Emotion on the Edge: Air Quality Sensors Decoded as a Real-World Emotion Indicator

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***Abstract*—As the research community increasingly focuses on quantifying emotional states in real-world scenarios, there is a growing need for edge computing. In this work, we present a novel approach to on-device emotion classification through the development of a low-cost hand-held device. This device incorporates a range of environmental air quality factors, including Particulate Matter, Nitrogen Dioxide, Carbon Monoxide, Ammonia, and Noise. Our research addresses the current limitations in the field of emotional state measurement by leveraging environmental air quality data, which has been previously linked to affective states. This on-device approach not only offers an alternative to resource-intensive emotion recognition methods but also contributes to the development of more practical and affordable solutions for emotion assessment. The preliminary results of our device's performance in real-world scenarios suggest its effectiveness in quantifying emotional states through air quality factors, with the model achieving 95% accuracy demonstrating accurate on-device classification without the need for external high-processing power.**

***Index Terms*—Emotion, Real-World, On-Device, Classification, Edge-Computing, Air Quality**

I. Introduction

Pollution, in its various forms, presents a pressing global challenge that transcends geographical boundaries and socioeconomic disparities. The detrimental effects of pollution on the health and wellbeing of individuals have been a subject of concern for decades. Exposure to pollutants such as particulate matter has been linked to a range of health issues, including respiratory diseases, cardiovascular disorders, and even mental health problems [1], [2]. Little previous work has explored the impact of pollution on emotions due to its perceived irrelevance however our previous work demonstrates the correlation between pollutants and mental wellbeing [3]. This highlights the need for effective monitoring and mitigation of pollution's impacts has become increasingly urgent.

Recent advances in sensing technologies have ushered in a new era of real-world pollution data monitoring. These technologies enable us to gather precise and granular data on pollution levels in various environments, from densely populated urban areas to remote natural settings. The availability of such data provides an unprecedented opportunity to better understand the dynamics of pollution and its consequences on human health and wellbeing.

Artificial Intelligence (AI) offers a promising avenue for leveraging pollution data. Specifically, AI has the potential to enable the classification of individual wellbeing based on pollution data. This capability holds immense promise for public health research and intervention strategies. However, despite the potential benefits, there has been relatively limited focus on the practical deployment of AI-driven pollution-to-wellbeing classification systems.

Edge computing involves the execution of AI models on-device, close to the point of data collection, rather than relying on centralised servers for inference. This approach offers several advantages, including reduced data transmission requirements, lower operational costs, decreased latency, and improved privacy protection. Additionally, on-device classification reduces reliance on continuous connectivity, allowing the system to function in remote locations or in case of network outages.

The emergence of sensors and edge devices has opened new possibilities for real-time monitoring and classification of human wellbeing based on environmental data. When applied to the task of inferring wellbeing from pollution data, edge computing can facilitate the integration of AI-based solutions into everyday life, enabling more proactive and personalised approaches to addressing the health consequences of pollution exposure.

In this work, we demonstrate the feasibility of classifying emotions from environmental pollutants using a model deployed directly on a Raspberry Pi-based edge device. We optimise a decision tree model to deploy it on the memory-limited hardware. The model is trained on a dataset of environmental sensor data and associated wellbeing labels collected from user studies. The proposed system eliminates the need for off-device processing, enabling timely wellbeing monitoring without compromising user privacy.

The main contributions of this work is:

1) We present a custom-built, low-cost hand-held device for real-world emotion classification on the edge using environmental sensors.
2) We explore the use of a Random Forest model for the real-time monitoring of emotions.
3) We demonstrate that inference is possible on the edge, achieving real-time emotion inference without relying on

abundant computational resources like powerful servers or distributed computing.

The remainder of this paper is organised as follows; Section II explores the related works in the field and looks to the opportunities on-device processing can have in quantifying emotions in-situ. Section III discussed the methodology for this work defining the dataset and model architecture, finally concluding with the new prototype 'Enviro-Edge'. Section IV reviews the deployment of the device into the real work, detailing how the device was tested. Section V discusses the impact of the work and concludes with some future work for next steps.

II. Related Work

Embedded sensors such as heart-rate, electrodermal activity, heart-rate variability and blood volume pulse within wearable technologies offer a range of opportunities to assess the autonomic nervous system [4], which has been shown to model both positive and negative emotion [5]. In particular an elevated ElectroDermal Activity (EDA) a decrease of Blood Volume Pulse (BVP) [6] and a reduced heart-rate variability (HRV) [7] are common indicators or negative emotion as these variables simulate an activation for the sympathetic nervous system [8]. There has been significant work in the use of wearable technologies to detect the level of physiological arousal from variables such as HRV and EDA which have demonstrated that they can be inferred to assess emotional states in the real-world [9], [10].

In our previous work we have began exploring the impact of environmental variables namely air quality particulates and gases on mental wellbeing. The concept DigitalExposome offered a unique insight into how the use of environmental sensors could be used to quantify emotions when walking in urban environments [3]. This approach demonstrated emotions could be accurately inferred using air quality data achieving an F1-score 0.67 using a 1-D CNN, exceeding the same model using only physiological data which achieved an F1-score of 0.61. Furthermore, our work on emotions in semantic trajectories saw environmental data alone achieve an impressive F1-score result of 0.84 [11]. The results of these findings across both studies demonstrates that air quality data directly correlates with the sympathetic nervous system.

To date, most efforts on emotion classification have been focused around using large computational processing power to pre-process, extract and classify emotions after the point of collection [12], [13]. The concept of edge computing shows much promise for facilitating deployment of such sensing technologies in the real world [14]. Recent improvements in devices have enabled Raspberry Pis and other comparable single board computers to be used for deploying AI models due to their small portable size yet powerful processing capabilities [15].

Previous work shows hows physiological sensors can be used to detect stress processed automatically by an on-board computer under driving conditions [16]. However, this work relied on a large computer within the car which is not feasible for other real-world scenarios. More recent work has explored how the use of multiple models could be used to improve the accuracy of stress detection on a ultra-low power microcontroller by combining stress and activity recognition [17]. Similar work [18] in the area has focused on inferring a participant's activity from running, falling and normal state using a 1D CNN model achieving 97% accuracy.

However, little work has been carried out to explore the use of environmental sensors to classify emotions at the edge. While previous research has explored environmental monitoring there has been little consideration of how environmental monitoring, in particular how the environment impacts wellbeing, could be deployed into the real-world.

III. Methodology

In this work, we propose the development of a machine learning model that can perform real-time emotion classification directly on resource-constrained edge devices using only air quality data as input. Our goal is to design an artificial intelligence system that leverages advances in on-device inference to enable continuous monitoring of emotions based on real-world environmental factors, without relying on connectivity to the cloud or abundant computational resources. The overall methodology is depicted in Figure 1.

A. Dataset

The dataset used in this work uses previous data collected from our study DigitalExposome to collect real-world air quality data along with self-reported emotions. The study involved 40 healthy participants aged between 18-50 as approved by Nottingham Trent University Ethics Committee, application number 638. The experiment equipped each participant with two devices namely:

1) **Enviro-IoT** - An environmental monitoring device which continuously collected air pollution variables such as Particulate Matter (PM1), (PM2.5), (PM10), Nitrogen Dioxide (N02), Carbon Monoxide (CO), Ammonia (NH3) and Noise (dB) in the vicinity.
2) **EnvBodySens app** - Mobile application pre-loaded onto a Samsung smartphone for participants to self-report their emotions during the experiment activity. To measure the emotions of participants the app used the Personal Wellbeing Index for adults model [19], with a five-point Likert SAM scale using an emoji at each point as a way to replicate how the participant was feeling [20]. The approach of this model has been shown to be highly effective for self-reporting emotional states [21].

The devices accompanies the participants as they strolled along a predetermined route within the vicinity surrounding Nottingham Trent University's Clifton Campus continuously gathering data on environmental pollutants and self-reported emotions.

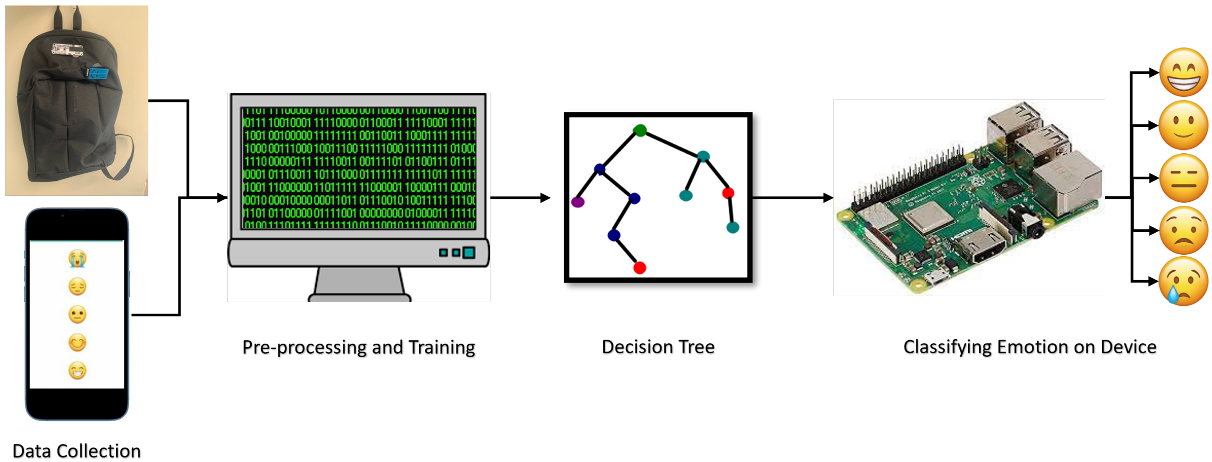

Fig. 1. The system Architecture of the processes behind quantifying emotion on device within the urban environment.

B. Machine Learning Architectures

When considering a model architecture for the edge, there isn't a pre-defined model for use, particularly due to the resource-constrained nature of edge devices [17]. Selecting an optimal machine learning model architecture that can perform well despite the limited resources on edge devices is crucial. Therefore, we evaluated several lightweight classification models that are suitable for deployment on resource-constrained edge hardware:

- Support Vector Machine (SVM): SVMs are effective for small datasets and have relatively low computational requirements. Using an SVM scored 0.56 (F1 Score).
- Decision Tree: Decision trees offer interpretable models that are easy to optimise for low-power devices. They work well for small datasets with limited features. Decision trees can also be converted to small rule-based classifiers. A decision tree performed the best at 0.95 (F1-Score).
- Random Forest: Random forests overcome overfitting limitations of single decision trees by training an ensemble of decorrelated trees. However, the resulting model size may be larger. A random forest model performed at 0.90 (F1-Score).
- Logistic Regression (LR): Logistic regression is a statistical model used to describe the relationship between one dependent variables and one or more independent variables. The model iteself does not require too many computational resources. The trained data using a LR model acheived 0.45 (F1-Score).
- Gaussian Naive Bayes (GNB): Gaussian Naive Bayes model operates on the assumption of feature independence, using the Gaussian distribution to calculate the probability of a given instance belonging to a particular class based on the probability distribution of its features. The trained data using a GNB model resulted in the worst performance at 0.38 (F1-Score).

We trained and tested each model using hold-out validation with a 20% test split. After preliminary experiments, we found that decision trees provided the best combination of high accuracy and low resource usage for our application. We trained a randomised decision tree classifier using scikit-learn on the DigitalExposome dataset. The model was trained to classify self-reported emotion labels based on the environmental sensor data features.

The results showed that Decision Tree was the best performing at 95% accuracy and due to previous successes with classifying emotions to a high level, we have used a Decision Tree model. This model was then exported as a pickle file and transferred onto the Raspberry Pi.

C. System Architecture

In this paper we introduce the 'Enviro-Edge' as a novel, low-cost hand-held device capable of on-device inference. The approach is capable of measuring environmental air quality factors to quantify the impact of emotions in-situ within an urban environment. This process removes the need for powerful systems and extensive deep learning models to unravel the link between urban environments and emotions which has been explored in previous work [22].

The Enviro-Edge device uses a range of off-the-shelf hardware and sensors encased within a 3D printed box which reduces the overall cost and simplifies the design process. A schematic involving a Raspberry Pi connected to a range of environmental sensors to confirm compatibility, ensure sensor accuracy, and achieve the desired level of precision is shown in Figure 2.

The 'Enviro-Edge' system comprises of multiple hardware components, for sensing, processing and to display the classification result as detailed below.

1) **Raspberry Pi 3 B+**: Raspberry Pi is a versatile and affordable single-board computer that has gained popularity for its wide range of applications. The Raspberry Pi 3 B+ is powered by a quad-core ARM Cortex-A53 CPU, providing adequate processing power for a variety

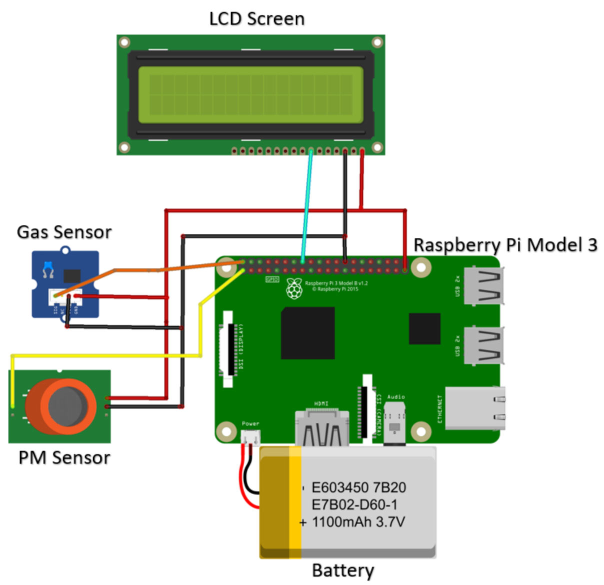

Fig. 2. Hardware schematic comprising of the Raspberry Pi Model 3+, environmental sensors including Gas Sensors (monitoring Nitrogen Dioxide, Carbon Monoxide and Ammonia), Particulate Matter (1.0, 2.5 and 10), Noise sensor and battery.

of tasks and operates at a clock speed of 1.2 GHz. It provides a flexible platform for deploying machine learning models to classify data in the real-world.

2) **LCD Screen**: Connected to the Raspberry Pi is a small 0.96" colour LCD screen that serves as a visual aid which informs the user in real-time of the changes in emotions from 1 (very sad) to 5 (very happy).
3) **Particulate Matter Sensor**: As one of the most harmful environmental pollutants, Particulate Matter (PM) is commonly built-in within air quality sensing systems. PM sensors work by having a small fan that draws air through the device and past a laser which detects both the concentration number and size of the particles in the surrounding air. The sensor within the hand-held device used is PMS5003 PM sensor which has previously been correlated for use in the real-world [23]. Previous studies have shown that the addition of particulate matter supports the classification of emotions [11].
4) **Nitrogen Dioxide Sensor**: Nitrogen Dioxide (NO2) is one of the most highly reactive gases as a result from aerosols and combustion processes for fossil fuels within the environment [24]. This provides a simple, low-cost approach to capture the levels of concentration of Nitrogen Dioxide within the urban environment. The data is obtained through converting the analogue voltage readings using a digital converter, resulting in resistances. NO2 has been shown to result in increased stress [25] and worsened emotions [11].
5) **Carbon Monoxide Sensor**: Similarly the Carbon Monoxide (CO) sensor is compact and low-cost, capturing the total concentration levels within the urban environment. There has been significant research conducted highlighting issues caused by carbon monoxide on human health with respiratory and cardiovascular illnesses [26]. More recently, there is work to show the impact of short-term exposure of CO on physiological and behavioural issues [27].
6) **Ammonia Sensor**: Within the environment, Ammonia (NH3) is one of the most common gases in the atmosphere [28]. Research has shown the impact of Ammonia largely depends on the level of gas concentration but can result in swelling of the airways and long-term issues in the respiratory system [29]. In recent years, some attempts have been made to quantify the impact of Ammonia towards emotions [11].
7) **Noise (dB) Sensor**: Sensors to capture sound are often used within environmental sensing systems. Primarily, these sensors work by detecting the overall intensity of sound waves by using an in-built microphone, peak detector and an amplifier. Previous work on the impacts of noise demonstrate significant causes of health related conditions such as cardiovascular [30] and more recently focusing on the impact towards mental wellbeing [3] and emotions [31].

Using the above hardware components, a two-step prototype was developed and devised to house the electronics within a 3D printed case designed to protect the materials in the hand-held device, as depicted at Figure 3.

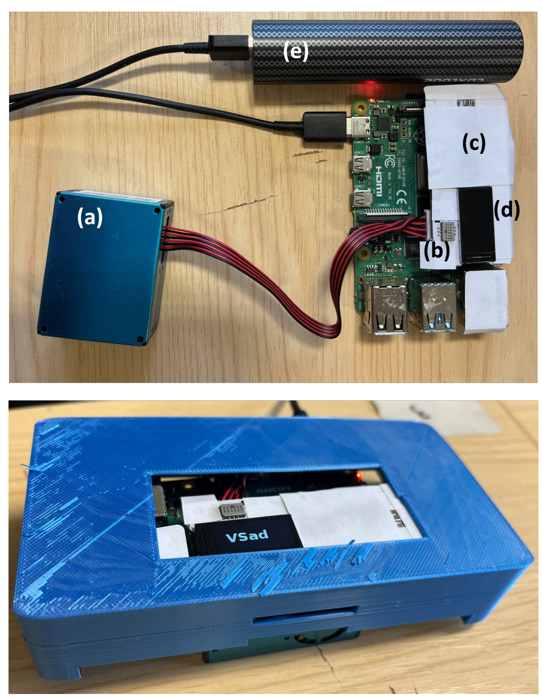

Fig. 3. Development process of the two prototypes (Top) Raspberry Pi connected to Particulate Matter (a), Nitrogen Dioxide (b), Carbon Monoxide (b), Ammonia (c), visual LED screen (d) and powered by battery (e). Final prototype (Bottom) with all electronics encompassed within a 3D printed box.

IV. Deployment

To evaluate real-world feasibility, we deployed the decision tree model on a Raspberry Pi 3 B+ edge device. The Pi was equipped with particulate matter, nitrogen dioxide, carbon monoxide and ammonia gas sensors to collect environmental data. Sensor readings were collected and pre-processed locally on the Pi and then passed to the model for emotion inference.

In this approach we have developed a Python application that acquires and aggregates sensor data over fixed intervals collecting 8 samples. After each interval, the data is normalised and input to the decision tree model to classify the predicted emotional state. The application visualises the output of the model on a small LCD display attached to the Pi, enabling the real-time monitoring of emotion from air quality data.

The use of on-device processing provides several advantages over a traditional cloud-based deployment for this application. Performing inference at the edge eliminates privacy concerns associated with transmitting raw sensor data to the cloud [32]. It also reduces reliance on continuous connectivity and mitigates against network failures.

A. Results

We conducted an 'in-the-wild' test to assess the performance and reliability of the model classifying emotion on-device.

To compare the accuracy prediction of the Enviro-Edge device, the data from 40 participant's in the DigitalExposome dataset namely emotion label, latitude and longitudinal were aggregated together and plotted on a heatmap, as depicted at 'Ground Truth' in Figure 4. The heatmap demonstrates that walking in green spaces (left-handside of the map) highlights a mixture of happy and very happy emotions. Whereas walking along busy, polluted spaces (right-handside) results in a very negative or negative emotions.

The results for Enviro-Edge device shown in Figure 4 were generated by a single participant walking the same route as performed in the 'Ground Truth' Heatmap. Whilst walking the pre-determined route the Enviro-Edge device recorded the changes in predicted emotion which were saved to on-board storage. Subsequently, these results were downloaded and used to visualise the route.

Analysis of the results incorporating predicted emotion, latitude and longitudinal for the Enviro-Edge using the real-world data demonstrates that classifying at the edge is comparable to the ground truth results. Similar to the ground truth, green spaces predicted a very happy or happy emotion whereas busy, polluted spaces resulted in a prediction very negative or negative impact on human emotions.

Contrasting the two maps in Figure 4 highlights that the Enviro-Edge device is accurate in predicting emotion using air quality factors as a basis for classifying on-device. While the inferred emotions are not identical to the original dataset this is because the real-world air quality differed during this test. However, this test demonstrates that the device functions independently to infer emotional state in the real-world from air quality data in real-time.

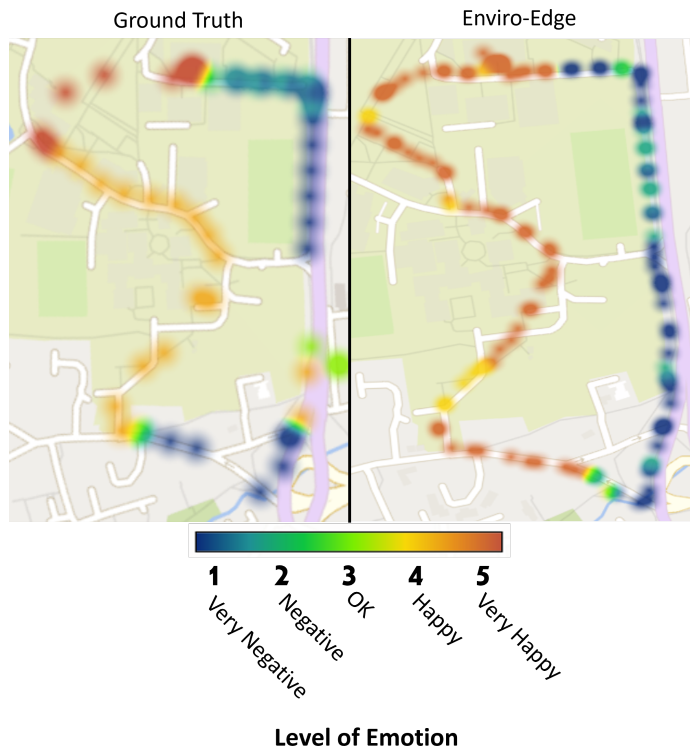

Fig. 4. Plotting participant label from DigitalExposome dataset (left) and the on-device inference using Enviro-Edge (right)

Despite the constraints of the low-power Raspberry Pi hardware, we found that the model was able to classify wellbeing states in real-time with an average inference latency of 8.45ms. Furthermore, the system was able to function continuously during periods lasting several hours on battery power demonstrating the feasibility of on-device inference and real-world deployment.

While limitations of this work were encountered such as the possibility of external factors impacting emotion, this study aimed to evaluate real-world performance which is vital to enable successful deployment. Furthermore, the contribution of this work is the edge deployment of the system enabling its use in real-world environments; it was therefore necessary to collect real-world data to train the model.

V. Conclusion and Future work

In this work, we have demonstrated the ability to deploy a machine learning model for classifying emotions from real-time environmental pollution data directly onto a resource-constrained edge device. This approach continues and extends previous studies [3], [11], [33] by quantifying the impact of the environment on emotions in-situ. Our results indicate that accurate real-time inference is possible using only the limited compute capabilities of a Raspberry Pi. The decision tree model was able to classify emotional states with 95% accuracy compared to ground truth labels, despite being deployed on low-power hardware.

The ability to classify emotional states in real-time using only ambient environmental data provides exciting possibilities. Our edge device can enable continuous monitoring during everyday activities without requiring body-worn sensors. This can help identify personalised environmental factors that impact emotions. The edge approach also allows for rapid localised interventions based on the inferred affective state.

In the future, the on-device model could be enhanced further by incorporating physiological signals like heart rate along with environmental data for more robust inference. Advances in edge hardware will also enable more sophisticated models to be deployed. Overall, this work demonstrates the feasibility of performing real-time emotion monitoring using on-device intelligence, paving the way for innovative healthcare and wellness applications.

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