Learning Methods for IoT: Use Cases of Air Pollution Monitoring

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CERTIFICATE

It is certified that the work contained in this thesis, titled "Learning Methods for IoT: Use Cases of Air Pollution Monitoring" by Nitin Nilesh, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date	Advisor: Dr. Sachin Chaudhari

To

Make this world a better place.

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Abstract

Air pollution monitoring is crucial for assessing the health risks posed by pollutants, identifying pollution sources, and developing effective strategies for reducing pollution and protecting public health. The Indian government has taken initiatives, which provides real-time air quality data to the public and raises awareness of air pollution levels. The initiative measures several pollutants, including Particulate Matter (PM), and categorizes Air Quality Index (AQI) level into six categories ranging from "Good" to "Severe". The air pollution sensors employed for calculating the AQI are associated with several limitations. Consequently, the central objective of this thesis is to estimate the AQI without relying on any pollution sensor. To achieve this goal, the proposed methodology employs real-time traffic data and images to estimate the AQI in real-time.

Firstly, this thesis propose an image processing based technique to estimate the AQI levels using traffic images and weather parameters, which can be used in rural and sub-urban areas where sensors are hard to deploy and maintain. This approach allows for real-time estimation of AQI through smartphones and can be used portably. The proposed method achieves up to 90% accuracy for the AQI classification. Furthermore, a feature-rich dataset is made publicly available to encourage further research.

After that, a novel method based on the Internet-of-Things (IoT) and Machine Learning (ML) is proposed to estimate the AQI using real-time traffic data. To build a rich traffic dataset, PM monitoring nodes were deployed in 15 diverse traffic scenarios across Indian roads, and digital map service providers were utilized. Three ML models, namely Random Forest (RF), Support Vector machine (SVM), and Multi Layer Perceptron (MLP), were trained on this dataset to predict AQI categories into five levels. Experimental results demonstrate an accuracy of 82.60% and an F1-score of 83.67% on the complete dataset. In addition, individual node datasets were used to train ML models, and the behavior of AQI levels was observed.

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Chapter 1

Introduction

1.1 Motivation

The IoT is rapidly becoming one of the most transformative technologies of the 21st century. It refers to the interconnection of everyday objects, devices, and machines through the internet, enabling them to communicate, share data, and perform tasks without human intervention [2]. From smart homes and cities to autonomous vehicles and wearable devices, IoT is reshaping the way we live, work, and interact with the world around us. With the recent advancements in Artificial Intelligence (AI) based algorithms, IoT devices has become more intelligent, adaptive, and autonomous [3]. AI techniques such as ML, Deep Learning (DL), and Natural Language Processing (NLP) are being used to analyze the vast amounts of data generated by IoT devices and extract insights that can be used to optimize operations, improve decision-making, and enhance user experience. Learning algorithms can be used to analyze and interpret data in real-time, which is critical for many IoT applications. These algorithms can learn from the data and improve their accuracy over time, which can help identify patterns, trends, and anomalies that might otherwise be missed.

Real-time air pollution monitoring is one of the significant applications of IoT, which has recently gained substantial attention from researchers worldwide, resulting in a considerable body of work in this domain [4, 5, 6]. Air pollution monitoring using IoT involves using connected sensors and devices to collect data on air quality in real-time. These sensors can be deployed in various locations, including homes, roads, and public spaces, to provide more localized information about air quality. In India, air pollution is a major public health issue, with many cities consistently ranking among the most polluted in the world [7]. To monitor air pollution, India has implemented a network of monitoring stations across the country that measure levels of pollutants such as particulate matter, nitrogen oxides, sulfur dioxide, and ozone [8]. However, the current air quality monitoring network in India covers only a small number of cities and is often inadequate to provide a comprehensive understanding of the problem. Many areas, particularly in rural and remote regions, are not covered by monitoring stations, leaving the people living in those areas at risk. Even when monitoring stations are available and equipment is functioning correctly, there can be issues with the quality of the data collected. For example, data may be missing or incomplete, or there may be inconsistencies in the way data is collected and processed. In addition to the aforementioned issues, the use of sensors for air pollution monitoring presents several challenges. The sensors require regular maintenance, such as replacing parts, cleaning, and ensuring proper power supply and internet connectivity, to provide accurate measurements. Additionally, high-quality sensors can be expensive, which may make it difficult to set up extensive monitoring networks, especially in low-income or developing countries. To ensure the effectiveness and practicality of air pollution monitoring systems that use sensor technology, it is crucial to consider these challenges when designing monitoring programs.

The objective of this thesis is to address the difficulties encountered in air pollution monitoring through the use of sensors. In particular, the thesis aims to devise an alternative mechanism for estimating the AQI that does not rely on the deployment of specific environment-based sensors. By doing so, this approach seeks to overcome some of the limitations and costs associated with sensor-based monitoring, and offer a more flexible and scalable solution for air quality estimation. The proposed mechanism involves two methods: an image-based air quality estimation algorithm that uses learning methods to predict the AQI on Indian roads, and a method that uses maps data and weather parameters to predict the AQI. A feature-rich dataset is collected for the Indian scenario, which includes seasonal variability, to evaluate the performance of both methods. The thesis provides a detailed comparison of the proposed methods with existing methods, and presents a thorough analysis of the results.

1.2 Summary of Contributions

The main contributions from this thesis are presented in the chapters mentioned as follows -

- **Chapter 4**
  - Proposed a novel methodology based on the IoT to estimate the real-time AQI into five distinct levels. This is achieved by utilizing both traffic images and weather parameters in the estimation process.
  - The proposed methodology is innovative in that it represents the first instance of such a technique being employed on Indian roads. This approach provides a more detailed and accurate assessment of AQI in real-time, which is of great significance in tackling air pollution and promoting public health.
  - Collection of a comprehensive traffic dataset containing 5048 images, as well as accompanying weather data and ground truth PM values. The dataset was obtained from various locations throughout the city of Hyderabad in India, and covers different seasons to provide a diverse and representative sample. This novel dataset will facilitate the development and evaluation of new methods for air quality estimation using traffic images and weather parameters in the context of Indian cities.

  - The proposed method achieved overall 82% accuracy considering PM variation due to season. We show a significant improvement in the accuracy of AQI estimation using images when compared with existing work.

- **Chapter 5**

  - Proposed a methodology that combines IoT and ML techniques to estimate the real-time AQI into five levels incorporating real-time traffic data, vegetation information, and weather parameters into the estimation process.
  - A novel and extensive traffic dataset has been gathered, comprising approximately 210,000 data points. This dataset includes traffic data, such as the mobility rate of traffic, vegetation information of the surrounding along with weather information such as temperature and relative humidity, and co-located ground truth PM values.
  - The dataset covers a period from January 2022 to May 2022 and includes samples from 15 distinct locations throughout Hyderabad, India. The acquisition of this rich and diverse dataset will aid in the development and evaluation of new methods for air quality estimation using traffic and weather data in the context of Indian cities.
  - An ML algorithm, which is both straightforward and efficient, has been employed to estimate the AQI level. The utilization of this algorithm facilitates the development of a fast and real-time pipeline that requires minimal processing.
  - The proposed method achieved an overall accuracy of 82.60% with an F1-Score of 83.67%. We also show the results on individual traffic locations to better understand the scenario.

1.3 Structure of Thesis

The rest of this thesis is organized as follows-

- **Chapter 2** offers a concise introduction to the IoT, including a discussion of its four-layer architecture. The chapter also explores various applications of IoT and the challenges associated with its implementation.

- **Chapter 3** provides the motivation for monitoring air pollution using various learning algorithms through IoT. The discussion is mainly around the motivation and initiatives taken by the Indian government behind air pollution monitoring, and learning methods used to compute the AQI using images and numerological data.

- **Chapter 4** introduces a methodology to predict the AQI in five levels, utilizing traffic images and weather parameters. The chapter also addresses the impact of seasonal variability on PM and its influence on the estimation of AQI during different seasons.

- **Chapter 5** presents a novel methodology based on the IoT and ML to estimate the AQI in five levels, utilizing real-time traffic data, vegetation information, and weather parameters from a newly-collected, feature-rich traffic dataset. This methodology is designed to be straightforward and efficient, allowing for fast and real-time estimation of AQI with minimal processing.
- **Chapter 6** presents the overall conclusion and future directions of the thesis.

Chapter 2

An Overview on IoT

This chapter provides a comprehensive overview of the IoT and discusses its various applications and challenges. In addition, it presents a detailed explanation of a four-layer IoT architecture, which serves as a fundamental framework for IoT implementation. By introducing this architecture, the chapter aims to provide readers with a better understanding of the different layers involved in IoT deployment and how they interact with one another to enable efficient and effective IoT applications.

2.1 Introduction to IoT

The term IoT denotes the networking of embedded computing devices in commonplace objects (referred to as "things" in IoT) via the internet, which empowers them to exchange data and perform consequential actions based on the information received. IoT is a combination of multiple disciplines, which includes:

- Sensor technologies: Sensors are integral to developing IoT-based solutions as they detect and convert environmental stimuli into discernable signals for both human and machine interpretation.
- Networking: IoT is nothing without a network to support it. Networking helps in communicating with multiple devices in real time with the help of networking protocols. The networking protocols provide connectivity, power, policy, compute, security and manageability at scale to IoT deployments.
- Embedded systems: At the crux of an IoT ecosystem lies the embedded system, which serves as the fundamental computing element in electronic devices. Comprising an integrated circuit housing a microcontroller designed for specific tasks, these low-power units aid in the processing and transmission of data.
- Artificial Intelligence: The precise value of IoT is determined at its analysis step. This is where AI technology plays a crucial role. AI helps obtain meaningful insights from data acquired through sensors. AI can also be referred to as the "brain" of the IoT.

- Cloud computing: Cloud computing and IoT exhibit a symbiotic relationship, as the former facilitates the seamless recording, capturing, processing, analysis, and storage of vast amounts of data generated by IoT devices. Cloud computing assumes responsibility for ensuring storage and security of data in IoT-based applications, and concurrently acts as a vital intermediary between the IoT platform and big data.

This entire network of sensors, embedded systems, communication channels, and algorithms that performs these tasks is called the IoT [9]. Fig.2.1 illustrates various disciplinary areas, devices and components connected and working together. IoT can also be defined as the analysis of data to generate a meaningful action, triggered subsequently after the interchange of data. The scope of IoT is not just limited to getting the devices connected, but rather is more about exchanging meaningful information from one device to another to acquire purposeful results.

2.2 IoT Architecture

IoT architecture refers to the combination of components such as sensors, microcontrollers, protocols, and cloud services that devise IoT networking systems. Any IoT architecture is divided into layers that allow developers to sense, analyze, monitor, and maintain the system's integrity. The architecture of IoT is a multi-step process through which data flows from devices connected to sensors, gets processed on microcontrollers/microprocessors, is sent through a network, and then through the cloud for storage and other usages [10]. With continuous development, IoT is proposed to grow even further, providing users with new and improved experiences. Although many researchers have defined IoT architecture

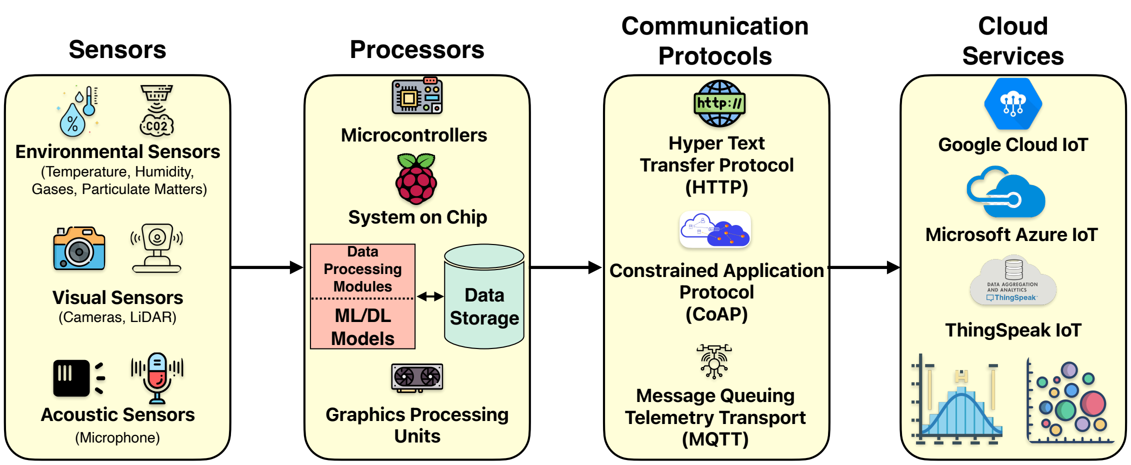


Figure 2.1: A four-layer IoT architecture consisting sensors, processors, communication protocols and cloud services.

between four to six layers [11, 12, 13], this thesis presents a four-layer IoT architecture (Fig. 2.1) comprised of 1. Sensors, 2. Processors, 3. Communication protocols, and 4. Cloud services.

Sensors - There are many different types of sensors used in IoT devices, each designed to measure different physical properties or environmental conditions. Some common examples include:

- Environmental sensors: These sensors measure environmental parameters such as temperature, humidity, light, air quality, and pressure.

- Visual sensors: These are sensors that can detect and capture images or video, which can be used for various applications such as surveillance, object recognition, or augmented reality.

- Acoustic sensors: These are sensors that can detect and measure sound waves or vibrations. They are commonly used for various applications such as noise monitoring, speech recognition, or structural health monitoring.

- Motion and proximity sensors: Motion sensors are capable of detecting movement or changes in motion that occur within their field of view. Conversely, proximity sensors are capable of detecting the presence of objects located within their range without the need for physical contact. Accelerometers, gyroscopes, infrared sensors, and ultrasonic sensors are some examples of these types of sensors.

These are just a few examples of the many different types of sensors used in IoT devices. The specific type of sensor used will depend on the application and the data that needs to be collected.

Processors - IoT devices use a variety of processors, depending on the specific requirements of the device and the application. Here are some examples of processors used in IoT:

- Microcontrollers (MCUs): MCUs are small, low-power processors designed for embedded systems. They are commonly used in IoT devices that require simple data processing and control functions. *Atmel AVR and ARM Cortex-M* are the famous processors used in IoT belongs to this category.

- System-on-Chip (SoC): SoCs are integrated circuits that combine multiple components, such as microprocessors, memory, and input/output interfaces, onto a single chip. They are commonly used in IoT devices that require more advanced processing capabilities. One of the most famous examples of these kind of processor in use is *Raspberry Pi*.

- Graphics Processing Units (GPUs): GPUs are specialized processors designed for graphics processing. They can also be used for general-purpose computing and are often used in IoT devices that require high-performance computing capabilities.

The choice of processor will depend on the specific requirements of the IoT device and the application. Factors such as power consumption, processing speed, and data storage capacity will also play a role in the selection of the processor.

Communication Protocols - Communication protocols are essential for IoT devices to exchange data and communicate with other devices and systems. Here are some examples of communication protocols commonly used in IoT:

- MQTT (Message Queuing Telemetry Transport): This is a lightweight publish-subscribe protocol designed for IoT devices with limited processing power and bandwidth. It is commonly used for machine-to-machine (M2M) communication and is often used in applications such as home automation, smart energy, and asset tracking.
- HTTP (Hypertext Transfer Protocol): This is a standard protocol used for transmitting data over the internet. It is commonly used in IoT applications for cloud-based services, such as remote monitoring and control.
- CoAP (Constrained Application Protocol): This is a lightweight protocol designed for IoT devices with limited processing power and memory. It is commonly used for IoT applications that require low-latency communication, such as smart cities and industrial automation.

These are just a few examples of the many different communication protocols used in IoT devices. The specific protocol chosen will depend on the requirements of the device, such as the range, data rate, power consumption, and security requirements.

Cloud Services and User Interface: Cloud computing plays a critical role in IoT by providing a scalable, reliable, and cost-effective platform for storing and processing the massive amounts of data generated by IoT devices and systems [14, 15]. IoT devices generate vast amounts of data, and cloud storage provides a scalable and cost-effective way to store and manage this data. Cloud platforms provide powerful data analytics capabilities that enable businesses to derive insights from the vast amounts of data generated by IoT devices. These insights can help businesses optimize their operations, reduce costs, and improve customer experiences. Cloud storage can also provide data redundancy and disaster recovery capabilities, ensuring that IoT data is always available and secure. Cloud platforms can easily scale to accommodate the growing number of IoT devices and the increasing volume of data they generate. This makes it possible for organizations to quickly and easily add new devices and services as needed, without having to invest in expensive infrastructure upgrades. Cloud services are categorized as 1. Infrastructure as a Service (IaaS) - Amazon Web Services (AWS), Microsoft Azure, ThingSpeak, etc. 2. Platform as a Service (PaaS) - Heroku, Google App Engine, Microsoft Azure, etc. 3. Software as a Service (SaaS) - Salesforce, Dropbox, Office 365, etc.

The User Interface (UI) is the primary means through which users interact with IoT devices and systems. The UI is the interface that allows users to control, configure, and monitor IoT devices and

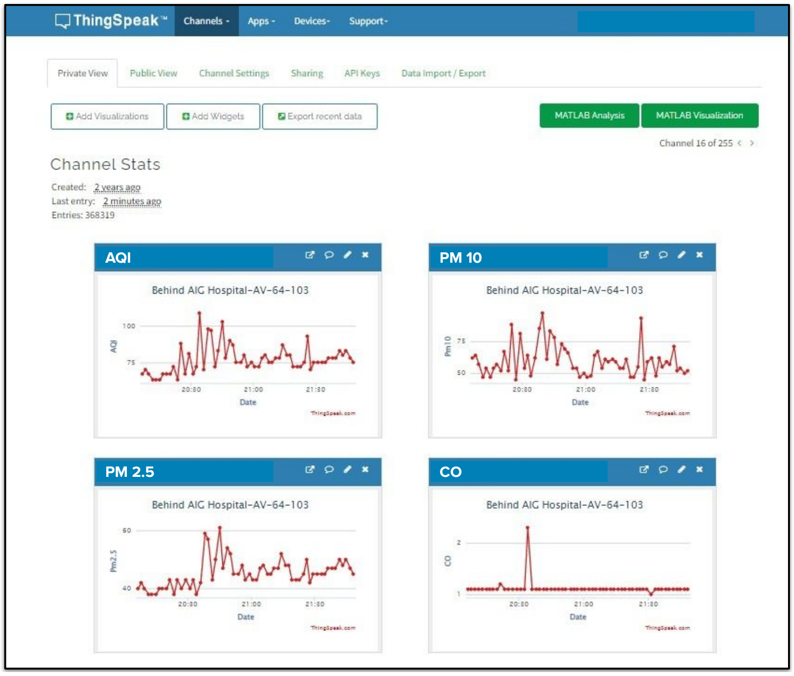


Figure 2.2: An exemplar of the ThingSpeak user interface showing the graphs for stored data. (Best viewed in color).

systems, and it can take many different forms, including mobile apps, web-based dashboards, voice assistants, and smart displays. One of the key benefits of a well-designed UI in IoT solutions is that it can make IoT devices and systems more accessible and user-friendly. A good UI can provide a seamless user experience, making it easier for users to interact with IoT devices and systems, and reducing the need for specialized technical knowledge. Another benefit of a good UI in IoT solutions is that it can enhance the user's understanding of the data generated by IoT devices and systems. A well-designed UI can provide users with clear and concise visualizations of data, making it easier for them to understand and interpret the data generated by IoT devices and systems. Fig. 2.2 shows the web-based user interface from ThingSpeak [16], a popular cloud-based IoT analytics platform developed by MATLAB. This interface allows users to create customized dashboards which enables real-time monitoring of IoT devices and data, allowing users to quickly identify trends, anomalies, and insights allowing them to make data-driven decisions.

2.3 IoT Applications

IoT has revolutionized the way we interact with our environment by enabling various devices to connect and communicate with each other. As a result, the applications of IoT are diverse and far-reaching, spanning across a broad range of industries, including smart cities, healthcare, transportation, agriculture, manufacturing, and many more. By leveraging IoT technology, these applications can enhance efficiency, increase productivity, and improve decision-making processes. As the IoT continues to evolve, the potential for new and innovative applications is virtually limitless, making it an exciting field to explore. Here are some emerging areas of IoT:

- **Smart cities**: Smart city is a concept that uses IoT technologies to improve the quality of life for citizens in urban areas. Smart city solutions involve integrating various technologies such as sensors, networks, and data analytics to optimize the use of resources, enhance public services, and improve the overall livability of a city. Some of the applications which includes under smart city are: 1. Traffic management, 2. Environmental monitoring, 3. Water management, 4. Public safety, 5. Waste Management etc. The Indian government has recognized the potential of smart city solutions in IoT to address key urban challenges and improve the quality of life for citizens.

    1. Smart traffic management: Several cities in India, including Bangalore, Delhi, and Mumbai, have implemented smart traffic management solutions such that intelligent traffic signaling systems and real-time traffic monitoring that use sensors and data analytics to optimize traffic flow and reduce congestion [17].
    2. Energy management: Several cities in India, which includes tourism spots, have implemented smart energy management solutions that use sensors and data analytics to monitor and control energy usage in public spaces and buildings [18]. This includes technologies such as smart lighting and energy-efficient buildings.
    3. Air quality monitoring: IoT-enabled air quality monitoring systems can detect and mitigate the harmful effects of air pollution by measuring air quality parameters and transmitting real-time data to cloud platforms for analysis and reporting. In India, air pollution is a significant issue, and the National Air Quality Monitoring Program (NAMP) [19] and the Central Pollution Control Board (CPCB) [8] monitor air quality across the country. IoT-enabled air quality monitoring systems have the potential to significantly improve air quality monitoring, providing real-time data that can help individuals, businesses, and governments take appropriate action to reduce pollution levels.
    4. Smart water management: IoT has emerged as a promising technology for smart water management systems. By integrating sensors, communication networks, and data analytics, IoT can provide real-time monitoring and control of water resources, leading to efficient and sustainable water management. One application of IoT in smart water management is the development of smart meters for water usage monitoring [20, 21]. These smart meters can track water usage in real-time and provide insights into consumption patterns, leak detection, more accurate billing systems, and water quality. This can lead to optimized usage and reduced wastage of water.

The utilization of IoT in smart city applications presents numerous potential use cases that can contribute towards fostering a sustainable and advanced way of living. The opportunities for leveraging IoT technology in this context are practically limitless.

- **Healthcare**: Healthcare is a critical sector where IoT has immense potential to improve the quality of care and access to medical services [22, 23]. In India, where there is a shortage of healthcare professionals and infrastructure [24], IoT-based solutions can help overcome these challenges and improve healthcare outcomes. Some of the key applications of IoT in healthcare include medical device monitoring, smart hospitals, medical supply chain management etc. IoT-based medical device monitoring is one of the key application of IoT in healthcare. Medical devices such as ventilators, Electro Cardio Gram (ECG) machines, and infusion pumps can be remotely monitored and managed using IoT technologies [25, 26]. This can help improve the safety and efficiency of medical procedures and reduce the risk of errors and complications. IoT technologies can enable the development of smart hospitals [27], another key application of IoT in healthcare that use sensors and data analytics to improve operational efficiency, reduce wait times, and enhance patient care. This includes technologies such as smart beds, connected medical devices, and real-time patient tracking. IoT technologies can improve the efficiency and transparency of the medical supply chain [28], enabling hospitals and clinics to track inventory, reduce waste, and ensure the timely delivery of medical supplies. This is particularly relevant in a country like India, where access to medical supplies can be a challenge in some areas.

- **Remote Triggered Labs**: IoT technology has enabled the creation of remote triggered labs, which allow researchers and students to perform experiments and interact with equipment remotely [29, 30, 31, 32]. This technology is particularly beneficial for educational institutions or research facilities that have limited laboratory resources, as it enables them to conduct experiments without the need for expensive lab equipment or a physical lab space. Remote triggered labs are typically equipped with sensors, cameras, and other IoT devices that enable users to remotely monitor and control experiments. For example, sensors can be used to monitor temperature, pressure, and other environmental conditions, while cameras can be used to capture images or videos of experiments as they are being conducted. Users can then view the data and images in real-time via a web-based interface [33], and can control the equipment remotely to adjust experimental parameters as needed. Overall, the use of IoT in remote triggered labs can revolutionize the traditional learning experience and provide students with more opportunities to learn and explore various fields.

- **Autonomous vehicles**: Autonomous vehicles, also known as self-driving cars, are an exciting application of IoT technology [34]. They use a combination of sensors, machine learning algorithms, and real-time data to navigate roads and safely transport passengers and cargo without human intervention. Autonomous vehicles have the potential to revolutionize transportation by improving safety, reducing congestion, and increasing efficiency. They can also provide new mobility options for people with disabilities and the elderly. Autonomous vehicles can be integrated with smart city infrastructure to improve traffic flow, reduce emissions, and improve safety. They can also be used to provide transportation services in underserved areas.

These are just a few examples of the many applications of IoT. As the technology continues to evolve, we can expect to see IoT being applied in new and innovative ways across various industries.

2.4 Challenges in IoT

While IoT offers many benefits, there are several challenges that must be addressed to ensure the success and widespread adoption of the technology. Here are some of the key challenges facing IoT:

- **Sensors cost and maintenance**: The IoT relies heavily on sensors, which are critical components in collecting data and providing valuable insights for various applications. However, the cost of sensors remains one of the primary challenges in IoT implementation. The initial cost of purchasing sensors can be expensive, especially when deploying a large number of sensors. The cost of sensors can also vary depending on the type, accuracy, and range of data they can collect. Sensors require regular maintenance and occasional replacement. For instance, some sensors need battery replacements, while others require periodic calibration. These maintenance and replacement costs can add up over time, increasing the overall cost of IoT implementation.

- **Performance**: Performance challenges in IoT are a common concern for organizations and developers implementing IoT solutions. IoT solutions typically involve a large number of devices and sensors. As the number of devices increases, the system must be able to scale to accommodate the additional load. Ensuring that the system can handle the increased volume of data and traffic is critical for maintaining performance. On the other hand, many IoT devices rely on batteries, which can limit their processing power and data transmission capabilities. Power management strategies must be employed to optimize battery life while maintaining device performance.

- **Real-time Implementations**: Latency is a significant concern in IoT solutions, particularly in applications that require real-time or near-real-time data processing. Latency can be caused by several factors, including network congestion, data processing delays, and device performance. Real-time implementation in IoT involves collecting data from sensors, processing it, and taking action based on the results. Minimizing latency requires a well-designed architecture that optimizes data transmission, processing, and storage.

- **Deployment**: Deploying IoT solutions can be a complex and challenging process, and there are several challenges that organizations may face. One of the most significant challenges is ensuring that IoT devices and systems can work seamlessly together. IoT devices and systems often come from different vendors and may use different protocols and standards, making interoperability a significant challenge. Another significant challenge is ensuring that IoT devices and systems are secure. IoT devices are vulnerable to security threats such as hacking, malware, and data breaches. Ensuring that IoT devices are secure requires robust security measures such as encryption, access control, and monitoring. IoT devices generate vast amounts of data, and managing and analyzing this data can be challenging. Organizations need to have effective data management strategies in place to ensure that data is stored, processed, and analyzed efficiently and effectively. Scalability is also a significant challenge when deploying IoT solutions. IoT systems need to be designed to handle large volumes of data and support the increasing number of connected devices. Ensuring that IoT systems can scale effectively requires careful planning and infrastructure design.

- **Security and Privacy**: With the proliferation of IoT devices, there is a growing concern about security and privacy. IoT devices are vulnerable to cyber attacks, and many devices lack sufficient security features, making them easy targets for hackers. Additionally, the large amounts of data collected by IoT devices raise concerns about data privacy and the potential misuse of personal information.

Addressing these challenges will require collaboration between industry leaders, government agencies, and other stakeholders. As IoT continues to evolve, it is essential to prioritize security, interoperability, and scalability to ensure the technology's widespread adoption and success.

Chapter 3

Learning Methods for IoT on Air Pollution Monitoring

This chapter provides the motivation for monitoring air pollution using various learning algorithms through IoT. The discussion is mainly around the motivation and initiatives taken by the Indian government behind air pollution monitoring, and learning methods used to compute the AQI using images and numerological data.

3.1 Motivation

Air pollution monitoring is the process of measuring and assessing the concentration of pollutants in the air. It is an essential tool for identifying and tracking the sources and levels of pollutants e.g. $PM_{2.5}$ (fine PM or particles with aerodynamic diameter less than 2.5 μm) and PM_{10} (coarse PM or particles with aerodynamic diameter between 2.5 μm and 10 μm) in the environment.

One of the main reasons for air pollution monitoring is to protect public health. Air pollution is linked to a range of health problems, including respiratory diseases, heart disease, and even cancer. Monitoring air pollution helps to identify areas where air quality is poor and take measures to reduce exposure to harmful pollutants. Another important reason for air pollution monitoring is to evaluate the environmental impact of air pollution. Monitoring helps to evaluate the impact of air pollution on the environment and take measures to reduce it. Corporations such as Google have equipped some of their Street View vehicles with air pollution sensors to measure air quality on a street-by-street basis in various cities [35]. In addition, startups in India have developed hardware and methodologies for real-time estimation of AQI [36].

Air pollution monitoring is essential for developing and implementing pollution control strategies. Monitoring data provides valuable information for the development and implementation of pollution control strategies. This helps to ensure that the most effective measures are put in place to reduce air pollution. For example, monitoring data can be used to identify the sources of pollutants and target mitigation efforts. It is important for governments, organizations, and individuals to invest in air pollution monitoring and use monitoring data to inform policy and decision-making. In this thesis, the focus is to monitor and predict the AQI where $PM_{2.5}$ and PM_{10} are the main contributors.

3.2 Air Pollution Monitoring Initiatives in India Using Weather Stations

India has taken several initiatives for air pollution monitoring to address the growing concerns over air quality. Here are some of them:

National Air Quality Monitoring Programme (NAMP): The NAMP [19] is a program launched by the Central Pollution Control Board (CPCB) in 1984 to monitor the ambient air quality in urban and industrial areas of India. The program aims to collect air quality data from various monitoring stations across the country to assess the status and trends of air pollution and to take appropriate measures to control it. Under the NAMP, air quality monitoring is conducted for pollutants such as particulate matter (PM_{10} and $PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), and lead (Pb). The data collected under the NAMP is used to generate AQI, which is a measure of air quality that helps the public understand the level of pollution in their area and take necessary precautions.

Continuous Ambient Air Quality Monitoring System (CAAQMS): The CAAQMS [37] was established in India in 2009 as part of the NAMP to supplement the traditional manual monitoring of air quality with real-time data. The system consists of several monitoring stations located in different parts of the country, including major cities, industrial areas, and sensitive regions such as hill stations and coastal areas. The CAAQMS is a network of real-time air quality monitoring stations that provide data on pollutants like particulate matter, sulfur dioxide, nitrogen dioxide, carbon monoxide, and ozone. The CAAQMS uses advanced instruments such as automatic gas analyzers, particle counters, and meteorological sensors to measure air quality parameters in real-time. The data collected is transmitted to the CPCB's central server for analysis and dissemination. Fig. 3.1 shows the CAAQMS network spread across India.

National Clean Air Program (NCAP): The NCAP [38] was launched in 2019 with the aim of reducing air pollution levels by 20-30% in 102 cities across the country by 2024. The program focuses on implementing measures like increasing the number of monitoring stations, controlling emissions from industries and vehicles, and promoting public awareness. Under the NCAP, each city is required to develop a city action plan that includes measures to reduce emissions from various sources, such as industries, vehicles, and households. The program also includes provisions for strengthening the air quality monitoring network, improving public awareness, and promoting research and development in the field of air pollution control.

Air Quality Early Warning System: In India, CPCB has developed an air quality early warning system called SAFAR (System of Air Quality and Weather Forecasting and Research) [39]. SAFAR provides air quality forecasts for Delhi, Mumbai, Pune, Ahmedabad, and other cities based on real-time data from air quality monitoring stations and weather models. The system provides a color-coded AQI based on the concentration of pollutants in the air and the potential health impacts. SAFAR also provides health advisories and recommendations for the public and authorities to reduce exposure to air pollution. The system can also provide information on the types of pollutants present in the air,

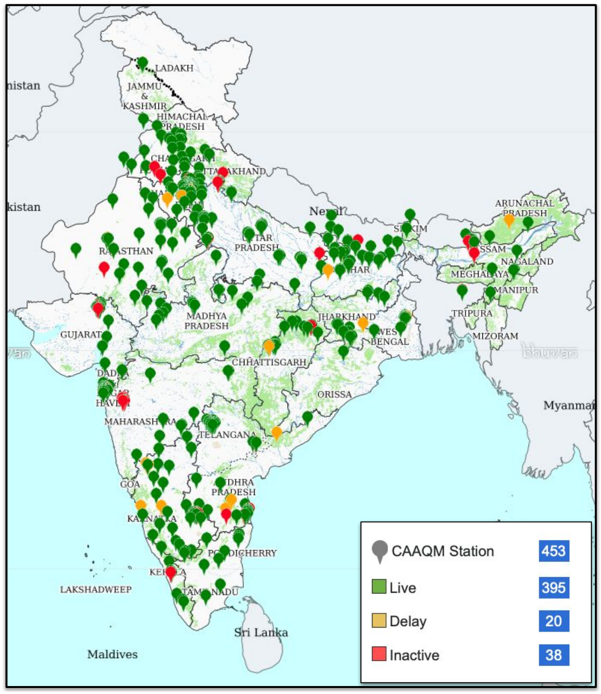


Figure 3.1: Network depicting CAAQMS nodes installed in the various locations of India. (Best viewed in color).

their concentrations, and potential health impacts. This information can help the public take necessary precautions, such as avoiding outdoor activities, wearing masks, and using air purifiers.

3.3 Learning Algorithms Used in IoT for Air Pollution Monitoring

Learning algorithms are increasingly being used in air pollution monitoring to estimate, predict, and control the level of air pollution. Machine learning algorithms, such as artificial neural networks, decision trees, and deep learning algorithms such as Convolutional Neural Network (CNN) [40], Long Short-Term Memory (LSTM) [40] etc., have been applied to various air quality parameters, such as particulate matter ($PM_{2.5}$ and PM_{10}), carbon oxides (CO_x), sulfur dioxide (SO_2) etc. These algorithms use data from various sources, such as meteorological data, traffic data, satellite images, and sensor networks, to predict air quality levels. They can analyze the complex relationships between the input data and the air quality parameters to estimate the level of air pollution accurately. As mentioned in section 2.4, one of the main challenges in IoT is sensor cost and maintenance. To address this issue, researchers globally have developed innovative methods that can provide the AQI without requiring the use of PM sensors, thereby avoiding the associated inconvenience. Using machine learning techniques, researchers make predictions of the AQI by analyzing images and additional parameters like temperature and humidity. These predictions rely on historical data to estimate the AQI.

When it comes to using IoT for air pollution monitoring, the data collected can be divided into two types: 1. numerical data, which includes data in the form of numbers such as concentration of pollutants, and 2. image-based data, which includes data in the form of images such as satellite imagery or pictures of pollutants. To analyze and understand this data, learning algorithms are used. This thesis aims to cover the methods used to teach these algorithms to work with both types of datasets (numerical and image-based) for air pollution monitoring using IoT.

3.3.1 Learning Algorithms on Numerical Data

To compute air quality, a wide range of data can be collected from various sources in the environment. Some of the important data that can be collected includes 1. Concentration of various gases in the atmosphere (e.g. $PM_{2.5}$ and PM_{10}, carbon oxide, etc.), 2. Meteorological data such as temperature, humidity, wind speed, etc. 3. Geographic data: land use, topography, and transportation patterns can provide additional context for interpreting air quality data. 4. Satellite imagery: remote sensing data can provide a broader picture of air quality across larger geographical areas. 5. Emission inventory data: data on the amount and type of emissions from sources such as vehicles, industries, and power plants can be used to estimate the expected air quality in an area. Researchers worldwide have utilized these data sources, applying learning methodologies to compute the AQI [41, 42, 43, 44].

In [41], LSTM network was used to predict AQI on a dataset collected in Chennai, India. The dataset consists of measurements of various pollutants such as particulate matter ($PM_{2.5}$ and PM_{10}), Ozone (O_3), Sulphur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Carbon Monoxide (CO), Lead (Pb), and Ammonia (NH_3). Apart from this, relative humidity, atmospheric pressure, wind speed and wind degree was also collected in the interval of 15 minutes. The dataset was collected for a duration of one year. Before being used to train the LSTM network, the data was preprocessed and normalized. The LSTM network was then used to predict the AQI level based on the available data on pollutants.

In [42], LSTM network was used to forecast $PM_{2.5}$ levels in Santiago de Chile. The article discusses the use of air pollution and meteorological measurements over a ten-year period in Santiago, Chile to analyze the behavior of three different zones. The study uses a method based on discrete cosine transforms and photochemical predictors to rebuild missing data. Deep learning techniques, particularly the LSTM model configured with a 7-day memory window, were found to be more effective at capturing critical pollution events than traditional multi-layer neural networks. The LSTM model also outperformed deterministic models currently used in Santiago, Chile.

CNN-LSTM model was used in [44] to improve the accuracy of air quality prediction for Beijing, China. A dataset consisting meteorological values was collected for a duration of one year. The model consists of two parts: a CNN layer and an LSTM layer. The use of the CNN layer allows the model to efficiently extract important features from the data. These features are then passed to the LSTM layer, which is able to capture the temporal dependencies of the data. By combining these two layers, the model is able to accurately predict future air quality data. The study compared the prediction accuracy of the CNN-LSTM model with several other ML and DL models. The results show that the CNN-LSTM model outperformed all other single prediction models in terms of accuracy. In particular, when compared to the SARIMA model, which is a representative time series model, the CNN-LSTM model showed significant improvements in its indicators. The MAE and RMSE of the CNN-LSTM were reduced by 3.17% and 5.46% respectively, and the R^2 score was improved by 8.45%

3.3.2 Learning Algorithms on Image-based Data

The improvement of image quality and the increased availability of smartphones and video surveillance equipment, along with the growing use of artificial intelligence, has made it feasible to use image processing and machine learning to detect air quality in images. The process of acquiring and collecting images has become simpler and more convenient, enabling the use of these technologies for air quality detection. The general public can readily capture images of their surroundings using their mobile phones and employ existing air quality image recognition models to analyze the images and obtain relevant air quality data. This information can be used to prompt individuals to take prompt action to mitigate air pollution risks. Employing images for air quality detection can significantly decrease the dependence on specialized hardware and equipment, as well as reduce the labor and resources needed for equipment upkeep. This approach is therefore more efficient and convenient. Additionally, it can enhance the precision of air quality monitoring across different spatial scales.

In [45], CNN was employed to estimate air pollution levels based on photos. Specifically, the CNN was designed to classify images based on their corresponding PM2.5 index. A pollution images dataset which includes photos shots taken in Beijing was collected. The architecture of the CNN consisted of 9 convolutional layers, 2 pooling layers, and 2 dropout layers. An improved version of the rectified linear unit was utilized as the activation function to address the issue of gradient disappearance. To address the air pollution classification problem, a negative log-log ordinal classifier with graph Softmax classifier was utilized.

In [46], a VGG-16 CNN architecture was utilized along with transfer learning on a dataset that was manually created to predict the AQI into different categories. The dataset consisted of 591 images that were collected from public cameras located in Beijing, China. The corresponding PM data was also collected from the nearest air quality monitoring station. After training a CNN model on the images, the authors classified the AQI into three categories: Good, Moderate, and Severe. The CNN-based model achieved a maximum accuracy of 68.74%.

In [47], ResNet-50 [48], which is a well-known CNN model, was used alongside support vector regression (SVR) to predict the $PM_{2.5}$ index of outdoor images. This approach involved integrating both image and weather data. The authors used two PM image datasets available for this study. The first dataset is called the Shanghai dataset, which includes 1885 photos captured at the Oriental Pearl Tower in Shanghai, China, at different times of the day. The second dataset is the Beijing dataset, which was created by the authors and contains 1514 photos obtained from a Beijing tourist website. The photos in this dataset were taken at different locations throughout Beijing City. The results of the experiment indicated that incorporating weather features with CNN can enhance the accuracy of $PM_{2.5}$ estimation from images.

The use of ResNet architecture for estimating air quality levels is proposed in [49] through a model known as AQC-Net. This model employs camera equipment to capture scene images and extract feature information, which is subsequently classified to estimate air quality. A self-supervision module (SCA) is incorporated to enhance the interdependent channel maps and improve feature representation by reconstructing the global context information of the feature map. Moreover, a high-quality outdoor air quality data set (NWNU-AQI) of images was gathered, comprising 5 different scenes, and labeled with real-time monitoring data from corresponding air quality monitoring stations. The collection of images was carried out over the course of two years, encompassing a range of weather conditions, seasons, and time periods of the day. According to the experimental results, the SCA module was found to be effective in improving the accuracy of the model's classification. The results also indicate that it is more suitable for air quality rating assessment compared to other methods.

In this chapter, the importance of air pollution monitoring is discussed, along with the initiatives taken by the Indian government to address this issue. The chapter also focuses on the use of learning algorithms in the IoT for estimating air pollution, including methodologies that utilize numerical and image-based datasets.

Chapter 4

Image Based Learning Methods for Air Pollution Monitoring

Typically, cities only have a limited number of air pollution monitoring stations that are of high quality but also expensive. However, by deploying a dense network of low-cost air pollution monitors based on the IoT, it is possible to increase the spatial resolution of pollution data. This means that more areas within the city can be monitored for pollution, providing a more comprehensive understanding of air quality across the city. This can help to identify pollution hotspots and to develop targeted interventions to improve air quality in specific areas [50, 51, 52].

Electronic gadgets are also available in the market that can monitor air quality and report the concentration of PM from which AQI can be computed. These devices, however, demand maintenance with time due to their limited lifetime. For example, SDS011 by Nova Fitness is one of the most widely used laser-based PM sensors. The datasheet [53] of this sensor claims a lifetime of 8000 hours which is roughly one year.

Instead of using a pollution monitoring, the AQI can also be determined with the help of image processing-based technique. Image based AQI calculation can serve the purpose in rural and sub-urban areas where sensors are unavailable. In general, sensors require regular maintenance. In addition, having an image-based AQI estimation allows portability through smartphones as a user can capture a traffic image and estimate the AQI in real-time. In this chapter, a method is proposed to estimate the AQI levels using traffic images and weather parameters instead of pollution monitoring sensors.

4.1 Related Work

In recent years, some work has been done in the field of air quality measurements using DL paradigms. Few of them [54, 55, 56] use deep learning-based algorithms on meteorological data-based air quality estimation, while some of the work incorporates images from different locations to compute air quality [57, 46]. [57] extracts various numerical and categorical from an image using image processing algorithms and applies Support Vector Regression (SVR) to train and predict PM values. Their dataset contains 6587 images collected from a fixed scene with respective $PM_{2.5}$ value, weather data, and geographic location spanning three cities of China. The SVR model performs good for the two cities but fails on the third city because of the narrow range of $PM_{2.5}$ values.

[46] uses CNN architecture along with transfer learning on a manually created dataset. The dataset contains a total of 591 images collected across different seasons from a Beijing tourist website with their respective $PM_{2.5}$ values. The air quality is categorized into three levels, i.e., good, moderate, and severe. Overall, the proposed method achieved 68.74% classification accuracy. However, [46] did not justify achieving the mentioned accuracy and what precisely the CNN model learned from the images to predict the AQI.

The main contributions of this work are as follows:

- An IoT-based novel methodology is proposed to estimate the real-time AQI into five levels using traffic images and weather parameters. To the best of the authors' knowledge, this work is the first of its kind to achieve this on Indian roads.
- An entirely new traffic dataset is collected on Indian roads containing 5048 images and related weather data with co-located ground truth PM values. The dataset contains samples across the Indian city of Hyderabad in different seasons.
- The proposed method achieved overall 82% accuracy considering PM variation due to season. We show a significant improvement in the accuracy of AQI estimation using images when compared with existing work [46].

4.2 Hardware Setup

Fig. 4.1 shows the block architecture of the hardware developed for this experiment. A Raspberry Pi Zero W (Rpi0) Microcontroller Unit (MCU) and a PiCamera are connected to it to capture and process the vehicle images. The other sensors that were interfaced with the MCU include BME280

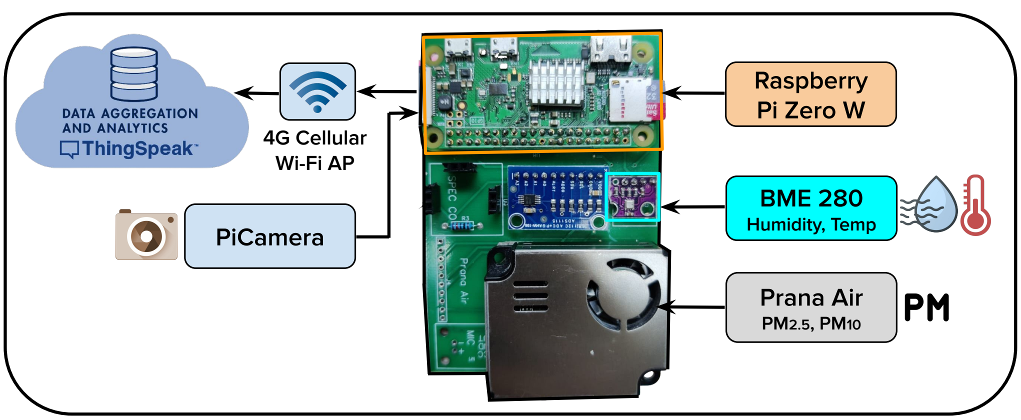


Figure 4.1: Block and circuit diagram of the hardware setup.

for temperature and humidity. A *Prana Air* [58] sensor was used for measuring the $PM_{2.5}$ and PM_{10} concentrations. It is a reliable PM sensor, as shown in the study done by [59]. The data collected from *Prana* sensor was used to calculate the AQI, which also served as the ground truth for the ML algorithm developed for this experiment. The hardware setup is capable of sending the processed data into a remote server, making it suitable for edge computing. A sample from each sensor was collected once in every 30s by the MCU. The sample is processed using the methodology defined in the upcoming sections. A Cellular 4G-based Wi-Fi access point was used to send the data to the remote server.

4.3 Measurement Campaign And Dataset

With the help of the hardware setup mentioned in the previous section, a traffic dataset was collected, containing images of traffic and the measurement of pollution levels. The device was placed on top of a car. The car was driven during the daytime and captured variations, including different scenarios (urban and sub-urban areas), traffic conditions, and pollution levels. The dataset was captured across Sep'21-Dec'21, comprising two seasons, monsoon and winter. The attempt was to get a diverse dataset. A total of 5048 samples were collected in this duration. Datapoints collected between Sep'21 and Oct'21 were considered for the monsoon season. The rest of the data collected during Nov'21- Dec'21 was accounted for the winter season. Fig.4.2 shows the routes traveled during this campaign in the metro city of Hyderabad, India. Each captured image is associated with co-located respective sensor values, i.e., temperature, humidity, $PM_{2.5}$, and PM_{10} measurement. The AQI level is computed using the $PM_{2.5}$ and PM_{10} values as per the Central Pollution Control Board, India [8], and categorized into five classes which are as follows: 1. **Good** (0 - 50) 2. **Satisfactory** (51-100) 3. **Moderate** (101-200) 4. **Poor** (201-300), and 5. **Severe** (>300). The distribution of the collected data in terms of the AQI level and month is shown in Fig. 4.3.

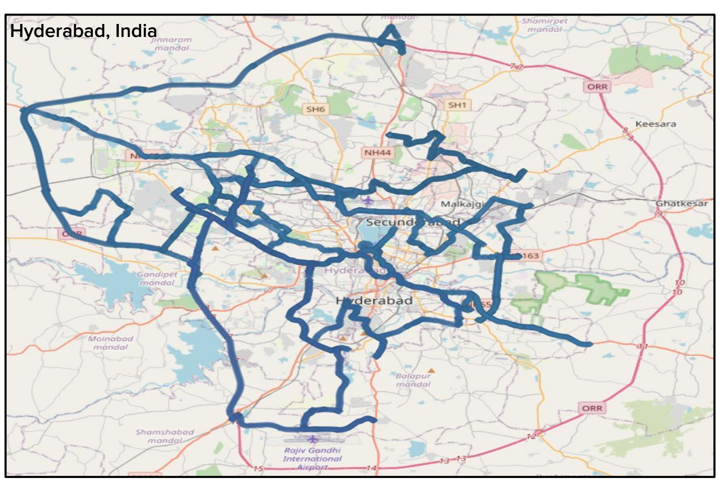


Figure 4.2: Street view of routes traveled during measurement campaign (Total distance = 1000 km).

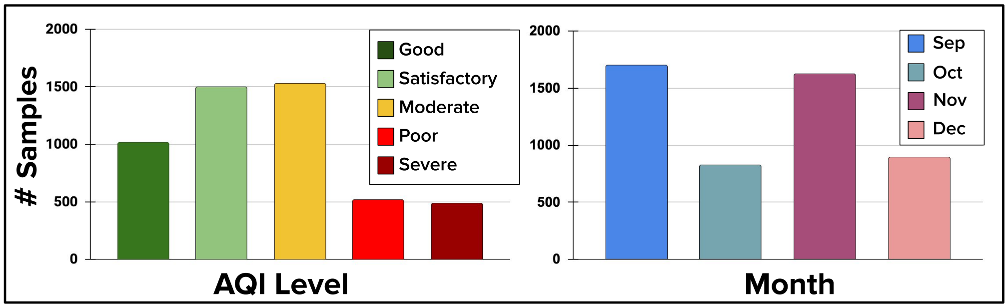


Figure 4.3: Left: Frequency of the AQI levels in the collected dataset. Right: Frequency of samples collected across months. (Best viewed in color).

Table 4.1: Distribution of type of vehicles in the detection and localization dataset.

Vehicle	Bike	Car	Truck	Bus	Rickshaw
Count	103608	90520	27837	18745	32280

4.4 Proposed Methodology

We propose a novel methodology to estimate AQI using traffic images for Indian roads. A pipeline for the same is shown in Fig. 4.4. Firstly, the image features are extracted using DL and image processing methods and concatenated with sensor features to generate a feature dataset. Further, an ML model is trained on the feature dataset to estimate the AQI level.

4.4.1 Image Features Extraction

The central idea of this work is to estimate the air pollution i.e. AQI based on the traffic images. Hence, features were derived from the collected images to use it further for AQI calculation. From the given image, all the pollution-emitting vehicles were detected and their respective count was used as an image feature. To detect the vehicles from a given image, You-Only-Look-Once version 5 (YOLOv5) [60] was trained on Indian Driving Dataset (IDD) [61].

IDD is an object detection and localization dataset that includes images covering highways and lanes with various traffic scenarios and illumination conditions. The objects in the images are annotated (drawing a bounding box around the object) finely with their respective classes. Although the IDD has 34 unique labels containing every possible object in the traffic, our use case is limited to identifying objects which contribute to air pollution. Hence, five pollution-emitting vehicle classes were picked which are as follows: 1. **Motorcycle** 2. **Car** 3. **Truck** 4. **Bus** 5. **Autorickshaw**. As the classes are limited, all the images containing the above-defined classes from the IDD were selected. The rest of the images were discarded, resulting in a subset of the IDD. There were a total 37869 images in the resulting dataset for which the object frequencies are shown in Table 4.1.

To quantify the vehicles present in the image, YOLOv5 algorithm was used. YOLOv5 is an object detection and localization algorithm which uses Convolutional Neural Network (CNN) as the feature extractor to detect and localize multiple objects in a given image. The final output of YOLOv5 for a single image is: detected objects (classification) and their bounding box (regression). YOLOv5 was trained on the above-defined custom IDD.

4.4.2 Image Visibility Score Calculation

As the camera can only take images of the traffic and road condition in front of the test-vehicle, the information received by the image is limited in terms of scope. It is essential to capture the air pollution generated by the other elements, e.g. constructions (road, buildings etc.), fire etc as well. To capture the essence of pollution caused by other sources, the visibility of the image is computed using Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) [62] which is a no-reference Image Quality Assessment (IQA) metric. As visibility is a subjective matter, a human evaluated dataset named TID2008 [63] which has 1700 images and their respective quality scores is used as image visibility score reference. The output of BRISQUE algorithm for a given image is a number between 0 to 100, where 0 signifies the best, and 100 signifies the worst visibility. An example of image visibility metric calculation can be seen in Fig. 4.4.

4.4.3 Feature Vector Generation

A feature vector is generated corresponding to each sample defined in the dataset collected in Section 4.3. The steps are as follows:

(a) Image features: Firstly, the image is passed to the trained YOLOv5 model, which detects the count of pollution-emitting vehicles present in the image. The detection includes the count for each type of vehicle, i.e., bus, car, truck, motorbike, and autorickshaw (total 5), and is treated as the image feature vector. After that, the visibility score of the image is computed using the BRISQUE algorithm. The output of this algorithm is a single number and contributes as an image feature vector.

(b) Sensor features: Finally, the corresponding sensor values, i.e., temperature and humidity, are concatenated to the image feature vector to produce the complete feature vector of size 8×1 for the given sample. An example of the feature vector is shown in Fig. 4.4.

(c) Label: The associated $PM_{2.5}$ and PM_{10} concentration values obtained from the reference PM sensor are used to generate the label for a given sample. An AQI value is computed using these sensor-detected values and categorized into one of the five AQI levels mentioned in section 4.3. The categorized AQI level is used as the corresponding label.

After processing the above-defined steps for all the samples in the dataset, a $m \times 8$ sized data matrix $\mathbf{M}$ is obtained, where m is the total number of samples present in the dataset. A $m \times 1$ sized vector y containing the corresponding labels is also obtained.

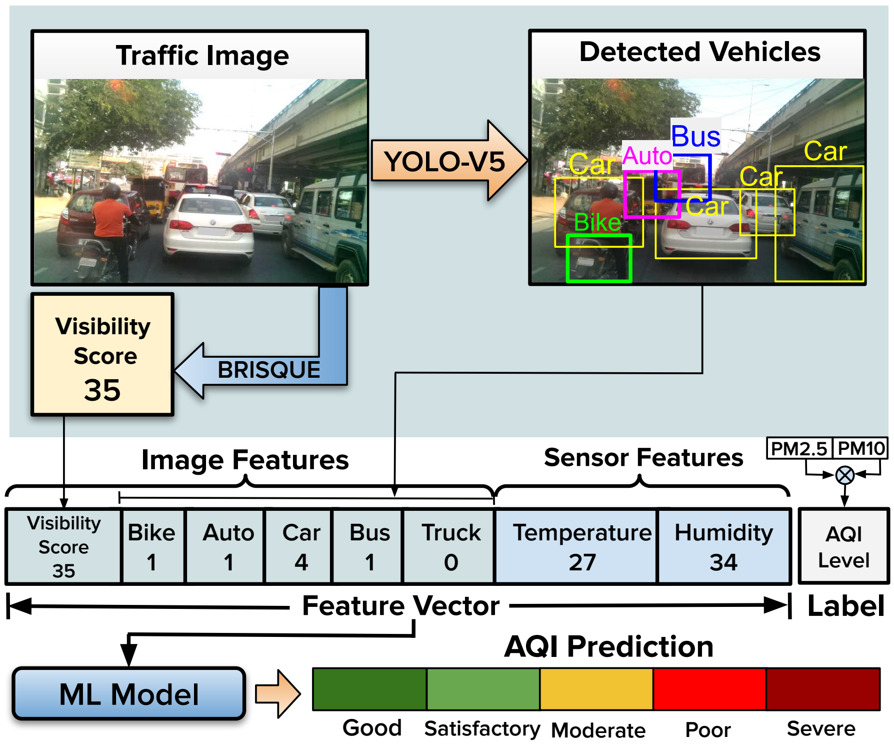


Figure 4.4: Algorithmic pipeline of the proposed method. Firstly, the image is passed to the trained YOLOv5 and BRISQUE algorithm to generate the image features. Then it is concatenated with corresponding sensor features to generate a complete feature vector with the corresponding label. Finally, an ML model is used to train and detect the AQI into five categories. *(Best viewed in color)*

4.4.4 Training

With the help of the dataset $\mathbb{M}$, and the corresponding label vector y, an ML model was trained to classify the samples into five different AQI levels. As this is a supervised learning problem, where all the dataset features have continuous values, a classification-based ML model was trained to predict the AQI for a given sample. To choose the best performing ML model, three different ML models that best suit the data were experimented: 1. RF 2. SVM and 3. MLP. Each of the models has five classes (AQI levels) as output.

Firstly, standard normalization was performed on all the dataset features as part of feature engineering. This preprocessing step ensures that the feature values are centered around the mean with unit standard deviation. After this, the normalized dataset was split into the training and validation part using K-fold cross-validation strategy with 10 folds. This step ensures better model generalization ability than standard train/test split and minimizes the occurrence of bias estimation. The ML model was trained and validated on each fold separately. To evaluate the ML model, the average of the metrics (accuracy and F1 score) of the validation part across all the ten folds were calculated.

Detection: To compute the AQI for a given traffic location, the PiCamera captured the image, which is passed to the YOLOv5 and BRISQUE algorithm to compute the count of each type of vehicle and image visibility score respectively. The sensors provided the corresponding temperature and humidity values. After this, using the image and sensor features, a feature vector of size 8×1 was created and passed to the trained ML model to detect the AQI level. All the computation related to AQI estimation (YOLOv5, BRISQUE and ML model) are performed on Rpi0 itself and only the estimated AQI is sent to the remote server, thus making it suitable for edge-computation.

4.5 Experiments & Results

The YOLOv5 model was trained for 25 epochs and converted into a *TensorFlow Lite* [64] model to run on Rpi0 . Fig. 4.5 shows evaluated metrics of the trained YOLOv5 model. An example of YOLOv5 output can be seen in Fig. 4.4.

For RF model, the number of decision trees was set to 100, and the split criterion was *entropy*. Tree pruning mechanisms were used to avoid overfitting. For SVM model, the regularization parameter was set to 5, and the *RBF* kernel was used. In the case of MLP model, three hidden layers, each having 20 neurons with *ReLU* activation function, was used to train for 100 epochs. All the ML models were implemented using the *Scikit-learn* [65] ML library. To detect one sample using the methodology proposed, the Rpi0 took around 20 seconds.

Table 4.2 shows the R^2 score of the features with respect to the AQI. It can be seen that all features have a positive correlation with the AQI in the range of 0.2-0.4. This indicates the partial dependence of the AQI on these features.

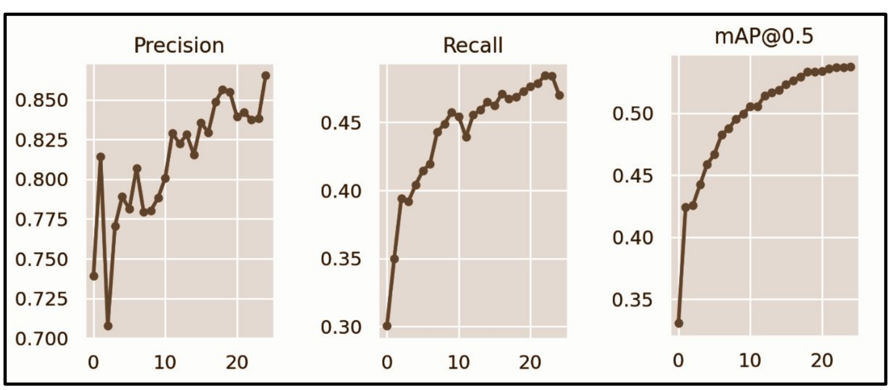


Figure 4.5: YOLOv5 training results. X-axis of each graph represents number of epochs and Y-axis represents respective values. Final results at epoch 25 report 86.54% precision, 47% recall and 53.75% *mAP@0.5*.

Table 4.2: R^2 score of features w.r.t AQI

	Vehicles	**Temperature**	**Humidity**	**Visibility**
AQI	0.33	0.29	0.31	0.41

Table 4.3: Performance of various methods on overall and season-wise data. Note that the ML methods (SVM, MLP, RF) were trained on features extracted using method described in section 4.4.3.

Method	**Monsoon**		**Winter**		**Overall**	
	Acc	F1	Acc	F1	Acc	F1
SVM	0.86	0.85	0.74	0.72	0.77	0.76
MLP	0.90	0.89	0.78	0.74	0.79	0.78
RF	**0.91**	**0.90**	**0.80**	**0.78**	**0.82**	**0.81**
CNN [46]	0.71	0.70	0.61	0.61	0.67	0.65

The ML models were trained and validated for the dataset mentioned in Section 4.3. As there are seasonal variations in PM values [66], we trained three different models each for: 1. Monsoon dataset (samples collected between Sep'21 - Oct'21) 2. Winter dataset (samples collected between Nov'21 - Dec'21), and 3. Overall dataset (combining Monsoon and Winter dataset) . The results obtained for all three datasets are presented in Table 4.3.

For the overall dataset, the RF model achieved an accuracy of 82% and an F1-score of 81%. For the data points of monsoon season, it is observed that the RF classifier performs the best with an accuracy of 90.32%. The main reason for this relatively high accuracy is better training of the model as there are significantly high number of data points with low AQI values in monsoon season. Hence, most of the data points belong to the first two categories. This is more evident from the Fig. 4.3 that shows the category-wise distribution of dataset. Categories named as "Good" and "Moderate" account for 50% of the collected data points, which leaves significantly less room for the misclassification of the samples. On the other hand, RF is the best performing model for Winter dataset as well, with an accuracy of 80.14%. It is relatively low as compared to the monsoon season as the data is spread over all categories of AQI, which also increases the chance of misclassification.

To compare our proposed method with the existing work, we applied the method proposed in [46], which used plain CNN on each of the three datasets mentioned above and observed an overall accuracy improvement of 15%. The main reason behind this improvement is how features from images are extracted. As a traffic image can have different objects, our work emphasizes focusing only on those responsible for air pollution. On the other hand, applying plain CNN on the images straight-forward fails to identify this paradigm.

4.6 Conclusion

In this chapter, a simple and efficient method for classifying the AQI based on images using a combination of supervised learning algorithms, including ML and DL, on an IoT device is presented. The experimental results show that the proposed method achieves an accuracy of up to 90% for the AQI classification. Additionally, a feature-rich dataset was created and made publicly available to encourage further research. However, the current work is limited to predicting the AQI only during daylight hours, and future work will include scaling the method for nighttime and collecting data during the summer season. Furthermore, there are plans to collect data and predict AQI for different cities as well.

Chapter 5

Maps Based Learning Methods for Air Pollution Monitoring

In the preceding chapter, a new approach was introduced to calculate the AQI in real-time for road traffic using images and weather parameters. The central concept behind this approach was to obtain an understanding of the number of vehicles present on the road using traffic images which contributes towards air pollution. Nevertheless, there are other ways to obtain the same information, such as utilizing real-time maps information, which includes information about the traffic flow of a particular road. This chapter presents an alternative approach that utilizes real-time traffic data to estimate the AQI.

5.1 Related Work

There has been some work in recent years in case of estimating air pollution with the help of traffic and meteorological data using ML paradigms [67, 68, 69, 70, 71]. [67] collected a dataset from weather and air stations, including wind data, temperature, relative humidity, air pollution data, and ten agents present in the air. Fixed video cameras obtained vehicle information to collect traffic data. Various ML models were tested on the features extracted from the dataset. However, this method limits the AQI calculation to specific areas due to video camera installation to get traffic data. [68] used ML models to predict roadside $PM_{2.5}$ and PM_{10} values on the dataset collected at 19 air quality monitoring sites in London, while [69] used RF models to analyze the PM_{10} trends for 31 air quality monitoring sites in Switzerland. [70] used ML-based approach to determine the air pollution level in a typical street canyon. A dataset has been collected in Zagreb city (capital of Croatia) containing PM_{10}, NO_2, and other pollutants on a daily basis for approximately three years. However, instead of finding the AQI in categories, a real number using a regression-based approach is calculated. [71] used an ML-based approach to predict the roadside particle mass concentration ($PM_{2.5}$ and PM_{10}) and particle number counts based on traffic and meteorological data in London, UK. The dataset was obtained from an air quality monitoring site in London and sampled hourly for a period of seven years. In this work also, instead of calculating the AQI as a category, the value of all the pollutants has been calculated as real numbers using the regression approach.

In all the above articles, the data has been obtained using meteorological sites over a period of years. However, PM values are spatially sensitive and can differ by a good margin in nearby locations. Hence, in this article, the ground truth data such as $PM_{2.5}$, PM_{10}, feature values such as temperature, and relative humidity are collected through a dedicated PM monitoring node [1]. The nodes are placed in close proximity so that the values obtained are as accurate as possible to the respective location. This data collection process ensures that the sensor values are co-located and accurate. Secondly, this article aims to predict the AQI category instead of a real-valued number. Calculating a level for the AQI makes it more user-friendly and intuitive.
The specific contributions of this work are as follows:

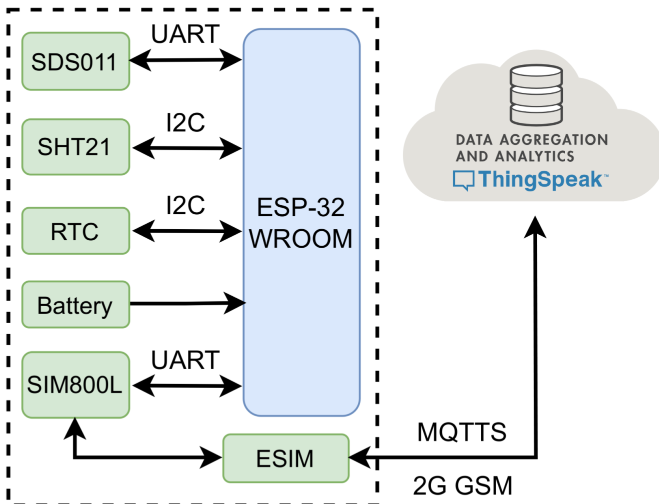
- An IoT and ML-based methodology is proposed to estimate the real-time AQI into five levels using real-time traffic data and weather parameters. To the best of the authors' knowledge, this article is the first of its kind to achieve this on Indian roads.
- A completely new rich traffic dataset has been collected containing approximately 210,000 data points, including traffic information (such as the mobility rate of the traffic), weather information (temperature and relative humidity) and co-located ground truth PM values. The dataset contains samples across the 15 different locations in Hyderabad from Jan'22 - May'22.
- A simple yet effective ML algorithm is used to estimate the AQI level, which enables the whole pipeline to be fast and real-time with minimal processing.
- The proposed method achieved an overall accuracy of 82.60% with an F1-Score of 83.67%. We also show the results on individual traffic locations to better understand the scenario.

5.2 IoT Network

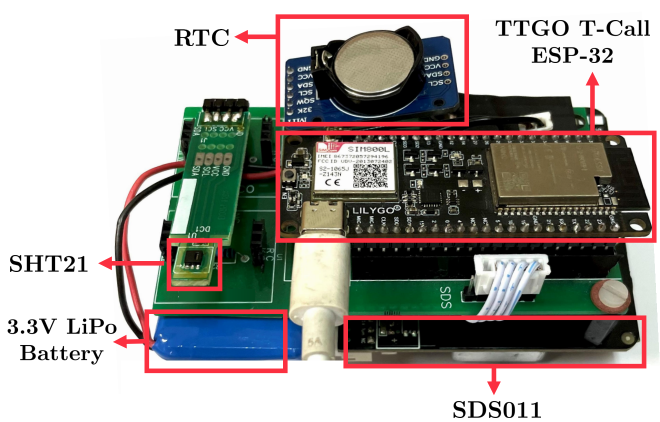
Figs. 5.1(a)-5.1(b) show the block architecture and the circuit board, respectively, of the IoT PM monitoring device deployed in the main road and junctions. Each node consists of TTGO T-Call ESP32

Table 5.1: Specifications of sensors used in the developed PM monitoring node.

Sensors	**Specification**	**Value**
SDS011 [53]	Measurement parameters	$PM_{2.5}$ & PM_{10}
	Operating Temp Range	-20°C to +50°C
	Operating RH Range	0-70%
SHT21 [72]	Measurement parameters	Temp & RH
	Operating Temp Range	-40°C to +125°C
	Operating RH Range	0% RH to 100% RH



((a)) Architecture



((b)) Circuit board

Figure 5.1: PM monitoring node and architecture [1]

[73] based microcontroller and sensors for PM, temperature and humidity; additionally, it has a real-time clock (RTC) and Li-Po battery. The specifications of the sensors used are given in Table 5.1. Nova PM SDS011, which is a light scattering principle-based sensor, has been used for measuring the concentration of fine particulate matter $PM_{2.5}$ and PM_{10}, as it has been shown to have the best performance with beta attenuation mass (BAM) compared to other low-cost sensors [74]. As concluded in reference, that temperature (Temp) and relative humidity (RH) impact PM concentration and also the light scattering-based PM sensors do not perform reliably well at extreme temperature and humidity conditions. SHT21 is used to monitor these parameters for the reliability of SDS011 sensor readings.

The controller reads data from all the sensors periodically at a frequency of 30 sec and offloads it to ThingSpeak, a cloud-based server employing MQTTS. The SDS011 and SIM800L modules are connected to the controller through the UART protocol, while the SHT21 and RTC are connected through the I2C protocol. The device is powered using a 3.3V rechargeable lithium polymer ion battery. An AC-to-DC Power adapter and an onboard battery management circuit are used to charge the battery. As the deployment is outdoor, the sensor node is enclosed in a polycarbonate box of IP65 rating, which protects the node from dust and water.

Fig. 5.2 shows the location of the nodes and the traffic status of the roads (on an average day). These locations are used to collect the real-time traffic data as well as sensor data. These locations mainly contain major city roads and include a mixture of heavy and light traffic. The total distance covered is approximately 15 kms spanning an area of 6 km^2.

5.3 Dataset Collection

In this work, a dataset is collected using the PM monitoring node defined in the section 5.2, with the help of digital map service providers. A 5-dimensional feature vector has been accumulated for each data point in the dataset, where the features are

- Traffic Mobility Rate (TMR)
- Humidity
- Temperature
- Normalized Difference Vegetation Index (NDVI)
- Time of the day (categorized as morning, afternoon and evening)

After concatenating all the features accumulated from the samples in the dataset, a $m \times 5$ data matrix M is obtained, where m is the number of samples present in the dataset. A $m \times 1$ sized vector y containing the corresponding label for each sample is the respective AQI category computed using $PM_{2.5}$ and PM_{10} values. Next, some of the important parameters such as TMR, NDVI, and AQI categorization are explained in more detail.

5.3.1 Traffic Mobility Rate

Traffic on the road is defined as the rate of mobility of the vehicles present on the road. In standard speaking terms, high traffic refers to the slow mobility of the vehicles and vice versa. There are several ways to get the traffic status of a specific location (road) using various digital map service providers, e.g., Google Maps, HERE Maps, Bing Maps, etc. An application programming interface (API) from HERE Maps [75] is used for our use case to collect the traffic data in real-time. HERE Maps RESTful web API provides location-aware features such as traffic and weather information. For a given location (latitude and longitude) with the desired radius, HERE Maps API returns a list of roadways and their traffic information in real-time.

One of the vital traffic information provided by HERE Maps API is the mobility score of a given road, also known as the Jamming Factor (JF). The JF is a real number between 1 and 10 and is categorized as follows: 1. **Free** traffic flow (0 - 4) 2. **Sluggish** traffic flow (4 - 8) 3. **Slow** traffic flow (8 - 10). As for a given location, there are multiple roadways and each roadway has a JF associated with it, we calculate

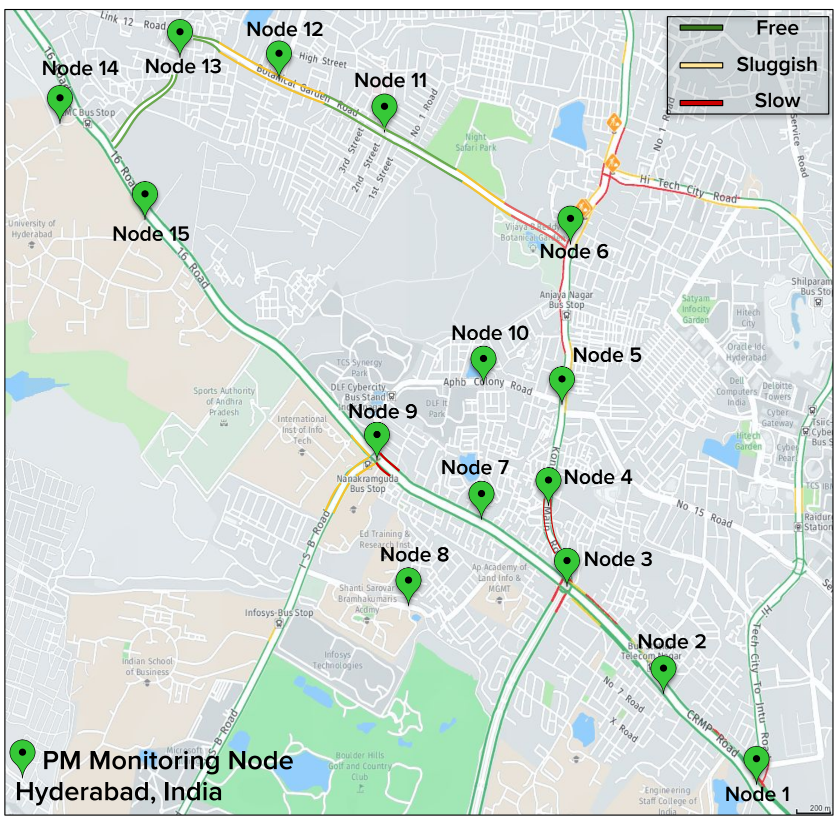


Figure 5.2: Locations of the 15 PM monitoring nodes on the map along with the traffic status. (Best viewed in color)

the final traffic mobility rate (TMR) as follows:

$$T = \frac{1}{n}\sum_{r=1}^{n} J_r \tag{5.1}$$

where J_r is the JF of the r^{th} road and n is total number of roads for any given location.

The traffic parameters are collected every 30 seconds between 0800 hrs and 2100 hrs across the month of Jan'22-May'22. A total of approximately 210,000 samples have been collected in this duration. One of the significant reasons to collect the data in the daytime is to predict the behavior of air quality only in the presence of traffic, as in the night-time, the traffic is negligible.

5.3.2 NDVI Score

The NDVI [76] is a graphical indicator that indicates the presence of vegetation in a particular area. It is a technique to classify the land as green, barren, etc., using satellite images of the earth. [77] shows that vegetation is a sound-absorbent of PM. It helps settle the dust and acts as a natural bio-filter against the PM. In our case, we try to locate the vegetation areas for the given map in Fig. 5.2 and then relate the PM values captured by the sensor. As the vegetation in an area can affect the AQI category, it is essential to consider this score while predicting the AQI. NDVI score is calculated as follows:

$$\text{NDVI} = \frac{R_{nir} - A_{red}}{R_{nir} + A_{red}} \tag{5.2}$$

where R_{nir} is the amount of reflection on the vegetation area in near-infrared spectrum and A_{red} is the amount of absorption onto the vegetation area in the red range of the spectrum. The NDVI value ranges between -1 to $+1$, where -1 indicates a high probability of water body and $+1$ indicates a high probability of vegetation in that area. For our paper, the NDVI values for the 15 locations were collected every month as the change in the vegetation is very slow.

5.3.3 AQI Categorization

Each sampled data point of the dataset is associated with co-located respective node sensor values, i.e., temperature, relative humidity, $PM_{2.5}$, and PM_{10} measurement. The AQI level is computed using the $PM_{2.5}$ and PM_{10} values as per the Central Pollution Control Board, India [8], and categorized into five classes which are as follows: 1. **Good** (0 - 50) 2. **Satisfactory** (51-100) 3. **Moderate** (101-200) 4. **Poor** (201-300), and 5. **Severe** (>300).

5.4 Proposed Methodology

The main idea of this work is to predict the AQI for a given traffic scenario. We propose a simple yet effective methodology to predict the AQI category using the dataset defined in section 5.3. The pipeline

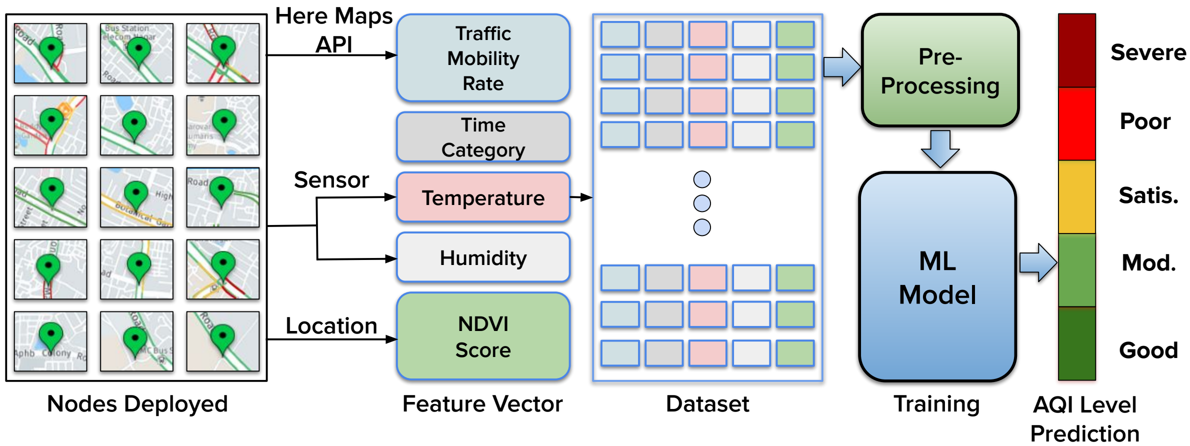


Figure 5.3: Algorithmic pipeline for the proposed methodology. Using the nodes deployed and their location, TMR has been calculated using HERE Maps API. After that, the NDVI score and weather information (temperature and humidity) are concatenated to make a 5-dimensional feature vector dataset. Further, this dataset is used to train the ML model to predict the AQI level. (Best viewed in color)

shown in Fig. 5.3 explains the proposed methodology. Firstly, the dataset is preprocessed, and then used to train the ML model. Further, the trained ML model is used to predict the AQI category for a given test sample.

5.4.1 Preprocessing

The first step before training the ML model is to preprocess the dataset M obtained in section 5.3 so that it follows characteristics helping better model generalization. Standard normalization is applied to the dataset for data preprocessing to achieve zero mean and unit standard deviation. This step ensures that all the samples in the dataset follow a similar data distribution and helps converge faster while training the model. After this, a *MinMax* scaler is applied to the dataset, transforming all the features into a range of 0 to 1. This step ensures that all the features of the dataset are in the same range avoiding any kind of bias in the model. The whole preprocessing step is defined as follows:

$$M_s = \frac{M - \mu_M}{\sigma_M} \quad \text{(Standard normalization)}, \tag{5.3}$$

$$M' = \frac{M_s - \min(M_s)}{\max(M_s) - \min(M_s)} \quad (\textit{MinMax} \text{ scaling}) \tag{5.4}$$

where μ_M and σ_M is the mean and standard deviation of M along the columns respectively.

5.4.2 Training

With the help of preprocessed dataset, M' defined in the above section, and the corresponding label vector y, a ML model was trained to classify the samples into five different AQI categories. As this is a supervised learning problem, a classification-based ML model was used. The dataset's features M' contain both kinds of values, i.e., continuous and discrete. All the values in the dataset are well normalized with a similar range of values. Due to these factors, we chose ML models that best suit the dataset. We experimented with three different ML models: 1. Random Forest (RF) [78], 2. Support Vector Machine (SVM) [79] and, 3. Multi-Layer Perceptron (MLP) [80] and choose the best performing model after hyperparameter tuning. Each model's output was set to five classes depicting the respective AQI categories.

While training, the training dataset M' was split using the K-fold cross-validation technique with ten folds. The ML model was trained and validated on each fold separately. This is a paradigm used while training the ML models to increase the generalization ability of the model. During the evaluation of the ML model, four metrics were calculated: 1. Accuracy, 2. Precision 3. Recall, and 4. F1-score on the validation part and mean was taken across all ten folds.

5.4.3 Detection

At the time of detection, firstly the traffic mobility rate is fetched using the HERE Maps API for a given location. After that, the NDVI score for that particular area is obtained. These values are concatenated with humidity and temperature of the location along with the time of the day making a feature vector of size 5×1. This feature vector was first preprocessed using the methods defined is subsection 5.4.1. After this, the trained model was used to predict the AQI category into one of the five classes.

5.5 Results

As discussed in the proposed methodology (section 5.4), a total of three models were experimented and trained to classify the AQI on the dataset defined in section 5.3. For the RF model, the number of decision trees was set to 200 as the number of samples in the dataset is large, and the split criterion was *entropy*. To avoid overfitting and get better convergence while training the RF model, tree pruning mechanisms were used. For the SVM model, the *regularization* parameter(*C*) was set to 8 with *Radial Basis Function* kernel. In the case of the MLP model, five hidden layers with neuron sizes 128, 64, 32, 16, and 8, respectively, with *Rectified Linear Unit* (ReLU) non-linear activation function, was used to train for 100 epochs. All these models were implemented using *Scikit-Learn* [65], which is a popular python-based ML library. As these ML models do not have much parameters to train, they are computationally very light and took only a few microseconds while inferencing on single test sample.

Table 5.2: Importance of features w.r.t AQI

TMR	**NDVI**	**Temperature**	**Humidity**	**Time of the Day**
0.32	0.29	0.19	0.11	0.09

Table 5.3: Performance of the various ML models on overall dataset.

ML Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
RF	**82.60%**	**84.73%**	**82.63%**	**83.67%**
MLP	79.31%	77.98%	79.43%	78.70%
SVM	78.52%	77.13%	78.67%	77.89%

Table 5.2 shows the importance of the features in the dataset while computing the AQI. It can be observed that the feature traffic mobility rate and NDVI score play an essential role with the support of temperature and rest other features.

The ML models were trained and validated for the dataset mentioned in section 5.3. As the dataset is collected on a total of 15 different nodes at different locations, the environmental factor around them is diverse. Due to this reason, two types of ML models were trained: 1. ML model on the overall dataset, and 2. Individual ML models for each node's dataset. Each model's performance was evaluated on four different metrics named accuracy, precision, recall, and F1-score. The results obtained for the overall and individual nodes are reported in Table 5.3 and 5.4 respectively. For the overall dataset, the RF model performed the best with an accuracy of 82.6% and an F1-Score of 83.67%. In the case of the individual dataset, it can be observed from Fig 5.2 that Node 6, 8, and 11 are near high vegetation areas. For these nodes, the AQI level for most of the data points fell in the first two categories, i.e., “Good” and “Satisfactory”. Hence, the model's task was easier for these nodes and performed better than the rest of the node's data.

On the other hand, for Node 1 and 3, the traffic mobility rate is high as they are placed at road junctions. For these nodes, the TMR varied mainly from “Sluggish” to “Slow”, resulting in Poor to Moderate AQI levels with some instances of Severe as well.

5.6 Conclusion

This chapter introduced an IoT-based technique to predict the AQI from traffic and location data in real-time. Location-based features like traffic mobility rate, NDVI score, and sensor-based features like temperature and relative humidity were used to train the ML model. Additionally, a dataset having around 210,000 samples that contain traffic and weather information is collected and to be released in

Table 5.4: Performance of the ML model on individual node's dataset. Please note that the best performing ML model result is shown.

# Node	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
1	79.69	78.16	79.93	79.03
2	79.56	78.11	81.03	79.54
3	78.21	79.55	78.26	78.90
4	78.51	79.36	79.61	79.48
5	79.86	78.75	78.42	78.58
6	82.78	84.70	81.72	83.18
7	78.95	79.90	79.3	79.59
8	80.15	82.42	81.98	82.20
9	79.56	79.96	79.90	79.92
10	78.98	82.49	80.29	81.37
11	81.67	84.60	81.26	82.89
12	82.94	84.31	80.82	82.52
13	79.88	84.78	79.30	81.94
14	81.05	83.44	80.37	81.87
15	82.63	79.96	78.65	79.29

the public domain to promote further research. Experimental results show an F1-Score of 83.67% for the overall dataset, while experiments on node-specific datasets show the sensitiveness of the location. ML model performance on locations having high vegetation index performs better than others, specifically where the vegetation is low, and traffic is peak.

Chapter 6

Concluding Remarks

6.1 Conclusions

The focus of this thesis is on exploring the effectiveness of learning methods in estimating air pollution levels on Indian roads by utilizing images and traffic data. The introductory chapter highlights the primary challenge associated with traditional methods for monitoring air pollution, specifically the need to use sensors, which requires regular maintenance, calibration, and can be expensive when implemented on a larger scale. Moreover, accessibility to remote areas and the quality of data obtained using such sensors is also a crucial factor that needs to be taken into consideration. The proposed approaches will help in the low-cost scalability of air pollution monitoring on large scale, where sensor deployment is not feasible or costly.

In chapter 4, we present a straightforward yet efficient method for classifying the AQI based on images using a combination of supervised learning algorithms, including ML and DL, on an IoT device. The experimental results demonstrate that the proposed method achieves an impressive accuracy of up to 90% for AQI classification. To facilitate further research in this area, we have also created a feature-rich dataset that is publicly available.

In chapter 5, we present an innovative IoT-based technique for real-time prediction of the AQI using traffic and location data. Our method relies on a combination of location-based features, such as traffic mobility rate and NDVI score, as well as sensor-based features like temperature and relative humidity to train the ML model. Moreover, to facilitate further research in this field, we have collected and plan to publicly release a dataset containing approximately 210,000 samples that include traffic and weather information. The experimental results demonstrate an impressive F1-Score of 83.67% for the overall dataset. Additionally, our experiments on node-specific datasets highlight the sensitivity of the location factor. Specifically, we observe that the ML model performs better in locations with a high vegetation index compared to those with low vegetation and peak traffic.

In conclusion, this thesis tackles the challenges associated with using sensors for air pollution monitoring by proposing an alternative mechanism to estimate the AQI without the need for environmental sensors. The proposed mechanism involves two methods, an image-based air quality estimation algorithm, and a method that uses maps data and weather parameters to predict the AQI. The thesis collects a feature-rich dataset for the Indian scenario, including seasonal variability, to evaluate the performance of both methods. The thesis presents a detailed comparison of the proposed methods with existing methods and provides a thorough analysis of the results. The research findings of this thesis provide a significant contribution towards developing an efficient air pollution monitoring mechanism that can help in improving the air quality of cities, especially in developing countries where the use of sensors is limited.

6.2 Future Directions

- Looking ahead, there are several potential avenues for future research and development of the proposed AQI prediction method. One limitation of the current work is that it is restricted to predicting AQI during daylight hours only. Therefore, future work will involve scaling the method to predict AQI during night-time as well. This will require incorporating additional features and data sources, such as street lighting conditions and traffic flow at night.

- Moreover, the current work is limited to collecting data during a particular season, and there is a need to collect data during the summer season to account for seasonal variations. Additionally, including more environmental factors like wind direction and speed, and topographic features like elevation and land-use, can further enhance the accuracy of the AQI prediction.

- The proposed method utilizes only one camera to capture road images for AQI prediction. However, it is possible to improve the accuracy of AQI estimation by using multiple cameras that capture both the front and rear views of the road. This can provide a more comprehensive understanding of the sources of pollution and their distribution, which can be useful for identifying potential mitigation strategies.

- Furthermore, there are plans to extend the application of the proposed method to different cities as well. Collecting data from multiple locations can help identify factors that are unique to each city, and can improve the performance of the model by accounting for regional variations in air quality.

Related Publications

Directly related to this thesis

Conference Papers:

- Nitin Nilesh, Ishan Patwardhan, Jayati Narang, Sachin Chaudhari, "IoT-based AQI Estimation using Image Processing and Learning Methods" *IEEE World Forum for Internet-of-Things (WF-IoT)*, 2022.
- Nitin Nilesh, Jayati Narang, Ayu Parmar, Sachin Chaudhari, "IoT and ML-based AQI Estimation using Real-time Traffic Data" *IEEE World Forum for Internet-of-Things (WF-IoT)*, 2022.

Patents Filed

- Ishan Patwardhan, Nitin Nilesh, Jayati Narang, Sachin Chaudhari, "Portable Air Quality and Traffic Monitoring Device" India Patent Appl. Num. 202 241 004 682, February, 2022.

Not directly related to this thesis

Conference Papers:

- Animesh Das, Viswanadh Kandala, Rishabh Agrawal, Akshit Gureja, Nitin Nilesh, Sachin Chaudhari, "Using Miniature Setups and Partial Streams for Scalable Remote Labs" *IEEE Future Internet of Things and Cloud (FiCloud)*, 2023 (under review).
- Ayush Kumar Lall, Ansh Khandelwal, Nitin Nilesh, and Sachin Chaudhari, "Improving IoT-based Smart Retrofit Model for Analog Water Meters using DL based Algorithm" *IEEE Future Internet of Things and Cloud (FiCloud)*, 2022.
- Viswanadh Kandala, Om Kathalkar, Piyusha Vinzey, Nitin Nilesh, Sachin Chaudhari, and Venkatesh Choppella, "CV and IoT-based Remote Triggered Labs: Use Case of Conservation of Mechanical Energy" *IEEE Future Internet of Things and Cloud (FiCloud)*, 2022.
- Ayush Kumar Lall, Ansh Khandelwal, Rhishi Bose, Nilesh Bawankar, Nitin Nilesh, Ayush Kumar Dwivedi, Sachin Chaudhari, "Making Analog Water Meter Smart using ML and IoT-based Low-Cost Retrofitting" *IEEE Future Internet of Things and Cloud (FiCloud)*, 2021.

Patents Filed:

- KS Viswanadh, Nitin Nilesh, Om Kathalkar, Sachin Chaudhari, Venkatesh Choppella, "System and Method for Implementing an Experiment Remotely Using a Computer Vision Technique" India Patent Appl. Num. 202 241 050 702, September, 2022
- Ayush Kumar Lall, Nitin Nilesh, Ansh Khandelwal, Rhishi Bose, Nilesh Bawankar, Ayush Dwivedi, Sachin Chaudhri, "System and Method for Digitizing a Reading in an Analog Water Meter Using Machine Learning" India Patent Appl. Num. 202 141 021 341, September, 2022

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