Inhalation Configuration Detection for COVID-19 Patient Secluded Observing using Wearable IoTs Platform

Sulaiman Sulmi Almutairi[1*], Rehmat Ullah[2], Qazi Zia Ullah[3], and Habib Shah[4]
[1] Department of Health Informatics, College of Applied Medical Sciences, Qassim University, 51452, Kingdom of Saudi Arabia
[e-mail: ssmtiery@qu.edu.sa]
[2] Department of Computer Systems Engineering, University of Engineering and Technology, Peshawar, Pakistan
[e-mail: rehmatullah@uetpeshawar.edu.pk]
[3] COMSATS University Islamabad Attock Campus, Attock, Pakistan
[e-mail: zia_comsian@yahoo.com]
[4] College of Computer Science, Department of Computer Science, King Khalid University Abha, Kingdom of Saudi Arabia
[e-mail: hurrahman@kku.edu.sa, habibshah.uthm@gmail.com]
*Corresponding author: Sulaiman Almutairi

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Abstract

Coronavirus disease (COVID-19) is an infectious disease caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus. COVID-19 become an active epidemic disease due to its spread around the globe. The main causes of the spread are through interaction and transmission of the droplets through coughing and sneezing. The spread can be minimized by isolating the susceptible patients. However, it necessitates remote monitoring to check the breathing issues of the patient remotely to minimize the interactions for spread minimization. Thus, in this article, we offer a wearable-IoTs-centered framework for remote monitoring and recognition of the breathing pattern and abnormal breath detection for timely providing the proper oxygen level required. We propose wearable sensors accelerometer and gyroscope-based breathing time-series data acquisition, temporal features extraction, and machine learning algorithms for pattern detection and abnormality identification. The sensors provide the data through Bluetooth and receive it at the server for further processing and recognition. We collect the six breathing patterns from the twenty subjects and each pattern is recorded for about five minutes. We match prediction accuracies of all machine learning models under study (i.e. Random forest, Gradient boosting tree, Decision tree, and K-nearest neighbor. Our results show that normal breathing and Bradypnea are the most correctly recognized breathing patterns. However, in some cases, algorithm recognizes kussmaul well also. Collectively, the classification outcomes of Random Forest and Gradient Boost Trees are better than the other two algorithms.

Keywords: COVID-19, SAR, Breathing Abnormality, IoTs, Wearable Sensors, Machine Learning.

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1. Introduction

The Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) virus causes the unique coronavirus illness (COVID-19) [1], which attacks the human lungs directly, causing severe respiratory damage. A severe case of this illness might result in serious respiratory failure [2]. Because COVID-19 greatly effects on the respiratory system, it's reasonable to believe that breathing changes might occur during the early stages of infection [3]. Very still, a grown-up respiratory rate ought to be somewhere in the range of twelve and twenty breaths each minute. It becomes sporadic assuming when less than twelve or more than twenty breaths each minute. Abnormal respiratory rates might be slow, shallow, fast, intense, or a combination of these. Unfortunately, these irregular breathing patterns happen in such a way that the patients are unable to perceive them. U. Saeed *et al*, in [4] have discussed six different human respiratory/breathing patterns (i.e. Biot, Kussmaul, Eupnea, Sighing, Bradypnea, and Tachypnea). Eupnea is a standard respiratory with a typical musicality and recurrence brought about by a solid way of life, however biot is a serious breathing condition with slow time periods of no-breaths brought about by vertebral meningitis or head wound. On the other hand the breathing pattern of bradypnea is gentle and narrow caused by a concussion, sleeping medications, a metabolic disease or a stroke. Respiratory tension causes sighing, which can be caused by dyspnea, anxiousness or dizziness. In contrast tachypnea has a fast and narrow pattern that is caused by stress, fever, shock, or exercise. At last, kussmaul (arises because of metabolic acidosis, diabetic ketoacidosis, or renal disappointment) is a serious and quick respirational example.

In the literature, many technologies and strategies for examining and classifying distinct breathing patterns have been published. Spirometry is the best technique in hospitals for determining air volume and flow during inhalation and exhalation, however the patient must go to the hospital for this. As a result, techniques and systems that allow patients to be monitored remotely and efficiently are necessary [5]. Inductance pneumography [6], electrical impedance pneumography (EIP) [7], and capnography [8] are some of the other breathing methods utilised in hospitals. Camera-based sensing and RF sensing are examples of non-contact measurements. A thermal imaging camera or a depth camera can be used for camera-based sensing [9]. Both of these camera-based systems have drawbacks; for example, thermal imaging is sensitive to ambient heat [10], while depth cameras are costly and computationally intensive. The wearable mask device can correctly monitor and recognise critical respiratory characteristics such as respiratory rate, tidal volume, respiratory minute volume, and exhalation peak flow rate [11]. The C-Band detecting approaches were utilized by a few creators [12] for various well-being observing issues like respiratory discovery, quake, and persistent obstructive pneumonic illness cautioning, though the Res-Beat plot was intended to quantify the pace of breath [13].

The ever-growing Internet of Things (IoTs) promotes further efficient and comprehensive healthcare through wearable and interconnected devices. These connect numerous wearable sensors, mobile devices, cloud storage, and data centres to interact, communicate, gather, and exchange data across a wired or wireless network [14]. Data from IoTs devices may be studied in depth to create insights and helps in decision-making. Deep Learning/ Machine Learning (ML/DL) algorithms are at present being used for this reason, and they are dislodging more customary methodologies because of their ability to deal with a lot of information. Different machine learning techniques have been routinely employed to swiftly identify possible coronavirus infections from real-time data [15].

Following are the main purposes of this proposed work:

- A platform to get and perceive breathing configurations and anomalies using wearable sensors.
- IoTs framework for minimizing spread through isolating the COVID-19 susceptible and patients.
- Performance comparison of various machine learning algorithms for better recognition accuracy for the breath pattern for COVID patient breathing difficulties

The rest of the paper is organized as follows:

Section 2 briefly introduces the background and related works. Sections 3 explains the proposed framework and methodology. Section 4 discusses results and performance comparison, and at last we close this investigation in segment 5.

2. Research Foundation

In this part, momentarily we center on the foundation and the connected work done in regard to the stage employed for breathing patterns recognition, sensor situating, and investigation of various AI-enabled techniques for COVID-19 detection.

According to recent medical studies, a person infected with COVID-19 has a different respiratory pattern than someone who has the flu or a normal cold. An irregular breathing rate is one notable sign of COVID-19 infection; those infected with COVID-19 have faster breathing [43].

Doctors use a medical instrument called a spirometer in hospitals to monitor how much air a person breath in and out, as well as the pace with which they breathe. Spirometry is a test that is used to identify asthma, chronic obstructive pulmonary disease (COPD), and other respiratory disorders. Spirometry can also be used on a regular basis to evaluate a person's lung status and see if a therapy for a chronic lung problem is improving their ability to breathe. Regardless, many approaches have been utilized to identify breathing patterns in real time, which can be useful in COVID-19 infection prediction, diagnosis, and screening [16]. In [3], machine learning (ML) algorithms and radio frequency sensor methods (based on software-defined radio (SDR)) are combined. That identify and categorize various patterns of breathing. For classification, machine learning algorithms are used, and their performance is measured in terms of accuracy, training time, and prediction speed. For automatic breathing patterns detection a harmless breathing examination innovation is fostered in [17]. They used convolutional neural network for breathing event detection and patterns classification. It delineates that breaking down chest and stomach development information through wearable sensors utilizing deep learning gives a subtle approach to checking breathing patterns. Breathing patterns that are abnormal might be fast, slow, deep, or shallow, or a mix of these. Eupnea, tachypnea, bradypnea, sighing, Biot, and kussmaul are some of the various breathing patterns [18]. Eupnea is normal breathing, but bradypnea is shallow and slow breathing; the opposite if which is Tachypnea i.e., shallow, and fast breathing. Kussmaul is a profound and quick breath, sighing is inhalation hindered by numerous full breaths, and biot is a full breath with expanding terms of no inhalations. An assessment of the &gesund framework's respiratory rate location was proposed in [19]. &gesund is a health-assistance system that uses smartwatches to automatically capture extensive long-term health data. The study demonstrated the feasibility and accuracy of using a wristwatch to monitor respiration rate as a non - intrusive way of gathering long-term health data. In [11], there is a wearable, independent, totally coordinated cover gadget for thorough breath following in free-living settings. In a wearable and wireless way, the wearable mask device may offer full respiratory information. It uses Principal Component Analysis (PCA) methods to unfailingly measure peak flow rate, breathing rate, respiratory minute volume, and, tidal volume as well as detect the subject's individual respiration pattern. Using a machine learning approach, the breathing patterns were identified based on EEG data in [20]. It proposed a technique for reducing the negative implications of mouth inhalation on brain activity. Machine learning can accurately predict the direct implication of oral and nasal inhalation on mental performance using EEG data.

A harmless SDR-based technique is proposed in [4] with advanced machine learning algorithms. The device is intended to identify and monitor six different human breathing patterns, both normal and disordered, including eupnea, bradypnea, tachypnea, biot, kussmaul and sighing. It is a practical method for identifying and classifying numerous breathing patterns in an indoor scenario. In [21], an novel solution is proposed for linked health utilizing software-defined radio (SDR) technology and artificial intelligence to give an innovative solution by remotely monitoring vital signs such as breathing and other connected health throughout the quarantine (AI). In [22], a platform that uses Software Defined Radio (SDR) technology is proposed to identify COVID-19 signs such as coughing and irregular breathing, as well as track human motions. Using several approaches such as peak detection, Fourier transformation and zero-cross detection, this platform reliably records slow, normal, and fast breathing at a rate of 10, 20, and 28 breaths per minute, respectively. To improve outdoor safety, a hybrid IoT based monitoring system is proposed [23] that takes into account both health and safety. In this system, safety indicators and health signs both from surroundings and users are collected using wearable devices. Wi-Fi signals [24], thermal imaging-based solutions [25] and capacitive field sensing [26], are promising techniques for data detection. Additionally, smart watches are capable to detect heart and breathing movements and can easily communicate directly or through smartphones [19].

The current area of research is the use of wearable devices to monitor breathing patterns and their recognition. McClure et al. [17] developed a deep learning detection system that uses skin-worn sensors along with one dimensional Convolutional neural network. Another work analyzed the performance and stability of BreathPrint by RNN based models. Detecting breathing patterns from speech using wearable devices also becomes an important field of research. In this area, Strik et al. [27] explore machine learning approaches and find their effectiveness in recognizing breathing patterns during speech. Cho et al. used Convolutional neural network to identify deep breathing [18]. Different authors identified and recognized various normal and abnormal breathing using wearable devices and machine learning architectures that include wearable mask along with principal component analysis techniques [11], bi directional and attentional GRU, LSTM algorithms [28], Complex tree, Coarse and Ensemble subspace KNN [3], SVM, decision tree [21], and LDA, bagged trees [29]. COVID-19 cough and breath recognition is done by Khriji [30] in which he proposed a wearable devices and LSTM based model to differentiate COVID patients from those of healthy individuals. Comprehensive details from the literature are given in **Table 1**.

Our work for example the Gradient Boost Trees based prediction achieved F1 score of 0.95 for each of class 1 and class 2. While the mean F1 score of all six classes achieved is 0.89. Whereas the mean F1 score (i.e. (0.92+0.87+0.51+0.57+0.63+0.72)/6) of reference [17] from literature is 0.70. Thus our system outperformed the reference [17] results.

Table 1. Examination and Correlation of Allied Work

Ref. No	Dataset	Sensors/ Technology	Position	Breathing Patterns	Algorithm	Accuracy
[17]	100 normal people	Accelerometer, gyroscope	Attached to the chest and upper abdomen of each subject	Normal, sighing, focal rest apnea, obstructive rest apnea, coughing, and yawning	1-D CNN	F1 score 92%, 87%, 72%, 51%, 57%, 63%
[19]	From 2 sleep patients for 2 nights	Smartwatch (Accelerometer, gyroscope, PPG)	Wrist	Ballistopneumo-graphy based respiratory rate detection	&gesund	89%
[11]	IRB reference protocols # STUDY00006562	Wearable Mask device, Sensirion SFM3000 flow sensor	Mouth	Respiratory rate, tidal volume, respiratory minute volume, breath temperature	PCA	Correlation factors are 1, 0.0009, 0.0009, 0.997
[20]	20 subjects	EEG, EOG, ECG	Scalp	Nose and mouth, mouth breathing with O_2 supply	Linear discriminant analysis RF	98%
[28]	Respiratory signal of 20 subjects (12 females, 8 male)	Depth camera	Subjects were at 1-4m from the depth camera	Eupnea, Tachypnea, Bradypnea, biots, Cheyne-stocks, Central apnea	BI-AT-GRU, BI-AT-LSTM, GRU, LSTM	94.5%
[3]	5 sets from 5 persons (150 experiments)	Radio Frequency sensing techniques	-	Eupnea, Bradypnea, Tachypnea, Biot, Sighing, Kussmaul	Ensemble subspace KNN, Quadratic SVM, Coarse KNN, Complex Tree	98.6%, 97.3%, 94.2%, 99.4%
[31]	76 patients from a sleep laboratory	3D cameras	The camera is installed in the ceiling, aimed at the patient.	Normal breathing, Abnormal Breathing	CNN	61.87%
[30]	Publicly available Data for sick and non-sick people produced for Pfizer Digital Medicine Challenge	Smartphone and wearable sensors	-	Audio signal for Coughing, Sneezing, and breathing	LSTM	80.26%

[14]	2 datasets from 13 subjects	Wearable respiratory and activity monitoring system, Breathing sensor, Accelerometer,	chest-worn band	9 respiratory parameters for 15 activities	Hybrid hierarchical classification (HHC)	97.22%
[32]	2 males, 2 females. Data collected for 5 mins	Wearable RIP sensors	-	Breathing recordings for reading aloud, food intake, resting, smoking	Peak detection Algorithm	96.6%
[33]	328 cough sounds from 150 patients	-	Data is taken from different online and offline sources	COVID-19, Asthma, Bronchitis, and Healthy	deep neural networks and TabNet	95.04% and 96.83%
[34]	Sounds from about 7000 unique users.	A mobile app	-	Sore throat, dry and wet cough, muscle ache, short breath, headache, Tightness, smell taste loss	Logistic Regression, Gradient Boosting Trees and (SVMs)	80%
[35]	Video data from five subjects (3 h for each subject)	MS Kinect Sensor v2	In front of the subject in the direction of 45° at a distance of 2.5 m.	Apnea	-	-
[36]	Three breathing events from Single person	USRP	the distance between the subject and USRPs antenna keep it as 0.4 meters	normal, shallow, and heavy	KNN, DT, Discriminant Analysis (DA), Naive Bayes (NB)	91%
[24]	10 participants	Wi-Fi devices	-	Breathing and Heart rate Pattern: Positive, Negative	Dynamic Time Warping algorithm	94%
[37]	4 samples from 2 subjects	BD and FLIR camera	-	Eupnea, Tacypnea, Kussmaul, Apnea, Cheyne–Stokes, Moderate obstructed, Severe obstructed, Plateau after inhale-exhale, and Nasal Flaring.	A nearest neighbor data association (NNDA) and nearest neighbor Kalman filter (NNKF) based algorithms, multi-class SVM	60%

[38]	-	Ultra-wideband Radar	Radar gadget at 20 cm distance from the chest of an individual while lying on the bed in an ordinary state.	Bradypnea, tachypnea, motion, eupnea, and apnea	1-D CNN, SVM, MLP, LDA	93.9%

3. Proposed platform for COVID-19 Patient Recognition (C-PR)

In this segment, we portray the proposed stage, information obtaining from sensors, features extraction, and the classifiers utilized for recognition of breathing patterns acquired from sensors.

3.1 Software of the proposed COVID-19 Patient Recognition system

Fig. 1 shows the complete design of the proposed system that comprises of three primary parts. In the first part it extracts sensors data and preprocess the acquired data to be suitable for recognition system in the second part of the architecture. In the second part it extracts features from the sampled data (taken from preprocessing system) and trains machine learning models on training dataset. Trained models are then tested on the test dataset for prediction metrics comparisons of the models. The tested models are deployed in real-time environment for real-time analysis. In the third section the prediction results are displayed for monitoring by the domain expert (doctor) and/or user. The doctor can prescribe medications and suggest further medical explorations in medical laboratories. The proposed system provides the firsthand knowledge and recommendation about the patient conditions.

3.1.1 Data Collection

For data collection, we fixed the Meta-wear sensors module (that includes accelerometer and gyroscope) on the lower abdomen of the participant. We fixed the accelerometer and gyroscope sampling frequency to 50 Hz by configuring the sensors module.

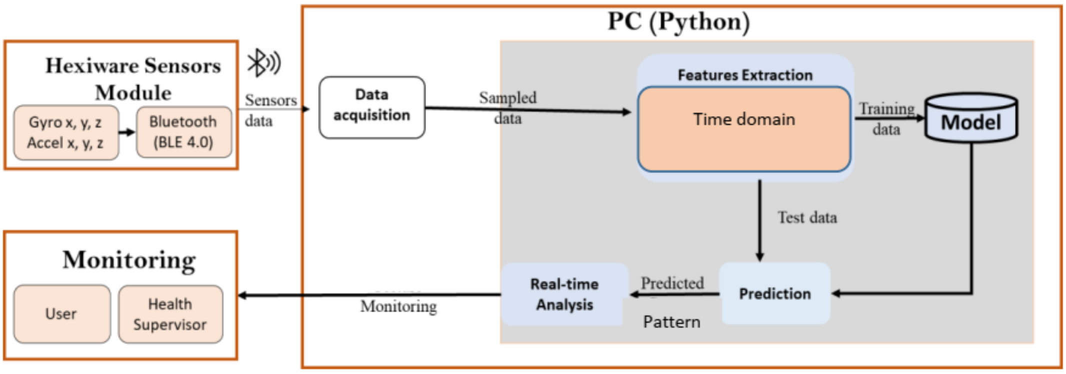

Fig. 1. Detailed architecture of the proposed work

Table 2 describes the configuration of the sensor attached to the body in terms of quantization and sampling. Dimensions for both gyroscope and accelerometer are x-axis y-axis and z-axis.

Table 2. Information about the Sensors Configuration

Sensor	Sampling frequency	Quantization level
Accelerometer	50Hz	16-bit
Gyroscope	50Hz	16-bit

Meta wear device, which contains built-in sensors, can be configured using an android/IOS application called metabase[1] that is available online. Sensor devices and the Metabase app. are connected via Bluetooth. The data collection included 20 participants (of ages from 25 to 30) who recorded various breathing patterns. We have collected the six breathing patterns from each subject and each pattern is recorded for about five minutes. We conducted the experiments in a small room—10 square feet. The participant sat on a chair, and the sensor module was fixed on lower abdomen. The participants were asked to mimic six breathing patterns. The subject were not allowed to make any movement that can cause noise. The breathing patterns that we followed are: Normal, Bradypnea, Tachypnea, Biot, Kaussmaul and Sighing. **Fig. 2** shows the actual representation of these breathing types. **Table 3** shows the breathing patterns for which data is recorded and their respective labels.

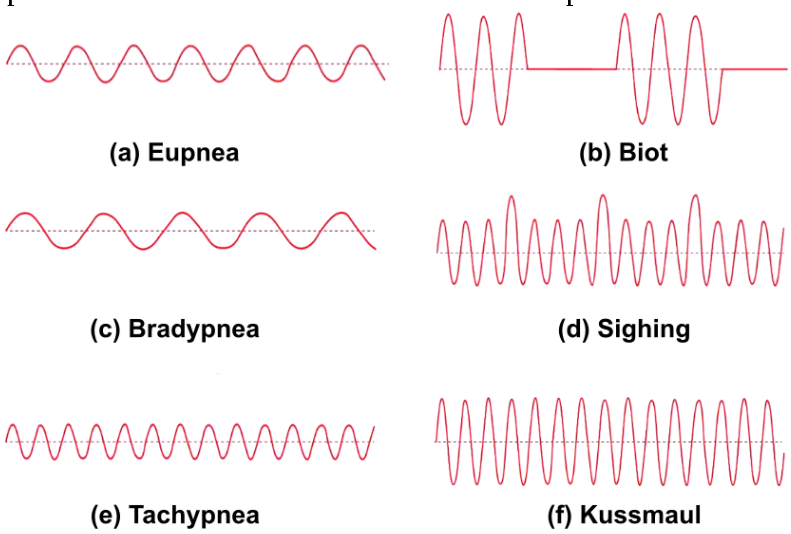

Fig. 2. Different breathing patterns [4]

Table 3. Breathing patterns encoding

Breathing Pattern	Class	Label-Code	Breathing Pattern	Class	Label-Code
Normal	Class 1	1	Biot	Class 4	4
Bradypnea	Class 2	2	Kussmaul	Class 5	5
Tachypnea	Class 3	3	Sighing	Class 6	6

[1] https://mbientlab.com/tutorials/MetaBaseApp.html

3.1.2 Techniques for Extracting Features and Encoding

The gathered information is restricted to the window size of 15 seconds. The sets of features are extracted from the window. Then features are encoded to their respective labels. The encoded labels are used for training and testing machine learning models. The trained and tested models are used for deployment in real-time environment.

Mathematical details of features extracted in time domain are given below in equations (1-7). The input symbols represent axes values of the accelerometer and gyroscope. For example x_i in equation (1) represents accelerometer axis sample value taken at rate of 50 samples per second.

Mean Feature: This feature is the arithmetic mean of the accelerometer and gyroscope data using equation (1).

$$\boldsymbol{\mu = \frac{1}{N}\sum_{i=0}^{N-1} x_i} \quad (1)$$

Standard Deviation (SD): This feature is formulated from the spread of sensors data about the mean feature as given in (2),

$$\sigma = \sqrt{\frac{\sum_{i=0}^{N-1}(x_i-\mu)^2}{N}} \quad (2)$$

Entropy: Entropy given in (3), is useful to differentiate between activities.

$$\text{Entropy} = -\frac{1}{N}\sum_{i=0}^{N-1} x_i \log x_i \quad (3)$$

Cross correlation: Cross correlation as given in (4), helps to differentiate between activities.

$$\text{Cr} = \frac{C\,(x,y)}{\sigma_x\sigma_y}$$

Whereas, C is covariance, and Cr represents cross correlation

$$C\,(x,y) = \frac{\sum_{i=0}^{N-1}(x_i-\mu_x)(y_i-\mu_y)}{N-1} \quad (4)$$

Zero-Crossing (ZC): The number of times the signal crosses zero and changes its sign is alluded to as zero-crossing. We consider ZC as given in (5) for the accelerometer along three axes. Mathematically, it can be written as:

$$\text{ZC} = \text{COUNT}\,(\{(x_i > 0)\ \text{AND}\ (x_{i+1} < 0)\}\ \text{OR}\ \{(x_i < 0)\ \text{AND}\ (x_{i+1} > 0)\}), \quad 0 \le i \ge N-1 \quad (5)$$

Root Mean Square (RMS): RMS given in (6), is the square root of the mean square.

$$\text{RMS} = \sqrt{\frac{1}{n}\sum_i x_i^2} \quad (6)$$

Peak Value: Peak value given in (7), is defined as the highest value obtained by an alternating quantity during one cycle.

$$V_p = V_{RMS} * \sqrt{2} \tag{7}$$

3.1.3 Data Set Training and Testing Split

We have divided the dataset into training and testing datasets with the ratio of about 90: 10. The 90 percent of data is used for training the ML models, while the remaining 10 percent for testing purpose. As mentioned in section 3.1.1, we have collected 6 breathing patterns from 20 participants. Then from each breathing pattern we have extracted 7 features as discussed in section 3.1.2. Thus in total our dataset has 11980 samples and each has 7 features, of which we have used 10780 samples for training and remaining 1200 samples for testing the trained ML models.

3.2 Classification Algorithms for the Proposed Work

In this study we classified our sensors encoded dataset using multiple machine learning models. We conduct our experiments for each ML model in two phases. First we train the model with training dataset and in second phase use the testing dataset for evaluating the trained model. We then find the testing classification metrics for each pattern's actual versus predicted labels using the confusion matrix.
In our study we have used four classification models (i.e. K Nearest Neighbor, Decision Tree, Random Forest, and Gradient Boost Trees) and compared their prediction results on test dataset.

3.2.1 K-Nearest Neighbour

The K Nearest Neighbor (KNN) classifier uses a lethargic learning approach, which infers that finding the connection between input qualities and their comparing labels happens after a test input is gotten. This technique discovers K number of neighboring samples that are similar to test input from the training data. The new label for test inputs is predicted using these examples and their accompanying labels. This proximity is achieved either via the Manhattan distance or the Euclidean distance (i.e. distance from each labelled class to new test example) [39].

3.2.2 Decision Tree

To make it simpler to comprehend, the decision tree receives knowledge in the form of a tree, which may alternatively be represented as a collection of discrete rules. The potential to use multiple feature subsets and decision rules at different stages of classification is the major benefit of the decision tree classifier. A decision tree classifier's performance is determined by how successfully the tree is built from the training data [40].

3.2.3 Random Forest

Random forest is a versatile, simple machine learning technique that, in most cases, gives excellent results even without hyper-parameter adjustment. Because of its flexibility and simplicity, it is also one of the most often used algorithms (it can be used for both regression and classification tasks). The random forest technique is a classification approach that uses numerous decision trees to take the judgments of many weak learners. Pruning (i.e. trade-off amid exactness and complication) these trees can often assist preclude over-fitting. Without trimming, there will be a lot of complexity, a lot of time spent, and a lot of resources used. This classifier aids in the prediction of patterns [41].

3.2.4 Gradient Boosted Tree (GBT)

Gradient boost tree is a prevalent classifier (machine learning model) because of its versatility, excellent modelling accuracy, and simplicity of understanding. It uses the same tree averaging approach as the random forest. Instead of dealing with trees with a lot of fluctuation, it creates little trees one by one. A new tree is added each time the iteration happens. It is continually working on the regression mistake that is still present [42]. Friedman invented this approach known as Gradient Boosted Tree. In numerical optimization of caste boosting, GBT is a framework that statistically approaches the error minimization by adding up weak learners. It employs the gradient descent method. It functions as an additive model that progresses in stages. In the system whenever a new weak learner is added, the old one stays the same and is frozen.

4. Results and Discussion

In this part of our research we describe results extracted from prediction experiments conducted on test data labels for each classifier. We have evaluated each classifier on performance metrics like accuracy, and precision. The plots of results and their confusion matrices are shown in respective classifier section.

For Random Forest and Gradient Boost Trees, we have calculated the information gain for various tree depths and number of trees. **Fig. 3** shows the results for Random Forest algorithm.

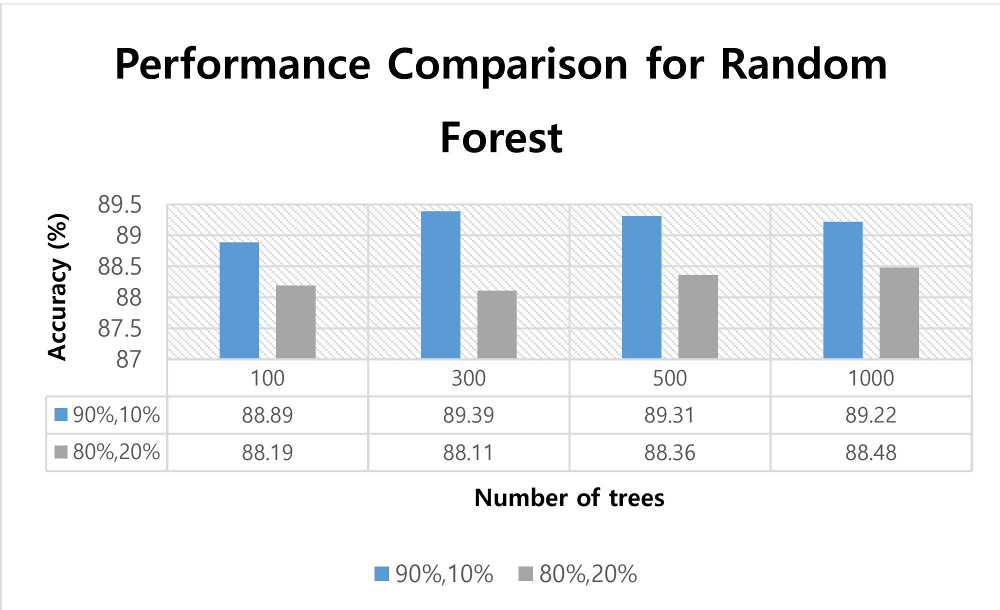

Fig. 3. Performance Comparison of Random Forest

The confusion matrix for the maximum accuracy achieved by random forest is given in **Table 4**. The precision given in **Table 4** describes that how accurately the random forest has predicted positive. That is out of the total positive predicted samples, how many of them are actual positive. For example from the dataset 199 samples are precisely predicted as 1 while other 12 samples predicted as label 1 are actually label 2 (4 samples), label 3 (1 sample), label 4 (3 samples) and label 6 (4 samples). The predicted precision percentage for label 1 is 94.31, for label 2 is 94.74, for label 3 is 98.86, for label 4 is 84.00, for label 5 is 90.177, and for label 6 is 82.4. On other hand the recall used in **Table 4** describes that how many samples of the total actual positive (i.e. true positive + false negative) samples the random forest has predicted as positive. The dataset contains total 207 samples for the label 1 of which 199 samples are predicted as label 1, while 5 samples are predicted as label 2, 2 samples are predicted as label 3 and one sample is predicted as label 4. The percentage recall for class labelled as 1 is 96.14, for class labelled as 2 is 91.84, and for class labelled as 3 is 93.00. The recall for classes labelled as 4, 5, and 6 are 83.58%, 88.06%, and 83.33% respectively.

Table 4. Confusion Matrix of Random Forest Classification

Actual / Predicted	**1**	**2**	**3**	**4**	**5**	**6**	**Class Precision**
1	**199**	4	1	3	1	4	94.31%
2	5	**180**	1	3	0	1	94.74%
3	2	4	**186**	8	1	6	89.86%
4	1	4	5	**168**	12	10	84.00%
5	1	1	2	4	**177**	11	90.177%
6	1	3	5	15	11	**160**	82.47%
Class Recall	96.14%	91.84%	93.00%	83.58%	88.06%	83.33%	

Fig. 4 shows the Receiver Operating Characteristics (ROC) curves of random forest classification for each class. For normal breathing and bradypnea classes Area Under the Curve (AUC) values are 0.97 each out of 1. While for tachypnea and kussmaul the AUC values are 0.94 each out of 1. The AUC for each of biot and sighing breathing patterns is 0.90.

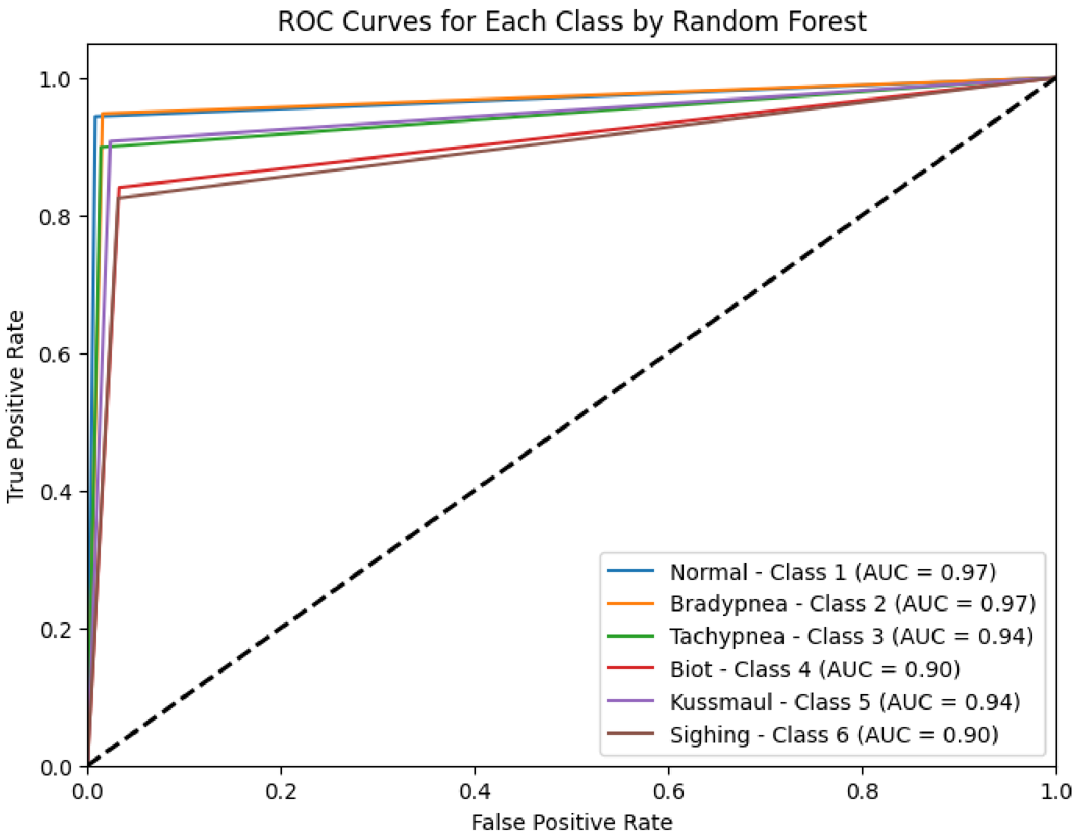

Fig. 4. Class-wise Receiver Operating Characteristic Curves by Random Forest

Fig. 5 shows the results for Gradient Boost Trees. The figure shows that on average the accuracy increases with increasing the number of trees.

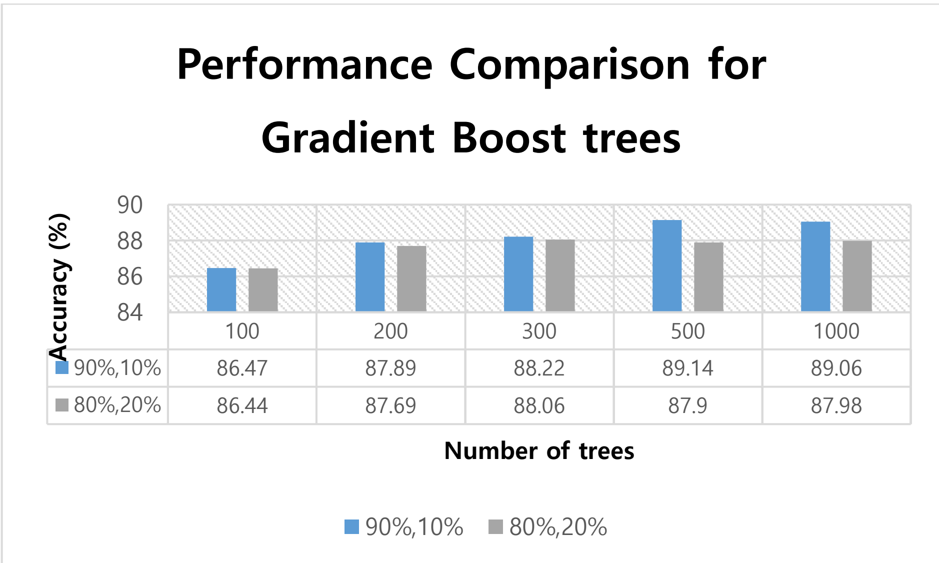

Fig. 5. Performance Comparison of Gradient Boost Trees

The confusion matrix for the maximum accuracy achieved by gradient boost trees is given in **Table 5**. The precision for class labelled as 1 is 94.71%, for class labelled as 2 is 95.34%, for class labelled as 3 is 87.56%, for class labelled as 4 is 83.50%, for class labelled as 5 is 89.80%, and for class labelled as 6 is 83.77%. Whereas the recall percentages for classes labelled as 1, 2, 3, 4, 5, and 6 are 95.17, 93.88, 91.50, 83.08, 87.56, and 83.33 respectively. The total data set samples for labels 1, 2, 3, 4, 5, and 6 are 207, 196, 200, 201, 201, and 192 samples respectively. Out of the 207, 196, 200, 201, 201, and 192 samples for labels 1, 2, 3, 4, 5, and 6 the gradient boost trees model predicted accurately 197, 184, 183, 167, and 160 samples respectively.

Table 5. Confusion Matrix of Gradient Boost Trees Classification

Actual / Predicted	1	2	3	4	5	6	Class Precision
1	**197**	4	2	3	1	2	94.71%
2	3	**184**	1	2	1	2	95.34%
3	3	2	**183**	11	2	8	87.56%
4	1	2	6	**167**	12	12	83.50%
5	2	2	2	7	**176**	8	89.80%
6	2	3	6	11	10	**160**	83.77%
Class Recall	95.17%	93.88%	91.50%	83.08%	87.56%	83.33%	

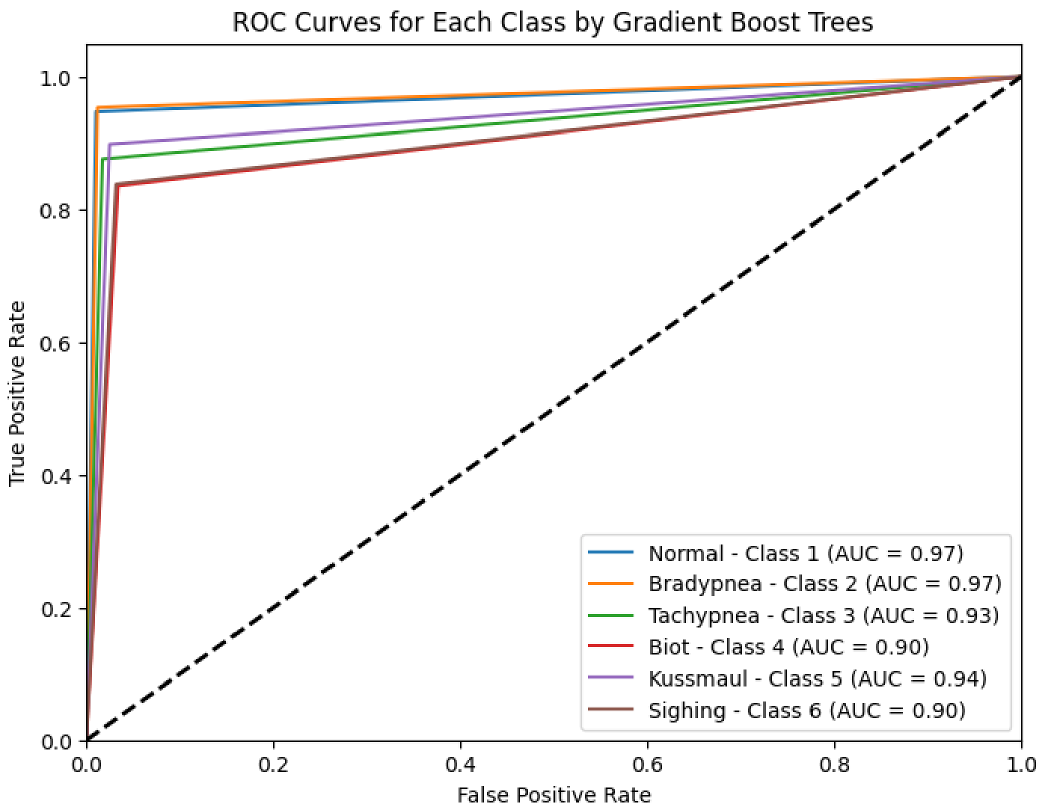

Fig. 6. Class-wise Receiver Operating Characteristic Curves by Gradient Boost Trees

Fig. 6 shows the class-wise Receiver Operating Characteristics (ROC) curves of gradient boost trees classification. For normal breathing and bradypnea braething patterns the Area Under the Curve (AUC) values are 0.97 each out of 1. While for tachypnea AUC value is 0.93 and for kussmaul the AUC value is 0.94 out of 1. The AUC for each of biot and sighing breathing patterns is 0.90.

For Decision Tree, we have calculated the information gain for variable depth of the tree for two different ratios for training and testing datasets. The results are shown in **Fig. 7**.

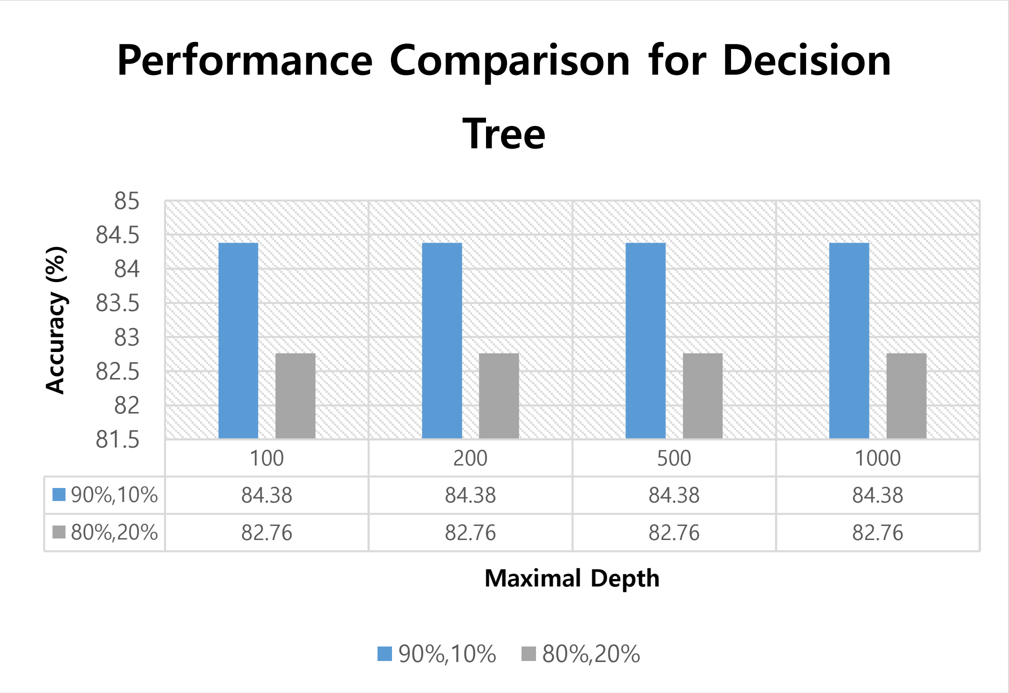

Fig. 7. Performance Comparison of Decision Tree

The confusion matrix for the maximum accuracy achieved by decision tree is given in **Table 6**. The precision for class labelled as 1 is 89.27%, for class labelled as 2 is 85.22%, for class labelled as 3 is 84.80%, for class labelled as 4 is 77.45%%, for class labelled as 5 is 91.35%, and for class labelled as 6 is 78.57%. Whereas the recall percentages for classes labelled as 1, 2, 3, 4, 5, and 6 are 88.41, 88.27, 86.50, 78.61, 84.08, and 80.21 respectively. Out of the 207, 196, 200, 201, 201, and 192 samples for labels 1, 2, 3, 4, 5, and 6 the decision tree model predicted accurately 183, 173, 173, 158, 169, and 154 samples respectively.

Table 6. Confusion Matrix of Decision Tree Classification

Actual / Predicted	1	2	3	4	5	6	Class Precision
1	**183**	7	2	6	4	4	89.27%
2	11	**173**	3	6	3	7	85.22%
3	6	5	**173**	14	1	6	84.80%
4	3	5	13	**158**	11	14	77.45%
5	1	2	2	4	**169**	8	91.35%
6	3	4	7	14	14	**154**	78.57%
Class Recall	88.41%	88.27%	86.50%	78.61%	84.08%	80.21%	

Fig. 8 shows the class-wise Receiver Operating Characteristics (ROC) curves of decision tree classification. For normal breathing the AUC value is 0.93 and for kussmaul the AUC value is 0.94 out of 1. The AUC values for each of tachypnea and bradypnea braething patterns is 0.91. The AUC for each of biot and sighing breathing patterns is 0.87 out of 1.

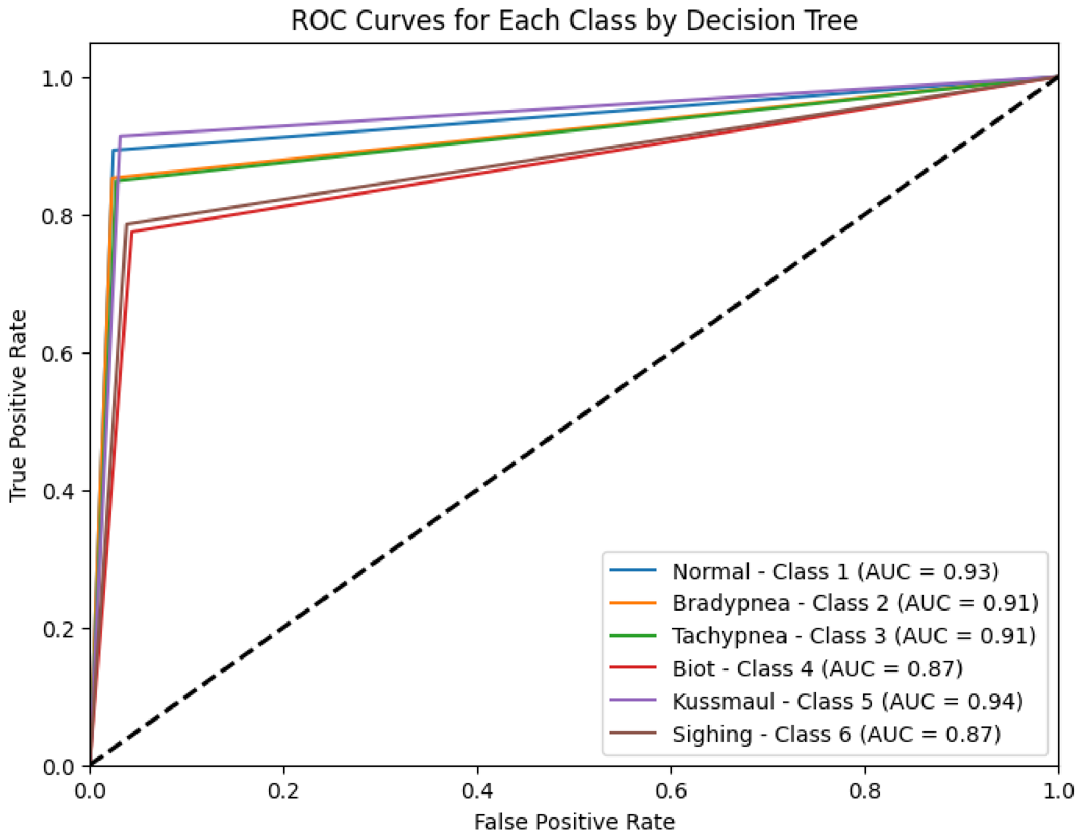

Fig. 8. Class-wise Receiver Operating Characteristic Curves by Decision Tree

We have utilized 10 folds cross approval technique for KNN and thought about the outcomes based on distances i.e., Euclidean and Manhattan. The consequences of KNN calculation are displayed in **Fig. 9**.

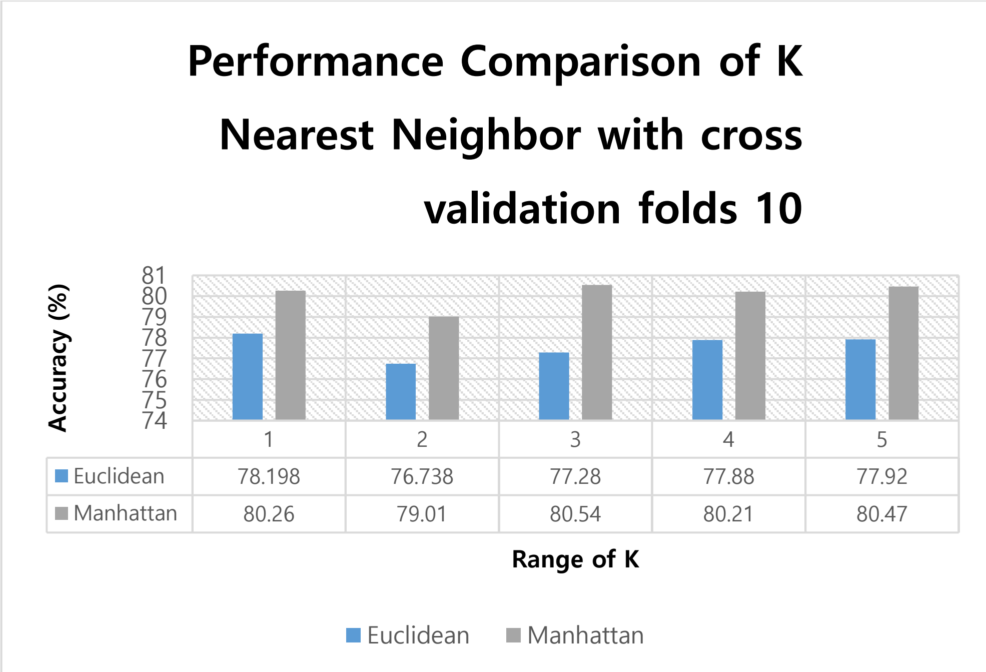

Fig. 9. Performance Comparison of KNN

The confusion matrix for the maximum accuracy achieved by KNN is given in **Table 7**. The precision for class labelled as 1 is 83.3%, for class labelled as 2 is 74.9%, for class labelled as 3 is 77.8%, for class labelled as 4 is 79.5%, for class labelled as 5 is 87.5%, and for class labelled as 6 is 80.5%. Whereas the recall percentages for classes labelled as 1, 2, 3, 4, 5, and 6 are 89.1, 83.1, 80.4, 76.2, 85.5, and 68.2 respectively. As the KNN model has no training mechanism that is, it makes predictions whenever it is subjected to the dataset. Thus in our experiment KNN is applied to the whole dataset. While the results for random forest, gradient boost trees, and decision trees discussed previously are based on the test dataset only. Out of the 2213, 2175, 2070, 1928, 1967, and 1628 samples for labels 1, 2, 3, 4, 5, and 6 the KNN model predicted accurately 1844, 1629, 1611, 1533, 1722, and 1311 samples respectively.

Table 7. Confusion Matrix of KNN Classification

Actual / **Predicted**	**1**	**2**	**3**	**4**	**5**	**6**	**Class Precision**
1	**1844**	109	29	32	30	25	83.3%
2	139	**1629**	83	42	24	44	74.9%
3	52	139	**1611**	117	23	62	77.8%
4	56	113	152	**1533**	54	103	79.5%
5	38	52	42	77	**1722**	83	87.5%
6	84	133	153	127	114	**1311**	80.5%
Class Recall	89.1%	83.1%	80.4%	76.2%	85.5%	68.2%	

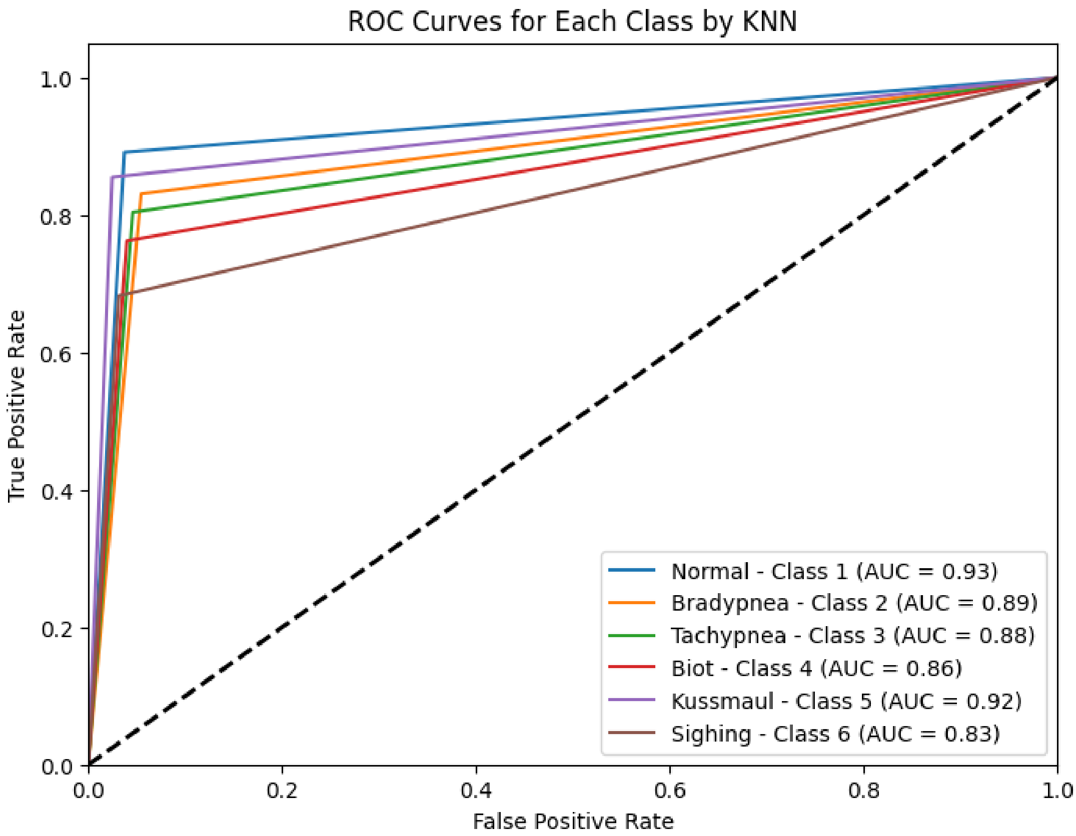

Fig. 10. Class-wise Receiver Operating Characteristic Curves by KNN

Fig. 10 shows the class-wise Receiver Operating Characteristics (ROC) curves of KNN classification. For normal breathing the AUC value is 0.93 and for kussmaul the AUC value is 0.92 out of 1. The AUC values for tachypnea and bradypnea braething patterns are 0.88 and 0.89 respectively. The AUC for biot breathing pattern is 0.86 and for sighing breathing pattern the AUC is 0.83 out of 1.

From the results shown, normal breathing and Bradypnea are the most correctly recognized breathing patterns. However, in some cases, algorithm recognizes kussmaul well also. Overall, the performance of Random Forest and Gradient Boost Trees is better than the other two algorithms.

5. Conclusion and Future Directions

We presented sensors-based IoTs system solving abnormal breathing pattern detection and identification problem in order to minimize the COVID-19 spread. In traditional COVID-19 monitoring and quarantine management is done through medical staff that increases chance of the spread. The proposed wearable IoTs framework consists: (i) wearable sensors at the belly position for breathing pattern data acquisition (ii) Bluetooth layer to pass the data and messages between sensors and server (iii) server layer for data storage, recognition, and visualization; and (iv) Client Application layer for remote monitoring, health assessment, and providing feedback. We collected the dataset of six breathing patterns from twenty subjects. We compared four machine learning algorithms and among them the Random Forest and

Gradient Boost Trees achieved the better detection results with AUC from 0.90 to 0.97. The Gradient Boost Trees based prediction achieved F1 score of 0.95 for each of class 1 and class 2. While the mean F1 score of all six classes achieved is 0.89. Whereas the mean F1 score (i.e. (0.92+0.87+0.51+0.57+0.63+0.72)/6) of reference [17] from literature is 0.70.
We suggest further investigation of breathing patterns detection in a noisy environment that will make the system robust and more reliable in the future.

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Dr. Sulaiman Almutairi is a distinguished data governance consultant, serving as the Director of Quality Scholarship Services at the Ministry of Education. He also holds the position of Assistant Professor of Health Informatics at Qassim University. Dr. Almutairi holds a Ph.D. in Biomedical Informatics from Rutgers University, New Jersey, USA, and completed his Master's in Information Technology at RMU, USA, following a Bachelor's degree in Computer Science from Bluefield State University, USA. With a tenure at Qassim University since 2005, Dr. Almutairi has held various pivotal roles, including Vice Dean of Planning, Development, and Quality. He has showcased his expertise as a data governance consultant at prominent tech firms in Saudi Arabia, such as Elm and SITE. Additionally, he served as a cultural mission diplomat representing Saudi Arabia in Canada and contributed globally as a data consultant at Development Gateway and UNICEF. His areas of expertise encompass, Data Governance, Bio-Informatics, Information and Policy and Software Development.

Rehmat Ullah is working with the Department of Computer Systems Engineering, University of Engineering and Technology, Peshawar. His research interests include artificial intelligence, computer vision, geo-visualization, and geo-visual analytics. He is the author of more than twenty articles with total citations of 244.

Qazi Zia Ullah was born in Maidan Bandai Village, Dir Lower, KPK, Pakistan in 1981. He received B.S. degree in eomputer engineering from COMSATS University Islamabad, Abbottabad Campus, M.S. degree in electrical engineering from the University of Azad Jammu & Kashmir, Mirpur, in 2010 and enrolled in Ph.D. degree in computer engineering in 2013 at Bahria University Islamabad. From 2006 to 2008, he was a lecturer with Peshawar College of Engineering Affiliated with UET Peshawar. From 2008 to 2011, he was lecturer with Azad Jammu & Kashmir University. From 2011 to 2012, he was lecturer with COMSATS Institute of Information Technology (now COMSATS University Islamabad), Attock Campus. Since 2012, he has been an Assistant Professor with the COMSATS University Islamabad, Attock Campus. He is the author of five articles and the reviewer of twelve articles. His research interests include resource management in cloud computing and cluster computing environments, evolvable hardware, digital systems design, heterogeneous networks, multi-objective optimization, neural networks, genetic programming and embedded systems, computer vision, robotics and artificial intelligence.

Habib Shah received the Ph.D. degree from the Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, in 2013. He is an Assistant Professor and the Head of the Research Unit, College of Computer Science, King Khalid University, Saudi Arabia. He has successfully published more than 50 articles in various international SCI and Scopus journals and conference proceedings. His research interests include artificial intelligence, learning algorithms, data mining techniques, the IoT, and time series analysis and optimization. He is an editorial board member, the guest editor and act as a reviewer for various journals and conferences as well. He has also served as a program committee member and co-organizer for numerous international conferences/workshops.
Currently, he is working on three research projects of KKU and KSA.