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Blood Pressure Estimation Using Emotion-Based Optimization Clustering Model

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Abstract

The features of human speech signals and emotional states are used to estimate the blood pressure (BP) using a clustering-based model. The audio-emotion-dependent discriminative features are identified to distinguish individuals based on their speech to form emotional groups. We propose a bio-inspired Enhanced grey wolf spotted hyena optimization (EWHO) technique for emotion clustering, which adds significance to this research. The model derives the most informative and judicial features from the audio signal, along with the person's emotional states to estimate the BP using the multi-class support vector machine (SVM) classifier. The EWHO-based clustering method gives better accuracy (95.59%), precision (97.08%), recall (95.16%) and F1 measure (96.20%), as compared to other methods used for BP estimation. Additionally, the proposed EWHO algorithm gives superior results in terms of parameters such as the silhouette score, Davies-Bouldin score, homogeneity score, completeness score, Dunn index, and Jaccard similarity score.

Keywords

Audio signals; Emotion recognition; Enhanced grey wolf spotted hyena optimization; Clustering; SVM; Optimization algorithm.

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1 Introduction

The most fundamental characteristic of human beings, which makes them quite different and intelligent from other living organisms, is emotions, and they are a necessary part of conversation. Among the expansive views of prevalent man-made innovations, such as artificial intelligence (AI), the ability to distinguish the psychological pattern from human speech has attained a wide range of applications and advantages (Guizzo *et al*., 2020). Emotional features of speech signals are pivotal and essential for more stable and effective human-machine connection, communication, and collaboration. Emotion recognition is the fundamental research domain for investigating emotional data and a crossing point of AI and human correspondence investigation to overcome any barrier between human and machine collaborations, which has drawn significant consideration in the modern era (Wang, 2020; Mustaqeem & Kwon, 2020). Speech signals assume a significant part in different ongoing human-computer interaction (HCI) applications, such as clinical examinations, sound reconnaissance, lie identification, sports, customer service centres, diversion and more. Speech emotion recognition (SER) is considered the superior method of human-computer interaction (HCI) (Mustaqeem & Kwon, 2020). SER is the legitimate and secured communication means for information exchange and plays a significant role in human-machine collaboration (Issa, 2020; Nie, 2020). In the medical domain, audio-based analytical frameworks are created to investigate the measure of sorrow and misery, and some SER frameworks are intended for medical care communities to screen the condition of the utterer for manic depression (Grewe & Hu, 2019).

Numerous scientists are contributing to this area, where researchers try to invent an intelligent machine for distinguishing their emotions from speech (Badshah, 2013; Nie, 2020). Because of the mutual connection between ecological, physical, and passionate components, blood pressure (BP) will consistently be an oscillating hemodynamic occurrence. BP is perhaps the main physiological sign that shows the patient's primary health care data. At the point when the heart beats, the BP oscillates between systolic BP (SBP) and diastolic BP (DBP). Unfortunately, 1.13 billion individuals worldwide have hypertension (high BP), which is recognized as a high-level risk factor for different illnesses, for example, coronary failure, visual deficiency and cerebral stroke (Nie *et al*., 2020). A few techniques have been created to screen BP consistently because continuous BP checking is significant for the analysis of hypertension and the forecast of heart sicknesses (Lee, 2017; Xia, 2019). Photoplethysmography (PPG) is generally utilized as an apparatus to identify the blood flow level variation in the microvascular system (Martínez, 2018). Because of its straightforwardness and non-invasiveness, the PPG measuring device has been generally utilized in gadgets, mostly for the wellness-following component (Mottaghi, 2014; Farki, 2021).

The research concentrates on developing emotion-dependent BP estimation using a clustering-based emotion recognition model from the audio signal collected from humans. The selection of the discriminative features and the development of a compelling feature selection model are focused on in this research. For this, the EWHO algorithm is proposed to enumerate the benefits of this research. The pre-processing is applied to the gathered human audio signals, and it is followed by the feature extraction process to extract the essential features. The emotions from the features are clustered using the proposed EWHO, which is developed by integrating SHO (Dhiman & Kumar, 2017) and GWO (Mirjalili *et al*., 2014). These clustered emotions are given as input to the multi-class SVM classifier for the BP estimation. The prime significance of the research article is listed below:

- The EWHO is a search-based bio-inspired algorithm, formed by integrating the hunting characteristics of the hyena (Dhiman & Kumar, 2017) and the grey wolf (Mirjalili *et al*., 2014). It is used to achieve the overall best results by maintaining the exploration and the exploitation phase for fine-tuning the hyperparameters of the SVM in estimating the BP.
- The highly discriminative features are selected and clustered through the proposed EWHO to enhance the accuracy of the BP estimation. This novel algorithm overcomes the problem of local minima and gives a reasonable convergence rate.

The spotted hyena optimization (SHO), grey wolf optimization (GWO), swarm optimization (SO), and other bio-inspired algorithms are used to find a solution for complex and non-linear limited industrial dilemmas (Dhiman & Kaur, 2019; Dhiman & Kumar, 2019b). Although SHO is a novel system, it is broadly applied to resolve numerous industrial problems (Dhiman & Kumar, 2019a). Some optimization algorithms such as the rat swarm optimizer (RSO) are used to work out the various demanding optimization challenges such as racing and tackling behaviours of rats (Dhiman *et al.*, 2021).

Research contribution:

1. The EWHO algorithm is proposed to cluster emotional states using human audio signals, which provides a better tradeoff between intensification and diversification to provide high global optimal convergence.
2. The unnecessary signs from the audio signals are detached using an adaptive filter and the spectral characteristics are obtained to create a feature map.
3. The SVM classifier is utilized to estimate BP from the emotional states and the audio-spectral features.
4. The evaluation of the approach is carried out through the available datasets and real-time data collected from 10 subjects within the age group 20 to 65.
5. The relative evaluation is performed for the existing and the proposed BP estimation model, which proves the effectiveness of the proposed audio emotion-dependent BP estimation model.

2 Literature Review

Some of the conventional methods utilized for BP estimation are elucidated in this sub-section. Wang *et al.* (2020) presented the dual-sequence LSTM (DSLSTM) model for emotion recognition. Reduction in parameters and enhancement in weighted accuracy are the significant benefits of the system. Yet, the DSLSTM system requires more resources for training. Nie *et al.* (2020) utilized a correlation-based graph convolutional network (C-GCN) for the emotion recognition process. The C-GCN method progresses the judgment of video descriptors. However, the C-GCN model requires additional labels for validation. Mustaqeem *et al.* (2020) suggested the ConvLSTM method, which enhances recognition accuracy. The huge memory consumption is the main drawback of the system. Mustaqeem and Kwon (2019) used a deep-stride convolutional neural network (DSCNN) for an effective recognition system. The latency is the main issue with the DSCNN that degrades its performance. Mustaqeem and Kwon (2021) utilized a multi-learning trick (MLT) based on a one-dimensional dilated convolutional neural network (DCNN) for emotion identification from audio signal. The prime significance of the system is that it attains high recognition accuracy. The increased energy consumption is the main issue experienced in MLT-DCNN. Mustaqeem *et al.* (2020) presented the deep bi-directional long short-term memory (BiLSTM) method for emotion recognition. Though the system improves classification accuracy and computational complexity, the technique is prone to overfitting issues due to insufficient training data.

Guizzo *et al.* (2020) utilized multi-time-scale convolution layer (MTS CNN) methods for emotion identification from audio-speech signals. The significant enhancement is the prime advantage of the MTS CNN method. Yet, MTS CNN system is not adaptable to high-dimensional data. Issa *et al.* (2020) presented a one-dimensional deep CNN for emotion extraction from audio signals. The one-dimensional deep CNN improves the performance of the recognition model. Yet, the system fails to determine the optimal feature. Harfiya *et al.* (2021) presented photoplethysmography (PPL) and LSTM-based signal-to-signal translation for BP estimation. The PPL and LSTM-based system provides a precise and promising outcome over an enormous number of subjects. Yet, the PPG signals are prone to the tuning of the hyperparameters. Lee *et al.* (2020) utilized a bidirectional long short-term memory network (LOSO). The main issue experienced is data insufficiency due to the low quantity of data comprising subjects diagnosed with hypertension. Yang *et al.* (2021) presented a hybrid deep-learning model for BP estimation. The tuning of the hyperparameters is mandatory to design an accurate model.

Song *et al.* (2021) presented a multivariate gaussian distribution for blood pressure estimation based on a neural network. The system effectively expresses the relation between the data. Yet, the system suffers from performance deterioration due to a negligible training dataset. Argha *et al.* (2021) utilized a bidirectional long short-term memory recurrent neural network (BiLSTM-RNN), which effectively reduces the absolute mean error value to BP estimation. The performance degradation because of the noise in the auscultatory waveforms is the main issue in the BiLSTM-RNN system. Tian *et al.* (2001) developed a CNN network for human facial emotion detection that extracted essential features from the face such as landmarks and distance.

3 Proposed Methodology

Hypertension is known as a high-danger factor for different illnesses, for example, coronary failure, visual deficiency, and cerebral stroke. Hence, an effective method is proposed in this research for audio emotion-dependent BP estimation using a clustering-based emotion recognition model. The proposed BP estimation method is comprised of four processes, namely audio pre-processing, feature extraction, emotion clustering and BP estimation phase. A graphic representation of the proposed methodology is shown in Figure 1. In this research, the proposed EWHO algorithm forms the emotional groups from the audio of individuals and the BP estimation is performed using the multi-class SVM, which categorizes the audio grounded on the cepstral and spectral features with their respective emotional groups into the classes, such as usual, pre-hypertension and hypertensive individuals.

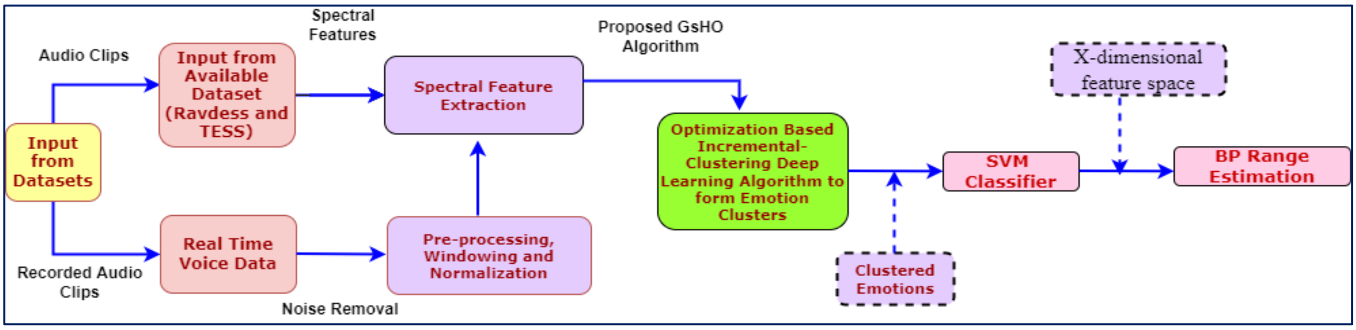

Figure 1. *Proposed audio emotion-dependent BP estimation using the clustering model.*

The technique will assist the person in monitoring their BP in the real time and will predict unforeseen alarming medical emergencies, thereby alerting for timely medical assistance.

3.1 Audio pre-processing

Audio signals collected from humans are considered as the input of the proposed BP estimation method. The audio signals are easily contaminated by external factors, such as noise and unwanted signals. These external factors deteriorate the performance of the classifier and the quality of the audio signals. Hence, in the pre-processing stage, the external noises are removed from the audio signal to enhance its quality. Further, the raw audio data are converted into structured data in the pre-processing stage. An adaptive filter is utilized to eliminate interference from the input audio signal. The adaptive filter is a digital filter with self-modifying characteristics to adapt automatically to changes in the input signal.

3.2 Feature extraction

The feature extraction process is a significant task employed in the proposed BP estimation process in which features are extracted from audio signal. The feature extraction solves redundancy issues and establishes informative features from the audio, which enhances the estimation performance by reducing the generalization steps in the deep learning process. The most relevant features, such as the Mel Frequency Cepstral Coefficient (MFCC), spectral centre, spectral crest, spectral skewness, spectral kurtosis, spectral flux, tonal power ratio and spectral flatness are extracted by means of the feature extraction process, which helps the EWHO algorithm identify the individual's emotional state from their voice signal.

3.3 Clustering model based on proposed EWHO algorithm for emotional state-based grouping of speech signals

Clustering is a significant task to be executed in the proposed audio emotion-dependent BP estimation method for identifying the individual's emotional state from their speech signal. The clustering process organizes emotional states with the same qualities under the same groups. A cluster is a group of individuals with similar emotional states and in this research seven emotional groups are considered. The clustering process can be achieved by various algorithms and all the conventional algorithms, such as SHO, ant colony optimization and GWO, become stuck in local optima sluggishness (Dhiman & Kumar, 2017; Mirjalili, 2014). To avoid converging to the local optimal point, the EWHO algorithm is proposed, which offers a superior balance between intensification and diversification, thereby providing a higher global optimal convergence.

3.3.1 Motivation

In the machine learning domain, a metaheuristic algorithm is built to find an optimized solution to a given complex problem. Some of these algorithms are motivated by biological activities of animals or birds. Metaheuristics is an approach in heuristics to solve complex minimization or maximization problems (Dhiman, 2021). To achieve the optimized solution and to obtain feasible good quality solutions to new complicated optimization problems, researchers have turned to the use of metaheuristic algorithms. Over the last six decades, bio-inspired optimization algorithms have achieved enormous recognition. They have been widely used in engineering and across various non-engineering disciplines (Dhiman & Kaur, 2019). The proposed algorithm helps solve the optimization issues by choosing the optimal weights of the SVM classifier and the clustering of emotional states from human audio signal.

High BP and other diseases such as diabetes, which may lead to life-threatening situations, must be controlled during the early stage, and monitored regularly (Li *et al.*, 2019). Nowadays, many elderly people are affected by high BP, and it threatens the life of many people. There is thus a current need to accelerate the accuracy and reliability of blood pressure calibration techniques in day-to-day life. The use of cuffless blood pressure techniques to treat high blood pressure and cardiovascular events will enhance the efficiency and safety of people suffering from hypertension, cardiovascular disease and other conditions (Yang *et al.*, 2021).

3.3.2 Mathematical framework of proposed EWHO algorithm

The mathematical model is comprised of social hierarchy, the encompassing, poaching, exploitation and exploration stages.

1) Social hierarchy: As mentioned above, the EWHO always prefers to reside in a group and all the representatives in the group are divided into monarch (M), subordinates (X), comrades (K) or servants (Z). Among them the fittest solution is regarded as M, the second finest solution is regarded as X, the third finest solution is regarded as K and Z is the worst solution. In the proposed algorithm, the poaching is directed by the first three representatives ($M, X\ and\ K$), while Z must follow the orders of these representatives (Dhiman & Kumar, 2017).

2) Encompassing the target: The search agents encompass their target prey during the poaching process. The mathematical model for the encompassing stage is represented by the following equations (Dhiman & Kumar, 2017; Mirjalili, 2014).

$$E = \left|\bar{\alpha}.\bar{\nu}_{\Gamma}(t) - \bar{\nu}(t)\right| \tag{1}$$

$$\bar{\nu}(t+1) = \bar{\nu}_{\Gamma}(t) - \beta.E \tag{2}$$

where the present iteration is denoted by t, β and α are the co-efficient vectors, ν_{Γ}denotes the position vector of a target, $\bar{\nu}(t+1)$ refers to the position of the search agents and E refers to the best solution (Dhiman & Kumar, 2017). The coefficient vectors are estimated as

$$\alpha = 2.\Re_1 \tag{3}$$

$$\beta = 2l.\Re_2 - l \tag{4}$$

The l is estimated in the following equation (Dhiman, 2017; Mirjalili, 2014).

$$l = 5 - \left(I * (5/I_{max})\right) \tag{5}$$

Where I represents iteration in the range of 1,2…,max$_I$. To establish the appropriate estimation between the exploitation and exploration phase, $\vec{l}$ is directly reduced from 5 to zero throughout the maximum iteration (I_{max}). More exploitation is attained as there is an enhancement in the iteration value. The random vectors are represented as $\Re_1$and $\Re_2$in [0,1].

3) Poaching stage: The search agent always prefers to hunt or poach in a group and depends on the organization of trusted teammates and the ability to perceive the location of the target. To characterize the aptitude of the search agent's position of the target of the prey and to mathematically represent the poaching strategy of the search agent, we assume that the best candidate inherits better knowledge about the prey. The other search agents create a cluster, a trusted group with the best agent to update their position (Dhiman & Kumar, 2017). Therefore, the best solution obtained by the candidate is given as:

$$E_s = |\alpha.\nu_s - \nu_o| \tag{6}$$

$$\nu_o = \nu_s - E\beta \tag{7}$$

$$\vec{C_s} = \vec{\nu}_s + \vec{\nu}_{s+1} + \ldots.. + \vec{\nu}_{s+N_s} \tag{8}$$

where $\vec{\nu_s}$ demonstrates the location of the best search agent, $\vec{\nu_o}$ demonstrates the location of the other search agent, and $N_s$indicates the number of search agents (Dhiman, 2017; Mirjalili, 2014).

$$N = T_{nos}\left(\vec{\nu}_{s,}\vec{\nu}_{s+1}, \vec{\nu}_{s+2} \ldots\ldots.\left(\vec{\nu_s} + R_3\right)\right) \tag{9}$$

where R_3 is the random vector between [0.5,1] , T is the count of all the possible solutions, nos demonstrates the number of the solutions, after addition of the random variable R_3, which is related to the best optimal solution (Dhiman & Kumar, 2017).

4) Exploitation: The value of the s vector needs to be reduced to a mathematical model for the exploration phase. The alteration in the random vector $\vec{\beta}$ is decreased from 5 to 0 throughout the iteration. The mathematical representation of exploitation is given below.

$$\vec{\nu}_{pos}(t+1) = \frac{C_s}{N} \tag{10}$$

where $\vec{v}(t+1)$ reserves the best possible solution and upgrades the location of the search representatives according to the location of the best search representatives (Dhiman & Kumar, 2017).

5) Exploration: The search representatives search for the target, concerning the location of the cluster of the search agents which live in the vector C_s. They tend to move away from each other to explore and attack the target. Therefore, they utilize β, a random variable 1 or less than -1 to move away from the target.

The proposed EWHO algorithm consists of different phases, namely (a) population initialization phase, (b) parameter initialization, (c) fitness value estimation, (d) choosing the best search agent, (e) position updating phase, (f) declaration of the optimal solution, and (g) termination.

***a) Population initialization*:** The proposed EWHO algorithm is a population-based algorithm. Hence, the initialization of the population is the first and foremost process involved in the proposed EWHO algorithm. The mathematical representation of the population initialization is formulated as

$$P_{tot} = \{P_{1,}P_2 \ldots\ldots\ldots P_n\} \tag{11}$$

***b) Parameter initialization*:** Parameter initialization is the second phase involved in the proposed EWHO algorithm. The parameters, such as α, β, and l are initialized in this phase.

***c) Fitness value estimation*:** The fitness value is estimated for every search agent, which helps to choose the best solution for the optimization issue.

***d) Choosing the best search agent*:** The next phase employed in the proposed EWHO algorithm is choosing the best search agent.

***e) Updating the position of the search agent*:** While considering the social hierarchy, the best solution attained by the search agent depends on the monarch (M), subordinates (X) and comrades (K). The position of the search agent based on the social hierarchy is mathematically formulated as:

$$\vec{v}(t+1) = \frac{\vec{v}_1 + \vec{v}_2 + \vec{v}_3}{3} \tag{12}$$

where $\vec{v}_1$, $\vec{v}_2$ and $\vec{v}_3$ are formulated concerning the monarch (M), subordinates (X) and comrades (K).

$$\vec{v}_1 = \vec{v}_M - \vec{\beta}_1.\vec{E}_M \tag{13}$$

$$\vec{v}_2 = \vec{v}_X - \vec{\beta}_2.\vec{E}_X \tag{14}$$

$$\vec{v}_3 = \vec{v}_K - \vec{\beta}_3.\vec{E}_K \tag{15}$$

The updated solution of the search agent based on the social hierarchy is formulated as:

$$\vec{v}_h(t+1) = \frac{\vec{v}_M - \vec{\beta}_1.\vec{E}_M + \vec{v}_X - \vec{\beta}_2.\vec{E}_X + \vec{v}_K - \vec{\beta}_3.\vec{E}_K}{3} \tag{16}$$

The final position depends on the monarch (M), subordinates (X) and comrades (K) in the exploration phase. In other terms, the monarch, subordinates, and comrades evaluate the position arbitrarily around the target (Dhiman, 2017; Mirjalili, 2014).

***f) Declaration of optimal solution*:** The following process is declaring the best solution for optimization issues to avoid local convergence. The final obtained position is achieved by integrating the best solution based on the location of the target and based on the social hierarchy (Dhiman, 2017; Mirjalili, 2014). The final updated solution is formulated as:

$$\vec{v}_{best}(t+1) = 0.5\left[\vec{v}_h(t+1)\right] + 0.5\left[\vec{v}_{pos}(t+1)\right] \quad (17)$$

Substituting the best solution based on position and the best solution based on social hierarchy in Equation (17) and the final best update solution is given as:

$$\vec{v_{best}}(t+1) = 0.5\left[\frac{\vec{v_M}-\vec{\beta_1}.\vec{E_M}+\vec{v_X}-\vec{\beta_2}.\vec{E_X}+\vec{v_K}-\vec{\beta_3}.\vec{E_K}}{3}\right] + 0.5\left[\frac{\vec{v}_s+\vec{v}_{s+1}+\ldots..+\vec{v}_{s+N_s}}{N}\right] \quad (18)$$

Equation (18) is the best update solution, which is estimated based on the characteristics of poaching characteristics of hyenas and grey wolves (Dhiman, 2017; Mirjalili, 2014). All the conventional algorithms, such as SHO, ant colony optimization, and whale optimization, become stuck in local optima stagnation, as they often converge to the local optimal point. To avoid converging to the local optimal point, we propose the EWHO algorithm, which provides a better tradeoff between intensification and diversification, thereby providing a higher global optimal convergence.

Here, the convergence at the local optimal solution is eliminated by incorporating the adaptive poaching tactics of the hyena to exploit the feature space more deeply. The proposed EWHO algorithm helps to achieve the global best results with a rapid convergence rate. It helps to solve the optimization issues by choosing the optimal weights of the SVM classifier and the clustering of the emotional states.

g) Termination phase: The above stages are sustained until the extreme iteration and the global optimal solution is obtained. The proposed EWHO algorithm is used in this research to group persons based on emotional groups using recorded audio speech signals, and the grouping is done in such a way that each emotional group shares similar characteristics. Such grouping of the emotional groups is performed based on the spectral features and cepstral features extracted from the audio. Once the emotional groups are established, the BP estimation is performed using the SVM classifier from the individual’s emotional state information and audio information.

3.4 BP estimation using SVM classifier from emotional states and audio spectral-cepstral features

The SVM classifier is widely utilized in different types of engineering applications. In this study, BP estimation is performed using the multi-class SVM classifier, which handles over-fitting issues and performs well on unstructured and semi-structured data. The SVM classifier is handy in the prediction process and is highly capable of dwelling with complex data. Hence, the SVM classifier is used for the BP estimation. The individual’s emotional state identified using the EWHO optimization algorithm along with the cepstral-spectral features of the audio is provided to the input layer of the multi-class SVM classifier, for the practical BP estimation. The X-dimensional input is fed to the classifier to estimate the BP. The SVM considers the input data as an X-dimensional feature space that consists of the cepstral-spectral features of the audio with the corresponding emotional state information. The proposed EWHO algorithm helps to achieve the global best results with a rapid convergence rate. It helps to solve the optimization issues by choosing the optimal weights of the SVM classifier and the clustering of the emotional states.

Notably, the output classes considered in this research are three, namely normal, hypertension, and pre-hypertension. Hence, instead of using the binary SVM classifier, this research uses the multi-class SVM classifier for the BP estimation.

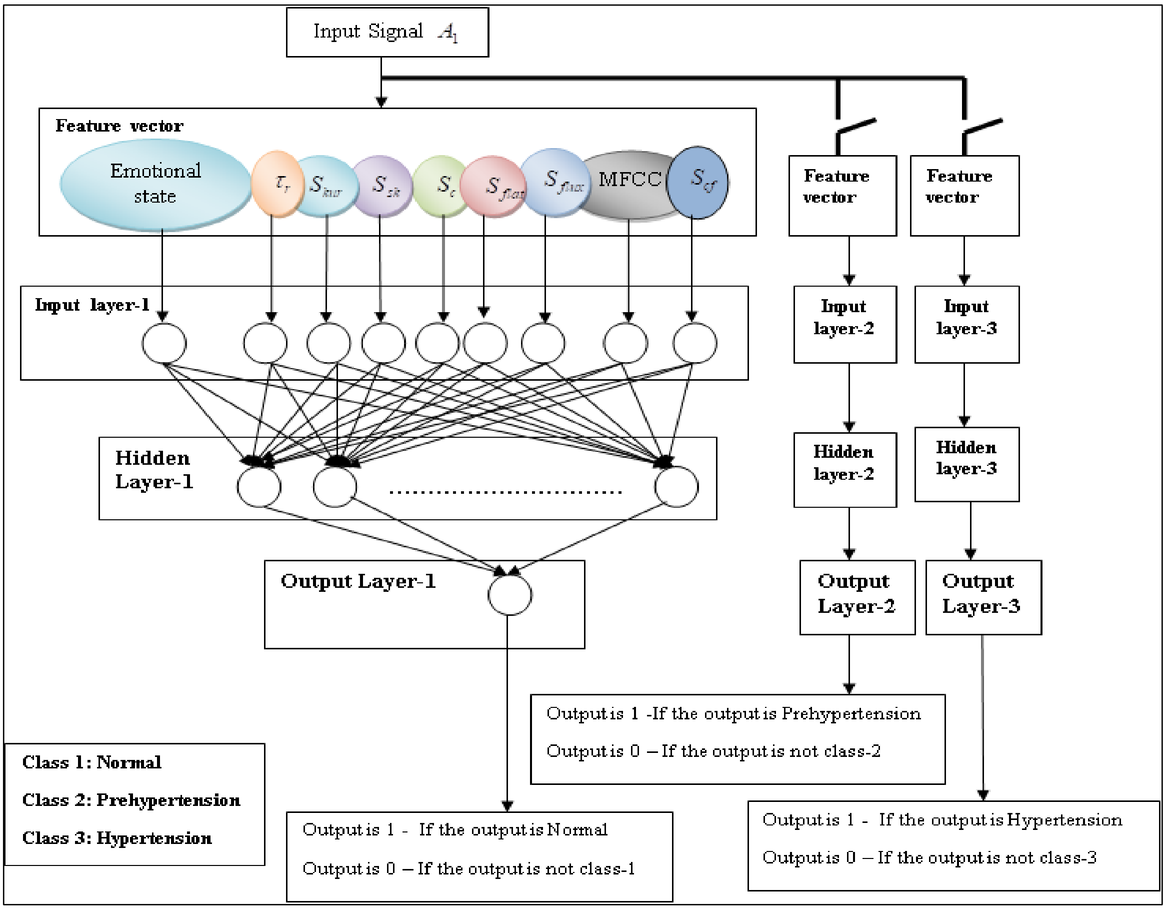

Figure 2. *BP estimation model architecture.*

The hyperplane is mathematically represented for linearly separable data as shown in Equation (19):

$$df(I) = \omega.I + b = \sum_{i=1}^{X} \omega_i I_i + b = 0 \tag{19}$$

where $df(I)$ represents the decision function, ω is the weight of the dimensional vector, and b is the bias of the scalar (Alkan & Gunay, 2012).

The position of the hyperplane is determined by the weight and bias, which separates the space and must follow the limits given below:

$$\Upsilon_i(I_i.\omega + b) - 1 \geq 0 \Leftrightarrow \begin{cases} df(I_i) = I_i.\omega + b \geq 1, \Upsilon_i = +1 \\ df(I_i) = I_i.\omega + b \leq -1, \Upsilon_i = -1 \end{cases} \tag{20}$$

The hyperplane that generates the maximum limit is called the optimal hyperplane and the independent variable is given as ϑ and the error penalty is given as Ep. The solution of the hyperplane is represented as:

$$\phi(\omega, \vartheta) = \frac{1}{2}(\omega.\omega) + Ep(\sum_{i=1}^{n} \vartheta_i) \tag{21}$$

The independent variable ϑ determines the gap between the limit and the sample on the other side of the limit (Alkan & Gunay, 2012). The calculation of this gap is carried out as,

$$V(A) = \sum_{i=1}^{n} A_i - \frac{1}{2}\sum_{i,j=1}^{n} A_i A_j \Upsilon_i \Upsilon_j \, ker(I_i, I_j) \tag{22}$$

$$\sum_{i=1}^{n} \Upsilon_i A_i = 0, Ep \geq A \geq 0, i = 1,2\ldots\ldots n \tag{23}$$

The function $ker(\Upsilon_i, \Upsilon_j)$ represents the function kernel that returns the dot product of the feature space maps of the original data point (Alkan & Gunay, 2012). The X-dimensional input feature vector, which is the input to the classifier, trains the classifier and at the time of the testing phase, the output is derived using the classifier and the output label is represented as follows:

$$Y_i^1 = \begin{cases} 1; OutputisClass - 1(Normal) \\ 0; NotClass - 1 \end{cases} \tag{24}$$

$$Y_i^2 = \begin{cases} 1; OutputisClass - 2(Prehypertension) \\ 0; NotClass - 2 \end{cases} \tag{25}$$

$$Y_i^3 = \begin{cases} 1; OutputisClass - 3(Hypertension) \\ 0; NotClass - 3 \end{cases} \tag{26}$$

where Y_i^1, Y_i^2, and Y_i^3 are the output classes from the multi-class SVM classifier. For establishing the corresponding output for the BP estimation, the multi-class SVM is trained using the features of the class outputs. The SVM in layer 1 is trained for normal BP, the SVM in layer 2 is trained for pre-hypertension, and the SVM in layer 3 is trained for hypertension. The architecture of the multi-class SVM is depicted in Figure 2.

4 Experimental Setup of Proposed Methodology

The experimental analysis is implemented in Python and the system configuration of experiments includes Python 2020 community edition running on the Windows 10 operating system with 8 GB memory.

Table 1. *Data collection tools.*

Design types	Study objective
Measurement	Blood pressure analysis
Devices	Boya BY-M1 Omni directional microphone, Omron hem 7120 blood pressure monitor
Factor	Diagnosis
Sample	Homo sapiens

4.1 Dataset description

The RAVDESS and TESS datasets, which are publicly available, are used for the emotion clustering phase. These datasets can be downloaded from https://www.kaggle.com/uwrfkaggler/ravdess-emotional-speech-audio (RAVDESS Emotional speech audio, Emotional speech dataset) and https://tspace.library.utoronto.ca/handle/1807/24487 (Toronto emotional speech set, TESS, Collection) respectively. Along with these two datasets, the real-time data set is collected from 10 subjects in the age group of 20 to 65, which provides the collection of the essential signals and blood pressure values of the subjects.

Table 2. *Emotional states and sentences.*

Emotions	Sentences
Neutral	Please close the door.
Calm	Raju feels relaxed after a walk.
Happy	I was on cloud nine when I got the new job.
Sad	I am unwell.
Angry	How dare you?
Fearful	I can't watch horror films; they give me goosebumps.
Disgusted	Yuck! How are you eating such food?
Surprised	Wow! What a beautiful flower?

The blood pressure and the audio signals are collected from 5 female and 5 male subjects. This database is mainly created for the accurate estimation of BP, which helps the physician examine the BP of a person from their speech signals. Among the 10 subjects, three subjects are affected by high blood pressure and the remaining subjects are normal. All the readings are taken by a clinical expert.

The blood pressure is recorded by Omron hem 7120 digital blood pressure monitor with intelligence technology. The Omron hem 7210 is an automated blood pressure monitor that operates on the oscillometric principle for precise measurement. Table 1 summarizes the data collection tools and their descriptions. This device is used to monitor irregular heartbeats along with blood pressure. The variations in the blood pressure with different emotions are recorded to provide accurate BP estimations. The BP readings are taken from the subjects for eight different emotions, namely happiness, neutral, calm, sad, angry, fearful, disgusted, and surprised with 10 trials for each emotion. The subjects are exposed to different environments to induce different emotions in them. The subjects' voices are recorded in audio files, which may play for 5 to 10 sec. The audio is recorded by using Boya BYM1 omnidirectional Lavalier condenser microphone, which is designed for DSLR, camcorders, audio recorders and PCs. The emotional states and the sentences considered in this study are listed in Table 2.

The EWHO algorithm groups the individuals under these seven emotional states. The dataset consists of the subjects' systolic pressure, diastolic pressure, and pulse. The readings are taken from the subjects in three types, before breakfast (fasting condition), two hours after breakfast, and after lunch. These datasets are used to train the classification and to provide non-invasive cuffless BP estimation. The subjects' audio is recorded in the mp3 file format. The dataset consists of 800 files (10 subjects x 8 emotions x 10 samples) with a total file size of 116 MB. The BP data are saved in the csv file format. These datasets are mainly created to support the research into BP estimation based on emotional states and audio features.

4.2 Performance metrics

Accuracy, precision, recall and F1 measure are the performance metrics analysed in this research. The terms used in performance analysis are TP, TN, FP, and FN. *TP* represents the true positive value, *TN* represents the true negative value, *FP* represents the false positive value, and *FN* represents the false negative value.

a) Accuracy: Accuracy defines the confidence of the weights to a specific value. Accuracy is mathematically represented as

$$Accuracy = (TP+TN)/(TP+TN+FP+FN) \tag{27}$$

b) Precision: It is the closeness of the measurements to each other. Precision is mathematically represented as

$$Precision = TP/(TP+FP) \tag{28}$$

c) Recall: It is defined as the number of positive predictions among all other prediction values. Recall is mathematically represented as:

$$Recall = TP/(TP+FN) \tag{29}$$

d) F1 measure: Precision and recall are combined to form the score of the F1 measure:

$$F1= (2 * Precision * Recall)/(Precision + Recall) \tag{30}$$

5 Comparative Result Analysis

The comparison of the results is carried out for both clustering performance and classification performance.

5.1 Comparative analysis of clustering performance

The performance metrics such as clustering accuracy, silhouette score, Davies-Bouldin score, homogeneity score, completeness score, Dunn index and Jaccard similarity score are evaluated to determine the clustering performance.

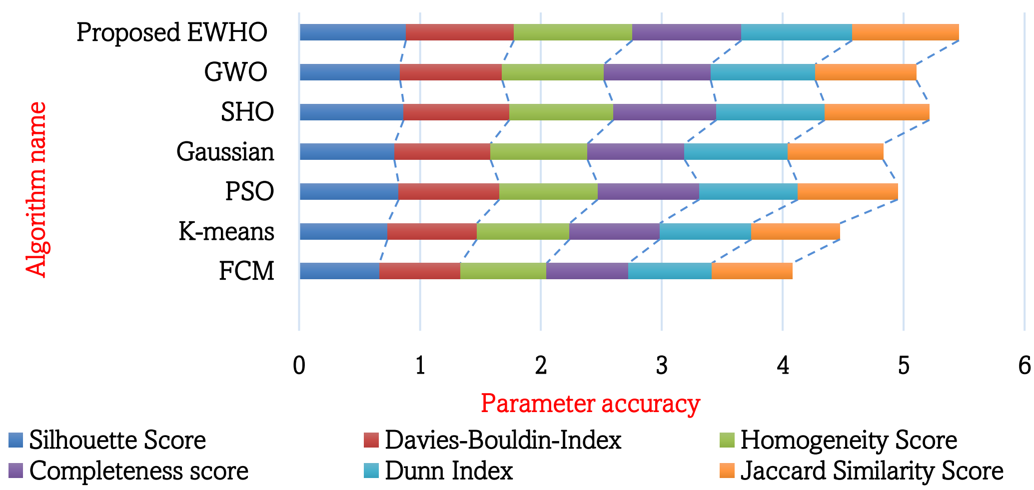

Figure 3. *Comparative analysis of proposed and existing algorithms.*

As shown in Figure 3, the proposed EWHO-based clustering algorithm attains better results compared to the existing methods in term of silhouette score, Davies-Bouldin score, homogeneity score, completeness score, Dunn index and Jaccard similarity score.

The value of the silhouette varies from −1 to +1. A high value of the silhouette score shows that the object well belongs to its cluster and is poorly matched to its neighbour clusters. The proposed EWHO method gives the highest silhouette score of 0.88. It shows a performance improvement of 24.82%, 17.21%, 6.76%, 10.88%, 2.10% and 5.45% compared to methods such as the FCM, k-means, PSO, Gaussian mixture, SHO-based clustering, and GWO-based clustering.

The Davies-Bouldin score is defined as the ratio of within-cluster distances to between-cluster distances. The proposed EWHO-based clustering algorithm attains the highest Davies-Bouldin score of 0.89. It shows a performance improvement of 24.82%, 17.21%, 6.76%, 10.88%, 2.11% and 5.46% compared to methods such as the FCM, k-means, PSO, Gaussian mixture, SHO-based clustering, and GWO-based clustering.

The proposed EWHO-based clustering algorithm attains the highest homogeneity score of 0.9800. It shows a performance improvement of 14.06% compared to the existing GWO-based clustering methods. A higher completeness score indicates that all the data points that are associated with a given class are members of the same cluster.

The experimental outcome shows that the proposed EWHO-based clustering algorithm attains the highest completeness score of 0.90. It shows a performance improvement of 2.15% compared to the existing SHO-based clustering methods. The main objective of the Dunn index is to recognize the sets of clusters that are dense.

The higher value of the Dunn index value indicates better clustering. It shows that the clusters are well separated. The proposed EWHO-based clustering algorithm attains the highest Dunn index of 0.92, which shows a performance improvement of 24.83% compared to the existing FCM methods. The Jaccard similarity score is a likeness measure between groups that is used to measure the stability of a cluster. The experimental outcome shows that the proposed EWHO-based clustering algorithm attains the highest

Jaccard similarity score of 0.88, showing a performance improvement of 17.21% compared to the existing k-means clustering methods.

5.2 Comparative analysis of classification performance

For evaluating classification performance, a comparative analysis is carried out on two more factors, namely the percentage of training data and the k-fold analysis. The effectiveness of the BP estimation model is revealed by analysing the key features, namely accuracy, precision, recall and the F1 measure.

a) Analysis based on training percentage

Figure 4 illustrates the comparative analysis based on the training percentage. The comparative analysis in terms of accuracy concerning the training percentage is depicted in Figure 4a). At 40% of training, the accuracy of 78.55% gradually increases with an increase in the training percentage, and it attains 94.09% of accuracy at 90% of training. The comparative BP estimation method using a Gaussian mixture attains an accuracy of about 73.56% at 90% of training, which is lower than the accuracy attained by the proposed EWHO-based clustering method.

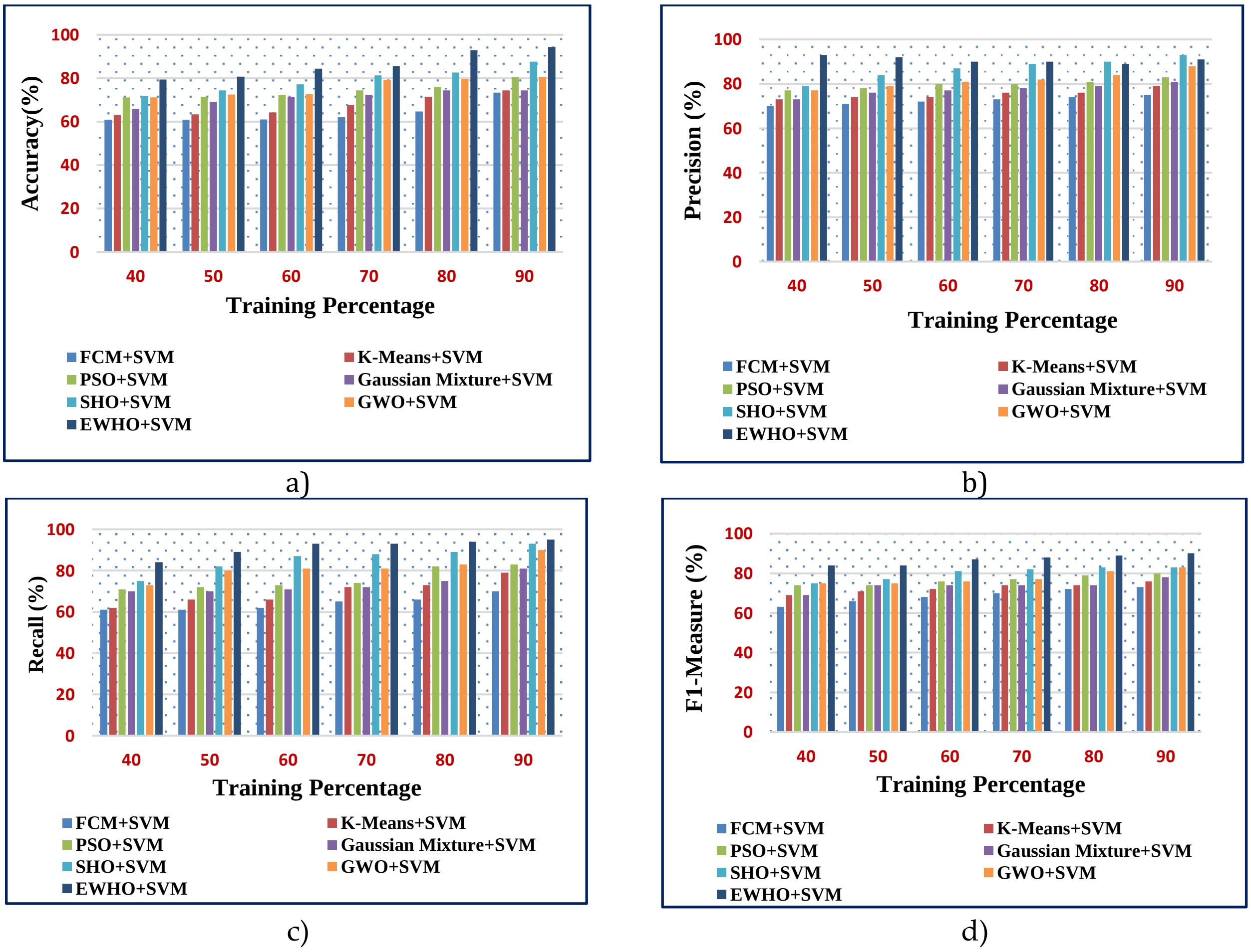

Figure 4. Comparative analysis based on training percentage in terms of a) accuracy, b) precision, c) recall and d) F1 measure.

Figure 4b) shows the comparative evaluation of the BP estimation method in terms of precision. The graph shows that the proposed EWHO-based clustering method attains a better precision value compared to the conventional methods. For instance, methods such as k-means and the PSO attain a precision of about 77.76 and 81.69, whereas the proposed EWHO-based clustering method attains an accuracy of about

91.99% at 90% of training, Hence, the proposed EWHO method beats all the other techniques in terms of precision.

Figure 4c) depicts the recall attained by the proposed methodology in terms of the training percentage. Conventional methods such as the FCM and the k-means clustering attain a recall of 68.93% and 77.76% respectively, while the proposed EWHO-based clustering method attains a recall of 94.85%, which is comparatively higher than that of the traditional methods. The figure demonstrates the dominance of the proposed EWHO-based clustering method in terms of recall.

The comparative evaluation based on the F1 measure is demonstrated in Figure 4d). From the figure, it is evident that the proposed EWHO-based clustering dominates other conventional BP estimation techniques in terms of the F1 measure. The conventional methods of SHO-based clustering and GWO-based clustering attain F1 measure of about 81.69 and 81.66, which is slightly lower than the proposed EWHO method.

b) Analysis based on k-fold values

Figure 5 illustrates the comparative analysis based on the k-fold values. The comparative analysis in terms of accuracy to the k-fold value is depicted in Figure 5a). When k-fold=2, the accuracy of the proposed EWHO-based clustering method is found to be 71.92% and it gradually increases with an increase in the k-fold value, and it attains 95.38% of accuracy at 90% of training.

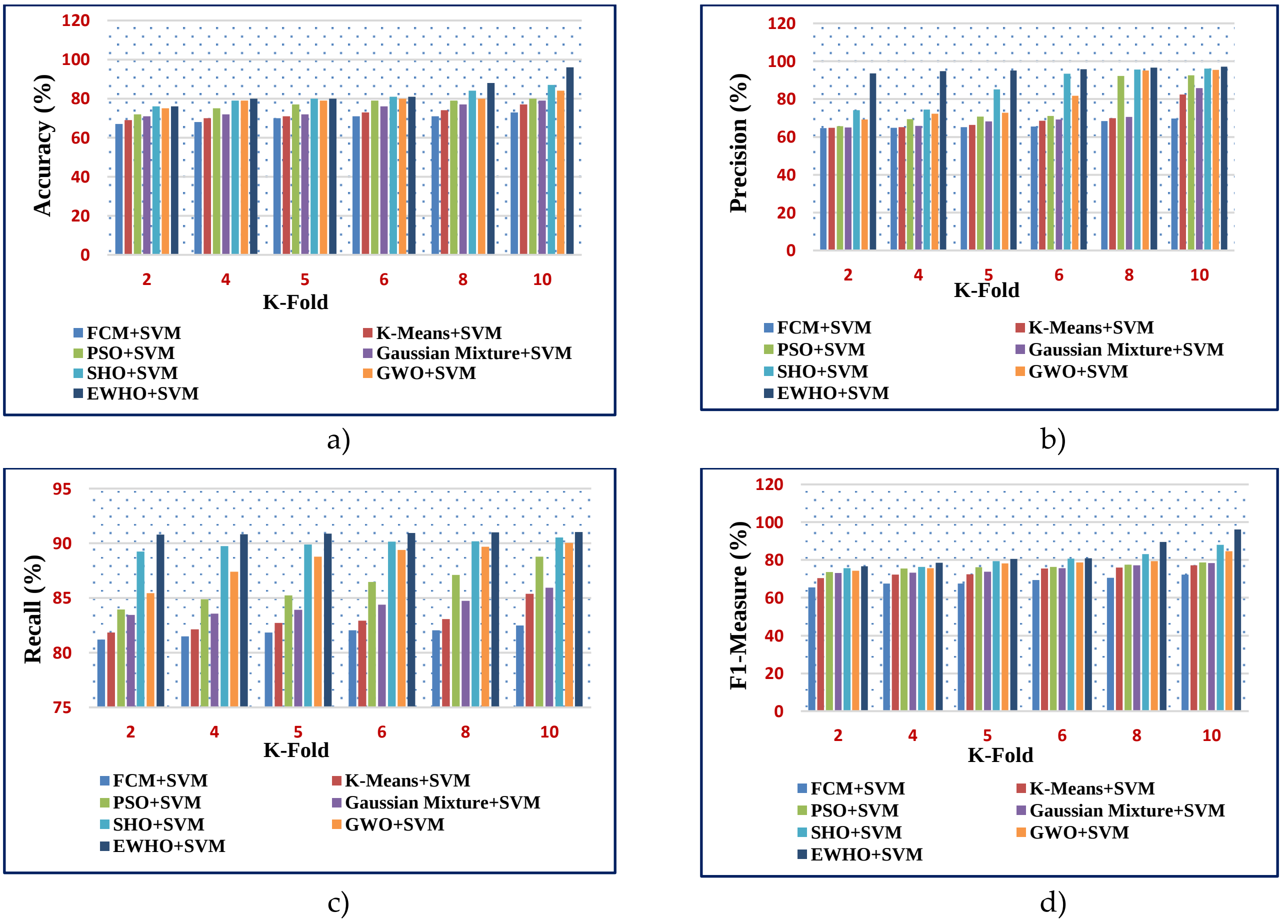

Figure 5. *Comparative analysis based on K-fold in terms of a) accuracy, b) precision, c) recall and d) F1 measure.*

The comparative BP estimation method using a Gaussian mixture attains an accuracy of about 78.37% at k-fold=10, which is lower than the accuracy attained by the proposed EWHO-based clustering method.

Figure 5b) represents the comparative analysis of the BP estimation method in terms of precision based on k-fold analysis. From the graph, the proposed EWHO-based clustering method attains a higher precision value compared to the conventional methods. For instance, K-means and the PSO attain a precision of about 81.66% and 92.43%, whereas the proposed EWHO-based clustering method attains an accuracy of about 96.85% at k-fold=10. Hence, the proposed EWHO beats the other methods in terms of precision.

Figure 5c) depicts the recall attained by the proposed methodology based on the k-fold value. Conventional methods, such as the FCM and the k-means clustering attain a recall of 81.82% and 84.69% respectively, while the proposed EWHO-based clustering method attains a recall of 94.85% at k-fold=10, which is a comparatively better result than those of the traditional methods. The figure demonstrates the dominance of the proposed EWHO-based clustering method in terms of recall.

The comparative analysis in terms of the F1 measure is illustrated in Figure 5d). The proposed EWHO-based clustering outperforms all the other conventional BP estimation method in terms of the F1 measure. For example, conventional methods such as SHO-based clustering and GWO-based clustering attain F1 measure of about 87.23% and 83.89% respectively, which is slightly lower than the proposed EWHO method.

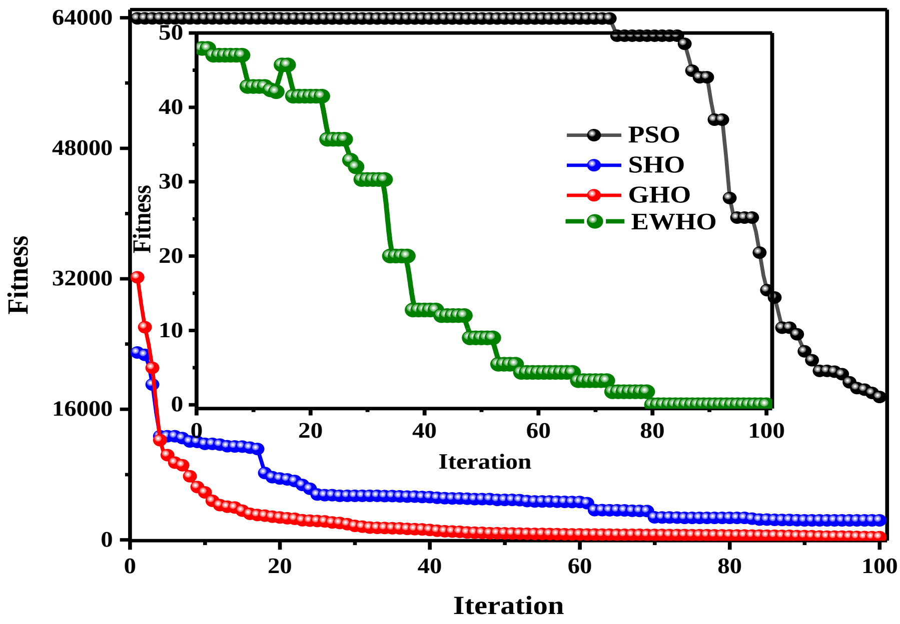

Figure 6. *Convergence analysis of existing and proposed EWHO algorithm.*

5.3 Convergence analysis

The convergence analysis of the proposed EWHO optimization algorithm is depicted in Figure 6, in which the traditional optimization algorithms such as PSO, SHO and GWO are compared to show the performance enhancement. As shown in the inset graph, at the first iteration, the fitness acquired by the proposed EWHO is 47.91, whereas the traditional PSO, SHO and GWO acquired the values of 63,925.79, 22,954.73 and 32,179.11, respectively.

At the final 100th iteration, the proposed method converges approximately to zero value, which is not acquired by the other methods. Thus, we can see from the figure that the elevation in the iteration value makes the convergence faster for the proposed EWHO optimization algorithm than for the existing methods.

5.4 Comparative discussion

The comparative study is done by changing the training percentage from 40 to 90% and the maximum values of accuracy, precision, recall, and the F1 measure are attained at 90% of training. The maximum values of accuracy, precision, recall and F1 measure achieved by the proposed EWHO-based clustering method are found to be 94.09%, 91.99%,94.85% and 89.38% respectively, which is comparatively higher than the competing methods. The most efficient results are obtained when the k-fold value=10. Recall and the F1 measure achieved by the proposed EWHO-based clustering method are found to be 94.09%, 91.99%, 94.85% and 89.38% respectively, which is comparatively higher than the competing methods. Also, the clustering performance of the proposed EWHO in terms of parameters such as the silhouette score, Davies-Bouldin score, homogeneity score, completeness score, Dunn index and Jaccard similarity score is better compared to existing algorithms. The proposed EWHO+SVM for non-invasive BP estimation can be utilized for real-time application processing, as the proposed method acquired better results compared to the competing techniques.

The suggested technique acquires the emotions of the human being through the speech signal, and it is utilized for the estimation of the BP. Hence, in the proposed method, the intervention of a human expert is not essential, and it can be utilized for real-time processing. The proposed EWHO algorithm can balance the diversification and the intensification phase for acquiring the global best solution for solving the optimization issues in clustering the emotions and BP estimation.

6 Conclusion

Emotions play an essential role in identifying a person’s mental state and variations in an individual’s BP occur depending on the emotional state. A classifier based on an effective emotion clustering model was proposed in this work for BP estimation from audio signals. BP estimation is practically applied in multiple health applications for monitoring patients’ health. The intelligence-based algorithm known as EWHO plays a significant role in selecting the emotional groups that boost the performance of the BP estimation. The signals gathered from the audio are pre-processed and fed into the feature extraction process to extract the essential features from the signal. Finally, based on the clustered emotions, the BP estimation is performed using the SVM, where the tuning of the classifier is performed using the proposed EWHO optimization algorithm. The algorithms help to obtain the global best solution by maintaining balanced randomization and local search criteria for estimating the BP by considering the cepstral and spectral features along with the emotional states. The experimental results show that the accuracy, recall and F1 measure achieved by the proposed EWHO and SVM classifier are comparatively higher than those of the competing methods. Also, the EWHO algorithm gives good results in terms of parameters such as silhouette score, Davies-Bouldin score, homogeneity score, completeness score, Dunn index and Jaccard similarity score.

However, the accuracy still needs to be enhanced for the processing of real-time applications. Thus, in the future, a novel framework will be designed for BP estimation with real-time application validation. At present, the proposed work focuses only on a person’s BP estimation using audio signals. As the human voice is closely related to the person's mindset, it can be used to identify the person's mental health. In the future, diseases related to mental disorders such as depression, bipolar disorder and other mood disorders can be addressed using audio signals.

Additional Information and Declarations

Conflict of Interests: The authors declare no conflict of interest.

Author Contributions: V.R.: Conceptualization, Data curation, Methodology, Investigation, Project administration, Resources, Validation, Writing – Original draft preparation. P.M.: Conceptualization, Project administration, Validation, Supervision, Writing – Reviewing and

Editing. S.P.: Methodology, Data Visualization, Supervision. C.M.: Formal analysis, Data Visualization, Writing – Reviewing and Editing. R.D.: Formal analysis.

Institutional Review Board Statement: Ethical review and approval were waived for this study due to the use of a fully anonymized dataset. Obtaining the dataset of speech and blood pressure cannot cause physical stress on the participants.

Informed Consent Statement: Patient consent was waived due to fully anonymized dataset.

Data Availability: The data that support the findings of this study are available from the corresponding author. The used datasets are listed in Section 4.1.

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