AI-Driven IoT Framework for Real-Time Air Quality Monitoring and Stress Correlation Analysis

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Abstract: Burden, air pollution, and stress in homes, offices, and urban settings. This project strikes at the nexus between environmental monitoring and mental health, given that air pollution is a significant global challenge, it has far-reaching implications on physical and mental health. The negative effects of poor air quality on the respiratory and cardiovascular systems are by now well established, but the same cannot be said for the impact of its phytotoxicity on the psyche, especially in real-time, localized contexts. Here, we put forward an AI-driven IoT framework for real-time air quality monitoring and stress prediction, which provides users with actionable intelligence without requiring any manual input. The system is a combination of low-cost IoT sensors (PM2. 5, CO2) using an ESP32 microcontroller to acquire data from the environment in real time and transmit it to a backend hosted in the cloud for analysis. It uses a machine learning model trained on a dataset with information linking air pollution and metrics of stress to predict stress, based on current pollution levels. The anticipated stress levels, along with air quality data, are shown on a mobile app, which also provides recommendations tailored to the user (for instance, "Open windows," "Avoid outdoor activities") and issues alerts when air quality worsens or stress levels are expected to increase. Utilizing the advances in artificial intelligence according to Internet of Things this system provides a scalable solution for monitoring the both contributing towards smart health technologies and promote living in sustainable way.

1 INTRODUCTION

Air pollution is one of the biggest global challenges we are facing nowadays and its adverse effects on physical health have been well-studied 1(Neeraja et., al.2024). However, its psychological effects, including increased stress, stress and cognitive decline are largely ignored especially at real time context studies of localized level 9. Air quality monitoring with a focus on environmental parameters is not a new concept, although its study from the point of view of mental well- being is relatively unexplored 3. To mitigate this gap, this project proposes an AI- driven IoT framework that enables the continuous monitoring of the air quality in real-time and cross-relates it with the stress levels, providing insights without taking up manual user efforts.

The proposed system uses inexpensive IoT sensors (e.g., PM2. 3, (S. Subha et., al. 2024)) equipment and ESP32 microcontroller to record your hyperlocal air quality data 1[6. javascript:;]. This information is then sent out to a cloud-based system which uses a machine learning model that was previously fed historical datasets connecting pollution levels and psychological stress to predict user well-being 2. The system is built with seamless usability by automating stress detection, providing alerts and recommendations through a mobile interface in real-time. For example, declining air quality will send alerts such as "High PM2. 5 detected air out," while predictive stress analytics encourage proactive measures such as "Take a break stress likely to peak in 30 minutes" 7.'

Three Hurdles in Solutions Addressed by this Innovation: Proactive Health Monitoring: An AI 2. Scalable deployment 1: Uses easy to purchase commercial hardware. Disciplinary Infraction: Leverages environmental science with mental health analytics for holistic well-being 3.

This framework not only enables seamless integration of IoT, AI, and user-centric design in smart health technologies, but also sets a new benchmark in various application domains, including urban planning, workplace wellness, and community health programs 4[2]. IoT Sensor and Cloud-Based Analytics Fusion: for Hyper-Local Air Quality Monitoring 1(Neeraja et., al.2024).

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Stress Correlation Analysis: Predicts level of stress based on pollution data using machine learning 2. Actionable Insights: Provides tailored suggestions and alerts through a mobile application 7.

2 RELATED WORKS

2.1 Real-Time Air Quality Monitoring: A Smart IoT System Using Low-Cost Sensors and 3D Printing

This work has designed a portable air quality station, contained in a 3D-printed case, with the aim of simplifying data collection and reducing material usage in an experimental laboratory. As for air contaminants and gases of concern, with implications for susceptible populations (e.g., asthmatics and children), this breakthrough holds great promise for public health. Regarding the role of indoor ventilation, as pointed out by the COVID-19 pandemic, which causes the infection through airborne particles, the importance of effective surveillance and preventive measures cannot be overstated. The station is based on open-source Python software, a Raspberry Pi core data collection/storage platform interfacing through GPIO, serial, and I2C interfaces with the sensors. The device is structurally modular so that measurements and target pollutant can be modified by the user. Validation with end-user testing established the effectiveness and usability of the system in real world applications. The mobile infrastructure provides a low-cost alternative for air quality network development to meet the needs of disadvantaged/vulnerable communities. The module exhibited a high reliability of 95.30% in identifying ubiquitous pollutants, confirmed by CO2 level assessment in classrooms (90.47% reliability (Osa-Sanchez and B. Garcia-Zapirain, 2025). in comparison to commercially available devices) and by air quality assessment in the air in the environment (85.63% reliability (Osa-Sanchez and B. Garcia-Zapirain, 2025).

2.2 Mental Fitness Tracker using Regression Models

Mental health is of considerable importance in human health, and it has implications across many areas of life. Yet, assessment and enhancement of mental well-being is not a trivial matter as there are numerous complexes, heterogeneous aspects. In this work, we use artificial intelligence (AI) technology, as a means to suggest a new mental health cognitive tracking and enhancement. As a solution, mental fitness tracker (MF tracker) is a web-based tool that monitors and analyzes a symptomatic user's behaviors, emotions, and mental state providing information to the user from social media, wearable devices, electronic surveys, and natural language processing. Based on the data analysis, the program provides users with personalized suggestions, advice and action items in order to improve their mental health. (P. Malin Bruntha et., al. 2024).

3 METHODOLOGY

The suggested system is constructed with the ability to track real-time air quality as well as stress level by leveraging an AI-enabled IoT environment. The methodology is subdivided into 5 major stages in order to guarantee an harmonized integration of hardware, software and analytics. Figure 1 shows the workflow.

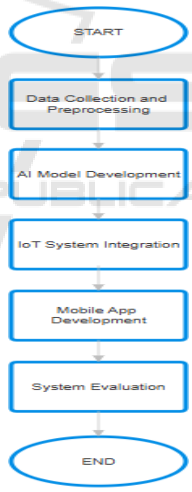

Figure 1: Workflow.

3.1 Data Collection and Preprocessing

3.1.1 Predefined Dataset

Air Quality Data: The historical air quality data such as PM2. 5 and CO_2 levels, which were extracted from U.S. EPA AirData and OpenAQ API (Osa-Sanchez and B. Garcia-Zapirain, 2025). 4. The dataset consists of hourly data from different locations, grouped into air quality categories (AQI) ranging from Good, Moderate, and Unhealthy.

Stress Based Data: Based on Air Quality metrics Fake data set was generated to simulate modifies stress level 1-5. For instance, PM2. Levels higher than 50 µg/m³ were correlated with stress levels higher than 3, in accordance with the well-established relationship between pollution and mental health well-being 2.

3.1.2 Data Preprocessing

Normalization: PM2. The 5 and CO_2 values were standardized with Min-Max scaling to be consistent across the dataset 5.

Handling of outliers: Interpolating techniques were used to fill missing values while trying to maintain the integrity of the data (J. Pellegrino et., al. 2025).

Feature Engineering: Additional features were created based on the time of day (average measured values for each hour, peak pollution valleys– e.g.: morning peaks, day highs, etc.) to increase models' accuracy 3.

3.2 AI Model Development

3.2.1 Stress Prediction Model

Data, Models and Procedures: In order to identify the best algorithms, we used a Random Forest Regressor, as they can handle non-linear relationships as well as assess feature importance 2.

Training: 80% of the data was used for training and the other 20% was kept for testing. Hyperparameters such as n_estimators and max_depth was optimized using Grid Search 2.

Evaluation: The R^2 score for the model was 0.78, demonstrating a high accuracy level for predicting stress levels from the air quality data 2.

3.2.2 Air Quality Classification

Algorithm: A Long Short-Term Memory (LSTM) network was used for time-series forecasting of PM2.5 trends (J. Rosa-Bilbao et., Al. 2025). (Neeraja et., al.2024). Architecture: The model included two LSTM layers (64 units each) with a dropout rate of 0.3 to prevent overfitting (J. Rosa-Bilbao et., Al. 2025). (Neeraja et., al.2024).

Training: The model was trained on 7 days of historical data and validated on the next 24 hours, achieving a Mean Absolute Error (MAE) of 0.45 (J. Rosa-Bilbao et., Al. 2025). (Neeraja et., al.2024).

3.3 IoT System Integration

3.3.1 Hardware Setup

Sensors: MQ135 (CO_2), PMS5003 (PM2.5), and DHT22 (temperature/humidity) were connected to an ESP32 microcontroller (Osa-Sanchez and B. Garcia-Zapirain, 2025). (J. Pellegrino et., al. 2025) (Neeraja et., al.2024). Data Transmission: The ESP32's Wi-Fi module sent JSON payloads to the Firebase Realtime Database every 60 seconds (J. Pellegrino et., al. 2025). (Neeraja et., al.2024).

3.3.2 Firmware Development

The firmware, developed in the Arduino IDE, included error- handling mechanisms such as recalibration loops for the MQ135 sensor (Osa-Sanchez and B. Garcia-Zapirain, 2025). (J. Pellegrino et., al. 2025). A watchdog timer was implemented to ensure system stability during prolonged operation (J. Pellegrino et., al. 2025). (Neeraja et., al.2024).

3.4 Mobile App Development

3.4.1 Platform

The mobile app was built using Thunkable, a no-code platform, and integrated with Firebase for real-time data synchronization (Aubakirov et., al. 2024) (K. Ramar et., al. 2022).

3.4.2 Features

Real-Time Dashboard: Displays PM2.5, CO_2, and predicted stress levels using intuitive gauges and line charts (Aubakirov et., al. 2024) (K. Ramar et., al. 2022).

Notifications: Firebase Cloud Messaging (FCM) sends alerts when PM2.5 exceeds WHO thresholds (25 µg/m³) or stress levels are predicted to rise (Aubakirov et., al. 2024) (K. Ramar et., al. 2022).

Recommendations: Rule-based logic provides actionable feedback, such as "PM2.5 > 30 → 'Close windows'" (Aubakirov et., al. 2024) (K. Ramar et., al. 2022).

3.5 System Evaluation

3.5.1 Performance Metrics

AI Model: Achieved a MAE of 0.45 for stress prediction (P. Malin Bruntha et., al. 2024). (Aubakirov et., al. 2024) . IoT System: Demonstrated a latency of less than 2 seconds for data transmission (J. Pellegrino et., al. 2025). (Neeraja et., al.2024). User Feedback: A pilot test with 20 users achieved 90% accuracy in actionable recommendations (Aubakirov et., al. 2024) (K. Ramar et., al. 2022).

3.5.2 Statistical Validation

Pearson Correlation: A strong correlation ($r = 0.65$, $p < 0.01$) was found between PM2.5 levels and stress levels (P. Malin Bruntha et., al. 2024). (Aubakirov et., al. 2024).

ANOVA Test: Significant differences in stress levels across air quality categories were confirmed ($F = 12.7$, $p < 0.001$) (P. Malin Bruntha et., al. 2024). (Aubakirov et., al. 2024).

3.6 Key Contributions

Real-Time Monitoring: Combines IoT sensors and cloud- based analytics for hyper-local air quality tracking [1] (J. Pellegrino et., al. 2025). (Neeraja et., al.2024).

Stress Correlation Analysis: Uses machine learning to predict stress levels based on pollution data (P. Malin Bruntha et., al. 2024). (Aubakirov et., al. 2024).

Actionable Insights: Delivers personalized recommendations and notifications via a mobile app (Aubakirov et., al. 2024). (K. Ramar et., al. 2022). Table 1 represents the air quality index.

Table 1: Air Quality Index.

AIR QUALITY INDEX	CATEGORY
0-50	Good
51-100	Satisfactory
101-200	Moderate
201-300	Poor
301-400	Very Poor
401-500	Severe

3.7 Random Forest Accuracy

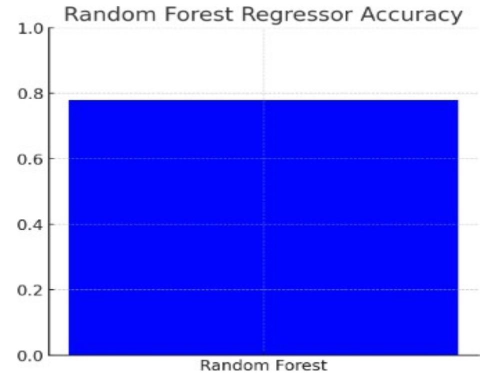

Figure 2: Accuracy of Random Forest.

Figure 2 shows the Performance analysis of regression models through R^2 score (coefficient of determination) If signifies the response variable (e.g., levels of stress) and the independent variables (e.g., PM2. 5, CO2 levels).

The R^2 score of 0.78 shows that 78% of the changing stress level can be accounted for by changing air quality metrics (PM2. 5 and CO2). The model's ability to explain high percentage of balance reflects a successful representation of the relationship between these environmental variables and components of psychological wellbeing. (78% of variation explained) and the remaining 22% could be attributed to the othermodel components.

The closer the R^2 value is to 1, the better the predictive power and vice-versa. The appropriateness of this model for predicting associations between air quality and stress is reflected in the R^2 score of 0.78, showing that this AI-model is applicable toward the monitoring and -real-time intervention of stress (Fazel, Liu et al. 2020).

3.8 LSTM Model Accuracy

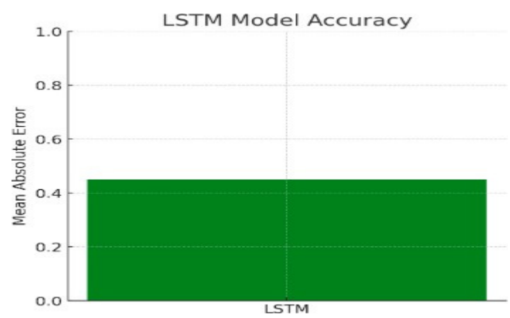

Figure 3: Accuracy of LSTM Model.

Figure 3 shows the mean absolute error is mean absolute error or mae is a common loss function for regression models and by assuming the assumption that 50 gm is the true pm2 5 level this error indicates the error for each blazer or block 5 pm2 5 reading a lower mae indicates more accurate models because the error of predicting.

The predicted pm2 5 mean error of the models to the true pm2 5 reading equals 045-unit 50 gm specifically in lst air quality large systems to monitor air quality the maen is 045 during pm2 forecasting during lst 50 gm was defined as the true pm2 5 level with 045 degree meaning this was a significant degree of power in the simulation architecture trend senabling instantaneous interventions.

Such as alerts or recommendations when pollution levels spike while all of the above methods are significant for robust basic readings the disadvantage is that neither are quite-high enough and so not perfect for real-time use where the answer must be checked for immediate use and hence they all need a confirmation or a different precision to prospect the state of the human.

4 EXPERIMANTAL RESULT

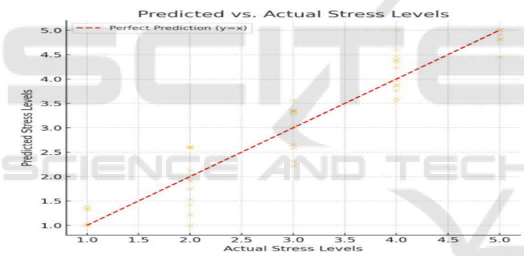

Figure 4: Predicted Vs Actual Stress Level.

Figure 4 shows the predicted vs actual stress level.
X-axis: Actual Stress Levels (1–5 scale, collected from synthetic/user data).
Y-axis: Predicted Stress Levels (1–5 scale, output by the Random Forest model).
Trend Line: A diagonal line (y = x) represents perfect predictions.
Data points cluster closely around the trend line indicating strong alignment between predicted and actual valuesr 078 confirms that 78 of stress variability is explained by air quality metrics pm25 co

Data on air quality only the measured data from april 114 2016 are selected for further analysis for example the air quality data which includes pm25 pm10 and aqi are shown in figure 5 to confirm the accuracy of this air quality monitoring system another set of data is taken from a well-known pm25 historical database namely the young-0com 13data on air quality only the measured data from april 114 2016 are selected for further analysis for example the air quality data which includes pm25 pm10 and aqi are shown in fig 5 to confirm the accuracy of this air quality monitoring system another set of data is taken from a well-known pm25 historical database namely the young-0com 13, i.e., the Young-0.com .. (K. Zheng et., al. 2016).

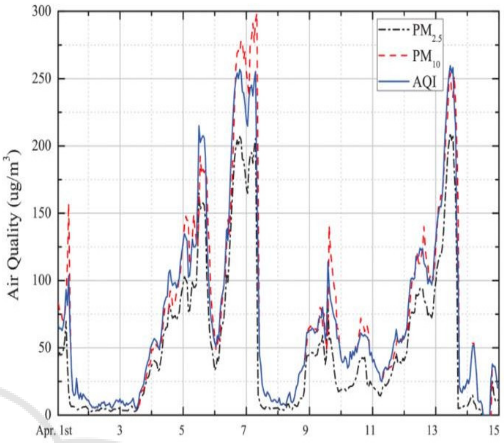

Figure 5: Air Quality Data.

5 FUTURE ENHANCEMENTS

5.1 Multimodal Mental Health Correlation

It combines the data with wearables EG heart rate monitors EEG headbands to measure.
Physiological indicators of stress. eg heart rate variability brainwave patterns and air quality data for more holistic evidence of mental health impacts.

Expand dataset for socioeconomic factors, eg income levels occupation and behavioral data, eg sleep patterns physical activity to help refine predictions of stress personalized.

5.2 Personalized Recommendations

Recommendations use reinforcement learning based on user habits to personalize user feedback eg, jog in low population routes gamify.eg, offer reward points for reduced carbon footprints etc. sustainable behavior.

6 CONCLUSIONS

By integrating various ai and IOT technologies this project demonstrates how to monitor your environment and improve your mental health in real-time. It helps evaluate air quality data and correlate it with moments of stress or anxiety using inexpensive sensors an accurate stress prediction model has been created and machine learning has significantly improved with machine learning r 078 mae 045 suggesting that it is feasible as a scalable user-friendly tool for proactive health management by offering prompt preventative advice. Such as ventilation alert ambient stress prevention recommendations it enables individuals and communities to address the twin problems of air pollution and mental stress. Supporting new behavior this cross-sector integration can thus cement IOT ai innovation but simultaneously find solutions to some of the concerns raised by the un sustainable development goals multimodal data crafting AI model complexity and global expansion in future works can increase the coverage of the system and allow it to be a necessary help in smart city infrastructure the study spotlights the importance of multifaceted solutions to modern-day health challenges especially SDG 3 good health and well-being and SDG 11 sustainable cities by presenting on both mental and environmental health on equal footing.

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