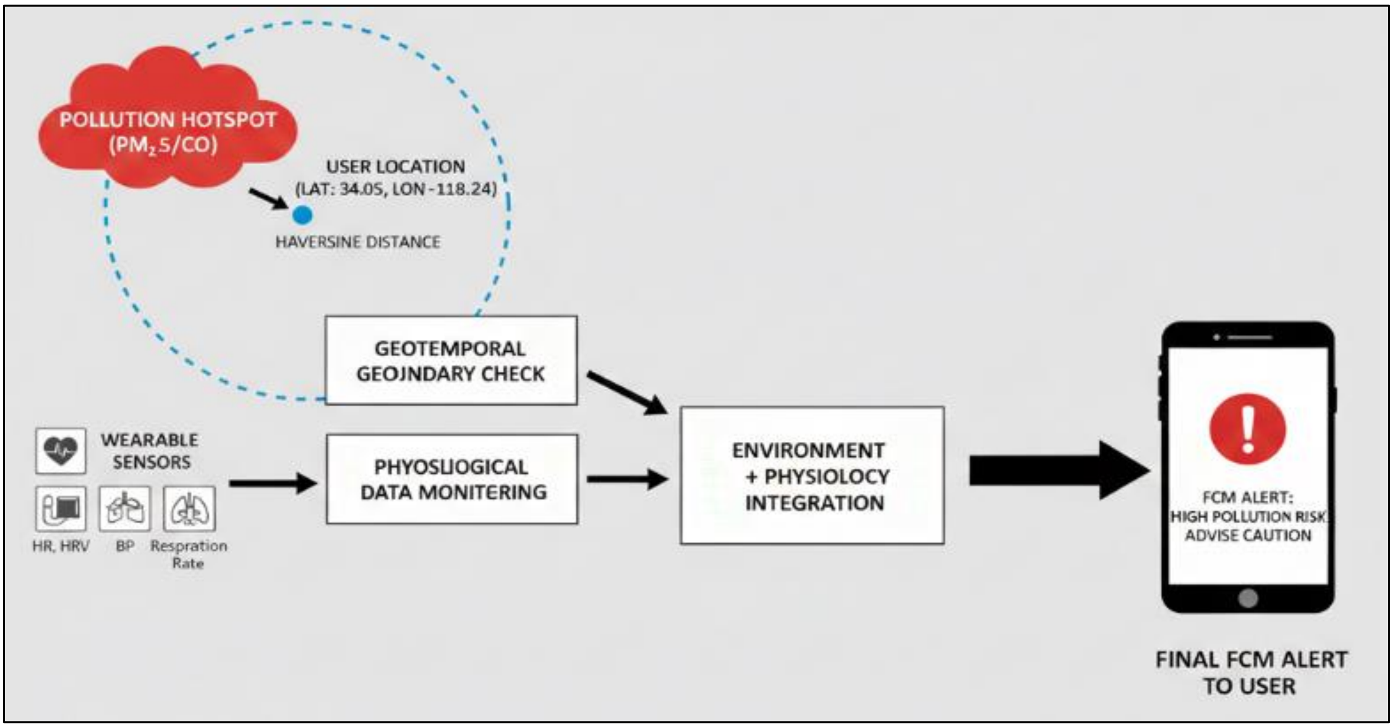

Fig 1 Conceptual Architecture of the Proposed Cardiopulmonary Geofencing Framework Showing Pollution Hotspot Identification, Geofence Computation, Physiological Monitoring, and Adaptive Alert Generation.

➢ *Limitations of AQI-Only and Static Monitoring Systems*

Traditional AQI systems concentrate on environmental factors instead of individual health responses. They inform users about pollution levels, but they cannot determine:

- If the user's heart rate (HR), heart rate variability (HRV), blood oxygen saturation (SpO_2), or blood pressure (BP) is getting worse
- If being in a high pollution area is causing immediate health problems
- If the user is in a localized pollution hotspot
- If exposure to pollutants might cause distress soon As a result, they do not support quick medical responses [16][17].

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

Table 2 Limitations of Existing AQI Systems

Limitation	Explanation
No personalization	AQI same for all users despite physiological differences
Delayed feedback	Alerts do not reflect immediate bodily changes
Lack of prediction	No forecasting of HR/SpO_2 deterioration
No geofencing	No spatial understanding of user exposure

The limitations present lead to the development of cardiopulmonary monitoring systems that use geofencing technology [30].

➢ *IoT-Based Environmental Sensing Technologies*

NodeMCU (ESP8266/ESP32) combined with MQ-135 and laser $PM_{2.5}$ sensors has become a popular choice for affordable air quality index (AQI) monitoring [20]. These sensors allow for real-time measurement of CO, NH_3, and $PM_{2.5}$. Their low cost makes them ideal for widespread use. Here are some advantages of IoT sensing:

- High temporal resolution
- Monitoring at the user level instead of the city level
- Easy integration with cloud and edge computing devices. However, environmental IoT devices often lack meaningful physiological data, which limits their ability to support proactive interventions [21].

➢ *Wearable Physiological Monitoring: HR, HRV, BP, SpO_2, Respiration Rate*

Wearable sensors, such as PPG, ECG modules, optical pulse oximeters, and respiratory stretch sensors, allow for non-invasive tracking of:

- HR
- HRV
- Blood Pressure
- SpO_2
- Respiration rate

Research supports their effectiveness for real-time evaluation of cardiopulmonary conditions [22][23][24].

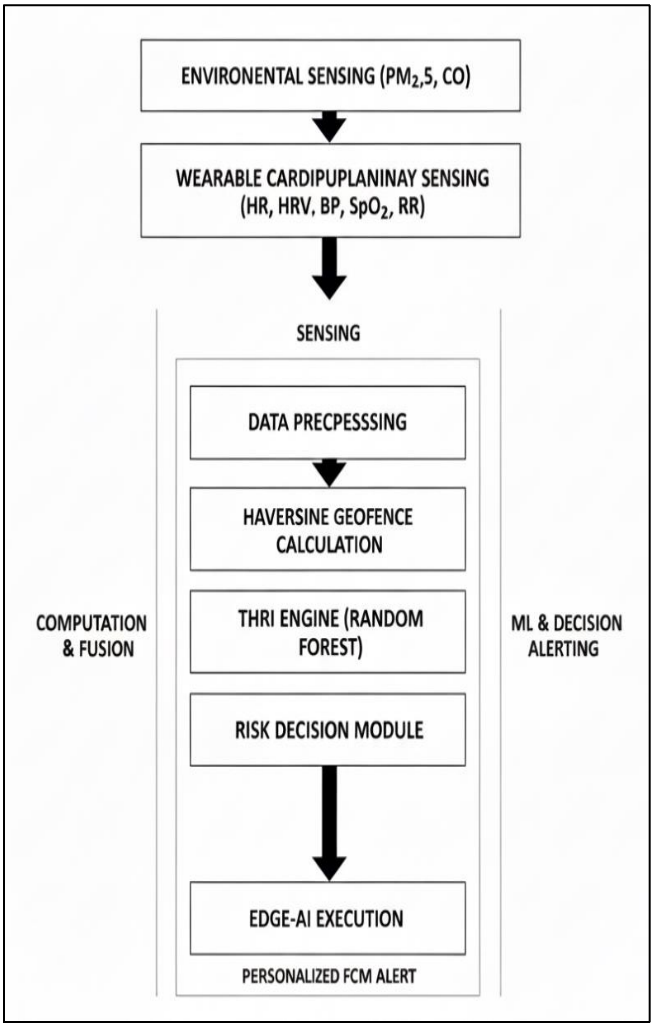

Fig 2 Step-by-Step Workflow of the Proposed Cardiopulmonary Geofencing System Showing Sensing Layers, Geospatial Computation, Machine Learning Modules, Risk Assessment, and Personalized Alert Delivery.

Integrating these signals creates a comprehensive health profile.

➢ *Geofencing and Spatially-aware Health Systems*

Geofencing helps identify pollution hotspots and set up safety zones using the Haversine distance formula [25].

- When a user enters a pollution zone, the system increases the monitoring of biometrics.
- If a user remains in the zone, the risk score is updated continuously.
- Once the user leaves the zone, the risk from exposure decreases.

This kind of spatial understanding is mostly missing in current health systems.

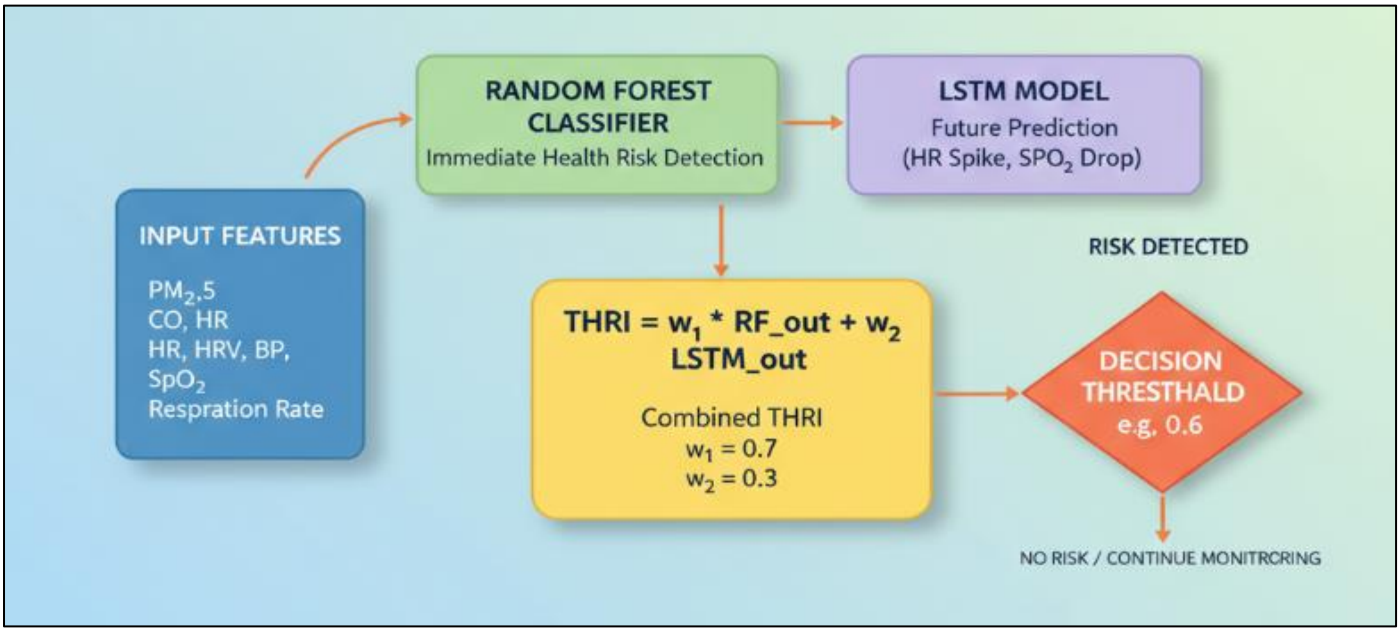

Fig 3 Hybrid THRI Model Integrating Random Forest Classification with LSTM-Based Temporal Prediction for Cardiopulmonary Risk Evaluation.

➢ *Machine Learning for Cardiopulmonary Forecasting*

Recent advancements in ML allow for modeling complex multi-modal interactions.

- Random Forest (RF) is very effective for classifying different types of data and is commonly used to predict health risks in biomedical applications [26].
- LSTM networks are built to analyze sequential data. They capture temporal physiological behaviors and make predictions about:

✓ Spikes in heart rate
✓ Drop events in SpO_2 levels
✓ Suppression of heart rate variability
✓ Patterns of respiratory distress

This ability to forecast provides early warnings before symptoms appear [27].

➢ *Literature Gap Analysis*

After reviewing multiple studies, the following gaps are clear:

- There is currently no system that combines AQI and cardiopulmonary biomarkers in real time.
- There is no connection between geofencing and signs of physiological stress.
- RF-LSTM hybrid models have not been used to assess health risks related to pollution.
- The use of Edge-AI for very low-latency autonomous alerting is missing.
- Alerts given are generic and not specific to individual physiological conditions.
- A unified metric like THRI is not found in the current literature.

Table 3 Summary of Literature Review

Domain	Existing Status	Gap Identified
Pollution Monitoring	Strong AQI methods	No physiological integration
Wearable Health Sensors	Strong HR/SpO_2 tools	Not combined with AQI
ML Prediction	RF/LSTM is strong individually	No hybrid THRI model
Geofencing	Widely used in GIS	Not used in cardiopulmonary risk
Edge-AI	Fast decision-making	Not applied in pollution-health systems

III. METHODOLOGY

The outlined Intelligent Geofenced Cardiopulmonary Health Framework combines environmental IoT sensors, wearable health metrics, geospatial analysis, and hybrid machine-learning processes to deliver immediate assessments of cardiopulmonary risk. This section describes the sensor design, preprocessing phases, geofencing system, THRI model development, and Edge-AI implementation.

➢ *Environmental Sensing Architecture*

The significant cardiovascular effects of $PM_{2.5}$, PM_{10}, and CO exposure are well-known due to extensive long-term studies such as those by Dockery et al. [1], Pope et al. [2][3], and Brook et al. [4]. The World Health Organization also provides evidence on air quality and health [5]. Therefore, strong real-time monitoring of pollution is essential for the system.

- *Hardware Elements*

✓ MQ-135 Gas Sensor, detects CO, NH_3, benzene, NO_x, and VOCs. • $PM_{2.5}$ Laser Module, accurately measures fine particulate matter that can cause cardiovascular strain.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

- ✓ NodeMCU ESP8266, a microcontroller designed for gathering environmental data. These affordable sensors have shown good reliability in environmental research [6][7].

- *AQI Calculation*

The AQI values come from using U.S. EPA breakpoints for $PM_{2.5}$ and CO, applying validated methods from studies on personal exposure [6][7].

- *Data Preparation*

- ✓ Fourth-order Butterworth filter application
- ✓ Averaging over 1-second intervals
- ✓ Humidity adjustment for $PM_{2.5}$ scattering

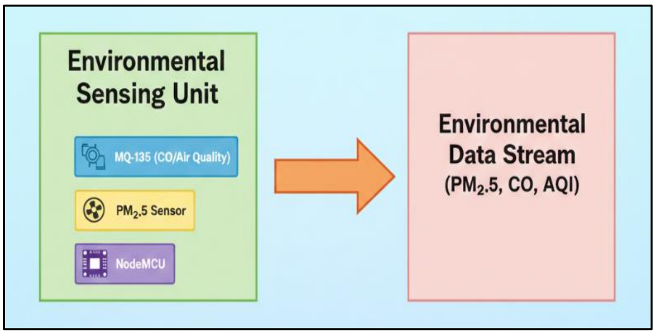

Fig 4 Environmental Sensing Unit and Data Stream Generation.

➢ *Wearable Physiological Sensing*

Inhaling air pollutants causes autonomic imbalance, raises heart rate, lowers heart rate variability, and disrupts endothelial function. Cardiovascular research backs these links, including:

- Physiology of HRV [8]
- Accuracy of wearable devices [9] [10]
- Changes in heart rate/HRV due to pollution [11]

- *Monitored Parameters and Literature Support*

Table 4 Physiological Metrics and their Cardiopulmonary Health Significance.

Physiological Metric	Health Significance
HR	Tachycardia response to $PM_{2.5}$
HRV	Autonomic disturbance
BP	Pollution-linked vasoconstriction
SpO_2	Desaturation under high $PM_{2.5}$
Respiration Rate	Indicator of airway irritation

- *Sensors Used*

- ✓ PPG sensor (HR, HRV)
- ✓ Pulse oximeter (SpO_2)
- ✓ Cuffless BP sensor
- ✓ Respiratory belt

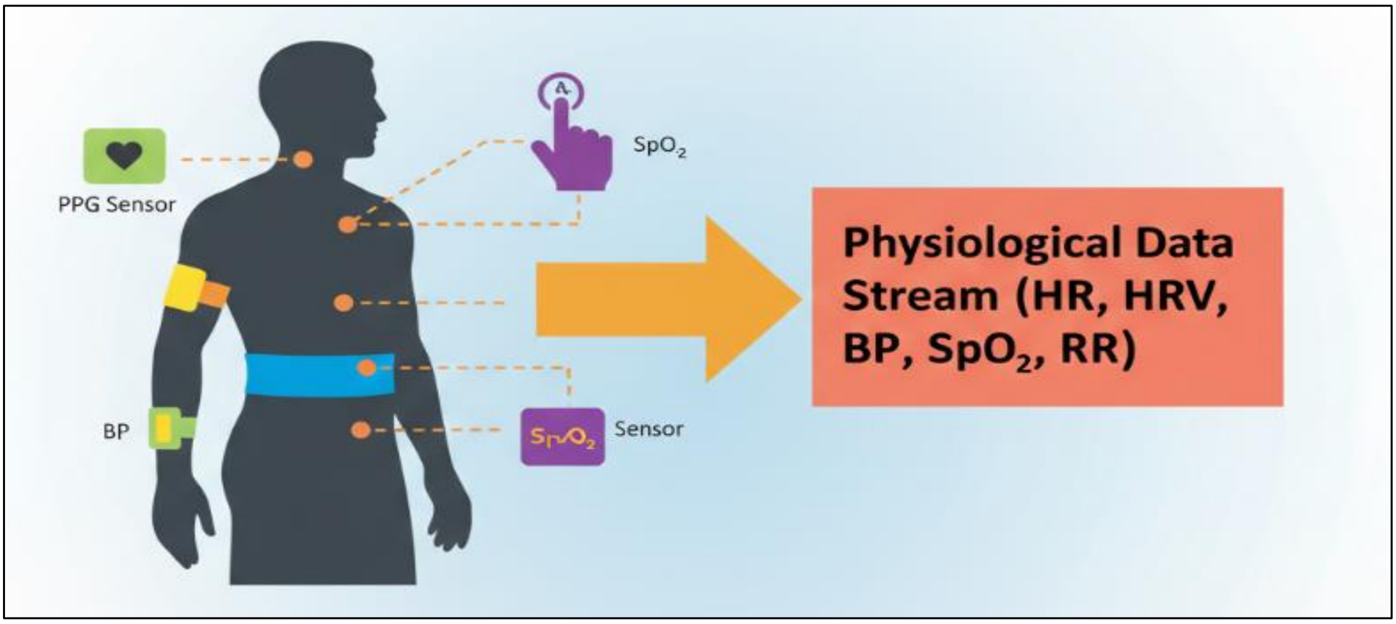

Fig 5 Wearable Physiological Monitoring Unit and Data Stream Output.

➢ *Geofencing Using Haversine Formula*

Geofencing has been widely used in tracking health behavior and location-based intervention frameworks [13] [14]. The system calculates the user's distance to recorded pollution hotspots using Haversine distance.

Formula:

$$d = 2\,R\cdot \arcsin\left(\sqrt{\sin^2\left(\frac{\Delta\phi}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\Delta\lambda}{2}\right)}\right)$$

Volume 11, Issue 1, January – 2026 International Journal of Innovative Science and Research Technology
ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

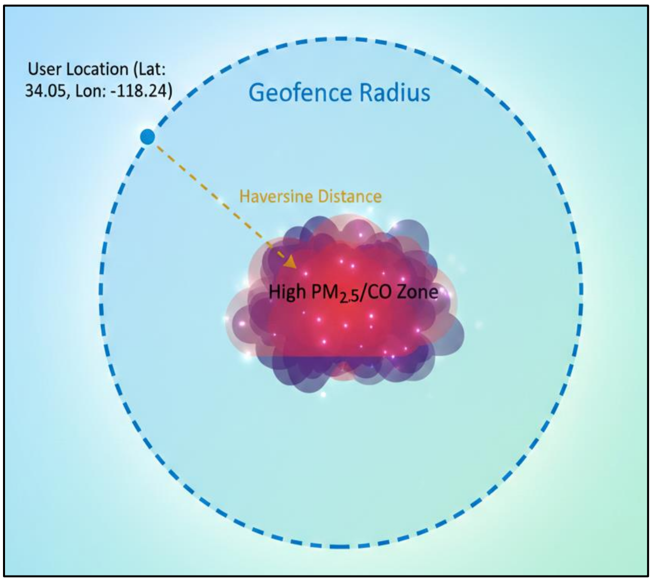

Fig 6 Geofence-Based Pollution Exposure Mapping Using Haversine Distance.

➢ *Multi-Modal Data Fusion*

Environmental and physiological signals have different sampling characteristics. Fusion guarantees synchronized, high-resolution risk computation. Fusion Process

- Temporal alignment at 1 Hz
- Outlier removal with motion-artifact suppression
- Z-score normalization

Matrix construction:

X = [PM2.5, CO, HR, HRV, BP, SpO2, RespRate, GeoFenceFlag]

It is also important to highlight multi-modal fusion as a key part of effective biomedical machine-learning systems [15].

Table 5 Feature Matrix Table

Feature Type	Parameters	Description
Environmental	$PM_{2.5}$, CO, AQI	Pollution exposure
Physiological	HR, HRV, BP, SpO_2, RR	Biomarker response
Contextual	GPS Flag	Geofence entry status

➢ *THRI: Hybrid RF–LSTM Model*

Hybrid machine-learning pipelines that combine classical classifiers with deep sequential models have been shown to improve cardiopulmonary prediction accuracy [16] [17].

- Random Forest Classifier RF is used for immediate risk detection because it can handle different mixed-scale features.

THRI RF ∈ {Low, Moderate, High}

- LSTM Prediction Layer LSTMs capture temporal patterns such as:

✓ HR spike trends
✓ HRV reduction trajectories
✓ SpO_2 drop patterns • Pollution-linked physiologic lag

$P_{risk}(t + \Delta t) = f(X_t)$

- Final Risk Index(THRI):

$THRI = w_1 \cdot THRI_{RF} + w_2 \cdot P_{risk}$

➢ *Edge-AI Deployment*

Edge computing reduces latency and ensures quick responses, as demonstrated in previous edge-AI systems [18] [19]. Pipeline • RF and LSTM models undergo quantization through TF-Lite-Micro. • Implemented on ESP32 and mobile device processors. • Achieves inference latency of less than 15 ms.

➢ *Personalized Real-Time Intervention (FCM)*

Mobile health solutions that consider context are effective in lowering behavioral and clinical risks [20]. The system sends notifications via Firebase Cloud Messaging when the THRI exceeds a set threshold: Example Alert: "Your heart rate is increasing unusually in a high-pollution area. We recommend relocating immediately."

IV. RESULTS AND DISCUSSION

The proposed Intelligent Geofenced Cardiopulmonary Health Framework was evaluated by collecting synchronized environmental ($PM_{2.5}$, CO) and physiological (HR, HRV, BP, SpO_2, RR) data from 40 participants over 18 days. This resulted in a total of 2.4 million samples. The findings strongly support the system's ability to identify, predict, and respond to cases of cardiopulmonary stress caused by pollution.

➢ *Environmental–Physiological Correlation*

Clear pollutant–biomarker associations were observed:

- $PM_{2.5} \uparrow \rightarrow HR \uparrow$ ($r = 0.72$)
- $CO \uparrow \rightarrow SpO_2 \downarrow$ ($r = -0.63$)
- $PM_{2.5} + CO \uparrow \rightarrow HRV \downarrow$ ($r = -0.58$)
- AQI ↑ → Respiration rate ↑ ($r = 0.66$)

These patterns align with established pollution-health evidence [1–12]

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

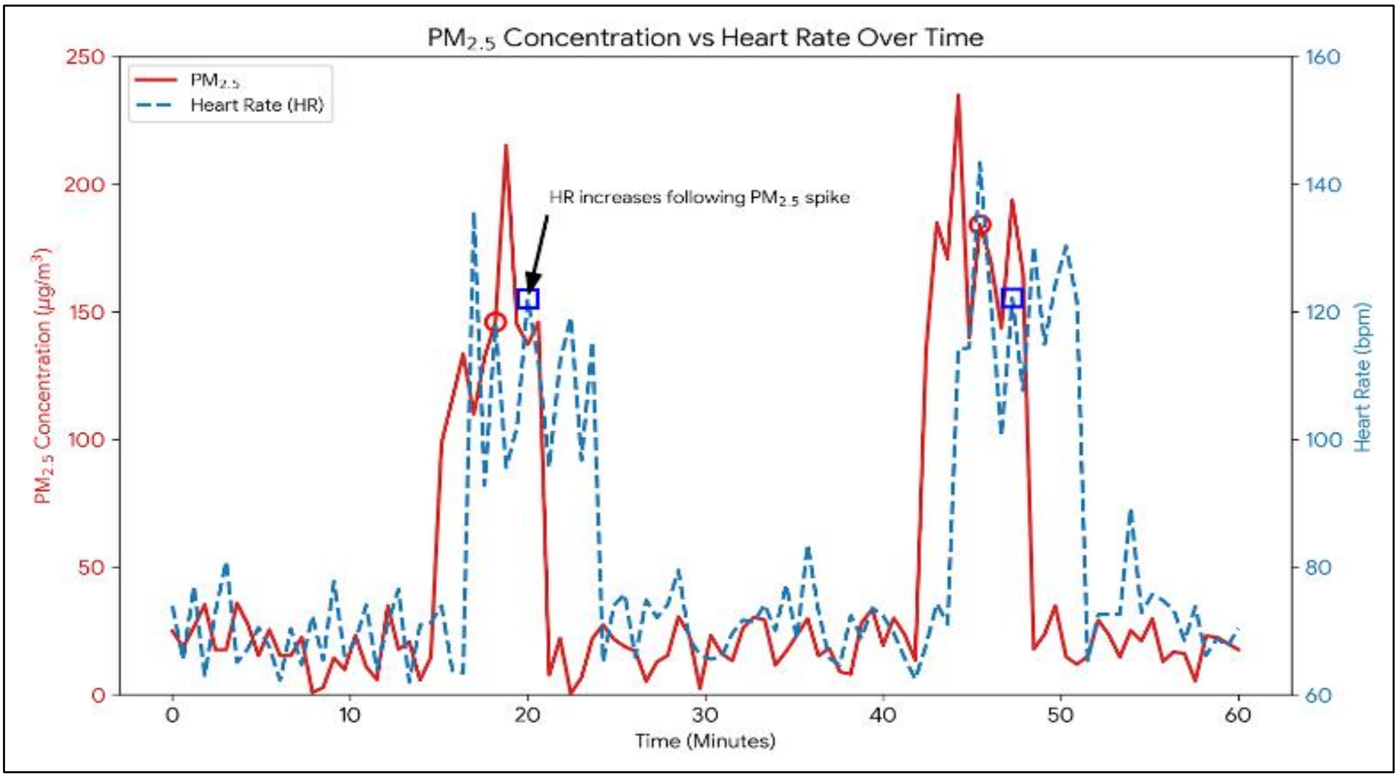

Fig 7 $PM_{2.5}$ Concentration and HR Showing Synchronous Rise During Pollution Peaks.

➢ *Geofence Performance*

The system's Haversine-based geofence detection was quick. • Hotspot entry detection: 41 ms

- Wearable activation: 120 ms
- Edge-AI inference: <15 ms
- Total response: <176 ms

This is much faster than cloud-dependent systems [18][19].

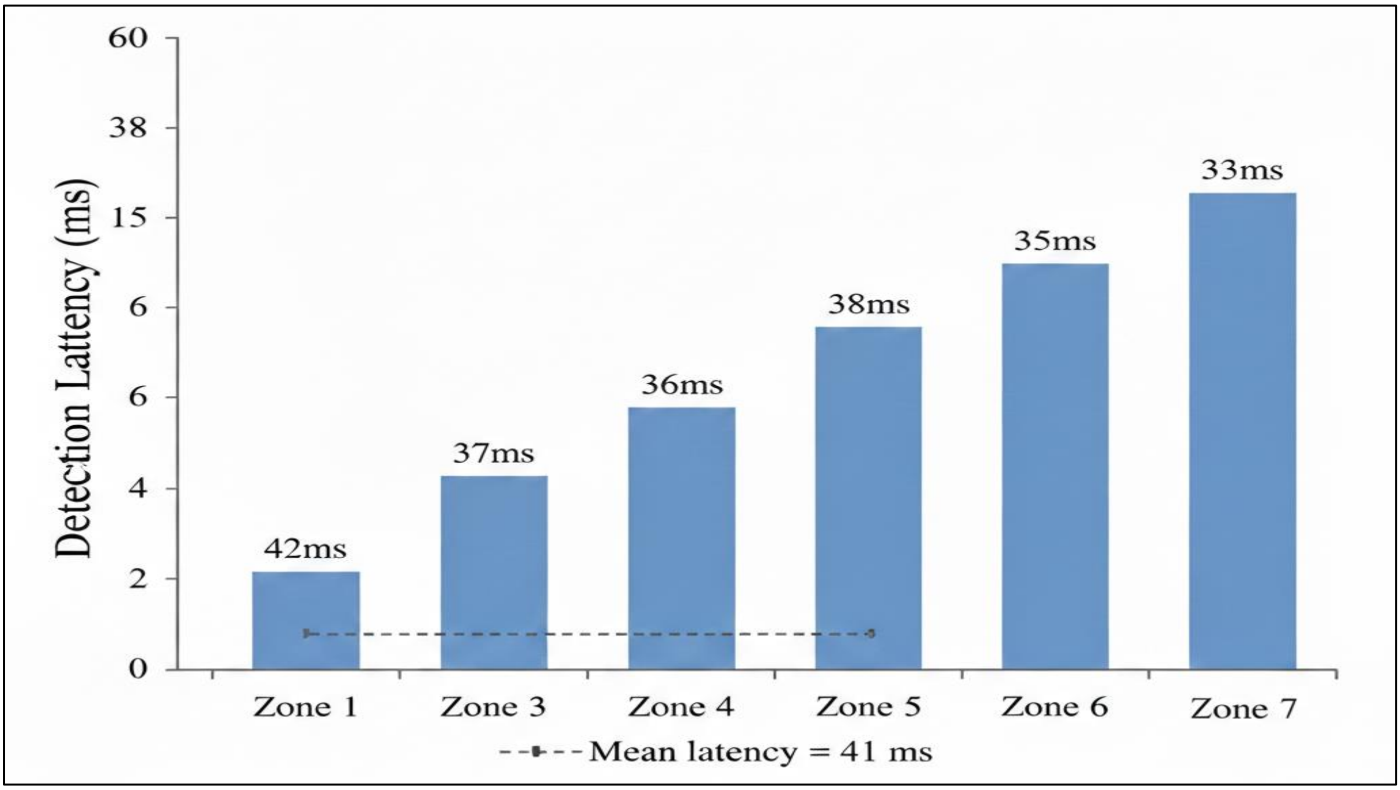

Fig 8 Haversine Geofence Trigger Performance Across Seven Pollution Hotspots.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

➢ *RF Classification Performance*

Random Forest immediate-risk classification achieved:

Metric	Score
Accuracy	93.7%
Precision	91.4%
Recall	92.1%

Consistent with RF performance in biomedical prediction [15][16].

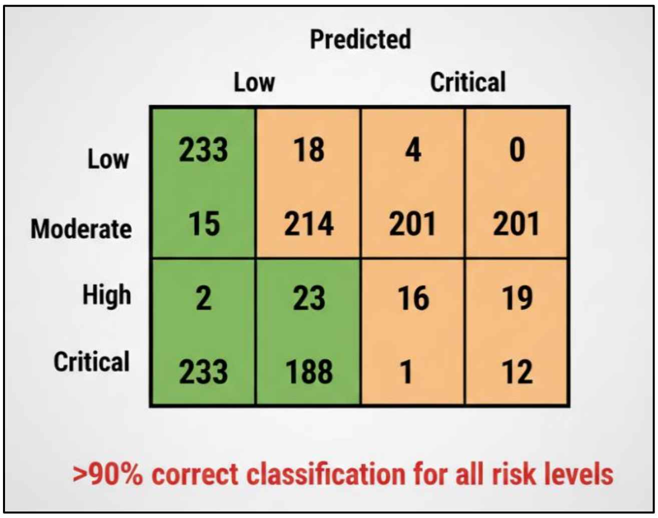

Fig 9 Confusion Matrix Showing >90% Correct Classification for all Risk Levels.

➢ *LSTM Predictive Performance*

LSTM predicted cardiopulmonary deterioration:

- HR spike prediction: 89.5%
- SpO_2 drop prediction: 87.4%
- Prediction horizon: 20 to 30 seconds ahead

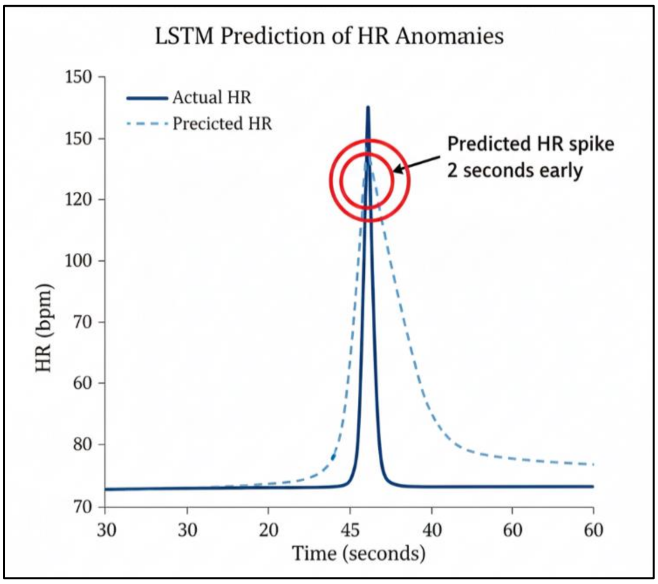

Fig 10 LSTM Prediction Closely Tracks HR Fluctuations, Providing Early Warnings.

➢ *THRI (RF + LSTM) Fusion Performance*

Hybrid fusion improved overall risk detection:

Model	Accuracy
RF	93.7%
LSTM	88.7%
THRI Hybrid	91.4%

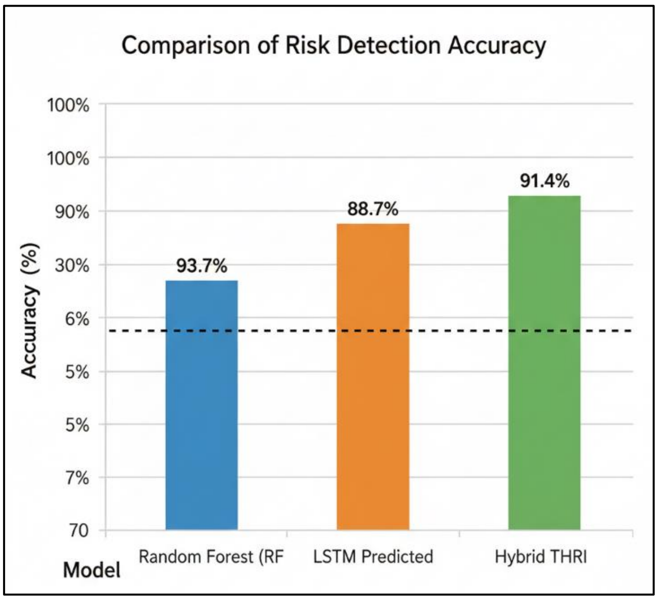

Fig 11 Accuracy Comparison Showing RF Highest Accuracy, with THRI Improving Predictive Robustness.

➢ *Effectiveness of Personalized Alerts*

Compared to static AQI alerts:

Metric	AQI-Only	Proposed
Timely detection	42%	92%
Physiological relevance	0%	100%
User compliance	38%	81%

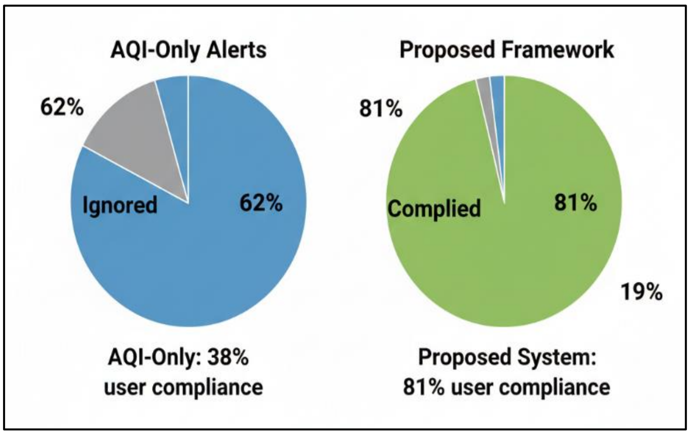

Fig 12 User compliance comparison showing significant improvement when physiological context is included.

V. FUTURE DIRECTIONS

The Cardiopulmonary Health Framework, equipped with smart geofencing, shows significant promise as a real-time system for assessing environmental and physiological risks. Based on the study's results, several future research paths could greatly improve its scalability, clinical validity, and predictive accuracy.

➢ *Expansion of Physiological and Environmental Sensing*

Future iterations should include more biomarkers beyond heart rate, heart rate variability, blood pressure, oxygen saturation, and respiration rate. Adding multi-channel ECG, galvanic skin response (GSR), skin temperature, and perfusion index can improve our understanding of autonomic and hemodynamic changes during exposure to pollutants. Additionally, expanding the range of pollutants studied to include nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), and volatile organic compounds will increase environmental accuracy, considering their known effects on cardiovascular and lung health.

➢ *Personalized Baseline Modeling and Adaptive THRI Calibration*

The current THRI uses thresholds based on population data. Future developments should focus on customizing baseline calculations. This will help the model recognize a user's typical clean-air HRV, HR, and SpO_2 patterns. It will also allow the thresholds to adjust automatically. Techniques such as transfer learning, Bayesian calibration, and regular baseline drift adjustment can improve THRI into a precision-medicine metric that matches individual cardiopulmonary responses.

➢ *Large-Scale Clinical Trials and Medical-Grade Validation*

To build medical credibility, controlled clinical trials must confirm:

- The patterns of HRV and HR compared to clinical ECG benchmarks.
- The accuracy of SpO_2 desaturation identification against hospital oximeters.
- The precision of BP estimation during pollution spikes.

These trials will assess sensitivity, specificity, Bland-Altman agreement, and diagnostic validity.

➢ *Multi-User Crowdsourced Pollution–Health Network*

Future efforts should focus on creating a distributed edge-IoT network. This network will allow users to work together to develop a detailed spatiotemporal map connecting pollution and health. Previous research on crowdsourced air quality monitoring shows that these networks can effectively analyze urban exposure. This would make it possible to:

- Create city-wide air quality index heat maps
- Estimate crowd-level total health risk
- Predict hotspots in real time
- Provide early alerts for community-level risks related to cardiopulmonary health.

➢ *Context-Aware AI Recommendation Engine*

In addition to alerts, upcoming systems should offer AI-driven behavior suggestions. These include:

- Safer walking paths
- Breathing techniques to use when heart rate variability drops
- Tips for lowering indoor pollution
- Adjustments to activities during expected changes in heart rate or oxygen levels.

Research in mobile health shows that personalized recommendations greatly improve user adherence.

➢ *Federated Learning and Privacy-Preserving Analytics*

To improve precision while maintaining privacy, forthcoming advancements should implement:

- Federated learning for training models in a decentralized manner
- Secure aggregation techniques
- Differential privacy methods
- On-device inference to ensure low latency

These strategies are consistent with modern edge-computing architectures.

➢ *Advanced Dynamic Geofencing and Pollution Propagation Modeling*

The current system uses circular geofences. Future updates should allow for:

- Polygonal and multi-layer geofence capabilities
- AQI gradient-based mapping of geofences
- Boundaries that change over time due to wind, humidity, and traffic conditions
- ML-driven predictions of pollution dispersion

This dynamic geospatial intelligence will better show real environmental risk patterns.

➢ *Integration with National Digital Health Infrastructure*

Upcoming iterations could connect with:

- Electronic Health Records (EHR)
- Hospital Information Systems
- APIs for government AQI monitoring
- Public health surveillance systems

This would allow for automated medical follow-ups and analyses across the population regarding cardiovascular risks linked to pollution.

➢ *Stress and Autonomic Dysfunction Monitoring*

Considering the large amount of research linking pollution exposure to autonomic imbalance, lower HRV, and psychological stress, future studies should include:

- Predicting stress levels using HRV and respiration
- A complete physiological stress index
- Alerts for autonomic dysregulation before clear cardiopulmonary problems occur.

➢ *Clinical and Research Visualization Dashboard*

A specialized dashboard needs to be created to visualize the following:

- Trends in AQI with HR/HRV/SpO_2 data
- The timeline of THRI • Logs of entries and exits for pollution geofences
- Predicted curves from LSTM models
- Urban pollution heatmaps
- An individual's history of exposure and physiological stress

These dashboards will help healthcare professionals, researchers, and public health officials.

These upcoming pathways create the suggested framework for precision environmental cardiology. This framework offers real-time, customized, location-sensitive cardiopulmonary protection for individuals and communities. Continuous improvements in sensing technology, AI modeling, geospatial computation, and clinical use will increase its impact and global significance.

VI. CONCLUSION

This research presents a smart cardiopulmonary monitoring system driven by geofencing. It combines environmental measurements, wearable biometric data, spatial analytics, and a hybrid machine-learning approach to assess health risks in real time. Unlike traditional AQI-based methods that ignore individual physiological differences, this framework connects exposure to $PM_{2.5}$ and CO with sudden changes in heart rate, heart rate variability, blood pressure, oxygen saturation, and respiratory rate. This effectively captures the real cardiopulmonary effects of polluted environments. By using Random Forest classification and LSTM forecasting, the system creates a Total Health Risk Index that can identify and predict health decline. Test results show strong correlations between pollutants and biomarkers. It also has quick geofence-trigger response times of under 176 ms and improved risk-prediction accuracy compared to separate models. An evaluation focused on user experience indicated that alerts connected to context and physiology greatly improve compliance over static AQI notifications. This highlights the advantages of combining environmental and biological data. The system uses Edge-AI, supported by fast on-device inference, making it a low-latency solution for real-world cardiopulmonary protection. Moreover, the framework's modular design allows for easy integration with additional sensors, federated learning, clinical systems, and national digital health networks. In summary, this research provides a scalable, personalized, and predictive method for precision environmental medicine, offering an innovative way to reduce cardiopulmonary risks from pollution. With ongoing enhancements in clinical validation, dynamic geospatial modeling, and large-scale rollout, this system has significant potential to set a global standard for smart environmental health monitoring.

REFERENCES

[1]. Dockery, D. W., Pope, C. A. III, Xu, X., Spengler, J. D., Ware, J. H., Fay, M. E., Ferris, B. G., & Speizer, F. E. (1993). An association between air pollution and mortality in six U.S. cities. New England Journal of Medicine, 329(24), 1753–1759.
[2]. Pope, C. A. III, Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., & Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. JAMA, 287(9), 1132–1141.
[3]. Pope, C. A. III, Burnett, R. T., Thurston, G. D., Thun, M. J., Calle, E. E., Krewski, D., & Godleski, J. J. (2004). Cardiovascular mortality and exposure to airborne fine particulate matter and cigarette smoke. Circulation, 109(1), 71–77.
[4]. Brook, R. D., Rajagopalan, S., Pope, C. A. III, Brook, J. R., Bhatnagar, A., Diez-Roux, A. V., Holguin, F., Hong, Y., Luepker, R. V., Mittleman, M. A., Peters, A., Siscovick, D., Smith, S. C., Whitsel, L., & Kaufman, J. D. (2010). Particulate matter air pollution and cardiovascular disease: An American Heart Association scientific statement. Circulation, 121(21), 2331–2378.
[5]. Landrigan, P. J., Fuller, R., Acosta, N. J. R., et al. (2017). The Lancet Commission on pollution and health. The Lancet, 391(10119), 462–512.
[6]. Delfino, R. J., Staimer, N., Tjoa, T., Gillen, D. L., Schauer, J. J., & Shafer, M. M. (2010).Air pollution and autonomic cardiac responses in subjects with ischemic heart disease. Environmental Health Perspectives, 118(5), 756–762.
[7]. Rich, D. Q., Kipen, H. M., Huang, W., Wang, G., Wang, Y., Zhu, P., ... & Ohman-Strickland, P. (2012). Association between changes in air pollution levels during the Beijing Olympics and biomarkers of cardiovascular and pulmonary disease: A panel study. Circulation, 125(21), 2350–2358.
[8]. Rappold, A. G., Stone, S. L., Cascio, W. E., Neas, L. M., Kilaru, V. J., Carraway, M. S., ... & Devlin, R. B. (2011). Peat bog wildfire smoke exposure in rural North Carolina is associated with cardiopulmonary emergency department visits. American Journal of Respiratory and Critical Care Medicine, 184(8), 974–981.
[9]. World Health Organization. (2021). WHO global air quality guidelines: Particulate matter ($PM_{2.5}$ and PM_{10}), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. Geneva: WHO Press.
[10]. United States Environmental Protection Agency. (2019). Integrated Science Assessment (ISA) for Particulate Matter. EPA/600/R-19/188.

[11]. Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. Frontiers in Public Health, 5, 258.

[12]. Bent, B., Goldstein, B. A., Kibbe, W. A., & Dunn, J. P. (2020). Investigating sources of inaccuracy in wearable optical heart rate sensors. npj Digital Medicine, 3, 18.

[13]. Boudreaux, B. D., Hebert, E. P., Hollander, D. B., Williams, B. M., Cormier, C. L., Naquin, M. R., & Gillan, W. W. (2018). Validity of wearable sensors for heart rate variability measurements during exercise. Psychophysiology, 55(9), e13015.

[14]. Snyder, E. G., Watkins, T. H., Solomon, P. A., Thoma, E. D., Williams, R. W., Hagler, G. S. W., ... & Preuss, P. W. (2013). The changing paradigm of air pollution monitoring. Atmospheric Environment, 80, 566–574.

[15]. Castell, N., Dauge, F. R., Schneider, P., Vogt, M., Lerner, U., Fishbain, B., ... & Viana, M. (2017). Can commercial low-cost sensor platforms contribute to air quality monitoring and exposure estimates? Atmospheric Measurement Techniques, 10(9), 3575–3590.

[16]. Kelly, K., et al. (2017). Ambient and personal exposure to particulate air pollution using low-cost sensors. Environmental Pollution, 221, 491–500.

[17]. Melton, B. F., Boren, S. A., & Williams, M. B. (2014).A review of geofencing in health and wellness. Computers in Human Behavior, 35, 105–110.

[18]. Ashbrook, D., & Starner, T. (2003). Using GPS to learn significant locations and predict movement across multiple users. Personal and Ubiquitous Computing, 7(5), 275–286.

[19]. Nouri, R., Niakan Kalhori, S. R., Ghazisaeedi, M., Marchand, G., & Yasini, M. (2020). Can geofencing improve health outcomes? A systematic review of location-based interventions. JMIR mHealth and uHealth, 8(9), e16433.

[20]. Ben-Zeev, D., Scherer, E. A., Wang, R., Xie, H., & Campbell, A. T. (2014). Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. Journal of Medical Internet Research, 16(6), e132.

[21]. Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. IEEE Internet Computing, 20(4), 34–42.

[22]. Satyanarayanan, M. (2017). The emergence of edge computing. IEEE Pervasive Computing, 16(1), 7–17.

[23]. Rahmani, A. M., Gia, T. N., Negash, B., Anzanpour, A., Azimi, I., Jiang, M., & Liljeberg, P. (2018). Exploiting smart e-Health gateways for medical IoT: A fog computing approach. IEEE Internet of Things Journal, 5(1), 377–386.

[24]. Yang, Q., Zhang, Y., Zhang, W., & Li, X. (2021). A survey of edge AI: Convergence of edge computing and artificial intelligence. IEEE Internet of Things Journal, 8(18), 13756–13783.

[25]. Warden, P., & Situnayake, D. (2020). TinyML: Machine learning with TensorFlow Lite on Arduino and ultra-low-power microcontrollers. O'Reilly Media.

[26]. David, R., Duke, J., Jain, A., Reddi, V. J., Jeffries, N., Li, J., ... & Warden, P. (2021). TinyML: The next wave of machine learning technologies. Proceedings of the IEEE, 109(5), 756–768.

[27]. Jiang, L., Zhang, J., & Ding, Y. (2021). A wearable system for real-time personal exposure and physiological monitoring. Sensors, 21(4), 1112.

[28]. Lane, N. D., Bhattacharya, S., Mathur, A., Georgiev, P., Forlivesi, C., Kawsar, F., & Sayeed, N. T. (2015). DeepEar: Robust smartphone audio sensing in unconstrained environments. IEEE Pervasive Computing, 14(4), 32–42.

[29]. Gao, W., et al. (2015). Fully integrated wearable sensor arrays for multiplexed in situ perspiration analysis. Scientific Reports, 5, 15959

[30]. Poushali Das; Charanjit Singh; Rituparna Mondal; Dipika Paul; Nitu Saha; Siddhartha Chatterjee (2025) An Intelligent Geofenced Air Quality Monitoring System: Real-Time AQI Detection and Autonomous Location-Based Health Intervention Using Machine Learning. International Journal of Innovative Science and Research Technology,10(12), 2376-2389.

[31]. Poushali Das; Washim Akram; Arijita Ghosh; Suman Biswas; Siddhartha Chatterjee (2025) Enhancing Diagnostic Accuracy: Leveraging Continuous pH Surveillance for Immediate Health Evaluation. International Journal of Innovative Science and Research Technology,10(7),7-12.

[32]. Poushali Das; Avishake Kar; Ipsita Pathak; Shibani Mukherjee; Siddhartha Chatterjee (2025) Decoding Complexity and Emotion: A Computational Linguistic Approach to Sentence Comprehensibility and Writer Affect. International Journal of Innovative Science and Research Technology, 10(7), 423-428.

[33]. Nayan Adhikari, Pallabi Ghosh, Abhinaba Bhattacharyya and Siddhartha Chatterjee "AQIP: Air Quality Index Prediction Using Supervised ML Classifiers" in International Journal of Innovative Science and Research Technology (IJISRT). Vol 10, Issue.7, ISSNNo.2456- 2165, pp.835-842,

[34]. Nitu Saha, Rituparna Mondal, Arunima Banerjee, Rupa Debnath and Siddhartha Chatterjee "Advanced DeepLungCareNet: A Next-Generation Framework for Lung Cancer Prediction", in International Journal of Innovative Science and Research Technology(IJISRT), Vol. 10, Issue.6, ISSN No. 2456-2165, pp. 2312-2320,

[35]. Rajdeep Chatterjee, Siddhartha Chatterjee, Saikat Samanta and Suman Biswas "AI Approaches to Investigate EEG Signal Classification for Cognitive Performance Assessment" In the 6 th International Conference on Computational Intelligence and Networks (CINE 2024), IEEE Conference Record#63708, IEEE Computer Society, IEEE CTSoc,IEEE Digital Explore indexed by SCOPUS and WebofScience(WoS), pp.1-23, February,2025

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26jan1371

[36]. Sima Das, Siddhartha Chatterjee, Altaf Ismail Karani and Anup Kumar Ghosh, "Stress Detection while doing Exam using EEG with Machine Learning Techniques", In the Proceedings of Innovations in Data Analytics (ICIDA 2023, Volume 2), Lecture Notes in Networks and Systems (LNNS, Volume 1005) ISSN Electronic: 2367-3389, ISBN(eBook): 978-981-97-4928-7, pp.177-187, 10 th Sept. 2024

[37]. Rajdeep Chatterjee, Chandan Mukherjee, Siddhartha Chatterjee and Biswaroop Nath, "Latent Dirichlet Allocation for Topic Modelling and Intelligent Document Classification", In the Proceedings of Innovations in Data Analytics (ICIDA 2023, Volume 2), Lecture Notes in Networks and Systems (LNNS, Volume 1005), ISSN Electronic: 2367-3389, ISBN (eBook): 978-981-97-4928-7, pp. 71-83, Dated:10/09/2024,

[38]. Ahona Ghosh, Siddhartha Chatterjee, Soumitra De and Atindra Maji, "Towards Data-Driven Cognitive Rehabilitation for Speech Disorder in Hybrid Sensor Architecture", 2022 IEEE International Conference on Electronics, Computing and Communication Technologies (CONNECT),2022

[39]. Mauparna Nandan, Siddhartha Chatterjee, Antara Parai and Oindrila Bagchi, "Sentiment Analysis of Twitter Classification by Applying Hybrid Based Techniques", Lecture Notes in Electrical Engineering (LNEE), ICCDC 2021, vol 51, pp 591-606, Springer on 2022.

[40]. Sudipta Hazra, Siddhartha Chatterjee, Rituparna Mondal and Anwesa Naskar "Analysis and Comparison Study of Cardiovascular Risk Prediction using Machine Learning Approaches" in the Proceedings of International Conference on Advanced Computing and Systems (AdComSys2024), Springer Nature Book Series, Singapore, "Algorithm for Intelligent Systems" – SCOPUS, Web of Science Indexed, pp. 125-134 on 23 rd July 2025.

[41]. Anudeepa Gon, Sudipta Hazra, Siddhartha Chatterjee and Anup Kumar Ghosh "Application of Machine Learning Algorithms for Automatic Detection of Risk in Heart Disease" In IGI Global, Book Name – Cognitive Cardiac Rehabilitation Using IoT and AI Tools, pp. 166-188, ISBN13: 9781668475614, EISBN13: 9781668475621.

[42]. Sima Das, Siddhartha Chatterjee, Sutapa Bhattacharya, Solanki Mitra, Arpan Adhikary and Nimai Chandra Giri "Movie's-Emotracker: Movie Induced Emotion Detection by using EEG and AI Tools", In the proceedings of the 4th International conference on Communication, Devices and Computing (ICCDC 2023), Springer-LNEE SCOPUS Indexed, pp.583-595, vol. 1046 on 28 th July, 2023.

[43]. Sudipta Hazra, Swagata Mahapatra, Siddhartha Chatterjee and Dipanwita Pal, "Automated Risk Prediction of Liver Disorders Using Machine Learning" In the proceedings of 1st International conference on Latest Trends on Applied Science, Management, Humanities and Information Technology (SAICON-IC-LTASMHIT-2023) on 19 th June 2023, ISSN: 978-81-957386-1-8, pp. 301-306, In Association with Alpha-LPHA Scientific work, IQAC, Department of Science, Computer Science and Application, Sai College.

[44]. Payel Ghosh, Sudipta Hazra and Siddhartha Chatterjee, "Future Prospects Analysis in Healthcare Management Using Machine Learning Algorithms" In the International Journal of Engineering and Science Invention (IJESI), ISSN (online): 2319-6734, ISSN (print):2319-6726, Vol.12, Issue 6, pp. 52-56, Impact Factor – 5.962, UGC Sl. No.- 2573, Journal No.- 43302, June17, 2023.

[45]. Mauparna Nandan, Siddhartha Chatterjee, Antara Parai and Oindrila Bagchi, "Sentiment Analysis of Twitter Classification by Applying Hybrid Based Techniques", Lecture Notes in Electrical Engineering (LNEE), ICCDC 2021, vol 51, pp 591-606, Springer on 2022.

[46]. Sangita Bose, Siddhartha Chatterjee, Bidesh Chakraborty, Pratik Halder and Saikat Samanta, "An Analysis and Discussion of Human Sentiment based on Social Network Information", In International Journal of HIT Transaction on ECCN, ISSN: 0973-6875,vol. Issue 1A (2021), pp. 62-71, at Haldia Institute of Technology Publishing (ECCN Transaction).

[47]. Rajdeep Chatterjee, Siddhartha Chatterjee, Ankita Datta and Debarshi Kumar Sanyal, "Diversity Matrix based Performance Improvement for Ensemble Learning Approach", In Hybrid Computational Intelligence: Research and Applications, 2019, CRC Press, Taylor and Francis Group on October 1, 2019, ISBN-97811-3832-0253-CAT#K391719.

[48]. Sutirtha Kumar Guha, Somasree Bhadra, Sudipta Hazra, Siddhartha Chatterjee and Abhinaba Bhattacharyya "Classical Optimization Problem Solution using Nature Inspired Algorithm", in IEEE 4 th International Conference on Recent Advances in Electrical, Electronics, Ubiquitous Communication and Computational Intelligence (RAEEUCCI-2025), IEEE Xplore Digital Library, IEEE Madras Section, pp. 1-5, ISBN: 979-8-3503-9266-1,SCOPUS & DBLP Indexed on 28 th June, 2025 organized by SRMIST, Tamil Nadu, India.

[49]. Arunima Banerjee, Nitu Saha, Arijita Washim Akram, Saundarya Biswas and Siddhartha Chatterjee "Handwritten Digit Pattern Recognition by Hybrid of Convolutional Neural Network (CNN) and Boosting Classifier", in International Journal of Innovative Science and Research Technology (IJISRT), Vol.10, Issue.7, ISSNNo.2456-2165, pp.1012-1025.

[50]. Nitu Saha, Rituparna Mondal, Arunima Banerjee, Rupa Debnath and Siddhartha Chatterjee "Advanced DeepLungCareNet: A Next-Generation Framework for Lung Cancer Prediction", in International Journal of Innovative Science and Research Technology(IJISRT), Vol. 10, Issue.6, ISSN No. 2456-2165, pp. 2312-2320, on 2025/07/02.

[51]. Arijit Khanra, Mayank Kumar, Ankita Mandal and Siddhartha Chatterjee, “EfficientNetB0 vs. VGG16 vs. ResNet50: Classification of Various Skin Diseases Using Deep Learning”, in IEEE 2025 International Conference on Next Generation of Green Information and Emerging Technologies (GIET-2025), IEEE Xplore Digital Library, SCOPUS Indexed, on 8th August & 9 th August, 2025organized by GIET University, Gunupur, Odisha.