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A Project Work Phase-I (18CSP77)
Report on

"Tamper-proof Air Quality Management System"

Project Report submitted in partial fulfillment of the requirement for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted by

ASHWINI J	**1KS18CS007**
KRUTHIKA S VASISHT	**1KS18CS035**
NIKITHA M	**1KS18CS062**
SRIVIDYA H.R.	**1KS18CS099**

Under the guidance of
Dr. Vaneeta M
Associate Professor
Department of Computer Science & Engineering
K.S.I.T, Bengaluru-560109

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

K. S. Institute of Technology

#14, Raghuvanahalli, Kanakapura Road, Bengaluru - 560109 2021 - 2022

K. S. Institute of Technology

#14, Raghuvanahalli, Kanakapura Road, Bengaluru - 560109

Department of Computer Science & Engineering

CERTIFICATE

Certified that the Project Work Phase-I (18CSP77) entitled **"TAMPER-PROOF AIR QUALITY MANAGEMENT SYSTEM"** is a bonafide work carried out by:

ASHWINI J	**1KS18CS007**
KRUTHIKA S VASISHT	**1KS18CS035**
NIKITHA M	**1KS18CS062**
SRIVIDYA H.R.	**1KS18CS099**

in partial fulfillment for VII semester B.E., Project Work in the branch of Computer Science and Engineering prescribed by **Visvesvaraya Technological University, Belagavi** during the period of October 2021 to January 2022. It is certified that all the corrections and suggestions indicated for internal assessment have been incorporated. The Project Work Phase-I Report has been approved as it satisfies the academic requirements in the report of project work prescribed for the Bachelor of Engineering degree.

…………………………	..…………….………	…..…..……………………
Signature of the Guide	**Signature of the HOD**	**Signature of the Principal/ Director**
[Dr. Vaneeta M]	[Dr. Rekha B. Venkatapur]	[Dr. Dilip Kumar K]

DECLARATION

We, the undersigned students of 7th semester, Computer Science & Engineering, KSIT, declare that our Project Work Phase-I entitled "**TAMPER-PROOF AIR QUALITY MANAGEMENT SYSTEM**", is a bonafide work of ours. Our project is neither a copy nor by means a modification of any other engineering project.

We also declare that this project was not entitled for submission to any other university in the past and shall remain the only submission made and will not be submitted by us to any other university in the future.

Place: Bangalore
Date: 02-02-2022

Name and USN		Signature
ASHWINI J	**(1KS18CS007)**	………………….
KRUTHIKA S VASISHT	**(1KS18CS035)**	………………….
NIKITHA M	**(1KS18CS062)**	………………….
SRIVIDYA H.R.	**(1KS18CS099)**	………………….

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ASHWINI J
KRUTHIKA S VASISHT
NIKITHA M
SRIVIDYA H.R.

ABSTRACT

Air pollution has been marked as one of the vital issues of metropolitan areas around the world and is an acute problem which leads to detrimental effects on human health and living conditions. Therefore, there is a need to monitor the pollution levels to inform people about the status of current air quality. This is done by an index called Air Quality Index (AQI) that maps the concentration of various pollutants into a single value. The analysis of pollution data often lacks transparency to outsiders, which may lead to wrong decisions regarding environmental regulations. This has led to a need for a publicly available, scalable, and tamper-proof pollution monitoring system for use by authorities, private citizens and researchers alike.

To address these challenges, we propose to build a model using machine learning algorithms that can be used to predict the air quality and store that information in the blockchain. The use of Machine learning algorithms helps in determining the air quality index and that of blockchain technology ensures a public and permanent, tamper-proof record of all air quality data and such a solution could solve problems of data reliability that persist in pollution monitoring.

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INTRODUCTION

Urbanization and industrial expansion have been blamed for the majority of the environmental pollution. Air pollution is a major threat to the environment. Manufacturing and technology advanced after the Industrial Revolution, resulting in an increase in factories and industries. These factories polluted the environment by emitting smoke into the atmosphere. Most industrial townships had unplanned growth, with businesses breaking rules and regulations and harming the environment both with water and air pollution. In some circumstances, air pollution in megacities surpasses the permissible limit, raising concerns.

Factories, mines, furnaces, smelters, waste disposal units, and other similar plants that lack suitable filters produce a significant amount of gases and particles that might pose a health threat to human life. In order to save money and time, most industries continue to use obsolete technologies to make waste-generating products, and most organisations mostly use traditional ways to produce high-end merchandise. Several small scale businesses and factories that benefit from government aid to operate their day-to-day operational processes regularly break environmental regulations and emit considerable amounts of dangerous pollutants into the atmosphere.

The government considers the gravity of the content and, through government organizations, regulates the amounts of air pollution at each industrial site. A consignment agency's air pollution measurement test is one of them, and it has a variety of negative implications, including inspection timing, inaccuracy, manipulation, and alteration. With data on air quality, plans and data-driven recommendations can be developed to mitigate the possibly severe implications. These suggestions, on the other hand, are based on the Air Quality Index (AQI) numbers.

As shown in Fig. 1.1 AQI is a scale that spans from 0 to 500. The greater the AQI value, more the polluted the air is and the bigger the risk to one's health. For example, an AQI of less than 50 indicates healthy air quality, whereas AQI of 300 or more indicates hazardous air quality. For each pollutant, an AQI value of 100 denotes an ambient air concentration that is roughly equal to the national short-term ambient air quality level for human health and the environment.

AQI Category, Pollutants and Health Breakpoints

AQI Category (Range)	PM_{10} (24hr)	$PM_{2.5}$ (24hr)	NO_2 (24hr)	O_3 (8hr)	CO (8hr)	SO_2 (24hr)	NH_3 (24hr)
Good (0–50)	0–50	0–30	0–40	0–50	0–1.0	0–40	0–200
Satisfactory (51–100)	51–100	31–60	41–80	51–100	1.1–2.0	41–80	201–400
Moderately polluted (101–200)	101–250	61–90	81–180	101–168	2.1–10	81–380	401–800
Poor (201–300)	251–350	91–120	181–280	169–208	10–17	381–800	801–1200
Very poor (301–400)	351–430	121–250	281–400	209–748	17–34	801–1600	1200–1800
Severe (401–500)	430+	250+	400+	748+	34+	1600+	1800+

Fig. 1.1 Air Quality Index Category Range

Multiple contaminants combine to cause pollution in the air. The principal pollutants that cause high pollution are particulate matter PM2.5 and PM10. Ground-level ozone, SO2, carbon monoxide, No2, along with other important pollutants in the air are only a few examples. Because of growing industrial air pollution, the ozone layer is decreasing, which is critical for the survival of the planet's ecosystems. The greater imbalance of gasses in the atmosphere causes global warming as well. There are six categories in the AQI. Each level of health concern relates to a particular category. The categories have their own color schemes which makes it easy for people to detect whether air quality in their neighborhood has reached harmful levels.

However, because sensors may not provide AQI measurements instantly, estimating AQI from sensor values can be difficult. This report presents a method for assessing the quality of air by linking sensor data to an AQI score with the help of prediction models. Machine learning algorithms equip us with tools for forecasting air pollution levels so that people can take preventative efforts to reduce pollution. The use of a blockchain to secure AQI values that may be tampered with for immoral objectives represents the work's uniqueness. The blockchain was utilized to verify that the measured data was immutable and transparent.

We discuss the techniques of the air quality management system widely used today which includes a ML model that predicts the AQI, and the same is stored in a tamper-proof distributed database using blockchain technology. We present a list of research papers that helps in overcoming the challenges of the existing system and finally we present our model that helps to predict air quality accurately and store it on the blockchain.

Chapter 2

LITERATURE SURVEY

Paper [1] explores how successful several current prediction models are in forecasting the AQI values based on input values. In this paper, the focus is on analyzing the meteorological factors that affect the air quality in New Delhi by making use of existing regression models, as well as a comparison of the performance of these models to understand their feasibility, given proper data. Linear regression, neural network regression, Lasso regression, Decision Forest, ElasticNet regression, Extra trees, XGBoost, Boosted decision tree, Ridge regression and KNN are some of the regression models utilized in the prediction system. The findings reveal that most of the models attain an accuracy of almost 85%, and the Extra Trees Regression model has the highest accuracy.

This paper [2] uses a dataset that consists of the concentration of pollutants and meteorological factors. The dataset consists of twelve attributes: Temperature,NO (Nitrogen Monoxide), CH4 (Methane), NOx (Nitrogen Oxides), CO (Carbon Monoxide), NMHC (Non-Methane Hydro-Carbons), NO2 (Nitrogen Dioxide), O3 (Ozone), PM10 (Particulate Matter), PM2.5 and SO2 (Sulfur Dioxide). The new attribute is selected from the attributes in the dataset. The AQI is calculated based on the pollutants or attributes that have the highest effect on air pollution, ie,. the highest row-wise value. This research shows how air quality may be efficiently analyzed and predicted using machine learning techniques such as ANN, SVM, and Random Forest. ANN, SVM, and Random Forest models, on the other hand, have accuracy scores of 90.4%, 93.5%, and 99.4%, respectively. The author Dyuthi Sanjeev concludes that the Random Forest model to be the most efficient model among the three.

The purpose of Timothy M's [3] research is to produce predictive models that can be utilized to generate data-driven solutions to reduce the risk of air pollution using integrated gas sensors and machine learning algorithms. This research presents a method for assessing quality of air by developing prediction models that link sensor data to an air quality score. The models are created using several supervised machine learning methods, including the k-nearest neighbors, support vector machine, Naive-Bayesian classifier, random forest, and neural network, which showed an accuracy of 98.67%, 97.78%, 98.67%, 94.22%, and 99.56% respectively.

In Aditya C R's [4] paper, the work employs logistic regression to determine if a data sample is polluted or not and auto regression is used to forecast future PM2.5 values based on previous PM2.5 data. We can keep PM2.5 levels below the harmful range by knowing what they will be in the following years, months, or weeks. This algorithm is used to predict PM2.5 levels using machine learning and determine the air quality based on a dataset of daily atmospheric conditions. The proposed system accomplishes two goals. One, based on supplied atmospheric variables, detects PM2.5 levels and two, predicts PM2.5 levels for a specific date. The suggested technology will help the public as well as meteorologists to detect and forecast pollution levels and take action appropriately. This will also aid in the establishment of a data source for small towns that are frequently ignored in comparison to larger cities.

The purpose of the paper [5] is to examine numerous existing predictive models and analyze the success of their application in predicting data from the area under study, such as seismic events and to create an architectural model that combines many existing prediction models and generate reliable air quality predictions using the related meteorological input data. Two techniques for air quality prediction are proposed and evaluated: a mix of LSTM and convolutional neural networks, and one-dimensional convolutional neural networks. The findings reveal an accuracy of around 78% in predicting air pollution levels.

Based on the LSTM deep learning method, Yue-Shan Changa presents an Aggregated Long Short-Term Memory model (ALSTM) in this paper [6]. Local air quality monitoring stations, stations in neighbouring industrial regions, and stations for external pollution sources are all combined in this model proposed in this study. To create the ALSTM forecasting model, the author used data with 17 attributes gathered by Taiwan Environmental Protection Agency from 2012 to 2017 as the training data, and we tested the model using data collected in 2018. The author ran some tests to compare novel ALSTM model to LSTM, GBTR (Gradient Boosted Tree Regression), SVR (Support Vector Machine based Regression), and other models in the prediction of PM2.5 for 1–8 hours, and evaluated them using RMSE, MAE, and MAPE. The proposed system has three aggregation-learning models employed in the Aggregated LSTM model: i. overseas characteristics, ii. neighbourhood features, iii. local characteristics. For various station types, the system generates three predictive characteristics. The data is generated using fully connected LSTM predicted functional data, and the system trains data on a continuous basis, with reverse propagation adjusting weights after each batch. The findings show that the proposed model can significantly increase prediction accuracy.

In Mahmoud Reza Delavar's paper [7], weekly and monthly data, topography, meteorological, and pollutant rate of two nearest neighbors were utilized as input factors. Inorder to predict air pollution, machine learning algorithms were employed. These algorithms include regression support vector machines, artificial neural networks, spatially weighted regression and auto-regressive nonlinear neural networks with external input. The error percentage was lowered and improved by 57%, 47%, 47%, and 94%, respectively, using a prediction model that was proposed to improve the aforementioned methodologies. For monthly missed meteorological data, Fourier series and spline approaches were used for daily and weekly missed meteorological data. Using machine learning and statistical approaches, this study offers a unique approach for air pollution prediction in metropolitan areas based on both stationary and non-stationary pollution sources.

M. Lücking et al. [8] in this paper, offers a software design for Pollution monitoring system (PMS) on the basis of distributed ledger technology and the long-range protocol, which offers flexible, transparent, and energy-efficient monitoring of environmental data.Many unresolved difficulties such as lack of data authenticity or tamper-proneness of stored data in the operation of pollution monitoring system were addressed by distributed ledger technology in a Hyperledger Fabric blockchain. In LoRaWAN, public-key cryptography and digital signatures were used to explore how the battery-powered and low-energy sensor nodes are integrated into distributed ledger technology . The analysis of various consensus methods, digital signature schemes, and the proposed design for a decentralized pollution monitoring system with low-energy sensor nodes aid in resolving the performance security trade-off in the IoT.

Daniele Sofia [9] provides a blockchain management system as a solution for ensuring the accuracy of sensitive data. It was possible to get temporal traceability of data transmitted by an air quality monitoring network with high geographical and temporal resolution. It was feasible to save data on the average concentrations of zones which are considered as city's main areas on the Ethereum blockchain. Air quality data is provided by an IoT based sensor network, which includes particulate matter PM10 and PM2.5, volatile organic compounds (VOC), and nitrogen dioxide (NO2) concentrations. This data, recovered from a typical Not Only Structured Query Language (NoSQL) database and structured according to particular specifications, will be automatically transferred to the Ethereum blockchain every day, with the option to manually specify the time of interest. As a result, the blockchain technique has been employed to unambiguously record data provided by air quality monitoring networks.

Sina Rafati Niya's paper [10] proposes an automated solution involving a distributed IoT and Blockchain-based system for water and air quality measurement, monitoring and storage in locations such as lakes, mountains, cities and factories. The proposed pollution monitoring system uses LoRa to overcome IoT protocols' high-power consumption and long-range transmission limitations. The Ethereum Blockchain is used to store and retrieve data collected by IoT sensors, making it completely decentralized. Due to this, data integrity is ensured and data is captured automatically and collected without the need for user intervention. Four different types of sensors for measuring turbidity, potential hydrogen (PH), carbon dixide (CO2), and carbon monoxide (CO) were observed to find a high level of accuracy with non-falsified experimental values and expected measurement timelines. This system suggests two approaches, one where Ethereum Light Client (ELC) is deployed on LoRa gateways. This approach highlights the need for installing blockchain full nodes in the IoT sensors. The other approach is where ELC is installed on the LoRa sensor nodes and the web server receives data from sensor nodes and has a full node installed on it. The data generated by IOT sensors is sent to the blockchain, which also acts as proof of pollution in that area.

The proposed platform in paper [11] collects real-time air pollutants using IoT sensors based on 5G wireless network, generated at industrial locations, real-time air pollution data that transmits and maintains encrypted blockchain data through a periodic blockchain transaction to the cloud and index measurement service. This system facilitates real-time monitoring of pollution levels in industrial workplaces while also preventing data falsification and tampering. The 5G wireless network manages massive amounts of data gathering and bulk traffic to store data on edge nodes and core networks, and edge computing enables near real-time analysis of the acquired data in this platform. Edge computing is also resource efficient since it uses virtual system technologies to handle data acquired through IoT in real time. A 5G wireless network with wireless access networks and core network segments can send data to Edge computing data storage. The encryption technology in blockchain and the distributed messaging protocol it uses improve data processing efficiency and data exchange while ensuring data integrity. Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS) are cloud-based services.

Chapter 3

PROBLEM IDENTIFICATION

Environmental pollution is dangerously increasing all over the world as a result of rapid industrialization. Industrial pollution is one of the major causes of air pollution. Abundant industrial pollutants pollute the natural environment, causing it to be unstable, unpleasant and dangerous for both the physical and biological environment.

The government is investigating this problem and has enacted a number of tough regulations to combat it. Local governments (e.g., public environmental agencies) are currently entrusted with a large portion of the responsibility for monitoring industrial emissions and developing policies to reduce industrial air pollution. However, delegating the system's operation and maintenance to local government agencies led to a lack of transparency with respect to sensor data collection, processing, and storage.

Consequently, external parties find it difficult to validate pollution analyses as only a few data analysts are ultimately responsible for the cleaning of data, preprocessing, and analysis, which can lead to erroneous public policy decisions and health risks. Transparency in the collection, storage, and analysis of pollution data should be enforced to avoid such incorrect policies by allowing cross-validation by third parties and to promote better decision-making regarding the improvement of the quality of air.

The current system for tracking pollutants emitted by industry is centralized, non-transparent, and prone to data manipulation. This is why we need to come up with a solution to this issue that provides a tamper-proof management system.

Chapter 4

GOAL AND OBJECTIVES

4.1 GOAL

To build a machine learning model to predict the air quality Index along and the category of it and store it on Blockchain. We propose to build a tamper-proof air quality management system which comprises a ML model to predict the AQI along with its category and the same gets stored in a distributed ledger using blockchain technology.

4.2 OBJECTIVES

- Machine learning is used to reduce errors, improve accuracy and efficiency as we are working with large data. Further, since not all industries emit the same pollutants, using a ML model will help improve the calculation of AQI.
- A blockchain-based solution ensures a public, permanent, and tamper-proof record of all air quality data, and such a solution could overcome data dependability issues that plague pollution monitoring today.
- As this system will do most of the work such as storing the pollutant emission data and reporting to the Pollution Control Board, PCB periodically, the PCB members will not have to invest a lot of time and resources into this, but instead can just manage via this system.
- This proposed system will help the central and state pollution board manage pollutants from industries.

Chapter 5

SYSTEM REQUIREMENT SPECIFICATION

- A client application that acts as a medium of information exchange.
- **Software Requirements:**
    - A software requirements specification is an abstract description of the services that the system should deliver as well as the limitations that it must operate under. It should solely describe the system's outward behavior and should not include any information about the system's architecture. It's a solution that explains what services the system is intended to deliver and the constraints under which it must operate in natural language with graphics.
    - OS: Linux, Windows 10
    - Preferred browser: Google Chrome
    - Blockchain: Hyperledger Fabric
- **Hardware Requirements:**
    - Hardware requirement analysis: The term "analysis" refers to the process of defining and analyzing a comprehensive collection of operational, functional, performance, quality, design, criticality, interface, and test requirements.
    - Processor: Intel Core i5 1.3GHz (Turbo Boost up to 2.6GHz) with 3MB shared L3 cache
    - 4 GB memory
    - 1 Gbit/s network
    - 120GB SSD

Chapter 6

METHODOLOGY

6.1 Our proposed system

The proposed system mainly has three modules : the machine learning model, Blockchain network, and Client application. The machine learning model is to be trained using industrial air pollution data and supervised learning algorithms such as random forest, SVM, etc to predict the Air Quality (AQI) and respective quality category of the given input data. The algorithm that gives the best accuracy will be considered. The design of the ML model has these phases as shown in Fig. 6.2. The dataset we are currently considering is from one of the biggest industrial areas of Southeast Asia, i.e., Peenya, Bangalore. We have collected this data from the Central Control Room for Air Quality Management. The dataset consists of parameters such as PM10, PM2.5, NO, NO_2, NO_x, NH_3, SO_2, CO, O_3, temperature, etc. over the course of 12 years from 2010 to 2021. Further, the dataset is cleaned and partitioned into training and testing data. After which the model can be trained and validated. In the Hyperledger fabric blockchain, chain code will have the ML model deployed in it. Once the client supplies the data to the blockchain, the chain code that has the ML model will start executing. After successful execution, the output will be stored on the distributed ledger as shown in Fig. 6.3.

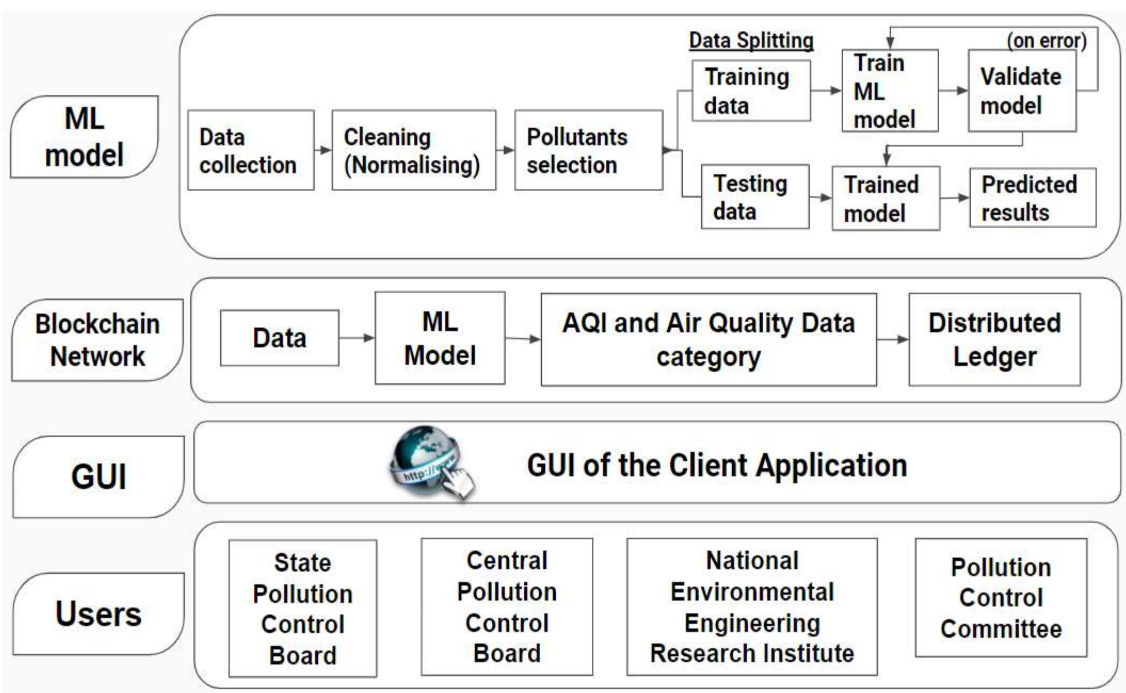

Fig 6.1. Project modules

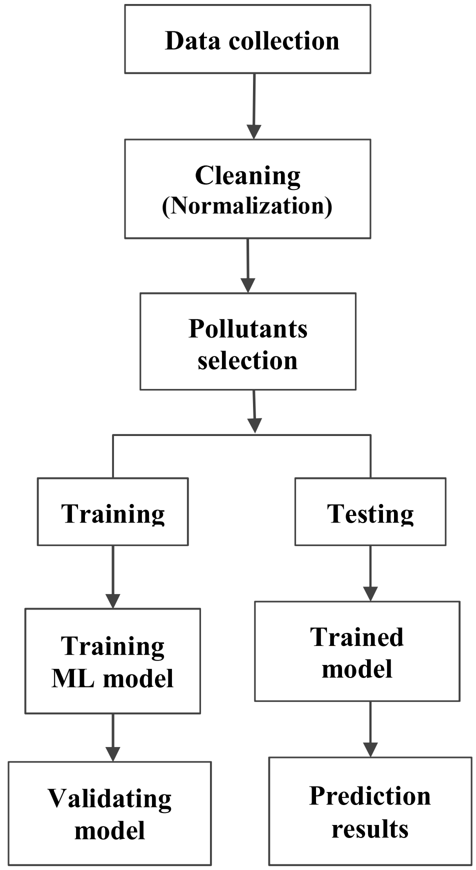

Fig. 6.2. Flow of proposed Machine Learning methodology

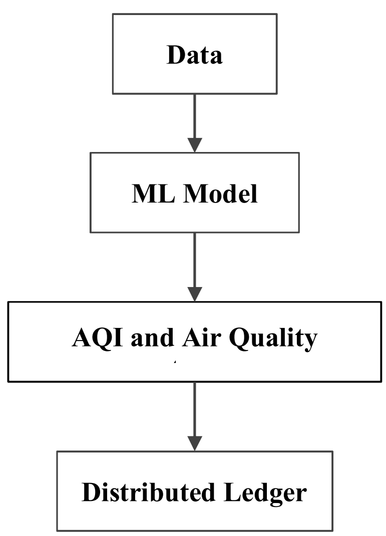

Fig. 6.3. Flow of proposed Blockchain Methodology

6.2 Artificial Neural Network

Artificial neural networks (ANNs), often referred to as neural networks (NNs), are computer devices that are designed after the biological neural networks that make up animal brains. Artificial neurons are a collection of linked units or nodes in an artificial neural network (ANN) that loosely emulate the synapses in a biological brain. Each connection, like synapses in the brain, may relay messages to other neurons. An artificial neuron takes input, evaluates it, and then transmits messages to the neurons with whom it is linked. [2][3][7]

6.3 LSTM

In the realm of deep learning, long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture. The LSTM network has feedback connections, unlike traditional feedforward neural networks. The standard LSTM unit consists of three gates namely input gate, output gate and a forget gate. LSTM networks are best suited for operations such as categorizing, analyzing, and making predictions based on time series data since there can be unanticipated gaps between significant occurrences in a time series.[5][6].

6.4 Random Forest

Random forests, also known as random decision forests, are an ensemble learning method for classification, regression, and other problem statements that use a huge number of decision trees to train. The output of a random forest for classification problems is the class selected by the majority of trees. In regression tasks, the mean or average prediction of the individual trees is returned. The issue of decision trees overfitting their training set is addressed using random decision forests. In the vast majority of circumstances, random forests outperform choice trees, but they are less precise than gradient enhanced trees. On the other hand, data characteristics can influence their performance.[2][3]

6.5 Support Vector Machine

For Classification and Regression, SVM is a common Supervised Learning technique. I t is most typically employed for classification issues in ML. The purpose of the SVM method is to discover the optimum line or decision boundary for dividing n-dimensional space into classes so that fresh data points may be placed in the proper category easily in the future. The optimal choice boundary is represented by a hyperplane and its extreme points are chosen by it. The SVM algorithm is called after support vectors, which are extreme examples. [2][3][7]

6.6 Hyperledger Fabric blockchain

Hyperledger Fabric is a distributed ledger platform that is open, tested, and enterprise-ready. It features sophisticated privacy controls, ensuring that only the information you want to be shared is shared with the "permissioned" (known) network participants.

Distributed ledger technology (DLT) enables the operation of distributed ledgers, which are fault-tolerant (Byzantine) distributed databases.Local copy of data is maintained on each node of distributed ledger, and new data gets added to the ledger as transactions. New transactions are verified with digital signatures and they are stored in the memory of nodes, which is further passed to other DLT nodes in the network.Eventually, validated transactions get appended directly to the ledger,or stored in a a block,which will further be added to the ledger. The majority of DLT consensus mechanisms are crash fault-tolerant or Byzantine fault-tolerant. Crash fault tolerance means to obtain consensus across all validators, in spite of some nodes temporarily being unavailable. Private-permissionless, private-permissioned, public-permissionless, and public-permissioned are the four types of distributed ledgers.

Compared to public-permissionless distributed ledgers, private-permissioned distributed ledgers typically provide more flexibility i.e., maintainability, greater performance, maximum throughput and a higher degree of transparency.[8]

Chapter 7

APPLICATIONS

The major purpose of the AQI is to offer citizens warnings and keep them up to date on current circumstances. This is pivotal for vulnerable groups like the children, elderly, and the disabled. or people with respiratory or heart problems. Such people should stay indoors when the air quality is low.

CEMS (Continuous Emission Monitoring System) is a real-time air and water pollution monitoring system that is used in India to track industrial emissions.
The industries themselves must use an online platform to report ongoing emission data.
This is where the data's lack of openness comes into play, as industries may alter the values before submitting them to pollution control bodies.

Our proposed system is useful for the Central and State Pollution Control Boards to manage the Industrial air pollutant emission data in a permanent, tamper-proof and secure manner. This helps the PCBs to take appropriate measures when the emissions from industries are not within the acceptable range.

Chapter 8

CONTRIBUTION TO SOCIETY AND ENVIRONMENT

- A tamper-proof, transparent and secure software must be designed and developed. Our application aims to achieve this by using blockchain.
- Our proposed system helps control air pollution.

REFERENCES

[1] S. Mahanta, T. Ramakrishnudu, R. R. Jha and N. Tailor, "Urban Air Quality Prediction Using Regression Analysis," TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), 2019, pp. 1118-1123, doi: 10.1109/TENCON.2019.8929517.

[2] Dyuthi Sanjeev, 2021, Implementation of Machine Learning Algorithms for Analysis and Prediction of Air Quality, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 10, Issue 03 (March 2021)

[3] T. M. Amado and J. C. Dela Cruz, "Development of Machine Learning-based Predictive Models for Air Quality Monitoring and Characterization," TENCON 2018 - 2018 IEEE Region 10 Conference, 2018, pp. 0668-0672, doi: 10.1109/TENCON.2018.8650518.

[4] C R, Aditya & Deshmukh, Chandana & K, Nayana & Gandhi, Praveen & astu, Vidyav. (2018). Detection and Prediction of Air Pollution using Machine Learning Models. International Journal of Engineering Trends and Technology. 59. 204-207. 10.14445/22315381/IJETT-V59P238.

[5] Stojov, Vladimir & Koteli, Nikola & Lameski, Petre & Zdravevski, Eftim. (2018). Application of machine learning and time-series analysis for air pollution prediction.

[6] Yue-Shan Chang, Hsin-Ta Chiao, Satheesh Abimannan, Yo-Ping Huang, Yi-Ting Tsai, Kuan-Ming Lin, An LSTM-based aggregated model for air pollution forecasting, Atmospheric Pollution Research,
Volume 11, Issue 8, 2020.

[7] Delavar, M.R.; Gholami, A.; Shiran, G.R.; Rashidi, Y.; Nakhaeizadeh, G.R.; Fedra, K.; Hatefi Afshar, S. A Novel Method for Improving Air Pollution Prediction Based on Machine Learning Approaches: A Case Study Applied to the Capital City of Tehran. *ISPRS Int. J. Geo-Inf.* 2019, *8*, 99.

[8] M. Lücking et al., "The Merits of a Decentralized Pollution-Monitoring System Based on Distributed Ledger Technology," in IEEE Access, vol. 8, pp. 189365-189381, 2020, doi: 10.1109/ACCESS.2020.3028430.

[9] Sofia, D.; Lotrecchiano, N.; Trucillo, P.; Giuliano, A.; Terrone, L. Novel Air Pollution Measurement System Based on Ethereum Blockchain. *J. Sens. Actuator Netw.* 2020, *9*, 49.

[10] S. R. Niya, S. S. Jha, T. Bocek and B. Stiller, "Design and implementation of an automated and decentralized pollution monitoring system with blockchains, smart contracts, and LoRaWAN," NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium, 2018, pp. 1-4, doi: 10.1109/NOMS.2018.8406329.

[11] Yohan Han, Byungjun Park, Jongpil Jeong, A Novel Architecture of Air Pollution Measurement Platform Using 5G and Blockchain for Industrial IoT Applications,Procedia Computer Science, Volume 155,
2019.

APPENDIX-I

Survey on Industrial Air Quality Management System

Dr. Vaneeta M
Associate Professor,
Department of Computer Science,
K S Institute of Technology,
Raghuvanahalli,
Bangalore,560109
vaneetam@ksit.edu.in

Kruthika S Vasisht
Department of Computer Science,
K.S. Institute of Technology,
Raghuvanahalli, Bangalore,
560109,
kruthikasvasisht@gmail.com

Nikitha M
Department of Computer Science,
K.S. Institute of Technology,
Raghuvanahalli, Bangalore,
560109,
nikithamofficial@gmail.com

Srividya H.R.
Department of Computer Science,
K.S. Institute of Technology,
Raghuvanahalli, Bangalore, 560109,
srividyahr21@gmail.com

Ashwini J
Department of Computer Science,
K.S. Institute of Technology,
Raghuvanahalli, Bangalore, 560109,
ashwinisamak93@gmail.com

ABSTRACT

Air pollution is known to be one of the most important problems of cities all over the world, and industrial emissions play a major role in affecting the air quality. Tracking the pollution levels is the need of the hour, where pollution levels can be analyzed with the help of an index called the Air Quality Index (AQI). However, the existing system that analyzes industrial air pollution data lacks transparency and is prone to tampering which is a hindrance to better decision making. Therefore, a tamper-proof air quality management system is to be designed using blockchain technology. This paper performs a survey on various techniques and challenges in predicting AQI and storing the air quality data in a transparent distributed ledger and also lists some research papers that aid with this issue.

1. INTRODUCTION

Urbanization and industrial expansion has been blamed for the majority of the environmental pollution. Air pollution is a major threat to the environment. Manufacturing and technology advanced after the Industrial Revolution, resulting in an increase in factories and industries. These factories polluted the environment by emitting smoke into the atmosphere. Most industrial townships had unplanned growth, with businesses breaking rules and regulations and harming the environment both with water and air pollution. In some circumstances, air pollution in megacities surpasses the permissible limit, raising concerns.

The government considers the gravity of the content and, through government organizations, regulates the amounts of air pollution at each industrial site. A consignment agency's air pollution measurement test is one of them, and it has a variety of negative implications, including inspection timing, inaccuracy, manipulation, and alteration. With data on air quality, plans and data-driven recommendations can be developed to mitigate the possibly severe implications. These suggestions, on the other hand, are based on the Air Quality Index (AQI) numbers as shown in Fig. 1.

However, because sensors may not provide AQI measurements instantly, estimating AQI from sensor values can be difficult. This report presents a method for assessing the quality of air by linking sensor data to an AQI score with the help of prediction models. Machine learning algorithms equip us with tools for forecasting air pollution levels so that people can take preventative efforts to reduce pollution. The use of a blockchain to secure AQI values that may be tampered with for immoral objectives represents the work's uniqueness. The blockchain was utilized to verify that the measured data was immutable and transparent.

We discuss the techniques of the air quality management system widely used today which includes a ML model that predicts the AQI, and the same is stored in a tamper-proof distributed database using blockchain technology. We present a list of research papers that helps in overcoming the challenges of the existing system and finally we present our model that

AQI Category, Pollutants and Health Breakpoints

AQI Category (Range)	PM_{10} (24hr)	$PM_{2.5}$ (24hr)	NO_2 (24hr)	O_3 (8hr)	CO (8hr)	SO_2 (24hr)	NH_3 (24h
Good (0–50)	0–50	0–30	0–40	0–50	0–1.0	0–40	0–200
Satisfactory (51–100)	51–100	31–60	41–80	51–100	1.1–2.0	41–80	201–400
Moderately polluted (101–200)	101–250	61–90	81–180	101–168	2.1–10	81–380	401–800
Poor (201–300)	251–350	91–120	181–280	169–208	10–17	381–800	801–120
Very poor (301–400)	351–430	121–250	281–400	209–748	17–34	801–1600	1200–18
Severe (401–500)	430+	250+	400+	748+	34+	1600+	1800+

Fig. 1. Air Quality Index(AQI) Category Range

helps to predict air quality accurately and store it on the blockchain. Further the paper is organized as: A literature review of the air quality management system in Section 2. Our model of Tamper-proof air quality management system in Section 3 followed by conclusion and future work in Section 4.

2. LITERATURE REVIEW

Paper [1] explores how successful several current prediction models are in forecasting the AQI values based on input values. In this paper, the focus is on analyzing the meteorological factors that affect the air quality in New Delhi by making use of existing regression models, as well as a comparison of the performance of these models to understand their feasibility, given proper data. Linear regression, neural network regression, Lasso regression, Decision Forest, Elastic Net regression, Extra trees, XGBoost, Boosted decision tree, Ridge regression and KNN are some of the regression models utilized in the prediction system. The findings reveal that most of the models attain an accuracy of almost 85% and the Extra Trees Regression model has the highest accuracy.

This paper [2] uses a dataset that consists of the concentration of pollutants and meteorological factors. The dataset consists of twelve attributes: Temperature, Nitrogen Monoxide, Methane, Nitrogen Oxides, Sulfur Dioxide, Ozone, Carbon Monoxide, Non-Methane Hydro-Carbons, Nitrogen Dioxide, and Particulate Matter (PM10 and PM2.5). The new attribute is selected from the attributes in the dataset. The AQI is calculated based on the pollutants or attributes that have the highest effect on air pollution, ie. the highest row-wise value. This research shows how air quality may be efficiently analyzed and predicted using machine learning techniques such as Artificial Neural Network, Support Vector Machine and Random Forest models with accuracy scores of 90.4%, 93.5%, and 99.4%, respectively. The author Dyuthi Sanjeev concludes that the Random Forest model to be the most efficient model among the three.

The purpose of Timothy M's [3] research is to produce predictive models that can be utilized to generate data-driven solutions in order to cut back on the risk of air pollution using integrated gas sensors and machine learning algorithms. This research presents a method for assessing quality of air by developing prediction models that link sensor data to an air quality score. The models are created using several supervised machine learning methods, including the, support vector machine, k-nearest neighbors, neural network, random forest and Naive-Bayesian classifier which showed an accuracy of 97.78%, 98.67%, 99.56%, 94.22% and 98.67% respectively.

In Aditya C R's [4] paper, the work employs logistic regression to determine if a data sample is polluted or not and auto regression is used to forecast future PM2.5 values based on previous PM2.5 data. We can keep PM2.5 levels below the harmful range by knowing what they will be in the following years, months, or weeks. This algorithm is used to predict PM2.5 levels using machine learning and determine the air quality based on a dataset of daily atmospheric conditions. The proposed system accomplishes two goals. One, based on supplied atmospheric variables, detects PM2.5 levels and two, predicts PM2.5 levels for a specific date. The suggested technology will help the public as well as meteorologists to detect and forecast pollution levels and take action appropriately. This will also aid in the establishment of a data source for small towns that are frequently ignored in comparison to larger cities.

The purpose of the paper [5] is to examine numerous existing prediction models and assess the level of success of their application in predicting data from the area under study, such as seismic events and to create an architectural model that combines many existing prediction models and generate reliable air quality predictions using the related meteorological input data.Two techniques for air quality prediction are proposed and evaluated: a mix of convolutional neural networks and LSTM, and one-dimensional convolutional neural networks. The findings reveal an accuracy of around 78% in predicting air pollution levels.

According to the LSTM deep learning method, Yue-Shan Changa presents an Aggregated Long Short-Term Memory model (ALSTM) in this paper [6].The strategy presented in this work incorporates regional air-quality monitoring stations, stations in neighboring industrial zones, and stations for external emission sources.

To create the ALSTM forecasting model, the author used data with 17 attributes gathered by Taiwan Environmental Protection Agency from 2012 to 2017 as the training data, and we tested the model using data collected in 2018. The author ran some tests to compare novel ALSTM model to LSTM, GBTR (Gradient Boosted Tree Regression), SVR (SVM based Regression), and other models for 1–8 hours, in the prediction of PM2.5 and evaluated them using RMSE, MAE, and MAPE. The proposed system has three aggregation-learning models employed in the Aggregated LSTM model that are overseas characteristics, neighborhood features and local characteristics. For various station types, the system generates three predictive characteristics. The data is generated using fully connected LSTM predicted functional data, and the system trains data with reverse propagation adjusting weights on a continuous basis, after each batch. The findings show that this proposed model can significantly increase prediction accuracy.

In Mahmoud Reza Delavar's paper [7], weekly and monthly data, topography, meteorological, and two nearest neighbors' pollutant rates were utilized as input factors. In order to predict air pollution, machine learning algorithms were employed. These algorithms include artificial neural networks, regression support vector machines, spatially weighted regression, and auto-regressive nonlinear neural networks along with an external input. The error percentage was lowered and improved by 47%, 57%, 47%, and 94% respectively, using a predictive model that was suggested in order to improve the above mentioned methodologies. Fourier series and spline approaches were used for daily and weekly missed meteorological data. Using machine learning and statistical approaches, this study offers a unique approach for prediction of air pollution in metropolitan areas based on both stationary pollution and non-stationary sources.

M. Lücking et al. [8] in this paper, offers a software design for Pollution monitoring system (PMS) on the basis of distributed ledger technology and the long-range protocol, which offers monitoring that is flexible, transparent, and energy-efficient.Many unresolved difficulties such as storing data that is not authentic or prone to tampering in the operation of pollution monitoring system were addressed by distributed ledger technology in a Hyperledger Fabric blockchain. In LoRaWAN, public-key cryptography and digital signatures were used to explore how the battery-powered and low-energy sensor nodes are integrated into distributed ledger technology. The analysis of various digital signature schemes,consensus methods, and the prototype for a decentralized pollution monitoring system with low-energy sensor nodes aid in resolving the performance security trade-off in the IoT.

Daniele Sofia [9] provides a blockchain management system as a solution for ensuring the accuracy of sensitive data. It was possible to get temporal traceability of data transmitted by an air quality monitoring network with high geographical and temporal resolution. It was feasible to save data on the average concentrations of zones which are considered as city's main areas on the Ethereum blockchain. Air quality data is provided by an IoT based sensor network, which includes PM10, PM2.5, volatile organic compounds, and

Nitrogen dioxide concentrations. This data, recovered from a typical Not Only Structured Query Language database and structured according to particular requirements, will be automatically transferred to the Ethereum blockchain daily, with the option to manually specify the time of interest. As a result, the blockchain technique has been employed to unambiguously record data provided by air quality monitoring networks.

Sina Rafati Niya's paper [10] proposes an automated solution involving a IoT and Blockchain-based system for measurement of air and water quality of factories, lakes etc, monitoring and storing the same. The proposed pollution monitoring system uses LoRa to overcome high-power consumption and long-range transmission limitations of IoT protocols. The Ethereum Blockchain is used to store and retrieve data collected by IoT sensors, making it completely decentralized. Due to this, data integrity is ensured and data is captured automatically and collected eliminating the need for manual interference. Turbidity, carbon dioxide, carbon monoxide (CO), and potential hydrogen were all measured using four different types of sensor and a high level of accuracy with non-falsified experimental values was observed. This system suggests two approaches, one where Ethereum Light Client is deployed on LoRa gateways. This approach highlights the need for installing blockchain full nodes in the IoT sensors. The other approach is where Ethereum Light Client is installed on the LoRa sensor nodes and the web server receives data from sensor nodes and has a full node installed on it. The data generated by IOT sensors is sent to the blockchain, which also acts as proof of pollution in that area.

The proposed platform in paper [11] collects real-time air pollutants using 5G wireless IoT sensors, generated at industrial locations and maintains encrypted blockchain data through a periodic blockchain transaction to the index measurement service and cloud. This system facilitates real-time monitoring of pollution levels in industrial workplaces while also preventing tampering of data. The 5G wireless network handles a huge amount of data gathering and bulk traffic to store data on edge nodes and core networks. Edge computing aids real-time analysis of the acquired data on this platform. It is also resource efficient as it uses virtual system technologies to handle real-time IoT data. A 5G wireless network with wireless access networks and core network segments can send data to Edge computing data storage. The encryption technology in blockchain and the distributed messaging protocol improves the efficiency of data processing and data exchange ensuring integrity of data.

3. METHODOLOGY

3.1 Our proposed system

The proposed solution mainly has three modules: the machine learning model, Blockchain network, and Client application as shown in Fig. 2. The machine learning model is to be trained using industrial air pollution data and supervised learning algorithms such as random forest, SVM, etc to predict the Air Quality (AQI) and respective quality category of the given input data. The algorithm that gives the best accuracy will be considered.
The design of the ML model has these phases as shown in Fig. 3. The dataset we are currently considering is from one of the biggest industrial areas of Southeast Asia, i.e., Peenya, Bangalore. We have collected this data from the Central Control Room for Air Quality Management. The dataset consists of parameters such as PM10, PM2.5, NO, NO2, NOX, NH3, SO2, CO, O3, temperature, etc. over the course of 12 years from 2010 to 2021. Further, the dataset is cleaned and partitioned into training and testing data. After which the model can be trained and validated. In the Hyperledger fabric blockchain, chain code will have the ML model deployed in it. Once the lient supplies the data to the blockchain, the chain code that has the ML model will start executing. After successful execution, the output will be stored on the distributed ledger as shown in Fig. 4.

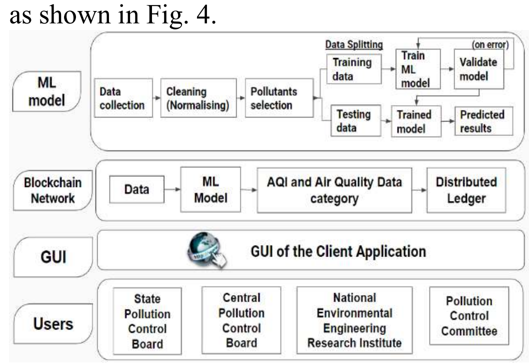

Fig. 2. Project Modules

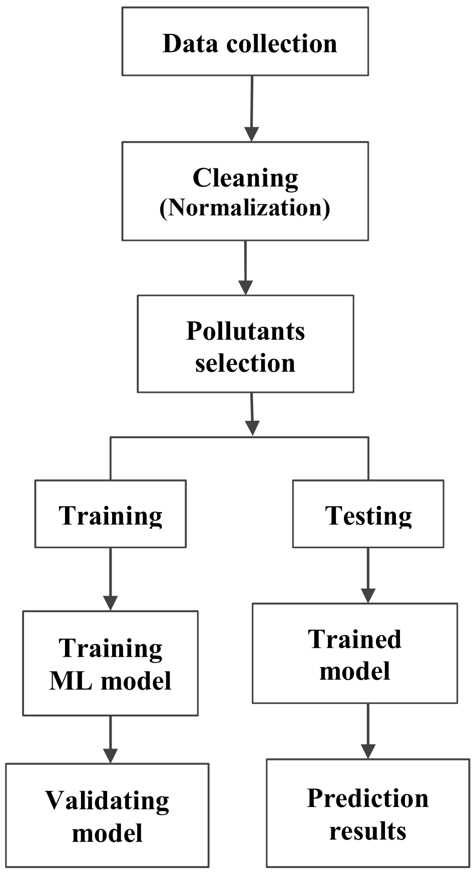

Fig. 3. Flow of proposed Machine Learning methodology

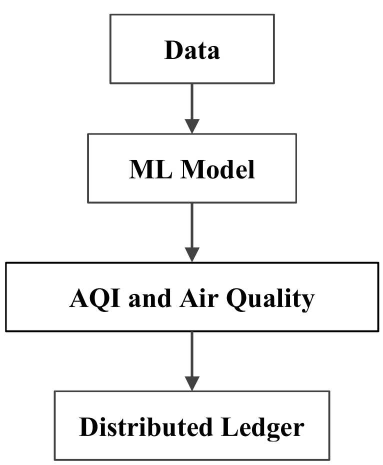

Fig. 4. Flow of proposed Blockchain methodology

3.2 Artificial Neural Network

An artificial neuron network (ANN) is a computational technique based on the structure and functionalities of biological neural networks and is a collection of units known as Artificial neurons. An artificial neuron takes input, evaluates it, and then transmits messages to the neurons with whom it is linked.

3.3 LSTM

In the realm of deep learning, long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture. The LSTM network has feedback connections, unlike traditional feed forward neural networks. The standard LSTM unit consists of three gates namely input gate, output gate and a forget gate. LSTM networks are best suited for operations such as categorizing, analyzing, and making predictions based on time series data since there can be unanticipated gaps between significant occurrences in a time series.[5][6].

3.4 Random Forest

Another supervised learning technique, Random Forest is utilized for both classification and regression. The Random Forest Algorithm builds decision trees based on the available data samples, then gets predictions from each of them, and finally votes on the best solution. Random forests are better than choice trees in the majority of cases, however they are less exact than gradient enhanced trees. Data features, on the other hand, can have an impact on their performance.[2][3]

3.5 Support Vector Machine

SVM is a common Supervised Learning technique for both classification and regression. It is most typically employed for classification issues in ML. The purpose of the SVM method is to discover the decision boundary for dividing n-dimensional space into classes so that fresh data points may be placed in the proper category easily in the future. Using kernel methods data is transformed and the optimal choice boundary is represented by a hyperplane and its extreme points are chosen by it. A polynomial-based kernel will be used in the SVM. For SVM with more than two predictors, polynomial-based kernels provide superior accuracy and performance. The SVM algorithm is called after support vectors, which are extreme examples. [2][3][7]

3.6 Hyperledger Fabric blockchain

Hyperledger Fabric is a distributed ledger platform that is open, tested, and enterprise-ready. It features sophisticated privacy controls,

ensuring that only the information you want to be shared is shared with the "permissioned" (known) network participants.
Distributed ledger technology (DLT) enables the operation of distributed ledgers, which are fault-tolerant (Byzantine). Each node of distributed ledger maintains a local copy of data and new data gets added to the ledger as transactions. New transactions are verified with digital signatures and they are stored in the memory of nodes, which is further passed to other DLT nodes in the network. Eventually, validated transactions get appended directly to the ledger, or stored in a block, which will further be added to the ledger. The majority of DLT consensus mechanisms are crash fault-tolerant or Byzantine fault-tolerant. Crash fault tolerance means to obtain consensus across all validators, in spite of some nodes temporarily being unavailable. Private-permissionless, private-permissioned, public-permissionless, and public-permissioned are the four types of distributed ledgers.
Private-permissioned distributed ledgers typically provide more flexibility i.e., maintainability, greater performance, maximum throughput and a higher degree of transparency compared to public-permissionless distributed ledgers. [8]

4. CONCLUSION

The existing method for tracking pollutants emitted by industries is a centralized one with a lack of transparency and the potential for data tampering. We present the design of a tamper-proof air quality management system using a machine learning model to predict the AQI along with its quality category and store it on Blockchain.
In this survey paper, we have briefly reviewed the common machine learning algorithms used to predict the AQI. The use of machine learning has improved prediction accuracy. We found that the most commonly used methods used to predict AQI are Support Vector Machine, LSTM, Random Forest, and Artificial Neural Network. We have also gathered that a blockchain-based solution can solve problems of data reliability in pollution monitoring and also ensure a permanent, tamper-proof record of all the air quality data of industries. Hence, air quality reports of industries can be generated in a reliable and transparent manner and necessary actions can be taken by both the industries and the government to reduce pollution, which will benefit society and the environment.

5. REFERENCES

[1] S. Mahanta, T. Ramakrishnudu, R. R. Jha and N. Tailor, "Urban Air Quality Prediction Using Regression Analysis," TENCON 2019 - 2019 IEEE Region 10 Conference (TENCON), 2019, pp. 1118-1123, doi: 10.1109/TENCON.2019.8929517.

[2] Dyuthi Sanjeev, 2021, Implementation of Machine Learning Algorithms for Analysis and Prediction of Air Quality, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 10, Issue 03 (March 2021)

[3] T. M. Amado and J. C. Dela Cruz, "Development of Machine Learning-based Predictive Models for Air Quality Monitoring and Characterization," TENCON 2018 - 2018 IEEE Region 10 Conference, 2018, pp. 0668-0672, doi: 10.1109/TENCON.2018.8650518.

[4] C R, Aditya & Deshmukh, Chandana & K, Nayana & Gandhi, Praveen & astu, Vidyav. (2018). Detection and Prediction of Air Pollution using Machine Learning Models. International Journal of Engineering Trends and Technology. 59. 204-207. 10.14445/22315381/IJETT-V59P238.

[5] Stojov, Vladimir & Koteli, Nikola & Lameski, Petre & Zdravevski, Eftim. (2018). Application of machine learning and time-series analysis for air pollution prediction.

[6] Yue-Shan Chang, Hsin-Ta Chiao, Satheesh Abimannan, Yo-Ping Huang, Yi-Ting Tsai, Kuan-Ming Lin, An LSTM-based aggregated model for air pollution forecasting, Atmospheric Pollution Research,
Volume 11, Issue 8, 2020.

[7] Delavar, M.R.; Gholami, A.; Shiran, G.R.; Rashidi, Y.; Nakhaeizadeh, G.R.; Fedra, K.; Hatefi Afshar, S. A Novel Method for Improving Air Pollution Prediction Based on Machine Learning Approaches: A Case Study Applied to the Capital City of Tehran. *ISPRS Int. J. Geo-Inf.* 2019, *8*, 99.

[8] M. Lücking et al., "The Merits of a Decentralized Pollution-Monitoring System Based on Distributed Ledger Technology," in IEEE Access, vol. 8, pp. 189365-189381, 2020, doi: 10.1109/ACCESS.2020.3028430.

[9] Sofia, D.; Lotrecchiano, N.; Trucillo, P.; Giuliano, A.; Terrone, L. Novel Air Pollution Measurement System Based on Ethereum Blockchain. *J. Sens. Actuator Netw.* 2020, *9*, 49.

[10] S. R. Niya, S. S. Jha, T. Bocek and B. Stiller, "Design and implementation of an automated and decentralized pollution monitoring system with blockchains, smart contracts, and LoRaWAN," NOMS 2018 - 2018 IEEE/IFIP Network Operations and Management Symposium, 2018, pp. 1-4, doi: 10.1109/NOMS.2018.8406329.

[11] Yohan Han, Byungjun Park, Jongpil Jeong, A Novel Architecture of Air Pollution Measurement Platform Using 5G and Blockchain for Industrial IoT Applications, Procedia Computer Science, Volume 155, 2019.

Tamper proof Air Quality Management System

by Srividya H R

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