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An IoE-SVM Based Statistical Investigation to Measure Effect of Air Pollutant Substances on Student's Attention Level

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Abstract. The air pollutant in a specific region is mainly responsible for the respiration-related health problem. But the effect of these pollutants is also creating cognitive related issues and hence degrades the attention level of the students. As a result, their educational performance and learning ability reduce to a great extent. This study is to reveal the effect of the air pollutant on the educational outcomes of a student by measuring their attentiveness in the class using the Internet of Everything (IoE). As the effect of ambient air quality is different from region to region. This investigation is performed upon 33 schools of the Odisha region in India. An IoE-SVM Based approach is employed to evaluate the attentiveness of the student in different regions. The result shows that the PM_{10} and NO_2 are mostly affecting the student's attentiveness and hence cognitive response. The result shows that a 1% increase in PM_{10}, NO_2, and SO_2 levels would decrease the test score by 0.049%, 0.14%, and 0.18% respectively.

Keywords. Attention level, EEG signal, air pollution, academic performance, SVM, IoE, air quality index.

1 Introduction

In few decades, the air quality in different parts of the world is degrading drastically [1]. The degradation of AQI (Air Quality Index) is due to many causes, which are different from place to place depending upon the geographical position as well as through the economic and social development.

In recent years, the AQI in major cities of the world increasing rapidly due to the rapid industrialization and socio-economic developmental works [2]. This trend is not only growing in the metropolitans but also in the small cities of developing countries like India. In developing countries, the government has also taken some initiatives to urbanize small towns and villages.

As a result, industrialization comes to these rural areas of developing countries, and hence the air quality is also degrading in these areas day by day [3].

Due to the increase of air pollutants in different areas of developing countries, the people in those areas are facing severe respiratory-related problems [4].

This leads to cause of adverse health conditions due to continuous exposure to the pollutant in those areas [5]. As lower aged-group, people are more sensitive and hence more vulnerable to these pollutants that increase the cognitive defects in them [6].

Constant exposure to these air pollutants beyond their admissible level, which is prescribed by the World Health Organization (WHO) [7] and central air pollutant committee of different countries can degrade student's performance in terms of physically and academically.

In recent years, many types of research are going on to enhance educational outcomes by implementing different learning management

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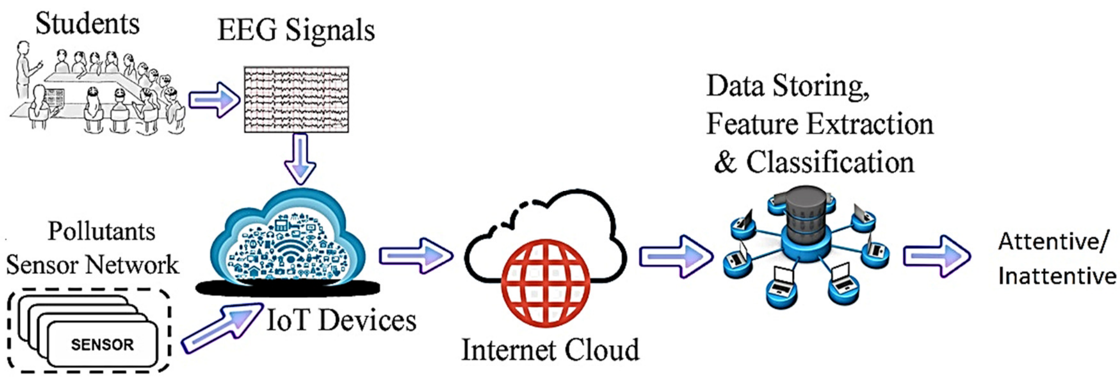

Fig. 1. Air pollutant receiving system using IoT

Table 1. Description of sensors for the air pollution detection

Name of the Sensor	Sensed Gas	O. V	Sensitivity Range
HPMA115S0 [43]	PM_{10}	5V DC	1000ug/m3
Dust sensor Module GP2Y1010AUOF [44]	$PM_{2.5}$	2.5V to 5.5V	0.5V/(100ug/m3)
MQ-7 [45]	CO	5V DC	(10-1000) ppm
GS+4NO2 [46]	NO_2	5V DC	(0-30) ppm
MQ-136 [47]	SO_2	5V DC	(1-200) ppm
MQ-131[48]	Ozone	5V DC	(10-1000) ppm

*O. V- Operating Voltage

systems using innovative learning methodology [8].

However, the impact of air pollutants on the educational outcome hasn't yet been revealed. The attendance in school and colleges, attention level, activeness, a fast response are some parameters to measure the student's performance academically. These parameters are greatly affected by air pollutants in different regions.

The air pollutants above the prescribed level can lead to an increase in absenteeism in school and an increase in mortality rate [9]. On the other hand, the education system is facing new challenges due to the intervention of Information and Communication Technology (ICT) in education [10].

The ICT has not only affected higher education but also lower grade students. Some researchers have investigated the factors that influence the transformation of a physical laboratory to a virtual laboratory using ICT in Amman [11].

In the last decade, the Internet of Things (IoT) gains its popularity due to its low-cost and easy implementation architecture. Some of the fields such as traffic control systems, health care systems, home automation, etc. have been exploited by using IoT [12-13]. Recently some research has been carried out to improve the educational system using IoT [14-15]. This study is to investigate the effect of lower and higher levels of air pollutants on the student's academic performance by using the internet of things.

This study has been carried out in 33 different schools of Odisha in India at different regions. The geographical positions of these schools are spread across the state covering the coastal area, hilly area, industrial area, etc.

1.1 Motivation

Nowadays, the impact of different environmental factors on educational outcomes has gained

Table 2. Neuro-frequency bands and their associated activities

Name of F.B.	F.R. in Hz.	V.R.in μV	R. O	Activity
Alpha	(8-13) Hz.	(30-50) μV	Parietal and occipital	In a state of consciousness, quiet or rest
Beta	(14-30) Hz.	(5-20) μV	Frontal	Conscious or alert thinking or receiving stimulation
Theta	(4-7) Hz.	Less than 100μV	Parietal and temporal	Emotional pressure, distraction, deep relaxation
Delta	(0.5-3) Hz.	(100-200) μV	Central region	Deep sleep, unconscious, anesthetized
Gamma	(31-50) Hz.	(5-10) μV	Highly localized	Selective attention

F.B.- Frequency Band
F.R.- Frequency Range
V.R.-Voltage Range
R.O- Region of occurrence

interest due to pollution in different geographical areas. As pollution level is different from place to place within a certain geographical area, hence we can see a diversified impact of this pollution level on the educational outcomes. However, the economic condition, the social condition of the students is different from place to place. Hence, a deep investigation is required to see the impact of these factors on educational outcomes.

Nowadays, IoT has gain popularity due to its low-cost architecture. The sensing ability enhances the capability of IoT to reach remote areas for data collection. These data are the vital inputs for an effective data analysis system that can measure the impact of environmental factors on the education system.

1.2 Contributions

This system is to study the effect of air pollutants in the Odisha region of India on the student's academic performance or learning outcomes. This study is also about setting up a low-cost infrastructure to get the data of different air pollutants across the Odisha region of India.

As each air pollutants has some impact on learning outcomes, this paper is to investigate and find out the statistical relationship between the air pollutant and learning outcomes.

Hence, a relationship between air pollutants and learning outcomes can be established across the country. This paper is presented as follows.

In Section 1, the introductory description of the present scenario of the air pollutant in a different geographical area with the attention level is discussed. In Section 2, past researches are presented. In Section 3, the geographical scenario of the research area is discussed.

The air pollutant and their effects on learning outcomes are presented in Section 4. In Section 5, the materials and methods are discussed which includes air pollutant receiving system using IoT, measurement, and analysis of attentiveness, etc.

In Section 6, an experimental setup is presented. The result is discussed in Section 7. Section 8, describes the concluding notes and the scope of future work.

2 Literature Review

In recent years, many researchers have identified the impact of air pollutants on hospital admission, mortality rate, cognitive response, etc. [16]. The most important air pollutants are PM_{10}, $PM_{2.5}$, i.e. the particulate matter whose diameter is less than 10 microns and 2.5 microns respectively.

Along with these pollutants, Ozone (O_3), NOx, Sulphur Dioxide (SO_2) are also the major

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Fig. 2. Neurosky brainwave sensor

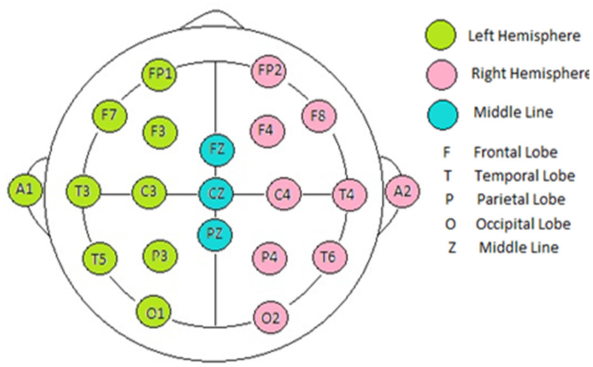

Fig. 3. Focal position of placing sensor electrodes

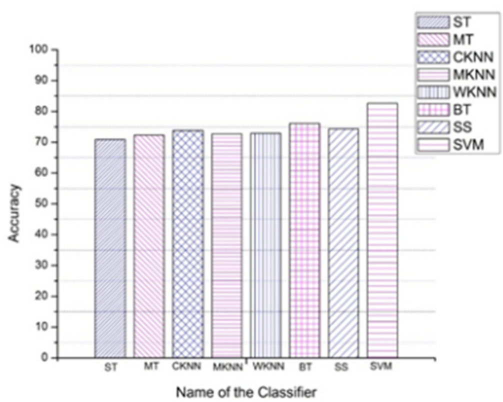

Fig. 4. Comparisons of Different Classifier for Accuracy in Predicting Attention Level

hazardous pollutants that have to be taken into consideration. The concentration of these air pollutants is also differing from season to season [17].

According to Gramsch et al., the concentration of particulate matter is greater during the autumn and winter season and the concentration of ozone is higher during the spring and summer seasons [18].

From many types of researches, it is also revealed that the effect of air pollutants is different from developing countries to developed countries [19]. As the resources like health care access are quite different from developing country to developed country, hence the research done by Arceo et al. reveals that the estimated facts for the developing countries can't be valid for the developed countries when establishing a relationship between pollution with health [20].

Therefore, the study is carried out to find out the correlation between air pollutants with the attentiveness of the students which is greatly influenced the learning outcomes. Carroll shows in their research that continuous exposure to these harmful pollutants can lead to continuous respiratory diseases and hence increases the absence rate in the school or college [21].

This also reduces their learning capability. Many researchers also trying to establish the relationship between a student's health condition to their cognitive response. To record student's cognitive responses, they have used BCI (Brain-Computer Interface) system to transfer the brain signals to a system for further analysis and actionable measures [22].

Some researchers have used EEG (electroencephalogram) signals to analyze the attentiveness of the human being [23]. But the location of the scalp from where the EEG signal has to be taken is a very critical issue that has been identified by Yaomanee et al. [24].

Some researchers also compared the utilization of EEG signal and ECG electrocardiogram) signal analyzer for the classification accuracy for attentiveness [24]. In an experiment conducted by Li et al., the level of attentiveness is measured when the subjects are given brain power-related work to be done [25].

To identify the level of attentiveness, many researchers have used different classifiers, i.e. SUM, K-Nearest Neighbors (KNN), and Naive Bayes [26]. According to Calderon et al. 2008 and Wang et al., 2009, the development of the brain

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Table 3. Comparison of machine learning methods for attention prediction

Classification Method	Accuracy	Precise (%)	Recall (%)	AUC	F-Measure	G-Mean
Simple tree (ST) [57]	70.9	64.34	63.94	0.784	0.767	0.708
Medium Tree (MT) [57]	72.3	69.75	67.89	0.779	0.738	0.717
Coarse KNN (CKNN) [57]	73.8	71.69	70.26	0.825	0.816	0.734
Medium KNN (MKNN) [57]	72.7	78.91	77.36	0.893	0.838	0.723
Weight KNN (WKNN) [57]	72.9	73.67	76.14	0.836	0.819	0.725
Bagged Trees (BT) [57]	76.1	81.22	79.93	0.899	0.874	0.753
Subspace (SS) KNN [57]	74.3	78.49	76.89	0.816	0.798	0.738
SVM	**82.6**	**80.32**	**86.63**	**0.845**	**0.805**	**0.845**

and cognitive ability is greatly affected by the constant exposure to air pollutants [27-28].

Suglia et al., 2008 discussed the relation of air pollutant with the absenteeism, fatigue and neurological problem which leads to poor academic performance [29].

Some researcher (Pope, Dockery, 2006 and Russel et al., 2009) suggests that the excessive presence of PM_{10} and $PM_{2.5}$ have a negative cognitive response [30]. Graft et al., 2012 investigated the effect of O_3 on brain performance and found that if O_3 increased by 10ppb, then it leads to a decrease in productivity by 5.5% [31].

Some researchers also pointed out that the children's performance in the area of high concentration of air pollutants such as industrial areas and mining areas have poor academic performance than that of the children's in the less air pollutant area such as hilly areas (Wang et al., 2009) [32]. Zweig et al. conducted a test in California to test the effect of PM_{10}, $PM_{2.5}$, and NO_2 on academic performance [33].

The evidence collected from their research indicates that a 10% decrease in PM level would decrease the test score by 0.15% for PM_{10}, 0.22% for $PM_{2.5}$, and 0.34% for NO_2 respectively. Zaletelj and Kosir use a machine-learning algorithm to estimate the attentiveness of the student using 2D and 3D data that is collected by Kinect One sensor [34]. They have used the facial and gestures of the body to classify the attentiveness which greatly impacts the academic performance.

3 Environmental Condition of Odishga

Odisha is a state which is situated on the east coast of India [35]. As of India, it is also a densely populated area. This state is also very rich in minerals which enhances the large mining and industrialization in the state.

The coastal belt of the state is densely populated in comparison to other regions of the state as a result the vehicular emission in these areas is quite high. In recent years, the major cities have faced the worst fog situation that the state has ever experienced.

The cities like Bhubaneswar, Cuttack, Balasore, Paradeep, and Berhampur are worst affected by vehicular emission, demolition work, and constructional work.

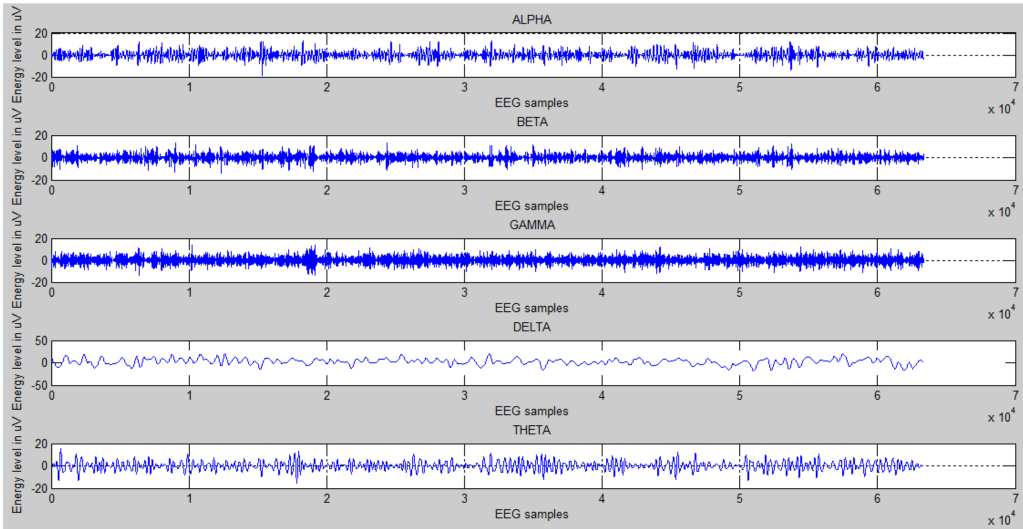

Fig. 5. Energy Level of five sub-band frequencies of EEG signal, i.e. alpha, beta, theta, delta, and gamma

The cities like Angul, Talcher, Raygada, Rourkela, and Jharsuguda which are situated in the central and northwest part of Odisha are affected by industrial pollution along with vehicular pollution.

In these cities, the temperature goes beyond 450 C in the summer season. The annual average PM_{10} level in these cities is around 300 ppm [36]. The average SO_2, NOx in these cities is around 9.2 and 25.6 respectively.

The Keonjhar and Sundargarh districts are highly affected by the PM levels as these areas are having major mines in India. So the average PM level in these areas goes beyond 400 to 500 ppm.

In a report published by the Central Pollution Control Board of India that six cities of Odisha among 200 cities of India are marked as the worst polluted [37]. Due to this reason, the number of patients suffering from cardiovascular diseases, bronchitis, and tuberculosis is increasing in these cities of Odisha.

4 Air Pollution and Its Effect on Learning Outcomes

Many researchers have identified the link between different air pollutant concentration levels, mortality and morbidity events.

According to Ponce (2012), around 4000 people die prematurely due to high concentrations of air pollutants which leads to cardiopulmonary diseases every year [38].

Ostro et al. (1999) have done a study on children under 3 to 15 years to analyze the effect of PM_{10} and Ozone [39]. They found that the children within the lower age group have lower respiratory symbols and the cognitive response is also low as compared to other age groups.

In the same manner, the higher concentration of ozone also increases hospital admission as investigated by Brunell et al. [40]. These air pollutants beyond at a certain level effects the growth of the brain, decrease the cognitive response, increases absenteeism, fatigue, etc. Due to these effects, the attention level also decreases which leads to poor academic performance.

5 Materials and Methods

In this section, a brief note about the materials used for the design of an air pollutant receiving system along with the methods used for measuring the attentiveness of the subject is discussed.

This section also reveals a detailed analysis of the attentiveness and inattentiveness of the test

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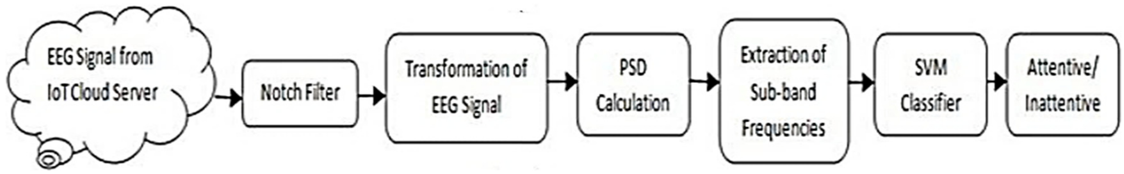

Fig. 6. Measurement of Attentiveness using EEG Signal

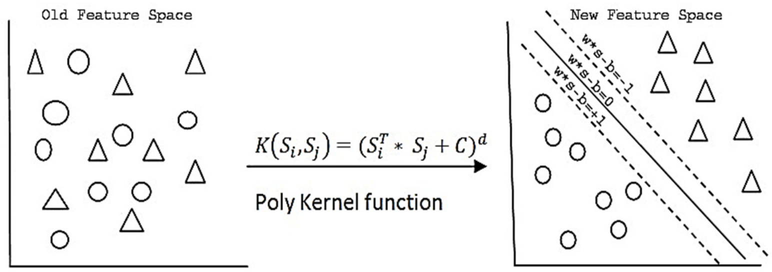

Fig. 7. SVM high dimensional feature space

subject (students) using Support Vector Machine (SVM).

5.1 Air Pollutant Receiving Station using IoT

To receive the data from the different locations, the proposed system is designed with a low cost and portable system using IoT. As recently IoT has gained popularity due to its diversity in its applications, it can be utilized to get information whenever we want it at a very low cost even from a remote location (Marques et al., 2019) [41]. In proposed system consist of a Raspberry Pi 3B+ board (IoT prototype Board) to collect the data from the different locations across the Odisha region.

To sense the different air pollutants, gas sensors are used. A detailed system for air pollutant receiving stations using IoT is shown in figure 1. The sensors are selected based on the sensitivity, power requirement and cost. To keep the initial installation cost low, some MQ series gas sensors are used (Sabuag et al., 2019) [42].

Before utilization of these sensors, all the sensors are preheated for about 48 hours and the sensors are properly calibrated in an isolation chamber as per the datasheet of the sensors. The details of the sensors are given in table 1.

The brainwave sensors are used to generate the EEG signals from the subjects and fed to the Raspberry Pi board to transmit the data to the cloud server. All these sensors are connected to the Raspberry Pi IoT prototype board (Pi, 2015) which is a SOC (System on Chip) [49].

A python program is continuously running inside the Raspberry Pi board whenever the board is connected to the power supply.

These boards and sensors require very little power usually +5VDC power and light in weight. The total system can be installed very easily at any remote location. The data collected from these sensors will be transmitted to the server by using the internet as the Raspberry Pi board has the inbuilt Wi-Fi chip embedded in it. The data is stored in a database in the server for further analysis.

5.2 Measurement of Activeness Using EEG Sensor

The attentiveness of a human being is the neurological activity of the brain [50]. Therefore, EEG sensor is a perfect candidate to measure any fluctuations that arise due to any activity of the body and brain according to Belle et al.

These sensors are capturing the electroencephalography signals called EEG signals from the brain scalps when the classes are going on to measure the attentiveness of the subject [51].

Traditionally the teacher has to identify which student is paying attention and who is not but this

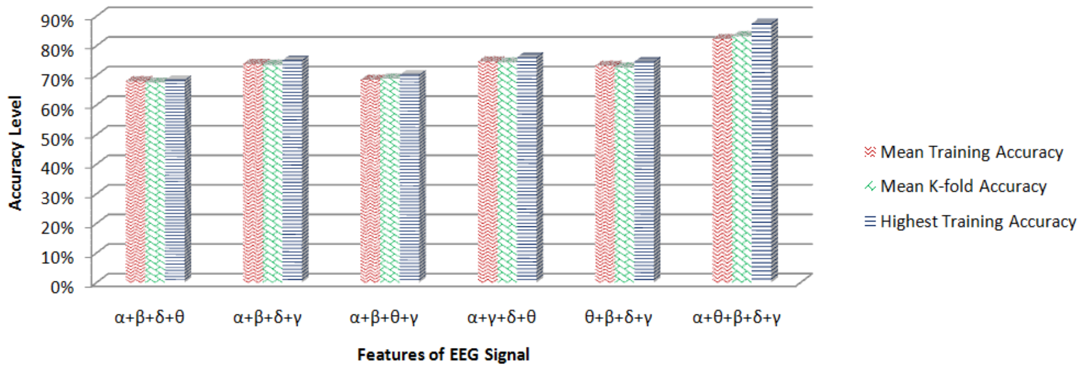

Fig. 8. Classification accuracy using different features, i.e. alpha, beta, theta, delta, and gamma

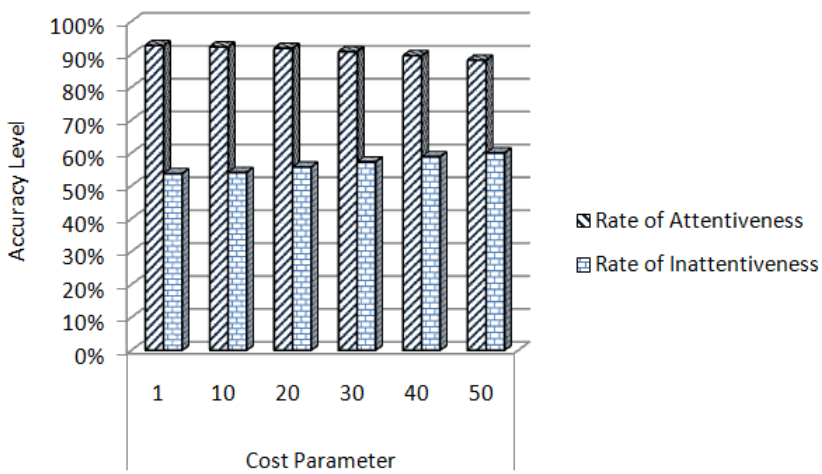

Fig. 9. shows the rate of attentiveness and rate of In-attentiveness concerning the cost function.

task is very tedious and energy-consuming. In online classes, the teacher is also unable to judge a student's attentiveness by looking at them in the video. So, whether the session is interactive or non-interactive can't be effectively determined by the teacher.

But whether the class is online or offline means face to face in a classroom, during a lecture or practical session the brain of each student generates different EEG signals in a certain band of frequency which is the base to detect the attentiveness of the student [52].

These frequency bands are associated with a certain activity of the brain and these activities can't be controlled by a normal person without training and practice. The activity associated with these frequency bands is given in Table 2 [53-54].

The proposed system consists of a brain sense device, i.e. Neurosky brainwave sensor [55], Raspberry Pi IoT prototype board, and a python program to differentiate the EEG signals. This brainwave sensor is fitted on the head of a student as shown in figure 2. A 10-20 EEG system is presented in figure 3 which is universally accepted for monitoring the EEG signals from the human brain [56].

In this system, different focal points are pointed from where the EEG signals can be monitored. Among all these focal points, two focal points in the head, i.e. FP1, FP2 result in the signal related to the attention of a person which is presented in

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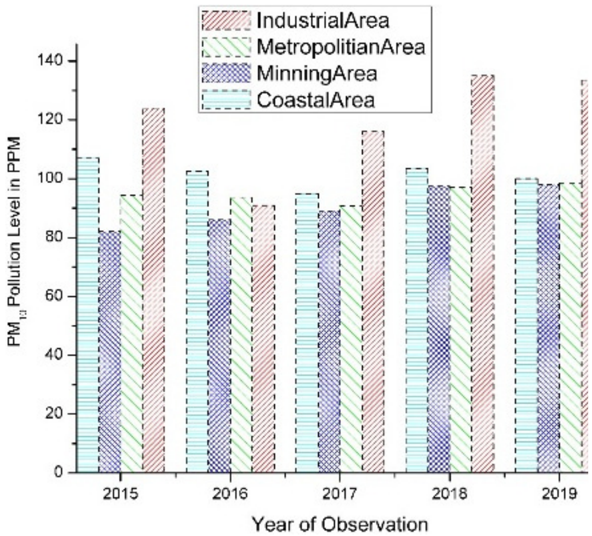

Fig. 10. Year-wise regional average of concentration of PM_{10}level in Odisha

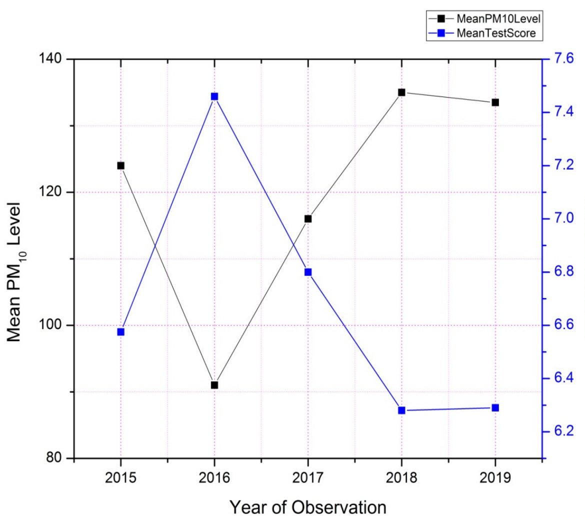

Fig.11. Comparison of test score with concentration of PM_{10} in Industrial Area of Odisha.

figure 3. The EEG signals are collected from these focal points by Neurosky Brainwave sensors and transmitted to the Raspberry Pi module through Bluetooth technology as shown in figure 1.

After collecting the EEG signals, the Raspberry Pi module segregates the signals and resends them to the IoT cloud server through Wi-Fi technology. The server receives the EEG signal values along with the air pollutant sensor value at the same time and stores them in a database for further analysis. In this work, the degree of attentiveness is classified with some well-known classifiers which is described in subsequent section.

5.3 Preprocessing of EEG Signal and Feature Selection

Before applying the SVM classifier, the features of EEG signals have to be extracted. Figure 5 represents a flow diagram for the measurement of attention level. The EEG data are collected and processed by a notch filter for the removal of the artifacts from the signal.

The signals are sampled at 512 Hz. The sampled signals are transformed into the frequency domain and the PSD (Power Spectral Density) of the sampled signal is calculated by the following formula:

$$\text{Power}(n) = \frac{s(n)s^*(n)}{N}, \tag{1}$$

where $S(n)$ is the sampled signal at the rate 512. $S*(n)$ is the complex conjugate of the signal. N is the sampling rate. As EEG signal consists of five sub-band frequencies, i.e. alpha, beta, theta, delta, and gamma, each frequency band possess a certain energy level are shown in figure 5 which is calculated as:

$$\text{Energy}_{\text{alpha}} = \sum_{f=8}^{13} \text{Power}(n), \tag{2}$$

$$\text{Energy}_{\text{beta}} = \sum_{f=14}^{30} \text{Power}(n), \tag{3}$$

$$\text{Energy}_{\text{gamma}} = \sum_{f=4}^{7} \text{Power}(n), \tag{4}$$

$$\text{Energy}_{\text{delta}} = \sum_{f=0.5}^{3} \text{Power}(n). \tag{5}$$

The extraction of sub band frequencies is then fed to the SVM for the determination of attention level. The interdependencies of all the energy sub-bands exist in between them as investigated by Hasegawa et al., the ratio of these energy levels can be taken as a feature of the attentiveness [58]:

$$\text{Rate of attentiveness} = \frac{\text{Energy}_{\text{alpha}}}{\text{Energy}_{\text{beta}}}. \tag{6}$$

All five features are calculated and are processed for classification using SVM.

5.4 SVM Classifier

In this study, an SVM classifier is used to classify whether a student is attentive or inattentive during the test. SVM creates a model to construct a hyperplane in its high dimensional feature space.

This hyperplane segregates the attentiveness or inattentiveness using the EEG signal. A polynomial kernel function is used to identify each sample from the dataset to project into the high dimensional feature space.

A parallel line is constructed on both sides of the hyperplane that differentiates the attentiveness. The SVM tries to maximize the difference between the parallel lines as shown in figure 7. The difference of parallel lines denotes the lesser the classification error rate. The kernel function is represented in equation 7:

$$K\left(S_i, S_j\right) = \left(S_i^T * S_j + C\right)^d. \quad (7)$$

After the SVM calculation and classification, to determine the accuracy of the classifier, k-fold cross-validation is performed. All the samples are partitioned into the k subset. From this subset, one subset is taken as testing data and k-1 subsets are taken as training data. To determine the accuracy, the above process is repeated for k times.

As per our research, there is no globally accepted valid dataset of EEG signal that represents the activeness or inactiveness state of mind. So, to find the exact trace of the EEG signal sub-bands for classifying attentiveness, initially a physical method is used where the students will be asked whether he is attentive or not during the class and simultaneously his EEG signals are recorded.

Then an IoT-SVM method is used to determine the attentiveness and matched with the previously recorded EEG signal which is recorded during physical method.

Two test scenarios are created in this method; one is to respond to the English phrases and respond to some questionnaire and the other is the same scenario but in presence of a noisy environment. In these two methods, the sub-bands are traced and marked.

The test subjects are asked whether they are attentive or not. If the test subject is unsure about its state of mind, then that response is discarded.

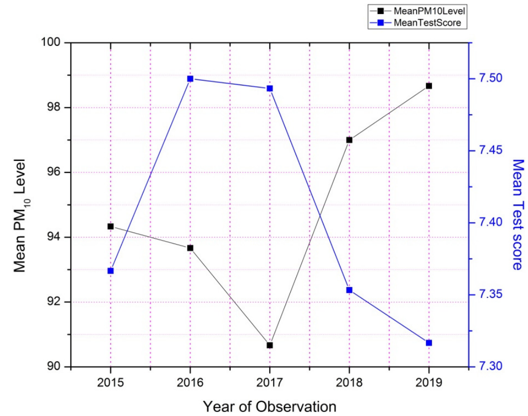

Fig.12. Comparison of test score with concentration of PM_{10} in metropolitan area of Odisha.

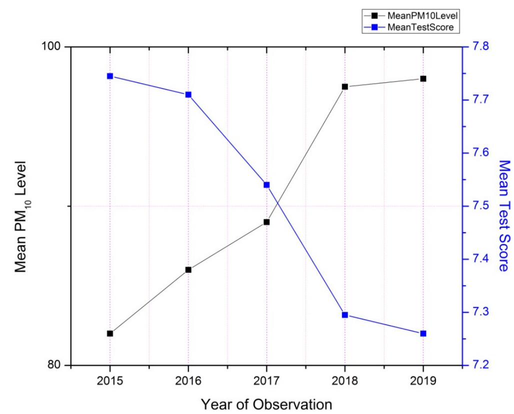

Fig.13. Comparison of test score with concentration of PM_{10} in minning area of Odisha

Likewise, a set of 3894 attentive and 2987 inattentive samples are collected. To have unbiased classification accuracy, a total of 1000 attentive and inattentive EEG signals are selected randomly for the classification.

As the attentiveness of men and women differs from each other, thus two classifications are developed for testing. Initially, a single feature is employed for the classification but the accuracy level is near about 50%. Thus, multiple features are used for classification to improve accuracy that are alpha, beta, delta, theta, gamma.

In our study, the value for k-fold is 5. Therefore, 200 samples are used for testing, and the remaining is used for training samples. The classification accuracy using different features is shown in figure 8.

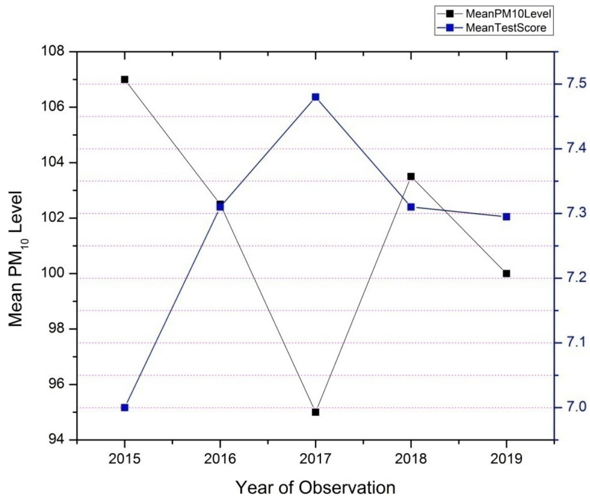

Fig. 14. Comparison of test score with concentration of PM_{10} in coastal area of Odisha

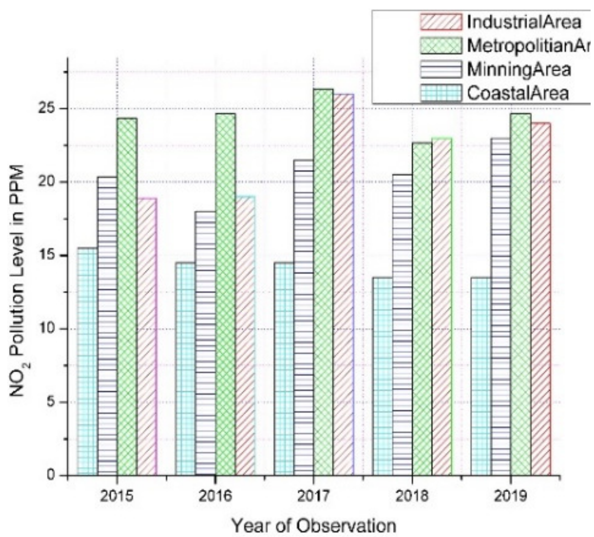

Fig.15. Year-wise regional average of concentration of NO_2 in Odisha

In the proposed study, it is also found that the rate of attentiveness and inattentiveness is also affected by the cost function of the poly kernel function denoted in equation 7.

The rate of attentiveness is decreasing as the cost function increases and the rate of inattentiveness increases as the cost function increases. Figure 9 shows the rate of attentiveness and rate of attentiveness concerning the cost function.

6 Experimental Setup

Initially, 10 cities of Odisha are selected and are categorized as Industrial area, Metropolitan area, Minning area, and Coastal area. The cities such as Angul, Rourkela are categorized as Industrial areas and Bhubaneswar, Cuttack, Sambalpur are categorized as metropolitan areas whereas Keonjhar, Sundargarh, Talcher are categorized as Mining areas and Puri, Paradeep are categorized as Coastal areas.

Around 33 schools are selected from these areas. The data is collected from these schools. While selecting the students from these schools, some points have been taken into consideration such as their family health condition, Family Income, student's medical history, the smoking habit of a parent, etc., as these factors can affect the student's performance in the test.

As there is no valid dataset of EEG signal for the evaluating attentiveness present, the EEG signals are validated manually on the test subjects preliminarily. In our test, the EEG signals and the air pollutant data are collected from 33 schools in different districts of Odisha, India. From each school, 15 male and 15 female students were selected for the test.

The selections of these students are purely random. Before experimenting, it is confirmed that any test subject has not undergone any meditation techniques to control the brain signals.

The test subjects were given the brain sensor module to wear for about 5 minutes to get familiar with the module and avoid discomfort during the test. The EEG signals were collected from each test subject during different subjects taught to them.

In between the class, the test subjects were also asked to do some tasks and read some phrases. The degree of attractiveness or inattentiveness is categorized according to the test subjects. Initially, all the test is conducted in every month. Thereafter the frequency of the test is doubled. The corresponding air pollutant levels are also measured simultaneously on such days.

The BSE (Board of Secondary Education) results from the schools are taken into consideration to validate the outcomes which is a standard examination conducted by Govt. of Odisha for the secondary school students.

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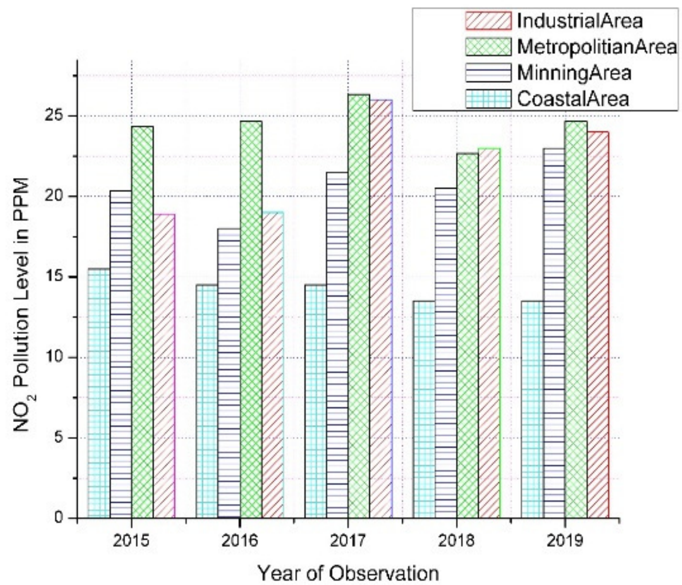

Fig.16. Year-wise regional average of concentration of SO_2 in Odisha

Table 4. Correlation between air pollutants

Pollutants	PM_{10}	$PM_{2.5}$	SO_2	NO_2	CO	O_3
PM_{10} Mean	1.00					
$PM_{2.5}$ Mean	0.568	1.00				
SO_2 Mean	0.018	0.628	1.00			
NO_2 Mean	0.728	0.868		1.00	0.876	
CO Mean	0.197	0.843		0.876	1.00	
O_3 Mean	-0.332	-0.431	-0.739	-0.573	-0.542	1.00

7 Result and Discussion

This section is divided into two subsections. One is to analyze the factors influencing attentiveness accuracy and in the second subsection, the impact of air pollutants upon the test score of the participant students is discussed. Initially, the investigation is carried upon the effect of different EEG features on attentiveness.

Different features are extracted from the EEG signal, which is collected from the IoT devices. These features are used to classify whether a student is attentive or inattentive. The effect of the performance of a student can be measured from his attentiveness.

Thus, to classify the attentiveness, the SVM classifier is used as it is found to be the best classifier among other classifiers compared in table 3. In our experimentation, we found that the accuracy level of attentiveness is optimum when all the features are taken into the consideration.

The comparison of accuracy levels is presented in figure 8. In our proposed system, it has also come into notice that as the cost parameter of the poly kernel function increases, the attentiveness rate decreases and vice versa.

After identifying the attentiveness of a student, we further investigate the effect of air pollutants on the student's attentiveness and upon their test scores.

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Table 5. Concentration of PM_{10} in different cities of Odisha

Name of the City	2019		2018		2017		2016		2015	
	M. H. A	A. A	M.H. A	A. A	M. H. A	A. A	M. H. A	A. A	M. H. A	A. A
Angul	161	105	163	103	182	96	198	100	234	106
Talcher	203	94	206	96	200	91	233	94	267	93
Rourkela	274	162	265	167	339	136	217	82	278	142
Sambalpur	288	86	287	85	110	82	92	79	89	68
Sundargarh	234	102	230	99	221	87	183	78	172	71
Jharsuguda	154	103	153	106	136	91	117	87	106	82
Bhubaneswar	297	102	290	100	242	96	314	109	302	113
Cuttack	248	108	246	106	160	94	257	93	196	102
Paradeep	324	108	317	119	238	112	250	117	283	123
Puri	172	92	167	88	152	78	367	88	166	91

*M.H.A-Maximum Hourly Average
**A.A-Annual Average

Table 6. Comparison of test score for different concentration of PM_{10} in different cities of Odisha

Name of the City	Year-2019		Year-2018		Year-2017		Year-2016		Year-2015	
	PM_{10} Level	Test Score	PM_{10} Level	Test Score	PM_{10} Level	Test Score	PM_{10} Level	Test Score	PM_{10} Level	Test Score
Angul	105	7.10	103	7.12	96	7.32	100	7.14	106	7.14
Talcher	94	7.38	96	7.32	91	7.45	94	7.38	93	7.41
Rourkela	162	5.48	167	5.44	136	6.28	82	7.78	142	6.01
Sambalpur	86	7.67	85	7.72	82	7.78	79	8.01	68	8.12
Sundargarh	102	7.14	99	7.27	87	7.63	78	8.04	71	8.08
Jharsuguda	103	7.12	106	7.10	91	7.45	87	7.63	82	7.78
Bhubaneswar	102	7.14	100	7.24	96	7.32	109	7.08	113	6.84
Cuttack	108	7.14	106	7.10	94	7.38	93	7.41	102	7.14
Paradeep	108	7.14	119	6.84	112	6.94	117	6.88	123	6.55
Puri	92	7.45	88	7.78	78	8.12	88	7.78	91	7.45

*M.H.A-Maximum Hourly Average
**A.A-Annual Average

The air pollutant level of different areas across Odisha is collected from the year 2015 to 2019.

The air pollutant level data from 2015 to 2018 are collected from the State Pollution Control Board database and for 2019, the data is generated from the sensors connected with the IoT devices. The collected data is further analyzed to find out the effect of air pollutants on the student's academic performance using Wald statistical test.

In this proposed system, the impact of air pollutants concerning the test report is measured and analyzed. The test report consists of two tests. The first test is English phrase reading and responding to some queries. The second test is doing some math problems. As the first test is upon linguistic acquisition, it is greatly influenced by the feature 'delta' activity of the brain.

From the experimentation, it is found that the feature 'delta' and 'gamma' activity have more impact on attentiveness rate. In some research, it is also proposed that the feature 'theta' and 'beta' activity have minimal effect on the attentiveness

Table 7. Concentration of NO_2 in different cities of Odisha

Name of the City	2019		2018		2017		2016		2015	
	M.H.A	A.A	M.H.A	A.A	M.H.A	A.A	M.H.A	A.A	M.H.A	A.A
Angul	34	26	35	25	32	25	31	24	33	25
Talcher	33	31	34	29	37	31	29	24	36	27
Rourkela	36	22	32	21	43	27	35	14	32	13
Sambalpur	45	23	43	21	27	20	19	17	20	17
Sundargarh	26	15	23	12	20	12	21	12	24	14
Jharsuguda	34	20	31	18	24	20	24	20	23	19
Bhubaneswar	52	18	50	16	36	25	61	25	43	24
Cuttack	46	33	42	31	42	34	38	32	40	32
Paradeep	24	13	21	12	25	14	22	14	27	15
Puri	26	14	25	15	29	15	31	15	33	16

*M.H.A-Maximum Hourly Average
**A.A-Annual Average

Table 8. Concentration of SO_2 in different cities of Odisha

Name of the City	2019		2018		2017		2016		2015	
	M.H.A	A.A	M.H.A	A.A	M.H.A	A.A	M.H.A	A.A	M.H.A	A.A
Angul	21	10	20	9	18	9	14	9	14	10.8
Talcher	17	11	15	10	13	10	12	10	12	8.5
Rourkela	22	14	20	14	26	21	30	12	15	5.1
Sambalpur	41	6	39	5	8	4	5	4	5	2.5
Sundargarh	20	8	18	8	16	7	14	6.2	14	7
Jharsuguda	25	11	24	10	20	11	18	13	16	12
Bhubaneswar	16	2	15	2	21	2	25	2	24	2
Cuttack	10	5	9	4	7	5	7	4	6	2
Paradeep	36	21	35	19	52	20	43	22	40	21
Puri	7	3	5	2	5	2	16	2	7	2

*M.H.A-Maximum Hourly Average

rate. But to get better classification accuracy, all features must be taken into consideration. Figure 9 shows the effect of rate of attentiveness and inattentiveness concerning cost parameters. It shows that the rate of inattentiveness is about 50%, which means there are still more factors exist that influence the inattentiveness.

The regions of the state are categorized into four groups', i.e. Metropolitan region, the Mining region, the Industrial region, and the coastal region. Table 5 shows the annual average level of PM_{10} and the maximum hourly average level of PM_{10}. The test score for the math and text reading measures the attentiveness of the students.

The test score is calculated on that day when the concentration of PM_{10} level is around the annual average level. Table 6 shows the comparative data of PM_{10} concentration with the test scores of different cities of Odisha. The mean PM_{10} level of different geographical areas for the year 2015-2019 is presented in figure 10.

The comparative graphical representation of the mean PM_{10} level with the mean test score for different regions is presented from figure 11 to

Table 9. Statistical description of pollutant and test score

Variables	Year-2019	Year-2018	Year-2017	Year-2016	Year-2015
Mean of PM_{10}	106.20	106.90	96.30	92.70	99.10
Mean of NO_2	21.50	20	22.30	19.70	20.20
Mean of SO_2	9.1	8.3	9.1	8.42	7.29
Standard deviation of PM_{10}	19.81	23.1922	16.7003	12.8413	23.1250
Standard deviation of NO_2	6.56	6.6833	7.3643	6.4127	6.403
Standard deviation of SO_2	5.37	5.3965	6.7733	6.2136	6.1075
Mean of Test Score	7.07	7.093	7.36	7.513	7.25
Standard deviation of Test Score	0.59	0.64	0.49	0.39	0.66

Table 10. Effect of pollutant on test score

Pollutant	(1)	(2)	(3)	(4)	(5)
PM_{10}	-0.328	-0.738^{a}			
NO_2	-0.846		-2.024^{b}		
SO_2	-0.763			-1.998^{b}	
O_3	0.372				0.284

figure 14 respectively. Likewise, the mean NO_2 level and SO_2 level for a different region of Odisha from the year 2015 to 2019 is presented in figure 15 and figure 16 respectively. The annual average level of PM_{10} in the cities is between 86 to 162 ppm (parts per million) for the year 2019 presented in Table 5.

Table 6 shows the mean test score for different areas for the year 2019. The test score for the year 2015 to 2018 is taken from the database created from the IoT devices in the year 2019 when the air pollutant level is nearer to that level.

Table 7 and Table 8 represent the concentration of NO_2 and SO_2 for a different region of Odisha. The test score is also calculated for the other air pollutants. Some of the pollutants do not have any significant impact on the test score thus excluded from the experiment like ozone. According to the study, the concentration of ozone increases in the spring and summer seasons.

In those days, the result shows a negative impact on the test score as expected but does not have a significant impact on test score [59]. During the experimentation, it is also come to notice that there is a correlation between the air pollutants. The effect of all air pollutants except ozone has a significant impact on the test score [60].

The correlation table for air pollutants is shown in table 8. In this work, the test score is measured keeping one air pollutant as a variable at a time and others as explanatory variables.

For experimentation, we have used all the major air pollutants to measure the effectiveness on the test score. A Wald test is performed for statistical analysis which reveals that all the four air pollutants, i.e. PM_{10}, NO_2, SO_2 have a significant impact on attentiveness as well as on the test score.

As we know that Wald test is used to investigate the degree of significance level for an independent variable over a model, we have used it to investigate the significance level of different air pollutant on test score individually and then collectively their influence on the test score.

The statistical analysis is presented in table 10. The significance of all the air pollutants to the test score is presented in column (1). From column (2) to column (5), the significance level of an individual air pollutant is shown. Here it is found that the Ozone has no impact on the test score.

Thus, data collected for Ozone have been discarded and is eliminated from the analysis part. However, the PM_{10} is the only air pollutant that has a statistically significant effect on the test score as shown in table 9. Thereafter it is also found that PM_{10}, NO_2, SO_2 have a statistically significant effect on the test score but on the other hand, Ozone shows a positive sign which reflects that it does not affect the test score statistically.

The magnitude of effect on test score by the coefficients is calculated and found that an increase in the level of concentration of PM_{10} in standard deviation results in 0.028 points decreases in test score. In the same way, an increase in one standard deviation of NO_2 and SO_2 would result in a decrease in test scores by 0.08 points and 0.104 points out of 10 points respectively.

A relevant statistically elasticity measurement is also calculated here for those who do not familiar with the measurement units of air pollutants and the findings are: for 1% increase in PM_{10}, NO_2 and SO_2 level would decrease the test score by 0.049%, 0.14%, and 0.18% respectively.

This study also reveals that the test score is heavily affected by PM_{10} when the test is conducted upon below grade 5 students. The effect is quite low when considering relatively higher-grade students. In some cases, when the concentration level of PM_{10} is beyond 250 ppm, the test score for math decreases by 2.8 percent for every 10 units increase in concentration level.

Similarly, the other pollutant like NO_2 and CO is closely associated with the concentration of level of PM_{10}. All the results show that there is a negative nonlinear relationship between the test score and the concentration of air pollutants.

The significance level of different air pollutants is given on table 10 using Wald statistics. This clearly shows that the PM_{10} concentration level has the most significant effect on the test score. The joint significance value using Wald statistics is 39.87. From the statistical analysis, it has found that all the air pollutant has some effect on the test score.

8 Conclusion and Future Work

This study reveals a clear relationship between the air pollutant and the test score. From the experimentation, it is clear that the test score decreases due to a lack of attentiveness in presence of a higher concentration of air pollutants. The PM_{10} level is the most significant effect on the test score of a student while NO2 and SO2 have some effect on the test score. In this work, it is also revealed that the measurement of attentiveness depends upon some sub-bands of EEG signal but the measurement of inattentiveness depends upon some other factors that will be a future case of study.

The air pollutants are not only responsible for creating health problems but also degrading the performance of the student. The govt. along with the people of each area should take an effective measure to reduce the air pollution level, which will reduce the effect of long-term cognitive problems in the future generation of the country.

Cutting-edge technology like block chain, cloud computing, artificial intelligence can be utilized to securely investigate the real-time data in a virtual class environment for further analysis and to create a future road map to reduce the air pollutant. Furthermore, the effect of sound pollution and water pollution on the cognitive response and attentiveness of the student would be investigated in future work.

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