ANALYSIS OF AIR POLLUTANTS BY MACHINE LEARNING AND DEEP LEARNING ALGORITHMS

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Abstract

Suprememetropolises' air is filthy these days, and toxinsensurestood added to brand it uniformfurther deadly. Air toxic waste can stayinstigatedviamutuallyanthropoidtooregularbustle. Human activities add pollutants to the air such as sulphur oxides, carbon dioxide (CO2), nitrogen oxides, carbon monoxide (CO), chlorofluorocarbons (CFC), prime, and mercury. We apply machine learning approaches to detect air pollution in this suggested system. Machine learning is a popular technology for predicting and classifying input in order to forecast the output. The amount of pollution in the air staysdignifiedby means of three machine learning processes: Random Forest Regression (RFR), Decision Tree Regression (DTR), k-nearest neighbour (KNN), and Support Vector Machine (SVM). Constructedgoing on a statistics collection comprising of diurnaldistinctivecircumstances in a certain metropolitan and several graphs, this organismendeavors to anticipate smoothalsodiscover air quality. In this research, we look at how digital cameras can be recycled to discover the amount of toxic wastenow the troposphere. Digital cameras are inexpensive and widely utilized in a variety of settings, many of which are open to the public.

KeyTerms:*Air pollution,Monitoring,Machine learning,Algorithm,Digital camera*

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1.Introduction

Air toxic wastefirebasissyndromes, hatreds, in additionuniformpassing to individuals; it can likewiseorigindestruction to furthercorporealcreatures such by way ofwildlife and nourishmentgarners, and possibly willdestruction the acceptedsetting (meant forsample, weatherconversion, ozone exhaustionotherwiselocalepoverty) or elsefabricatedenvirons (meant for sample, acerbicshower). Mutuallymortalbustletooacceptedprogressionscanistercause air toxic waste.Air toxic waste is a substantialthreatdynamicaimed at a numeral of toxic waste-linkedsyndromes, comprisingrespirationaltoxicities, coresyndrome, COPD, stroke and lung cancer.Growing evidence suggests that air pollution exposure may be associated with reduced IQ scores, impaired perception, enlargedhazard for psychiatric syndromes such by way ofdownheartednessalsounfavorable perinatal well-being. Humble air superiority has remote-getting consequences on hominoidwell-being, although it mostly distresses the respirationalin addition tocardiacorganisms. Separablerejoinders to air toxinscontrastprovisionaltaking place the category of toxin, the gradation of acquaintance, too the being'swell-beingprominence and heredity. Outside air toxic waste is the sole culprit.

As a result, reducing toxinradiations is the primary goal of numerousworkableenlargement programmers, particularly folks involving insolentmetropolises. The foremost cause of air superiority degradation is smolderconsumeon or after factories, toxic waste from supremacyfloras, and smolderconsumeas ofinnumerableautomobiles. Individuals advanced auxiliarykeen on the twenty-first century as a result of the Industrial Revolution. Pollution worsened as industry expanded rapidly. Vehicles that generate smoke are another source of air pollution. These fumes accumulate in the environment, endangering humans and destroying the ozone coating. This study focuses on monitoring air toxic waste via video treating. The environment provides unhygienicvideos.These videos are compared to other, pollution-free videos. The diffusion process is performed on such videos, and the ratio factor is calculated using the images. One of the project's advantages is that the proposed technology works well for increased noise levels. Another advantage is the analysis of fair noise illumination.

With insufficient prior knowledge,

traditional corporealclassical-foundedapproaches are impotent to include all contributing aspects, while statistics-obsessedprocedures missing corporealconstrualmay wellconsequence in poor generality capacity. The neural network benefits from physical knowledge to achieve consistent performance with decreased variation and increased robustness against negative background conditions.Weput forward a saliency-conscious CNN charteraimed atliner recognition that includes complete ship discriminating topographies such by way ofcavernousarticle, salience atlas, in additionshoreline before to succeedin elevationrecognitionexactitudetooexistent-phaseenactment. This model predicts the groupingas well aspoint of liners using CNN moreover corrects the location using worldwidedivergenceestablishedstrikingprovince identification. We also citation coastal statistics and use it in CNN and salience recognition to get furtherexactliner placements. We train and evaluate our classical on Dark Net using CUDA 8.0 and CUDNN V5, and we employ existent-domaingraphicaldouble datasets. In positions of precisiontoohustle, the experimental findings suggest that our classical surpasses demonstrative alternatives (Faster R- CNN, SSD, and YOLOv2).

2.RelatedWork

T. L. Youdet al[1] addressed about the fine-grained air pollution monitoring is gaining popularity around the world. Despite the growing number of static and mobile sensing technologies, an inference method is still required to gain a thorough picture of the urban air environment. With insufficient prior knowledge, traditional physical model-based methods are unable to include all contributing aspects, while data-driven methods missing physical interpretation may result in poor generalisation capacity. This study provides a multi-task learning system that combines the physical model with the data-driven model, each of which has advantages. It improves a neural network's data learning with the help of prior knowledge on air dispersion, and it also controls the impact of the knowledge using a tenable weighting coefficient. Evaluations on a real-world deployment in Foshan, China demonstrate that, with a resolution of 500m500m15min, the suggested technique beats the state-of-the-art methods by 7.9% error reduction and 6.2% correlation enhancement. The neural network benefits from physical knowledge to achieve consistent performance with lower variation and more robustness against negative background conditions.

H. Kaplan [2]Inshore ship identification in real time is critical for efficient monitoring and management of marine traffic and transit for port management. Due to the timeliness of acquisition, current ship detection technologies, which are mostly reliant on remote sensing or radar readings, rarely match real-time requirements. To achieve real-time detection, we propose in this research to leverage visual values acquired by an on-land surveillance camera network. Nevertheless, because of the complicated backdrop of visual values and the variety of ship types, traditional convolution neural network (CNN)-based algorithms are either erroneous or slow.We propose a saliency-aware CNN framework for ship recognition that includes complete ship discriminating features such as deep feature, salience map, and coastline before to achieve high detection accuracy and real-time performance. This model predicts the category and position of ships using CNN and corrects the location using global contrast based salient region identification. We also extract coastal information and use it in CNN and salience detection to get more accurate ship placements. We train and evaluate our model on Dark Net using CUDA 8.0 and CUDNN V5, and we employ real-world visual image datasets. In terms of accuracy and speed, the experimental findings suggest that our model surpasses representative alternatives (Faster R- CNN, SSD, and YOLOv2).

Haanet al[3]this article presents study on Poor air quality is a serious threat to people's health and a major issue in many nations. The states and trends of air quality have been thoroughly studied in the literature, but the examination of time-space relevance behaviour and the relationship between air quality and pollutant propagation has been overlooked. This study builds an air quality propagation network, describes the interaction process between various sites, and mines the critical stations over the entire region using the theory of complex networks. The analysis begins with the usage of pollutant monitoring data from the Beijing-Tianjin-Hebei region. Monitoring stations are abstracted into network nodes, and edge sets are built using pollutant pathways determined by calculations of the spatial and temporal reachability. The weight of the network throughout the propagation process is assigned for reflecting the interactive degree of stations by adding up the effect of the paths of the propagation network at various timestamps. Second, to identify the influential pollution region, the Page Rank algorithm assesses the significance of nodes in the propagation network. Afterwards, key stations are determined while taking into account both the quantity and quality of propagation linkages. The findings of the experiment confirm the accuracy of the network and the node ranking algorithm by demonstrating the relevance of the node rank distribution and the actual pollution state. This work offers a solid theoretical framework for the prompt prevention and management of air pollution, as well as a foundation for the choice of monitoring station locations.

V.M.Madhuriet al [4]this paper aims to

investigate possible impact of air pollutants over the climate change on Indian subcontinent using remote sensingmethod. Satellite derived column aerosol optical depth (AOD) is a cost effective way to monitor and study aerosols distribution andeffects overalongtimeperiodisthemajoradvantageoft hepaper Whereas, themajorlimitationisthetopography.

Rajakumariet al[5] In this paper, a multi-point deep learning model for highly dynamic air quality forecasting was suggested. It is based on convolutional long short term memory Conv(LSTM). Long short term memory (LSTM) and convolutional neural network (CNN) are combined in conv(LSTM) designs, which enable the mining of both temporal and spatial data characteristics. On top of the architecture of our model, uncertainty quantification techniques were included, and their performances were further investigated. have performed thorough experimental analyses utilising the Fusion Field Trial 2007 real and highly dynamic air pollution data collection (FFT07). The outcomes show that our suggested deep learning model outperforms cutting-edge approaches, including machine and deep learning techniques. We then discussed the outcomes of the uncertainty strategies and came to some conclusions.

3. ExistingSystem

Existing system [1] investigates the smoke and exhaust detection system that has been created for monitoring exhaust gases to enforce environmental rules and regulations. To ensure optimal air quality, the air quality monitoring system gathers information on contaminants from various locations. It is the most important issue at hand right now. The atmosphere is polluted by the release of dangerous gases from industrial sources, car emissions, etc. Currently, major cities experience levels of air pollution that are dangerously higher than the government-set air quality index standard. It significantly affects a person's health. The Machine Learning (ML) algorithms are capable of making predictions about air pollution. To increase the accuracy of predictions, machine learning (ML) integrates statistics and computer science. The Air EminenceDirectory is computed using machine learning (ML). In the direction of gather the dataset, various sensors and an Arduino Uno microcontroller are used at that point by forecasting the air quality using machine learning.

4. ProposedSystem

The major purpose staysjust beforeobserver the air toxic waste prevalent trendy the area.To anticipate whether the air quality is polluted or not, we apply a variety of machine learning processestrendy this exploration. We employ the well-known machine learning algorithms decision tree, KNN, and unsystematicwoodland in this suggested system. These algorithms are commonly used for problems involving categorization and prediction.

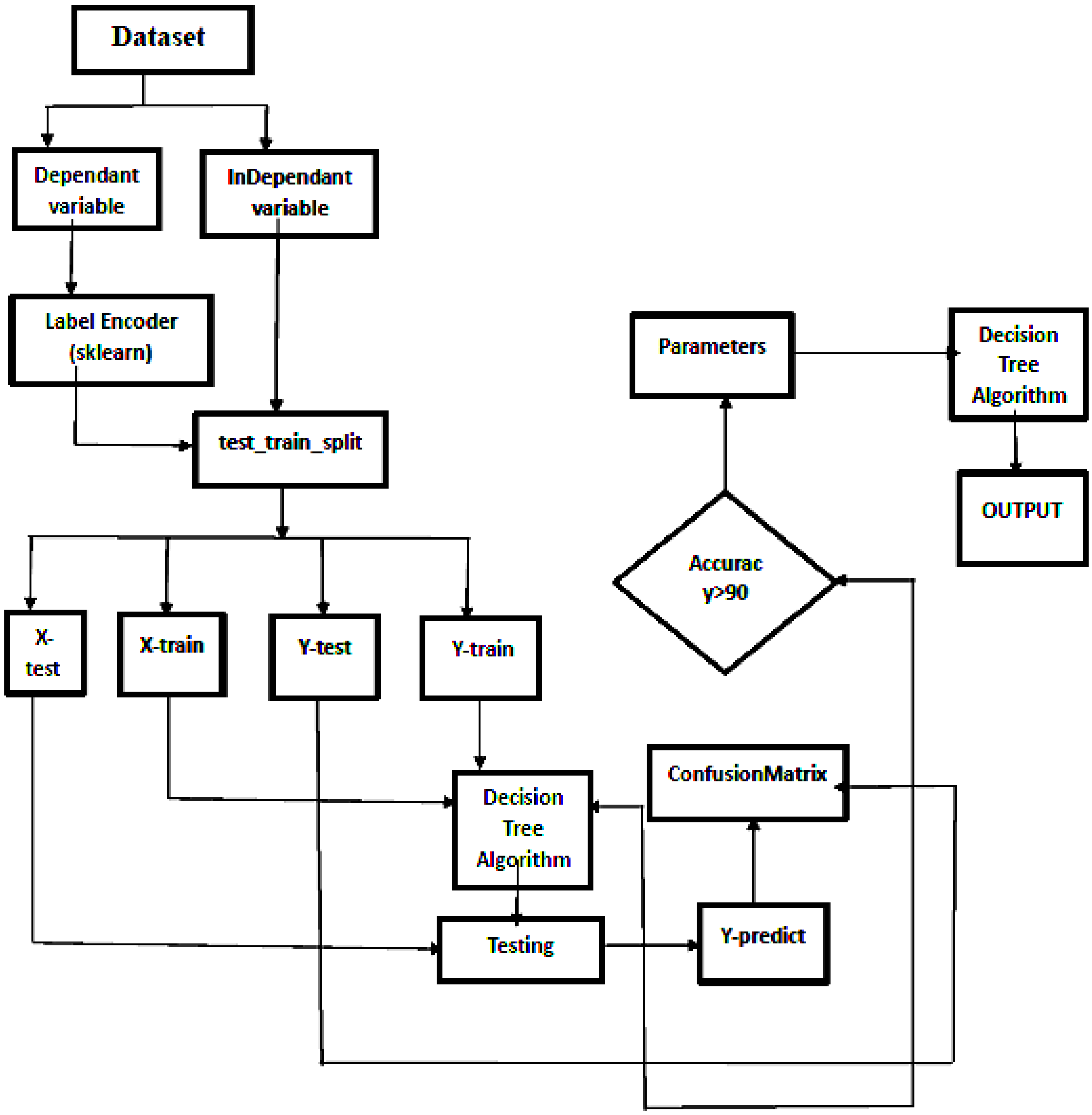


Figure 1.Proposed system Block Diagram

A sizable data set of bad gas values has been collected using data from Kaggle and other sources, including co2, tylene, and benzene under air conditions.

NO	NO2	NOx	NH3	CO	SO2	O3	Benzene	Toluene	Xylene	AQI	STATUS
3.41	12.49	9.43	6.62	0.54	12.69	28.07	1.18	3.54	0.3	65	1
2.56	9.81	7.4	6.81	0.45	8.19	30.44	1.08	2.73	0.21	78	1
1.74	9.49	6.53	8.36	0.56	17.06	42.66	1.26	2.14	0.18	83	1
1.11	9.26	5.64	7.66	0.58	16.56	34.64	0.69	3.43	0.22	64	1
1.54	8.62	5.72	6.27	0.71	14.7	31.67	1.13	2.43	0.22	92	1
1.4	5.59	4.08	6.03	0.48	9.15	25.97	1.09	1.72	0.15	58	1
3.77	7.21	6.99	5.55	0.64	10.24	20.32	1.33	2.13	0.23	76	1
3.12	6.06	5.7	5.8	0.67	13.03	28.03	1.06	2.11	0.15	78	1
2.2	5.25	3.94	6.21	0.62	12.96	40.3	0.51	2.03	0.16	91	1
6.93	37.27	25.44	11.05	0.97	5.25	23.36	0.08	2.3	0.1	99	1
2.24	20.1	12.54	12.32	0.61	8.25	23.74	0.07	3.07	0.12	86	1
2.76	16.83	11.14	11.9	0.61	5.87	24.72	0.05	2.64	0.11	57	1
15.9	17.35	22.25	24.68	0.49	9.53	30.68	0.1	3.09	0.12	87	1
3.49	12.79	9.73	22.79	0.58	8.21	30.21	0.08	2.23	0.15	89	1
4.55	16.33	12.39	23.18	0.64	10.34	26.24	0.1	2.51	0.1	97	1
4.5	16.82	12.69	19.54	0.58	11.02	26.62	0.1	2.68	0.11	100	1
9.19	20.85	18.66	15.88	0.58	13.97	16.28	0.1	2.44	0.12	98	1
7.1	22.21	17.68	19.27	0.79	13.89	22.73	0.06	2.12	0.11	100	1
5.37	18.83	14.38	14.52	0.72	8.98	23.63	0.05	2.04	0.1	92	1
4.45	17.33	13.01	12.72	0.65	9.71	29.26	0.05	1.85	0.1	80	1
4.45	22.81	15.74	12.41	0.66	12.63	22.9	0.06	2.18	0.11	88	1
11.58	24.74	22.65	12.52	0.78	8.98	17.81	0.05	1.91	0.21	83	1

Table 1. Dataset Table

A. *Pre-Processing*

The statisticsestablished was obtained as of the Kaggle website. Past data was castofftowardsmoderate the extent of the informationagreed. The statistics, which is the collection of fundus ethics, obligationenergyconcluded various preparation platforms, such as finding missing values in the dataset, formerlyorganismnonstopnourishedobsessed by the exemplarysuch asinvolvement.

Find values are replaced, and label encoder processing is carried out in order to effectively test the model.

Three categories are used to group the input data set.

a. The dataset castoff to train or elsetrial the prototypical is referred to by means of the training dataset. This data is acknowledgedfor instance a statisticsagreed.

b. A test statistics set that is used to evaluate the model.

c. Validation data set, which is the dataset used to verify the model. The validation data set is charitytowardssortguaranteed the classic is not ended-timely, whereas thekeeping fitstatistics serves on the way to reduce the loss function.

The dataset is split into two sections, Training and Testing, after preprocessing is complete. While the model is validated using testing data, the model is trained using training data.

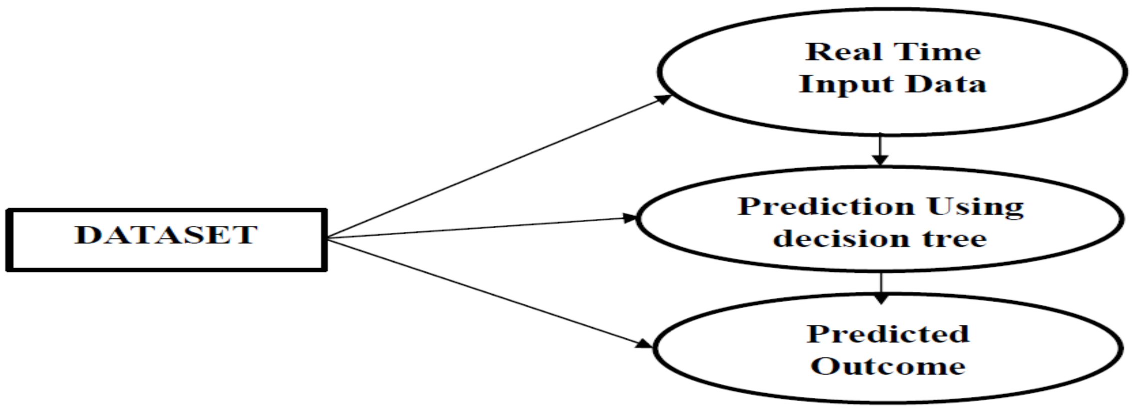


Figure 2.Use Case Diagram

A. Model Architecture

To anticipate whether the air quality is polluted or not, we apply a variety of mechanismwisdomprocesseshappening this research. We employ the well-known mechanismknowledgeprocessesresolutionsapling, knn, and unsystematicwoodland in this suggested system. These algorithms are commonly used for problems involving categorization and prediction.

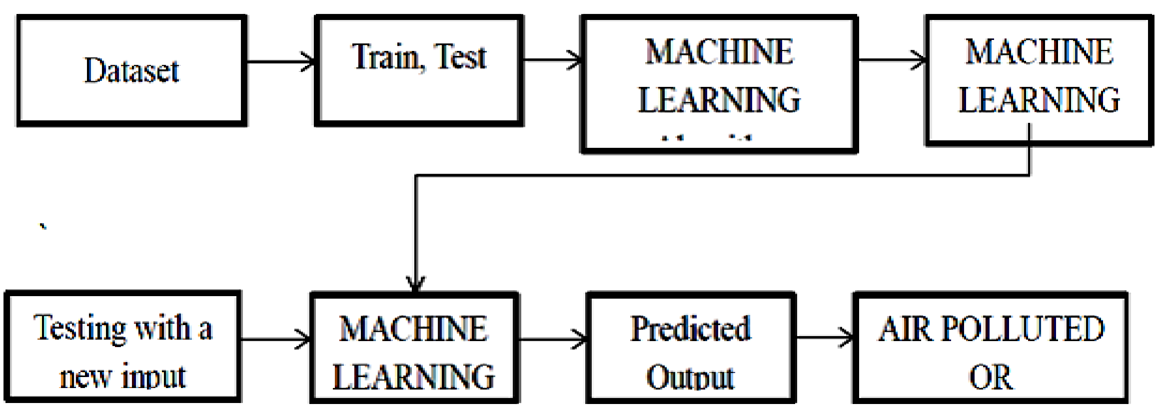


Figure 3.Prediction and classification diagram

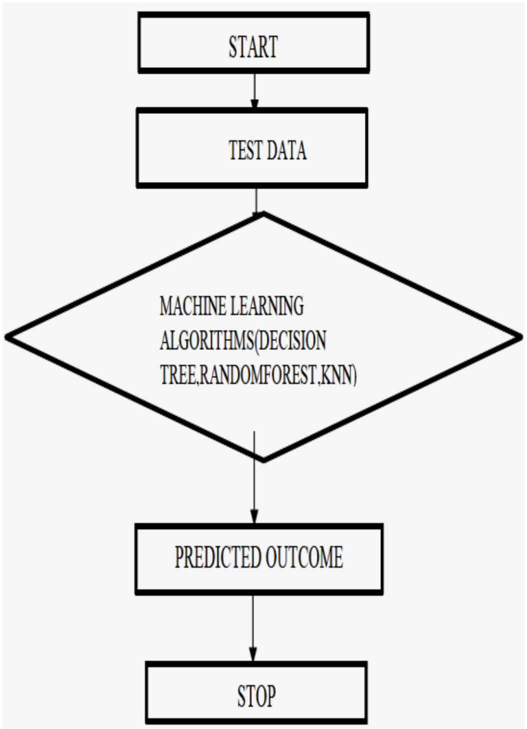
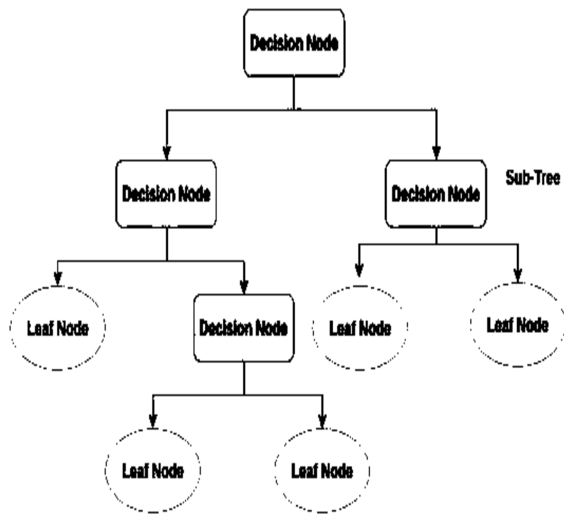


Figure 4. Low level design flowhart

5.Resolution Sampling Algorithm

A non-parametric or elsescattering-unrestrictedapproach, the decision saplingensures not be sure ofproceeding the conventions of a likelihoodscattering. In elevation dimensional statisticsfire be accurately pick upby means ofjudgmentgrasses.

The foundationknobfashionable a judgmentsaplingstays the knob that standsto be foundnext to the best. This oneexpansions the talenton the way todistributefilesestablishedproceeding the significance of an aspect. Recursive subdividing, by means of the labelrecommends, splits the saplingfashionablea number ofconducts. You firesortjudgmentsfurthereffortlesslyby means of this flowchart-resemblingcontext. It habitsconception, abundantidentical a flowchart illustration, in the direction ofpretendintellectualnext to the anthropoidglassy. Pronouncementgrassesstaymodestjust before grasp besides deduce for instance a



consequence.

Figure 5.Decision Tree algorithm

- To divide the archives, indicate the preeminent aspect expending Attribute Selection Measures (ASM).
- Halt the dataset up obsessed by slighter detachments and make that aspect a pronouncement knob.
- Begins sapling creation by means of continuing this method recursively in place of each one kid till one of the criterion will match: There are no more instances, no more attributes, and all of the tuples are

associated with the same attribute value.

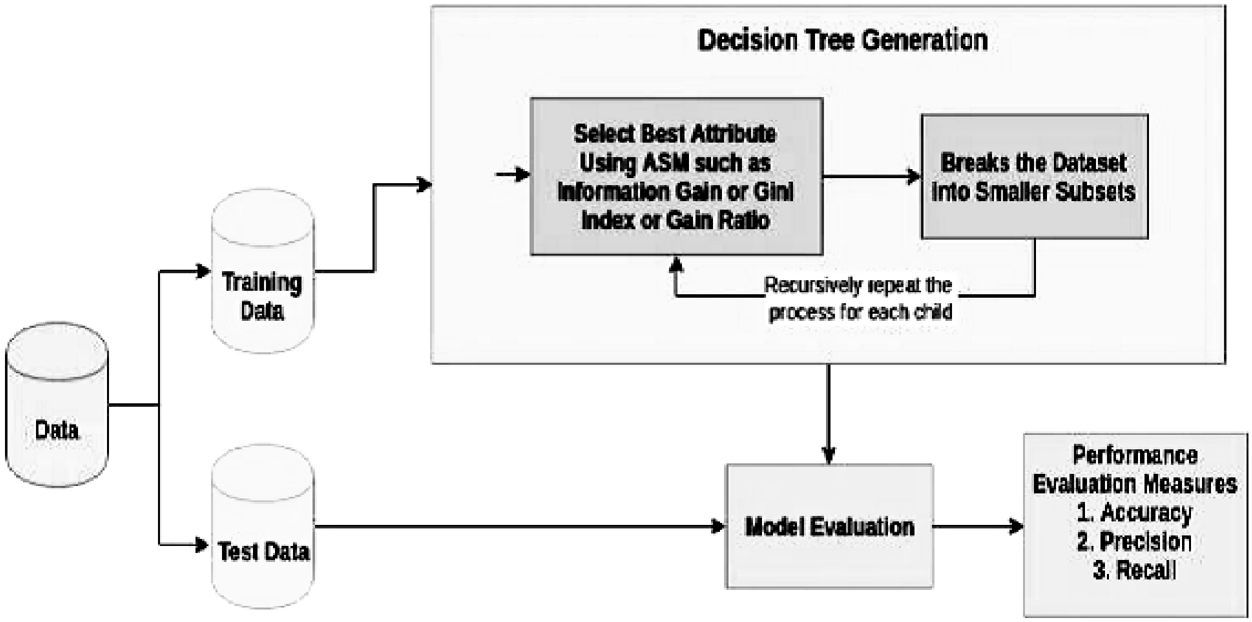


Figure 6. Pronouncementhierarchy Block diagram

6. K-Nearest Neighbour Algorithm

The supervised learning-based K-NN method maintains entirely of the unfilledstatisticsbesides categorizes ainnovativefilesfactestablishedproceedinglikeness. This revenues that as replacementstatistics is bred, it possibly willstayrapidly categorized obsessed by a suitable groupingspending the K-NN method. Although the K-NN technique can be castoffaimed atmutually classification also regression problems, it stayssupplementary frequently employedmeant forgrouping issues.

The succeedingset of rules can staycastoffnear describe just how K-NN mechanisms:

Footstep 1: Resolve which of the K neighbours you want.

Footstep 2: Regulate the K number of nationals' Euclidean distance.

Footstep 3: Based on the determined Euclidean deputy, select the K nearest neighbours.

Footstep 4: Computation how many statisticsfacts there are fashionableevery singlegroupingin the middle of these k neighbours.

Footstep 5: Put the innovativestatisticsfacts to the grouping where the nationalcomputationstaysuppermost.

Footstep 6: Our prototypicalstayswidespread.

Our first decision will be the numeral of nationals, so we'll preference k=5. We resolve then figure out how far apart the data points are from each other geometrically. We have already studied geometry, so we know what the Euclidean distance is between two points.

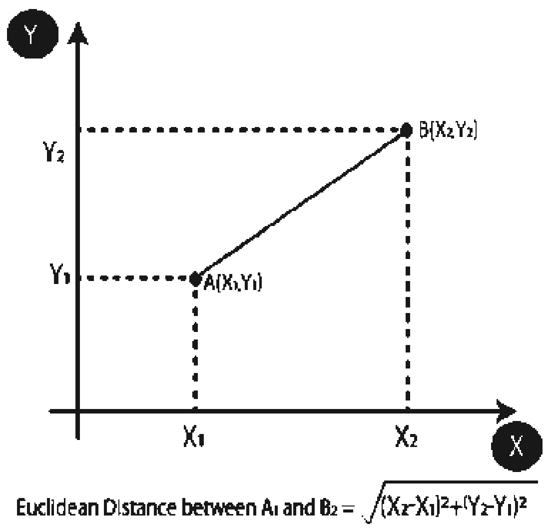


Figure 7: K-NN algorithm graph

7.Random Forest Algorithm

The unsystematicwoodlandforecasts the consequencecenteredtaking place the mainstreampolls of the projections in addition toconsumptions the forecastsas ofevery singlehierarchyby way ofinvolvement. Sophisticatedprecision is attainedin addition to over fitting is shunnedfor the reason that to the superiornumeral of saplingsfashionable the woodland. A supervised learning algorithm is the random forest. The trappingmanner's general tenet is that coalescingwisdomprototypesprogresses the expirationconsequence. Unsystematicwoodlandpartakes the main assistance of organismappropriatetowardsmutually classification in addition to regression concerns, which kindawake the widely held of up-to-datemechanismwisdomorganisms. Decision trees and bagging classifiers have virtually identical hyper parameters to random forest.

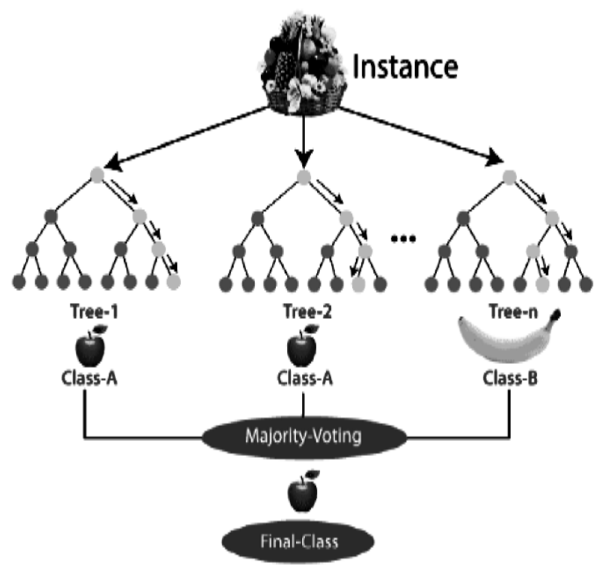


Figure 8: Random forest algorithm

The random forest model's hyper parameters are either utilized to make the model quicker or more predictive.

a. Improving the predictive capacity

The estimator's hyper parameter, or simply the number of trees built by the algorithm before taking the maximum voting or averaging the forecasts, is the first. Generally speaking, more trees improve performance and predictability, then again they moreoverdeliberatedejectedworking out. Do welltopographies, which stays the most structures that unsystematicwoodlandwould consider splitting a knob, is one moredecisiveagitated constraint. The documentation for each option that Sklearn offers is extensive. Min sample leaf is the final crucial agitatedconstraint. By doing so, the unadornedtiniest of greeneriesdesirable to divide an interiorknob is resolute.

b. Boosting the model's velocity

The estimator's hyper parameter, or simply the number of trees built by the algorithm before taking the maximum voting or averaging the forecasts, is the first. Generally speaking, more trees improve performance and predictability, then again they moreover deliberatedejectedworking out. Do welltopographies, which stays the most structures that unsystematicwoodland would consider splitting a knob, is one moredecisiveagitated parameter. The documentation for each option that Sklearn offers is extensive. Min sample leaf is the final crucial hyper constraint. By doing so, the unadornedtiniest of greeneriesdesirable to divide an interiorknob is resolute.

One artificial neural network that excels in mining local properties of data is the convolution neural network. Reduced complexity of the network model less weights, and increased biological neural network similarity enable the CNN to be used in a variety of pattern recognition applications with excellent results. In order to fully utilise the qualities of the data, such as localization, optimise network structure, and guarantee some degree of displacement invariability, CNN combines homegrowninsightexpanse, allocation the burden, the dropletfashionableplanetaryor elsestagecontrol group.

8.Convolution Neural Network Algorithm

One artificial neural network that excels in mining local properties of data is the convolution neural network. Reduced complexity of the network model less weights, and increased biological neural network similarity enable the CNN to be used in a variety of pattern recognition applications with excellent results. In order to fully utilise the qualities of the data, such as localization, optimise network structure, and guarantee some degree of displacement invariability, CNN combines homegrown insight expanse, allocation the burden, the droplet fashionable planetary or else stage control group.

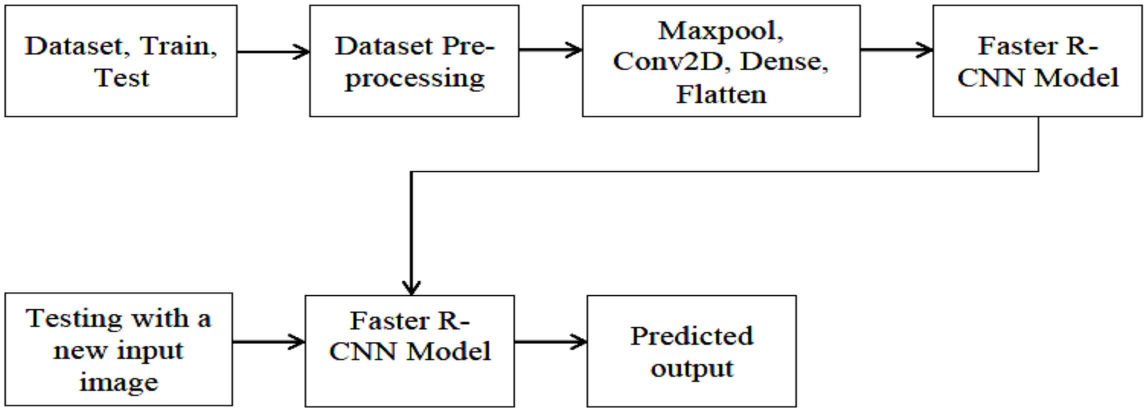


Figure 9: Block Diagram for CNN algorithm

In text classification and filtering, CNN models are used to extract features from text and convolve the text matrix. The filters' widths match the word vectors' lengths. The extractive vectors of each filter are then operated using max pooling. Each filter, which represents a digit, is then connected to cIn In text classification and filtering, CNN models are used to extract features from text and convolve the text matrix. The filters' widths match the word vectors' lengths. The extractive vectors of each filter are then operated using max pooling. Each filter, which represents a digit, is then connected to create a vector that represents this sentence and serves as the foundation for the final forecast. These models use a somewhat complex algorithm where each layer's convolution operation is followed by a max pooling operation order to achieve suitable values for the testing phase. The CNN network performance has been examined to determine the ideal number of hidden nodes and epochs.

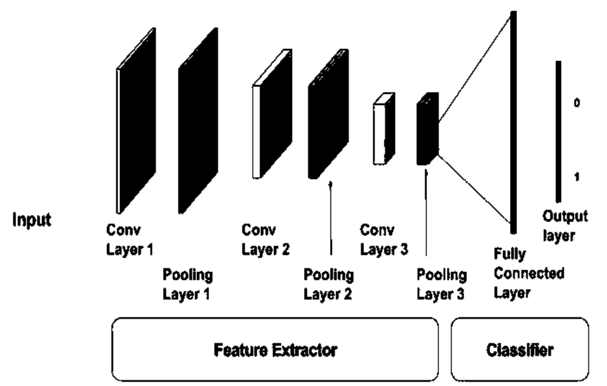


Figure 10: Architecture of CNN

9.Softwares And Devices

The purpose of on fireexposureorganism is to observe moving objects as oftwofold different perspectives: above or by the side of the road to see the vehicle's back and along the ground to search for any potential smoke emissions from the vehicle's undercarriage. Two lanes may now be watched concurrently thanks to the installation. It follows that the camera positions must be selected consequently that a hugetruck cannot totally doubtful conceal a slighter car or else the consume emissions it produces. Apiece camera twosome comprises of a thermal camera and a camera intended forperceptible wavelengths. The camera visionsstandattuned such that it is possible to determine where a hotspot is located in the detectible wavelength camera vision when a thermal camera picks up on it. Potential exhaust pipe sites are found using the thermal camera, and the created smoke detection algorithm is then applied to the visible analysis of the area surrounding the prospective pipe position using a wavelength camera image.

For quality control and to guarantee the dependability of software, testing plays a very important role. Strictly speaking, testing can be defined as the act of running a programme in an effort to identify errors.

A test that finds a previously unknown fault is successful.

- One with a high likelihood of spotting flaws, should they exist, qualifies as a suitable test case.
- The tests can effectively identify any potential errors.
- The programme largely complies with trustworthy and high-quality criteria.

```
Testing Accuracy
ENTER THE NO VALUE= 3.41
ENTER THE NO2 VALUE= 12.49
ENTER THE NOx VALUE= 9.43
ENTER THE NH3 VALUE= 6.62
ENTER THE CO VALUE= 0.54
ENTER THE SO2 VALUE= 12.69
ENTER THE O3 VALUE= 28.07
ENTER THE Benzene VALUE= 1.18
ENTER THE Toluene VALUE= 3.54
ENTER THE Xylene VALUE= 0.3
ENTER THE AQI VALUE= 65
Predicted new output value: [1]
AFFECTED
KNN Accuracy of the model: 87.5%
KNN Confusion Matrix
[[7 0]
 [1 0]]
              precision    recall  f1-score   support

           1       0.88      1.00      0.93         7
           4       0.00      0.00      0.00         1

    accuracy                           0.88         8
   macro avg       0.44      0.50      0.47         8
weighted avg       0.77      0.88      0.82         8

Total Percentage AFFECTED =  52
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Figure 11: Output Accuracy

10. RESULTS AND DISCUSSION

A.Results of Machine Learning Algorithm

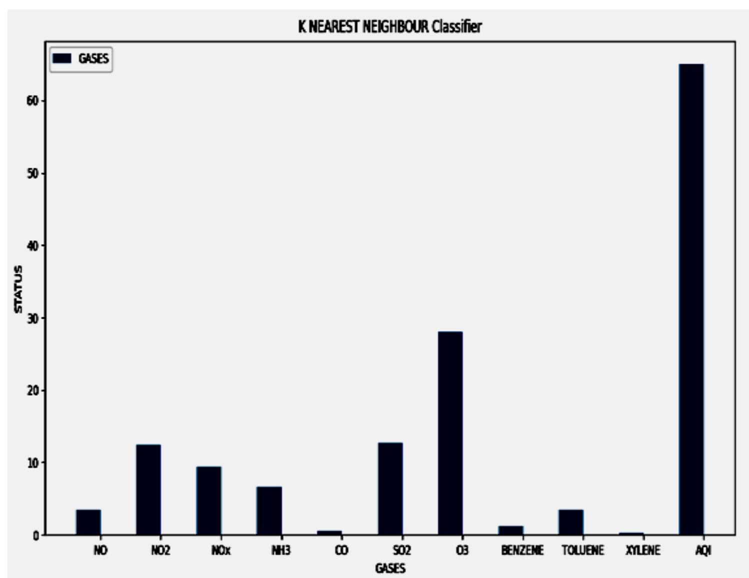

Figure 12: Results of KNN

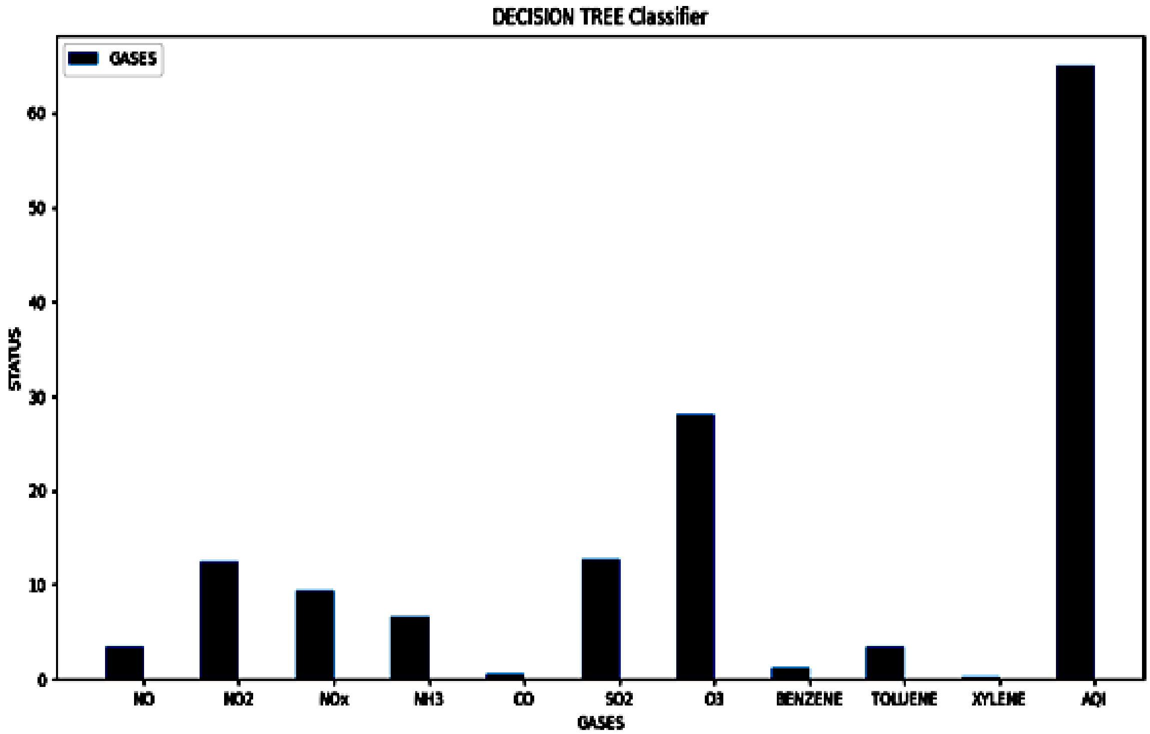

Figure 13: Results of Decision Tree

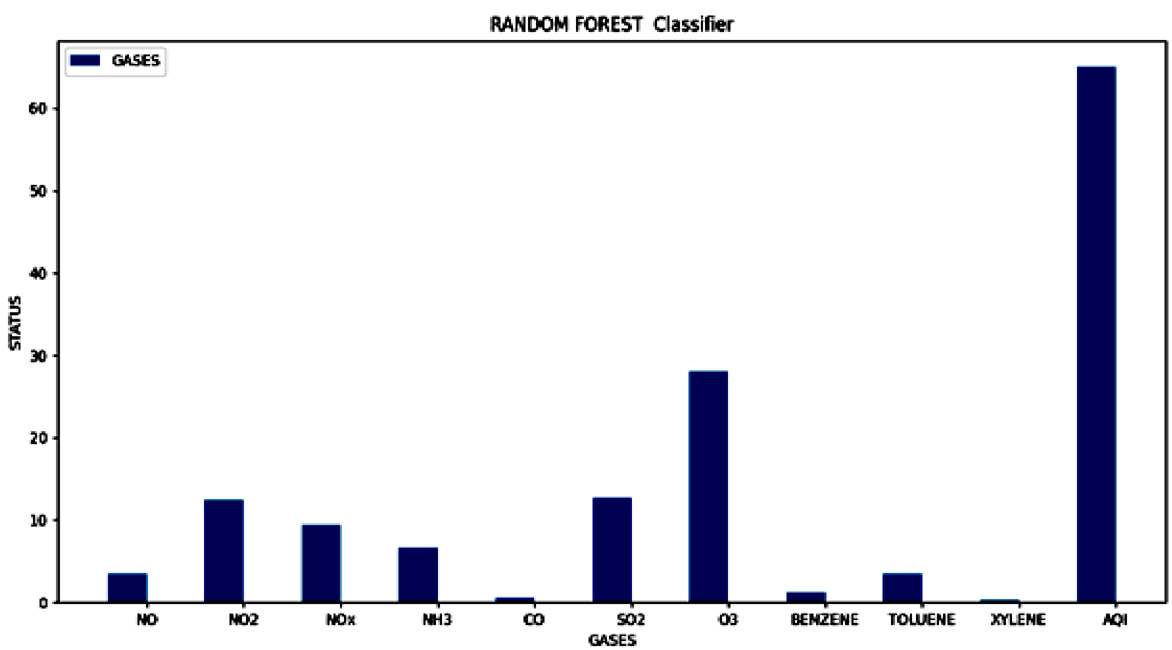

Figure 14: Results of Random forest

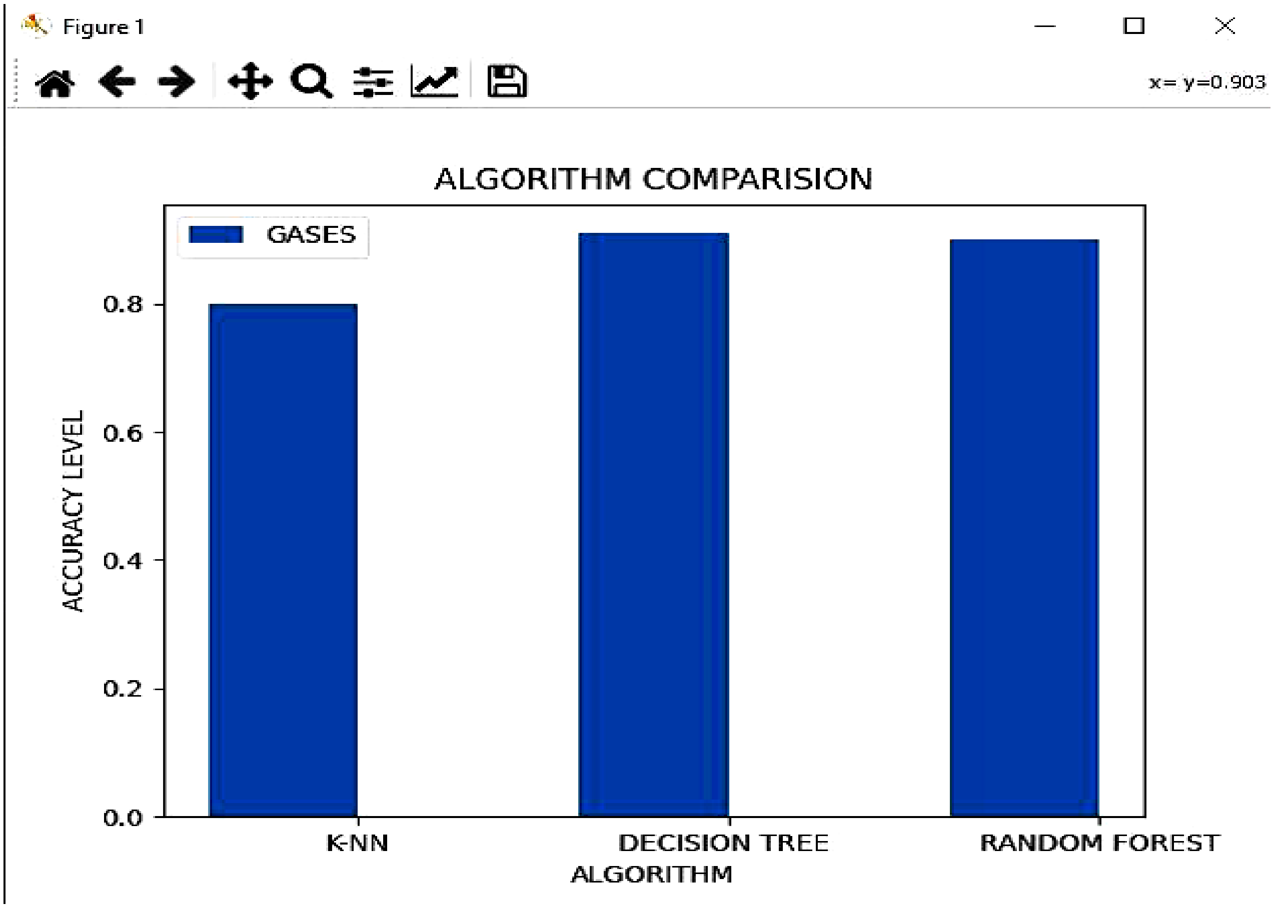

Figure 15: Comparison of Machine Learning algorithms

Finally, we were successful in implementing the air pollution predictor using machine learning. In the proposed system, we plot all dataset information, identify air quality, and perform a final comparison of all machine learning method outputs using a variability of mechanismwisdommethods, comprisingresolutionsaplings, unplannedplantations, and the KNN algorithm.

B. RESULTS OF DEEP LEARNING ALGORITHM

Figure 16: Input Image

Figure 17: Grayscale Image

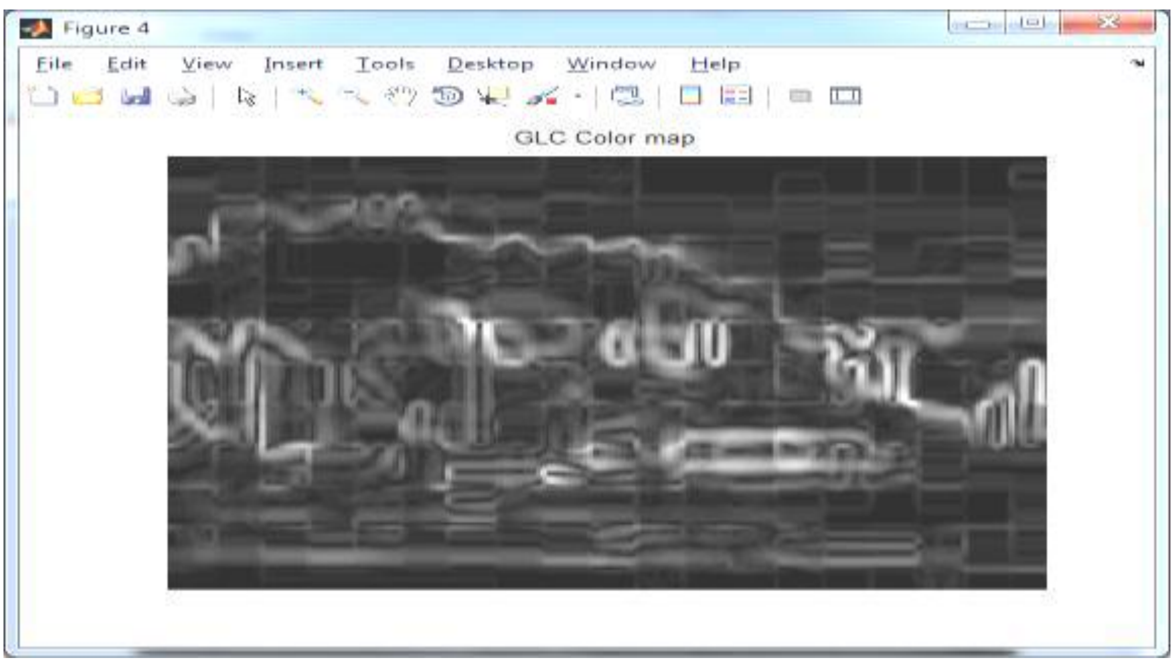

Figure 18: GLC Color map

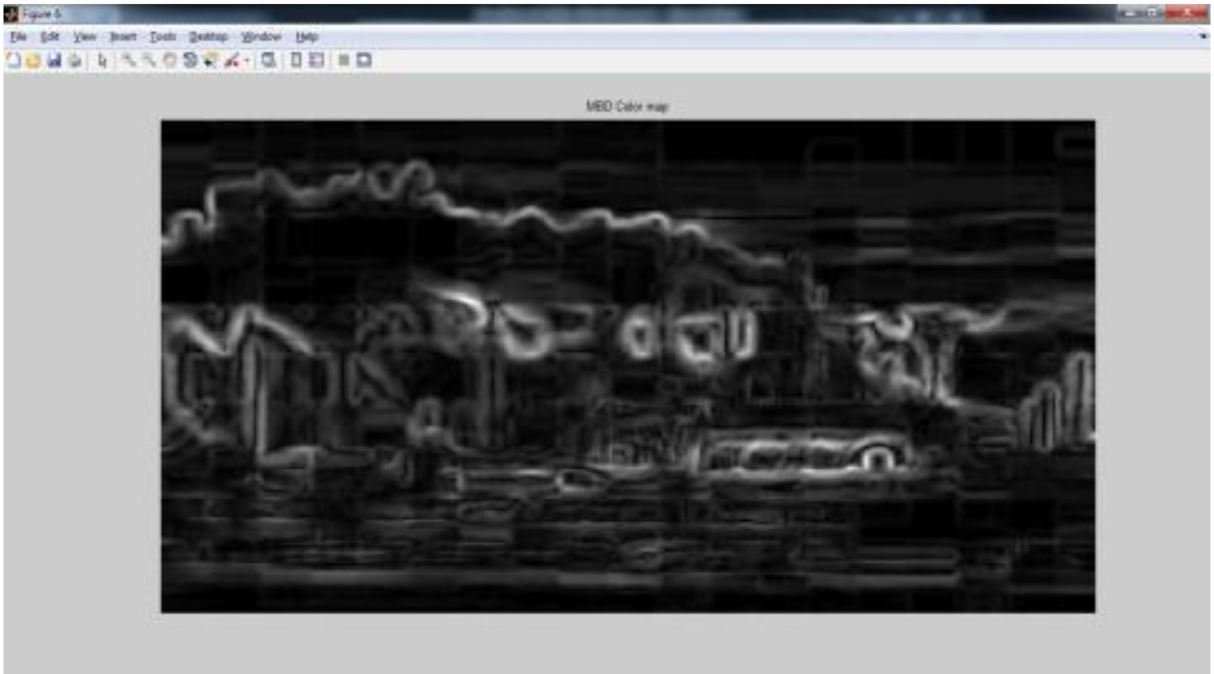

Figure 19: GD Color map

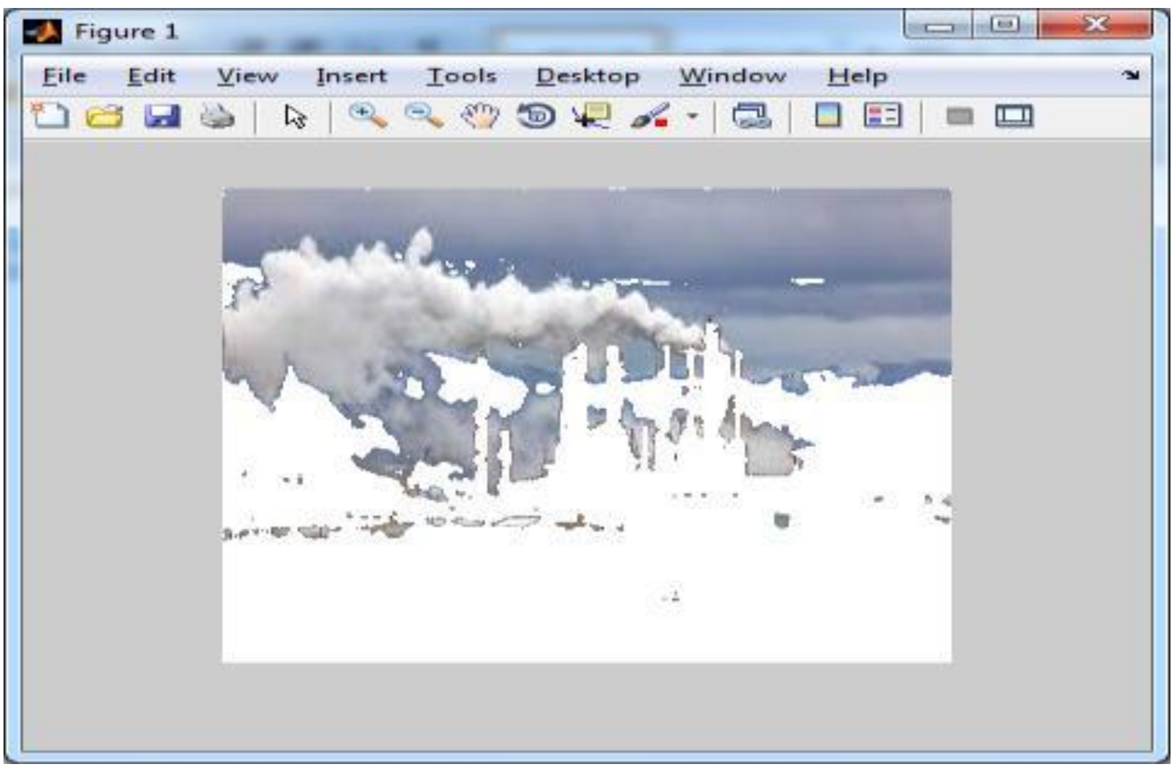

Figure 20: Air polluted area

With the goal of maximising the fitness function, the performance evaluation of this work is done in this section to demonstrate how the suggested technique performs better than the current system in terms of time and the quality of generated rules. In the suggested application, the CNN classification based on feature values that represent accuracy is the main focus.

11. Conclusion

Gases and particulate matter play a role in determining the quality of the air. When frequently breathed in, these contaminants lower the quality of the air, which can cause significant ailments. With the use of air quality monitoring devices, it is feasible to locate the presence of these toxics and keep an eye on the air's quality while also taking practical steps to improve it. As a result, there is an increase in productivity and a decrease in the health issues brought on by air pollution. Machine learning-based prediction models have been found to be more dependable and consistent.

Sensors and modern technologies have made data collection easy and accurate. Only machine learning (ML) algorithms can successfully handle the meticulous analysis required to produce precise and efficient predictions from such enormous environmental data. The KNN, Decision Tree, and Random Forest algorithm is utilised in order to predict air pollution, as it is more appropriate for prediction assignments. The CNN classification method, which evaluates the quality of the air, will be used to compare the old picture to the new one. The old picture is already executed time and accuracy with 92% updated. for instance, oxygen, carbon dioxide, etc. Many serious diseases may be brought on by air pollution. The health of people and the reduction of air pollution are greatly benefited by an effective air quality monitoring system. CNN has been suggested as the way for categorising the natural image into many groups according to their concentration. The experimental findings show that this technique supports the image-based concentration estimation to assess air quality.

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