University of Nevada, Reno

Predictive Modelling of Gas Concentrations in Tunnels Using Machine Learning.

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Mining Engineering

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ABSTRACT

This study introduces a machine learning methodology for predicting gas concentrations at specific location within a tunnel model. The machine learning model is trained using gas concentration data obtained from sensors placed at diverse locations. The procedural sequence commences with the acquisition of data through an experimental protocol designed for training the machine learning model. Subsequently, the K-Nearest Neighbor (KNN) model is employed for predictive computations. The efficacy of the model is assessed through a comprehensive case study. The findings demonstrate that the proposed methodology exhibits a high level of accuracy, affirming its robust performance in predicting gas concentrations within the tunnel model.

DEDICATION

I dedicate this thesis to my parents and brother, expressing gratitude for being my pillars of strength and guiding me along the correct path in my life.

Jai Bhavani, Jai Shivaji

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I would like to express my sincere appreciation to Dr. Javad Sattarvand, my advisor, for his unwavering support in realizing my aspiration for graduate education. His patience, motivation, enthusiasm, and profound insights have been instrumental in my academic journey.

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CHAPTER 1 : INTRODUCTION

The intake air of underground mines has a composition of 78% nitrogen, 21% oxygen and 1 % of other gases(Mcpherson et al., n.d.). Various emission such as Dust, Diesel Particulate Matter, gases from strata, blasting of explosives have resulted in change in composition of air. Various researchers have been studying these emissions to increase the scope of ability to understand its impact of health and safety on miners, environmental impact and technological advancements (Figure 1). With the increased availability of cost effective sensors and air monitoring systems, it has been now convenient to monitor the atmospheric condition of underground mines by companies like Barrick, Newmont & Kinross. The transformation of data generated by theses air monitoring systems into a predictive machine learning models is a significant benefit in exposure monitoring in mine environment.

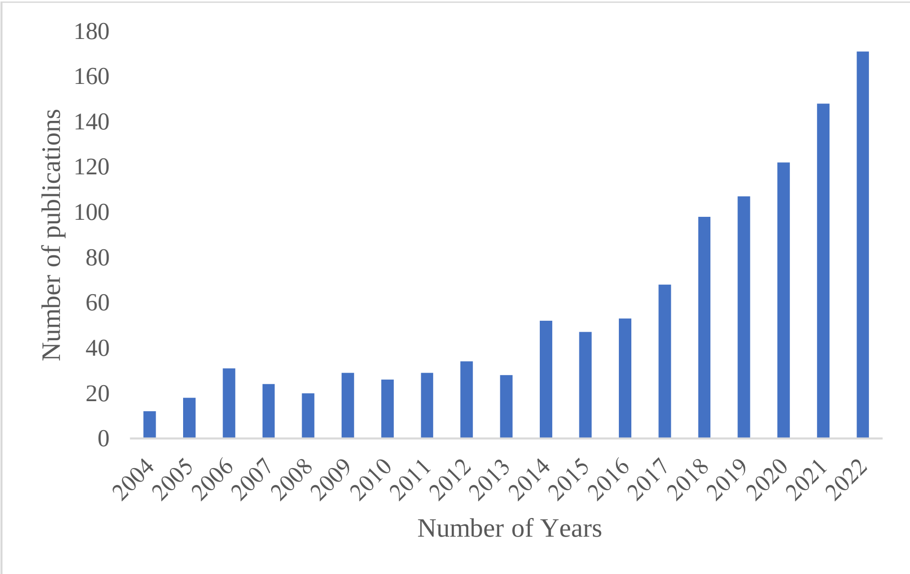

Figure 1 Increasing Research in the field of Emissions (Data taken from web of science).

This research constitutes a vital component of the NIOSH project entitled "Comprehensive Intelligent Exposure Management Systems." The overarching objective of this project is to formulate an advanced exposure management system, emphasizing the integration of machine learning techniques. The primary goal is to construct a predictive model derived from discerning trends in air quality data, This innovative approach seeks to enhance the capability of anticipating and managing potential occupational exposures, contributing to a more robust and intelligent framework for safeguarding the health and well-being of miners.

Some of the drawbacks of the current air monitoring practices which are addressed through this research work are (1) The air monitoring systems essentially monitor the constituents of air such as gas concentrations, humidity, dust but are unable to make a predictive analysis. This research aims to overcome this limitation by incorporating machine learning techniques, to enable predictive modeling of air quality trends. (2) The wealth of data generated by air monitoring systems can be intricate to interpret and translate into actionable insights. This research seeks to streamline data interpretation processes, ensuring that information derived from monitoring efforts is readily comprehensible and useful for understanding air quality dynamics.

This thesis is organized into 3 chapters, each of which is briefly outlined as follows:

Chapter 1: Introduction

An overview of challenges associated with the existing technology utilized for analyzing and monitoring air quality in the underground mines has been provided. The objectives of this research and the broader NIOSH project have also been elucidated.

Chapter 2: Literature Review

A review of an in depth examination of factors influencing the health and safety of underground miners, with a particular emphasis on CO_2, CH_4, CO, Dust and DPM. Furthermore, a concise overview of commercially accessible air monitoring systems designed for implementation in underground mines has been provided. Additionally, the literature review encompasses a comprehensive analysis of both supervised and unsupervised learning methods, shedding light on the existing body of knowledge in these areas.

Chapter 3: Predictive Model

This chapter proposes a methodology for developing predictive model for gas concentrations within a tunnel, employing a machine learning approach. Recognizing the need for effective training, an experiment was conducted to generate a diverse dataset reflecting variations in gas concentrations over time. The primary objective is to develop a model that not only accurately captures the variability in gas concentrations but also demonstrates practical applicability for air quality monitoring a management. The preliminary results indicate the K-Nearest Neighbor (KNN) demonstrates remarkable predictive capability among the tested algorithms, with a focus on assessing performance metrics such as R-squared (R^2) and Mean Squared Error (MSE). Furthermore, correlation analysis sheds light on interrelationships between gas concentrations at different locations, emphasizing the importance of certain factors, such as locations in the predictive model.

CHAPTER 2 : LITERATURE REVIEW

2.1 Factors Affecting the Health and Safety of Underground Miners

2.1.1 Carbon Dioxide

Several things can cause co2 release in underground mines. If the appropriates measures are not taken place it can cause serious risk to live of miners. According to (Monsé et al., 2014) inhaled CO_2 greater than 2% volume can be expected to cause adverse effects in the form of cardiovascular, respiratory, and neurophysiological results. Spontaneous Heating-It is a chemical process that occurs when oxidation of organic matter in coal starts which releases heat and gases, including CO2. This happens the carbon combines with oxygen from the air to from CO2.Explosives- Explosives releases carbon dioxide (CO2) through a process of combustion when they detonate. Combustion involves the reaction of explosive material with oxygen in the air leading to the formation of various gases, including CO2. Diesel Equipment- The diesel-powered machines and vehicles are essential for mining operations, but they can also contribute to the production of carbon dioxide (CO2). Diesel Engines operate on the principle of internal combustion. Diesel fuel is injected into the engine's combustion chamber, where it mixes with air. The mixture is compressed and ignited by a spark plug or through compression ignition. During combustion, the carbon (C) and the (H) in the diesel fuel react with oxygen (O2) from the air resulting in the release of CO2 and water vapor (H2O).Gas Outburst- The unexpected, variable-in-intensity emission of gas from coal seam is called as gas outburst.IT has been reported by (Black, 2019) in Australian coal mines that gas outburst can occur in areas with high gas content (> $16m^3$/t) and high concentrations of carbon dioxide (>95% CO2). The author also asserted that the CO_2 is more outburst prone than CH4 and more violent than CH_4.

2.1.1.1 Carbon Dioxide Release in Coal Mines.

One of the most frequent gases in the strata is carbon dioxide. The most significant sources of CO2 in coal mines is the combustion of coal itself through slow oxidation(*Gases_Found_in_Coal_Mines*, n.d.).It is generally called as black damp in mining terminology. Average black damp contains 10 to 15 per cent carbon dioxide and 85 to 95 % of nitrogen. It is mostly produced by underground fires and is present in the afterdamp of an explosion. It is always found in the return air of coal mines in small proportions. Concerns have been raised over the amount of coal mine carbon dioxide released during mining operations and the necessary ventilation needed to guarantee that work safety conforms with statutory limitations(W. Li et al., 2015). The quantity of gas released varies depending on how much coal is being mined. It is difficult to pinpoint the source of the emission. The parameter influencing the emission of carbon dioxide may vary from rank of coal seam, the depth of the coal seam, types of machines. Various indices are used for fire detection. CO_2 as an indicator is used in Young's ratio to detect oxidation of coal. The concentration of carbon dioxide, Nitrogen and oxygen is in percentages, while f represents return air concentration for the gas.

$$YR = \frac{(CO_{2f} - CO_{2i})}{0.265\ X\ N_{2f} - O_{2f}} \tag{1}$$

Similarly, there is CO/CO_2 ratio which is independent of oxygen which determines the change in the carbon monoxide produced to carbon dioxide produced as a function of the coal temperature.

$$\frac{CO}{CO_2} Ratio = \frac{(CO_f - CO_i)}{(CO_{2f} - CO_{2i})} \tag{2}$$

Morris Ratio is the ratio of amount of oxygen absorbed by the coal to the amount of oxidation produced by the coal.

$$MR = \frac{(N_{2f} - N_{2i})}{(CO_f + CO_{2f})} \tag{3}$$

Jones-Trickett Ratio (JTR) is the measurement of the amount of oxygen required to be consumed to produce the oxidation products compared to the amount of oxygen removed from the inlet gas stream.

$$JTR = \frac{(CO_{2f} + 0.75\, XCO_f - 0.25 XH_{2f})}{(0.265 XN_{2f} - O_{2f})} \tag{4}$$

C/H ratio is used to investigate the characteristics of the seal off fires and the nature of oxidation process. It calculates the proportion of carbon to hydrogen and estimates how much oxygen is consumed by mine gases.

$$\text{C/H Ratio } = \frac{6X(CO_2 + CO + CH_4 + 2C_2H_4)}{2X\left(\frac{N_2}{3.78} - O_2 - CO_2 + CH_4\right) - CO + C_2H_4 + H_2} \tag{5}$$

Table 1 Interpretation of Indices

Young's Ratio	<0.25 Normal Situation
	0.25-0.50 Heating
	>0.50 High intensity fire
CO/CO_2	<0.02 Normal Situation
	<0.05 Temperature of coal <60°C
	<0.10 Temperature of coal <80°C
	<0.15 Temperature of coal <100°C
	<0.35 Temperature of coal <150°C
Morris Ratio	From seam to seam, the actual figures differ. As the temperature rises, the ratio rises. In a sealed fire zone, it is sensitive to changes in the condition of the gases.
Jones-Trickett Ratio	<0.4 Normal situation
	<0.5 Methane fire possible
	<0.8 Coal, oil, belt fire possible
	<1.6 Timber fire
	>1.6 Error in analysis

2.1.1.2 Carbon Dioxide Release in Metal/Nonmetal Mines

NIOSH talks about recommending exposure limits for CO_2 in the metal mine should be 0.5 percent or 5000 parts per million for a 40-hour workweek. In normal air the carbon dioxide level is 0.035 percent but for 15 min of short-term exposure limit it is 3 percent. Since the CO_2 emissions in metal/ nonmetal mines is inconsistent it's hard to anticipate it's release. The constant worry about carbon dioxide in coal mines is one notable difference between the metal/nonmetal and coal mines. Mostly the carbon dioxide is produced in metal mine through the diesel engines operated machines through combustion process and it can be easily mitigated through proper ventilation.Mines also have detection capabilities and CO_2 emissions can be monitored using variety of devices. Therefore, monitoring is a frequent action that raises awareness of the potential risks associated with carbon dioxide.

2.1.2 Methane (CH4)

Methane stands out as one of the most feared gases in underground coal mining scenarios, arising from chemical decomposition of organic matter. It resides in cracks, spaces, pores and is released when penetrated by boreholes or mining excavations. It is not poisonous in nature but it is dangerous because it is explosive when it mixes with air. The explosibility of mixture of air and combustible gases like methane, carbon monoxide and hydrogen is explained by cowards diagram (Figure).

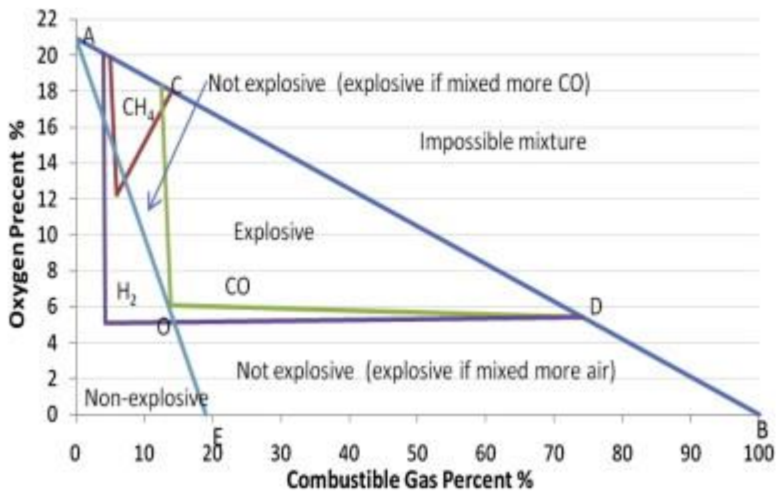

Figure 2 Coward explosive triangle for methane, carbon monoxide and hydrogen(Cheng & Luo, 2013).

When the methane released in the mine atmosphere undergoes dilution the explosibility depends on the percentage of methane and oxygen in mine air. The explosibility triangle explains if the percentage of methane-air mixture will be explosive in nature as well as produce an insight if it will be become explosive in future depending on the increase or decrease in air or methane concentration. The upper explosive limit (UEL) is 15 % where the gas mixture is not explosive. The explosive limit is between 5% to 15 % and lower explosibility limit is below 5 %, where the methane-air mixture do not light (Figure 2). Some of the ways to prevent the formation of explosive mixture is to have strong ventilation in the mining face. Another method in the application of water sprays on the cutting as well as excavating machines utilized for winning the coal. Ensuring proper air quality monitoring systems near the mining faces as well as the heavy machineries can also help in mitigating the risks associated with methane release in coal mines.

2.1.3 Carbon Monoxide (CO)

In the depth of the Earth, where valuable resources are unearthed to power our world, a silent yet deadly threat looms- carbon monoxide. For centuries, underground mining has been at heart of industrial progress, but with it comes the insidious presence of this colorless, odorless gas, capable of silently endangering the lives of miners and sustainability of mining operations. When CO is inhaled, it enters the bloodstream and forms a strong bond with hemoglobin and forms carboxyhemoglobin (COHb), which is the compound created when CO binds to hemoglobin, reduces the blood’s oxygen-carrying capacity and endangering lives. In mining, carbon monoxide is also known as white damp. Some of the known sources of CO in mines includes explosives, fires, exhaust of vehicle, heated lubricants and oils and spontaneous heating of coal. In United States, MSHA has set the permissible exposure limits (PELs) for CO in underground mines, These limits are set to protect the health and safety of miners. The PELs for CO for Time-Weighted Average (TWA) is 50 parts per million (ppm) for an 8-hour work shift and Short-Term Exposure Limit (STEL) is 400 ppm for any 15- minute period.

Table 2 CO exposure level and symptoms.

Exposure	Symptoms
70-100 PPM	Headache, Fatigue
150-300 PPM	Increased Dizziness, Vomiting, Reddened skin, Drowsiness, chest pain, impaired judgement, confusion, hallucination
>400 PPM	Convulsions, Coma, Brian Damage, Unconsciousness
=6400 PPM	Death

2.1.4 Dust Release in Underground Mines

Mining operations have generated significant amounts of airborne respirable dust in the past and present, leading to the development of lung illness in miners. Pneumoconiosis and silicosis in coal miners are among the lung illnesses that have harmed the health of thousands of mine workers around the world(Austin et al., 2021). Based on their effects on the environment, workplace health, physiological and combustible consequences, and source of generation, mine dusts can be categorized. The level of risk associated with different mine dusts substantially varies. . The crucial elements that determine whether dust is toxic to humans are its chemical makeup and particle size. Some dusts, such those produced in coal and sulfide ore mines, not only present a health risk but also have the ability to set off explosions due to spontaneous heating(Rao et al., 2020).Explosive dusts are quite concerning since they endanger the security of the mines. Detailed Classification of mine dust is given below(Paluchamy et al., 2021).

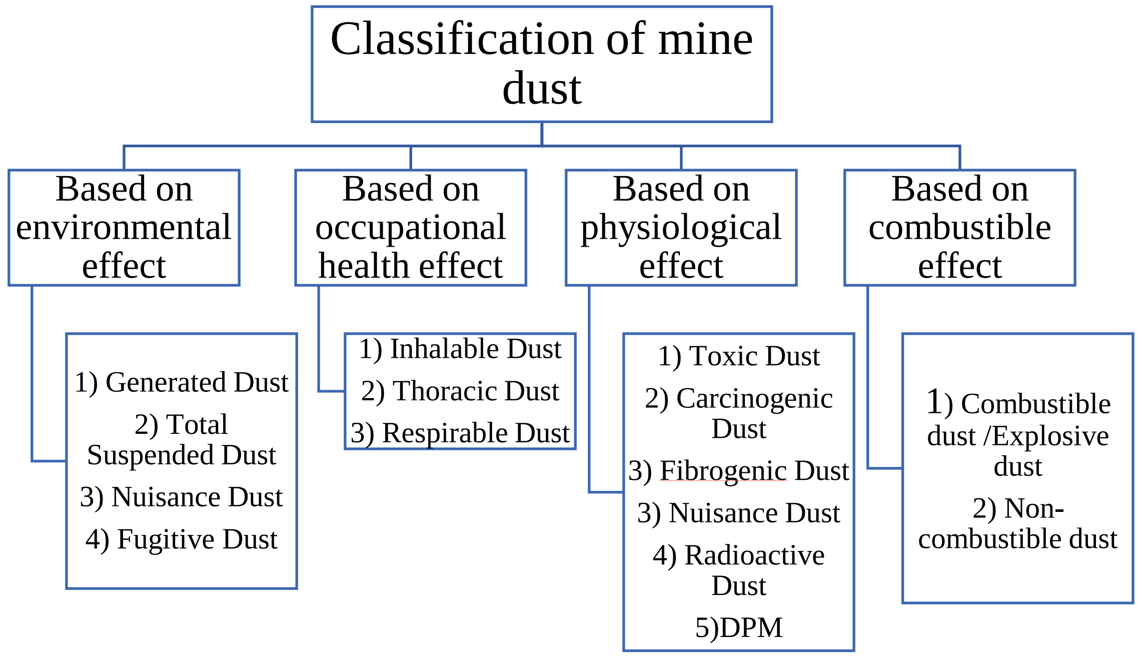

Figure 3 Classification of Mine Dust(Paluchamy et al., 2021).

According to their size fractions, which impact how well the human lungs work, airborne dust have been categorized as inhalable, thoracic, and respirable dust based on potential health risks (Figure 3). Figure 4 depicts the classification rules for dust fractions as agreed upon by ISO and the European Committee for Standardization .

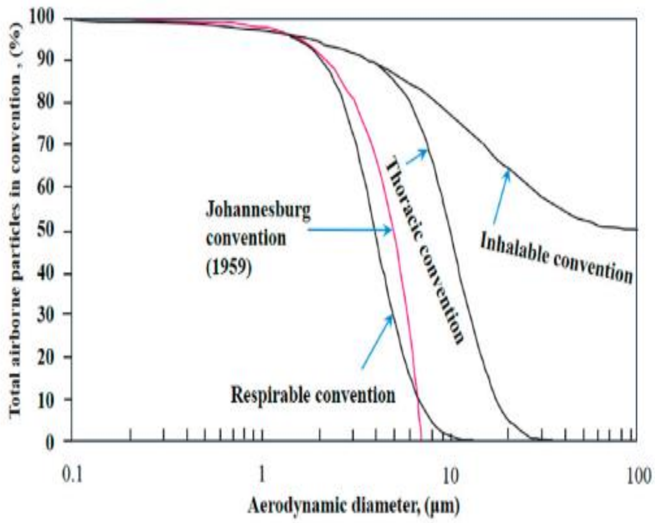

Figure 4 Inhalable, thoracic and respirable convention as percentages of total airborne dust and fine dust fraction according to the Johannesburg convention(Paluchamy & Mishra, 2021).

It also depicts the Johannesburg convention for fine dust fractions. The workers' exposure is measured using these convention curves, which are also used as a guide when developing dust sampling apparatus. part of airborne dust that enters the nose and mouth while breathing and is deposited in the upper respiratory tract is known as inhalable dust. The inhalable dust fractions also encompass the thoracic and respirable dust fractions with aerodynamic diameter of particles up to 100µm.(Wippich et al., 2020)The mass fraction of inhalable dust that passes through the larynx changes depending on each person's breathing pattern and is known as the thoracic fraction. The percentage of inhalable dust that enters the area of the lungs responsible for gas exchange (alveoli), is known as airborne respirable dust (ARD). The size variation is mainly between 0.1 and 10 mm, and the miners' health is of major concern when they breathe the air containing dust. The size distribution of particulate matter (PM) in ambient air is defined by the US Environmental Protection Agency (USEPA) as follows: inhalable particles, defined as particles with a diameter of less than 10 micrometers and smaller.; fine inhalable particles, defined as particles with a diameter of less than or equal to 2.5 micrometers (PM2.5); and coarse or thoracic coarse particles, defined as particles with a diameter greater than 2.5 micrometers. and less than or equal to 10 µm (PM10-2.5). Both the fine and coarse fractions of PM10—particles with aerodynamic sizes typically less than or equal to 10 µm are present(*PM Basics*, n.d.).

2.1.5 Diesel Particulate Matter (DPM)

Exposure to diesel particulate matter (DPM) in underground mining is a significant occupational health concern. Diesel engines are commonly used in underground mining operations for their power and reliability, but they emit DPM, which can have adverse health effects. Studies have concluded that long-term exposure to high concentration DPM could lead to increase the risk of negative health effects such as acute irritation, asthma, cough, light-headedness. In the united states, the Mine Safety and Health Administration (MSHA) has established a regulatory limit for diesel particulate matter (DPM) in metal / non-metal mines. The current regulations are designed around assessing an individual miner's exposure to diesel particulate matter (DPM). They stipulate that, within an underground metal/nonmetal (MNM) mine, a miner's daily exposure should not surpass an average concentration of 160 micrograms of total carbon (TC) per cubic meter of air (160TC $\mu g/m^3$) when measured as an 8-hour, time-weighted average concentration (TWA8)(*Title 30-Mineral Resources Chapter I-Mine Safety and Health Administration, Department of Labor Subchapter K-Metal and Nonmetal Mine Safety and Health Part 57-Safety and Health Standards-Underground Metal and Nonmetal Mines Subpart D-Air*

Quality, Radiation, Physical Agents, and Diesel Particulate Matter Diesel Particulate Matter-Underground Only, n.d.). Investigations have revealed that when the size of particles is less than 0.5 µm, the filtering capacity of the nose is notably low. In cases where the particle size is less than 1 µm, they have the ability to deposit in the deepest regions of the lungs. Figure 5 illustrates typical size distributions of diesel particles, both in terms of mass-weighted and number-weighted. It's evident that more than 90% of these particles have diameters below 1 µm, making them capable of reaching the deepest areas of the lungs. Numerous studies have provided evidence that airborne particulate matter, with DPM as a significant component, contributes to both respiratory mortality and morbidity.

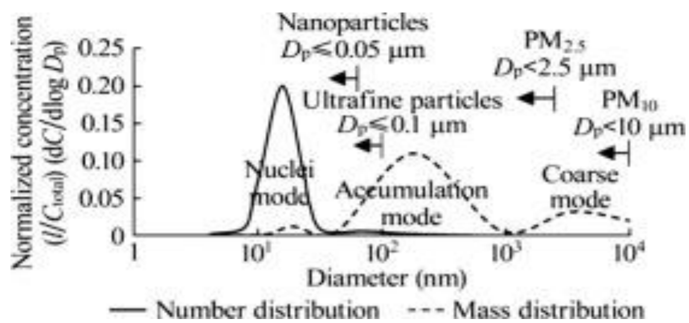

Figure 5 Diesel Particulate Matter Size Distribution(Chang & Xu, 2017).

2.2 Air Quality Monitoring Systems in Underground Mines.

Underground mining environments are often hazardous due to the presence of gases, dust, and other potential contaminants. Air monitoring systems are crucial for early detection of dangerous conditions, helping to prevent accidents and protect miners. These systems monitor the concentrations of gases like methane, carbon monoxide, sulfur dioxide oxygen, dust and Diesel Particulate Matter. High Concentrations of these contaminants can be lethal. Monitoring dust levels, including respirable dust is essential for assessing air quality and protecting miners from respiratory diseases. Monitoring temperature and humidity also plays an important to ensure that the working conditions are within safe limits for miners Figure 6.

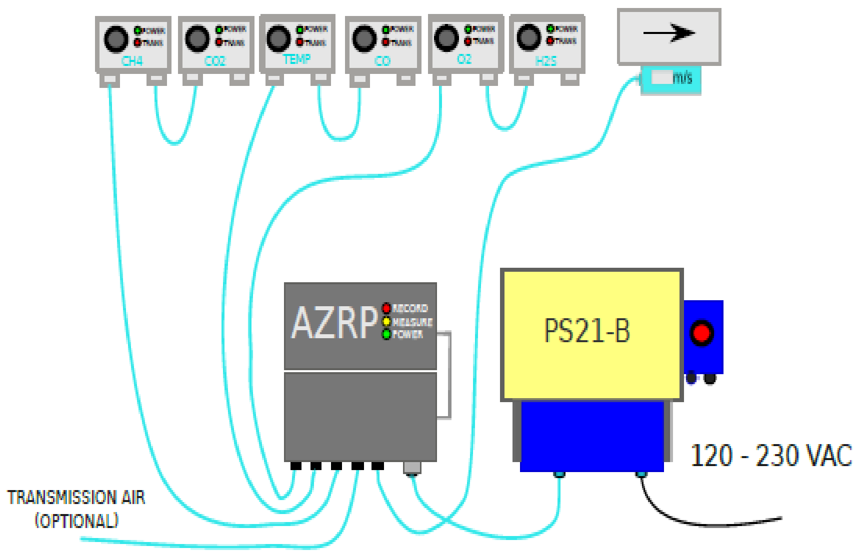

Figure 6 Air Monitoring System- Scheme.

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Figure 7 Vigilante AQS(<i>Vigilante AQSTM - Air Quality Station _ Maestro Digital Mine _ Maestro Digital Mine</i>, n.d.).

In earlier days, warm-blooded birds like munia were commonly used for gas detection due to their heightened sensitivity to CO. Then came the color changing detectors. These detectors contain chemicals that change color in response to specific gas concentrations, enabling gas percentage determination by matching the tube's color with a reference chart, as exemplified by P.S detector, Hoolamite detector, and Drager multi gas detector. Numerous companies have manufactured automatic detectors capable of measuring even trace gas concentration in mines. The often feature adjustable probes for reading from the roof, including products like Automatic fire damp detector, Interference methanometer and memac I. With the advancement in technologies, wireless air monitoring systems have made it easy to monitor real-time monitoring and data collection of air quality and environmental condition. These systems offers several advantages and applications in mining as well as various field, including environmental science, industrial safety and public health. The components responsible for collecting data are sensors and can be designed to measure various air quality parameters, including temperature, humidity, particulate matter (PM), gases (e.g.CO, CO2, NOx) and Volatile organic compounds. Wireless communication technology, such as Wi-Fi, Cellular networks or radio frequency (RF) is used to transmit data in real-time. from sensors to a central data point. The Fig show a typical air monitoring system used in underground mining. The data collected from the systems is processed further to provide valuable insights, trends and real time information about air quality conditions. Figure 7 shows Vigilante AQS and Table.3- Existing Air Quality System talks about available systems utilized in industry with its features, strengths and limitation. More flexible ways are handheld devices that can measure concentration with simple user interface but without the possibility of data analysis. The figure shows the examples of portable gas detectors.

Figure 8 Portable handheld devices(Dräger Pac® 6500 _ Draeger, n.d.),(GasBadge® Pro n.d.),*(*Tango TX1 Single-Gas Detector, *n.d.)*
Table 3 Existing Air Quality Monitoring Systems

Name of System	Features	Technology	System Capabilities	Advantages	Limitations	MSHA Approved
Vigilante AQS (<i>Vigilante AQSTM - Air Quality Station _ Maestro Digital Mine _ Maestro Digital Mine</i>, n.d.)	Multi-Gas Detection	Wireless Sensor Network	Real Time Alerts, Data Logging, Integration, Scalability	Real-Time Decision Support, Data Analysis ,Wireless Connectivity	Regular Maintenance, Calibration of Gas Sensors	Yes
Rajant Kinetic Mesh Network for underground monitoring(*Kinetic Mesh Networks for Underground Mining Https://Rajant.Com/Kinetic-Mesh-Networks-for-Underground-Mining/ 1/4 Don't Miss Rajant's World*	Wireless Mesh Connectivity. Self-Healing, High Bandwidth, Multiple Device Integration	Mesh Networking, Mobile Nodes	Real-Time Data Transmission, Geolocation, Integration	Reliability, Scalability, Reduced Downtime	High Initial Cost, Initial Setup Complexity	No

Music Benefit for CHOP Learn More Kinetic Mesh Networks for Underground Mining, n.d.)						
Sensidyne Gilian Air Sampling Pumps(*Gilian Air Sampling Equipment from Sensidyne AIR SAMPLING EQUIPMENT FOR MONITORING EXPOSURE TO AMBIENT PARTICULATES, GASES, OR VAPORS*, n.d.)	Versatile Sampling-dust, particulates, gases and vapors, Flow rate Option, Programmable specific sampling duration and flow rates, Compact and light weight	Positive Displacement Pump, Electronic Controls	Sample Collection, Data Logging, Portable	High Accuracy, Programmability, Portability, Data Logging	Limited Battery Life, Regular Maintenance	No
Fogmaker Underground Mine Solution(*0/23/23, 7:28 PM Protect Mining and Tunneling Equipment from Fire-Fogmaker Https://Fogmaker.Com/Business/Mining-and-Tunneling/ 2/6*, n.d.)	Fire Suppression, High Pressure Water Mist, Rapid Response, Customizable Design, User-Friendly Interface	High Pressure Water Mist, Automatic Detection, Integration	Fire Suppression, Quick Response, Customization, Integration	Rapid Fire Suppression, Automatic Activation, Customization, Safety	High Initial Cost, Regular Maintenance	No
Sick Maihak GmbH - Ventilation Air Methane (VAM) Monitoring System(Schibig et al., 2015)	Gas Detection, Real-time Monitoring, Data logging, Customization, Remote Monitoring, Alarms	Sensors, Wireless Communication, Data analysis	Real-time Monitoring, Data Storage, Customization	Data Accuracy, Historical Data Analysis, Remote Access	High Initial Cost, Regular Maintenance	No
Drager X-pid series (*Dräger X-*	Multigas Detection, Volatile	Photoionization Detection	Multi-Gas Detection,	Comprehensive Gas Detection,	Relatively High Cost,	No

Pid® 9500 _ Draeger, n.d.)	Organic Compound Compound (VOCs), Toxic gases , Photoionization Detection technology (PID), Real-Time Monitoring, Compact and Portable, Customizable Sensors, Ata Logging, User-Friendly Interface, Alarm and Alert System	(PID), Data Acquisition, Interchangeable Sensors	Real-Time Data, Customization	Real-Time Response, Portability, Interchangeable Sensors, User-Friendly	Periodic calibration sensors	
RAE systems by Honeywell (*Honeywell _ RAE Systems Gas Detection Equipment _ Safeware*, n.d.)	Wireless Gas Detection, Multi-Gas Monitoring, Mesh Network, Data logging, Real-Time Alerts, Integration, Portable Gas Detectors	Wireless Mesh Network, electrochemical , infrared , photoionization sensors, Real time data transmission	Remote Monitoring Adaptive Mesh Network, Comprehensive Gas Detection, Data Logging	Real-Time Monitoring, Scalability, Wireless Deployment, Data Integration. Cost Efficient	High initial setup cost, Routine Maintenance , Regular sensor calibration	No

Table 4 Development of new Air Quality Monitoring System for Underground Mining.

Author	Method	Strength	Limitations
H W Wu, ADS Gillies, 2008 (Wu & Gillies, n.d.)	Data collection, Network Simulation, Interpretation of data, Online Monitoring System, Testing and Optimization	Real-time monitoring, improved efficiency, data integration, safety enhancement.	Cost and implementation, Data Security, Sensitive, Sensor Reliability, system complexity.
Z.Agioutantis, K.Luxbacher, M.Karmis, S Schafrik, 2014(*Development of an Atmospheric Data-Management System for Underground Coal Mines Current Monitoring Technologies in US Coal Mines Figure 1-Simplified Layout of Sensor Deployment in US Coal Mines Figure 2-Data Acquisition for Atmospheric Monitoring in Coal Mines*, n.d.)	Data Collection, Data Management, Intrinsically Safe Components, Real-Time Analysis, Data Independence	Safety Compliance, Real-Time Monitoring, Data Integrity, Complex Analysis, Alarm Generation	Costly and Complex, Data Security, Maintenance and Calibration, Personnel training, Data Volume
Bharath Belle (Belle, 2014)	Continuous Real-Time Monitoring, Envisaged Benefits, Accuracy and Validation, Operational Factors	Continuous Monitoring, Operational Benefits, Data Confidence	Instrument Accuracy, Operational Variability, Data Validation, Costly implementation
J.H. Rowland III, S.P.Harteis,	AMS Usage Survey,	Regulatory Compliance, Impact	Data dependency, Lack of Qualitative Insights

L.Yuan (Rowland et al., 2018)		Assessment, Data Availability	
ByungWan Jo, Rana Muhammad Asad Khan 2018(Jo & Khan, 2018)	Arduino-based sensor modules, Data Transmission, Data Assessment, Artificial Neural Network, Performance Evaluation	Comprehensive Monitoring, Assessment Prediction, Efficiency, Safety Enhancement	Hardware Maintenance, Data Transmission, Data Security, Data Dependency
Mokhinabonu Mardonova , Yosson Choi, 2018(Mardonova & Choi, 2019)	Open Source System Development, Arduino, 3-D printing, MIT App inventor, Android Application	Cost-Effective, Remote Monitoring	Low- Precision, Scalability issues Generalizability
Bartlomiej Zietek, Aleksandra BAnasiewicz, Radoslaw, Zimroz, Jaroslaw Szrek, Sebastian Gola, 2020(Ziętek et al., 2020)	System Component- Gas Sensors, microcontrollers, Smartphone Integration, Data Collection, Data Analysis, Testing	Cost Effective, Real-Time Data, Portability, Accessibility, Safety Enhancement	Sensor precision, Scalability
Ankit Jha, Purushotham Tukkaraja, 2020 (Jha & Tukkaraja, 2020)	Laboratory Scale Model, Sensor Deployment, Data Interpretation, GIS tools, GIS tools, Safety and Comfort Optimization	Safety Enhancement, Data-Driven Decision, Visualization, Controlled Testing, Interdisciplinary Approach	Scale Model Representativeness, Sensor Accuracy, Const and Resource Intensity, Environmental Dynamics, Generalizability
Mahesh Shriwas, Christopher Pritchard, 2020(Shriwas & Pritchard, n.d.)	Sensors, control systems, software technologies. Data transport system, Industrial Internet of Things, Ventilation network simulators	Comprehensive Review, Identification of Challenges, Global Perspective, Interdisciplinary Approach	Technology Evolvement, Generalizability

	and control devices, Case studies		
Prasanjit Dey, S.K. Chaulya, Sanjay Kumar, 2021(Dey, Chaulya, et al., 2021a)	IOT-Enables Sensors Hybrid CNN_LSTM Model, Prediction of Mine Hazards, performance evaluation	Improved Safety and Productivity, Spatial and Temporal Feature Extraction, IoT Integration, Better Prediction Accuracy, Scalability	Data Dependency, Model Complexity, Generalizability, Maintenance and Deployment

Researchers have undertaken ambitious endeavors to develop cutting-edge systems that aim to revolutionize the management of air quality in underground mines. By harnessing advanced computer software and real-time data from ventilation airflow sensors, these innovative solutions aim to not only provide immediate insights into key ventilation system paraments but also enhance the overall safety and efficiency of underground mining operations.(Wu & Gillies, n.d.) have highlighted the development of sophisticated computer software that seamlessly connects real-time data from underground mine ventilation airflow sensors to a network simulation program. The resulting system enables immediate interpretation of key ventilation system data and operational changes, ultimately enhancing air quality management within underground mines.(Development of an Atmospheric Data-Management System for Underground Coal Mines Current Monitoring Technologies in US Coal Mines Figure 1-Simplified Layout of Sensor Deployment in US Coal Mines Figure 2-Data Acquisition for Atmospheric Monitoring in Coal Mines, n.d.) emphasize on development of intrinsically safe and approved monitoring components in US coal mines highlights the paramount importance of adhering to safety standards. The author also discusses the need for independent data validation and storage apart from filtering, data reduction and visualization processes. (Belle, 2014) enumeration of potential benefits resulting from real-time velocity monitoring underscores the practical approaches. Furthermore it emphasize on the ‘accuracy of instruments and the absence of clear guidance serves as a call to action for standardization in Ventilation Air Methane (VAM).(Rowland et al., 2018) talks about the ventilation surveys which were conducted in 1995 and 2003, offering insights into the historical landscape of mine safety technology. Of paramount importance is the recognition of regulatory requirements regarding early fire detection systems in belt haulage entries have evolved over time. Notably, the prohibition of point-type heat sensors and the shift to carbon monoxide (CO) sensors as mandated by MSHA as of December 31, 2009, represents a significant regulatory change. These insights in understanding the practical implication of safety regulation and technology adoption within the mining industry. (Jo & Khan, 2018) have introduced an IoT-based system for air quality monitoring in underground coal mines, expanding its capabilities to include assessment and pollutant prediction. The introduction of the Mine Environment Index (MEI) as a metric for evaluating air quality is a noteworthy advancement in mine safety technology. The Principal Component Analysis (PCA) based Artificial Neural Network (ANN) model demonstrates impressive predictive performance, highlighting the potential for this approach in advancing mine environmental safety. (Mardonova & Choi, 2019) have highlighted the growing significance of open-source technology in Industry 4.0, illustrating its diverse applications and its capacity to address industry-specific challenges. (Ziętek et al., 2020) acknowledges the critical nature of air-quality measurements in deep underground mines, emphasizing the complexities associated with ventilation, mine geometry and mine safety. A need for portable, personal devices to offer real-time information on gas hazards is recognized, particularly given the limitations of existing tools. The paper introduces an innovative system that overcome these limitations, employing low-cost gas sensors, microcontrollers and common smartphones for data storage, analysis and visualization. The adoption of smartphones as a versatile resource highlights the system's adaptability and potential for cost-effective data analysis.(Jha & Tukkaraja, 2020) underscores the paramount importance of monitoring and assessing underground climatic conditions as preventive measure to avert hazardous situations and possible disasters. Employing a laboratory scale model as the basis for experimentation, the research focuses on the real-time monitoring of ventilation parameters that directly impact miner safety. The data is collected by sensors, enabling the surveillance of key variables such as temperature, humidity and gas concentrations. The study introduces a predictive dimension by utilizing established ratios and indices to anticipate the presence of fire gases and conditions conducive to spontaneous combustion. The integration of GIS tools is a notable innovation, facilitating the real-time visualization of data on a mine map, thereby enhancing situational awareness and contributing to a safer and more comfortable working environment for underground personnel and equipment. (Shriwas & Pritchard, n.d.) have undertaken a comprehensive evaluation of real-time ventilation monitoring and control solutions, reflecting the growing emphasis on miner safety. The study's global perspective encompasses mining operations in Canada, Australia and the USA, exemplifying the real-world applications of ventilation monitoring and control systems.(Dey et al., 2021) presents a formidable alliance for addressing mine hazards using

IoT-enabled sensors and machine leaning. The model's utilization of a hybrid CNN-LSTM architecture excels in deciphering the complex spatial and temporal features within mine data. Noteworthy experimental results demonstrate the model's exceptional precision, as seen in its minimal mean square error and high correlation coefficients. The proposed CNN-LSTM model as a significant advancement, surpassing the capabilities of conventional CNN and LSTM models. (Balushi & Hussain, n.d.) also adopts an innovative approach by combining Wireless Sensor Networks (WSN) and the Internet of Things (IoT) to create a comprehensive monitoring and control system. The practical implementation uses Arduino UNO, a suite of sensors, and the ESP8266-01 WIFI module to enable data capture and IoT connectivity. The choice of ThingSpeak as an IoT platform empowers the system to serve as both an observatory dashboard and a control channel. The four-node network configuration is pivotal, with two nodes dedicated to data collection and the other two responsible for controlling ventilation and sirens. The paper signifies a remarkable leap in mine safety and operational control, showcasing the potential of IoT and WSN to transform the mining environment into a safer, monitored, and controlled workspace. The quest for enhancing safety and operational efficiency in underground mines has never been more urgent, given the complex and hazardous conditions faced by miners. The need to monitor a range of critical parameters such as gas levels, temperature, and airflow in real-time necessitates innovative solutions. The studies presented not only highlight the challenges in atmospheric monitoring in underground mines but also underscore the significant strides made in addressing these concerns.

2.3 Machine Learning

We know humans learn from their past experiences and machines follow instructions given by humans. Training machines to learn from past data and do what humans can do much faster is called machine learning. The scientist Arthur Samuel (1959) defined machine learning as a field of study that gives computers the ability to learn without being explicitly programmed(Samuel, n.d.). Basically, it is teaching machines how to handle data more effectively. With the abundance of data sets, we can make machines learn to find solutions to problems without explicitly programming them. There are many approaches to apply machine learning to handle large data sets.

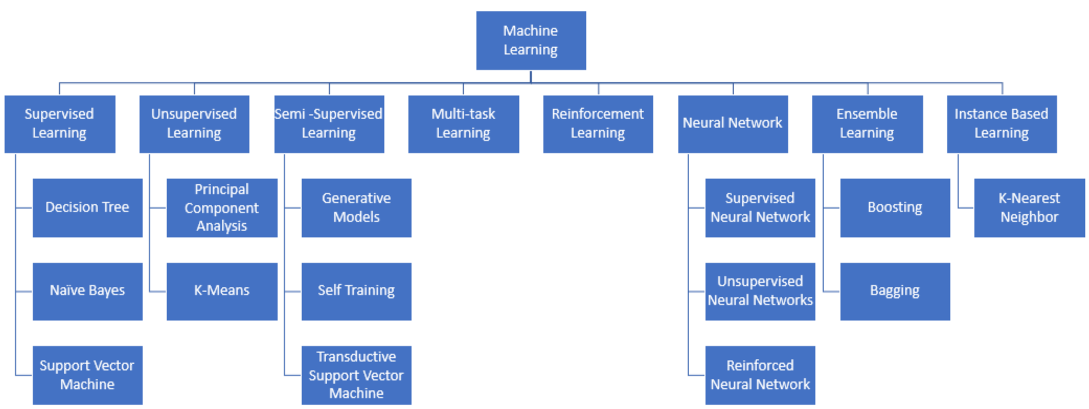


Figure 9 Types of Machine Learning Algorithm.

Using various algorithms (Figure 9) data can be effectively handled and processed for a wide range of task and applications. Depending upon the complexity of the problem a particular algorithm can be chosen, which best suits it. Some of the commonly used machine learning methods are listed below.

2.3.1 *Supervised Machine Learning*

Supervised Machine Learning is category of Machine learning where algorithm learns from a labelled dataset which is called as a model. The dataset has input labels and output labels. Both are corresponding to each other. The goal of supervised learning is to make a mapping function from input data to output labels so that the algorithm can make predictions on new, unseen data. The data is divided into two sets of training and test sets (Figure 10). The algorithm learns from the pattern generated by the training set and applies it to the test set for prediction or classification. The workflow of the supervised machine learning algorithm is shown below.

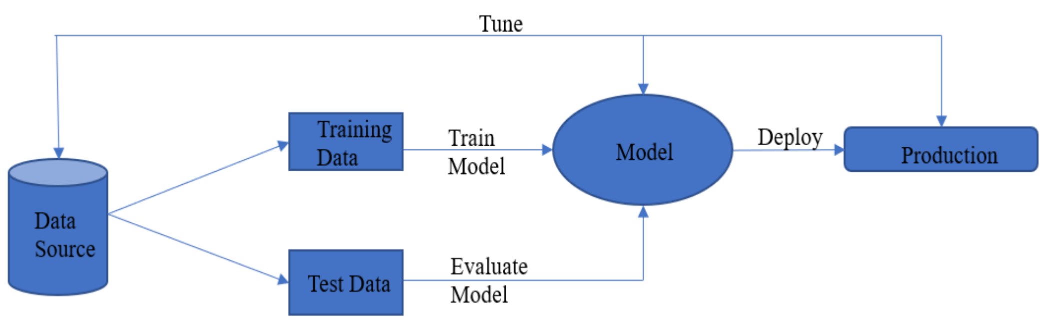


Figure 10 . Work Flow of Supervised Learning Model (Mahesh, 2018).

2.3.2 *Logistic Regression*

It is a statistical method used for binary classification. It is employed when the target variable has two possible outcomes, often denoted as 0 and 1 or “negative and “positive”, “spam” or “not spam”,” Yes” or “No”. It uses a sigmoid function to model the relationship between the input features and probability of the binary outcome. The sigmoid function is an S-shaped curve that maps a real-valued number to a value between 0 and 1. The formula for the sigmoid function is:

$$S(z) = \frac{1}{1+e^{-z}} \tag{6}$$

Where z is the linear combination of input features and their associated weights. z = $w_0 + w_1x_1 + w_2x_2 + \ldots\ldots + w_nx_n$, where w represents the weights, x represents the input features and n is the number of features. It assumes that there exists a linear decision boundary that separates the two classes. In a two-dimensional feature space the boundary is a straight line while in higher dimensions, it is a hyperplane. The optimal values for the weight coefficient (w) such that the sigmoid function fits the training data is found by optimization techniques like gradient descent. The probability that a given input belongs to one of the two classes can be predicted once the model has been trained. The output of the sigmoid function is represented by the probability and a threshold (usually 0.5) is applied to determine the predicted class. If the probability is greater than or equal to the threshold, the input is classified as belonging to one class; otherwise as belongs to the other class. The performance of the logistic regression models can be measured using metrics such as accuracy, precision, recall, F1-score, and the ROC curve. These metrics help assess how well the model classifies data points into correct classes. The major advantages of logistic regression include its simplicity and efficiency.

2.3.3 Decision Trees

A decision tree is a popular machine-learning algorithm used for both classification and regression tasks. It is a tree structure that recursively divides the dataset into subsets based on the most significant attributes, ultimately leading to a decision or prediction (Somvanshi

& Chavan, n.d.). The key factor behind the wide usage of decision trees is its ease of understanding, interpretation, and visualization. It has a top node at the beginning of the tree structure which is also known as the Root node. It is the representation of the entire dataset or the entire problem to be solved. The root node is connected with internal nodes which are right below it. Each internal node corresponds to a feature and represents a decision point. The algorithm evaluates the value of the associated feature for the data point currently being considered at each internal node. The possible outcomes based on the feature's value are represented by branches coming out from each internal node. For binary features (yes/no, true/false), there are typically two branches. For categorical features, there are many branches as there are unique categories. The tree continuously splits at internal nodes until a stopping criterion is met. The criteria can be a maximum depth for the tree, a minimum number of data points in a leaf node, or other user-defined conditions(Dietterich & Kong, n.d.). When stopping criteria are met, the final nodes are called "leaves" or "terminal nodes". Each leaf node is associated with a class label (in classification) or a numerical prediction (in regression). This is the decision made by the decision tree for data points that reach that particular leaf. To make a prediction or classification, begin with the root node and follow the decision path by evaluating the feature values at each internal node, moving down the tree until a leaf node is reached. The leaf node's class label or prediction is the final decision. The decision tree uses various criteria to determine the best attribute to split the data at each internal node. Common splitting criteria include Gini impurity and entropy for classification tasks and mean squared effort for regression tasks(Disha & Waheed, 2022; Granziol et al., 2019). The aim of the algorithm is to minimize impurity or error after each split. Figure 11 shows a simple explanation of the decision tree(*2011 IEEE Control and System Graduate Research Colloquium.*, 2011). Decision trees have a wide range of applications such as credit scoring, medical diagnosis, customer churn prediction, and gaming.

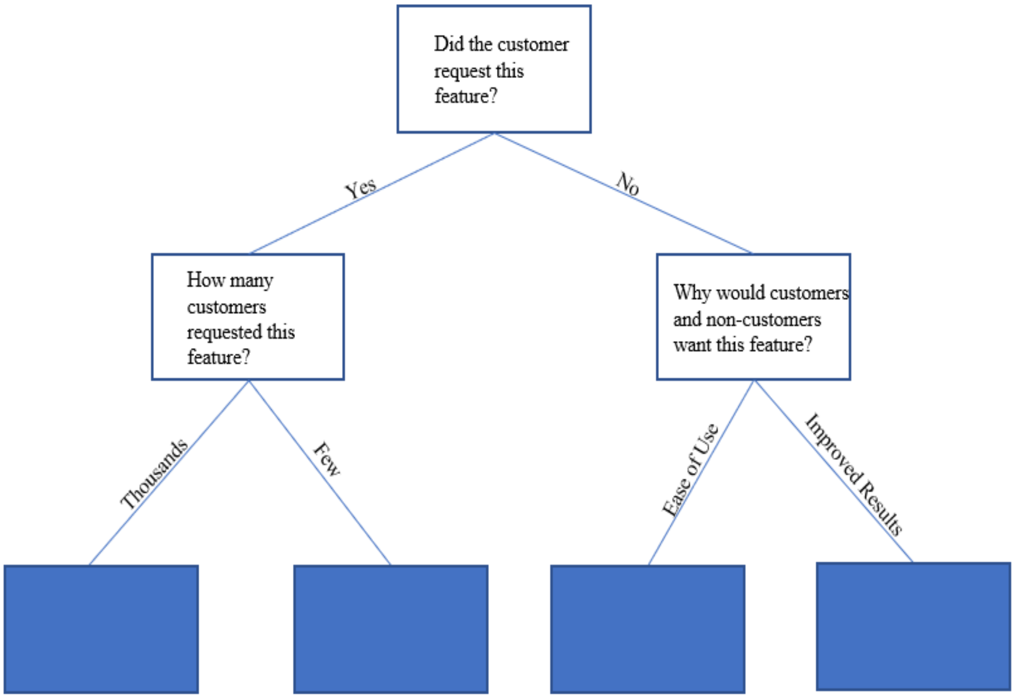


Figure 11 Example of a decision tree.

2.3.4 Random Forest

Random forest is a powerful ensemble learning technique used in machine learning for both classification and regression task. It is based on the idea of building multiple decision tress during training phase and then combining their predictions to improve accuracy and reduce overfitting. Figure 12 shows a basic flow chart of random forest methodology(Mahdi Abdulkareem & Mohsin Abdulazeez, 2021).

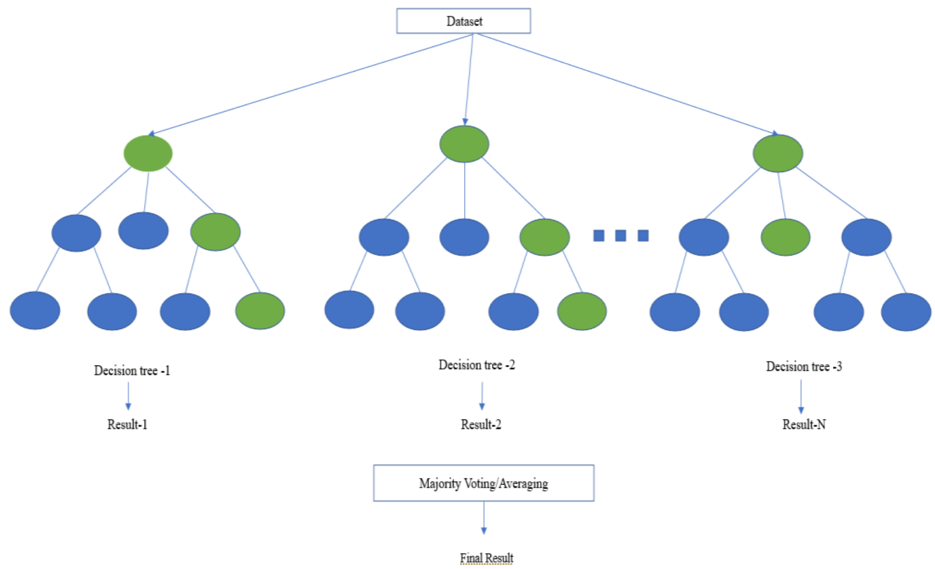


Figure 12 Flow Chart of Random Forest.

Random forest starts with creating multiple subsets of the original dataset through bootstrapped sampling. The bootstrap sampling is a method of crating subset by randomly selecting data points from original dataset with replacement. For each bootstrap sample a decision tress is constructed. The key difference from a standard decision tree is that at each node of the tree, when selecting a feature to split on, Random Forest only considers a random subset of the features which ensures diversity among the individual trees. After building all the decision trees they are used for prediction. In a classification task, each tree "votes" for a class, and the class that receives the majority of votes in the final prediction. In a regression task, the individual tree predictions are predicted and averaged to produce the final regression output. The fundamental idea behind Random Forest is ensemble learning which combines prediction from multiple trees to improve generalization performance(Belgiu & Drăgu, 2016). It reduces the risk of overfitting because the individual tree may overfit to different parts of the data by cancelling each other's errors when combined together. It can also provide a measure of feature importance. This is based on the reduction in impurity or reduction in mean squared error attributed to each feature when it is used in tree splits. Some benefit of using random forest is that it is very robust to outliers and noisy data. The ensemble nature of random forest helps in mitigating the overfitting of data and making them more generalizing to unseen data compared to single decision trees(Sagi & Rokach, 2018). Also building individual trees in random forest can be done in parallel making it suitable for parallel and distributed computing environments. Random forests are widely used in many applications including image classification, text classification, fraud detection, and stock price prediction.

2.3.5 Support Vector Machines (SVMs)

Support Vector Machines (SVMs) are a type of supervised learning algorithm that can be used for both classification and regression tasks. They are particularly well suited for tasks where there is a clear margin of separation between different classes or when dealing with high-dimensional data.

SVMs are often used for binary classification where the goal is to separate data points into one of the two classes. (e.g., spam or not spam, positive or negative sentiment). It aim to find a hyperplane (a higher-dimensional version of a straight line in 2D) that best separates the data points of one class from those of the other class. Figure 13 explains support vector machines. The hyperplane should maximize the margin, which is the distance between the hyperplane and the nearest data points of each class. These nearest data points are called support vectors. In cases where the data is not linearly separable in the input space, SVMs can still find a separating hyperplane by mapping the data into a higher – dimensional space using a “kernel function”. Common kernel functions include the linear kernel, polynomial kernel, and radial basis function (RBF) kernel. The choice of the kernel depends on the problem’s characteristics. By introducing the concept of “slack variables” SVMs allow for some miscalculation. The optimization objective of SVMs is to maximize the margin while minimizing the classification error, which is penalized based on the slack variables.

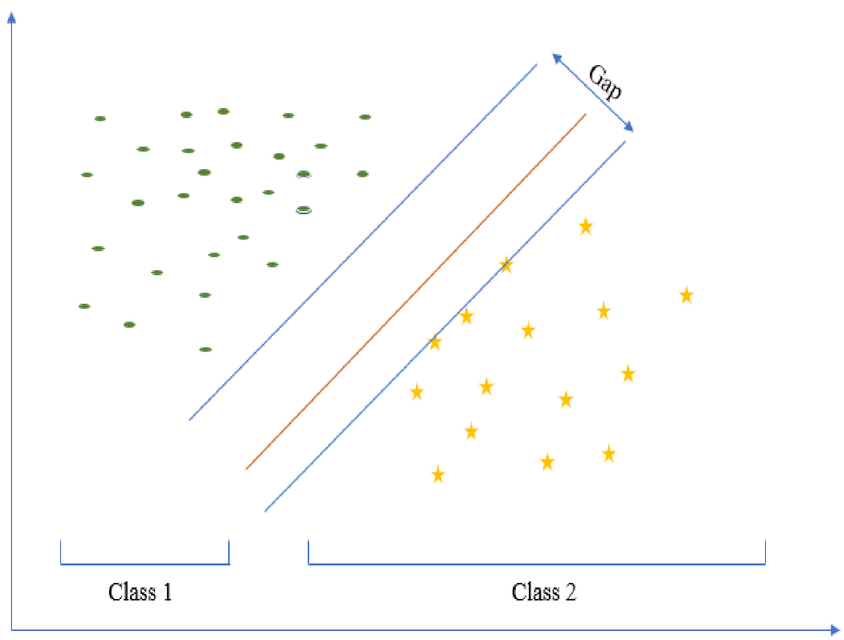


Figure 13 Support Vector Machine

2.3.6 K-Nearest Neighbour (KNN)

k-Nearest neighbor (k-NN) is a supervised machine algorithm used for both classification and regression tasks. It’s a simple and intuitive algorithm that makes predictions based on the similarity between the input data point and its k-nearest neighbors in the training dataset(*2019 International Conference on Intelligent Computing and Control Systems (ICCS).*, n.d.). The “k” in k-NN represents the number of nearest neighbors considered for making predictions. During the training phase of k-NN, the algorithm simply stores the entire training dataset which consists of labeled data points. Each data point in the training dataset includes features (input attributes) and the corresponding target values or class labels. For a classification task, when we want to predict the class label of a new, unseen data point, the algorithms calculate the distance (similarity) between this data point and all the data points in the training dataset(Sun et al., 2009). Depending on the nature of the data, it uses metrics that include Euclidean Distance, Manhattan distance, or cosine similarity. These distances help in figuring out which data points are closest to the new one based on the chosen distance metrics. The Euclidean distance can be measured from the formula below.

$$\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{7}$$

KNN for classification can be achieved by letting the k nearest neighbor vote. By counting how many neighbors belong to each class and picking the class with the most votes as the predicted class for the new data points. For regression, KNN can be applied by taking the average of the values (e.g., prices) of the k nearest neighbors. The average will be the prediction for the new data point. In classification, the prediction is a class (e.g., “apple” or “banana”), while in regression the prediction is a numeric value (e.g, the price of a house). KNN is simple and easy to understand with some consideration. It is important to select the right value of “k”. A small value of “k” is sensitive to noise, while a large “k” can smooth out the patterns. Using large datasets can use an assumption of similar data points which is not always true and requires more computation.

2.3.7 Unsupervised Machine Learning

Unsupervised machine learning is a category of machine learning where the algorithm is trained on a dataset without explicit supervision or labeled outcome (Figure 14). The algorithm tries to find patterns, relationships, and structure within the data on its own without being given specific instructions on what to look for. Unlike supervised learning the input data doesn't have predefined categories or target values but has features or attributes. Using clustering algorithms similar data are grouped together based on similarities or patterns they identify together within the data. For example, clustering to group customers with similar purchasing behavior. Dimensionality Reduction is another application of unsupervised machine learning. It uses Principal Component Analysis or t-distributed stochastic Neighbor Embedding (t-SNE) to help reduce the number of features in the data while retaining its essential characteristics. Anomaly detection can also be achieved from unsupervised learning. Data points that deviate from the expected patterns or behaviors are called anomalies. They are crucial in fraud detection, network security, and quality control. Unsupervised learning is also used for feature learning by discovering and representing relevant features or representations from data helping in improving the performance of machine learning models. Generative modeling is another application where the algorithm learns the underlying probability of the data. Generating new data samples that resemble the original data is achieved by applications like image generation with Generative Adversarial Networks (GANs).

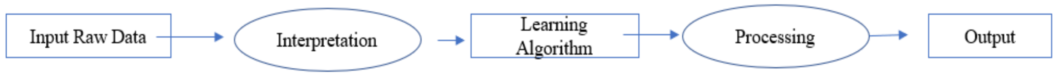


Figure 14 Flow chart of unsupervised Machine Learning.

It is widely used in data exploration, data processing and initial cases where we may not know what to look for initially, letting the algorithm uncover hidden insights within the data.

2.3.8 K-Means Clustering

It is an unsupervised machine learning algorithm used for partitioning a dataset into distinct groups or clusters based on similarity. Initially, the algorithm starts by randomly selecting K initial cluster centroids where K is a user-defined parameter representing the number of clusters. These centroids can be any data point in the dataset. Each data point in the dataset is assigned to the nearest centroid based on a distance metric commonly Euclidean distance. After that the algorithm calculates the new centroids for each cluster. The assignment and updating centroid is repeated until one of the stopping criteria is achieved. Eventually, the algorithm converges to a solution where the centroids stabilize, and the data points remain in the clusters assigned to them.

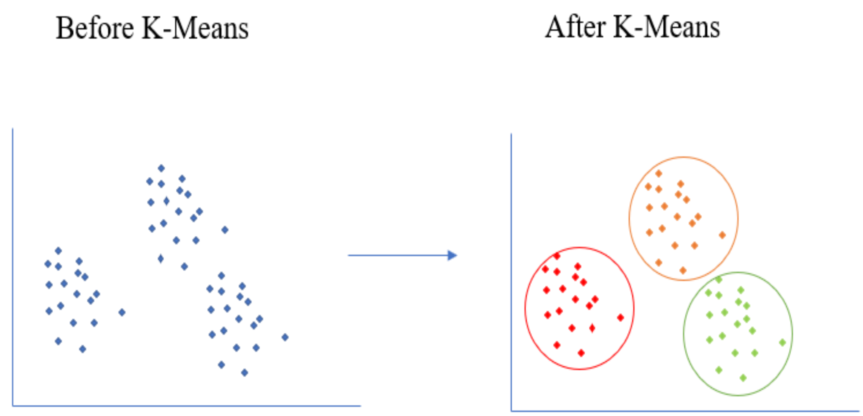


Figure 15 K-Means Clustering.

Here is an example of customer segmentation using k -means clustering. The above Figure 15 shows data on the left side. The data can be based on domain knowledge, business goals etc. After running K-means algorithm on the pre-processed data with the chosen value of K, the algorithm will cluster customers into K-segments based on their similarity in the selected features. Once the cluster is complete it can be interpreted for results. Each cluster represents a group of customers who share similar characteristics. For example, one cluster might consist of young, high-frequency shoppers, while another could include, occasional buys. This might involve creating personalized product recommendations, and targeted advertising. Thus, clusters represent the grouping of the data points based on their significant characteristics.

2.3.9 Artificial Neural Networks

Artificial Neural Networks also known as Neural Networks are fundamental concept in machine learning and are inspired by the structure and function of the human brain, mimicking the way that biological neurons signal to one another(Yaot, n.d.). The neural network consists of interconnected artificial neurons or nodes organized in layers: an input layer, one or more hidden layers and an output layer. The input layer receives the initial data or features, while the output layer produces the network prediction or output. The hidden layers perform intermediate computations helping the network learn complex relationships within the data.

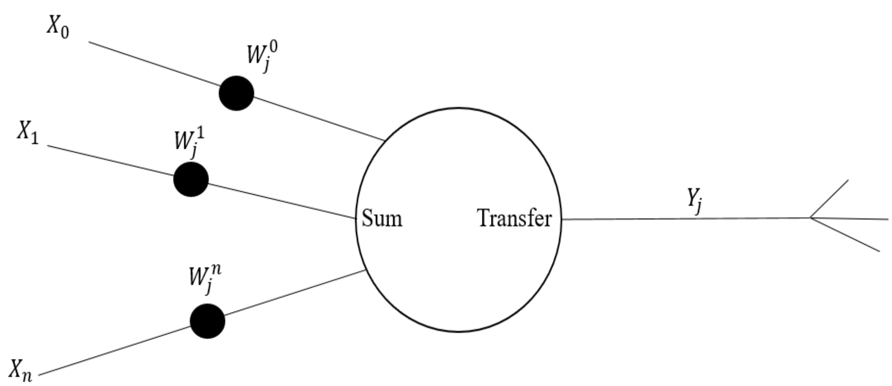


Figure 16 . A neuron (processing element).

Each connection between neurons has an associated weight which determines the strength of the connection Figure 16. Neurons in one layer are connected to neuron in the adjacent layer through weighted connections as well as bias term which allows the network to capture more complex patterns.

The neuron applies an activation function to the weighted sum of its input bias. Common activation function includes sigmoid, ReLU (Rectified linear Unit) and tanh (hyperbolic tangent)(Arora et al., 2016; Pratiwi et al., 2020; Shakiba & Zhou, 2021). The activation functions introduce non-linearity into the model, enabling neural networks to approximate complex, non linear functions. The relationship between the inputs $X_0 \ldots \ldots \ldots X_n$ of neuron j and its output Y_j is given by equation the following equations(Dougherty, 1995).

$$I_j = \sum_{i=0}^{n} W_{ji} X_i \qquad (summation) \tag{8}$$

$$Y_j = f\left(I_j\right) \qquad (transfer) \tag{9}$$

After feeding the data for making prediction through the network in a process called forward propagation(Kag & Saligrama, 2021). Each neuron in a layer receives input from the previous layer, calculates a weighted sum, applies the activation function and passes the result to the next layer. The process goes on until the output layer produces the final prediction. Neural networks learn from data through a process called training. During training, the network compares its predictions to the actual target values (ground truth) and adjusts the weights and biases to minimize the prediction error. Generally, a back propagation algorithm is used for this purpose, where errors are propagated backward through the network to update the weights.

A loss function also referred as cost function measures the difference between the predicted values and the true target values(Barron, 1989). The aim of training is to reduce the cost function and different tasks (classification, regression) may require different types of loss functions. Neural networks have hyperparameters, such as the number of hidden layers, the number of neurons in each layer, learning rate and batch size(Nikbakht et al., 2021). Tuning these hyperparameters is essential to achieve good performance and avoid overfitting. After training the neural network can be utilized to make predictions or classification on new, unseen data. These models have high flexibility in modelling relationship with data which makes them powerful tools in machine learning tasks. They have achieved remarkable success in the field of image and speech recognition, natural language processing, recommendation systems and more.

2.3.10 Related Studies

The table 5 presents strengths and drawbacks of each method presented by researchers for predictive approaches using machine learning. This table presents the methods, strengths and limitations of various methods and algorithms which are likely used in machine learning and data analysis. Support Vector Machines (SVM), Linear and Non-Linear Predictions Methods, Bayesian Networks, Chaotic Time Series Prediction, Time Series Neural Network, Artificial Neural Networks (ANN), ARIMA (Auto Regressive Integrated Moving Average), Particle Swarm Optimization, ADAM (Adaptive Moment Estimation), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) networks are all techniques used for predictive modelling. These methods are employed to make predictions or classifications based on historical data patterns or relationships within the data. It also highlights the challenges in implementing methods based on the scale of data. Many of these methods can be applied to a wide range of problems and making them versatile tools in machine learning. Techniques like neural networks (including CNNs and LSTMs) and SVMs can adapt to complex relationships in data, allowing them to model intricate patterns. All the methods mentions in table-5 are data driven and can learn patterns and representations from the input data. These methods have been successfully applied across various domains, including finance, healthcare, image processing, time series analysis. When properly tuned and trained, these methods can achieve high levels of prediction accuracy. Many methods especially neural networks require large amount of labelled data for effective training. Limited data can lead to overfitting or poor generalization. Some methods, such as neural networks and SVMs with complex kernals, lack interpretability. Understanding the inner workings of the model can be challenging. Techniques like neural networks, SVMs with complex kernels and optimization algorithms can be computationally intensive, requiring substantial computing resources, Many methods have hyperparameters that need to be carefully tuned for optimal performance. Sensitivity to hyperparameter choices can impact results. More complex models like deep neural networks may suffer from overfitting and require additional techniques like regularization to mitigate this issue. Some methods, like linear models make assumptions about the linearity of relationships in data which may not hold in all cases. It has been seen that some of the models might struggle with generalizing well to new, unseen data, especially if the training data is not representative of the entire problem space due to that achieving a comprehensive understanding of the model's decision making process, especially in complex models can be challenging, limiting their interpretability.

The successful application of machine learning models in real time scenarios involves considering various factors to ensure efficiency, accuracy and practicality. Real time applications demand low latency to provide timely responses. Consider the time it takes for the model to process inputs and generate predictions or decisions. Techniques like model quantization or model compression can be applied to reduce inference time. For dynamic and unpredictable usage patterns ensuring the model architecture and infrastructure can scale to handle increasing work load. Smaller models has faster inference times which is important for real time applications. Pruning unnecessary parameters or using techniques like knowledge distillation helps in optimizing models. It is essential that input data is preprocessed efficiently by considering techniques like feature engineering, data normalization and parallel processing to speed up data preparation. To adapt changing data distribution or trends it will be valuable to implement mechanism for continuous learning of model in some real time applications. It is also important to match the model's requirements with the available infrastructure, some model's may be resource intensive considering the hardware and computational resources available. In the application of dealing with streaming data, ensuring that the model can process and make predictions on data as it arrives in real time by using algorithms designed for streaming data or streaming data or implementing windowed processing will help in live data handling. Fault tolerance and reliability of real time models should be designed to handle failure gracefully. By implementing redundancy and backup systems to ensure reliability in case of model or system failures. If the real-time application involves sensitive data. It is crucial to address security concerns by implementing encryption, access controls and other security measures to protect both the model and the data. Regularly updating and retraining the model to ensure they remain accurate and relevant to the evolving data distribution helps in detecting model degradation or drift over time. Finally, it is important to address the cost associated to deploy and maintain the model as well as optimize resource usage to achieve cost-efficient real-time predictions.

Table 5 Approaches for gas concnetration predictions with strengths and limitations.

Authors and Years	Input type	Method(s)/Approach(es)	Strength(s)	Limitation
Jian-sheng Qian, Jian Cheng, and Yi-nan Guo, 2006 (Qian et al., 2006)	Data set	Two-Stage Multiple Support Vector Machines(SVMs), Mackey-Glass chaotic time series	Fast conversion, Enhanced Generalization Performance, Reduced Support Vectors	Complex tuning, Data Dependency
Marek Sikora, Zdzislaw Krzystanek, Bozena Bojko,Karol,Spiechowicz,2008(Sikora et al., 2008)	SMP-NT data	Linear and Non Linear Prediction Methods	Versatility, stable	Assumption dependence, Limited Modelling, Data Preprocessing
Oliver Obst, X.Rosalind Wang, Mikhail Prokopenko, 2008(Obst et al., 2008)	Network sensors readings	Echo State Networks, Bayesian Network Based Anomaly Detection	Real- time anomaly detection, Dynamic application	Complex tuning, limited interpretability
Ma Xian-Min, 2010(X. M. Ma, 2010)	Sensor Data	Chaotic time series, Time series neural network	Captures complex and non linear patterns	Less interpretability , Computationally intensive
Xian-Min Ma,2011(X.-M. Ma, n.d.)	Sensor Data	Correlation Integral Computation Algorithm (C-C)	Parameter Optimization, Noise Resilience, Chaotic Characteristic Identification	Noise challenge, Complexity less interpretability
Zhai Shengrui, Nie Baisheng, Liu Shuiwen, Wang Hui, Zhao Caihong, Li Qian, Li Hailong, 2011(Zhai et al., 2011)	Monitoring Station Data	Chaos System Predictability and Taken's Theorem	Chaos System Predictability, Phase Space Reconstruction, Optimal Parameter selection, Low Error and RMSE	Data Dependency, Complexity, Short Term Forecasting

Yanli Chai, 2011 (Institute of Electrical and Electronics Engineers., 2011)	Sensor Data	Support Vector Regression (SVR), Particle Swarm Optimization (PSO)	Improved Accuracy, Generalization Ability	Computational Complexity, Hyper parameter Sensitivity
Dong Dingwen,2012 (Dong, 2012)	Time Stamps, Gas emission Quantities	Q-T Model (Relationship between gas emissions quantity and time), Autoregression Model	Higher accuracy, flexibility, practical application.	Computational Complexity, Hyperparameter Tuning, Model Interpretability
Xincheng Hu, Shengqiang Yang, Xiuhong Zhou, Zhaoyang Yu,Chunya Hu, 2015,(Hu et al., 2015)	Gas Samples, Time Series Data, Effective Delay Time	Rescaled Range Analysis, Fractal Dimension Analysis, Risk Prediction Stages	Effective Risk Prediction, Non-Invasive Monitoring, Data Driven Approach	Data Availability, Generalization, Complexity
Yang Zongchag, Zhou Shaowu, 2015(Yang & Zhou, 2015)	Sensor data, Time Series Data	Elliptic Orbit Model, Auto Regressive Model	Intuitive Representation, Hourly Variation Model, Performance Comparison, Concise Approach	Data Requirement, Generalization, Complexity, Model Comparison
V.A.Nivin, V.V.Pukha,A.V.Lovchikov,R.G.Rakhimov, 2016(Nivin et al., 2016)	Time series data	Statistical Analysis, Time series Decomposition, Harmonic Analysis	Long-Term insights, Comprehensive Analysis, Harmonic Analysis. Data Characterization	Data Quality, Model Complexity, Generalization
Yue Geng, 2016(Geng, 2016)	Coal Mine Methan Concentration Time Series	Chaotic Characteristic, Delay Time and Embedding Dimension Calculation, Chaotic Sequential Phase Space Reconstruction, Particle Swarm Optimization, RBF Neural Network, Model Coupling	Chaotic analysis, Optimization, Model Comparison, Coupled Model	Data Quality, Model Complexity, Generalizability

Zhang Xiaoqiang, Cheng Weimin, Zhang Qin, Yang Xinxiang, Du Wenzhou, 2017	Airflow, gas concentration data	Chao Theory Analysis, Time series mapping, Chao prediction model, Safety forecasting and forewarning system, iterative refinement	Data integration, application of chaos theory, on field application	Real time data, Model Complexity, generalizability
Byung Wan Jo, Ran Muhammad Asad Khan, 2018	Gas concentration, temperature, humidity	Mine Environment Index, Principal Component Analysis, ANN	Real time monitoring, good predictive performance.	Sensitive to environmental conditions, periodic training.
Justyna Hebda- Sobkowicz, Sebastian Gola, Radoslaw Zimroz, Agnieszka Wylomanska, 2019(Hebda-Sobkowicz et al., 2019)	Time series data of gas concentration	Signa Segmentation, Statistical analysis	Safety Assessment, Blasting Moment Localization	Data availability, Safety probability
Pingyang Lyu, Ning Chen, Shanjun Mao, Mei Li, 2020(Lyu et al., 2020)	Time series gas concentration	Pearson Correlation Coefficient, ARMA Model, Chaos Model, Encoder-Decoder Model,	Multi-Step Prediction, Robustness	Data Quality, Model Complexity, Generalization
Rong Liang, Xintan Chang, Pengtao Jia, Chengyixiong Xu, 2020(Liang et al., 2020)	Gas concentrations	Laida criterion, Lagrange interpolation, Bidirectional Gated Recurrent Unit Neural Network, Adamax Optimization Algorithm, Loss Function	Improved accuracy, Effective optimization	Data quality, Model Complexity, Generalization
Xiucai Guo, Junkai Mao, 2020, (B. Xu et al., n.d.)	Time series data of gas emissions	Particle Swarm Optimization, Gated Recurrent Unit, Evaluation metrics	Improved Prediction Accuracy, Parameter Optimization, Evaluation Metrics	Data Quality, Complex Computation, Genetalization

Pengtao Jia, Hangduo Liu, Sujian Wang, Peng Wang, 2020(Jia et al., 2020)	Times series data	Preprocessing, pauta criterion, Lagrange interpolation, Spatial Reconstruction, Gated Recurrent Units, Loss function, Adaptive Moment Estimation (ADAM)	High Prediction Accuracy, Time-series utilization, high efficiency	Data dependency, model generalization, Complex computation
Michal Kozielski, Marek Sikora, Lukasz Wrobel, 2021(Grzegorowski et al., 2021)	Time series data from sensors	Classification, Regression, Time series analysis, Stream Data Analysis	Real-Time analysis, Versatility	Data Quality, Sensor Variability, Model Complexity, Generalization
Prasanjit Dey, S.K Chaulya, Sanjay Kumar, 2021(Dey, Chaulya, et al., 2021b)	Time series, spatial measurement	Hybrid Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks	Spatial-Temporal Analysis, Real-Time monitoring	Model Complexity, Generalization, Integration Challenges
Juan Diaz, Zach Agioutantis, Dionissios T. Heistopulos, Steven Schafrik, 2021(Diaz et al., 2021)	AMS data	Filtering, Outlier Detection, Gap-Filling, Homogenization	Data Quality Improvement, Correlation and Dependency, Predictive modeling	Computationall y intensive, Assumptions and interpolation
Xiucai Guo, Penglin Guan, Lekun Yang, Meng Du, 2021 (Guo et al., 2021)	Mine gas concentration	Wavelet Noise Reduction, Thresholding, Reconstruction, Autoregressive Integrated Moving Average (ARIMA) Modeling	Noise reduction, Improved Prediction Accuracy, Short Term Prediction, Comparative analysis	Model Complexity, Data availability, Parameter Selection, Short Term Focus
Prasanjit Dey, K. Saurabh, C.Kumar, D. Pandit, S.K Chaulya, S.K Ray, G.M.Prasad, S.K. Mandal, 2021(Dey, Saurabh, et al., 2021)	Gas sensor data	t-Distributed Stochastic Neighbor Embedding (t-SNE), Variational Autoencoder (VA), Bidirectional Long Short-Term Memory (bi-LSTM)	Multi-Gas Concentration Prediction, Dimensionality Reduction, Improved Prediction Accuracy, Real Time Monitoring	Data Quality, Model Complexity, Resource intensive

K. Kumari, Prasanjit Dey, Chandan Kumar, Dewangshu Pandit, S.S Mishra, Vikash Kisku, S.K Chaulya, S.K. Ray, G.M.Prasad, 2021(Kumari et al., 2021)	Gas concentrations	Uniform Manifold Approximation and Projection (UMAP) , Long Short- Term Memory (LSTM)	Fire status prediction, Multi gas concentration prediction , Dimensionality reduction, Deep learning approach, early warning	Data quality, Model Complexity, Resource intensive, generalization
ZhaoZhao Zhang, Qiang Dai, YinQin Zhu, 2021(Zhang et al., 2022)	Time series gas concentrations	Empirical Model Decomposition, Low-Pass Filtering, Phase Space Reconstruction, Conditional Fuzzy Clustering, Sub-Model Selection	Noise Reduction, Nonlinear Characteristics, Accuracy, Adaptability	Data Quality, Computationally intensive, Interpretability.
Ningke Xu, Xiangqian Wang, Xiangrui Meng, Haoqian Chang, 2021(N. Xu et al., 2022)	Gas concentrations data over time.	Improved Whale Optimization Algorithm (IWOA), Long Short Term Memory (LSTM) Neural Network, Complete Ensemble, Empirical Mode Decomposition with Adaptive Noise (CEEMSAN), Optimal Weight Combination	Improved Accuracy, Multi-Step Prediction	Computationally intensive, Model interpretability
Yuxin Huang, Jingdao Fan, Zhenguo Yan, Shugang Li , Yanping Wang, 2021(Y. Huang et al., 2022)	Real time streaming gas concentration data	Spark Streaming Framework, Autoregressive Integrated Moving Average (ARIMA) model, Support Vector machine (SVM) Model, SPARS Model	Real time prediction, Efficiency, Timeliness, learning characteristics	Computationally intensive, Model Complexity
De Huang, Yong Liu, Yonghong Liu, ying Song, Chagshou Hong, Xiangyang Li(D. Huang et al., 2022)	Concentration data	Mathematical Model, particle Swarm Optimization, Long Short-Term Memory, PSO-LSTM method	Timely Early Warning, Optimized Monitoring, Reliable	Model Complexity, Data overfitting
Mayank Sharma, Tanmoy Maity, Aniket Vatsa, Soumyadip Banerjee, 2021(Sharma et al., 2022)	Sensor data	Parameterized Residual Recurrent Neural Network (PR-RNN), Long Short Term memory (LSTM), Recurrent Neural Network (RNN), Artificial Neural Network (ANN), Graham's Ratio	High prediction accuracy	Complexity, Generalization

Xiangrui Meng, Haoqian Chang, Xiangqian Wang,2021(Meng et al., 2022)	Methane Concentration Data	Recurrent Neural Network (RNN), Long Short-Term memory (LSTM), gated Recurrent Unit (GRU), Combination Approach	Reduced RMSE Loss, overfitting Mitigation	Model Complexity, interpretability, Data preprocessing
Xianqian Wang, Ningke Xu, Xiangrui Meng, Haoqian Chang, 2021(Wang et al., 2022)	Real time gas concentration data	Long short-Term Model (LSTM), Light Gradient Boosting framework (LightGBM), LSTM-LightGBM model, Variable weight Combination	Improved prediction accuracy, Safety enhancement	Model Complexity, Data preprocessing
Hua Fu, Haofan Shi, Yaosong Xu, Jingyu Shao, 2022(Fu et al., 2022)	Factors contributing to gas outburst	Modified Snake Optimization Algorithm (MFISO), Temporal Convolutional Network (TCN), Phase Space Reconstruction, Hyper parameter Optimization, Tangent Based Rectified Linear Unit (ThLU)	Improved Prediction Accuracy, Incorporation of Multiple Strategies, Generalization	Model Complexity, parameter Tuning, Interpretability
Jie Liu, Qian Ma, WAnqing Wang, Guanding Yang, Haowen Zhou, Xinyue Hu, Liangyun Teng, Xuehua Luo. 2022(Liu et al., 2022)	Social Factor, Human related factors, Machinery	Evaluation Index System, Combined Assignment Model, Rough set theory, (RS-G1), Entropy-G-1 (Entropy Method), CRITIC-G1(CRITIC Method), GM(1,1) model, Quadratic Exponential Smoothing Method, ARIMA model	Comprehensive Assessment, Improved Assignment Accuracy, Prediction Accuracy	Model Complexity, Interpretability, Data-Driven Limitation
Chengyu Xie, Lei Chao, Yaguang Qin, Jie Cao, Yuhao Li, 2020(Xie et al., 2020)	Gas Concentrations	Correlation analysis, Short-term and Long-Term Memory Neural network, Random Forest Regression	Compressive Analysis, Correlation analysis	Data Quality, Model Complexity, Interpretability, Data Availibility
Juan Diaz, Zach Agioutantis, Dionissios T.Hristopulos, Steven Schafrik, Kray luxbacher, 2022(Diaz et al., 2022)	AMS data	Data preprocessing, Cross-Correlation, Autocorrelation, Cross-Covariance, Variogram, Autoregressive Integrated Moving Average (ARIMA)	Data driven approach, Statistical analysis, Time Series Modelling	Complexity, Generalizability, Assumptions

Jian Cheng, Jian-sheng Qian, Yi-nan Guo,2023(Cheng et al., 2006)	Gas concentration data	Data Partitioning, Fuzzy C-means Algorithm, Submodel Construction, Gaussian radial basis function kernels, output synthesis, fuzzy synthesis	Improved prediction accuracy, Generalization performance	Model Complexity, Data Dependence, Computational Resource
Yujie Peng, Dazhao Song, Liming Qiu, honglei Wang, Xuwqiu He, Qiang Liu, 2023(Peng et al., 2023)	Multivariate monitoring data	Sperman's rank correlation, Time series, spatial topology features, Dynamic optimization, Bi-directional long Short-Term Memory (Bi-LSTM)	Dynamic Indicator Optimization, Strong Correlations, High Predictive Accuracy	Data Quality, Model Complexity, data Generalizability
Juan Diaz, Zach Agioutantis, Dionissios T.Hristopulos, Steven Schafrik, Kray luxbacher, 2022(Diaz et al., 2023	Methane Gas Concentration	Univariate Autoregressive Integrated Moving Average (ARIMA), Multivariate Vector Autoregressive (VAR), ARIMA with Exogenous Inputs (ARIMAX)	Comprehensive Comparison, Multivariate Approach	Data quality, Model Complexity, generalizability
Chao Liu, Ailin Zhang, Junhua Xua, Chen Lei, Xiangzhen Zeng, 2023	Gas Concentration data	Feature selection with pearson coefficient , Long Short-Term Memory (LSTM), Adaptive Moment Estimation (ADAM) algorithm, Model optimization	Feature Selection, Time Series Modeling, High prediction Accuracy	Data Quality, generalizability, Complexity, Data sampling Interval
Chuan Li, Xianqiu Fang,Zhengua Yan, Yuxin Huang, Minfu Liang, 2023(C. Li et al., 2023)	Time series data	Autoregressive Integrated Moving Average (ARIMA) for linear predictions, Long Short-Term Memory (LSTM) for non linear predictions, Combined forecasting ARIMA-LSTM	Hybrid Approach, High prediction accuracy, Early warning	Data Quality, Generalization, Computational Resources, Hyperparameter Tuning, Interpretability
Tulio Dias, George Danko, (*Methane Concentration Forward Prediction Using Machine Learning from Measurements in Underground Mines*, 2021)	Atmospheric Condition data, Contaminant Concentration data	LSTM, Time-Series Filter	Long-term dependencies	Require large data Limited in handling non-linear dependencies

George Danko (Danko, 2021)	Real Continuous time series data over a sliding time window, quantum vector	Dynamic Quantum Operator (DQO), Least-square fit identification.	Real time identification, forward prediction	Data dependencies, complexity
George Danko (Danko, 2022)	Monitored Data, Physics based operator, functionalized data operator	Deconvolution Data Processing, Linearized FDO, Model identification	Predictive capability, analytical solution	False correlation, data quality issues.

CHAPTER 3 : PREDICTIVE MODEL

3.1 Proposed Method

In this study, a novel method has been proposed for the predicting the gas concentration of sensor “s1” using the data accumulated from 9 sensors (“s2” to “s3”) using K nearest neighbour (KNN) algorithm through an experimental setup built for data acquisition. This method comprises of steps depicted in Figure 17. These steps are thoroughly explained in the following sub-sections.

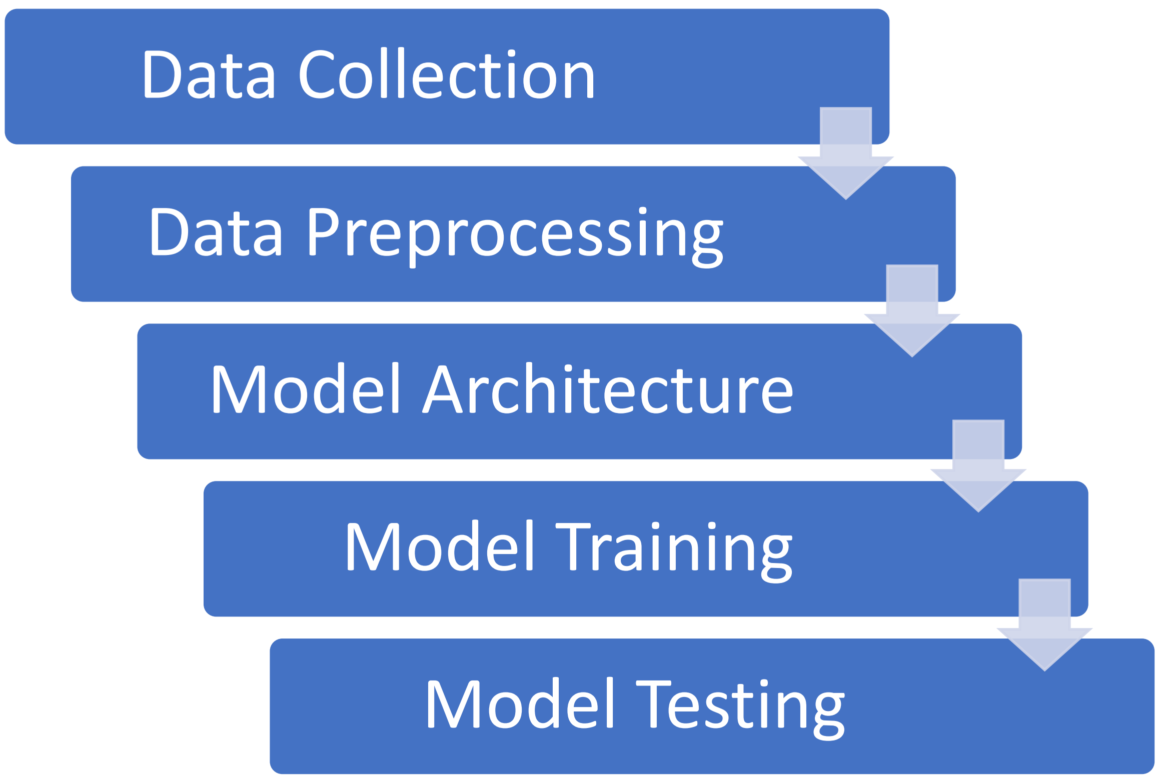


Figure 17 Flow chart of the proposed methodology

3.2 Data acquisition

The first step in this methodology is to collect the CO_2 concentration data from sensors. For this study, an experimental setup was established using a cylindrical pipe (Test section) of diameter 460 mm and length 2380mm. One end of the pipe is connected with a Fan (with variable frequency drive) and conical adapter, and the other end of the pipe is connected with extension for injecting gas (CO_2 and Argon Mixture).

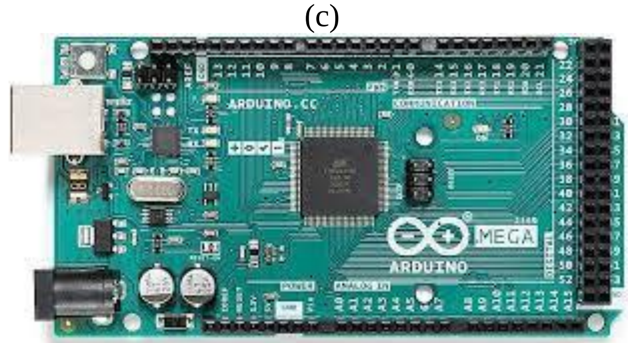
The pipe is equipped with 10 units of MH-Z19B CO_2 sensors. 5 sensors were established on the top and the bottom of pipe from inside in such a way that each sensor is 24 inches away from each other. The range of CO_2 sensors is from 0-5000 ppm and with the accuracy of ±50 ppm + 5 %. A data acquisition system is built using Arduino Atmega2560 which parse data from sensors with UART, rate = 1 sample/second in a form of list. A python program is prepared to store the list generated every second in an excel sheet.

The Figure 18 shows (a) Long View of experimental setup, (b) Tunnel Test Section, (c) MH-Z19C CO_2 , (d) Arduino Atmega2560 and (e) Schematic representation of experimental setup.

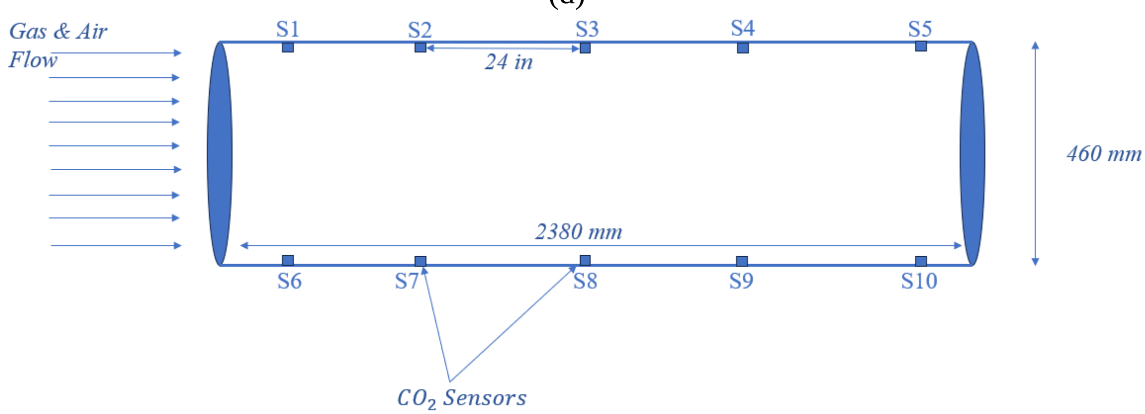
(a)

(b)

(c)



(d)



(e)

Figure 18 (a) Long View of Experimental Setup, (b) Tunnel Test Section, (c)) MH-Z19B CO_2 Sensor (d) Arduino Atmega 2560 (e) Schematic representation of experimental setup.

The experiment consisted of systematically introducing gas from a cylinder at different pressure levels at intervals as a period of min. The air flow of 0.3-0.4 m/s was prescribed for the experiment. For the initial 5 mins there was no gas introduced inside the tunnel model to warm up the sensors. Subsequent 10 minutes the gas pressure was increased to 5 psi. Following 5 minutes the gas pressure was further increased to 10 psi. For next 5 mins, the gas pressure was elevated to 15 psi. For another 5 minutes the gas pressure reached 20 psi. For 6.37 minutes the gas pressure was reduced to 0 psi, in the concluding 5 minutes the gas pressure was reintroduced at 5 psi and last minute the gas pressure was increased to 10 psi. A detailed overview of the experimental conditions and the corresponding variations in the gas pressure, a comprehensive Table 6 has been included below. Over a period of 30 minutes the data acquisition system collected 1800 sets of data for training and listing in the order of (s1, s2, s3, s4, s5,s6,s7,s8,s9,s10). For testing purposes another 1800 sets of data were generated by intruding gas at 15 psi for 30 Mins.

Table 6 Specific Time Interval and The Corresponding Variations in Gas Pressures Applied During The Experiment.

Time interval	Gas Pressure (PSI)
	Air Velocity = 0.3-0.4 m/s
0-5 mins	0
5-10 Mins	5
10-15 Mins	10
15-20 Mins	15
20-25 Mins	20
25-31 Mins	0
31-35 Mins	5
35-36 Mins	10

3.3 Data Preprocessing

The experiment consisted of systematically introducing gas from a cylinder at different pressure levels at intervals as a period of min. The air flow of 0.3-0.4 m/s was prescribed for the experiment. For the initial 5 mins there was no gas introduced inside the tunnel model to warm up the sensors. Subsequent 10 minutes the gas pressure was increased to 5 psi. Following 5 minutes the gas pressure was further increased to 10 psi. For next 5 mins, the gas pressure was elevated to 15 psi. For another 5 minutes the gas pressure reached 20 psi. For 6.37 minutes the gas pressure was reduced to 0 psi, in the concluding 5 minutes the gas pressure was reintroduced at 5 psi and last minute the gas pressure was increased to 10 psi. A detailed overview of the experimental conditions and the corresponding variations in the gas pressure, a comprehensive Table 6 has been included below. Over a period of 30 minutes the data acquisition system collected 1800 sets of data for training and listing in the order of (s1, s2, s3, s4, s5,s6,s7,s8,s9,s10). For testing purposes another 1800 sets of data were generated by intruding gas at 15 psi for 30 Mins.

Table 7 Specific Time Interval and The Corresponding Variations in Gas Pressures Applied During The Experiment.

Time interval	Gas Pressure (PSI)
	Air Velocity = 0.3-0.4 m/s
0-5 mins	0
5-10 Mins	5
10-15 Mins	10
15-20 Mins	15
20-25 Mins	20
25-31 Mins	0
31-35 Mins	5

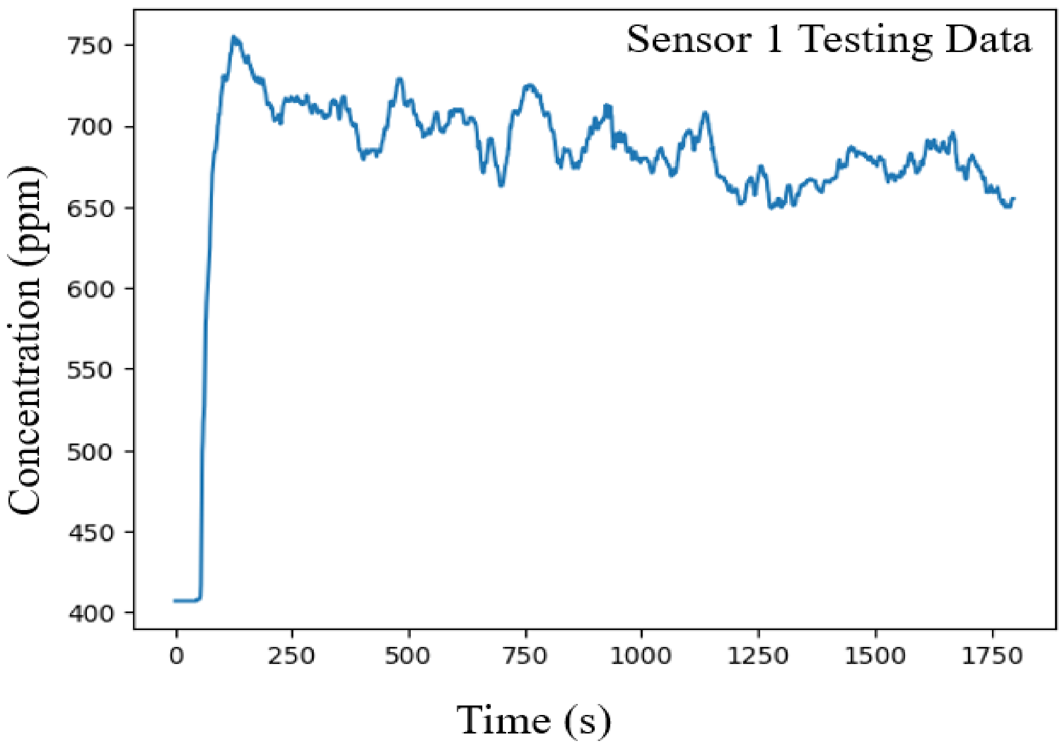
35-36 Mins	10

3.4 Model Training

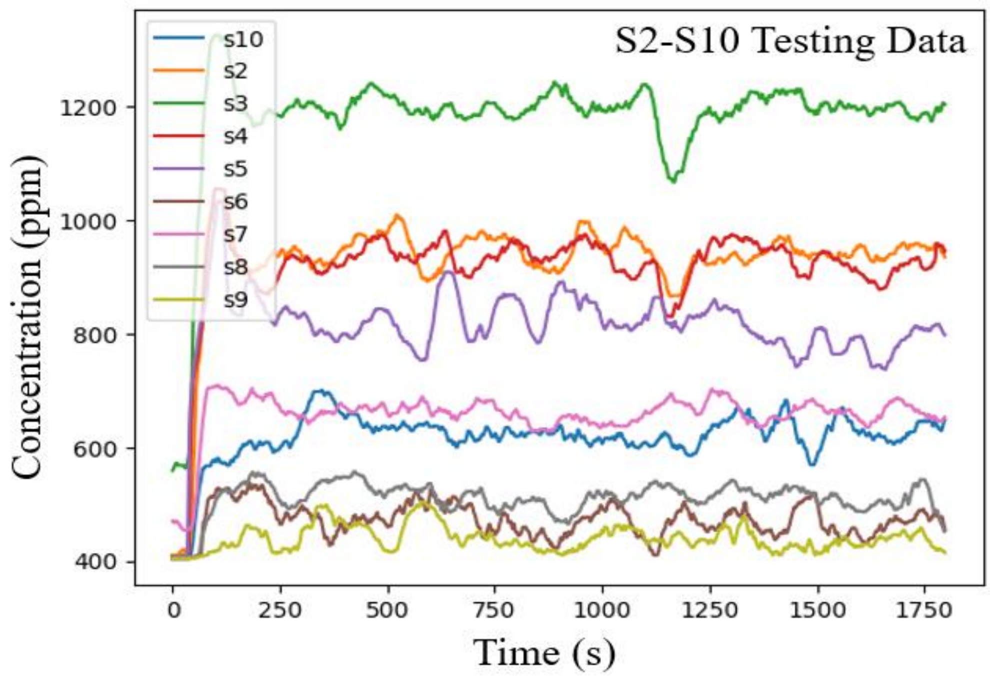
After feeding the data to the model, the ‘fit’ method is called to train the KNN regressor on the provided data. In the realm of machine learning, assessing the performance of a predictive model is crucial to understand its ability to make accurate and reliable predictions. One of the metrics widely utilized for regression tasks in the R-squared (R^2) score, a measure that quantifies the goodness of fit between the predicted values and the actual values. Basically, it is a statistical measure that provides insight into the proportion of variance in the target variable that is explained by the model. It’s value ranges between 0 and 1 where score of 1 indicates a perfect fit, meaning the model’s predictions closely align with the actual values indicating a high level of predictive accuracy. Conversely, a score of 0 suggests that the model is not capturing the variability in the data and might not be providing meaningful predictions and a negative R^2 score may indicate that the model is performing worse than a simple mean-based model. In this model, for the training data, the R^2 is 0.99 & the RMSE is 1.12, indicating that the model is effective in explaining the variance in the target variable (s1) based on the provided features.

3.5 Model Testing

After training the model with data of various gas concentrations with 1800 sets of data it is necessary to test the accuracy of the machine learning model for prediction. A data set of another 1800 data sets is prepared to test the accuracy by keeping the air velocity at 0.3 m/s and introducing CO_2 concentration at 15 psi for 30 mins. After acquiring the data from the data acquisition system, it is processed to feed into the model by preparing a data frame by selecting the sensor 1 data for targeting and later for the feature training. Figure 19 (a) & (b) shows the Sensor 1 and Sensor 2 – 10 data respectively.



(a)



(b)

Figure 19 (a) Sensor 1 Concentration over time for testing data, (b) Sensor 2 to Sensor 10 concentration over time for testing data

3.6 Results And Discussion

In the evaluation of the predictive machine learning model for sensor 1 using data from sensor 2 to sensor 10, the results reveal valuable insights into the model's performance. The graphical representation in Figure 21 (a) illustrates the relationship between the actual concentration and predicted concentration for sensor 1 using the KNN predictive model.

The visualization portrays a favorable scenario, with a majority of predicted gas concentrations at sensor 1 falling either on the ideal line or in a close proximity to it. The red dashed line, symbolizing the ideal scenario where actual values equals predicted values, serves a benchmark for accuracy. Points closely following this line suggest precise predictions, showcasing the model's capability to accurately predict concentrations at sensors 1. Instances where data points lie above the line indicate the model overestimating predicted gas concentration, while points below the line signify instances of underestimation.

Table 8 R^2 Score & Mean Squared Error (MSE) observed with various algorithms.

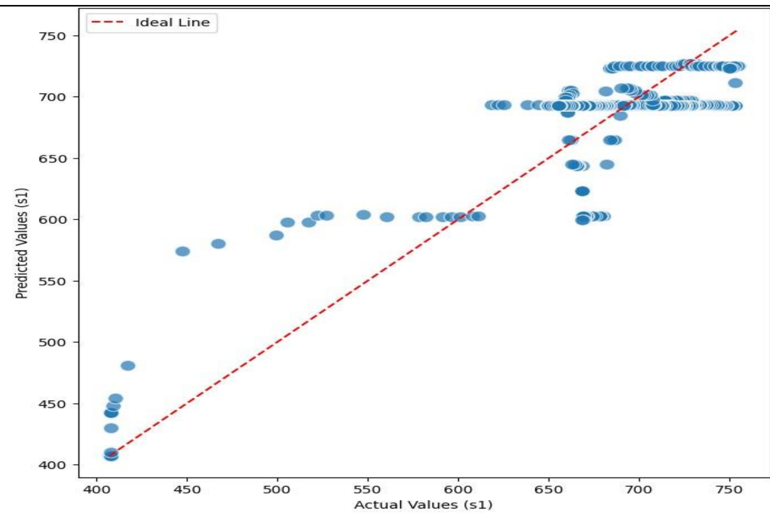
Model	R^2 Score	Mean Squared Error (MSE)
KNN (K-Nearest Neighbour)	0.82	541.72
LR (Linear Regression)	0.77	675.12
BLR (Bayesian Regressor)	-1.63	8036.65
GBR (Gradient Boost Regressor)	-4.28	16132.12
LGR (Light Gradient Boost)	-10.83	36117.69
RF (Random Forest)	-0.23	3762.29
SVM (Support Vector Machines)	0.35	1968.63
XGB (X-Gradient Boost)	-12.43	40995.37

To provide a quantitative assessment of the model's performance, the R-squared (coefficient of determination) value was calculated. The obtained R-squared value of 0.82 indicates a high level of accuracy in predicting sensor 1 concentrations, affirming the model's ability to align predictions closely with the actual values.

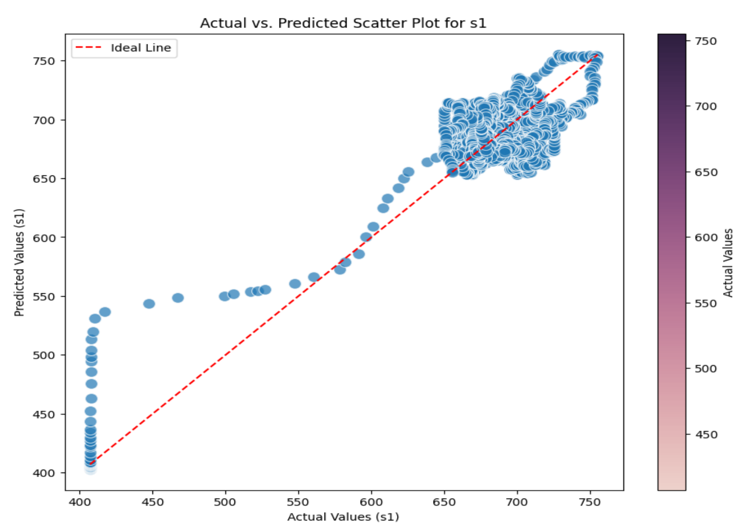
The assessment of multiple machine learning algorithms further underscores the effectiveness of the KNN model. Table 7 summarizes the R-squared scores and Mean Squared Error (MSE) for various algorithms, showcasing the relative performance of each. Notably, the KNN model outperforms other algorithms with an impressive R squared score of 0.82 and a relatively low MSE of 541.72.

This study also produces an insight regarding choosing the right machine learning model is crucial for achieving accurate predictions in each task. The selection of a model depends on the nature of the data, the underlying patterns, and the specific requirements of the problem at hand. The Linear Regression model explains around 77 % of the variability in the dependent variables in the data. The Mean Squared Error (MSE) is higher compared to KNN, but it still provides a measure of the average squared difference. The Support Vector Machine (SVM) model explains approximately 35 % of the variability, which is lower than the K Nearest Neighbor (KNN) and Linear Regression (LR) model. The result of the models Linear Regression & Support Vector Machine can be seen in Figure 21 (b) & (g) MSE The Gradient Boost Regression (GBR), Light Gradient Boost Regression (LGR), Random Forest (RF), Bayesian Regression (BLR) and X-Gradient Boost (XGB) performed poorly, as evidenced by the negative R-squared score and significantly higher MSE values. These models struggled to capture the underlying patterns in the data as shown in Figure 21 (c),(d), (e) ,(f) &(h).

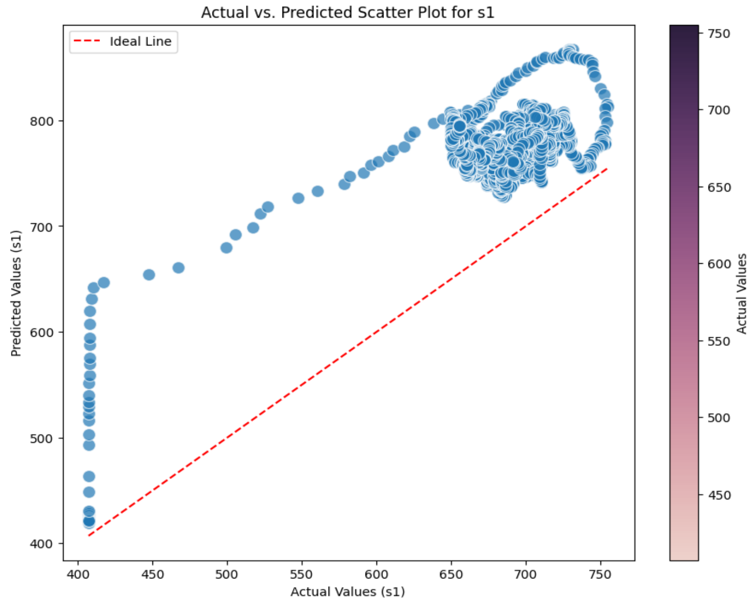
Figure 20 (i) provides an insightful exploration into the individual correlation coefficient of gas concentrations measured from sensor 1 to sensor 10. This correlation analysis allows us to understand the extent to which CO_2 gas concentrations vary across different location (s1-s10) based on the given dataset. The correlation is a statistical measure that describes the extent to which two variables (in this case concentration of gas at two locations) change together. It indicates the strength and direction of the linear relationship between two variables. The correlation coefficient is quantifying the degree to which the movement of gas concentration at one location corresponds to the movement in another. The magnitude of the correlation coefficient indicates the strength of this relationship. There are strong positive correlations between s2, s3, s4 locations. This suggests that if the CO_2 concentration is increasing at one location, it is likely to increase at the other location as well. This information is crucial for predictive modeling, indicating that certain locations tend to have similar trends in CO_2 levels.



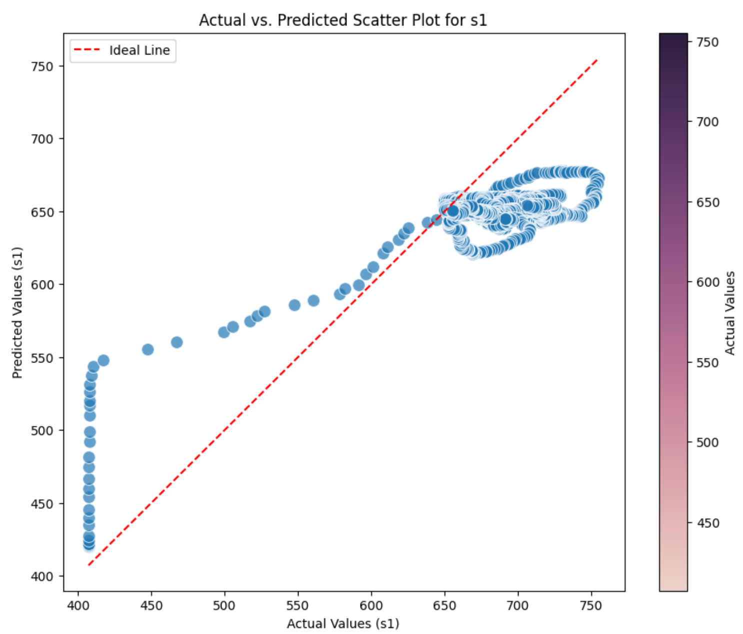
(a)



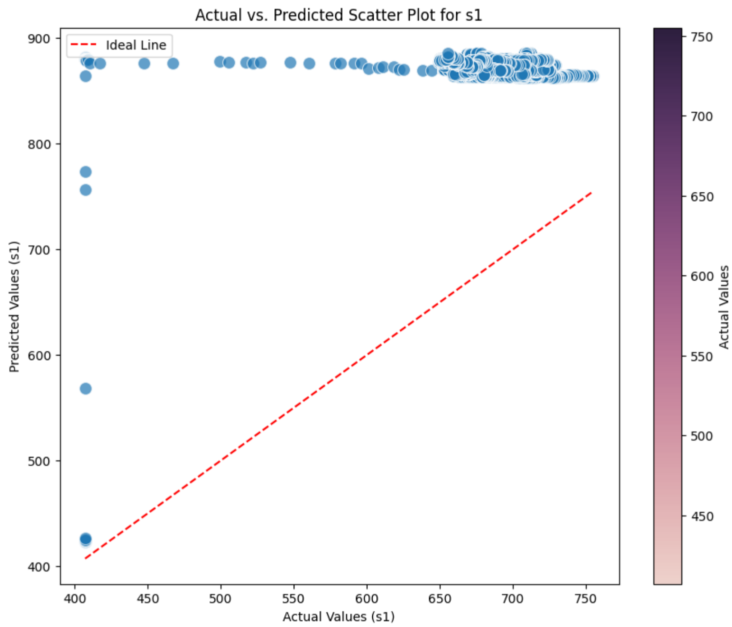
(b)


Actual vs. Predicted Scatter Plot for s1
Ideal Line
Predicted Values (s1)
Actual Values (s1)
Actual Values
400
450
500
550
600
650
700
750
800

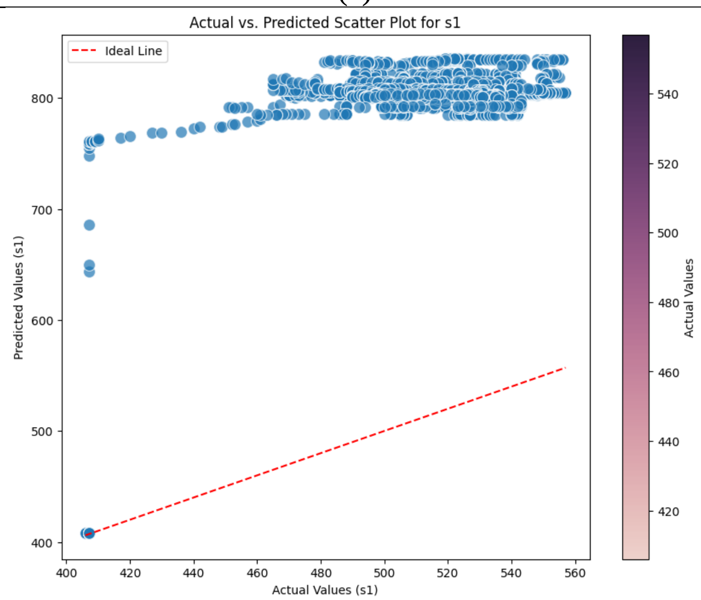
(c)


Actual vs. Predicted Scatter Plot for s1
Ideal Line
Predicted Values (s1)
Actual Values (s1)
Actual Values
400
450
500
550
600
650
700
750

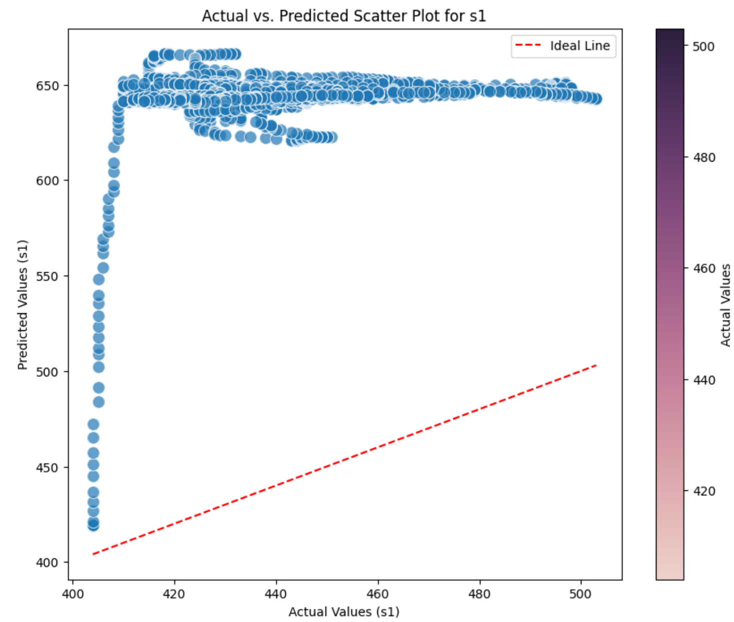
(d)


Actual vs. Predicted Scatter Plot for s1
Ideal Line
Predicted Values (s1)
Actual Values (s1)
Actual Values
400
450
500
550
600
650
700
750
800
900

(e)

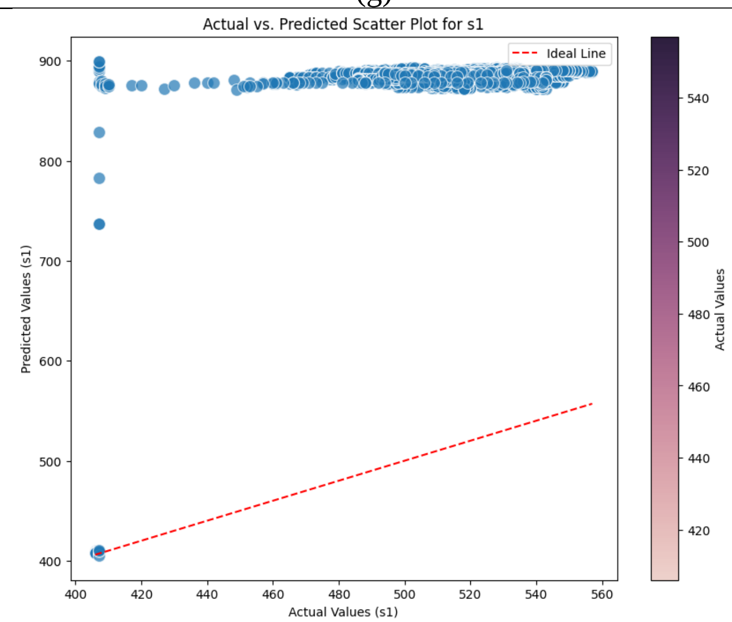

Actual vs. Predicted Scatter Plot for s1
Ideal Line
Predicted Values (s1)
Actual Values (s1)
Actual Values
400
420
440
460
480
500
520
540
560
600
700
800

(f)



Actual vs. Predicted Scatter Plot for s1
Ideal Line
Predicted Values (s1)
Actual Values (s1)
Actual Values
400
450
500
550
600
650
420
440
460
480
500

(g)



Actual vs. Predicted Scatter Plot for s1
Ideal Line
Predicted Values (s1)
Actual Values (s1)
Actual Values
400
500
600
700
800
900
420
440
460
480
500
520
540
560

(h)

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10
s1	1.000000	0.883780	0.885062	0.835539	0.742658	0.503947	0.864752	0.685611	0.319859	0.720329
s2	0.883780	1.000000	0.962738	0.933759	0.765693	0.450243	0.852961	0.647740	0.224953	0.757979
s3	0.885062	0.962738	1.000000	0.956350	0.787573	0.428118	0.840071	0.611495	0.221108	0.761658
s4	0.835539	0.933759	0.956350	1.000000	0.840506	0.427737	0.810909	0.581723	0.240109	0.759674
s5	0.742658	0.765693	0.787573	0.840506	1.000000	0.451195	0.725543	0.417717	0.106914	0.484257
s6	0.503947	0.450243	0.428118	0.427737	0.451195	1.000000	0.566515	0.488399	0.355239	0.202909
s7	0.864752	0.852961	0.840071	0.810909	0.725543	0.566515	1.000000	0.728346	0.317603	0.664934
s8	0.685611	0.647740	0.611495	0.581723	0.417717	0.488399	0.728346	1.000000	0.561558	0.693685
s9	0.319859	0.224953	0.221108	0.240109	0.106914	0.355239	0.317603	0.561558	1.000000	0.494458
s10	0.720329	0.757979	0.761658	0.759674	0.484257	0.202909	0.664934	0.693685	0.494458	1.000000

(i)

Figure 20 Actual Concentration Vs Predicted Concentration for sensor 1 using (a) KNN Predictive model. (b) Linear Regression (c) Bayesian Regression (d) Gradient Boost Regression (e) Light Gradient Regression (f) Random Forest (g) Support Vector Machines (h) X-Gradient Boost (i) Correlation matrix for testing data

Some correlations, like between s6 and s7 locations are moderate. This implies that there is a connection between CO_2 concentrations at these locations, it's not as strong as in the case of strong positive correlations. Understanding these moderate correlations can help in refining predictions and identifying locations that may deviate from the overall trend. Weak correlations are observed between s9 and other locations. This suggests that the CO_2 concentrations at location s9 may not be strongly influenced by the factors affecting the other locations. It is important to consider such weak correlations to avoid over generalization in predictive models. s2, s3,s4 seems to be highly correlated with other locations, making them important for predicting overall trends.

3.7 Conclusions

This study aims to propose a predictive model for gas concentrations in a tunnel using machine learning approach. In this work, an experiment is performed to generate data of gas concentration inside a tunnel model. The CO_2 has been introduced at various time intervals which generate a diverse dataset to ensure a through and effective training of the KNN model. A testing data set of same intervals has been utilized for validating the model. The results show that the proposed model is capturing around 82% of the variability in the CO_2 concentrations. This is a good result, suggesting a strong predictive capability.

Furthermore, the correlation analysis conducted in the study adds depth to our understanding off the interrelationships between gas concentrations at different locations. Strong positive correlations between specific locations, such as s2,s3 and s4 highlight the importance of considering these factors in the predictive model. This analysis contributes to the model's accuracy by acknowledging the tendencies of certain locations to exhibits similar trends in CO_2 levels.

The incorporation of machine learning showcases significant potential in predicting gas concentrations for air quality monitoring data. The ability to capture a substantial portion of the variability in CO_2 concentrations underscore the practical applicability of machine learning in environmental monitoring. The study showcases the promising future of machine learning applications in the realm of predicting gas concentrations, providing valuable insights for air quality monitoring and management.

3.8 Future Work

The presented research has shown the application of machine learning for predictive modelling of gas concentrations inside tunnel using data accumulated with 10 sensors. In future, more research will be done on the same methodology to improve the accuracy of prediction by increasing the number of sensors. Further, data collection will enhance the quality of training dataset for predictive analysis. Application of other machine learning algorithms on enhanced datasets needs to be investigated.

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