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Intelligent Novel Approach for Identification of Alcohol Consumers using Incremental Hidden Layer Neurons ANN (IHLN-ANN)-Based Model on Vowelized Voice Dataset

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Abstract: Alcohol consumption can have impacts on the voice, and excessive consumption can lead to long-term damage to the vocal cords. A new procedure to automatically detect alcohol drinkers using vowel vocalizations is an earlier and lower-cost method than other alcohol drinker-detecting models and equipment. The hidden parameters of vowel sounds (such as frequency, jitter, shimmer, harmonic ratio, etc.) are significant for recognizing individuals who drink or do not drink. In this research, we analyze 509 multiple vocalizations of the vowels (/a, /e, /i, /o, and /u) from 290 multiple records of 46 drinkers and 219 multiple records of 38 non-drinkers. The age group is 22 to 34 years. Apply the 10-fold cross-validation vowelized dataset on intelligent machine learning models and incremental hidden layer neurons of artificial neural networks (IHLN-ANNs) with Backpropagation. The findings showed that experimental ML models such as Naïve Bayes (NB), Random Forest (RF), k-NN, SVM, and C4.5 (Tree) performed well. The RF model performed best, with 95.3% accuracy. We also applied the incremental hidden layer (HL) neurons BP-ANNs model (from 2 to 5). In this analysis, accuracy increased proportionally with the incremental neurons (2–5) in the HL of the ANN. Now of 5 neurons HL ANN, the model performed with a highly accurate 99.4% without an over-fit problem. It will implement smartphone apps for caution and alerts for alcohol consumers to avoid accidents. Voice analysis has been explored as a non-invasive and cost-effective means of identifying alcohol consumers.

Keywords: Alcohol Consumers, Voice Parameters, Machine Learning, Neural Networks, ANN

1. Introduction

Alcohol consumption is a widespread and significant public health concern with numerous negative consequences for individuals and society. It can also lead to road collisions and injuries [1]. Accurate identification of alcohol consumption is essential for early intervention and prevention of the negative effects of excessive alcohol use. Voice analysis has emerged as a promising and non-invasive means of identifying alcohol consumption. [2] According to the World Health Organization (WHO), the average global alcohol consumption in 2019 was 5.8 liters of pure alcohol per capita (age 15 years or older), a slight decrease from 6.1 liters per capita in 2010. Men in the WHO European Region had the highest consumption in 2019 at 15.2 liters per capita, despite a declining trend since 2000. Alcohol has been an integral part of many societies and cultures for centuries, but it is also responsible for three million deaths each year. Of individuals aged between 20 and 39, roughly 13.5% of deaths are attributed to alcohol. There is a clear connection between alcohol use and its negative effects, such as mental and behavioral disorders, injuries, and non-communicable conditions. Alcohol use also has significant economic and social costs ([3] [4]).

Alcohol consumption is a widely prevalent issue with significant health, social, and economic implications [5]. Alcohol consumption has effects on the voice, with the main ones being dehydration, inflammation, nerve damage, acid reflux, and vocal strain. Alcohol is a diuretic, which means it increases urine production and can lead to dehydration. When the body is dehydrated, the vocal cords become dry, making it harder to produce sound, resulting in a raspy or hoarse voice. Alcohol can cause inflammation in the throat and vocal cords, making it harder to produce clear and smooth sounds, resulting in a voice that sounds

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scratchy, strained, or breathy [6]. Chronic alcohol consumption can cause damage to the nerves that control the muscles involved in speaking and swallowing, leading to a weak or hoarse voice, difficulty speaking loudly or projecting, or difficulty controlling pitch and tone. Alcohol consumption can increase the production of stomach acid and lead to acid reflux, which can irritate the vocal cords and cause inflammation or damage. Alcohol can also cause people to speak louder and more forcefully than usual, straining the vocal cords and leading to hoarseness or vocal fatigue. In general, alcohol consumption can affect the voice negatively, especially if consumed excessively or frequently. For people who rely on their voices for their profession, such as singers, actors, or public speakers, it is important to limit alcohol consumption or avoid it altogether to maintain vocal health [7]. Drinking plenty of water and avoiding smoking can also help keep the voice healthy. Early identification and intervention can help prevent the negative consequences of excessive alcohol consumption.

This research provides a detailed description of the social and personal impacts of alcohol consumption, as well as an in-depth discussion of alcohol use disorders, particularly those related to voice. It also explains how alcohol affects the acoustic system and how drinkers and non-drinkers can be identified through a vowel voice dataset. Furthermore, it presents a proposal model, Incremental neurons in HL of BP-ANN, which has better performance for the identification of alcohol consumers. Finally, it provides a detailed analysis of a novel approach and proposed methodology for the identification of drinkers, with comparisons to existing machine learning models. This research is a promising novel approach for identifying individuals who consume alcohol based on their voice patterns and could have important applications in the fields of healthcare and public safety. This approach has several advantages. First, it is non-invasive, as it does not require any physical tests or samples from the individual being evaluated. Second, it is fast and can process large amounts of data quickly, making it ideal for use in screening large populations. And, it has the potential to be highly accurate, as ANNs can learn complex patterns in data and make highly precise predictions.

The remaining sections of the paper are presented as follows:

- Section 2 provides a literature review of relevant background works related to alcohol consumption and voice.
- Section 3 outlines the proposed model and materials, including the construction and description of the dataset, parameters of voices, and description of BP-ANN approaches with GD (Gradient Decent) optimizers. Additionally, performance parameters and confusion matrix for classification analysis are described.
- Section 4 presents the analysis of the results, including the analysis of the dataset with statistical values, five experimental ML model performances, and simulation results of BP-ANN-based incremental neurons (2 to 5 neurons) HL models.
- Section 5 provides an analysis of comparison, with detailed discussions and comparisons of the proposed model against five experimental ML models and 2 to 5 HLs neurons of BP-ANN, as well as other works related to this research work.
- Finally, Section 6 concludes the paper by reporting the limitations of the research and suggesting future works related to the recognition of alcohol consumers utilizing voice datasets.

2. LITERATURE REVIEW

In this literature survey, we focus on background research works about the relationship between voice and alcohol consumption. For this, we collect significant research papers and abstracts from various high-quality journals. This survey includes a comprehensive review of relevant literature, including studies on the use of voice analysis for identifying alcohol consumers. Various authors apply different approaches and various models for identification of alcohol consumption with some limitations.

Voice analysis has been explored as a non-invasive and cost-effective means of identifying alcohol consumers. Some of the voice parameters are pitch, loudness, timbre, resonance, and range. Pitch is the perceived lowness or highness of a person's voice [8]. It is resolved by the frequency of vocal cord vibrations and is measured in hertz (Hz). Loudness is the perceived volume of a person's voice. It is defined by the sound wave intensity and is measured in decibels (dB). Timbre is the unique characteristic of a person's voice that differentiates it from others [9]. It is determined by the harmonics present in a person's voice and can be depicted as bright, warm, nasal, or breathy. Resonance refers to the way sound waves vibrate and resonate in the cavities of the head and throat, creating the unique sound of a person's voice. Range is the span of pitches a person can produce comfortably, from their lowest to their highest pitch. Johnson et al., (1990) [10] investigated whether voice recordings can reveal whether a person is intoxicated. The study found that alcohol consumption affects various aspects of speech, including speech rate, articulation, intonation, and overall speech quality. Specifically, the study found that in the intoxicated state, the individual had a slower speech rate, reduced articulation, decreased pitch variation, and a lower overall speech quality. In this analysis, they found that the individual in the intoxicated state was characterized by longer pauses, slower speech rate, and decreased pitch variation. The study also found that the individual had a decreased ability to accurately produce certain speech sounds. Wakista et al. (2014) [11] researched on the effects of an alcoholic beverage on supra-segmental features of voice, which include stress, intonation, and rhythm. For this analysis, they choose 50 male individuals that the age between 21 and 50. The study found that alcohol consumption led to a significant decrease in pitch range, pitch variability, and speech rhythm. There was an increase in the duration of speech pauses, suggesting a step-down in speech fluency. The study also found that the degree of impairment varied on the quantity of alcohol and varied on the individual's age and gender. One limitation of the study is that it only investigated the consequences of alcoholic drinks on supra-segmental features of speech.

Alcohol consumption can have a significant impact on a person's F0, which is the fundamental frequency of their voice. The effects of alcohol on F0 can also vary depending on the amount consumed, as well as other factors also. Hollien et al. (2001) [12] found that alcohol intoxication affected speech supra-segmental, with changes in intonation, speech rate, accentuation, and F0 range. For this research, they chose 35 young (males-19 and 16- females) individuals; investigated alcohol intoxication effects on speech suprasegmental, before and after consuming an amount of alcohol that would result in a blood alcohol concentration (BAC) of 0.10%. They examined speech that extend beyond individual phonemes or segments, such as stress, intonation, and rhythm. As per the result analysis, The participants showed a significant decrease in the F0 range which indicates a reduction in the ability to modulate pitch; intonation patterns were altered; speech rate increased significantly after alcohol consumption, with longer pauses between sentences; decrease in the ability to accentuate syllables. Ma et al. (2021) [13] presented a comprehensive existing literature review on voice features for the status of smoking estimation objective. The review provides an overview of the various voice characteristics. In this review, they studied their potential to identify smoking status, including fundamental frequency, shimmer, jitter, harmonics-to-noise ratio formants, and others. As per their findings, the HNR value rises when smoking is stopped. Additionally, jitter and shimmer are significantly reduced. The F0 value increases while abstaining from smoking and decreases once smoking is resumed. Schiel et al. (2012) [14] described the development of the first public corpus of alcoholization German speech and its analysis. The corpus was created by recording speech samples from individuals intoxicated to the point of impairment and then transcribing and annotating the recordings for analysis. The corpus consists of 120 speech samples from 40 participants, who were asked to perform a series of speech tasks while intoxicated to the point of impairment. The authors analyze the corpus to investigate how alcohol affects speech production and to explore the linguistic and non-linguistic features of alcoholised speech. The analysis focuses on various characteristics of speech production, including phonetics, prosody, syntax, and discourse, as well as non-linguistic features such as social and emotional cues. The researchers are investigating various features that could be used to distinguish intoxicated speech from sober speech, such as fundamental frequency (F0) in different contexts, rhythm parameters, and disfluencies. Landman (2018) [15] investigates the impact of alcohol on the vocal range using qualitative analysis. The analysis focused on three main areas: pitch range, volume, and tone quality. The results showed that after consuming alcohol, participants' pitch range decreased, with a significant decrease in the upper range. Additionally, the participants' volume increased, particularly in the mid-range, and tone quality became rougher and less controlled. The vocal range after drinking was significantly higher than their actual performance, suggesting that alcohol may impair a person's ability accurately assess their own vocal range.

Alcohol consumption can have a range of impacts on both animals and humans, although the specific effects can vary depending on the species and other factors such as the amount of alcohol consumed. Some of the researchers have experimented on alcohol consumption with animal and humans. Namazi et al. (2021) [16] carried out an analysis to find out how changes in brain activity related to the rhythmic pattern of a human voice. Shannon entropy and Sample entropy were used to analyze voice and EEG signals, and they made use of concepts related to complexity and information. They exposed ten subjects—five male and five female—to four distinct smells of varying complexity in order to influence brain activity. The authors evaluated the resulting changes in the voices of the subjects and calculated the Shannon entropy and sample entropy of the EEG and voice signals. Changes in the complexity and information content of voice and EEG signals are strongly correlated, with r values of 0.8659 and 0.9423, respectively, according to the findings. This study suggests that there is a strong correlation between the alterations of brain activity and the rhythmic pattern of voice, which can be evaluated using complexity and information concepts. Tisljár-Szabó et al. (2014) [17] examined alcohol effects and the ability to produce fluent and accurate speech. For this examination, they used 15 (8 male and seven female) mean age of 20.73+-1.79 students. As per the results and findings, alcohol consumption had a significant effect on speech production, and the participants significantly produced many speech faults (word substitutions and mispronunciations) when they consumed alcohol compared to when they had the placebo drink. Moreover, the participants' speech rate was also significantly slower when they consumed alcohol. As well, the study found that the consequence of alcohol beverage on delivered production varied depending on the type of speech task. In particular, the participants showed a greater increase in speech errors and slower speech rates when performing more complex speech tasks (such as a tongue twister task) compared to simpler speech tasks (such as reading out a list of words).

Olson et al. (2014) [18] researched the effects of alcohol on the learned songs of zebra finches, a species of bird known for their ability to learn and produce complex vocalizations. The researchers exposed male zebra finches to either water or an alcohol solution containing a concentration of 0.5 g of ethanol per kg of body weight and recorded their vocalizations. The main finding in this research, alcohol exposure affects the ability of birds to produce complex songs; alcohol exposure impairs the birds' capability to develop diverse vocalizations; alcohol exposure affects the ability of birds to learn and integrate new information. As per findings, alcohol may affect the ability of animals, including humans, to learn and produce complex vocalizations, which could have implications for communication and social interactions. Wang et al. (2019) [19] studied detecting alcohol intoxication through a ResNet-based model for the task of speech. The ResNet network was trained for 50 epochs, and the mean number of times it was trained was three. They discovered that the UAR (unweighted average recall) was only 0.633 when speaker normalization was not performed on the network. The UAR, on the other hand, increased to 0.677 when they carried out batch z-normalization using the actual speaker label. The performance also improved when they used the speaker label from clustering, and the UAR was 0.671. They extracted i-vector and used the predicted label from spectral clustering as the speaker label. They found that neither the baseline model nor the proposed model significantly degraded. Kang et al. (2018) [20] study the association between voice hygiene habits and the Korean (K-VRQOL) Voice-Related-Quality of Life among classical singers. For this research, they chose 128 (Males 35(27.3%) and Female 93(72.7%)) singers in South Korea who completed a questionnaire on their voice habits of hygienic and the K-VRQOL scale, which evaluates the effect of voice problems on an individual's life quality. The data collected was analyzed using correlation analysis, descriptive statistics, and analysis of multiple regression. The study found a substantial negative correlation between K-VRQOL scores and vocal problems, indicating that individuals with more severe vocal problems had lower life quality related to their voice; analysis of multiple regression showed that voice hygiene habits, particularly avoiding alcohol and smoking, were significant predictors of K-VRQOL scores. This study suggests that voice hygiene habits, particularly avoiding alcohol and smoking, are crucial for maintaining good vocal health and quality of life among classical singers. Terband et al. (2018) [21] investigated the relationship between fetal alcohol spectrum disorders (FASD) and speech impairments in boys. FASD is a spectrum of disorders induced by prenatal alcohol influence and can lead to a physical range, problems of cognitive, and problems of behavioral. Twenty-six children (twelve girls and fourteen boys) with typical development (ages 4.1–8.7) and ten boys with FASD participated in the study. The researchers conducted a comprehensive speech assessment, including measures of speech production, speech perception, and phonological awareness. The results showed that boys with FASD had lower scores on significant measures of speech production, speech perception, and phonological awareness compared to the control group. The findings have important implications for clinical practice, highlighting the need for early identification and intervention for speech impairments in children with FASD.

One of the most noticeable effects of alcohol on speech production is slurred speech. Alcohol can also lead to the impairment of cognitive functions such as attention, memory, and concentration, which are essential for fluent and accurate speech production. Schuller et al. (2014) [22] provide a comprehensive review of research on speaker states, particularly sleepiness, intoxication, and the challenges associated with detecting them in speech. The authors begin by discussing the importance of detecting speaker states, say sleepiness and intoxication in various settings, including driving and workplace safety. They then provide some research works on the detection of these states in a speech, highlighting the various acoustic features that have been shown to be effective in detecting sleepiness and intoxication, like changes in pitch, speech rate, speech intensity, etc. In this review, they note that continued research in this area is essential for improving safety in various settings and for better understanding the effects of intoxication and sleepiness on speech over the long term. Singer et al. (2007) [23] investigated the psychosocial factors that contribute to successful voice rehabilitation after laryngectomy surgery. Laryngectomy is a surgical procedure that involves the removal of the larynx (voice box), which can result in the loss of voice. The authors used several measures to assess the participants' psychosocial status, including the Hospital Anxiety and Depression Scale, the Life Orientation Test, the Social Network Index and Questionnaire of the Social Support. Van et al. (2018) [24] reviewed the literature on voice stress psychoanalysis and described four fundamental components of the framework: (1) physiological processes, (2) cognitive processes, (3) voice features, and (4) performance outcomes. They argued that understanding the interplay between these factors could provide new insights into human performance. Based on the idea of voice stress analysis, the review article proposed a new framework for comprehending the connection between effort and voice in human performance. Liu et al. (2019) [25] investigated how listeners deal with atypical pronunciations of words during speech perception. Specifically, the study examines whether listeners attribute unusual pronunciations to individual talker characteristics or to speech errors. The authors analyzed the data and found that the effect of atypical pronunciation on visual target identification was greater for words that were phonologically similar to their typical pronunciation. This suggests that listeners are more sensitive to deviations from expected pronunciations when the pronunciation deviates only slightly from the norm.

Alcohol consumption can have a significant impact on a person's ability to speak languages, particularly if they are not fluent in the language they are speaking. Alcohol is a depressant, which means it can slow down the central nervous system and impair cognitive function. Hendricks et al. (2019) [26] aimed to summarize and synthesize the findings from longitudinal studies on the effects of prenatal alcohol exposure on language, speech, and communication outcomes in children. The review included studies that followed children from birth to adolescence or young adulthood and assessed their language, speech, and communication abilities. Liu et al. (2018) [27] proposed a computational model that captures how listeners integrate acoustic cues and contextual information to infer the causes of speech sounds. For this, they conducted two experiments. In the first experiment, contestants were presented with a sequence of speech sounds and were asked to indicate which of two possible causes they thought produced the sounds. The causes were defined by different combinations of speaker identity, speaking rate, and vowel context. In the second experiment, participants listened to speech sounds with manipulated speaking rates and vowel contexts. The results showed that contestants were capable to use the acoustic cues to infer the speaking rate and vowel context of the speech sounds. The findings have implications for understanding speech perception and for the development of computational models of speech processing. Cooney (1998) [28] investigated how alcohol affects speech using acoustic analysis. The study involved recording the speech of participants before and after consuming alcohol and then analyzing the recordings to assess the alcohol effects on various acoustic measures of speech. The study found that alcohol consumption resulted in changes in several acoustic measures of speech, including pitch, intensity, and spectral tilt. Specifically, the outcomes revealed that alcohol consumption led to a decrease in pitch and intensity, as well as an increase in spectral tilt. The study also found that these results were more pronounced in female participants than in male participants. The author discusses the possible physiological mechanisms underlying how alcohol affects speech, including alterations in the tension of the vocal cords and the coordination of the muscles involved in speech production. The physical effects on the vocal cords and alcohol can also affect a singer's overall health and well-being, leading to fatigue, decreased lung capacity, and increased risk of illness [29][30]. These factors can all impact a singer's ability to perform at their best and may lead to long-term damage to the voice.

The goal of this survey is to review the existing literature on the use of voice analysis for identifying alcohol consumers, highlighting the limitations of existing approaches, and proposing a new approach that addresses these limitations. This literature survey aims to provide a critical analysis of existing approaches for identifying alcohol consumers using voice analysis and propose an intelligent novel approach that has the potential to improve accuracy and adaptability. The survey includes studies that investigate the relationship between alcohol consumption and various voice parameters, such as pitch, frequency, and formant patterns, and studies that examine the accuracy and reliability of voice analysis for identifying alcohol consumption.

3. MATERIALS AND MODELS

The proposed ML models for identifying alcohol consumers using a vowelized voice dataset can be implemented using a pre-processed vowelized voice dataset. In the pre-processing, we remove noise and normalize the audio levels. The pre-processed data is split into training and testing sets. The training set is used to train the model, while the testing set is used to evaluate the model's performance. For this, we use 10-fold cross-validation. We chose some suitable machine learning algorithms for this task. The chosen algorithms are k-NN, C4.5, SVM, and Random Forest algorithms, as well as NNs. The selected ML algorithm is trained on the training set using the extracted voice features. The performance of the model is evaluated using metrics like accuracy, precision, recall, and F1-score. A collection of voice recordings of people pronouncing different vowels. The dataset should include both alcohol consumers and non-alcohol consumers.

A. *Proposal Model*

Figure 1 shows the proposed model and describes the drinkers' identification system with voice data set utilizing incremental hidden layer (HL) neurons of the backpropagation ANN model. In this, we collected the voice records and personal information from drinkers and non-drinkers. All voice records have been vowelized (a, e, i, o, u). Before storing *.wav files in the storage, it removes the unwanted voice data from the original voice information. For the experiment, extract the vocalizations' hidden values with voice parameters like pitch, pulses, voicing, jitter, shimmer, and harmonica. Club the voice parameters of hidden values with relative persons' data with cleaning and normalization, then create the *.csv data file and store it in the secondary storage. Using the *.csv file, conduct the statistical analysis and apply intelligent incremental hidden layer neurons ANN classifier for the classification of drinkers and non-drinkers. After getting the optimal ANN model, examine the alcohol drinker's predictions with unknown voice parameter values. This model is useful for identifying alcohol consumers using mobile applications.

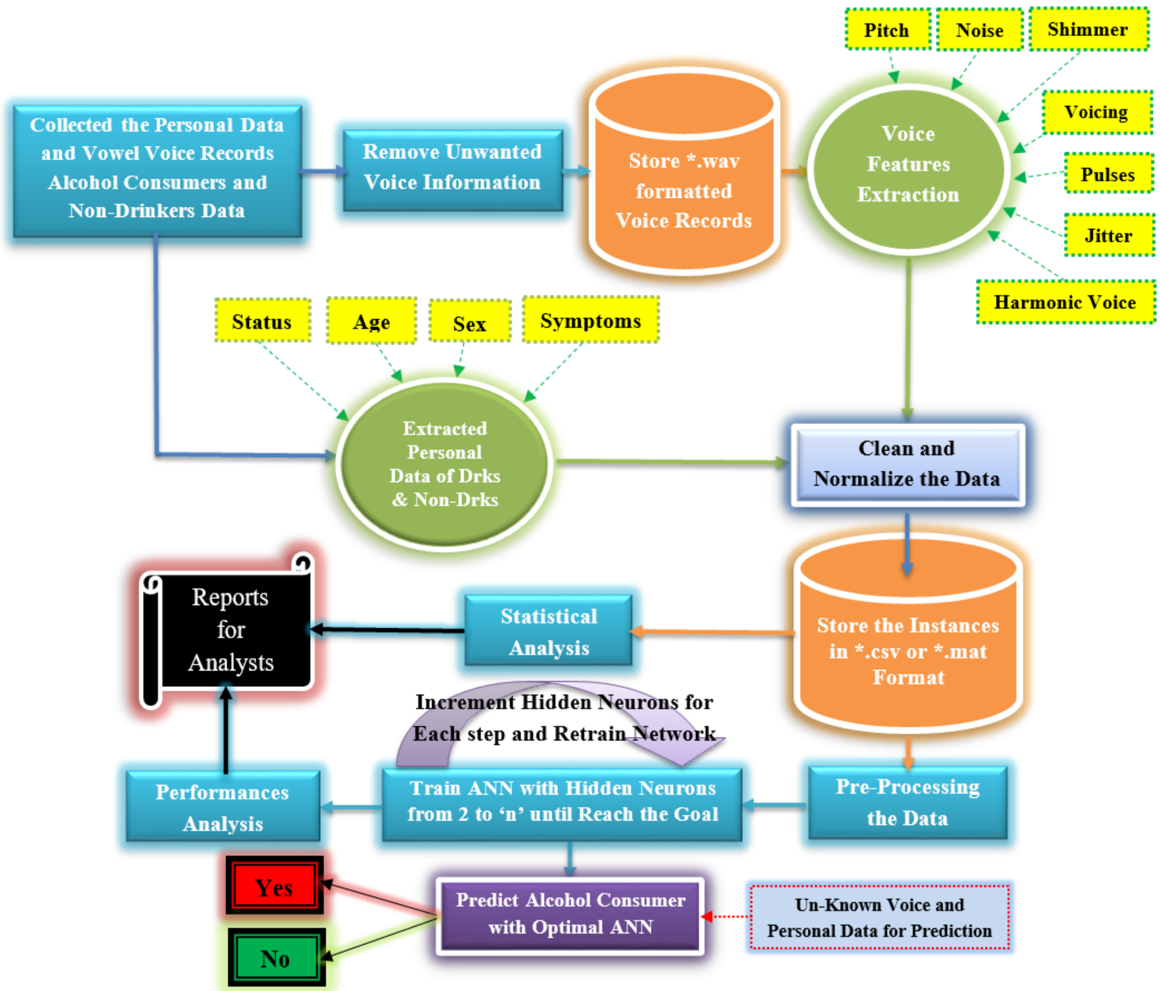


Figure 1. Incremental Hidden Layer neurons ANN Drinkers prediction proposal model

B. Dataset Description

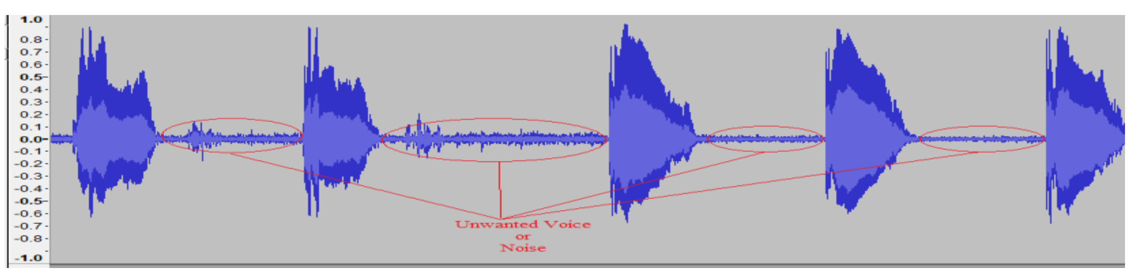
Table 3 depicts all attributes of the data, as well, as their data types and range values, which are also described. The whole set of data contains digital values. The vowels are described as a—1, e—2, and so on u—5. The pitch parameters are 5, which were mean values, median, STD, minimum, and maximum values. The target classes are two, which are 0 and 1. '0' represents non-drinkers, and '1' describes drinkers relatively. The selective information about the dataset is presented in table 3 that information about data attributes and their description.

Figure 2 (A) shows the unwanted voice data or noise marked with red circles. We have removed this noise data without affecting the original voice records. After removing the noise, the voice records have been shown in Figure 2(B) with green circles as indicators.

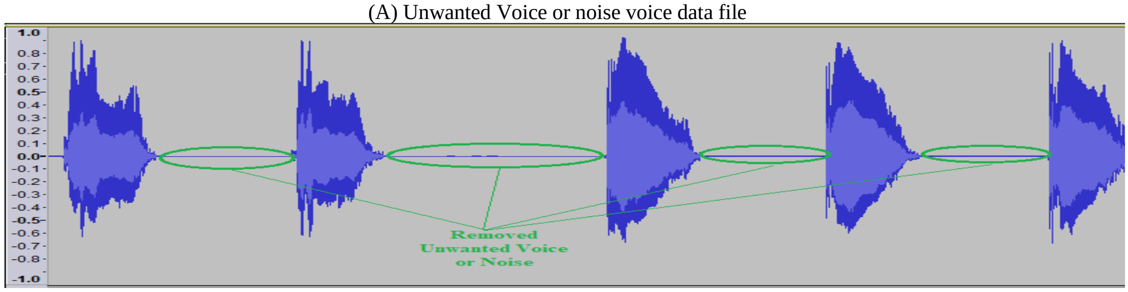
Slurred speech is a common symptom of alcohol consumption. Alcohol affects the central nervous system, which can lead to impaired motor function and coordination, including the muscles involved in speech production [31]. Specifically, alcohol can affect the muscles in the face, tongue, and throat, making it difficult to articulate words and form coherent sentences. Alcohol consumption can affect voice pulses, which are the small variations in frequency that occur in the human voice during speech [32]. Figure 3(A) shows the pulses associated with the pronunciation of the vowel sound '/a' by alcohol drinkers. The sound '/a' pulses appear to be lagging and narrow with flickers. Figure 3(B) shows the non-drinkers' voice pulses for the vowel sound '/a', revealing a clear difference in voice pulses compared to the drinkers.

TABLE I. ALCOHOL DRINKERS AND NON-DRINKERS VOICE DATASET DESCRIPTION

Sl. No	Attributes	Data Type	Description
1.	**Vowel**	Discrete (Integer)	Vowel Souds**1- a(105) ,2-e(105) 3-i (104) ,4-o,(101) 5-u (104)**
2.	**Age**	Continues (Integer)	Age of Drinkers and non-Drinkers range is **22 to 34 years**
3.	**Median pitch**	Continues (Real)	Median pitch in Hz (Hertz) range is **102.252 to 271.529 Hz**
4.	**Mean pitch**	Continues (Real)	Mean pitch in Hz (Hertz) **101.016 to 289.79 Hz**
5.	**Std. Div.**	Continues (Real)	Standard deviation Pitch in Hz between **0.886 to 141.719 Hz**
6.	**Minimum pitch**	Continues (Real)	Minimum pitch between **66.592 to 253.562Hz**
7.	**Maximum pitch**	Continues (Real)	Maximum pitch between **106.964 to 527.64 Hz**
8.	**No. of pulses**	Continues (Integer)	Number of pulses between **13 to118**
9.	**No. of periods**	Continues (Integer)	Number of periods between **12 to 117**
10.	**Mean period**	Continues (Real)	Mean period in seconds range is **0.00344 to 0.00991 seconds**
11.	**Std. Div. of period**	Continues (Real)	Standard deviation of period, range is **0.000029 to0.00306 seconds**
12.	**Fraction of UVFL**	Continues (Real)	Fraction of locally unvoiced frames range is **0 to 33.333**
13.	**No of Unvoiced**	Continues (Integer)	Number of unvoiced frames range is **0 to 19**
14.	**Total frames**	Continues (Integer)	Total number of frames range is **10 to 81**
15.	**Number of VBs**	Continues (Integer)	Number of voice breaks between **0 to 2**
16.	**Degree of VBs**	Continues (Real)	Degree of voice breaks range is **0.0 to 29.96(seconds/seconds)**
17.	**Jitter (loc.)**	Continues (Real)	Jitter (local) in % range is **0.26% to 4.93%**
18.	**Jitter (loc., abs)**	Continues (Real)	Jitter (local, absolute) in seconds range is **0.000014 to 0.000389**
19.	**Jitter (rap)**	Continues (Real)	Jitter (rap) in % range is **0.08% to 2.98%**
20.	**Jitter (ppq5)**	Continues (Real)	Jitter (ppq5) in % range is **0.1 to 3.51**
21.	**Jitter (ddp)**	Continues (Real)	Jitter (ddp) in % range is **0.24 to 8.92**
22.	**Shimmer (loc.)**	Continues (Real)	Shimmer (local) in % range is **1.81 to 23.35**
23.	**Shimmer (loc.,abs)**	Continues (Real)	Shimmer (local, dB) in decibel range is **0.157 dB to1.893dB**
24.	**Shimmer (apq3)**	Continues (Real)	Shimmer (apq3) in % range is **0.85% to 11.85%**
25.	**Shimmer (apq5)**	Continues (Real)	Shimmer (apq5) in % range is **1% to 15.16%**
26.	**Shimmer (apq11)**	Continues (Real)	Shimmer (apq11) in % range is **0.77% to 28.33%**
27.	**Shimmer (dda)**	Continues (Real)	Shimmer (dda) in % range is **2.55% to 35.55%**
28.	**Mean AC**	Continues (Real)	Mean autocorrelation: **0.658867 to 0.994578**
29.	**Mean NHR**	Continues (Real)	Mean noise-to-harmonics ratio: **0.005474 to 0.61314**
30.	**Mean HNR**	Continues (Real)	Mean harmonics-to-noise ratio: **3.197 to 26.516 dB**
31.	**Target Class (0 or 1)**	Discrete (Integer)	0-Non-Drinker **(219)** 1-Drinker **(290)**

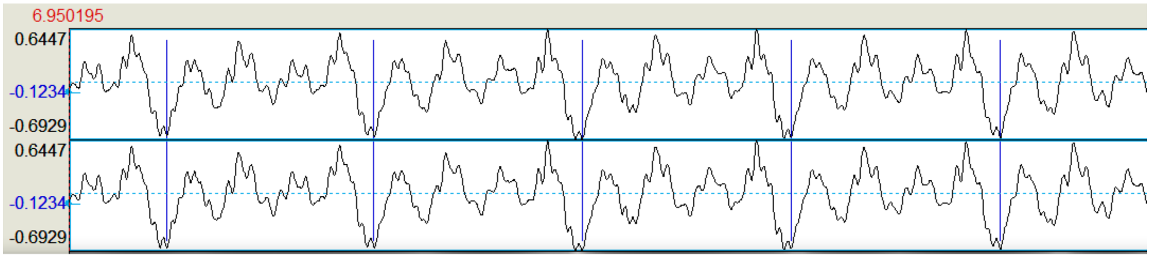


(A) Unwanted Voice or noise voice data file

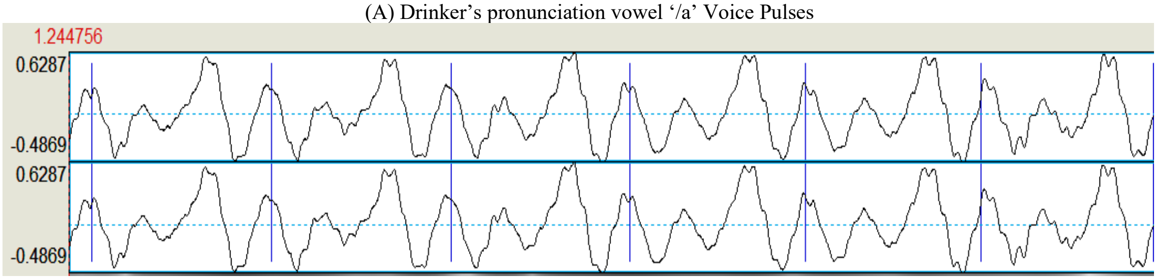


(B) Removed Unwanted Voice or noise voice file

Figure 2. Incremental Hidden Layer neurons ANN Drinkers prediction proposal model



(A) Drinker's pronunciation vowel '/a' Voice Pulses



(B)Non-Drinker's pronunciation vowel '/a' Voice Pulses

Figure 3. Difference between Alcohol Consumer and non-consumers voice pulses of pronunciation of '/a'

Figure 2 (A) shows the unwanted voice data or noise marked with red circles. We have removed this noise data without affecting the original voice records. After removing the noise, the voice records have been shown in Figure 2(B) with green circles as indicators.

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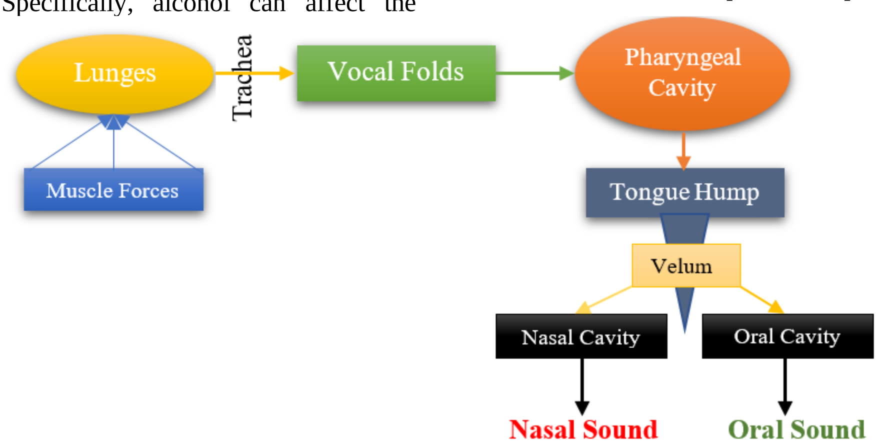

Figure 4. Model for Sound Produced by the Human

Sound is produced by the vocal system, which includes the tongue, pharynx, larynx, and lips. The vocal cords are housed in the larynx, also known as the voice box. As air passes through them, the larynx vibrates, resulting in sound waves [33]. The tension and thickness of the vocal cords, as well as the amount of air passing through them, determine the sound's pitch and volume. Figure 4 shows the model of producing sound in humans: Muscles force the lungs and make a sound from the nose and mouth. The air passes through the trachea to the vocal folds. The speech signal travels through vocal tract filters, which are produced by human vocal cords. Mainly, human speech contains two different classes: vowels and consonants in periodic sources and aperiodic or noisy sources. The vocal cords' fundamental frequency or vibration is the pitch, defined as F0 [34].

Pitch is the most noticeable acoustic attribute of the voice. According to this property, we can differentiate between genders in humans, as the pitch value of men's voices is lower than that of women's [35]. It affects humans in terms of characteristics, leadership qualities, and more. Pitch is an acoustic property of the voice and affects patterns of features associated with human processes, such as management abilities and dominance. Voice pitch also affects gender differences because a woman's pitch rate is higher than a man. Figure 5 shows the demographic results of the spectrogram of voice signals and its voice parameters.

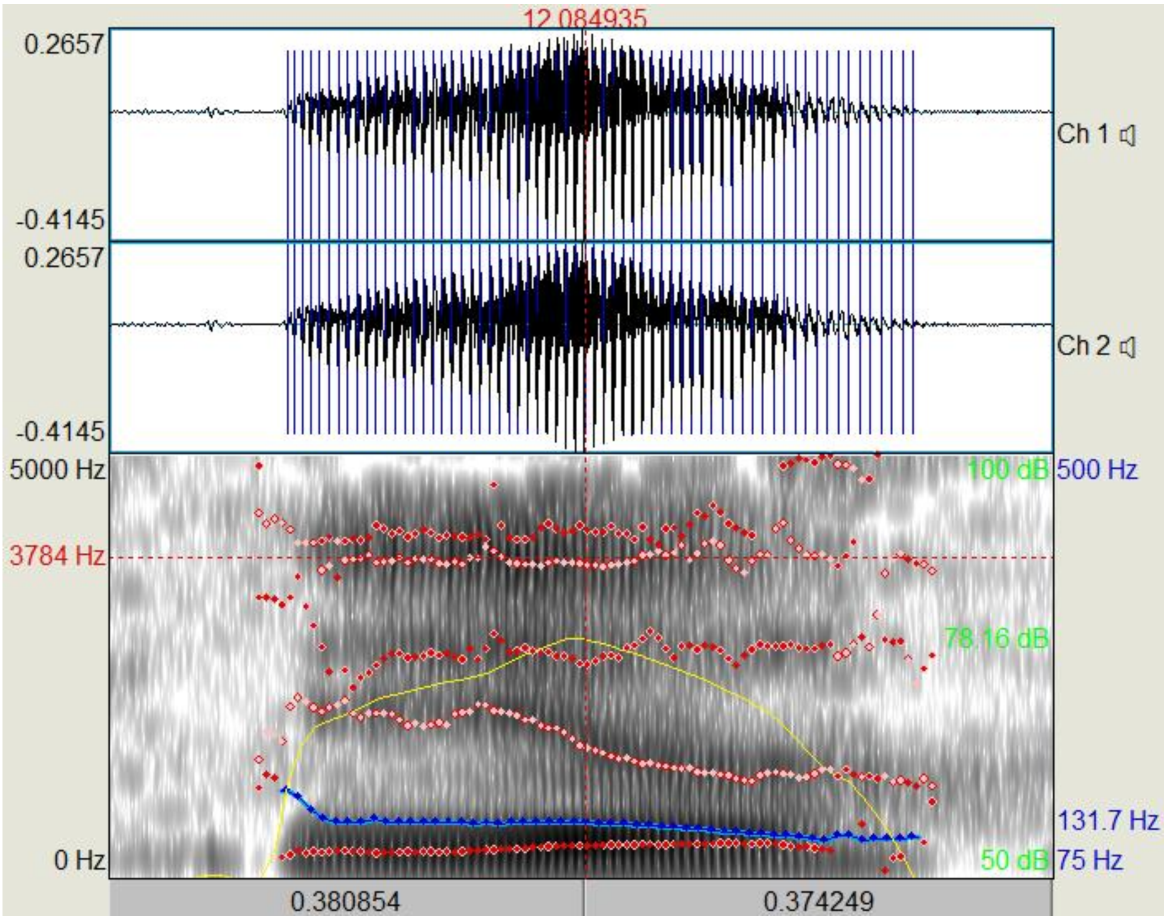

Figure 5. Spectrogram of voice signal

The values of voice parameters are calculated as equations (1) to (9).

$$jitter = \frac{1}{N_p - 1}\sum_{l=1}^{N_p} |T_l - T_{l-1}| \tag{1}$$

$$Jitter_{Re\,lative} = \frac{\frac{1}{N_p - 1}\sum_{l=1}^{N_p} |T_l - T_{l-1}|}{\frac{1}{N_p}\sum_{l=1}^{N_p} T_l} \times 100 \tag{2}$$

$$Jitter_{rap} = \frac{\frac{1}{N_p - 1}\sum_{l=1}^{N_p-1} \left|T_l - \left(\frac{1}{3}\sum_{m=l-1}^{l+1} T_m\right)\right|}{\frac{1}{N_p}\sum_{l=1}^{N_p} T_l} \times 100 \tag{3}$$

$$Jitter_{ppq5} = \frac{\frac{1}{N_p - 1}\sum_{l=2}^{N_p-2} \left|T_l - \left(\frac{1}{5}\sum_{m=l-2}^{l+2} T_m\right)\right|}{\frac{1}{N_p}\sum_{l=1}^{N_p} T_l} \times 100 \tag{4}$$

$$Shimmer_{dB} = \frac{1}{N_p - 1}\sum_{l=1}^{N_p-1} \left|20 \times log\left(\frac{A_{l-1}}{A_l}\right)\right| \tag{5}$$

$$Shimmer_{Re\,lative} = \frac{\frac{1}{N_p - 1}\sum_{l=1}^{N_p-1} |A_l - A_{l+1}|}{\frac{1}{N_p}\sum_{l=1}^{N_p} A_l} \times 100 \tag{6}$$

$$\text{Shimmerr}_{apq3} = \frac{\frac{1}{N_p - 1}\sum_{l=1}^{N_p-1}\left|A_l - \left(\frac{1}{3}\sum_{m=l-1}^{l+1} A_m\right)\right|}{\frac{1}{N_p}\sum_{l=1}^{N_p} A_l} \times 100 \quad (7)$$

$$Shimmer_{ppq5} = \frac{\frac{1}{N_p - 1}\sum_{l=2}^{N_p-2}\left|A_l - \left(\frac{1}{5}\sum_{m=l-2}^{l+2} A_m\right)\right|}{\frac{1}{N_p}\sum_{l=1}^{N_p} A_l} \times 100 \quad (8)$$

$$Harmonic_{NoiseRatio} = 10 \times log_{10}\frac{V_{AC}(T)}{V_{AC}(0) - V_{AC}(T)} \quad (9)$$

C. ANN Model

Artificial Neural Networks (ANNs) are ML model types that act as the human brain to solve complex problems. ANNs are composed of interconnected nodes, or "neurons," which work together to process and interpret input data [36]. These neurons are organized into layers, with each layer performing a specific task in the overall process. At the most basic level, an ANN model consists of three key components: an input layer, one or more hidden layers, and an output layer. The input layer receives data from the outside world, and the output layer produces the final result of the network's computation. The hidden layer(s) in between is where the actual processing takes place. The training process of an ANN model involves feeding input data into the network and adjusting the weights and biases of each neuron to minimize the error between the network's output and the actual output [37][38]. This work is done through a process called backpropagation, where the error signal is propagated backward through the network to adjust the weights and biases of each neuron.

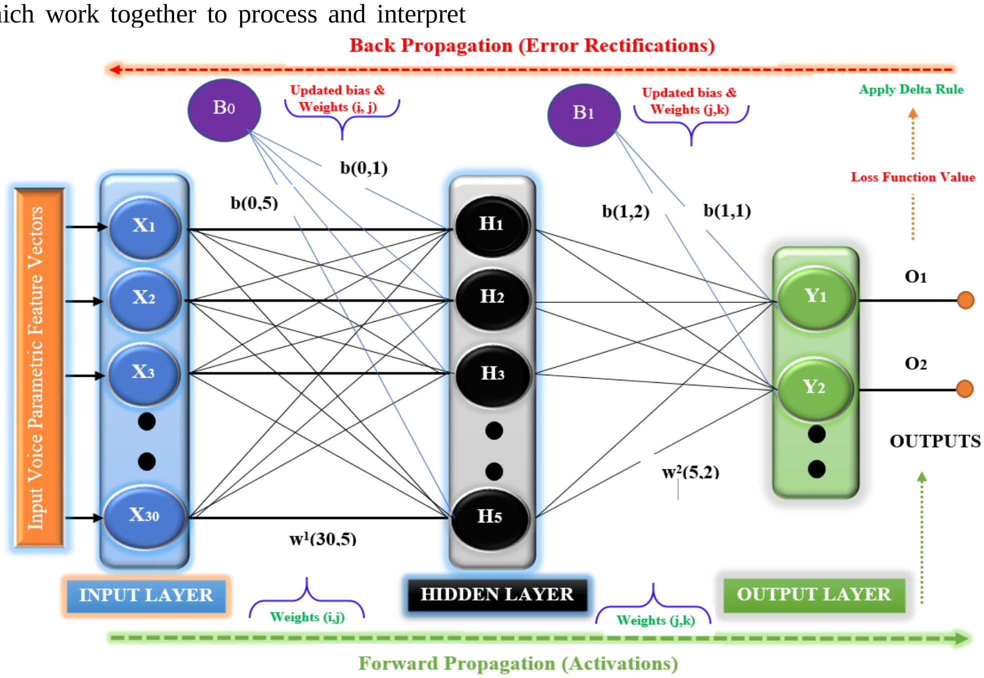

Figure 6. ANN Back Propagation model for Alcohol Consumers Detection

The artificial neural network (ANN) model for alcohol consumer detection analysis with a back-propagation algorithm is described in Figure 6. The input layer takes the input features or attributes X1, X2... X30 for identification with an objective or target class of either yes or no (drinker or not). The ANN is made up of three layers: the input (IL) layer, the hidden (HL) layer, and the output (OL) layer. The training of the NN is demonstrated with input- and output-based matches utilizing feature attribute values. Specifically, NNs perform this function by working with an input transformation set. According to our analysis, the number of HL neurons is optimized by two to five, and this can continue until the maximum accuracy is reached. In this process, the values of feature attributes are transformed through the HL, and then the predicted result appears at the OL. All these changes are based on the bias (B) and weight (W) values. During the training, the NN learns and adjusts the weight values to minimize the loss (L) between target and actual output values. These weights are adjusted using the gradient descent (GD) optimization process at each epoch. Compute the activations in the forward direction and allocate weights to the hidden layer neurons. The computation measures the loss function using the outputs and the original target values. Back-propagate to the output layer and update the weights of the relative neurons. Figure 7 shows the results of the forward-direction computations.

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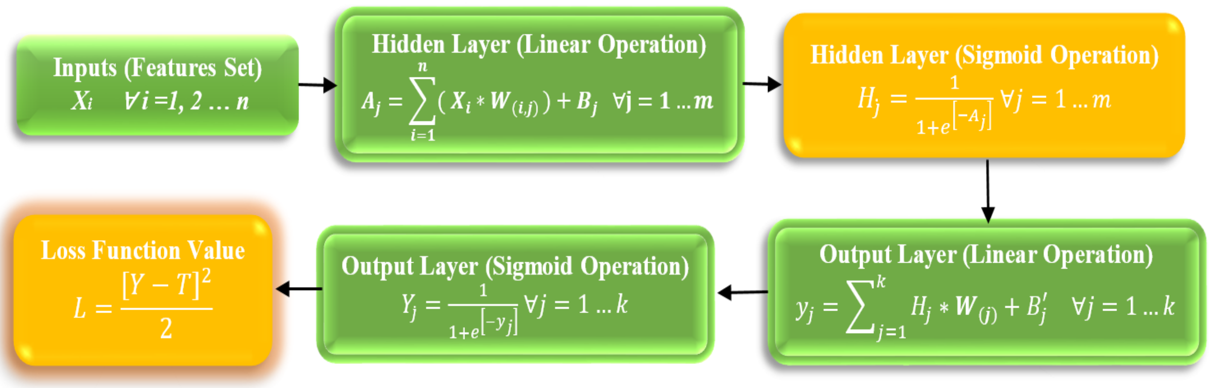

Figure 7. Figure 7. ANN Back Propagation Mathematical model

$$W^{(n+1)} = W^{(n)} + \varepsilon \frac{\partial L}{\partial W} \quad (10)$$

W represents the value of the weight, n denotes the nth value of the weight, the learning rate is denoted by ϵ, and L is the loss value; then, then ∂L/∂W is the gradient weight value to loss. This value is changed in the gradient descent cycle. The overall configuration of one feature neuron is determined using Equation (2).

$$A = XW + B \quad (11)$$

The activation value is multiplication of X and W, added B (Bias). This Eq. (12) is a linear operation.

$$\mathrm{A_i} = \sum_{j=1}^{n} \mathrm{X_{ij} W_j + B_i} \quad (12)$$

By above output is I/P of σ (activation function sigma). The value of i is 1, 2... m. In this, the used activation function is the sigmoid function represented in Eq. (13).

$$\sigma(x) = \frac{1}{1 + exp(-x)} \quad (13)$$

Compose the sequence OL neurons output Y or Yi that represented in eq. (14)

$$\mathrm{Y} = \sigma(\mathrm{A}) = \sigma(\mathrm{XW + B}) \text{ or}$$

$$\mathrm{Y_i} = \sigma(\mathrm{A_i}) = \sigma\left(\sum_{j=1}^{n} \mathrm{X_{ij} W_j + B_i}\right) \quad (14)$$

As per Eq. (14), we will compose the general equations that are Eq. (15) and (16) that represent H and Y values.

$$\mathrm{H} = \sigma(XW^1 + B_0) \quad (15)$$

$$\mathrm{Y} = \sigma(XW^2 + B_1) \quad (16)$$

The Eq. (17) depicts the error or loss L value in mean squared actual out value Y and target value T.

$$\mathrm{L} = \frac{1}{2}(Y - T)^2 \quad (17)$$

The Eq. (18) is derived with HL weights W2.

$$\frac{\partial L}{\partial W^2} = \frac{1}{2}\left[\frac{\partial([Y-T]^2)}{\partial W^2}\right] = \frac{1}{2}\left[\frac{\partial(Y^2)}{\partial W^2} - 2T\frac{\partial Y}{\partial W^2}\right] \quad (18)$$

As per Eq. (7) in Eq. (9) then get the solution in Eq. (19)

$$\frac{\partial L}{\partial W^2} = H\left[\frac{exp(-HW^2 - B_1)}{(1 + exp(-HW^2 - B_1))^2}\right]\left[\frac{1}{(1 + exp(-HW^2 - B_1))} - T\right] \quad (19)$$

D. *Gradient Decent - BP of ANN Analysis*

Figure 8 shows the general BP-ANN architecture for calculating loss functions. In this process, an input linear matrix X is given to the network, and the activation function A1 is applied with weights and bias values. The output of A1 is the input of the hidden layer neurons. Activation A2 is applied with bias B1 and weights W2, and then the output Y is obtained [39][40]. The loss of L value is calculated using the measures of Y and T with Eq. (18).

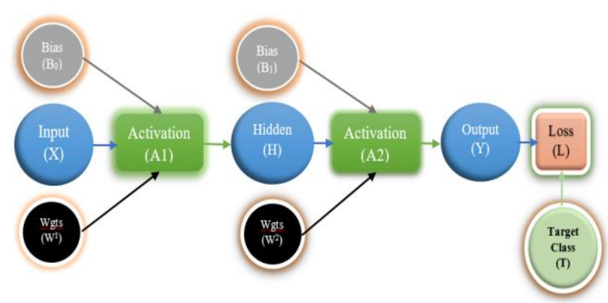

Figure 8. General BP-ANN Architecture for Loss Function computations

Figure 9 shows a detailed description of the weight-updating process using the backpropagation algorithm. In this process, the given model produces an output (O/P), which is compared to the target value, and the mean squared error value is calculated. If the error value is small or close to the goal, the process is stopped and an optimal

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NN model is produced. Otherwise, the weights of the neurons are updated, and the NN model is processed again. This procedure is repeated until the goal is reached.

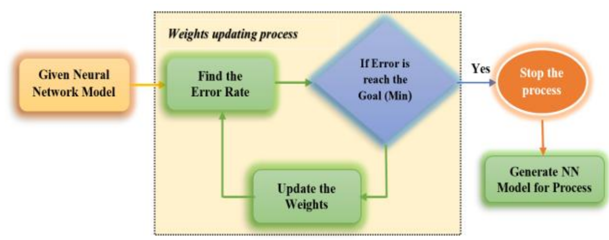

Figure 9. ANN Weights Updating BP-Process

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The Eq.10 derives the loss L with chain derivations with weights W2.

$$\frac{\partial L}{\partial W^2} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial W^2} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial W^2} \qquad (20)$$

The Eq. (11) defines the loss L value at HL along chain derivation.

$$\frac{\partial L}{\partial W^2} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial W^1} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial W^1} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial H}\frac{\partial H}{\partial W^1} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial H}\frac{\partial H}{\partial A_1}\frac{\partial A_1}{\partial W^1} \qquad (21)$$

The Eq. (12) and (13) derivation in back propagation error rectified values with respect to B1 and B0

$$\frac{\partial L}{\partial B_1} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial B_1} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial B_1} \qquad (22)$$

$$\frac{\partial L}{\partial B_0} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial B_0} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial B_0} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial H}\frac{\partial H}{\partial B_0} = \frac{\partial L}{\partial Y}\frac{\partial Y}{\partial A_2}\frac{\partial A_2}{\partial H}\frac{\partial H}{\partial A_1}\frac{\partial A_1}{\partial B_0} \qquad (23)$$

The cross entropy (CE) or loss function is derived as Eq. (24)

$$L(\mathrm{Y,T}) = \frac{1}{n}\left(\sum_{i=1}^{n}\left(\begin{matrix} -T^{(i)}\, log(Y^{(i)}) - \\ (1 - T^{(i)})\, log(1 - Y^{(i)}) \end{matrix}\right)\right) \qquad (24)$$

E. Confusion Matrix

In this, we present the importance of the confusion matrix (CM) of the machine learning (ML) model related to the analysis of alcohol consumers. The CM is a measurement of the performance of an ML model with two or more target classes' classification issues [69]. The measurements are actual and predicted values in four blocks: true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN). Using the confusion matrix (shown in Table II), we can compute some significant parameters, such as accuracy, the F1-value, specificity, precision, recall, etc. We can also measure the area under the receiver operating characteristic (AUC-ROC) curves. Table 4 shows the confusion matrix.

TABLE II. CONFUSION MATRIX

	Predicted values		
Actual Values	Classes	Drinker (1)	Non-Drinker (2)
	Drinker (1)	(1,1) TP	(1,2) FP
	Non-Drinker (2)	(2,1) FN	(2,2) TN

We have computed the parameters for performance accuracy values such as True Positive Rate (TPR), False Negative Rate (FNR), Positive Predictive Value (PPV), Sensitivity, Recall, Miss Rate, Specificity (SPC), True Negative Rate (TNR), Precision, False Omission Rate (FOR), Negative Predictive Value (NPV), Likelihood Ratio (LR), Accuracy (ACC), False Discovery Rate (FDR), Diagnostic Odds Ratio (DOR), and F1-Score. These performance parameters are specified in the equations below (Eq(s). 25–32).

$$Accuracy(ACC) = \frac{\sum True\ Positive + \sum True\ Negative}{\sum TotalPopulation} \qquad (25)$$

$$TPR = \frac{\sum True\ \mathrm{Positive}}{\sum Condition\ \mathrm{Positive}} \qquad (26)$$

$$FNR = \frac{\sum \mathrm{False\ Nagative}}{\sum Condition\ \mathrm{Positive}} \qquad (27)$$

$$FPR = \frac{\sum \mathrm{False\ Positive}}{\sum Condition\ \mathrm{Negative}} \qquad (28)$$

$$F_1score = 2 * \frac{Pr\,e\,cision * Re\,c\,all}{Pr\,e\,cision + Re\,c\,all} \qquad (29)$$

$$SPC \text{ or TNR} = \frac{\sum True\ \mathrm{Nagative}}{\sum Condition\ \mathrm{Negative}} \qquad (30)$$

$$Pr\,e\,valence = \frac{\sum Condition\ \mathrm{Positive}}{\sum Total\ \mathrm{Population}}. \qquad (31)$$

$$PPV \text{ or PRC} = \frac{\sum True\ \mathrm{Positive}}{\sum Pr\,e\,dicted\ Condition\ \mathrm{Positive}} \qquad (32)$$

4. RESULTS AND DISCUSSIONS

In this section, we conduct experiments on drinkers' datasets using statistical and classification models. Firstly, we analyze and describe the dataset in detail using statistical analysis such as the mean, median, minimum, and maximum values of each attribute for class 2 (non-drinkers), class 1 (drinkers), and the total dataset. After that, we analyze and discuss classification algorithms, including an ANN-based predictive model.

A. Statistical Analysis

In this section, we conduct experiments on drinker data sets using statistical and classification models. Firstly, we analyze and describe the data set in detail using statistical analysis such as the mean, median, minimum, and maximum values of each attribute for Class 2 (non-drinkers), Class 1 (drinkers), and the total. We gather personal and voice information from all individuals (drinkers and non-drinkers) with 509 vowels (/ 'a'/'e'/'i'/'o'/'u') voice records in *.wav format. After that, we analyze and discuss classification algorithms, including an ANN-based proposal model. We divide the data set into two class sets, which are the Class 1 set and the Class 2 set. We perform the statistical analysis on each class set, and after combining both classes, we again conduct the statistical analysis and get the total dataset's statistical results. The collected information contains age groups of 22 to 34 years for male personal data and their hidden voice record values. Class 1 group describes the drinkers, and Class 2 specifies the non-drinker specifications. As per statistical results, all mean and median values of pitch (mean, median, SD, min, and max) in Class 1 (drinkers) set are higher than those in Class 2 (non-drinkers), as is the case for the entire set. The number of unvoiced mean values in Class 1 is higher than in Class 2. All mean and median values of the jitter and shimmer voice parameters in Class 1 are higher than the values in the Class 2 set. Table III specifies the minimum and maximum values of all voice parameters concerning Classes 1 and 2 and the total data set. The age group of 22 to 34-year-olds is involved in all Class 2, Class 1, and full dataset categories. It describes the detailed analysis of the minimum and maximum values of every voice parameter such as mean pitch, median pitch, jitter, shimmer, harmonic ratio, etc.

TABLE III. STATISTICAL MEASURES MEAN AND MEDIAN VALUES OF ALL ATTRIBUTES THROUGH CLASS 2, CLASS 1 AND TOTAL SET

Attributes	Mean			Median		
	Class-1	Class 2	Total set	Class 1	Class 2	Total set
Age	29.10513	26.41379	27.57171	29	27	27
Median pitch	183.09015	138.3734	157.613	166.409	129.749	140.479
Mean pitch	191.26150	139.0441	161.5109	172.955	129.087	142.677
Std. Div.	31.55574	11.26888	19.99741	19.173	9.703	11.351
Minimum pitch	153.78539	120.9325	135.0676	134.831	116.1295	123.697
Maximum pitch	270.79840	160.098	207.7275	273.539	145.7995	167.905
No. of pulses	59.757991	49.1069	53.68959	59	48	52
No. of periods	58.109589	48.06207	52.38507	57	47	50
Mean period	0.00562	0.007398	0.006633	0.00588	0.007735	0.00702
Std. Div. of period	0.000757	0.000582	0.000657	0.00057	0.000579	0.000579
Fraction of UVFL	5.656735	0.948935	2.974491	3.571	0	0
No of Unvoiced	2.045662	0.472414	1.149312	1	0	0
Total frames	34.721461	36.95517	35.99411	34	36	35
Number of VBs	0.191781	0.02069	0.094303	0	0	0
Degree of VBs	1.965881	0.208159	0.964428	0	0	0
Jitter (loc.)	1.850183	1.181759	1.469352	1.77	1.02	1.3
Jitter (loc., abs)	0.000103	0.000089	0.000095	0.000093	0.000074	0.000082
Jitter (rap)	0.853607	0.436276	0.615835	0.76	0.315	0.49
Jitter (ppq5)	0.881187	0.443793	0.631984	0.8	0.34	0.52
Jitter (ddp)	2.559406	1.306862	1.845776	2.27	0.945	1.48
Shimmer (loc.)	9.234795	5.993103	7.387859	8.58	5.68	6.54
Shimmer (loc.,abs)	0.903361	0.601462	0.731356	0.87	0.5855	0.692
Shimmer (apq3)	4.420228	2.471517	3.309961	4.19	2.085	2.69
Shimmer (apq5)	5.483836	3.129034	4.1422	4.81	2.665	3.34
Shimmer (apq11)	7.533836	4.777724	5.963556	6.52	4.215	5.09
Shimmer (dda)	13.259178	7.413207	9.928468	12.57	6.255	8.07
Mean AC	0.897638	0.94832	0.926514	0.900901	0.957036	0.94016
Mean NHR	0.147506	0.067739	0.102059	0.138518	0.051095	0.07467
Mean HNR	12.955301	16.27091	14.84435	12.342	16.279	14.969

Table IV specifies the minimum and maximum values of all the voice parameters concerning Class 1, Class 2, and the total dataset. The age group of 22 to 34 years is involved in all Class 2, Class 1, and total dataset categories. It describes the detailed analysis of minimum and maximum values of every voice parameter, such as mean pitch, median pitch, jitter, shimmer, harmonic ratio, and so on.

TABLE IV. STATISTICAL MEASURES MINIMUM AND MAXIMUM VALUES OF ALL ATTRIBUTES THROUGH CLASS 2, CLASS 1 AND TOTAL SET

Attributes	Minimum			Maximum		
	Class 1	Class 2	Total Set	Class 1	Class 2	Total Set
Age	24	22	22	34	34	34
Median pitch	120.32	102.252	102.252	271.529	229.056	271.529
Mean pitch	122.994	101.016	101.016	289.79	227.555	289.79
Std. Div.	2.115	0.886	0.886	141.719	131.084	141.719
Minimum pitch	76.595	66.592	66.592	253.562	214.191	253.562

Maximum pitch	126.606	106.964	106.964	527.64	492.45	527.64
No. of pulses	25	13	13	118	107	118
No. of periods	24	12	12	117	106	117
Mean period	0.00344	0.00439	0.00344	0.00811	0.00991	0.00991
Std. Div. of period	0.000061	0.000029	0.000029	0.00292	0.00306	0.00306
Fraction of UVFL	0	0	0	33.333	30.159	33.333
No of Unvoiced	0	0	0	19	19	19
Total frames	20	10	10	69	81	81
Number of VBs	0	0	0	2	1	2
Degree of VBs	0	0	0	29.96	25.71	29.96
Jitter (loc.)	0.43	0.26	0.26	4.93	4.58	4.93
Jitter (loc., abs)	0.000022	0.000014	0.000014	0.000384	0.000389	0.000389
Jitter (rap)	0.15	0.08	0.08	2.98	2.56	2.98
Jitter (ppq5)	0.18	0.1	0.1	3.51	1.62	3.51
Jitter (ddp)	0.44	0.24	0.24	8.92	7.68	8.92
Shimmer (loc.)	3.19	1.81	1.81	23.35	17.63	23.35
Shimmer (loc.,abs)	0.302	0.157	0.157	1.893	1.543	1.893
Shimmer (apq3)	1.25	0.85	0.85	11.85	9.93	11.85
Shimmer (apq5)	1.79	1	1	15.16	11.18	15.16
Shimmer (apq11)	2.01	0.77	0.77	28.33	16.86	28.33
Shimmer (dda)	3.75	2.55	2.55	35.55	29.79	35.55
Mean AC	0.658867	0.736003	0.658867	0.993707	0.994578	0.994578
Mean NHR	0.006643	0.005474	0.005474	0.61314	0.420146	0.61314
Mean HNR	3.197	4.964	3.197	26.516	24.729	26.516

The figure 10 shows the class attribute drinkers and non-drinkers bar graph. The blue bar represents the Drinkers total voice records 290 and the orange bar represents the Non-drinkers with total count 219 records.

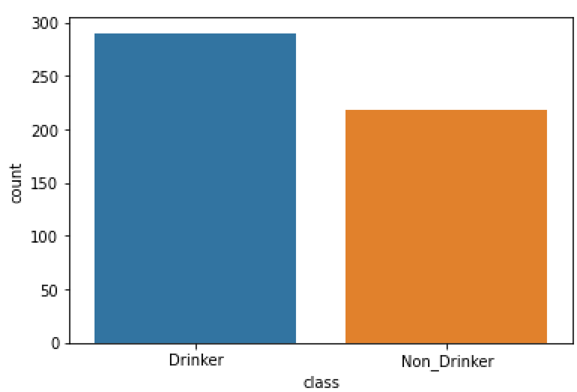

Figure 10. Class attribute Drinker and Non-Drinker Statistics

Figure 11 shows the correlation matrix for the Drinker and Non-Drinker Data attribute relations. The correlation values are between (-1, +1) values. The red color indicates the positive, and the color blue indicates the negative value. As per analysis, the mean pitch and median pitch, the attributes pulses and periods, jitter attributes, and shimmer attributes are correlated highly with each other that are nearer to value one. Some other attributes are negatively correlated with other attributes that are mean periods, mean autocorrelation, and mean harmonic to noise ratio values.

The correlation between the two variables has been measured. Correlation is derived from two things that are negative and positive. A positive correlation occurs when two factors or variables change in a similar way or the same direction; if one variable increases, then the other value also increases relatively. A negative correlation occurs when two factors move in the opposite or inverse direction, meaning that if one increases, then the other one decreases. If there are numerous factors and the objective is to find the correlation between these factors and store them using the proper data structure, the matrix structure is utilized. Such a network is known as a correlation matrix. A correlation matrix is a table that shows the correlation coefficients between all factors in the dataset. The correlation matrix is used to find closely related pairs of factors or feature variables. Using this matrix, analysts can analyze the relationships between multiple variables. The Pearson correlation coefficient can be calculated using the formula. If X and Y are two variables, $\bar{X}$ and $\bar{Y}$ are the means, and Xi and Yi are the individual values of X and Y, then the correlation calculation is computed as:

$$Correlation\ Value = \frac{\sum(X_i - \bar{X})((X_i - \bar{X}))}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}}$$

B. Machine Leaning Models and Analysis

In this, we have been analyzing the 5 ML models like k-NN, C4.5, SVM, and Random Forest algorithms using performance parameters like classification accuracy, AUC, precision, recall, and F1 value using confusion matrices. The input dataset is trained using 10-fold cross validation.

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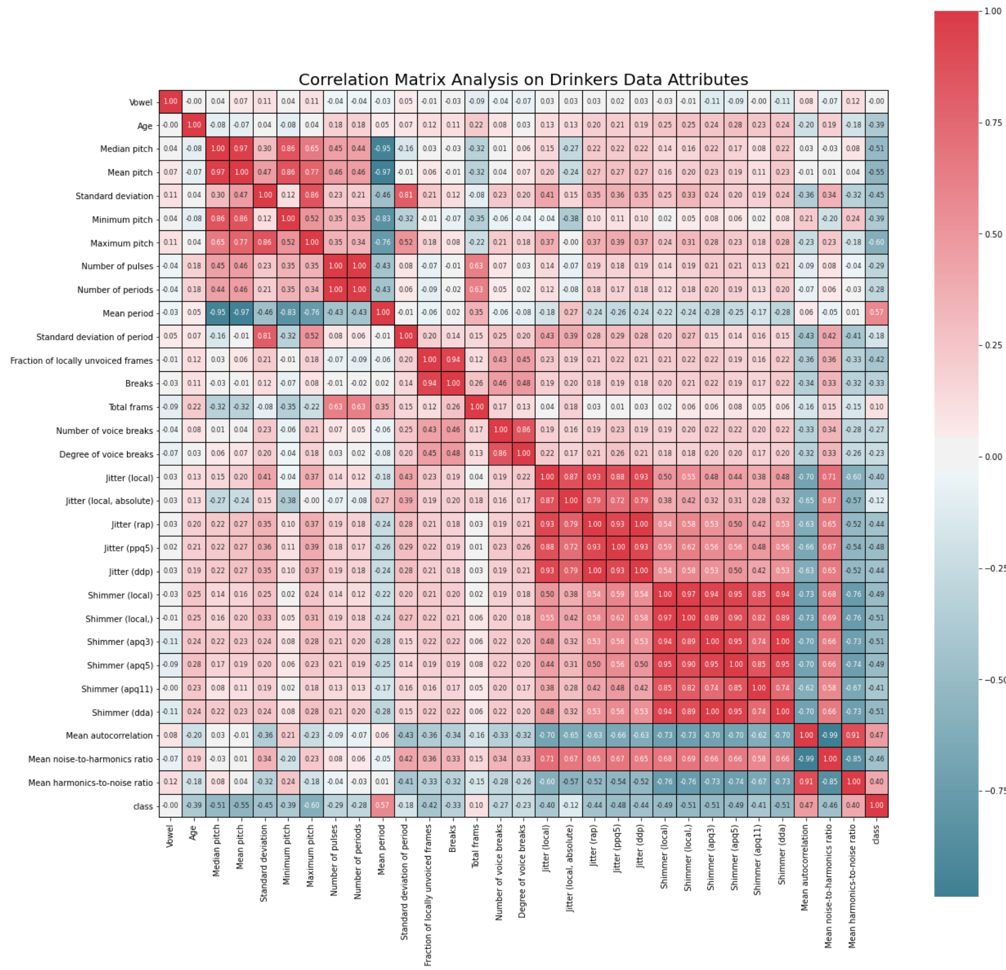

Figure 11. Class attribute Drinker and Non-Drinker Statistics

Confusion Matrix Analysis of Each Experimental ML Models:

Figure 12 shows the confusion matrices of all experimental ML models. We describe this in detail as follows. The k-NN is constructed with k = 5, and the metric distance is measured with Euclidean uniform weights. Figure 12(A) shows the confusion matrix of the k-NN: in class 2 (non-DRK), 187 cases are classified correctly, 32 cases are wrongly classified as instances in the DRK class, and 268 instances in class 1 are classified correctly, while 22 instances are classified incorrectly. The C4.5 computational ML model considers numeric and categorical attributes. For each categorical one, the C4.5 computes the information gained and chooses the most esteemed value in the selection process. It then uses the attribute to produce numerous results that have different values for attributes. In this, C4.5 has been configured with a binary tree with a minimum of 2 instances of leaves; not 5 lesser subsets split, and a maximum depth of the tree of 20. Figure 12(B) shows the confusion matrix of the C4.5: 206 cases of class 2 (N-DRK) are classified correctly, but thirteen sample cases are classified wrongly as instances in the DRK class; 277 sample instances of class 1 are classified correctly, but 13 examples are classified incorrectly.

Figure 12 (C) shows the confusion matrix of the SVM, wherein in class 2 (N-DRK) 200 case samples are classified correctly, and 19 case instances are classified incorrectly. 214 sample instances in class 1 are classified correctly, and 14 case instances are classified incorrectly. Figure 12(D) shows the confusion matrix of the RFs, wherein class 2 (N-DRK), 207 cases are classified correctly, and 12 samples are classified incorrectly, with these instances in the DRK

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class, and 278 sample instances in class 1 are classified correctly, but 12 case instances are classified incorrectly

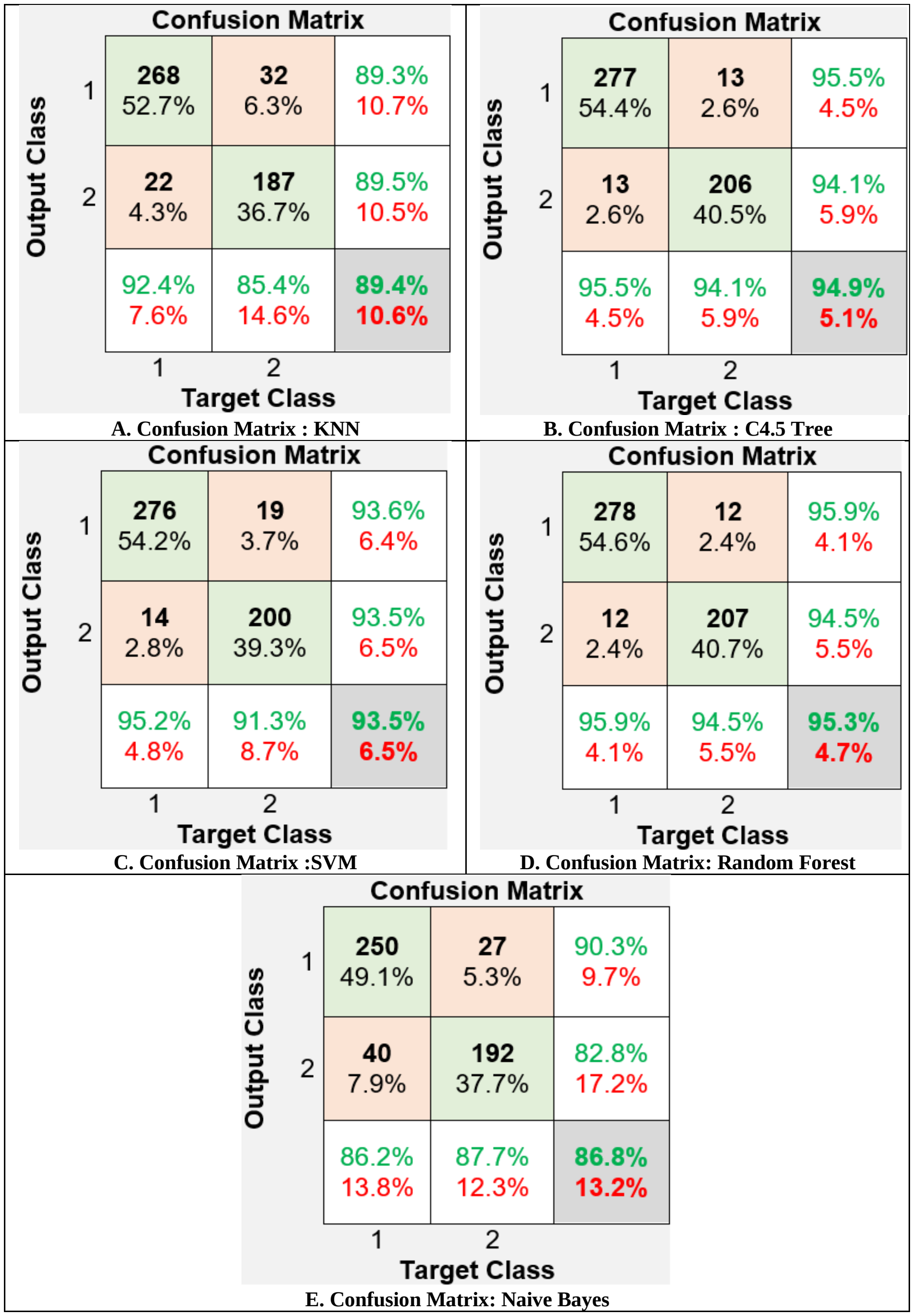


Figure 12. Confusion Matrix for all Experimental ML models

Figure 12 (E) shows that the confusion matrix of the NB correctly classified 119 cases of class 2 (N-DRK) and 250 sample cases of class 1. 27 examples of class 2 and 40 sample examples of class 1 were incorrectly classified.

Performance Parameters Analysis

We need to measure performance parameters such as accuracy, precision, recall, F1 score

K-NN Model: Table 8 shows the performance parameters of the k-NN that depicts class 2 (NDRKs), class 1(DRKs) parameter values, and average weight values also. The AUC and CA are equal performance values for both classes (N-DRK and DRK) and the values are 0.967936 and 0.89391 respectively. F1 and Recall values are somewhat higher in class1 than in class 2. The precision value of class 2 is 0.894737 superior to the class 1 value.

TABLE V. PERFORMANCE PARAMETER VALUES OF K-NN

k-NN	AUC	CA	F1	Precision	Recall
Class 2	0.967936	0.89391	0.873832	**0.894737**	0.853881
Class 1	0.967936	0.89391	**0.908475**	0.893333	**0.924138**
Avg. Wait	0.968887	0.89391	0.893569	0.893937	0.89391

C4.5 Model: Table 10 shows the performance parameters of the C4.5 that describe the class 2 (NDRKs), class 1(DRKs) parameter values, and average weight values. The AUC and CA are equal performance values for both classes (N-DRK and DRK), and the values are 0.953392 and 0.948919respectively. F1, Precision, and Recall values are somewhat superior in class1 than class 2 that the values are 0.955172, 0.955172, and 0.955172 respectively.

TABLE VI. PERFORMANCE PARAMETER VALUES OF C4.5

C4.5	AUC	CA	F1	Precision	Recall
Class 2	0.953392	0.948919	0.940639	0.940639	0.940639
Class 1	0.953392	0.948919	**0.955172**	**0.955172**	**0.955172**
Avg. Wait	0.958092	0.948919	0.948919	0.948919	0.948919

Figure 13 shows the visualization of the C4.5 tree. According to the analysis, the root node is the maximum pitch value. It will elaborate the tree according to conditions. If the Max pitch is less than or equal to 247.17, it checks the fraction of locally unvoiced frames; otherwise, it assures the total number of frames. If the full frames are less than or equal to 46, someone other than the algorithm may suspect a drinker; the next possible attribute to check is shimmer (local). If the shimmer (local) is less than or equal to 2.273, then we assume that it is possible to be a drinker (1.90) or a non-drinker (0.5). According to the C4.5 tree analysis, we can identify drinkers and non-drinkers with some crucial attributes such as mean pitch, mean period, mean noise, and so on. The detailed analysis is in Figure 15.

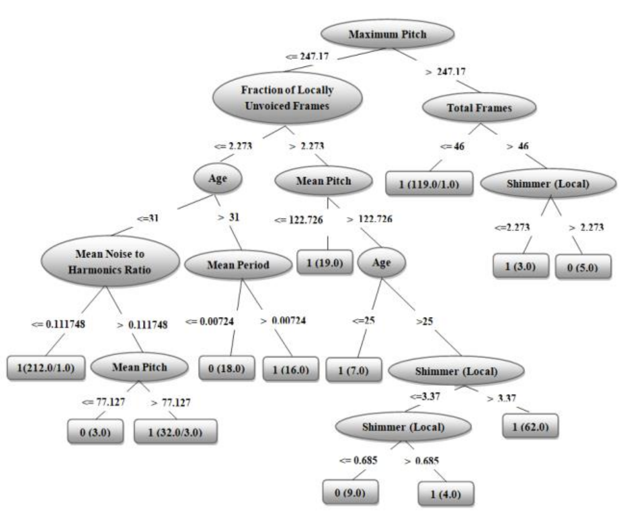


Figure 13. Visualization Tree of C4.5

SVM: In this, the SVM configured with the cost (C) is 1.00, and the regression loss ϵ value is 0.10 where the kernel is RBF (exp(-g|x-y|^2 where g = 0.001). The numerical tolerance is 0.001, and the iteration limit is 100. Table 12 shows the performance parameters of the SVM that describes the class 2 (NDRKs) and class 1(DRKs) parameters' merits and values. The average weight values are also calculated. The AUC and CA are equal performance values for both classes (N-DRK and DRK), and the values are 0.984565 and 0.935167, respectively. F1, Precision, and Recall values are somewhat superior in class1 than class 2, which are 0.94359, 0.935593, and 0.951724, respectively.

TABLE VII. PERFORMANCE PARAMETER VALUES OF SVM

SVM	AUC	CA	F1	Precision	Recall
Class 2	0.984565	0.935167	0.923788	0.934579	0.913242
Class 1	0.984565	0.935167	**0.94359**	**0.935593**	**0.951724**
Avg. Wait	0.984565	0.935167	0.93507	0.935157	0.935167

Random Forest (RFs): In this, the RF is configured that the number of trees is 10, several attributes considered at each spilled 5, replicable training mode discourses slipping subsets not lesser then 5.The table 14 shows the performance parameters of the RFs that it describes the class 2 (NDRKs) and class 1 (DRKs) parameter values, and average weight values also. The CA values of N-DRK and DRK are equal that the value is 0.952849. The CA, F1, Precision, and Recall values are somewhat superior in class1 than class 2 that are 0.952849, 0.958621, 0.958621, and 0.958621 respectively.

TABLE VIII. PERFORMANCE PARAMETER VALUES OF RANDOM FOREST

RFs	AUC	CA	F1	Precision	Recall
Class 2	0.988805	0.952849	0.952849	0.952849	0.952849
Class 1	**0.988805**	**0.952849**	**0.958621**	**0.958621**	**0.958621**
Avg. Wait	0.988805	0.952849	0.952849	0.952849	0.952849

Naive Bayes (NB): In this, the NB is configured using Bayes probability theorem. The table 16 shows the performance parameters of the NB that it describes the class 2(NDRKs) and class 1(DRKs) parameter values, and average waited for values also. The AUC and CA are equal performance values for both classes (N-DRK and DRK) that the values are 0.934371 and 0.868369 respectively. F1 and Precision values are somewhat superior in class1 than class 2 that are 0.881834 and 0.902527 respectively. The Recall value 0.876712 is in class 2 greater than class 1.

TABLE IX. PERFORMANCE PARAMETER VALUES OF NAIVE BAYES

NBs	AUC	CA	F1	Precision	Recall
Class 2	0.934371	0.868369	0.851441	0.827586	**0.876712**
Class 1	0.934371	0.868369	**0.881834**	**0.902527**	0.862069
Avg. Wait	0.934371	0.868369	0.868757	0.870283	0.868369

The figure 16 shows the analysis of ROC all ML methodologies. We analyze the target class 1 ROC curves. Each model ROC curve specified with each color that the SVM is specified with Aquamarine; NB is specified with orange, the k-NN is specified with purple, the RF model is specified with pink, and C4.5 Tree model specified with the dark green. The RF model performs well with 0.989 value of AUC; secondly, the SVM model presents 0.983 value of AUC. The AUC value of the NB model is 0.934 that performs least in comparison to other experimental models.

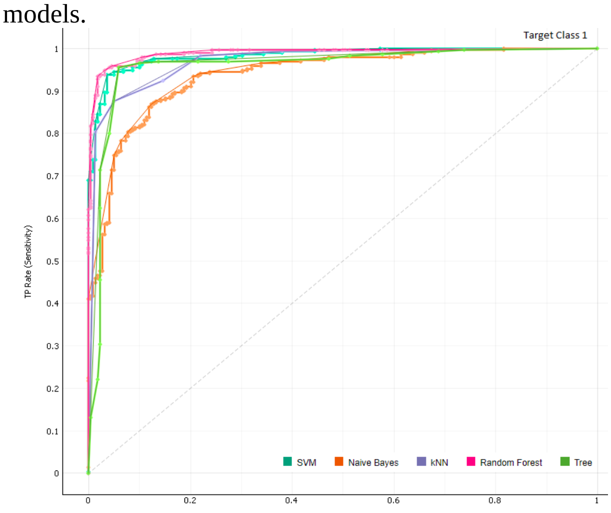


Figure 14. ROC curves of Experimental Machine Learning (ML) Algorithms

Experimental MLs Comparative Study Results

In this analysis, we compare all the experimental machine learning algorithms concerning the average performances (average weight of class 2 and class 1) parameters like F1, CA, AUC, recall, and precision values. As per the study, the RF model shows the best performance to compare other experimental models with classification accuracy 0.953 (95.3%), the value of precision is 0.953, and the recall value is 0.953, F1 value is 0.952, and measurement of AUC is 0.989. The superior values are depicted with bold and mark with + in table 17. The second highest performed model is the C4.5 model specified with * marked in table 17. The second highest AUC value is allotted to the SVM model. The detailed performance parameters values are shown in table 17.

TABLE X. COMPETITIVE ANALYSIS WITH AVERAGE PERFORMANCE PARAMETER OF ML VALUES

ML Model	CA	AUC	Recall	Precision	F1
k-NN	0.894	0.9689	0.894	0.894	0.893
C4.5	0.949*	0.958	0.949*	0.949*	0.948*
SVM	0.936	0.983*	0.935	0.936	0.935
RFs	**0.953+**	**0.989+**	**0.953+**	**0.953+**	**0.952+**
NB	0.869	0.934	0.869	0.870	0.868

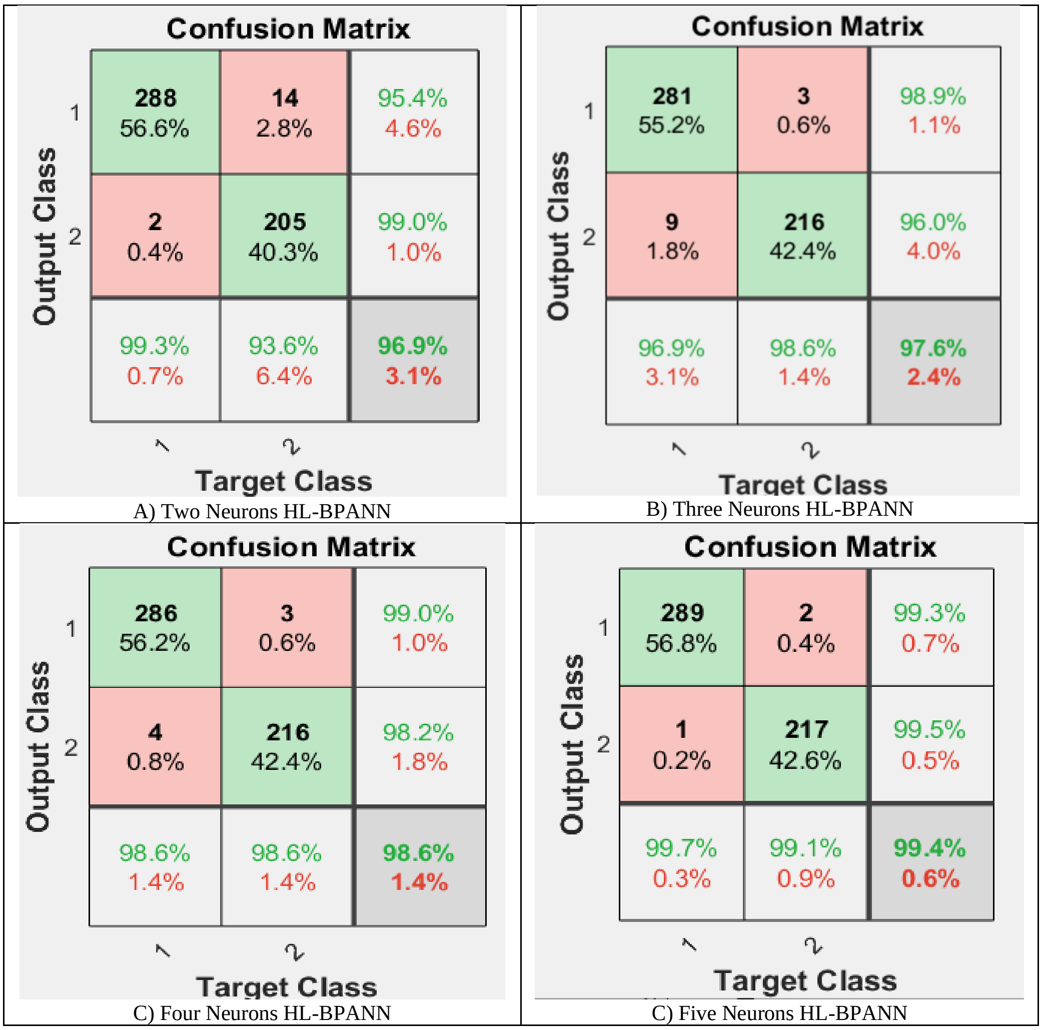
Artificial Neural Network (Incrementing neurons of HL) Models:

In this part, we have been compared and discussed incremental hidden layer neurons of BP-ANN models using each performance parameter like CA, AUC, recall, precision, F1, MSE, regression (R) and gradient values, and mue values. As per analysis, the five neurons HL BP-ANN gives the best solutions for the identification of alcoholics.

Confusion Matrices BP-ANN (2-5 HL Neurons) Models and Comparative Study on Performance Parameters

Figure 17 shows the analysis of confusion matrices of 2 to 5 neurons of HL BP-ANN models. Figure 17 (A) represents that two neurons of HL BP-ANN classified 288 instances of drinkers (class 1) correctly and two sample cases were classified wrongly. On other hand, there are 205 instances of class 2 (non-drinkers) were classified correctly and fourteen instances wrongly. The total accuracy of the two HL neurons BP-ANN was nearly 96.9%. Figure 17 (B) shows that three neurons of HL BP-ANN correctly classified 281 instances of drinkers (class 1) and nine instances were classified wrongly, and 216 instances of class 2 (non-drinkers) were classified correctly versus three sample instances wrongly. The total accuracy of the three HL neurons BP-ANN was 97.6%, which was better than two neurons HL BP-ANN. Figure 17 (C) recognizes four neurons of HL BP-ANN. It performed with the accuracy of class 1 was 98.6%, as well as 98.6% of the accuracy of class 2. Therefore, the total accuracy of the four HL neurons BP-ANN was nearly 98.6%. Figure 17 (D) depicts those five neurons of HL BP-ANN correctly classified 289 instances of drinkers (class 1), and one instance was classified wrongly. And there are 217 instances of class 2 (non-drinkers) that were classified correctly and two instances wrongly. The total accuracy of Five HL neurons BP-ANN was 99.4%.

Table 18 shows a competitive analysis of 2 to 5-neuron HL BP-ANN models with average performance parameters. We compared all the experimental 2 to 5-neuron HL BP-ANN models in terms of average performance (average weight of class 2 and class 1) of parameters such as CA, AUC, recall, precision, and F1-values. According to the study, the 5-neuron HL BP-ANN model shows the best performance when compared to other experimental BP-ANN models, with a classification accuracy of 0.9941 (99.4%), precision, recall, and F1-values of 1. The superior values are represented with bold and * marks in Table 18. The second highest performing model is the 4-neuron BP-ANN model, marked with the symbol +, with a classification accuracy of 0.99804 and AUC and precision values of 1. Therefore, we can conclude that the 5-neuron HL BP-ANN is the best model to predict drinkers with 100% accuracy. The test results also show 99.4% accuracy for this model.



A) Two Neurons HL-BPANN
B) Three Neurons HL-BPANN
C) Four Neurons HL-BPANN
C) Five Neurons HL-BPANN

Figure 15. Confusion Matrices of 2 to 5 HL BP-ANNs Model

TABLE XI. COMPETITIVE ANALYSIS WITH AVERAGE PERFORMANCE PARAMETER OF 2 TO 5 HL BP-ANNS MODEL

Model BP-ANNs	CA	AUC	Recall	Precision	F1
Two Neurons HL	0.96856581	0.9799	0.95364238	0.993103448	0.97297297
Three Neurons HL	0.97642436	0.9898	0.98943662	0.968965517	0.97909407
Four Neurons HL	0.98624754	0.9911	0.98620689	0.989619377	0.98791019
Five Neurons HL	**0.99410609**	**1**	**0.99312714**	**0.996551724**	**0.99483648**

ROC Curves of 2 to 5 HL neurons BP-ANN Models and AUC Analysis

Figure 18 shows the analysis of ROC curves for class 1 (drinkers) and class 2 (non-drinkers) neurons in the hidden layer (HL) of backpropagation artificial neural networks (BP-ANNs). The ROC is constructed between the values of specificity (X-axis) and sensitivity (Y-axis). The class curves are represented as blue (class 1) and green (class 2) colors in Figure 18.

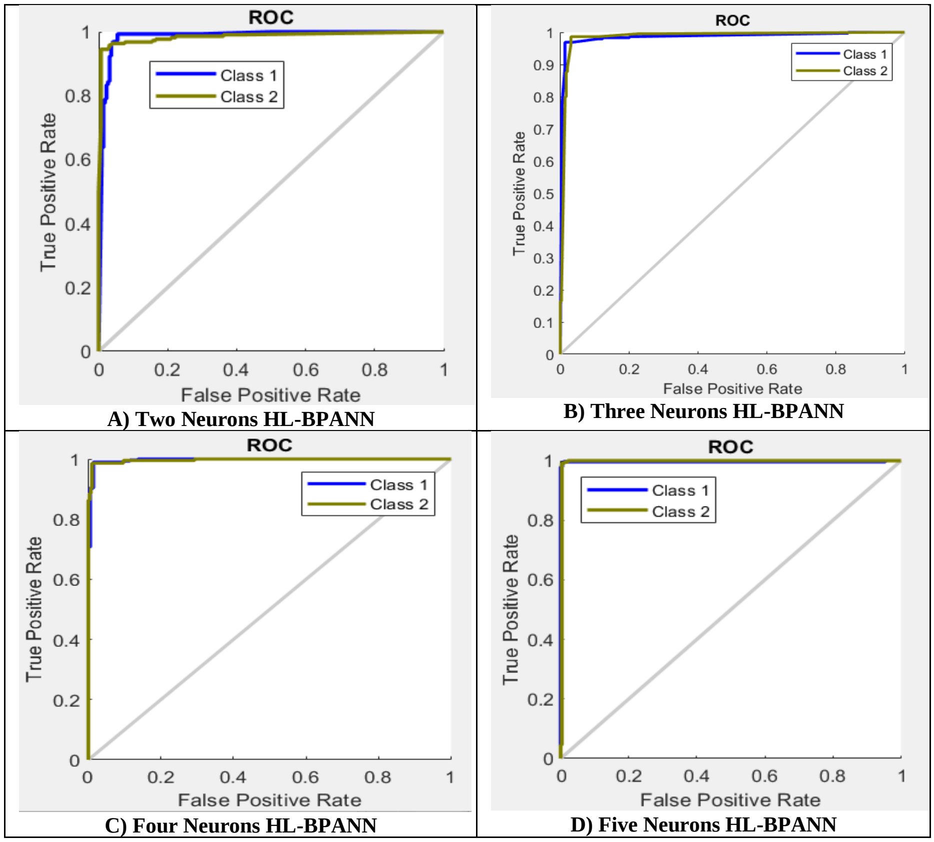


Figure 16. ROC class 2(non-drinkers) and class 1 (drinkers) curves analysis of 2 to 5 neurons HL BP-ANNs Models

Best Training Performances of 2 to 5 HL neurons BP-ANN Models and Comparative Analysis

Figure 19 depicts the study of the best training performances of 2-5 neurons (HL BP-ANNs). On the X-axis, the number of epochs is specified, and on the Y-axis, the MSE (mean squared error) values are specified. The line with dots indicates the best performance line indicator, and the red and blue color lines indicate the training and testing performances. Figure 19 (A) describes the two neurons' best HL BP-ANN ROC performance analysis. For this, the model uses 1000 epochs, and the performance value is 0.0069262. Figure 19 (B) specifies the three neurons' best HL BP-ANN ROC performance analysis. For this, the model uses 723 epochs, and the performance value is 0.0072902. Figure 19 (C) indicates the four HL BP-ANN ROC best performance analyses. In this, the model uses 1000 epochs, and the performance value is 0.0092679. Figure 19 (D) represents the five-HL BP-ANN ROC's best performance analyses. In this, the model uses 150 epochs, and the performance value is 0.0023297.

Error Histograms Analysis of 2 To 5 Neurons HL BP-ANN Models

Figure 20 shows the analysis of error histograms for 2–5 HL BP-ANN models. On the X-axis, the error values are specified as targets subtracted by the actual outputs, with targets represented as zero for non-drinkers and one for drinkers. The Y-axis specifies the number of instances. The blue and red bars indicate the number of training and testing instances with error values. The orange color bar indicates the zero-error line. The red color portions indicate the testing instances' error rate, and the blue color portions in the strip specify the training instances. Figure 20 (A) describes two neurons' HL BP-ANN error histogram with 20 bins. Most have error values of zero, and very few have error values of -0.05001 to +0.05001. The fewer data points' error values are very high (outside the boundary); some are -0.9502, and some are +0.9451. Figure 20 (B) specifies three neurons' HL BP-ANN error histogram with 20 bins. Most instances have error values of zero, and very few have error values of -0.04989 to +0.04989. The fewer data points' error values are very high; some are -0.9479, and some are +0.9479. Figure 20 (C) indicates four HL BP-

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ANN Error histograms with 20 bins. Most instances are in error values is zero, and very few are in the range of -0.04968 to +0.04968. Very few training data points are available for the boundary. Figure 20 (D) represents a five-HL BP-ANN error histogram with 20 bins. Almost all instances in the boundary error values are nearer to zero.

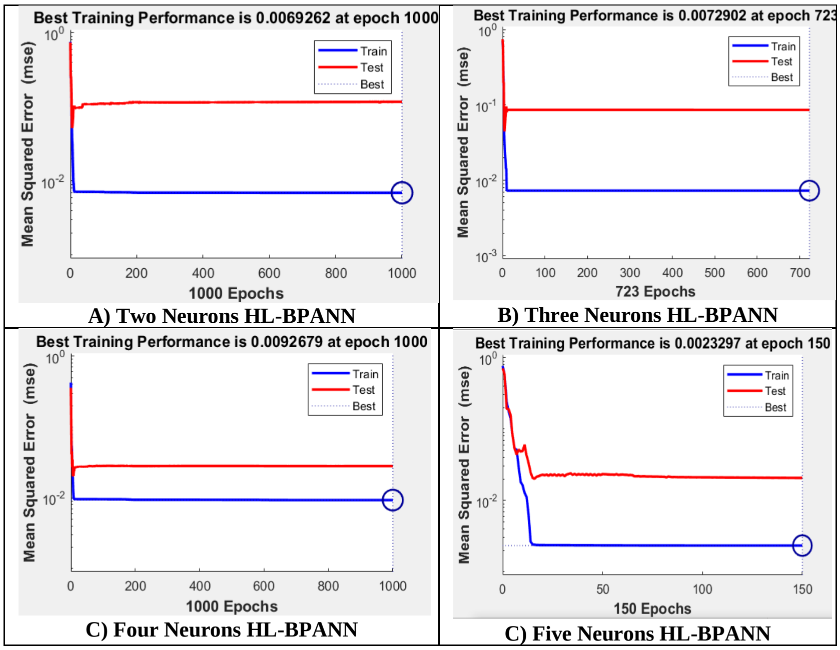

Figure 17. Best performance analysis of 2 to 5 HL BP-ANNs Models

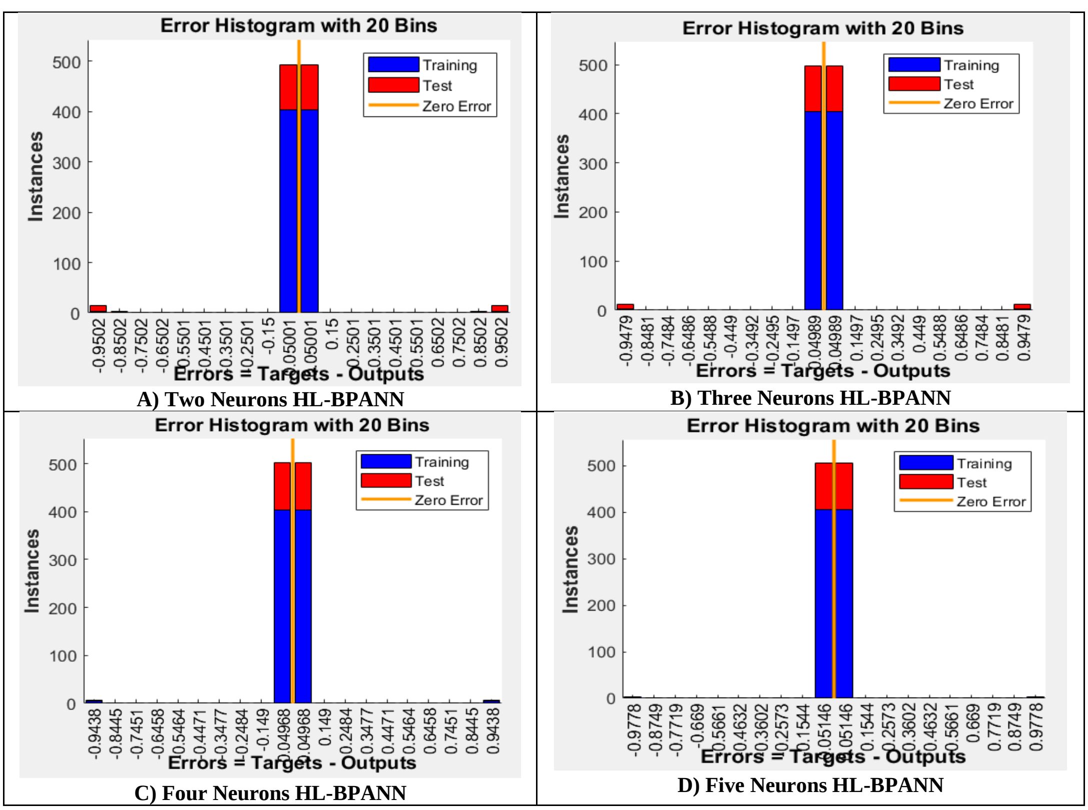

Figure 18. Error Histograms analysis of 2 to 5 HL BP-ANNs Models

TABLE XII. ANALYSIS OF BP-ANN MODELS TIME AND PERFORMANCES LIKE MSE, MU VALUES, R VALUE, ACCURACY VALUES

BP-ANN Model	Epoch	Time in Sec.	MSE	Gradient	R Value	Accuracy (%)
Two Neurons HL	1000	0.26	0.006926	4.4593e-06	0.94112	0.96856581
Three Neurons HL	723	0.17	0.007290	9.9071e-08	0.95327	0.97642436
Four Neurons HL	1000	0.21	0.009267	4.9862e-07	0.97364	0.98624754
Five Neurons HL	150	0.09	0.002329	9.3724e-08	0.98796	0.99410609

Table XII shows performance parameters of the BP-ANN models. In this analysis 5-HL-BPANN is performed well with less time (0.09 sec.) and epochs (150) than other (2-4 neurons HL) BP-ANN models.

5. DISCUSSIONS AND COMPARATIVE STUDY

Alcohol consumption has been shown to have various effects on the human body, including changes to the voice. Alcohol is a known irritant to the vocal cords, and excessive consumption can lead to inflammation and swelling. This can result in changes to the voice, including hoarseness and reduced vocal range. Chronic alcohol consumption has been linked to various voice disorders, including vocal nodules, polyps, and laryngeal cancer. These conditions can have long-lasting effects on the voice and may require medical treatment. Individuals who are dependent on alcohol and undergo detoxification may experience a range of withdrawal symptoms, including changes to their voice. This can include vocal tremors, hoarseness, and difficulty speaking. Research has shown that women may be more susceptible to the effects of alcohol on the voice, and older individuals may be at a higher risk for vocal changes due to alcohol consumption [41] [42]. Alcohol consumption affects the human body's motor system and leads to AUD. It directly affects the brain and leads to neurological diseases such as Alzheimer's, Parkinson's [43], and so on. The human body parts are affected by this bad habit, mainly the liver, heart, and kidneys [44]. It is closely related to the acoustic (voice) system, resulting in errors in speaking words, lagging, wrong wording, and changes in voice parameters such as voicing, pulses, and fundamental frequency (F0). Some research has shown this to be true concerning changes.

Many researchers focused on differentiating differences in voice parameter values in conditions of soberer and intoxication. Klinghol et al. (1988) [45] researched the relationship between intoxication of alcohol in low-level and speech signals. For this research, they used 11 male people's voices of text reading words in alcohol intoxicated and sober. They determined pitch (F0), SNR (SignalToNoise ratio), 1st (F1) to 2nd (F2) format frequencies ratio, LTAS, and frequencies speeds and determined differences in sober and intoxication. As per observations, they found SNR, F0, and LTAS were discriminated 5% error in both (somber and intoxication) conditions. Liquor intoxication is known to influence characteristics of the human way of behaving and consciousness. The most impacted system is speech production after beverage. Offrede et al. (2021) [46] researched Speech Languages and alcohol consumption. The main aim of this research is that compare the language L1-Duch and L2- English pronunciations after an alcoholic beverage. For the experiment setup, they chose 80 individuals who speak Dutch and English and are natives of Nederland, aged 20 to 64 (mean values is 31 and SD is 9.5). Speaking English rate is 3 to 9 out of 10, the mean value is 7.5, and SD is 1.2. The BAC (Blood_Alcohol_Concentration) levels were from 0.8 to 1.59. An additive mixed general methodology was used for this analysis. As per the analysis of results, participants' BAC affected negative pronunciation in L1 and had no critical outcome on the L2 language pronunciations. The table shows some research work about alcohol and acoustics with detailed results and analysis.

TABLE XIII. RESEARCH WORKS ON ALCOHOL EFFECTS ON ACOUSTIC ANALYSIS

Ref. No.	Author Ref.	Research Models and Description	Data set and Results
[47]	Leung et al. (2019)	The main aim is a health risk in Alcohol use of the youth and sex contrasts in liquor in LMIC. This examination exposed the sex divergences in the consequences and preponderance of liquor use among young people experiencing in middle and low-income nations.	271,156 students are participated age of 13 to 17 years Alcohol Use (Females = 56.15% and males=59.74%) from GSHS reports from 68 countries. As per reports, the male person had higher chances of alcohol or liquor use (OR=2.38 [1.91-2.96]), a history of intoxication (OR=2.64 [2.11-3.31]), and liquor-related issues (OR=1.72 [1.41-2.10]) than females.
[48]	Spindler et al. (2021)	Researched on AUD- (Alcohol Use Disorder) is related to GM-grey Matter volume.	27 studies are on AUD patients - 1045 and healthy controls -1054. GM decrease in AUD could interrupt the neurons network correspondence responsible for the neurocognitive damages concerned with high-pitched chronic alcohol utilization.
[49]	Vogel et al. (2021)	The main aim of the research is speech production effects linked with tobacco and	Gathering the data voice samples from the Controls individuals' group (40 members) using alcohol and tobacco, and 31 groups of

		alcohol versus CANNabis use. For this, they calculate acoustic parameters. Timing-broad like Mean pause length, pause length, Percent of pauses, and Speech rate; Timing-fine grained, Vocal Control and Vocal Quality, and so on.	adult-use cannabis. Alcohol (drinks) 90 % Controls (900 ± 2460) cannabis100 % (2678 ± 3765) p-value<0.001a effect size- 0.71 Tobacco (cigarettes) 28 % Controls (22 ± 54) cannabis 77 % (860 ± 1832) p-value<0.001a effect size-0.61. Control of the F0 value did not differ between the groups. Decrease in voice onset time, increased vocal effort, and decreased vocal intensity on the indication task (d=-0.568, p = 0.021) Spectral.
[50]	Davidson et al. (2001)	The theme of this research was evaluating the stimulant impacts of alcohol on humans and their behaviors. Stimulant subscale scores of the BAES were altogether more prominent for the liquor condition compared to the soda condition. Methods like ANOVA, Test sessions, Baseline assessment and administration, and Beverage conditions are used. Data analysis with ANOVA and ascending limb of the BAC curve methods.	19 subjects were analyzed. **Results: BAES level:** t-tests (t = 2.66, P>.005) found consumed alcohol compared to soda, the values are 5.0 ± 2.3 S.E.M. (alcohol) and 3.8 ± 2.3 S.E.M. (soda). **Activity levels:** ANOVA-effect of beverage F = 5.27 and P>.008 t-test: 82.8 ± 36 S.E.M. (alcohol) equated to placebo-alcohol that values are (t = 2.53, P < .007) 48 ± 43 S.E.M. (alcohol) or (t = 3.03, P>.001) (soda) 73.6 ± 28 **Speech production:** ANOVA alcohol -(10.2 ± 18.8 S.E.M.) placebo-alcohol (3.1 ± 13.4 S.E.M.) and soda (1.1 ± 14.8 S.E.M.) **Mood States Profile:** ANOVA did POMS difference score six subscales. No difference is in the mood of the beverage.
[51]	Braun et al. (2003)	Studied the effects of alcohol on speech, prosodic changes, fundamental frequency (F0), and breath alcohol concentration (BRAC). And also consider the parameters like verbosity, F0, and speaking tempo parameters like articulation pausing, rate, syllable rate. F0, calculated using SIFT and Cestrum-based algorithms.	The data was acquired from 33 male drinkers subjects that age between 19 and 24 years, group mean = 23± 20. Intoxication levels- below 0.08% BRAC. Syllables produced in sober 161 ± 46 and intoxicated condition 192 ± 54. **Semi-spontaneous speech F0 analysis:** At Max Ind. BRAC: < 0.08%, F0- sober:126.8, intoxicated: 133.7, At Max Ind. BRAC: > 0.08% F0-sober:125.4 intoxicated: 133.6 **Semi-spontaneous speech F0 Modulation:** At Max Ind. BRAC: < 0.08%, F0- sober: 17.9, intoxicated: 21.9, At Max Ind. BRAC: > 0.08% F0- sober: 21.9 intoxicated: 21.0
[52]	Moya et al. (2009)	Effects of alcohol on the speaker's speech of sober and intoxicated. Methodology is Stimulus Voice analysis. Each subject voice recorded in individual. The first recording is in sober condition and second in inebriated condition with 4.5 oz. (one and half oz. vodka, and fruit juice 3 oz.	The voice data is collected from 27 young students. The parameter or eight characteristics calculations in sober and inebriated conditions, that are Efficient, Reasonable, Self-Confident, Scholarly, Artistic, Theatrical, and Untrained parameters on Sober condition (4.98, 6.98, 5.83, 5.62, 2.50, 2.06 ,3.87) Inebriated condition (4.38, 6.34, 4.58, 5.18, 2.06, 1.40, 4.60) t-test values (2.10, 2.12, 3.84, 2.33, 2.29, 2.34, 2.90) P-Test values (0.05, 0.05, 0.001, 0.05, 0.05, 0.05, 0.01)

Some of the research is covered with acoustic and facial expressions of the drinkers. Some research deeply described culture, behavior, and way of speaking and social issues with alcohol consumption. Healthy voice represents the healthy mind without any neurological diseases like Parkinson's, Alzheimer's, and dementia [53] [54]. Sayette et al. (2012) [55] researched alcohol consumption's effects on social bonding and emotions. For this experiment, they chose 360 male and 360 female alcohol consumers and derived three groups that were unfamiliar with everyone. Participants consumed a dose of moderate alcohol for over 36 minutes. In the meanwhile, the sequence recorded facial and speech behaviors. The outcomes demonstrated that alcohol works with binding during group establishment. The impact of alcohol on social reactions during gatherings and collaborative interactions is concerning research. Kirchner et al. (2006) [56] researched alcohol effects on male drinkers' group formations. In this research, they chose 54 male social consumers collected into 3-man clusters of unknown individuals (strangers). All individuals from each cluster group were directed to either a 0.82 g/kg alcohol or a medicinal drug (placebo) to consume for 30 minutes. Alcohol consumption enhanced and expanded individual and group coordination levels with smiling and ways of behaving with speech over the long haul and better bonding with each other. Dysfunction of the Focal nervous system bringing about mental deficiency is likely the most damaging element of FAS (fetal alcohol syndrome). Greene et al. (1990) [57] examined the effects of FAS on speech and language. The inconsistencies count, and less extent of birth weight, are more delicate marks of FAS than language exploitation.

Comparative Study

According to a comparison with the background research work, this research approach is a novel and low-cost technology for the early identification of alcoholics with smartphone apps using voice signals. The model of five neurons (HL BP-ANN) is suitable as it classifies 99.4% of drinkers and non-drinkers. Figure 25 shows how each experimental ML model compares to others using the CA and AUC performance parameter values. All ML models have been represented on the X-axis, and the Y-axis represents the performance values (0 to 1). The blue bar represents the AUC values, and the brown bar specifies the CA in 0 to 1 value. The visualization reports indicate that the RF model's AUC and CA values (0.989 and 0.953) are superior to other experimental ML models. The SVM model's AUC value (0.983) is the second highest, and the CA value (0.936) is in the third position in the comparison.

According to the study and critical analysis of the background research work, the current research approach is a novel and low-cost technology for the early identification of alcoholics with smartphone apps using voice signals.

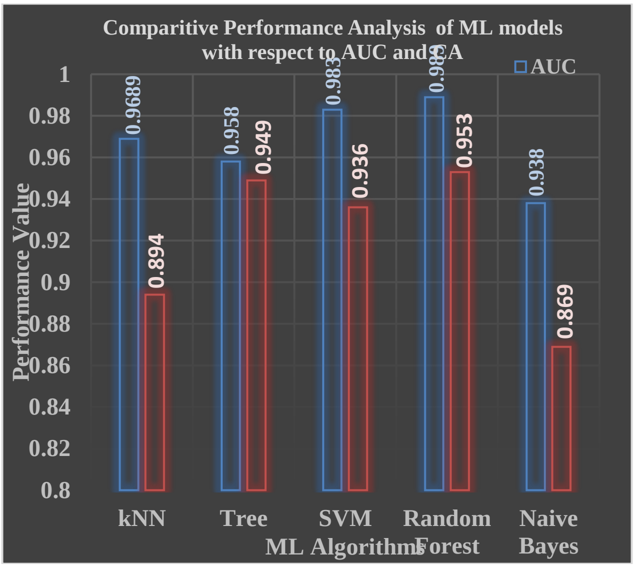

Figure 19. Comparative Analysis of AUC and Classification

The model of five neurons (HL BP-ANN) is suitable, as it classifies 99.4% of drinkers and non-drinkers. Figure 25 represents each experimental ML model's comparison to others using the CA and AUC performance parameter values. All ML models are specified on the x-axis, and the y-axis represents the performance values (0 to 1). The blue bar represents the AUC values, and the brown bar specifies the CA in 0 to 1 value. The visualization reports say that the RF model's AUC and CA values (0.989 and 0.953) are superior to other experimental ML models. Accuracy (CA) of Experimental Machine Learning (ML) Models. The SVM model's AUC value (0.983) is the second highest, and its CA value (0.936) is in the third position in the comparison. In both classes, we again conducted the statistical analysis and obtained the total dataset's statistical results. The collected information contained age groups of 22 to 34 years for male persons' data and their hidden voice record values. Class 1 set describes the drinkers, and Class 2 specifies the non-drinkers' specifications. According to the statistical results, all mean and median values of pitch (mean, median, SD, min, and max) in the Class 1 (drinkers) set are higher than those in Class 2 (non-drinkers), as is the case for the entire set. The number of unvoiced mean values in Class 1 is higher than in Class 2. All mean and median values of the jitter and shimmer voice parameters in Class 1 are higher than the values of the Class 2 set. Table 5 specifies the minimum and maximum of all voice parameter values concerning Class 1, Class 2, and the total dataset. The age group of 22 to 34-year-olds is involved in all Class 2, Class 1, and total dataset categories. It describes the detailed analysis of the minimum and maximum of every voice parameter value, such as mean pitch, median pitch, jitter, shimmer, harmonic ratio, etc.

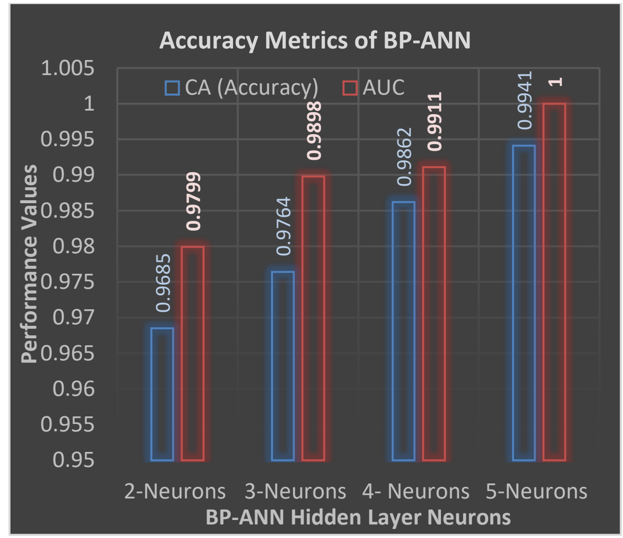

Figure 20. Competitive analysis with performance parameters AUC and CA of 2 to 5 neurons HL BP-ANNs Models

According to the critical analysis present research work is novel and suitable for the classification and predictions of alcohol drinkers. It is more sophisticated for early detection technology than other existing systems and tools. As per ML models analysis, the RF model is more efficient with 95.3% than other experimental ML models. In the general external background survey and internal comparative study, the proposal model 5-neurons HL BP-BP-ANN is the best solution for acoustic alcoholics' problem with classification accuracy 99.4%.

TABLE XIV. PROPOSAL MODEL VERSUS ALL OTHER EXPERIMENTAL MODELS

Proposal Models	CA (Accuracy)	AUC	Recall	Precision	F1
k-NN	0.894	0.9689	0.894	0.894	0.893
C4.5	0.949	0.958	0.949	0.949	0.948
SVM	0.936	0.983	0.935	0.936	0.935
RFS	**0.953**	0.989	0.953	0.953	0.952
Naive Bayes	0.869	0.934	0.869	0.870	0.868
2- HL ANN	0.9685	0.9799	0.9536	0.9931	0.9729
3- HL ANN	0.9764	0.9898	0.9894	0.9689	0.9790
4- HL ANN	0.9862	0.9911	0.9862	0.9896	0.9879
5- HL ANN	**0.9941**	**1**	**0.9931**	**0.9966**	**0.9948**

6. CONCLUSION

Heavy alcohol consumption is one of the evils in society because it impacts the socioeconomic system, and social and family lives. It also affects the human vocal cords, changing their voice at the time of alcohol consumption for various reasons. The Intelligent Novel Approach for Identification of Alcohol Consumers Using an ANN-Based Model on Vowelized Voice Dataset is a method for using artificial neural networks (ANNs) to identify individuals who consume alcohol based on their voice patterns. The approach involves collecting a dataset of vowelized voice samples from both alcohol consumers and non-consumers. The voice samples are pre-processed to extract features that are relevant for distinguishing between the two groups. These features might include measures of pitch, tone, and other acoustic characteristics of the voice. The pre-processed voice samples are then used to train an ANN model. The model is designed to learn the patterns and relationships between the extracted features and the corresponding labels of alcohol consumers or non-consumers. Once the model is trained, it can be used to predict the label of new, previously unseen voice samples. This novel study described the auto-detection of alcohol consumers using vowelized (/a /e /i /o /u) voice data with machine learning and neural network models. In this, five eminent existing machine learning models were used, such as Naïve Bayes (NB), Random Forest (RF), k-NN, SVM, and C4.5 (Tree). The RF algorithm was performed in existing machine learning models, with a classification accuracy value of 0.953. On the other hand, we used BP-ANN models that we increment the neurons in the Hidden Layer 2 to 5 and trained again for each increment step. The 5-neuron HL BP-ANN model performed better than all other experimental models, with 99.4% classification accuracy. Therefore, the 5-HL neurons BP-ANN is the best solution for this dataset. In this research, the exemplars used were only male individuals. So, further, we aim to include female drinker individuals, measure alcohol consumption quantity and quality for the detection training process with better models (PNN, 1-D CNN, and stacked auto-encoders), and construct equipment tools named the Voice Intentioned Transcript Alcohol Level Identification Tool.

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