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Stomach Disorder Detection and Analysis using Hybrid Learning Vector Quantization with African Buffalo Optimization Algorithm

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Abstract
The human digestive system's electrical activity may be recorded noninvasively by Electrogastrography (EGG). Electrogastrograms are recordings of the electrical activity produced by the stomach muscles. EGG Several gastrointestinal disorders may be diagnosed and their severity measured using EGG signal properties. The literature has several contributions to the categorization of EGG signals. The majority of them make use of either the EGG's frequency or time data. The wide variety of EGG signals is a challenge for current automated categorization methods. Therefore, this study's objective is to develop a lightweight classifier that achieves high classification accuracy while using little processing resources. To acquire normal and abnormal EGG signals at a reasonable cost, a three-electrode measuring device is created here, with classification performed by a hybrid of Linear Vector Quantization and the African Buffalo Search Algorithm (HLVQ-ASO). The results show that the information richness of recorded EGG signals from healthy persons is greater for EGG signals captured using a surface electrode with a contact diameter of 19 mm as compared to 16 mm. To demonstrate their validity and degree of classification accuracy, the results computed using the suggested classifiers are compared with the current classifiers like Artificial Neural Network, Multimodal Support Vector Machine (MSVM), and Improved Convolutional Neural Network (CNN). Additionally, the HLVQ-ASO-based classification method is effective in differentiating between normal and diabetic EGG signals, found a sensitivity of 97% and a specificity of 98.8%. For a dataset of 500 samples, the classification accuracy is 97%.

Keywords- Electrogastrogram (EGG), Hybrid of linear vector quantization, African buffalo search algorithm, Artificial neural network, Multimodal support vector machine (MSVM), Improved convolutional neural network (CNN).

1. Introduction

Electrogastrograms (EGGs) are electrical signals produced by the abdomen surface that may be recorded non-invasively using a technique called cutaneous Electrogastrography (EGG). These signals have a strong correlation with the digestive process (Levakov et al., 2023). Depending on the kind of EGG measuring instrument, surface electrodes are utilized to record electrical activity from the brain. Because it is non-invasive, this technology may be used to classify the pathological and physiological states of the digestive system with little effort and expense (Rebollo et al., 2018). Computational technologies, such as personal computers, can analyze EGG data and offer a number of accurate metrics, such as frequency and amplitude, that aid in the diagnosis of bradygatria and tachygatria (Komorowski et al., 2015). The typical individual's EGG signal reflects cycles per minute (cpm), generated by pacemaker cells called interstitial cells of intestine in the stomach corpus and antrum's muscular wall. Both bradygatria and tachygastria fall within the umbrella of aberrant EGG signals.

The contraction of stomach muscles is controlled by electrical impulses, and these signals may be recorded using an electrogastrogram. The electrode detects electrical impulses from stomach muscles and records the EGG for later analysis in the case of digestive system issues. Bradygastria, dyspepsia, nausea, tachygastria, ulcer, and vomiting are some of the conditions studied. The analysis of EGG data employs statistical parameters, the wavelet transform method, and a neural network strategy.

The frequency of the bradygastria is between 1.0 and 2.6 cpm, while the frequency of the tachygastria is between 3.7 and 10 cpm (Alagumariappan et al., 2017). Various neuromuscular disorders of the stomach are included in the diabetic gastropathy spectrum. An abnormal EGG signal characterized by Bradygastria, tachygastria, and other mixed dysrhythmias replaces the typical 3 cpm signal in patients with diabetic gastropathy (Koch et al., 1987). Diabetic individuals with upper gastrointestinal (GI) symptoms have been shown to have neuromuscular abnormalities, which has led to the identification of gastric dysrhythmias by a number of studies (Paramasivam et al., 2018). Figure 1 shows the normal EGG signal sample.

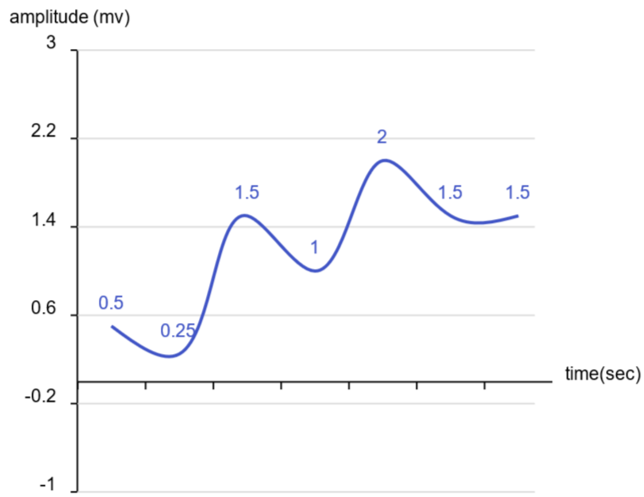

Figure 1. Normal EGG signal.

Because of its usefulness in investigating the physiology and pathophysiology of gastric motility problems, EGG is now widely used in both laboratories and hospitals (Alagumariappan & Krishnamurthy, 2018). The lack of knowledge of EGG with precise frequency and amplitude, as well as the difficulties in data collecting, have slowed development in this area since the first EGG recording was made on a person. Both the parameters and the therapeutic value of EGG are still up for dispute and study (Komorowski, 2018). Figure 2 shows the abnormal EGG signal sample.

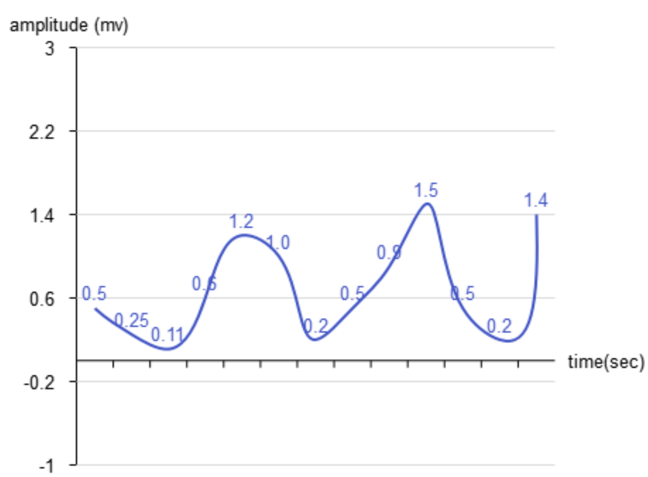

Figure 2. Abnormal EGG signal.

Therefore, it is necessary to standardize EGG recording and use cutting-edge analytic techniques for extracting and interpreting quantitative EGG characteristics, as well as to set a frequency range for normal subject and dysrhythmias subjects. To further understand EGG's potential therapeutic use, more outcome studies are required. Improvements in quantitative EGG analysis have piqued the attention of doctors and biological researchers in recent years. Although electrogastrogram is a completely non-invasive method for examining digestive issues, it is not yet widely used in India. To gain reliable answers, several researchers are focusing on this question. Acquisition and analysis of EGG to aid the physician in diagnosis of digestive system diseases at preliminary level with good degree of accuracy is the necessity of the day.

The goals of this study are as follows: the purpose of this study is to use Information theory to examine how the contact area of the surface electrodes affects the accuracy of recorded electrogastrograms. The goal of this study is to create a library of normal and diabetic EGG recordings by capturing EGG signals in clinical settings from people with and without Type II diabetes (Kurian & Rajalakshmy, 2022). The goal of this study is to employ appropriate feature extraction algorithms to extract the relevant characteristics from both normal and diabetic Electrogastrograms. The purpose of this work is to use a hybrid of linear vector quantization and the African buffalo search Algorithm to choose the important characteristics from retrieved EGG signal data (HLVQ-ASO). Using machine learning methods, design effective classification methods for identifying normal and diabetic electrogastrograms (Raihan et al., 2021).

The organization of paper is as follows; section 2 includes literature survey, section 3 includes proposed methodology, section 4 includes experimental analysis, section 5 includes discussion and section 6 includes conclusion and future work.

2. Literature Survey

Endoscopy, electrogastrography (EGG), and clinical evaluation are the three main methods for diagnosing digestive system diseases. Due to its inexpensive cost and lack of invasiveness, EGG has become the most used detection method. The contraction of the stomach muscles is controlled by electrical impulses that are measured and recorded during an EGG.

2.1 Acquisition Techniques of Electrogastrogram

The author recorded an EGG from a 5-week-old with pyloric stenosis using limb leads and found that it resembled an electrocardiogram (ECG) in that it had a slowly shifting baseline. The amplitude of the EGG rises during contractions, as shown by Coronel-Reyes et al. (2018). Based on an adaptive autoregressive moving average model, Amri et al. (2021) created a cutting-edge method of spectrum analysis. This approach provided more detailed information regarding the stomach's electrical activity's frequency fluctuations and better frequency resolution. Short-duration dysrhythmic events in stomach electrical activity are particularly amenable to detection with this method.

2.2 Electrogastrogram Interpretation

Subasi (2019) was the first to apply the spectrum analysis approach to EGG and then analyze EGG data using the Fourier transform. Soltani & Omid (2015) used statistical methods to look at the 7 ways in which EGG patterns varied between test individuals. The significance of the observed differences was determined using paired and unpaired students' t-tests. According to Gómez et al. (2021), typical values are those with the mean. If any of these values is significantly different from its normal range, a standard deviation between normal and abnormal is calculated. After a test meal, electrogastrography was used to identify the slow wave of stomach digest motility by AL-Dhief et al. (2021) who then decomposed the EGG signal using a multiresolution approach based on the Daubechies wavelet function.

As a straightforward and easy technique to deliver exact charts and identification about frequency characteristics to a refining (Howard et al., 2021) novel method for processing EGG signals based on wavelet transform has extremely excellent application potential. The necessity of choosing a mother wavelet with the right number of decomposition levels for filtering out noise in an electrocardiogram was investigated by Hegde et al. (2019). The authors claim that they received high quality signal for the wavelet db1 at first and fourth level of decomposition and sym3 for fourth level of decomposition.

Chaudhary & Mrachacz-Kersting (2021) utilized SPSS's analysis of variance (ANOVA) and range analyses to show how pressure and moisture content affect shape density and to weigh the relative relevance of the two variables in determining bio-fuel density. Parameterized statistical model pre-processing was used by Gauba et al. (2017) to segment brain vessels. After a first step of image processing, the authors fed the resulting brain picture into a parameterized statistical model, which allowed them to successfully segment the brain's finer vascular branches. To identify arrhythmias in the ECG dataset, Alhussein & Muhammad (2018) used Learning Vector Quantization (LVQ) neural networks. Based on these findings, the LVQ algorithm should be further investigated for use with any bio signals. Using a neural network (LVQ-ABO) framework, Nath et al. (2021) categorized lung sounds based on their wavelet coefficients. For the most accurate categorization of EGG signals as normal or pathological, Carson et al. (2021) suggested using a network with 6 or 7 hidden neurons. It was discovered that the difficulty in distinguishing between a normal and abnormal signal was due to the sluggish convergence rate and important user dependent factors.

In order to accurately and quickly diagnose cardiac arrhythmia and provide the patient with the help they need employed learning vector quantization, a medical diagnostic tool that uses a feature extractor paired with an Artificial Neural Network (LVQ-ABO) classifier (Zhang et al., 2021). The feature extractor is a cross-correlation method that makes use of frequency-domain cross-spectral density information. Artificial Neural Network (LVQ-ABO) for complicated pattern identification and classification tasks of EMG signals based on characteristics was reported by Krom et al. (2019).

Abraham et al. (2023) introduced a deep learning approach for the identification and classification of digestive diseases. Deep learning, a subset of machine learning, is employed to potentially enhance accuracy and efficiency in disease diagnosis. Published in Symmetry, the paper aligns with a journal known for its focus on mathematical and computational aspects. This suggests a quantitative and algorithmic approach to digestive disease identification. The adoption of deep learning signifies the utilization of cutting-edge technology in the medical domain. This approach has the potential to revolutionize the field of digestive disease diagnosis by leveraging the power of neural networks.

Aliyi et al. (2023) introduced the detection of gastrointestinal tract disorders using deep learning methods from colonoscopy images and videos. The paper specifically addresses the detection of gastrointestinal tract disorders, emphasizing the application of deep learning methods. This targeted focus suggests a practical application of advanced technologies in the diagnosis of gastrointestinal issues. The study utilizes colonoscopy images and videos, showcasing a commitment to leveraging diverse and rich data sources. This approach is significant in enhancing the comprehensiveness of the diagnostic process. Being published in Scientific African, the paper aligns with a journal focused on promoting African research. This reflects a contribution to the scientific community in the context of gastrointestinal disorders, potentially addressing regional healthcare challenges. Table 1 gives the comparison study of existing methodology and their merits, and demerits which are analyzed.

Table 1. Comparison of existing methodology.

References	Methodology	Advantage
Soltani & Omid (2015)	Monitoring of electrocardiograms (ECGs) in real time utilising internet of things platforms	An application for mobile devices that is combined with physiological monitors and environmental sensors and is linked to the internet.
Gómez et al. (2021)	LDA, NLR, SVM, and MLP are abbreviations for Linear Discriminant Analysis, Nonlinear Logistic Regression, Support Vector Machine, respectively (MLP)	When compared to the other three classifiers, the classification done using SVM yields more accurate results.
Al-Dhief et al. (2020)	Signals derived from the Heart Rate Variability (HRV)	Acquired features by the use of three separate classifiers, including generalised discriminant analysis, the fisher ranking technique, and the extreme learning machine.
Howard et al. (2021)	Three ECG measurements in the time domain, and three ECG measurements in the frequency domain	95 percent accuracy on learning datasets and 82 percent accuracy on testing datasets.
Hegde et al. (2019)	Networks based on Adaptive Resonance Theory and Learning Vector Quantization	Low accuracy when compared to the other conventional methods
Chaudhary and Mrachacz-Kersting (2021)	s K-Nearest Neighbor, Naïve Bayes, SVM and LVQ-ABO	The categorization of magnetic resonance imaging (MRI) scans as either normal or abnormal.
Nath et al. (2020)	Artificial neural network, support vector machine	Contrasted the various classification methods according to the merits and disadvantages of each, as well as the degree to which they achieve their categorization goals.

In each sub band, we calculated the maximum, minimum, mean, and standard deviation of the wavelet coefficient. The EEG signal is classified using a PSO-trained RBFNN that uses the extracted characteristics. Specificity, precision, accuracy, and the F-measure were used to assess the generated classifier's efficacy. The created PSO trained RBFNN's classification performance is compared to that of two benchmarks: an RBFNN trained using the gradient descent method, and an RBFNN trained using the standard PSO methodology. The constructed classifier had a 99 percent success rate, which was higher than any previous classifiers' success rates.

From reading up on bio signal classification, every classification method has its advantages and disadvantages. Researchers have devised a wide variety of methods. LVQ-ABO-based classification methods now dominate the field. Some writers improved the efficiency of LVQ-ABO by combining it with a bio-inspired approach. In addition, it has been shown that fully automated categorization of EGG signals with a high degree of accuracy is a difficult problem.

3. Methodology of Proposed Work

The myoelectrical recording is filtered using a combination of high-pass and band-pass techniques to isolate the spikes (higher frequency) above 1 Hz and the slow waves (lower frequency) below 1 Hz; a low-pass filter with a cutoff frequency of 1 Hz completes the signal acquisition. Figure 3 shows the methodology of the data collection of proposed work.

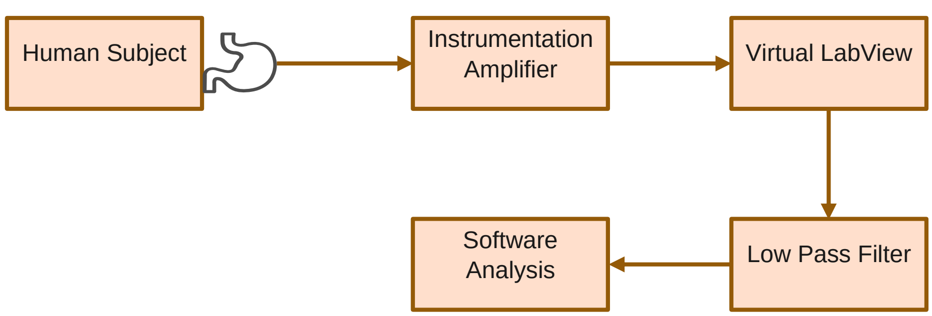

Figure 3. Methodology of data collection.

EGG data is acquired with the use of a DAQ card as shown in the block diagram in Figure 3. The signal is boosted and then sent to the data acquisition card (DAQ). LabVIEW is compatible with DAQ devices. The EGG data used in this study came from a medical institution. We utilized 200 different samples. The database includes both healthy and pathological male and female individuals of varying ages. Table 2 displays topic demographic information.

Table 2. Information pertaining to the individuals' demographics.

	(" Normal " (100))	Abnormal (100)
Men	35	30
Women	15	20
Age Group	35-50	33-55

The Table 2 provides demographic details of the subjects in a study categorized into two groups: "Normal" (100 individuals) and "Abnormal" (100 individuals). The subjects are further classified based on gender (Male and Female) and age ranges (35-50 for "Normal" and 33-55 for "Abnormal"). Here's a breakdown of the information:

(i) Gender Distribution

In the "Normal" group, there are 35 males and 15 females, making up a total of 50 subjects. In the "Abnormal" group, there are 30 males and 20 females, totaling 50 subjects. This breakdown provides insights into the gender distribution within each group.

(ii) Age Range Distribution

For the "Normal" group, subjects fall within the age range of 35-50, suggesting a focus on individuals in this specific age demographic. In contrast, the "Abnormal" group includes subjects with a broader age range, spanning from 33 to 55. This difference in age ranges may have implications for the study's objectives and outcomes.

To calculate statistical parameters from the subject's EGG in both fasting and postprandial states, a virtual instrumentation (VI) programmed is built in LabVIEW. Normal EGG parameters are compared to the values recorded before and after a meal. The statistical metrics and signal properties combined with correlation values are employed for the categorization of various digestive system illnesses. We employ a naive Bayes classifier, which is a straightforward probabilistic classifier based on applying Bayes theorem under strong (naive) independence assumptions, to categories the signals. The Bayesian theorem is the foundation of NBC. When the inputs have a high dimensionality, it works well. Maximum likelihood is used to estimate naive Bayes model parameters.

Statistical analysis provides strong empirical backing for research study feasibility evaluations. Bio signals such as ECG, EEG, etc. are analyzed using them extensively in order to diagnose diseases. Here, the frequency, amplitude, and power of the EGG signal, as well as other statistical characteristics, are determined. To calculate statistical parameters from the subject's EGG in both fasting and postprandial states, a virtual instrumentation (VI) programmed is built in LabVIEW. Normative values for EGG parameters are compared to those gathered from pre- and post-meal samples. Different gastrointestinal illnesses are categorized based on statistical metrics, signal properties, and correlation values. A naive Bayes classifier is a straightforward probabilistic classifier based on applying Bayes theorem under strong (naive) independence assumptions; this is the method used in Naive Bayesian Classification (NBC) for signal categorization. The Bayesian theorem is the foundation of NBC. When the inputs have a high dimensionality, it works well.

3.1 Pre-processing

Boltz-ABO and Gibbs's research in statistical physics uncovered the idea of order and disorder at the statistical level. According to Hegde et al. (2019), the quantitative relationship is stated as:

$$\text{entropy} = k\log\, D \tag{1}$$

where, k is the Boltz-ABO constant, and D is a quantitative measure of the system disorder. In the natural system, entropy appears to be a positive function of time and tends to reach a state of maximum,

$$H(\alpha) = \frac{1}{1-\alpha}\ln\left(\sum_{i=1}^{n}\, p_i^{\alpha}\right) \tag{2}$$

where, p-i is the probability that a random variable takes a particular value out of n possibilities. The entropy of a system increases as a function of the size of the probabilities associated with it, whereas it decreases as a function of the size of the probabilities associated with it. Given that the Renyi entropy is a monotonic function of the information, it may be used in lieu of the information content in any setting where that would be appropriate. The importance of the information that is included in EGG signals.

3.2 Feature Extraction

The capacity of a system to carry out work is what we refer to as its energy. Biological systems are the power converters that are naturally present on Earth. Electric signals are produced in parallel with biological activities, and these signals have close linkages to the dynamics of the system they are formed in (Kvedalen 2003).

$$\Psi[x(n)] = x^2(n) - x(n+1)x(n-1) \tag{3}$$

where, x is the true value of the EGG and n represents the total number of samples taken. In recent years, there has been a rise in the number of instances in which the Teager-Kaiser energy operator has been used in biological systems in order to calculate the worldwide variance in signal energy. In addition, the Teager-Kaiser Energy operator makes an effort to imitate the energy of the source of the signal rather than the energy of the signal itself. In the current investigation, the TKE operator was used in order to measure the energy level of the detected EGG signals for the purpose of conducting additional research. Hjorth parameters are used in order to provide a description of the temporal dynamics of the detected bio signals. In recent years, the methodology developed by Hjorth has been put to extensive use for the purpose of assessing the activity, mobility, and complexity of a variety of bio signals. In this study, we computed Hjorth descriptors such as Activity, Mobility, and Complexity for electroencephalogram (EEG) data that were obtained using surface electrodes with contact diameters of 16 mm and 19 mm respectively. An EGG signal's average power or variance may be measured using this task as a representation of the measurement.

$$\text{Activity} = \text{var}\,(y(t)) \tag{4}$$

where, y(t) is the raw data from the EGG. Mobility, which reflects the usual frequency of an EGG signal, is related to the pace of digestion, and this relationship may be shown mathematically. To get the mobility parameter, take the square root of the ratio of the signal's variances to its first derivative. This will give you the value for the mobility parameter. According to the findings of certain studies, a mobile EGG signal includes:

$$\text{Mobility} = \sqrt{\frac{\text{var}\,(y'(t))}{\text{var}\,(y(t))}} \tag{5}$$

The mobility parameter is a function that is calculated based on the standard deviation of the power spectrum. The degree of variability of an EGG signal may be inferred from the complexity of the signal. The following is a description of the complexity of an EGG signal:

$$\text{Complexity} = \frac{\text{Mobility}\,(y'(t))}{\text{Mobility}\,(y(t))} \tag{6}$$

The complexity parameter provides an indication of the degree to which the input EGG signals resemble a sine wave in its simplest form. As the shape of the signal becomes closer to that of a pure sine wave, the complexity begins to trend toward 1. Analyzing data relevant to the activity, mobility, and dynamics of biological processes as well as the complexity of biological systems is made possible by the computation of the Hjorth parameters.

The data are then segmented into windows of length n in the second stage, during which the integrated data is locally fitted to a polynomial-n (which is often linear), and the average fluctuation F(n) is computed as follows:

$$F(n) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \left(y(k) - y_n(k)\right)^2} \tag{7}$$

where, N is the total number of things that were seen. This technique performs measurements at a range of resolutions or window sizes while at the same time checking for instances of self-similarity (fractal characteristics). If power law scaling is present, the fluctuation plot, which is a double logarithmic (or "log-log") plot of F(n) vs. n, will have a linear relationship between the two variables. This is achievable since C is a constant. It is possible to compute the fractal dimension (D) of a time series by making use of the spectral exponent, which has the form and may be expressed as D = (5)/2.

One of the information theory methodologies that has the most potential for use in bio signal analysis is called Tsallis entropy. The Tsallis entropy is denoted by the notation-R:

$$H_R = \frac{1}{\alpha - 1}\left(1 - \sum_{i=1}^{n} p_i^{\alpha}\right) \tag{8}$$

where, denotes a genuine integer, and the probabilities have been stated. The entropy of the Tsallis decreases as the system becomes bigger. Tsallis entropy with five different orders (=0.2,0.4,0.6,0.8, and 0.9) were utilised to extract the information content of the EGG signals recorded from diabetics as well as healthy individuals who did not have diabetes.

The entropy of a picture may be represented by the equation shown below:

$$IM = -\sum_i P_i \log_2 P_i \tag{9}$$

where, P-i represents the probability that the difference between two adjacent pixels is equal to I and log-2 represents the logarithm with a base of 2.

The Hausdorff dimension is a measure used to characterize how complicated the geometry of a particular set is. The set may represent a trajectory of any dynamical system, and it is possible to rebuild it using the data that has been measured. Let's assume that the set A is the one whose dimension has to be determined.

$$\Gamma(A, D, r) = \lim_{r \to 0} \inf_{C(r,A)} \sum_i \delta_i^D \tag{10}$$

Provides a definition for a measure of the set A. The limit r→0 always results in a degenerate measure, either 0 or, and this holds true for the vast majority of different values of D. The box-counting dimension is an estimate of the Hausdorff dimension that is derived from the coverage of the set under investigation by a grid of a constant size with the grid size denoted by r. In this particular scenario, the Equation (11) becomes into,

$$\Gamma(A, D, r) = \sum_i r^D = k(r) r^D \tag{11}$$

The term "correlation" refers to a measurement of the degree to which one pixel is related to its neighbouring pixels over an entire picture. For an image that is fully positively or negatively linked, the correlation value should be 1 or -1 respectively.

$$\text{CORR} = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j} \tag{12}$$

The amount of energy is equal to the sum of the elements' squares in the GLCM matrix.

$$E = \sum_{i,j} p(i,j)^2 \tag{13}$$

The degree to which the distribution of components in the GLCM is same across all points is referred to as the homogeneity of the GLCM. For a diagonal GLCM, the homogeneity value is required to be 1.

$$H = \sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{14}$$

Fast Fourier Transform was used to determine the dominant frequency of both normal and diabetic EGG signals (FFT).

3.3 Classification

The classification method HLVQ-ASO is a combination of linear vector quantization and the African buffalo search algorithm. Combining learning vector quantization (LVQ) with the African buffalo optimization algorithm (ABO) reflects this trend by seeking synergies between a powerful classification technique and a nature-inspired optimization strategy. The motivation is grounded in the belief that the collaboration between LVQ and ABO can overcome individual limitations and yield a more adaptive, efficient, and accurate model for stomach disorder detection. LVQ's proficiency in supervised learning and classification is complemented by ABO's optimization capabilities, offering a holistic approach to handling complex medical data. This hybridization aims to not only improve classification accuracy but also enhance the model's adaptability to dynamic healthcare environments. By integrating these two diverse approaches, the motivation is to create a novel solution that contributes to the evolving landscape of machine learning applications in medical diagnostics.

The African Buffalo will be the only animal in Africa that can be milked for its milk and comes from the same family as domestic cattle. The African buffalo will have a reputation for being a fierce and hardy animal. The majority of animas will have a blackish-grey or dark-brown skin tone. Male and female buffalo both have curving, hard structures (horns) that unite in the center to form a protective shield over the top of the head (the boss).

The massively built animals will be the only ones capable of defending themselves and their pack in the face of danger, especially when they come into contact with lions.

The African Buffalo Optimization Algorithm (ABO) is inspired by the social behavior of African buffaloes and employs certain key principles and mechanisms in its optimization process. Here are the fundamental principles and mechanisms of ABOA:

- ABOA establishes a leadership hierarchy within the population, simulating the dominant roles observed in African buffalo herds. The hierarchy consists of leaders and followers, and this structure influences the decision-making process during the optimization.

- Buffaloes in a herd often collaborate and communicate to enhance their chances of survival. ABOA incorporates mechanisms for individuals in the population to share information, experiences, and solutions. This collaborative aspect aims to improve the overall exploration and exploitation of the solution space.

- ABOA incorporates a memory mechanism that allows individuals to remember and share valuable information about their past experiences. This memory helps the algorithm avoid revisiting less promising regions of the search space and promotes more efficient exploration.

- Social learning is a key mechanism in ABOA where individuals learn from the experiences of others in the population. This learning process enables the algorithm to adapt and improve its search strategy over time.

- ABOA dynamically updates the leadership hierarchy based on the performance of individuals in the population. Leaders influence the search direction, and their roles may change dynamically during the optimization process.

- ABOA seeks a balance between exploration and exploitation of the solution space. Exploration involves discovering new regions, while exploitation involves intensifying the search in promising areas. The algorithm aims to adaptively adjust the balance based on the problem characteristics.

- ABOA often incorporates adaptive mechanisms for controlling its parameters. This adaptability allows the algorithm to respond to changes in the optimization landscape, contributing to improved performance.

- ABOA takes inspiration from the survival strategies of African buffaloes in the face of challenges. The algorithm aims to mimic the cooperative and adaptive behavior observed in nature to enhance its efficiency in finding optimal solutions

The most common kind of animal to engage in combat with the lion in order to avoid extinction. Using the distress/readiness signal generated by herd animals such as bison in response to a predator or a herd of wild oxen keeping an eye on the pace (Abraham et al., 2023). A group may form for the express aim of shielding themselves against the extra kind of marauder encounter triggered by the suffering "waaa" notifications. The technique used to choose their fundamental leadership also highlights their well-known pleasant skills. The leader is responsible for deciding where to have lunch. Scientific inquiry has shown the mechanisms by which the majority's decisions will govern future events. The aforementioned tactic is implemented by setting an example and keeping a watchful eye throughout designated procedures.

In this performance, the standard deviation of the glance trajectory and the subsequent crowd trajectory will be about three degrees, well within the margin of estimating error. The herd plans to split up into smaller, more intimate groups at night, when the cattle are most likely to be staring closely at one another. Following the top wild ox enables the algorithm of African buffalo optimization to achieve adequate mistreatment, which includes doing thorough research on the hunting site and making use of information about other animals. African buffalo optimization relies on a small set of features, primarily those linked to a learning process, to ensure a fast rate of convergence. Depending on the emphasis placed on the procedure during the specified stage, these characteristics allow the animals to evolve towards more severe abuse or investigation.

Modeling the African buffalo's attentive ('maaa') and panicked ('waaa') alarms as it goes about its business of finding food allows for a process known as African Buffalo Optimization (A.B.O). Waaa calls will be used to inform animals of the presence of marauders, to forewarn those with weaker defenses of the danger that lies ahead, to proclaim dominance over a particular territory, or to articulate the inadequacy that lies with the least chance of escaping from predators in that area. The buffaloes will know to go to the protected area when the waaa alarm is being broadcast so that they may eat.

Alerts from the MAAA will be used to let the aforementioned creatures know where a safe, risk-free field is, to reassure themselves that the one they're already in is the safest possible option, and to encourage the weaker creatures by detailing the area's abundant food and pleasant ambiance (exploitation). The warnings will aid the animals in making the most efficient use of their time while they search for food. The African Buffalo Optimization algorithm uses a method that is predicated on the population methodology, which assumes that a group of separate animals would work together to solve the problem at hand.

Waaa (move on) and maaa (hang around) are buffalo calls that indicate whether they want you to leave or stay in their territory, respectively. With the help of modelling the interactive and jointly functioning features of the aforementioned buffalos, the proposed analysis will be the effort in the construction of the strong, quickly processing, competent, operative, though easier in employment of the technique which contain the huge volume of capability in investigation and utilization of the place for exploration.

By regularly monitoring and bettering the position held by the largest animal in the group, the aforementioned technique establishes answers to the convergence problems of prehistoric nature. If the situation of elevating a larger animal does not work with the given number of steps, the whole group will have to start again. The specified technique gives guarantee for the satisfactory inquiry. Using African Buffalo Optimization with a minimal feature set, focused only on aspects of the learning process, may solve the performance problem (lp1 and lp2).

Expression that describes the democratic process by which buffalos choose their leader from amongst themselves is a further step toward addressing the issue of insufficient research and use of the available space for finding solutions. In order to process each request, distribute resources, and modify the workload, an optimization approach is used together with this information. Workflow scheduling based on African Buffalo Optimization (ABO) is used to give users due credit for their contributions. Clustering uses it because of how quickly and well it works. ABO was designed primarily to address problems with existing computations, such as the genetic algorithm, simulated annealing, Ant colony optimization, and particle swarm optimization, including delays in generating solutions, stagnation, the use of a few parameters, and so on.

The animals' historical positional knowledge is mostly represented by the value of w.k. The ABO method is essentially a simulation of the aforementioned three key characteristics of the animal. The m.k will be used to describe the maaa alert of animal k (k=1,2,3,....,N), and the w.k will be used to characterize the waaa alert. The animal's navigating skills may be pinned down with some simple math using equation. The preceding is characterized as a group of solutions that applies to any possible animal and might be used to replace the current local maximum position. The group's prior knowledge of the animal is more important than its present position in determining which of two possible locations is most likely to be chosen.

$$m \cdot k + 1 = m \cdot k + I_p 1(\text{bgmax} - w \cdot k) + I_p 2(bp\text{max} - w \cdot k) \tag{15}$$

While w.k and m.k characterize exploration and utilization of the navigations, respectively, for the k-th. animal (k=1,2...N), lpl and, l-2. will be parameters associated with the learning mechanism, r l and, r-2. will be arbitrary values that lie in the range of [0,1], bgmax the group's greatest value of suitability, and bpmax, is the discrete animal's greatest value.

Buffalo group awareness is denoted by the existence of prior positional knowledge (m.k+1), which is one of three major parts of the Equation (15).

Possessing such comprehensive information on the above will be the basis of the aforementioned procedure, which offers great promise as a technique for creating the touring mechanism. The next proposed work defined the characteristics of the buffaloes' joint functionality, $I_p 1(\text{bgmax} - w \cdot k)$ which had previously been established. These animals will not only be excellent collaborators, but they will also be able to aggressively pursue the role of top animal in every aspect of their performance. The last part of the expression $I_p 2(bpmax - w \cdot k)$ records the astounding intelligence with which the aforementioned creatures operate. The capacity to identify the previous most profitable posture and how it relates to the current one is a feature of the aforementioned animals. Using the above method, animals are given more control over the problem-solving process. Therefore, in order to find optimal solutions, the African buffalo optimization makes use of the aforementioned information and competent supply of protective skills.

$$w \cdot k + 1 = \frac{(w \cdot k + m \cdot k)}{\mp 0.5} \tag{16}$$

Equation (16), fundamentally, drives the mentioned animals to the fresh position by adopting the consequence of Equation (16). Steps pertains to the African buffalo optimization are given below as Algorithm 1.

Algorithm 1. Methodology of linear vector quantization.

Step 1- Function for motivation $f(x)\ x = (x_1, x_2, x_n)T$.
Step 2 - Prepare the arbitrarily location of animals for nodes within the area of the solution.
Step 3- Improve the buffalo's values of appropriateness with the help of Equation 12.
Step 4 - Improve the animals’ position k in accordance with the bpmax. k in addition, bgmax. k utilizing $m \cdot k + 1 = \lambda(w \cdot k + m \cdot k)$. While ' λ ' will be the measure of duration.
Step 5- Examine the value of bgmax for the present of improvement. If yes, proceed to else, proceed to Step-2.
Step 6 - By not satisfying the termination condition, proceed to Step-3.
Step 7- Display - greatest optimal solution.

3.3.1 Hybrid LVQ with ABO

The LVQ selects two naturally optimal solutions from the set generated by the African Buffalo Optimization, using the latter as the parental method. Then, the GA (crossover and mutation) technique is used to choose the best route to the optimal solution (path). Using the above method, the approach gives a path to a solution that is optimal in nature, requiring the minimum amount of delay and the most energy. Algorithm 2 shows steps involved in the Hybrid LVQ-ABO optimization technique.

Algorithm 2. Hybrid LVQ-ABO optimization.

Step 1: Preparation of Preliminary Population Performed arbitrarily.
Buffaloes will be employed at nodes in the arbitrary style.
Step 2: Find out the Appropriateness of population with the help of subsequent expression $\text{mk}' = \text{mk} + \text{lp1}(bg - \text{wk}) + \text{lp2}(bp.\text{k} - \text{wk})(1)$.
while
Lp1, Lp2-Parameters for Training
Bgmax - Group's greatest appropriateness

Bpmax −k discrete animal's greatest appropriateness
Wk mk-investigation along with utilization of the navigation of kth buffalo $K = 1,2 \dots, N$.
Step 3: Replicate the mentioned procedure.
Choose parents from the population.
Carry out the Crossover operation with selected parents, producing the fresh Population.
Carry out the operation of Mutation over the freshly generated population.

The ABO generates a population to make decisions about which actions to take based on how much power each piece of infrastructure consumes.

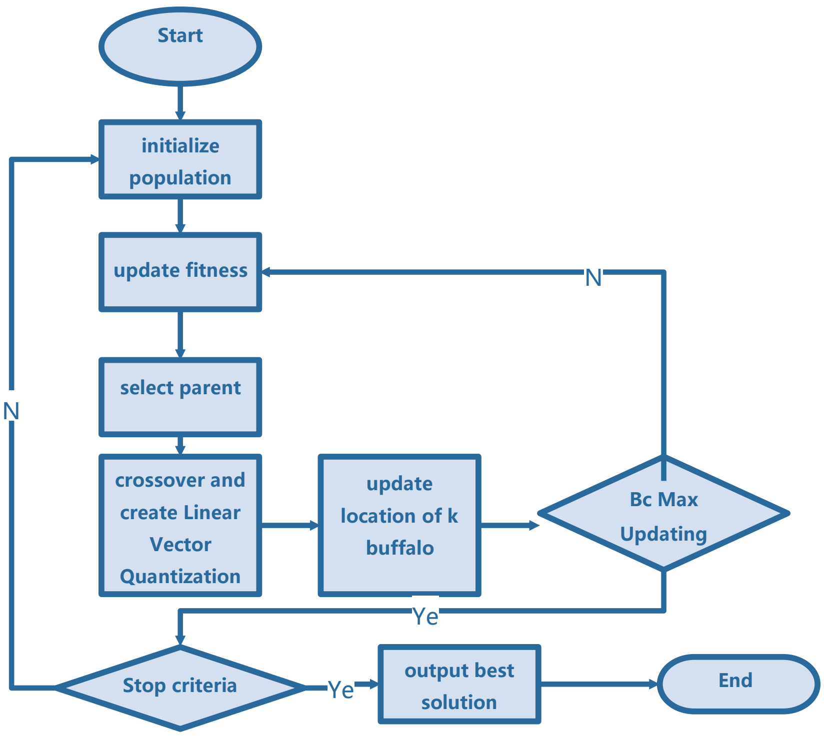

Figure 4. Flowchart of proposed work.

Figure 4 shows the flowchart of proposed work of Buffalo optimization with linear vector quantization. Buffalo optimizing the aforementioned statement, each animal (node) in a network has two types of alerts (messages) that are used to reflect the current energy condition of that node. All of the nodes in a network share the information stored in their collective energy with one another. The aforementioned plan incorporates many identification routes, from origin to final destination nodes.

4. Experimental Results

The result is a three-dimensional plot with time (in seconds), an EGG sample (in y), and amplitude (in mV) shown against one another in the z-axis. The graphic neatly displays the signal's peak count. Peaks are counted using a normal EGG rate of 3 cpm as a benchmark for abnormality detection. The meshc tool in MATLAB utilizes the db4 wavelet to produce a visualization in three dimensions. In order to get colors from the existing colormap, MATLAB linearly transforms the data in C. Matrixes X, Y, and Z must all have the same dimension as matrix C. It demonstrates unequivocally that 3cpm is there in the signal. Figure 5 illustrates the results of applying LVQ to raw EGG data and showing ambiguous peaks for normal EGG.

Classification Accuracy for normal EGG was calculated to be 61.71 percent due to ambiguous peaks. As a result, we denoised and analyzed every single signal shown in Figure 6. Table 3 lists the cpm values obtained from the 3-D plot, which are then utilized to categories the illnesses.

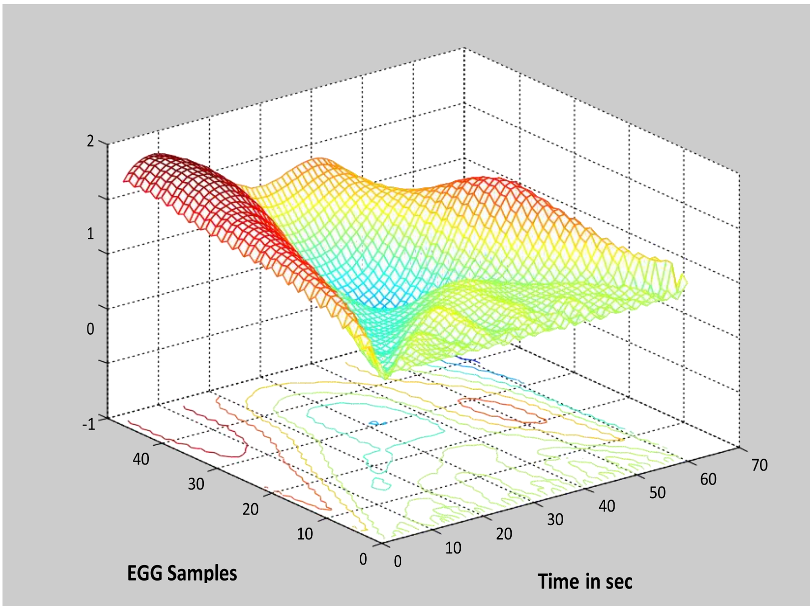

Figure 5. 3D dimensional plot with time.

Table 3. Classification of EGGs Utilizing CWT.

S. No.	EGG	Number of peaks (cpm)
1.	Vomit	4
2.	Ulcer	2.5
3.	Nausea	5
4.	Dyspepsia	4.5
5.	Tachygastria	9
6.	Stage 1	8
7.	Stage 2	7

In particular, when comparing coiflet with symlet at level 3, db4 has the lowest MSE value. To breakdown the EGG signal up to level 3, we employ the wavelet function db4 shown in Table 4.

The prominent frequency components of the signal are used to determine the optimal number of decomposition stages. The levels are selected such that the wavelet coefficients preserve information about the signal that is highly correlated with the frequencies needed for classification. Given that degrees of breakdown beyond three provide no useful information regarding EGG signals, we have arbitrarily set this parameter at three. Therefore, the signal is broken down into its component parts, D1 through D3, plus an additional approximation, A3.

The EGG signals of healthy people and those with conditions including bradygastria, dyspepsia, nausea, tachygastria, ulcer, and vomiting are transformed using a Daubechies (db4) (Aliyi et al., 2023) wavelet transform.

The wavelet coefficients are used to recreate the approximation and detail records. By layering on top of approximation A3, you may get approximation A2. The approximation A1 is generated by layering on top of the approximation A2 the finer features D2. When the approximate signal A1 is overlaid with the exact signal D1, we get the reconstructed signal. The 'I' indicates the window showing the EGG type found in the search results. Table 5 shows the performance metrics of proposed work in terms of DWT transforms.

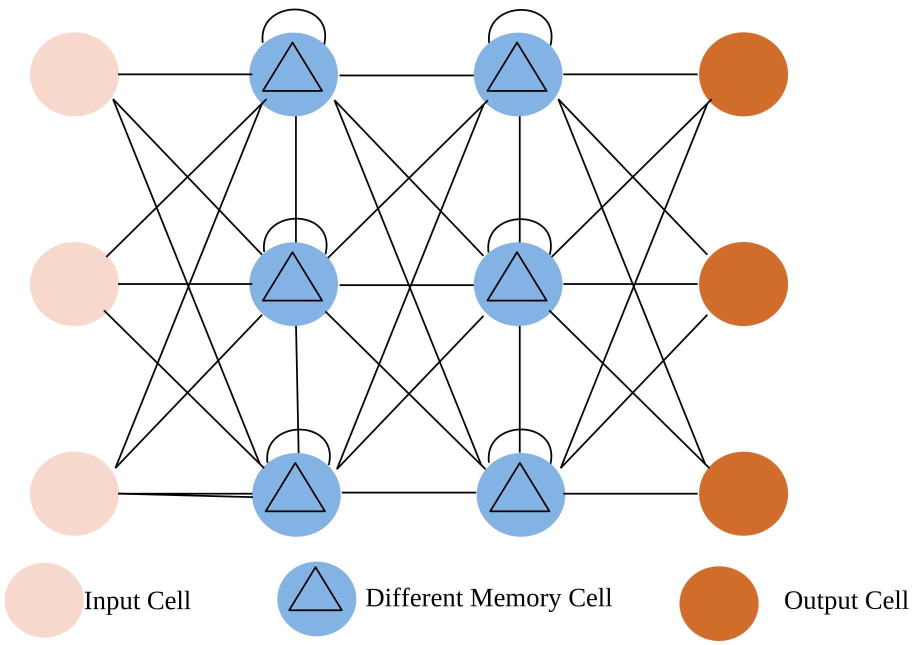

Figure 6. Function of LVQ-ABO.

Table 4. The Use of wavelets in DWT selection.

Wavelet	MSE				
	Level 1	Level 2	Level 3	Level 4	Level 5
db1	1.1116	1.1121	1.1136	1.1156	1.1211
db4	1.1113	1.1111	1.1117	1.1117	1.1116
db11	1.1211	1.1243	1.1276	1.1311	1.1319
coif5	1.1152	1.1147	1.1132	1.1142	1.1167
sym8	1.1118	1.1116	1.1117	1.1122	1.1121

Table 5. Measures of DWT's level of performance.

S. No.	Samples	DWT					
		Precision	Sensitivity	Specificity	F-measure	Time (sec)	Classification Accuracy %
1.	200	0.85	0.86	0.974	0.855	26	85.0
2.	300	0.86	0.87	0.976	0.865	28	86.0
3.	400	0.87	0.875	0.978	0.872	29	86.5
4.	500	0.89	0.885	0.980	0.887	30	87.0

Table 6 created for the various sample sets comprised of signals recorded in the lab using the same setup.

Table 7 provides an in-depth breakdown of the several metrics that are used in statistical testing, such as classification accuracy, F-measure, time, precision, and sensitivity. Across a total of 511 samples, the LVQ-ABO test reaches a sensitivity of 97 percent, a specificity of 98 percent, and an accuracy of classification of 97 percent, on average. The reading of a typical EGG signal is shown in Figure 7. This reading was obtained by utilising the Surface electrode with a contact diameter of 16 mm.

Table 6. Performance measures for DWT.

	211 samples							311 samples						
Predicted Classes	**Actual classes**							**Actual classes**						
	16.1	1.1	1.1	1.1	1.1	1.1	1.1	16.1	1.1	1.1	1.1	1.1	1.1	1.1
	1.1	31.1	1.1	1.1	1.1	1.1	2.1	1.1	51.1	1.1	1.1	1.1	1.1	1.1
	1.1	1.1	26.1	1.1	1.1	1.1	1.1	1.1	12.1	53.1	1.1	1.1	1.1	1.1
	1.1	1.1	1.1	34.1	1.1	1.1	1.1	1.1	1.1	1.1	43.1	1.1	1.1	1.1
	1.1	1.1	1.1	1.1	29.1	1.1	1.1	1.1	2.1	1.1	1.1	51.1	1.1	1.1
	1.1	1.1	1.1	1.1	1.1	36.1	1.1	1.1	1.1	1.1	1.1	1.1	48.1	1.1
	1.1	1.1	1.1	1.1	1.1	1.1	18.1	1.1	1.1	1.1	1.1	1.1	1.1	26.1

Table 7. Performance measures for LVQ-ABO.

S. No.	Samples	LVQ-ABO					
		Precision	**Sensitivity**	**Specificity**	**F-measure**	**Time (sec)**	**Classification Accuracy %**
1	211	1.94	1.949	1.986	1.945	6.5	95.1
2	311	1.955	1.95	1.986	1.95	6.5	95.6
3	411	1.96	1.95	1.987	1.955	7.5	96.5
4	511	1.965	1.97	1.988	1.965	8	97.1

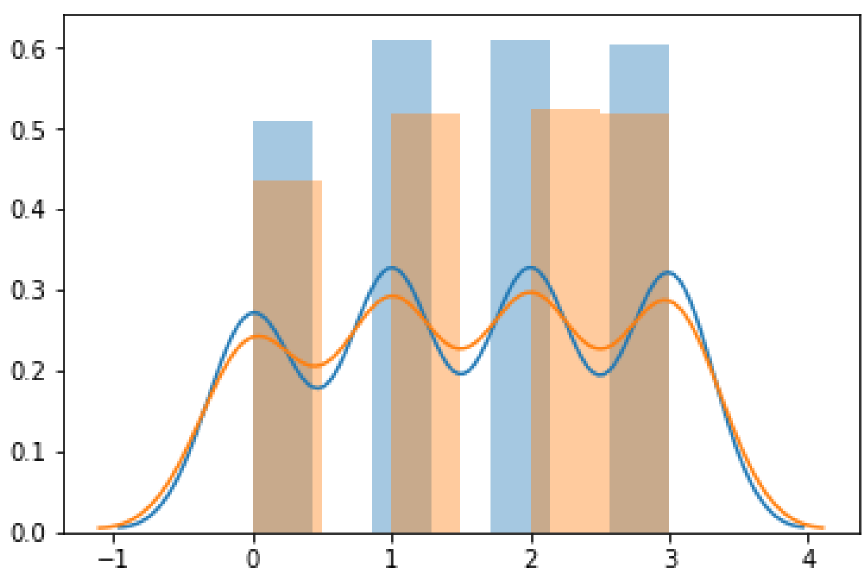

Figure 7. Typical electrogram obtained by using the Surface electrode and measuring it with a contact diameter of 16 millimeters.

Figure 8 compares the performance of the two heuristic approaches NN and LVQ-ABO investigated in this proposed work for classification of EGG disorders with respect to Classification Accuracy.

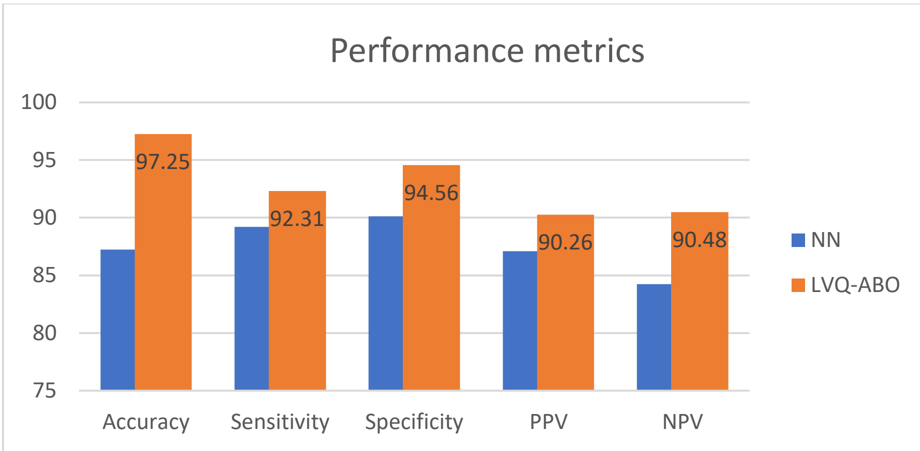

Figure 8. Performance measures of LVQ-ABO classifier.

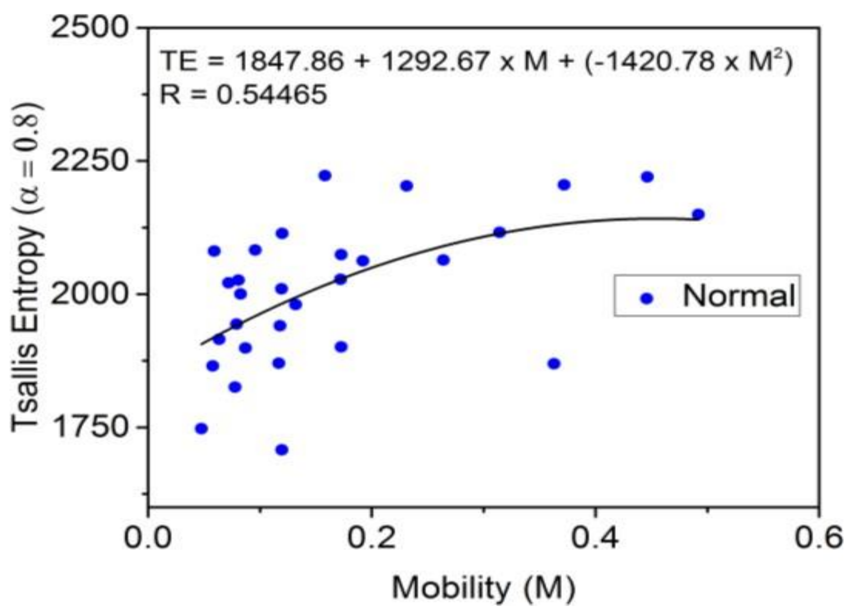

Figure 9. Entropy variation with mobility analysis.

Figure 9 illustrates how the values of descriptive statistical variables vary as a function of movement by comparing EGG signals from healthy persons. It has been shown that the mobility of diabetic EGG signals has a greater link with four of the eight descriptive statistical characteristics, and this connection includes skewness and kurtosis. It has also been noted that the skewness and kurtosis of normal EGG signals, as a function of mobility, are lower than those of diabetes EGG signals.

5. Discussion

Table 8 summarizes the work done to classify EGG signals using the different methods used in this proposed work by listing the sensitivity, specificity, and classification accuracy achieved for each method. When looking at the different categorization methods, it is clear that LVQ-ABO has the greatest Sensitivity and Specificity. LVQ-ABO also has the best classification accuracy because of this.

Table 8. Comparison existing methodology with proposed work.

S. No.	Techniques	Sensitivity %	Specificity %	Classification Accuracy \%	Time (Seconds)
1.	Naive Bayesian Classification [NBC]	78.1	96.3	78.1	45
2.	Continuous Wavelet Transform [CWT]	83.5	97.1	82.5	36
3.	Discrete Wavelet Transform [DWT]	88.5	98.1	87.1	31
4.	ART1 Neural Network	71	95.1	69.5	53
5.	Learning Vector Quantization [LVQ NN]	91	98.4	92.1	24
6.	Back Propagation Neural Network with MRAN	94	98.5	96.1	15
7.	Proposed [LVQ-ABO]	97.1	98.8	97.1	8

This is due to the fact that LVQ-ABO is a convergent unsupervised learning algorithm. Back propagation neural network with multi-rate activation network is the next best classifier. This is due to the fact that each buried neuron contributes a different amount to the network's final result. LVQ-ABO also has a lower temporal complexity. As a result, LVQ-ABO clustering methodology is deemed superior to the other six methods due to its ability to achieve a classification accuracy of 97% in only 8 seconds of calculation time. The findings may help the doctor decide whether or not to use the less invasive, but still invasive, method of EGG to investigate digestive system issues first.

The utilization of hybrid Learning Vector Quantization (LVQ) models, while offering promising advantages, introduces a set of challenges and limitations that necessitate careful consideration. The complexity arising from the integration of multiple algorithms poses difficulties in parameter tuning, demanding extensive optimization efforts. The interpretability of hybrid LVQ models becomes intricate, hindering a clear understanding of their decision-making processes. Moreover, the computational demands associated with diverse algorithm integration may limit the applicability of these models in resource-constrained environments or real-time applications. The effectiveness of hybrid LVQ is contingent on the individual performance of each constituent algorithm, making it susceptible to variations in dataset characteristics. Expertise in each integrated algorithm is crucial for successful implementation, further highlighting the need for skilled practitioners. Additionally, the risk of overfitting, limited theoretical foundations, and challenges in ensuring algorithm compatibility underscore the intricacies involved in designing and deploying hybrid LVQ models. Striking a balance between the benefits and limitations is essential to navigate the complexities inherent in these hybrid approaches effectively.

6. Conclusion and Future Work

In conclusion, the stomach plays a pivotal role in the digestive system, and disturbances in its functioning, often attributed to factors like poor dietary habits, pose significant health challenges worldwide. Traditional diagnostic tools such as endoscopy are invasive, prompting the exploration of non-invasive alternatives like the endoscopic gastrointestinal (EGG) test. This paper proposes strategies for EGG acquisition, employing statistical parameters, wavelet transform, and neural networks to analyze recorded EGG signals and classify gastrointestinal disorders. The LVQ-ABO technique, introduced in this study, exhibits promising results with a 97% sensitivity, 98% specificity, and 97% classification accuracy on a dataset of 511 samples. Notably, the efficiency of LVQ-ABO makes it suitable for real-time applications, outperforming conventional methods like NBC, Wavelet transform, and neural Networks. Future work could involve expanding the scope to include databases for various ailments, such as diarrhea and hepatitis, and training neural networks using cross-correlation values. Additionally, leveraging correlations between endoscope images and electrogastrograms (EGGs) may enhance the diagnosis of digestive system diseases, offering a potential avenue for further research and improvements in gastrointestinal healthcare.

Further exploration of the hybrid model's architecture and the interaction between LVQ and ABO could lead to enhanced performance. Investigating different configurations and structures may reveal optimal setups for specific types of stomach disorders. Research could focus on developing adaptive learning strategies within the hybrid model. This could involve dynamic adjustments to the learning rates or model parameters based on the evolving characteristics of the input data, improving adaptability. Enhancing the interpretability of the hybrid model is crucial for gaining the trust of healthcare professionals. Future research may delve into methods to make the model's decision-making process more transparent and understandable, facilitating its integration into clinical practices. Stomach disorder datasets often exhibit class imbalance, with certain disorders being less prevalent. Future research could explore techniques to address imbalanced datasets, ensuring that the model performs well across all classes and doesn't disproportionately Favor more prevalent conditions. Investigating the adaptability of the hybrid model to real-time and streaming data scenarios is essential for practical clinical applications. This could involve developing algorithms that allow the model to continuously learn and update its knowledge as new data becomes available.

Conflict of Interest

The authors confirm that there is no conflict of interest to declare for this publication.

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