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Recent advances in ecological aspect for prediction model based on ECG beat classification using neural network

Pimpale Y.[1]*, Gupta S.[1], Rana P.[2], Kumar V.[3]
[1]School of Electronics and Electrical Engineering, Lovely Professional University, Phagwara, Punjab, India
[2]Department of Computer Applications, CT Group of Institutions, CTIEMT, Jalandhar, Punjab, India
[3]Department of Applied Sciences, CT Group of Institutions, CTIEMT, Jalandhar, Punjab, India
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*to whom all correspondence should be addressed: e-mail: yogitaspimpale@gmail.com
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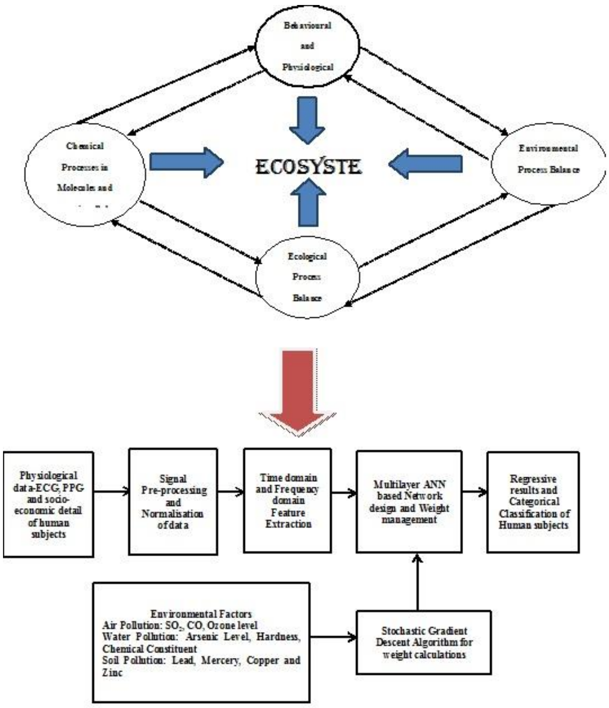
Graphical abstract

An awareness of environmental pollution's involvement might help develop preventive clinical counsel. This understanding can also help physicians, medical societies, public health authorities, environmental agencies, accountable care organizations, health insurers, and governments develop evidence-based societal strategies for preventing cardiovascular disease that link pollution prevention with behavioral and metabolic risk factor control.



Abstract

The ecological aspects such as environmental factors, socio-economic constraints, and demographic parameters are one of the key aspects of examining the health benefits of human subjects and are used as a ready reference in ecosystem modeling. Ecosystems are growing at an extraordinary speed around the world. Environmental factors are assumed to be responsible for over half of the global illness load. Environmental and ecological imbalances have a severe effect on public health, food security, global geopolitical and economic stability. The increased amount of environmental polluting factors eventually affects the health of humans and can cause diseases and disorders. Presently, there are various kinds of deadly diseases and disorders that are liable for affecting human health and impacting the eco framework of the whole world. The virus such as corona, swine flu, omicron, and others are one of the best examples for the research community to understand the vulnerability of human health to these unpredictable causes. As per the report of the world health organization every year more than ten million people are affected by such ecological and environmental disbalance. The impact of environmental factors on the functioning of several organs in humans appears to be significant. There is a need to understand this ecological model with the health of human subjects. In this study, a cohort-based data set of ecological pollutants and physiological signals such as ECG and anthropogenic data of human subjects were extracted from Maharashtra from 2015 to 2021. As per neural network-based hazard ratio was calculated and observed to be deplorable among unhealthy and health categories of human subjects. An environmental health hazard is a substance that has the ability to cause an adverse health event. This includes external physical, chemical, and biological factors to a person. An environmental health hazard is a substance that has the ability to cause an adverse health event. This includes external physical, chemical, and biological factors to a person. The accumulative ecosystem is responsible for overburdening organs of living beings and policymakers must focus on the facts of study for modern management framework designs. Such initiatives could result in a more robust understanding of the human health implications of increasing environmental change, impacting decision-

making in the environmental preservation and preventive health services.

Keywords: Ecological, anthropogenic, neural network, demographic parameters, ECG, corona, omicron, socio-economic, cohort-based.

1. Introduction

The ecology of the environment contains various interdependent factors which are correlated with demographic and continental behavior as shown in Figure 1.

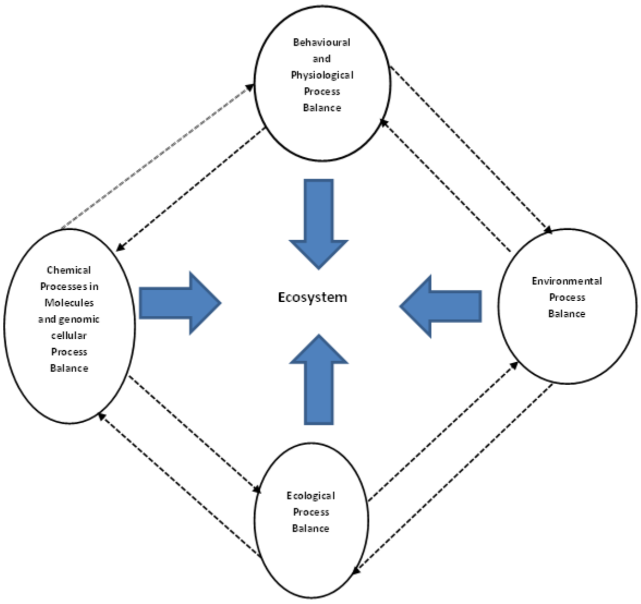


Figure 1. Ecosystem interrelations with physicochemical Process and balances.

In each continent, there is diversity in ecological aspects (Abdul *et al.,* 2015; Alvarez *et al.,* 2015; An *et al.,*2018). The key ecological factors are strongly established by the inhabitants of that area due to individual socioeconomic challenges. Presently, the key environmental factors such as an increase in anthropogenic and industry-related unethical practices of fuel burning, and waste management are impacting the balance of nature which causes the initiation of certain kinds of complications in the health of human subjects (Cosselman *et al.,* 2015; Cunningham *et al.,* 2020; Chen *et al.,*2021). There are various kinds of health issues that are originating in human subjects due to this ecological disbalance. As per the literature survey given in Table 1, the disorders such as lung diseases, Asthma, Arrhythmia, Alzheimer's, Cancer, and Neurological disorders are rapidly increasing in the population of various continents. In the Asia continent, China and India are the prime areas where the number of cases is exponentially increasing over a few decades. In these continents, these health issues are somehow depending on various kinds of biological disbalance, social connections, and technological features that are governing the lifestyle of these people. For a better understanding of the root causes, there are only a few studies that specifically underlie the role of disbalance in ecology causing initiates of disorders in a human subject (Du *et al.,*2016; Fiordelisi *et al.,*2017; Ferdous and Nemmar, 2020). The polluted ecological vulnerability is presently one of the most important tasks for the researchers to understand the modeling scenario for the preparation of solution-based protocols and frameworks for the betterment of humanity. Simultaneously, the challenges and associations related to forecasting ecological balances and public health care is a serious concern for the research community under dynamic situations. Till now, much work has been done to understand the effect of the specific factor of pollutants on human health which is somehow underestimating the joint causes for which the whole world is presently fighting. Till now, the key research perspectives and findings are reported in Table 1. Physical elements, biological variables, chemical factors, economic environment, socio-cultural influences, stress, personality, working conditions, and individual health are all included in the ecological approach to human health. These elements have an effect on human health. Air pollution is a complex mixture of gaseous and particulate components, each of which has negative effects on human health, including respiratory disorders, cardiovascular disease, and mental disorders. Loss of green spaces, unplanned built spaces, and increased anthropogenic emissions are major concerns in both developed and developing countries, particularly among the weaker sections of society, children, and the elderly population with preexisting medical conditions (Singh and Mall, 2020; Hamanaka and Mutlu, 2018). Arsenic, lead, cadmium, and copper exposure have been associated with a higher risk of cardiovascular disease and coronary heart disease. Physical influences include climate variation, temperature, and exposure to UV light. Disease vectors are biological variables. Agrochemical products are chemical factors. Toxicant pollution is a major environmental concern that has put human health and agricultural production at risk. Heavy metals and pesticides are among the most dangerous environmental toxins. Social aspects include employment, working conditions, culture, religion, money, education, and racial and gender discrimination (Chowdhury *et al.,* 2018; Alengebawy *et al.*, 2021). An awareness of environmental pollution's involvement might help develop preventive clinical counsel. This understanding can also help clinicians, medical institutions, public health authorities, environmental organizations, healthcare companies, and governments in developing evidence-based societal strategies for preventing cardiovascular disease that link pollution prevention with behavioral and metabolic risk factor control. The main cause of pollution is undesirable material released into the environment by human activity. This is another significant yet generally neglected risk factor for cardiovascular disease (Rajagopalan and Landrigan, 2021).

In human subjects, the biological aspects such as immunity, resistance to fight the diseases, and devolvement of antigens are getting reduced due to certain factors (Genchi *et al.*, 2017; Hasan *et al.,*2019; Gautam and Bolia, 2020). It may be hypothesized that these factors are directly related to disbalance ecology. As per the report, the functionality of human subjects is dreaded due to impurities in daily needs such as pure Food, Water, Ambient Environment, and healthy shelter (Genchi *et al.,* 2017). Among these disbalance ecological factors, the ambient environment is one of the prime suspects for contamination of human health. After that, polluted water and shelter are the secondary causes of degradation in human health. Overall, there is a need for studies that jointly modal the causes of all these ecological aspects to scale the effects on the organ of human health. As per the scarcity of research in this domain, the study has been headed towards the raised concern by a bilateral cohort study in the areas of India to better understands the effects with various special and temporal aspects from 2015 to 2021. In this cohort study, the physiological signals of human subjects were measured and neural network-based modeling has been done with independent ecological, demographic, and socioeconomic factors to understand the raised concern. A multilayer artificial neural network-based framework has been prepared to support the conclusions. In the following section the study design, instrumentation, and facts are discussed with conclusive results (Izah *et al.,* 2016; Hasan *et al.,* 2019). The accuracy of modals is also tested for surpassing the confounders and covariates. A confounding parameter is a factor that is associated with both the disease (dependent variable) and the factor under investigation (independent variable).

Table 1. The effect of specific pollutants on health of Human subjects estimated in reported cohort studies

Sr.No.	Name of the author	Ecological aspects	Affected part and mechanism of Human body Organs	Cases of Diseases and Disorders
1.	Yixing *et al.* (2015)	Particulate Matter (PM)	Heart (Indirectly injury by inducing systemic inflammation and oxidative stress in peripheral circulation)	Myocardial infarction, Cardiac arrhythmias, ischemic stroke, .Vascular dysfunction, hypertension atherosclerosis
2.	Kristen *et al.* (2015)	Trafic-related air pollution	Heart, Lung (Cellular and molecular effects lead to responses in various tissues and organs and eventually to cardiovascular effects)	Peripheral arterial disease, Ischaemic events, Arrhythmia events, Cardiomyopathy and heart failure
3.	Mohammed Abdul *et al.* (2015)	Arsenic	Integumentary, nervous, respiratory, cardiovascular, hematopoietic, immune, endocrine, hepatic, renal system. (Arsenic has able to induce epigenetic changes and genetic mutations)	Atherosclerosis, hypertension, arrhythmia and diabetes, cancer.
4.	Izah *et al.* (2016)	Heavy Metal Pollutant in potable Water	Liver, brain, kidney, nervous system, heart. (Cause mutation leading to chromosomal changes)	Cardiovascular, respiratory, cancer, organ damage, poisoning, neurological, haematological diseases.
5.	Antonella *et al.* (2017)	Air pollution and particulate matter	Heart, lung (ultrafine particles can penetrate deeper into the lungs and deposit in alveolar regions during mouth breathing and contributes to the development of cardiovascular events by inducing a systemic inflammatory condition or affecting the autonomic nervous system	Heart failure, hypertension, myocardial infarction, arrhythmia, lung cancer, lung inflammation, direct blood translocation, and autonomic regulation.
6.	Genchi *et al.* (2017)	Mercury Exposure	Central nervous system, kidney , brain, heart. (Mercury exposure effect on cardiac parasympathetic activity and heart rate variability,)	Hypertension, coronary heart disease, myocardial infarction, cardiac arrhythmias, carotid artery obstruction, cerebrovascular accident, atherosclerosis.
7.	Munawer (2017)	Coal combustion and post-combustion wastes	liver, kidney, cardiac tissue, heart, skin, lung. (some pollutants produced during coal combustion which thereby changes the air quality and leads to increased respiratory and cardiovascular diseases with underlying poor life expectancy rates.)	.malaria, chronic obstructive pulmonary disease ,lung cancers, destabilization of the heartbeat, skin cancer, asthma, and cough, headache, throat and nose irritations, leukaemia

8.	Olvera Alvarez *et al.* (2018)	Early life stress, air pollution	Heart, brain, lungs. (The effects of severe early life stressors that cause repeated biological stress responses , such as poverty, abuse, neglect, isolation, discrimination, humiliation, or violence. social factors interact with environmental factors via bio-behavioural pathways that in turn affect health.)	Increases adulthood risk for cardiovascular disease, stroke, diabetes, autoimmune disease, and certain cancers, depression.
9.	Zhen *et al.* (2018)	Particulate Air Pollution	Heart, lung (PM-caused CVDs include direct toxicity to the cardiovascular system.)	Systemic inflammation, oxidative stress, abnormal coagulation function, vascular dysfunction and disturbance autonomic nervous system, blood pressure.
10.	Roman *et al.* (2019)	Nano plastic	Human cell lines, immune system, Lung, the gastrointestinal tract, skin.	oxidative stress pro-inflammatory responses
11.	Hasan *et al.* (2019)	Water pollution	Infections in urinary and respiratory tracts, kidney, lung, effect on mind. (contaminated with several contaminants and show toxic effect on human health)	Typhoid, dysentery, diarrhoea, hepatitis A and hepatitis B, food poisoning, cholera, gastroenteritis, ascariasis, cryptosporidiosis, cancer.
12.	Gautam *et al.* (2020)	Air pollutants volatile organic compounds, and heavy metals	Lungs, eyes, skin and hair, liver, bones, mind, reproductive system, heart, blood.	Cancer, diabetes, myocardial ischemia, cerebrovascular ischemia, inflammation, oxidative stress, increaded coagulability, endothelial dysfunction, hypertension.
13.	Cunningham *et al.* (2020)	Air and water pollution	Skin, lung, heart, mental health (contaminated water and air increases the prevalence of a number of respiratory and cardiovascular diseases)	lung cancer, heart and lung diseases, and asthmatic attacks, hepatitis, typhoid fever, gastroenteritis, dysentery, cholera, diarrhoea, malaria, giardiasis, and intestinal worms, anaemia, yellow fever, and dengue, digestive cancer.
14.	Ferdous *et al.* (2020)	Silver Nanoparticles (AgNPs)	Liver, kidney, spleen, lung,heart, thymus, skin, brain, systemic circulation(transport and deposition of NPs smaller particle penetrate deeply into the alveolar region)	Mitochondrial damage, inflammation lung function, cardiac ischemic
15.	Chen *et al.* (2021)	Effect of paraquat	Lung, brain, kidneys, gastrointestinal tract, nervous system, and the immune system. (PQ toxicity through the olfactory nerve cross the blood-brain barrier into the central nervous system and then cause damage)	pulmonary fibrosis, heart oxidative stress ,myocardial damage, e digestive system dysfunction, acute respiratory failure and multiorgan dysfunction syndrome
16.	Shahrbaf *et al.* (2021)	Short-term and long-term exposure of the air pollutants	Oxidative stress, autonomic dysfunction, coagulation dysfunction, and inflammation.	myocardial infarction, sudden cardiac death, cardiac arrhythmias, and peripheral arterial disease

2. Materials and methods

2.1. Clustering of data

From 2015 to 2021, data on ecological imbalance and physiological data of human individuals were collected in Maharashtra, India. The ecological factors which are identified as the prime suspect of disbalancing are identified such as air pollution, water pollution, soil pollution, demographic causes, and socioeconomic challenges. Data related to these aspects have been collected from Indian Meteorological Department (https://mausam.imd.gov.in), and local pollution control boards. In Maharashtra, physiological data such as ECG, PPG, and other socio-economic survey-related data of human subjects were collected from Pravara Medical Trust, Loni, Maharashtra (https://www.pravara.com). In these NGOs, the free treatment of patients has been done by doctors and practitioners under licensed camps. The human subjects of all age groups were undergone routine measurement of signals in which healthy and non-healthy people underwent the physiological signal measurements. The physiological signal such as ECG, PPG, and other anthropogenic details was measured by the clinician and recorded for the research purpose with due consent of participants. The ECG signal was measured by the professional six-channel machine which was available at all clinics adopting a standard medical procedure. ECG parameters can help to determine the patient with certain diseases. Many ECG parameters have been studied earlier, including early repolarization, QTi/QT dispersion, signal-averaged ECG, VLP, and HRV. These parameters are obtained from ECG components, namely QRS complex, R wave, and T-wave. The QRS complex is a major wave in the ECG signal and its structure acts as the starting point for many classification algorithms by providing the basis for automated detection of many features. The PPG signal was measured by a standard infrared-based meter for the measurement of heart-related parameters. According to the Centers for Disease Control and Prevention (CDC), anthropogenic data is a helpful for assessment of overall health state, nutritional adequacy, growth and developmental pattern, severity of illnesses such as obesity and cognitive impairments and the risk of future disease. The anthropogenic parameter such as height, weight, head circumference, body mass index (BMI), and skinfold thickness, socioeconomic condition, history, or symptoms of diseases was measured through routine check-ups and surveys by these organizations. All the physiological measurements were done non-invasively and without the involvement of any kind of drug or synthesizer.

2.2. ANN-based modeling

In this modern era, ANN is one of the most adaptive tools for the estimation of correlations and predictive moves with database management (Cunningham *et al.,* 2020). The neural network can incorporate the uncertain and dynamic covariates with independent variables which are liable for affecting the dependent variable (Yadav *et al.,* 2021; Adriati *et al.,* 2021). In the existing modeling tools, the conventional statistical methods are somehow lacking the adjustment of multi-dependent variables and their relation estimations with various independent variables. They are not able to incorporate multiple inputs at a time. Another issue was an adjustment of covariates and estimation of weightage of confounders in the modeling Framework. These are the significant issues to straighten the hypothesis of results. ANN is one of the evolutionary models for adjustment of multi parameters with more than 90% testing accuracy for prediction rather than existing statistical models. (Wasimuddin *et al.,* 2020,) As shown in Figure 2, five phases have been designed to do the processing of physiological data under the confluence of ecological parameters (Cosselman *et al.,* 2015; Izah *et al.,* 2016; Hasan *et al.,* 2019).

Phase 1: Pre-processing and normalization data set

Phase 2: Design of Multilayer neural network and adjustment of weights with theirassociation

Phase 3: Validation of data using cross-entropy and sum of square error method.

Phase 4: Determination of power spectral density-based correlation coefficient

Phase 5: Preparation of training data set for cross-evaluation and frameworkmanagement.

For physiological signals such as ECG, the time domain and frequency domain features were extracted. There are many features in both categories but two features were selected based on their instance probability index during initiate correlation practices (Altay and Kremlev, 2018).

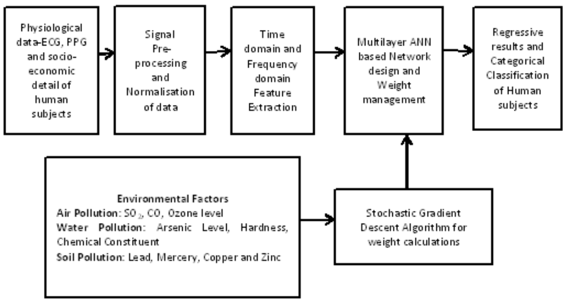


Figure 2. Design and development method for MLANN for Hazard ratio calculations and Estimation models.

3. Time domain features

Signal processing is essential for the analysis and interpretation of ECG signals. ECG signals are obtained by placing electrodes on body surface. It causes noise to contaminate ECG signals. Baseline wander, power-line interference, electromyographic (EMG) noise, and electrode motion artifacts are some examples of these noises. These noises act as impediments during ECG signal processing, so pre-processing of the ECG signal is essential for noise removal and rejection. As a result, filtering methods such as Baseline Wander Filters and Power Line Interference Filters are commonly used for preprocessing of ECG signals (Karnewar and Shandilya, 2022). In this work, the spectral entropy and skewness of the R–R interval were utilized as time-domain features because they may describe the regularity of the ECG signal in different scenarios. The three steps for measuring time-domain features are mathematical morphological filtering, R-wave position determination, and R-wave waveform extraction. We conducted a statistical analysis of the mean value, spectral entropy, and skewness of a signal segment's R–R interval (Hu *et al.,* 2020). The analysis of time and frequency domains for multicomponent non-stationary signals such as electrocardiograms (ECGs) is an important topic in signal processing. Because these biological signals are non-stationary and multicomponent, time and frequency domain analysis can be highly beneficial in determining the actual multicomponent structure. A signal's frequency spectrum indicates what frequencies are present in the signal. The interval between neighboring normal R waves is measured across the recording period in time domain analysis. In this study, the ECG data was analysed and various statistical parameters were calculated (Pinho *et al.,* 2019; Shadmand and Mashoufi, 2016).

3.1. Spectral Entropy

This parameter is known for the distribution of spectral power over time for module-based peak changes and helps to calculate the spread of energy in a signal having a high probability index (Abdul *et al.,* 2015; Cosselman *et al.,* 2015; Munawer, 2018). This parameter is used to represent the functioning of the different chambers of an organ's function of human subjects in depth for exhaust analysis. Mathematically, it is calculated as shown in Equations 1.1 to 1.4.

From the given signal in time domain $x(n)$

$$(K)=\sum_{n=0}^{N-1}x(n)W_N^{kn},0\le K\le N-1 \tag{1.1}$$

Where, $W_N=e^{\frac{-j2\pi}{N}}$.

The power spectral density $S(k)$. of the physiological signal

$$S(k)=\frac{1}{N} \tag{1.2}$$

The normal probability density function P_k has been scaled out using equation (1.3)

$$P_k=\frac{S(k)}{\sum_i S(i)} \tag{1.3}$$

The spectral entropy S_pE. is calculated using the Shannon eropy equation (1.4)

$$S_pE=\sum P_k \log P_k \tag{1.4}$$

3.2. Skewness

This time-domain parameter is used to calculate the averaged cubed deviation concerning the Standard deviation of the signal in the computation of variation under the mean of the selected portion (Kumar and Sharma, 2021). This parameter is significantly presenting the abnormalities in the Standard value in bivariate mode. Mathematically, it is calculated as shown in equations 2.1 to 2.3 (Abdul *et al.,* 2015; Cosselmant *et al.*, 2015; Hasan *et al.,* 2012).

$$Skewness=\frac{\sum_{i=1}^{N}\left(Y_i-\bar{Y}\right)^3}{(N-1)s^3} \tag{2.1}$$

Where $\bar{Y}$ -is the mean; -is the standard deviationl N -is the number of data points.

4. Results and discussion

The ecological polluting parameters such as Air Quality Index, Water Quality Index, and Soil Quality Index were collected from the concerned sites. Inur ecology, these pollutants are scaled by a standard electrochemical process and a standard normal range has been predicted to compare the measured value for observation of consequences on a local and global level. The anthropogenic and other natural processes are liable for a hike in the pollutants level which is several times higher in the concerned areas. The raised level of pollutants is ultimately affecting the living beings in various ways and can trigger diseases and disorders. The Air Quality Index (AQI) is shown in Figure 3. The AQI of selected sites was measured by the Pollution control board. It has been observed that the level of AQI was more than 150 in the sampling years and the interquartile value of AQI varied from 156 to 171. As per European Pollution Agency, the permissible level and safe level of AQI is varying from 50 to 100, but at sites, the level of AQI was 78% to 93.2% more than the permissible limits.

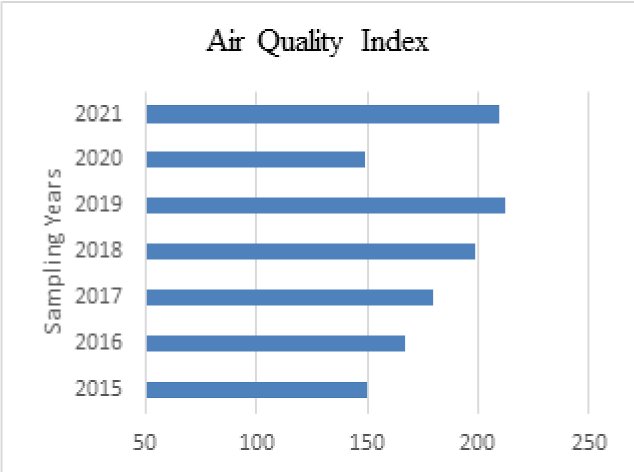


Figure 3. Air Quality Index at sampling site.

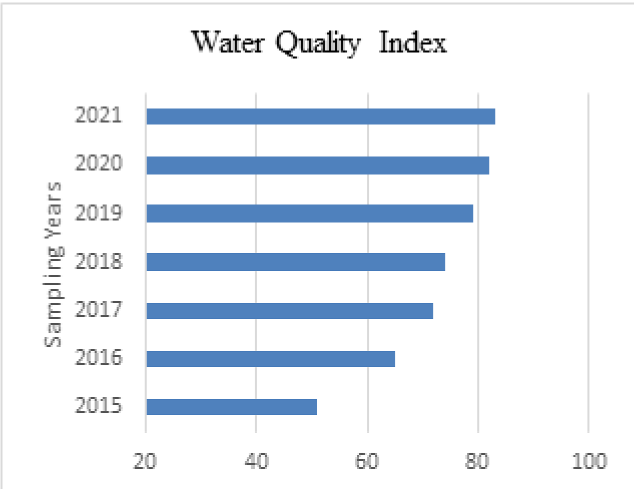


Figure 4. Water Quality Index at sampling site.

The Water Quality Index is shown in Figure 4. The pollution level in Water at the selected site varied from 53.2 to 84 in the concerned area. The lowest level of WQI is reported to be 50 and it is varied from more than

48% to 56% annually with the scaled level of the interquartile factor. As per the Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI), the permissible and safe level of water quality is varied from 10 to 50. But, the WQI of the sampling site has been observed to be very poor due to unethical practices in the area.

The Soil Quality Index of the sampling area is shown in Figure 5. The Soil related pollution i.e. mixture of metal and toxic elements in the area is also higher than the permissible limit. The SQI is varied from 2.1 to 6 which is 78.67% more than the safe level. The interquartile range of SQI has varied from 34 to 89% of the safe limit. From the measured data, it has been observed that the AQI, WQI, and SQI are extensively polluted in the concerned area. The main cause of pollution is the use of toxic products and ailments in the area without any precautionary values. The level of Index is several times higher than the permitted areas which are strongly hypothetical and leads to unbalanced health of living beings in the area.

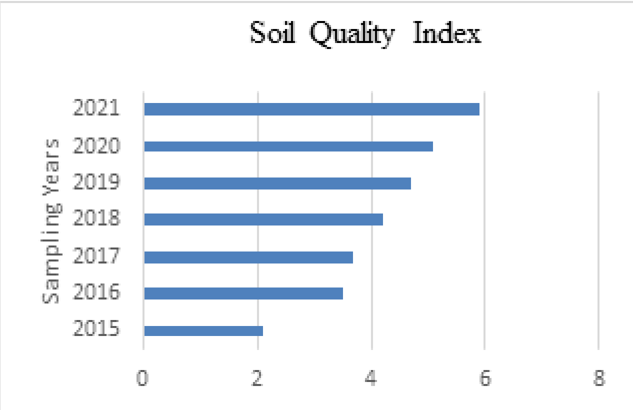


Figure 5. Soil Quality Index at sampling site.

Figure 6 shows the trend of Entropy which is measured from the ECG signal of human subjects in the areas during clinical trials. The feature such as entropy randomness is used to measure the variation in the vertical chambers of the Heart during their normal tenure. In 2015, the randomness in entropy was observed to be 0.92 which then dropped to 0.85. Similarly, in the consequences years, the level of droopiness occurred to 0.7. It has been observed that the randomness drops from 0.9 to 0.7 are a clear symbol of the Ecological burden on human subjects. The ECG signal of such healthy people is somehow under vent an ecological burden due to increment in AQI, WQI, and SQI. Figure 7 shows the trends of Entropy randomness value male and female wise for some extended analysis. During the sampling years, the dopiness of randomness is varying from 0.93 to 0.69 in both male and female subjects. The rate of drop is similar in both categories. The correlation factor of AQI, WQI, and SQI is equally related to the drop-down in physiological health of human subjects. In the sampling year 2018 to 2021, the correlation factor varied from -6.3% to -7.2% with a probability index (p-value) of 0.95. Even, it has been observed that the correlation factor is slightly higher in female subjects than in male subjects.

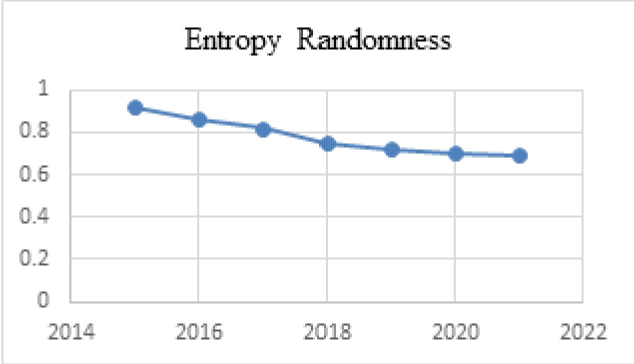


Figure 6. Entropy Randomness feature of ECG signal.

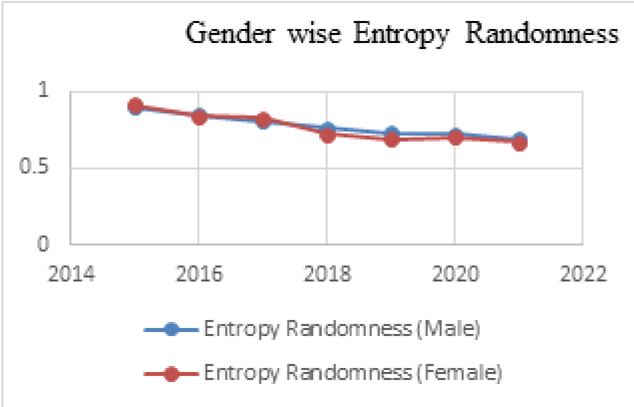


Figure 7. Gender wise Entropy Randomness feature of ECG signal.

The Second feature of the ECG signal is Skewness which is a key indicating factor to represent the deviation in the Ventricle chambers of the heart and veins. Figure 8 shows the variation in skewness-based deviation in ECG signal of sampled human subjects. In the collected data, the Skewness of ECG signal was relied on near 37 to 42 with a standard deviation of 1%. But, in consequent years, the value is reached more than 65. As per observation, every year 23 to 37% increment is observed in skewness deviation due overburden of AQI, WQI, and SQI of ecology.

Figure 9 shows the gender-wise Skewness variation in the ECG signal of sampled human subjects. Gender-wise trends are observed to be similar to Randomness. The female subjects have a higher declination factor than male subjects (Abdul *et al.,* 2015; Munawer, 2018).

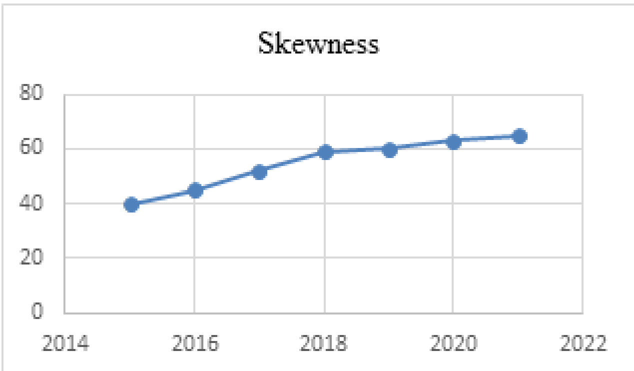


Figure 8. Skewness based deviation feature of ECG signal.

As per the analysis of results, it has been observed that the ecological burden is consequently depreciating the health of human subjects due to certain kinds of variations in physic logical parameters. The results are also supported by the clues given in the studies. As per studies, it has been observed that the time domain fealties of physiological signals are somehow concerned to indicate the health of human subjects. The ecological burden of AQI, WQI, and SQI is exponentially increasing due to certain activities relying upon the surroundings of human subjects (Alvarez *et al.,* 2018; Lehner *et al.,* 2019). Overall, it has been predicted that, if the burden of AQI, SQI, and WQI persists in the environment for a long time as per previous trends, then it will be difficult for pollution control agencies and NGOs to cure the consequences related to human health (Du *et al.,* 2016; An *et al.,* 2018; Lehner *et al.,* 2019; Shahrbaf *et al.,* 2021). This paper presents ECG classification, a preprocessing technique for noise removal, a classifier for ECG data classification, and performance measures for evaluating classifier accuracy. In terms of classification accuracy, neural networks are excellent for ECG classification. Many performance measures are used to assess neural network classification accuracy. Sensitivity, Specificity, and Accuracy are evaluation measures derived from the confusion matrix (Kuila *et al.*, 2020; Celin and Vasanth, 2018).Table 2 illustrates the classification of an ECG signal using various machine learning techniques.

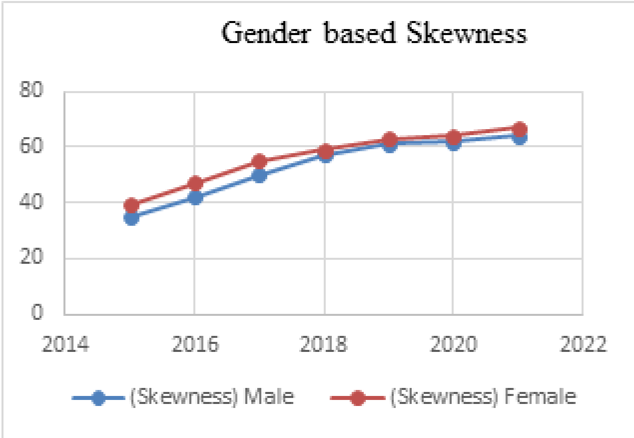


Figure 9. Skewness based deviation feature of ECG signal.

Table 2. Result for the different feature with comparison between the classifiers

Classifier	Performance measure
Multilayer probabilistic neural network	Sensitivity=99.02%
	Specificity=99.52%
	Accuracy=99.05%
Feed forward ANN and backpropogation learning algorithm	Accuracy=96.23%
PCA and Neuro fuzzy classifier	Accuracy =96%
SVM classifier	Sensitivity=91.71%
	Specificity=96.23%
	Accuracy=88.84%
SVM and genetic algorithm	Accuracy=93%
Fuzzy decision tree	Sensitivity=95.85%
	Specificity=83.33%
K-Nearest Neighbor	Accuracy=91.72%
Random forest	Accuracy=92.16%
CNN	Sensitivity=98.07%
	Specificity=93.13%
	Accuracy=95.42%

Improving environmental quality in key areas such as air, water, and soil can aid in disease prevention and health improvement. Considering human health issues from an ecological standpoint takes account of social, ecological, and biophysical determinants. Identifying several gaps and limitations in the research could lead to a more robust understanding of the human health impacts of accelerating environmental change and inform decision making in the realms of land-use planning, environmental conservation, and public health policy. Public health researchers bear a significant responsibility for conducting research that will assist society in understanding and avoiding the health impacts of global changes.

5. Conclusion

The undue ecological burden of raised levels in AQI, WQI, and SQI is a global issue for pollution monitoring and control agencies to profound some valuable actions. The unethical practices in the ecology exponentially raised the burden and with time, this burden is increasing due to low mixing rates and resistance of natural sources to dissolve then. Consequently, the health parameter of human subjects is depreciating. The hypothesis of these burden rendering parameters is observed by measuring the time domain-based features from ECG signals at sampling sites. The results are showing a steep decrement in skewness and entropy randomness parameters. The trend of ECG signal variation quartiles is a clear indication of health effects on the physiological structure of human subjects. The experimental results indicate the detection method's applicability and effectiveness for time-domain features. Using the classification method, we achieved high accuracy in discriminating between normal and abnormal signals, which will be useful in classifying healthy and unhealthy persons. In the future, there is a need to solicit ate such kind of environmental Engineering-based studies to understand the depth of the issue. Our results will raise the concern of pollution control agencies to accommodate such methods to reduce the ecological burden on human subjects.

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