Indoor Air Quality Detection Using Hybrid Machine Learning Techniques

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Abstract:

The neutral of this study is to prevent asthma by detecting air quality in indoor environments using machine learning techniques. To achieve this, the study collected 11,757 samples from three air quality datasets available in UC Irvine Machine Learning Repository and Kaggle. These samples were before separated into training and test datasets to quantify the concert of the Fake Neural Network (ANN) algorithm using performance metrics such as exactness, specificity, sensitivity, and precision. The results showed that the proposed ANN procedure completed an accuracy of 95.254%, while the Verdict Tree algorithm achieved an accuracy of 92.96%. The statistical analysis conducted showed a significant accuracy ratio of p (<0.05). The study concluded that ANN algorithm achieved improved than the Conclusion Tree algorithm for detecting air quality in the datasets considered.

Keywords: ANN, significant accuracy, preventing asthma.

Introduction:

Indoor air quality is crucial to the health of all living beings, as pollution exists not only in outdoor areas but also in indoor environments [1]. Since people spend about 90% of their time inside, it is important to keep clean indoor air to prevent health problems [2]. Indoor air pollution caused by burning solid fuels and freon gas releases from refrigerators leads to almost 1.5 million deaths annually [3]. In some cases, pollutant concentrations can reach hazardous levels active to 100 times higher than normal levels, posing a threat to human health [2,4]. The primary bases of indoor air pollution include chemical, building, besides office materials [5].

Chemical products like air fresheners and cleaning agents emit unpredictable carbon-based mixtures (VOCs), while building and office materials such as printers and carpets release contaminants like dust into the air [5,6]. Indoor air quality detection is relevant for a variety of settings, including industries, mines, hospitals, homes, and all types of workplaces.

Previous research has explored various approaches to predicting air quality. For example, a spatial-temporal ensemble model was introduced in [7], but ensemble models can be difficult to interpret. Yi et al. [8] proposed a DNN-based approach based on domain knowledge about air pollution, but this method requires a large amount of data to perform well. Soh et al. [9] developed an air value predicting system using data-driven models such as ST-DNN and CNN, but it requires a significant amount of training data and does not encode the position and orientation of the object. Tso et al. also investigated air quality prediction using methods such as Multiple Linear Regression, Verdict Trees, before Multi-layer Perceptron Artificial Neural Networks. However, reducing the number of inputs and simplifying the model was deemed more effective than using the original data. Tso et al. [10] demonstrated a forecasting method for the next day's air quality index consuming Multiple Linear Regression (MLR), Conclusion Tree, and many-layer Perceptron Fake Neural Network (ANN) models. However, they found that reducing the number of inputs and decreasing model complexity was more effective than using the initial data. As experienced researchers with a track record of working on diverse projects [11-14], we have decided to pursue this topic due to its growing importance.

In summary, the existing research on air quality detection is limited by factors such as the use of small sample datasets, complex and expensive devices, and chaotic environments. Additionally, previous studies have relied on data-driven approaches with few attributes considered as features. To address these limitations, the proposed work aims to overcome these challenges by utilizing a moderate-sized dataset, incorporating more attributes as features, using simple and accurate modeling techniques, and conducting in-home air quality detection. The impartial of the anticipated work is to detect air quality in the home environment to prevent asthma diseases. The study will use metal oxide sensor data and machine learning algorithms for automated detection.

Materials and Methods:

The Artificial Intelligence lab at Saveetha School of Engineering is currently conducting a project on air quality detection using machine learning techniques. The study comprises two simple groups for air quality detection, with a total sample size of 11,757 samples. The determination of the required number of illustrations for this analysis was carried out using G-power calculation. The air quality dataset, collected from Kaggle and UCI repository, undergoes preprocessing to handle missing data, replace null values, and standardize the data before being fed into the machine learning models. The dataset was divided into 80% training data and 20% testing data. The features of this preprocessed dataset serve as inputs for both the Artificial Neural Network (ANN) and Decision Tree (DT). The project is conducted by Pallienti Jahnavi and Prof. Kirupa Ganapathy from the Subdivision of Electronics and Communication Engineering, Saveetha University Chennai, India.

The proposed project is focused on using an ANN for air quality detection, which will be assigned to group 1. The dataset used in this study is sourced from the UCI archive and contains 9471 air quality recordings. The dataset was generated by gathering hourly measurements from five metal oxide chemical sensors integrated into an Air Quality Chemical Multisensor Device. This device calculates seven average response attributes. The placement of the device was in an Italian city, specifically in a heavily polluted area at the road level. The data were recorded continuously for a duration of one year. Additionally, hourly measurements of carbon monoxide (CO), non-metallic hydrocarbons (NMH), benzene, total nitrogen oxides (NOx), and nitrogen dioxide (NO2) were recorded using a certified reference analyzer situated in the same building.

The Indian air quality dataset (IAQD), compiled by Kaggle, includes information on 824 air quality measurements with seven different parameters for each measurement. The data has been collected in real-time from field instruments by the Indian Government and is being displayed in real-time without human intervention. However, it is possible that some inaccuracies or aberrant values may appear in the live data due to episodes or instrument malfunctions at any given time. The IAQD (Indoor Air Quality Detection) system integrates real-time data from different monitoring stations across India, providing information on the National Air Quality Index (AQI) values. This system measures various pollutants, including sulfur dioxide (SO2), nitrogen dioxide (NO2), particulate matter (PM10 and PM2.5), carbon monoxide (CO), ozone (O3), and other harmful substances. Additionally, a dataset named the Air Quality dataset (AQDS) has been discovered on Kaggle. It comprises 1462 air quality samples with nine different variables. The dataset incorporates real-time readings of the National Air Quality Index values obtained from various monitoring stations across India.

Table 2 displays the statistical features utilized to train the learning algorithm, encompassing the mean, standard deviation, slightest, 25th percentile, 50th percentile, 75th percentile, and maximum values of the variables. The learning process of the machine learning classifiers, including Artificial Neural Network (ANN), Logistic Regression, and Decision Tree, is described as follows. The ANN branch of machine learning draws inspiration from the biological neural networks found in the human brain, wherein artificial neural networks consist of interconnected layers of neurons, mirroring the structure of the human nervous system. Nodes are a type of neuron found in the brain. The majority of AI neural networks are composed of three layers (as shown in Figure 1). Inputs and their weighted sum are calculated using weighted summation and bias. Equation 1, as described by the authors of this article [16], represents this computation as a transfer function.

$$\sum_{i=1}^{n} \mathrm{wi} * \mathrm{xi} + \mathrm{b} \tag{1}$$

Activation functions play a crucial role in generating the desired output by taking the weighted sum as input and determining whether a node should be activated. The output layer is accessible only to the activated nodes. The type of activity being performed determines the available activation functions.

The comparison between the ANN and DT (Decision Tree) classifier conducted using the open-source platform Google Colab. The algorithm was executed utilizing the Python programming tool and a computer system equipped with a core i5 processor and 4GB RAM.The Linear ANN and Decision tree models are trained with 80% of the data, including all the extracted features, from the total sample size.

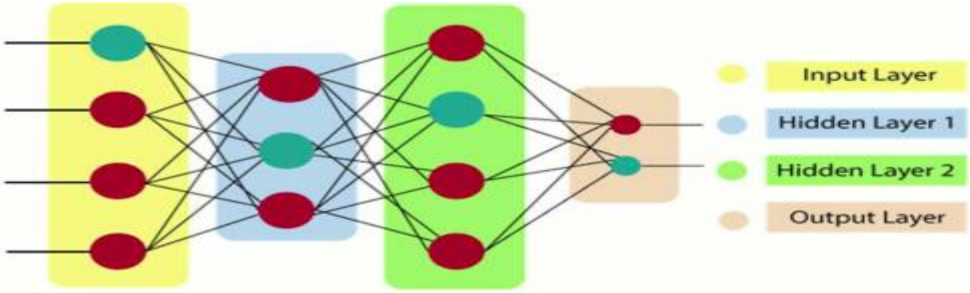

Figure 1 depicts the various types of layers that make up an Artificial Neural Network, including the Input layer, an Output layer, and Hidden layers.

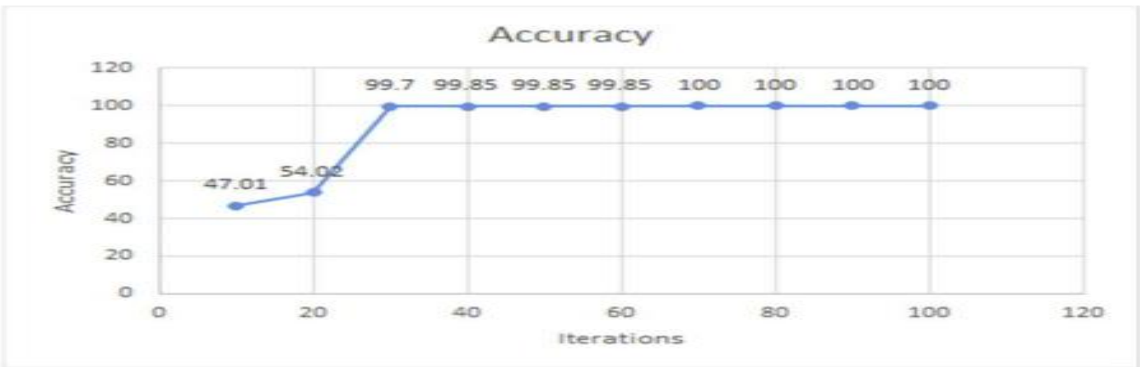

Figure 2, outlayer of Artificial Neural Network is demonstrated across multiple iterations. The graph illustrates that at the 30th iteration, the accuracy level of the ANN had increased to 99.7%. As the number of iterations increased, the accuracy level remained constant after the 70th iteration.

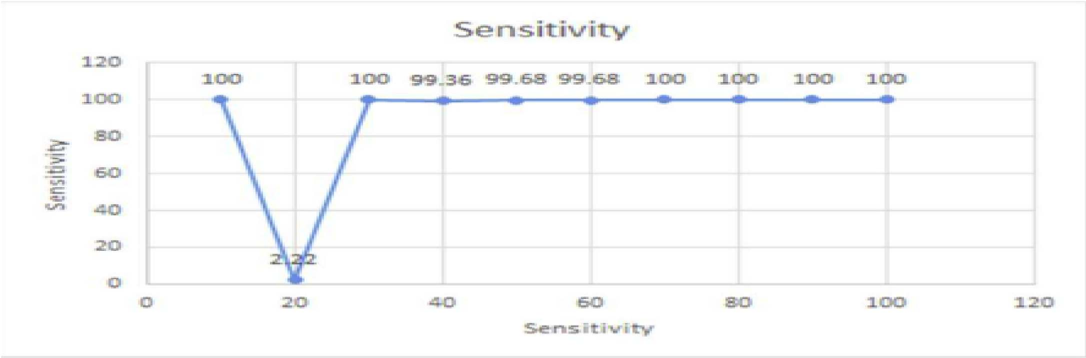

Figure 3 displays the Sensitivity performance of an Artificial Neural Network at various iterations. The graph indicates that there was a drop-in sensitivity at the 20th iteration, but as the number of iterations increased, sensitivity levels varied slightly and remained constant after the 70th iteration.

To train a machine learning model effectively to identify different classes, it is necessary to repeatedly iterate over the training process to improve its performance. After training, the model is then tested with random data to accurately identify the respective classes. Prior to applying the air quality dataset, which is available from Kaggle and UCI repositories, to machine learning models, pre-processing is required. This processing may include replacing missing data or values of null accompanied with the mean or median values, as well as standardizing the data. The pre-process dataset is used as input both ANN, Decision tree models, with 80% of the data used for training and 30% for testing. The independent variables in the data set include nation, state, town, home, last update, normal, minimum, maximum, and impurities, while the dependent variables are Accuracy and Sensitivity.

Results:

Table 1: presents data obtained from the UCI repository and Kaggle, indicating the number of ranges and attributes, as well as the number of classes. Table 2 displays the statistical features used to train the learning algorithm, which were derived from the data. The features encompass the mean, standard deviation, minimum, 25th percentile, 50th percentile, 75th percentile, and maximum values of the variables. The table further presents details on the learning processes employed by the artificial neural network (ANN) and support vector machine (SVM) classifiers. Table 3 provides a concise overview of the accuracy results obtained from the ANN and Decision tree classifiers across different datasets. The study shows that, in the Air quality dataset, the ANN algorithm achieved a detection accuracy of 94%, precision of 94%, sensitivity of 93%, and specificity of 96%. For the Indian air quality dataset, the accuracy was 97%, precision was 97%, sensitivity was 83%, and specificity was 96%. In the Air quality (Kaggle) dataset, the accuracy was 92%, precision was 92%, sensitivity was 93%, and specificity was 96%. Table 4 showcases the performance evaluation of the Artificial Neural Network (ANN) and Decision Tree algorithms based on mean accuracy, standard deviation, and standard error mean. The analysis reveals that the ANN algorithm outperforms the Decision Tree algorithm. Furthermore, Table 5 presents the statistical analysis of 10 samples, indicating that the K-Nearest Neighbors (KNN) algorithm exhibited a standard deviation of 2.4 and a standard error of 1.29114, while the (DT) algorithm demonstrated a SD (Standard Deviation) of 2.4 and a (SE) Standard Error of 0.7%. Furthermore, Table 5 presents the results of an independent sample test that was conducted on the accuracy values. The degree of significance indicates that our hypothesis is correct, as the sample size is less than 0.05. The results suggest that there is a significant change in the output values (dependent variables) due to alterations in the input values. Figure 2 displays a graph depicting the relationship between the number of iterations and the accuracy values. The graph indicates that the accuracy values are at their highest when the iteration values are at their lowest, and as the number of iterations increases, the values tend to become constant. Figure 3 displays the graph of the sensitivity of the ANN algorithm, which shows that there is a change in the sensitivity graph as the number of sources increases. Figure 4

show the graph of the specificity of the ANN algorithm. The graph shows a level of constancy as the iteration values increase. Figure 5 presents the graph of the precision of the ANN algorithm. The graph indicates a constant level when the iteration values increase. Figure 6 illustrates a comparison between the standard deviations of the Artificial Neural Network (ANN) and Decision Tree algorithms. Through the use of an independent t-test, We compared the two methods and found that there was a statistically significant difference between their mean accuracy values.

Figure 4 illustrates the concert of the ANN algorithm in relations of specificity for different iterations. The graph shows that at the 30th iteration, the accuracy level of the ANN algorithm increased to 99.7%. However, as the iteration level increased further, the accuracy became constant, and there was no significant improvement in the specificity performance beyond the 40th iteration.

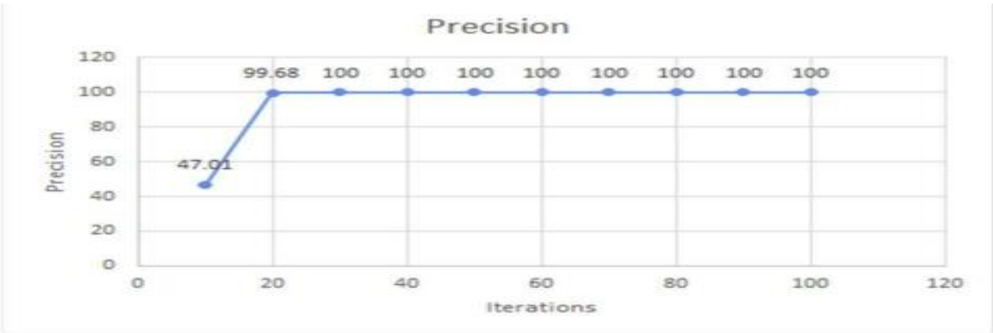

Figure 5 presents the precision performance of the ANN algorithm for different iterations. The graph shows that at the 10th iteration, the precision was 47.01%. However, at the 20th iteration, the precision performance increased significantly, reaching 99.68%. As the iteration level continued to increase, the precision performance became constant, and there was no significant improvement beyond the 30th iteration.

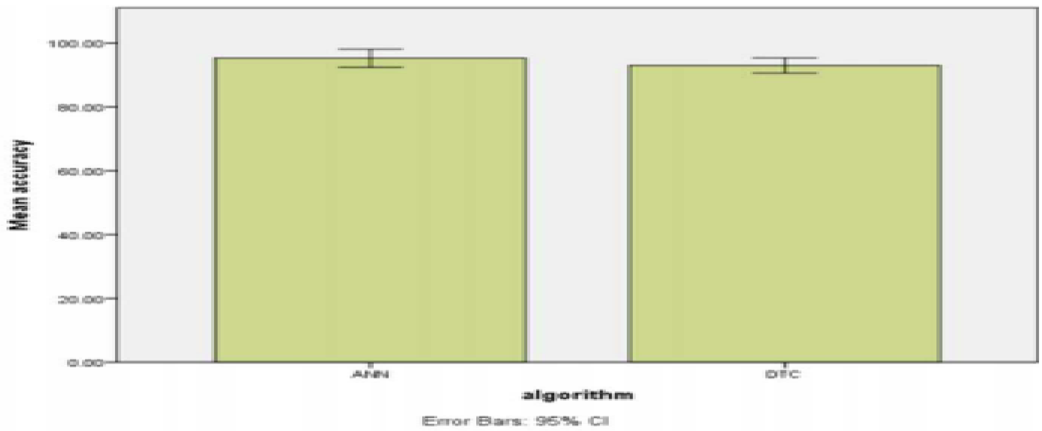

Figure 6 equates the mean accuracy of ANN and DT algorithms. The graph clearly depicts that the mean accuracy of the ANN algorithm is higher than that of the Decision tree classifier, suggesting that the ANN algorithm performs better in terms of accuracy.

Table 1 summarizes the attributes, ranges, and classes of different datasets. The Air Quality dataset collected from UCI has 9471 ranges, the Indian air quality dataset has 824 ranges, and the Air quality dataset collected from Kaggle has 1462 ranges, with 17, 7, and 9 attributes, respectively. Each dataset has a single class.

Datasets	No.of Ranges	Attributes	Class
Air quality dataset (UCI)	9471	17	01
Indian air quality dataset	824	07	01
Air quality dataset	1462	09	01

Table 2 displays the statistical features used for training the learning algorithm, which include mean, standard deviation, minimum, 25% quantile, 50% quantile, 75% quartile, and maximum. The table also presents the learning process of the ANN and Decision tree classifiers.

	Count	Mean	Std	Min	25%	50%	75%	Max
Country	824.0	0.00000	0.000000	0.0	0.00	0.0	0.00	0.0
State	824.0	7.701456	5.326127	0.0	2.00	8.0	12.00	16.00
City	824.0	27.763350	17.703816	0.0	17.00	18.0	39.00	70.0
Place	824.0	65.621359	38.238680	0.0	32.00	66.0	98.0	131.0
Last update	824.0	0.0000000	0.0000000	0.0	0.00	0.0	0.00	0.0
Avg	824.0	81.287621	77.302273	0.0	20.00	51.5	119.25	284.0
Max	824.0	120.520631	92.850889	0.0	36.75	106.0	183.25	322.0
Min	824.0	45.547330	55.642477	0.0	6.00	21.0	61.00	216.0
Pollutants	824.0	3.033981	2.018459	0.0	1.00	3.0	5.00	6.0

Table 3 provides a comparison of the ANN and Decision tree classification algorithms in expressions of their evaluation metrics, with Accuracy, Specificity, Sensitivity, and Precision, across various datasets. For the Air quality dataset, the ANN algorithm achieved an accuracy of 94%, precision of 94%, sensitivity of 93%, and specificity of 96%. In the Indian air quality dataset, the accuracy was 97%, precision was 97%, sensitivity was 83%, and specificity was 96%. In the Air quality (Kaggle) dataset, the accuracy was 92%, precision was 92%, sensitivity was 93%, and specificity was 96%.

DATA SET	ANN		DECISION TREE	
Air quality dataset (9471x17)	Accuracy	94	Accuracy	94
	Precision	94	Precision	92
	Sensitivity	93	Sensitivity	93
	Specificity	96	Specificity	92
Indian air quality dataset (824x7)	Accuracy	97	Accuracy	90
	Precision	97	Precision	80
	Sensitivity	83	Sensitivity	90
	Specificity	97	Specificity	95
Air quality dataset (1462x9)	Accuracy	92	Accuracy	90
	Precision	92	Precision	94
	Sensitivity	93	Sensitivity	93
	Specificity	96	Specificity	94

Table 4 presents an overview of the performance of the Artificial Neural Network (ANN) and Decision Tree algorithms, highlighting their mean accuracy, standard deviation, and standard error mean. The results demonstrate that the ANN algorithm outperforms the Decision tree algorithm. Furthermore, the statistical analysis of 10 samples reveals that the ANN algorithm exhibited a standard deviation of 3.3 and a standard error of 1.5%, whereas the DT algorithm demonstrated a SD of 2.4 and a SE of 0.7%.

	Groups	N	Mean	Std. Deviation	Std.Error Mean
ACCURACY	ANN	10	95.2540	3.92601	1.24151
	DECISION TREE	10	92.9610	3.33028	1.05313

Table 5 presents the outcomes of an independent sample test conducted to assess the accuracy and error of an atom detection system using the Support Vector Machine (SVM) and Artificial Neural Network (ANN) methods. The degree of significance is determined by checking whether the p-value is less than 0.05. This level of significance allows for the calculation of a 95% confidence interval.

Leven's Test for Equality of Variance	t-test for Equality of Means	95% Confidence Interval of the difference f sig

Accuracy		F	sig.	T	dif	Sig (2 - tailed)	Mean difference. Std	Error Difference lower upper equal	lower	upper
	Equal Variance assumed	.496	.490	1.408	18	.176	2.29300	1.62801	-1.12733	5.71333
	Equal variance not assumed			1.408	17.534	.176	2.29300	1.62801	-1.13386	5.71986

Discussion:

This study demonstrates that the ANN algorithm outperforms the Decision tree classifier in classifying air quality with an accuracy of 95.254% (p<0.0.5). The analysis was conducted on a dataset obtained from Kaggle, which includes various attributes defining the air quality condition and different ratios of normal and affected individuals. The findings point to the fact that the ANN exhibits superior classification performance when paralleled to the DT classifier.

The performance of the ANN algorithm in finding the air quality from the dataset considered in this study is moderate in terms of accuracy. However, it is important to note that the dataset collected from Kaggle needs to undergo preprocessing before applying it to the machine learning process, as highlighted in previous studies [17, 18].

In order to prepare the dataset for machine learning, various preprocessing steps should be taken, such as removing null values, converting categorical and float values to numerical values, removing unwanted attributes, and replacing mean or median values [19,20]. However, comparing the proposed work with existing studies is challenging due to differences in the type of air quality datasets, number of classes, and amount of data [21]. The analysis was performed using both SPSS and Python tools, where descriptive statistics were computed for the ANN and Decision Tree algorithms. In the study, the independent variables encompass input variables such as the nation, the state, the city, the location, the most recent update, and the average, maximum, minimum, and impurities. On the other hand, the dependent variables consist of output variables including accuracy, precision, sensitivity, and specificity. An independent t-test was utilized in order to analyze and contrast the performance of each algorithm.

Our institution is dedicated to conducting high-quality research based on strong evidence, and it has attained excellence across various disciplines [13, 22-23]. The inspiration and methodology of this study draw upon previous research works [25-30]. We are confident that this study contributes to our institution's esteemed legacy. In future endeavors, enhancing the accuracy of the ANN algorithm can be achieved by augmenting the training dataset with more data, exploring multiclass SVM approaches, and integrating other ANN methods. Additionally, converting multidimensional data into binary data can improve accuracy.

Most of the techniques have been utilized while utilizing and constructing many smart and intelligent frameworks such ML approaches [31], Mining Techniques [32], Deep Learning [33-34], Smart cities approaches [35], Round Robin Scheduling approach [36], Knowledge sharing practices [37-38], Data security and privacy approaches [39-40], predictive approaches [41-44], Explainable Artificial

Intelligence (XAI) [45-46] and Transfer learning approach [47] that may assist assistance in designing developing solutions for the rising issues in designing smart management systems.

Conclusion:

The accurate detection of air quality is crucial for reducing the risks associated with hazardous diseases. Based on the present analysis, it is recommended that the ANN algorithm provides significantly better performance in detecting air quality related to the DT. The ANN produced an accuracy of 95.254%, however the DT algorithm had an accuracy of 92.96%, based on the datasets used in this study.

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