Utilizing variable auto encoder-based TDO optimization algorithm for predicting loneliness from electrocardiogram signals

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Abstract

Several seniors and a substantial part of the general population are living in social isolation. This frequently occurs in vulnerability, isolation, and depression, which then have a poor impact on other health-related factors. A number of health problems, including a higher risk of cardio problems, are brought on by social isolation and loneliness. Electrocardiogram (ECG) usage for mental condition recognition enables accurate determination of a person's internal representation. The electrocardiogram (ECG) signals can be thoroughly analyzed to uncover hidden data that may be helpful for the precise identification of cardiac problems. ECG time-series information typically have great dimensions and complicated componentry. Using relevant information to guide training is among the main achievements of this type of learning. An ECG signal plays a significant part in the individual body's ability to manage behavior. Furthermore, loneliness identification is crucial since it has the worse effect on the circumstances that afflict persons. This study suggested an approach for detecting loneliness from an ECG signal to use a variable auto encoder-based optimization algorithm for ESN technique. The suggested approach consists of three phases for identifying a person's loneliness. Firstly, undecimated discrete wavelet transform is used to preprocess the acquired ECG data. Next, further characteristics are extracted from the precompiled signals using a variable auto encoder. For the precise categorization of loneliness in the ECG signal, a metaheuristic optimized ESN is, therefore, presented. The outcomes of the tests demonstrate that the suggested system with suitable ECG representations produces improved accuracy as well as performance.

1 Introduction

A personal feeling of loneliness is having unsatisfactory family members. Among the main cause of unhappiness in people's life is solitude, which is linked to having bad health

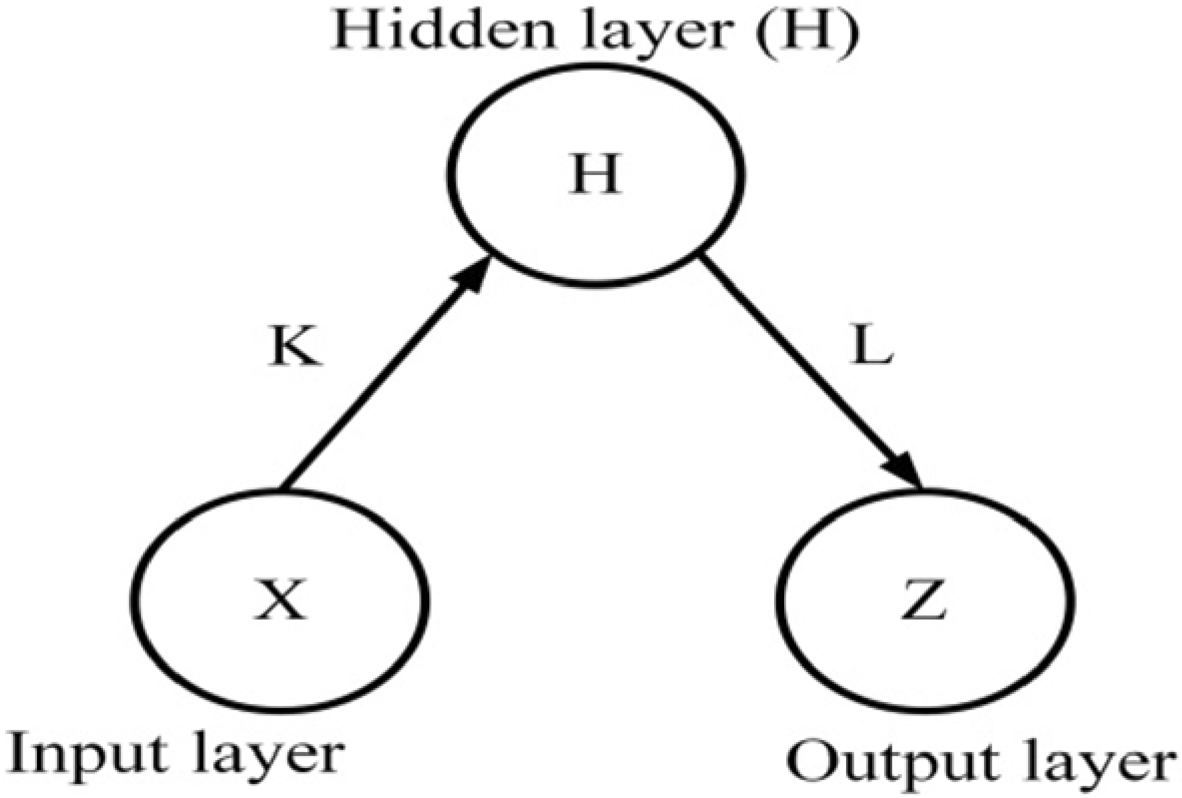
(Martín-María et al. 2020). Depending on people's ages and well-being, the volume of a social network either declines or rises (Luo et al. 2012). The urge for relationships may decline, especially in older adults. Although most conceptions of solitude refer to a feeling that one is isolated or alone in the world, solitude is essentially a mental condition. Those who are lonely experience vacant, lonely, and unwelcome feelings. Individuals who are solitary frequently want for human interaction, yet their mental state makes cultivating friendships more challenging. According to studies, anxiety, introverts, poor social skills, and social exclusion are all linked to solitary. Contextual aspects including physical isolation, relocation, and relationship breakdown are significant elements to solitude. Loneliness feelings can also result from the loss of a key someone in an individual's life. Moreover, it could be a sign of a mental illness like sadness. Depressed individuals frequently retreat socially, which might result in solitude. Loneliness may also add to the signs of depression, according to studies. Internal problems like poor self-esteem can also contribute to solitude. Insufficient self-assurance can result in feeling isolated and lonely because persons with low self-esteem frequently feel undeserving of others' consideration or respect (Cherry 2022). It has been established that psychological issues, bad work traits, and unhealthy habits are linked to a higher risk of disease (Anitha and Vanitha 2021).

Those who are socially isolated frequently experience solitude, although loneliness and social isolation are not the same thing. The uncomfortable sensation that comes along with differences between one's intended and real social ties is more aptly described as solitude, which can be considered of as experienced solitude (Pinquart and Sörensen 2003). Perspective suggests that isolation symptoms are associated with depressed symptoms, poor sleep, daytime sleepiness, decreased physical activity, and poor mental and cognitive well-being (Wilson et al. 2007). The COVID-19 epidemic has posed a threat to global health as well as psychological stress. The main method to halt the spreading of COVID-19 and its variations is self-quarantine or isolating. Those who are under quarantined experience tension, worry, despair, dread, and solitude. One major method used to detect unwelcome mental issues as early as possible is the development of sophisticated emotional identification. This can aid in the diagnosis and evaluation of mental health problems by medical professionals. Comprehensive, integrated, and reactive mental health and social care services in society settings are outlined, as are goals to improve governance and management in this area. People tension may be detected in a variety of ways, including through voice tone, facial gestures, and some others. The analysis of physical and physiological data could be utilized to determine a person's state of mind (Baig and Kavakli 2019). The processing procedures for a physical signal are simple but failing to reveal the genuine emotional state within. In contrast, because they are sensitive, physiological factors can find interior conditions. Physiological signals offer more benefits than physical signals, and they are more difficult to conceal and manage by a single component.

In order to combat the long-term impacts of stress, including such disorientation, increased blood pressure, sleeplessness, depression, headaches, and the difficulty making judgments, a lot of emphasis has been paid to the development of wearable devices for stress monitoring (Khowaja et al. 2021). Many academics have now created new strategies for the earlier detection of mental states in order to improve health systems. By the use of psychologic data, creating a trustworthy and efficient mental condition detection method is challenging (Kim 2007). Owing to the brain signals' superior capacity for reflecting individual activities, the ECG signal is more suited for mental condition identification than the EEG signal. Investigators have been drawn in large numbers to employ ECG signals because of the precision of ECG-based identification techniques. The electrical activity of the heart can be monitored by acquiring an electrocardiogram (ECG) signal, which can be done non-invasively. It implied a technique for automatic ECG-based solo diagnosis based on a robust ESN. In order to improve the ESN system's classification performance, it employs dynamic auto encoder-based techniques to feature extraction and optimization-based variable modification. Both an encoder and a decoder are necessary for the operation of an auto encoder. The input is compacted by the encoder, and the decoder makes an effort to reconstruct the original input from the encoder's compressed version. When training is complete, only the encoder type is kept, while the decoder version is thrown away. Electrical currents originating from the cardiac are detected to produce ECG signals. ECGs' latent data can be utilized to diagnose related illnesses or to sound an early warning sign of impending sickness. Consequently, it will be highly beneficial in the health sector if study can identify aberrant ECGs earlier and properly. Most ECGs have extended recording times, several parameters, and various complex elements. As a result, it is challenging to use machine learning in this area. Information representations that can deal with high dimension are a common goal for researchers. Despite ML's ability to give metrics for risk prediction and categorization, understanding the functional connections between inputs and outcomes, the impact of each characteristic on the simulated data, and the interplay between multiple options can be challenging. Yet, due to the structured nature of these sequence, it is challenging to identify an acceptable time-series illustration (Längkvist et al. 2014).

DNN approaches include auto encoders. It minimizes the degree of distortion while transforming an input data into an output sequence (Längkvist and Loutfi 2015). It is a synthetic feed-forward unsupervised neural network that offers effective data coding. It takes in data in a certain form so that it may be transformed in accordance with its dimensionality. Nowadays, auto encoder has been used more frequently for creating produced data structures. An auto encoder is a feed-forward neural network that automatically transforms data from one compressed format to another. As a data preparation approach, the encoder may be used to extract features from raw data for the purpose of training a separate machine learning model. A fully linked hidden state (H) is included in generalized auto encoder design so that the input data may be efficiently encoded for unsupervised classification. Auto encoders are frequently employed in data analysis, particularly when it comes to lowering the size of the information. The auto encoder system is divided into two parts: an encoding functional $H = K(X)$ and a decoding functional $Z = L(H)$ that reconstruct the source by recovering the information from the codes (Bengio and Glorot 2009). Figure 1 may be used to illustrate the typical auto encoder design, which entails mappings from an input X to an outcome Z (code H).

Fig. 1



The general auto encoder architecture

To better classify emotional strain, we used data normalization, auto encoding, and the ESN method. Separately classifying ECG data in the frequency domain and the time domain improved the stress classification model's accuracy. To map the input vector to the state vector, ESN uses pools of arbitrarily sparsely linked neurons in instead of the recurrent neural network's hidden units. The effectiveness of the stress categorization model was assessed using accuracy, F1-score, and recall curves. Utilizing ECG data, study presented an ensemble technique in this work to categorize the psychological stress of the Optimal Auto encoder-ESN system. A more modern RNN called the echo state network (ESN) is built on a hidden randomized reservoir at the levels of the hidden units. Convergence calls for a shorter processing time (Chouikhi et al. 2016). Estimation, categorization, and other activities have all been effectively completed by ESN. RNNs are commonly thought to be limited to temporal data due to their recurrence. To address categorization issues, study researched an ESN-based methodology. ESN usually consists of three layers. It has an input data that are randomly linked to the reservoirs, forming the following concealed layer. The method for handling categorization issues is dependent on ESN (Bianchi et al. 2016). The fundamental goal of this research is to combine ESN and auto encoder system components to provide more precise, effective, and efficient representations of data. Thus, ESN is viewed as a fresh representational space for recurrence of the initial data structures. ESN is researched as a multi-layer, fundamental system. Whether the information are temporal or not are irrelevant. Whatever concern is the reliability of the additional features that the Auto encoder-ESN method extracts from the old ones.

A novel model of RNN depending on randomly chosen reservoirs and straight readout mappings from the internal part is the echo state network (ESN). The inherent flexibility of ESNs matrices makes it a powerful tool for processing time series. When feeding a time series into a subsequent reservoir, ESN models stick to the same sampling approach as traditional RNNs. In other words, the sample order is a perfect match for the chronological order of the input time series. The clear distinguishing feature of ESN is the reservoir neurons' connection to one another via predefined sparse weight matrices that do not require tuning after initial creation. The ESN could generate an echo phase attribute once the reservoirs neuron has "echoed" all of the input data. Furthermore, ESNs have been successfully used in a number of sequencing fields, including batching bioprocesses, nonlinear structural management, time-series task categorization, time-series prediction, voice activation network traffic forecasting, and wind velocity prediction (Wang et al. 2019).

The remaining research work is presented in the following section. The earlier research on loneliness/stress detection was described in Sect. 2. The proposed VAE-OESN method for categorizing loneliness results is described in Sect. 3. Test results and a comparison of the proposed system with other strategies are presented in Sect. 4. Lastly, Sect. 5 concludes the findings and the work that has to be done in the future.

2 Related works

The support vector machine techniques used in this work offer a thorough exploration of the identification of internal stresses in individuals. Several behavioral and physiological issues, such as the development of serious depressive disorder, and stress-induced heart rhythm irregularities can be avoided with effective stress detection. Owing to the shutdown scenario brought on by the COVID-19 epidemics, stress might worsen the situation for heart patients and trigger other problems in healthy individuals. Thus, in this work, an ECG-based approach is provided where the ECG may be collected for the widely accessible handheld/portable tools that are increasingly widely used in numerous nations where individuals can take ECG on their own in their homes and gain basic information about their cardiac health. In order to create a framework for depression detection, study may also extract the RR duration, intervals, and EDR from the ECG. An open-access database called "drivedb" that is accessible at Physionet was utilized as the training set to confirm the suggested approach. After validating several SVM models by altering the ECG length, features, and SVM Kernel types, it was found that fine Gaussian SVM with Gaussian Kernel while employing all available components provided an adequate degree of accuracy. It works well when there are more characteristics than training examples, and it works well in higher dimensions. As just the support vectors influence the hyperplane, outliers have less of an effect. This observation highlights the value of including respiration and ventricle polarization data in depression detection, as well as the possibility of activity recognition from short-length information. It is going to be extremely helpful in identifying stress via portable ECG devices in locked down conditions in order to analyze mental health conditions without seeing a cognitive behavioral therapist at the clinic. This method also warns heart patients against overstress that might lead to serious arrhythmogenesis. Nevertheless, not all rural health-care centers and low-income groups of individuals will always have access to ECG recording and characteristic analysis methods. Large datasets cannot be used with this strategy (Rizwan et al. 2021).

As per stress accumulating, the mental stress that several individuals experience in contemporary society is a role in the development of several chronic illnesses, including depressed, cancers, and heart disease. As a result, it is crucial to consistently manage and track a patient's anxiety. This study presents an ensembles technique that uses a customized convolutional neural network (CNN)–long short-term memory (LSTM) structure to precisely identify mental stress levels. An alteration in the ECG signal occurs whenever an individual is under pressure. By deriving particular characteristics from ECG data and examining the results, anxiety signals may be categorized. To improve the effectiveness of the proposed stress forecasting model, we preprocessed ECG data using fast Fourier transform (FFT) and spectrograms to generate signals in the frequency and time domains during the training phase. The fast Fourier transform (FFT) is a speeded-up variant of the more familiar discrete Fourier transform (DFT). The FFT takes use of the fact that many of the identical multiplications are performed repeatedly by the conventional technique to generating the Fourier transform. Confusion matrix, ROC curves, and extremely precise curvatures were employed as quality assessment standards of the pressure classification algorithm. The correctness obtained using the suggested framework was 98.3%, which is an increase of 14.7% in comparison with earlier research findings. Consequently, this approach can aid in the management of stress-exposed individuals' mental well-being. Also, it could have the possibility of being used in a number of health-care systems, including home training, sleeping state analysis, and cardiac tracking, if paired with different biosignals such as EMG and PPG. This approach is ineffective since it requires additional training data to function properly (Kang et al. 2021).

The high incidence of road traffic accidents including stress serves as proof that traveling and tension is a risky mix that can result in collisions. Building a workable system that can accurately categorize driving level of stress is imperative in order to manage the considerable expenses associated with driving strain. The accuracy of a system for detecting drivers' levels of anxiety depends on hyper parameter optimization choices such as data segmentation. Hyper parameters in grid search have their range of values specified. After that, we use the Cartesian product to assemble all the potential combinations of hyper parameter values into a multidimensional grid. Then, we attempt every combination of grid settings until we find the optimal hyper parameter values. In assessing the method, hyper parameter configuration settings, which have a significant effect on system efficiency, are often hand-tuned. This tweaking procedure takes time and frequently relies on prior knowledge. There are additionally no universal ideal settings for hyper parameters settings. This paper offers a real-time driving strain tracking system and a metaheuristic technique to facilitate automatic hyper parameter adjustment. In the field of safe driving, this is the initial systematic investigation into improving windowing hyper parameters depending on ECG data. This strategy is to suggest a PSO-based methodology for choosing optimum or nearly optimum windowing hyper parameter settings. Utilizing sophisticated simulation, the effectiveness of the suggested framework is assessed on datasets: an open database and the gathered dataset. This dataset was acquired using a sophisticated simulation tool in the management system, while the DRIVEDB database was obtained in a real-world driving situation. Study shows that increasing the window-based hyper parameters results in a noticeable increase in reliability. Depending on the particular windowing hyper parameters, a most efficient constructed framework applies to the dataset and the open datasets obtained 92.12% and 77.78% reliability, accordingly. Due to its failure to yield the best possible option, this strategy is ineffective (Rastgoo et al. 2021).

To provide brand-new automatic ECG beat categorization algorithm that takes quality into account for accurate ECG arrhythmia detection in unsupervised health-care settings, the proposed approach is divided into three main phases: the evaluation of the ECG signal's reliability according to the earlier altered entire ensemble empirical mode decomposition and temporal features; the rebuilding of the ECG signal and the recognition of R-peaks; and the categorization of the ECG beats depending on rhythm separation, beat orientation, and normalized cross-correlation. Several normal and pathological ECG signals acquired from the common MIT-BIH arrhythmias dataset are used to evaluate the precision and reliability of the suggested technique. According to assessment process, the suggested quality-aware ECG beats classification approach may drastically reduce false alarm rates (FAR) in noise ECG recordings by 24%–93%. With and without noise reduction techniques, the R-peak analyzer achieves median sensitivities of 99.65% and productivity of 98.88%. The moniker "R-peak detector" is misleading because most ECG devices cannot identify the true R-peak. In practice, though, this probably does not matter because only the time disparities among R-peaks matter. Most detectors employ a threshold that accelerates the detection time and causal filters that slow it down. It also accomplishes a median positive productivity of 93.10% and productivity of 99.67%. Findings further demonstrated that by keeping the QRS complicated part intact and decreasing surrounding sounds to tolerable levels, the suggested ECG beat separation technique may increase accuracy of classification. The performance ECG beats classification techniques obtain better kappa scores for the classification performance that may be consistent as comparing to the beating classification techniques without the ECG grade evaluation system. Due to its sensitivity to noise, this technique is ineffective (Satija et al. 2018).

ECG signals have become the subject of current research on biometric authentication techniques. A typical form of confirmation is biometrics recognition using ECG signals while under an identical psychological strain situation. ECG-based biometrics under various psychological stress states is still difficult because variations in psychological stress have an impact on ECG signals. In this research, study offers a system for ECG-based biometrics under various psychological stress levels that combine human and automated characteristics and suggest a brand-new measure called the Stress Classification Coefficient, which evaluates the impact of various emotional stresses on the characteristics of variability in heart rate. This technique involves a three-step procedure to extract manually characteristics. Initially, HRV characteristics are extracted from the ECG signals. Second, the participants' mental health is assessed using a Gaussian mixture model fitted to HRV features. Given the similarities between KMeans and the Gaussian mixture technique, the latter is probably a probabilistic extension of KMeans. Its probabilistic quality makes GMM applicable to a wide variety of difficult issues that are outside the scope of KMeans. In order to lower the Stress Classification Factor, analyze the initial HRV characteristics using cluster centers. Moreover, a one-dimensional CNN is built to autonomously retrieve ECG signal components that are indicated. Eventually, the manual characteristic and the automated features are integrated, and the SVM framework is used to get the ultimate recognition rate. The ability of the suggested approach to conduct ECG biometrics under various psychological stress conditions is its key strength. The usage opportunities for ECG-based biometrics are expanded by the combining of manually and automated features. Depending on this approach, a research paired the Montreal modeling approach with a mathematical experimental in the laboratory to place 23 healthy individuals under various stress circumstances and measures their ECG signals. An median identification rate of much more than 95% may be attained using this approach to recognize the aforementioned data, and the median F1-score is 0.97. The strategy put out in this study is a potentially effective way to address the impact of various psychosocial pressures on ECG-based biometrics. It offers the potential for ECG-based biometrics measurements under various psychological stresses. Due to the small number of testers in this dataset, this strategy is ineffective (Zhou et al. 2021).

Generalized pressure forecasting methods function shoddily since stress is personal and manifests distinctively in each individual. Some person-specific ones offer solid forecasts, yet they are not adaptive and expensive to employ in real-world contexts. For instance, an individual tension surveillance system in an office setting would need to gather new information and training fresh models for each worker. Additionally, since stress is dynamic and dependent on unpredictable factors, once implemented, the systems would degrade and require costly periodical improvements. Physiological specimens from a wide population are used to develop a precise and individualized stress forecasting models using a straightforward, useful, and affordable calibrating approach. This method is validated using two stress datasets. The outcomes demonstrate that the method outperforms a generic model by a wide margin. For example, the reliability of a baseline model was just 42.5% ± 19.9%. But, study improved its reliability to 95.2% ± 0.5% using just 100 calibrating examples. Lastly, to enable other investigators to reproduce the observations, study makes the source code and the pertinent datasets available. Real-world situations are inapplicable for this technique (Nkurikiyeyezu et al. 2019).

Each year, a significant amount of injuries, occasionally fatal ones, are caused by road accidents. Anxiety has a significant part in influencing a driver's effectiveness among other things since it can impair judgments and situational awareness. In light of this, it might be advantageous to create a non-intrusive driving strain surveillance system that can detect the driver's erratic behavior. This research examined into a contactless method of assessing drivers' stress levels using thermal infrared imagery. A motoring simulation study involves the acquisition of thermal imaging, and the thermal properties of strain were examined in compared to a gold standard measure derived from contacting ECG. To calculate the SI using thermal information collected from face areas of interest, a data-driven multimodal ML method that utilizes the nonlinear SVR was used. The actual SI and the anticipated SI have a strong connection. The stressful condition was then divided into two categories depending on the projected SI. The classification results of the ROC analysis were excellent, with an AUC of 0.80, a specificity of 78%, and sensitivities of 77%. Due to the small amount sample size, this approach is not effective (Cardone et al. 2020).

Developing time- and event-based tension surveillance systems as a foundation for portable and e-health platforms designed to enable individualized therapies, both in clinic and distant situations, requires highly stressful identification. The majority of currently available systems, moreover, concentrate on binary or few class depression detection, which limits the amount of input they can provide and limits their usefulness and application in real-world circumstances. Utilizing ensembles learning and RNNs, which are the most appropriate structures for completing time-series regression problems, this research offers a different method that gets beyond the usual presentation of activity recognition as a supervised classification issue. Research developed and validated systems utilizing WESAD, a publicly multifunctional wearable database for tension and impact recognition, and established and calculated tension ratings based on several questionnaire surveys contained in the database to be utilized as actual truth. The ability of every predictive model for individualized stress levels has been tested using the Leave-One-Subject-Out cross-validation technique. Findings indicate that for the most of the people examined, nonlinear autoregressive networks with exogenous inputs, Random Forest (RF), and Least-Squares Gradient Boosting produce high-resolution individualized stress forecasts. With the primary objective of developing individualized stress management and relief techniques connected to the inferred stress intensity, the suggested predictions may be incorporated as assistance to judgment into a Decision Support System (DSS) for online stress assessment. This neural network's sluggish processing makes this strategy ineffective (Di Martino and Delmastro 2020).

Although research into how depressed and lonely affects younger and middle-aged, professionally engaged people are still essential, both conditions have been acknowledged as serious public health problems. The current study's objective was to determine if sadness and lonely among persons who were actively seeking employment may both individually anticipate workplace inefficiencies. A comprehensive, national sampling from this cross-sectional research was used. During July 1—July 31, 2018, a direct pen-and-paper interviewing was used to collect 1795 questions from Polish individuals who are currently employed. The random selection approach was used to choose the samples. A Patient Health Questionnaire (PHQ-9) to assess depression was incorporated into the study, along with the researchers' own questionnaires about lonely and workplace inefficiency. Depressed and lonely were included as determinants of inefficiencies at job in regression analysis, which were then uncorrected and modified for a number of sociodemographic, health-care, and employment-related variables. The impact sizes for lonely were larger than those for depressed in the unmodified analyses, although both conditions were separately linked to increased absences from and inefficiencies at job. The PHQ-9 scores, but not the lonely score, were linked to a higher likelihood of frequently considering leaving a job after controlling for all other factors. Lonely and depressed mood both anticipate occupational functioning and have varied effects on its many aspects. Professional lonely and depression must be addressed as a priority for public health. This approach is ineffective since certain unmeasured factors impacted the outcomes (Mokros et al. 2022).

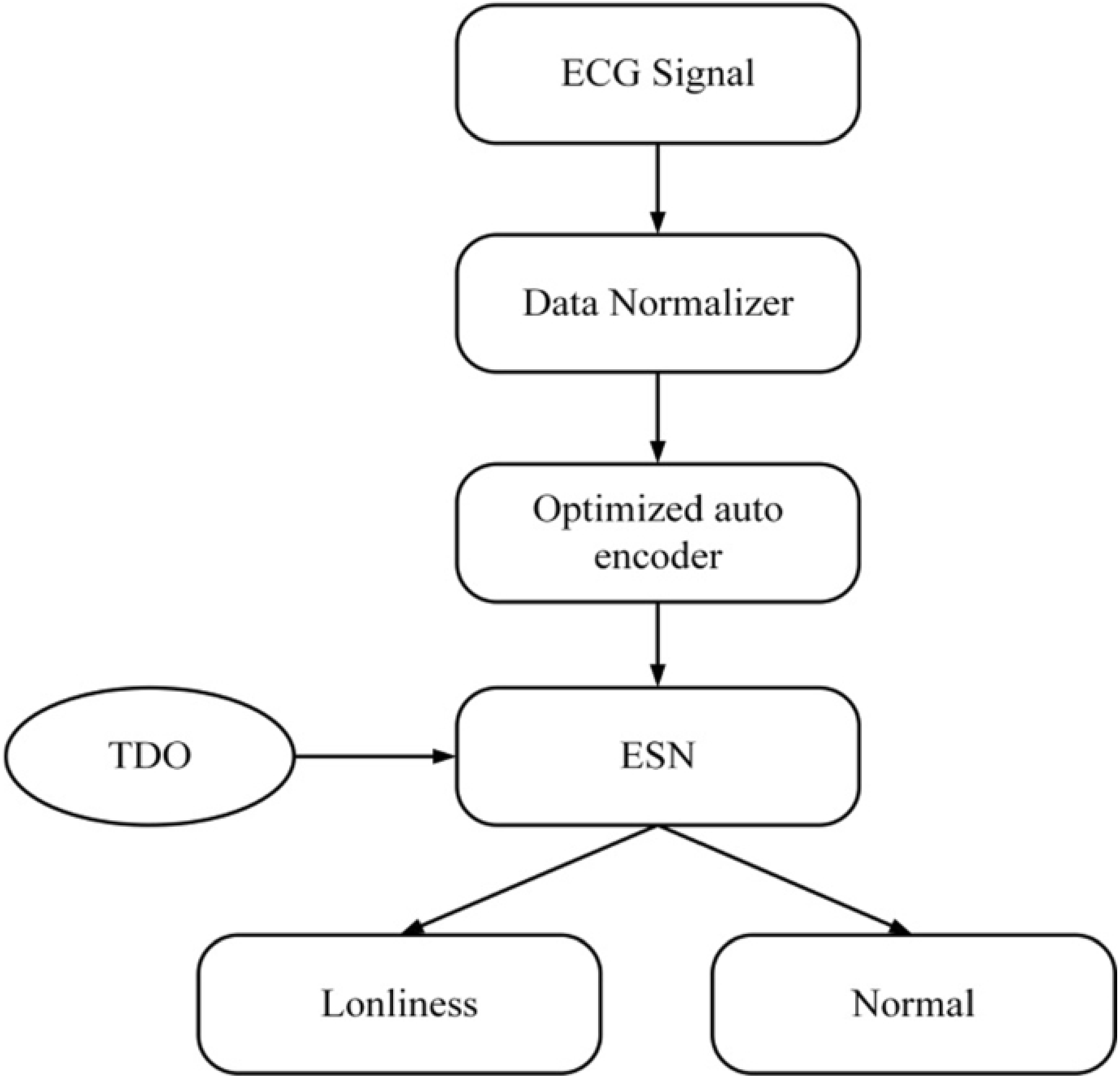
Health-care disorders, genetic susceptibility, stress, demographic variables, and moderate cognitive impairment are all recognized health risks for Alzheimer's disease as well as other forms of dementia. Little is known about the connection between lonely and social anxiety and Alzheimer, and there are few observational studies that take these hazard variables into consideration. In a study cohort of 2173 senior citizens who were not yet dementia patients and lived in the population, study looked at the relationship among social exclusion, feelings of isolation, and incidental dementia. Subjects were monitored for 3 years before an autonomous geriatric assessment for computer-assisted taxonomies and geriatric psychological condition were used to diagnose dementia. Using a logistic regression approach to account for sociodemographic variables, chronic disorders, anxiety, cognitive functioning, and functional abilities, researchers looked at the relationship among loneliness and social isolation and the dementia risk factors. Despite accounting for other risk variables, elderly adults who reported feeling depressed had a higher chance of developing dementia than those who did not. In a multivariable study, social isolation did not increase one's chance of dementia. In contrast with solitude, experiencing lonely is related with a higher chance of developing clinically dementia in later years and can be regarded as a major risk indicator that, by itself, merits therapeutic consideration regardless of cardiovascular events, depressed mood, or other confounding variables. A prodromal phase of dementia may be indicated by a sense of isolation. Knowing about the causes of loneliness may make it easier to spot at-risk individuals and create therapies that will enhance outcomes for elderly people who are at risk for dementia. This approach is unproductive since it did not look at whether cognitive decline and dementia are caused by lonely, or whether loneliness is a behavioral response to weaker cognitive (Holwerda et al. 2014). Table 1 represents that the previous work is used for predicting the loneliness/stress.

Table 1 Comparison of various methods for loneliness/stress prediction

3 Methodology

The suggested loneliness identification model's process flow is shown in Fig. 2. The four phases of the developed framework are data normalization, an optimized auto encoder, an ESN classification, and an effectiveness analyzer.

Fig. 2



Schematic representation of the proposed system for loneliness

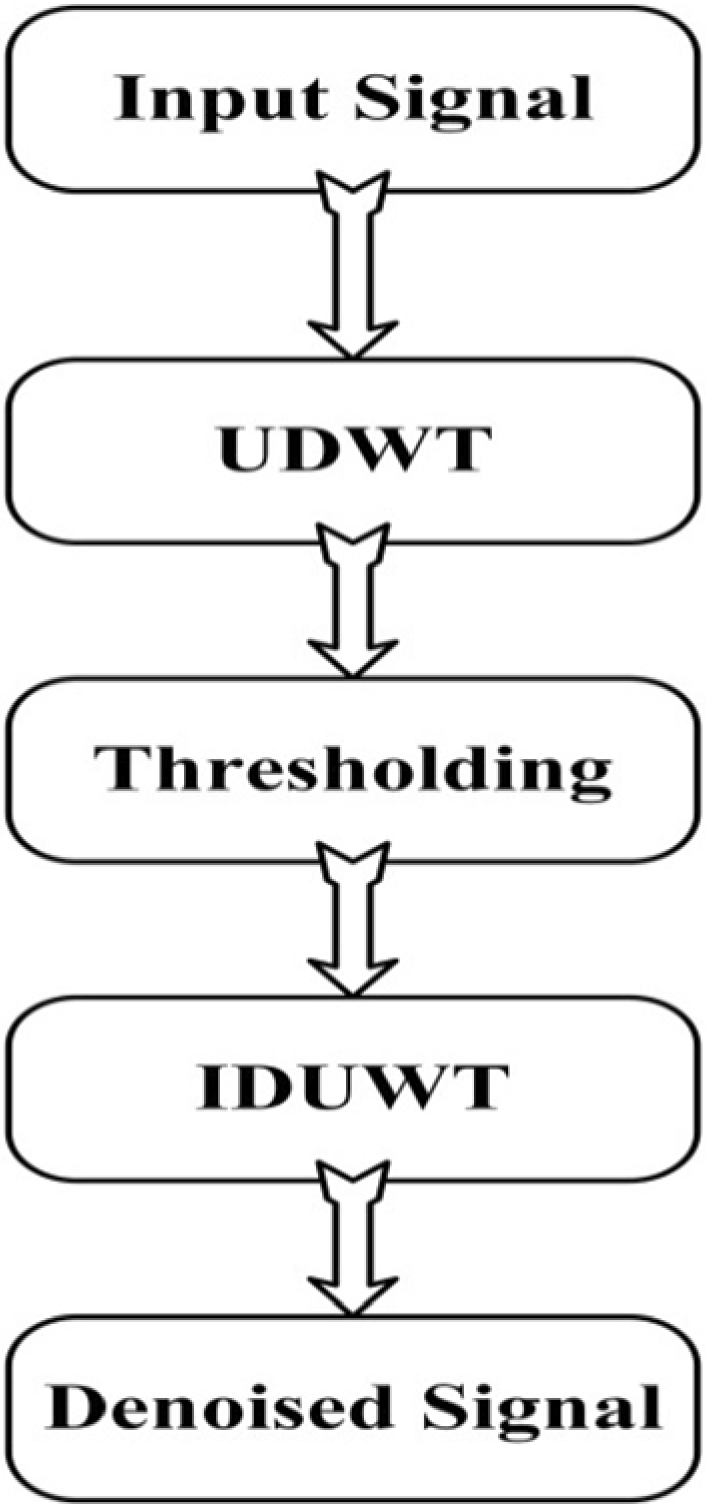
3.1 Data collection

Study utilized ECG signals from the Thiru Arutprakasa vallalar old age charitable trust located at Salem for this investigation. These datasets are made up of RR intervals from Holter ECG recordings sampled at 128 Hz that were captured by a single electrode during a single pulse. Specialists in the relevant fields classified the evidence as being either normal or abnormal. Every ECG signal is a lengthy series made up of 96 identically sized ventricular events. From 48 randomly selected records, 33 were determined to be normal and 15 to be abnormal. Typically, noise and abnormalities might be present in the frequency range of interest and manifest as the ECG signal itself, contaminating the recording ECG signal and giving it comparable properties. Study must analyze the raw ECG data in order to glean relevant details from the cluttered ECG signals. Preprocessing and feature retrieval are the two functional phases that may approximately be separated in ECG signal processing. The raw ECG signal's noise is removed or suppressed during the preprocessing phase, and the process of feature extraction takes out the signal's diagnostic data.

3.2 Data normalization

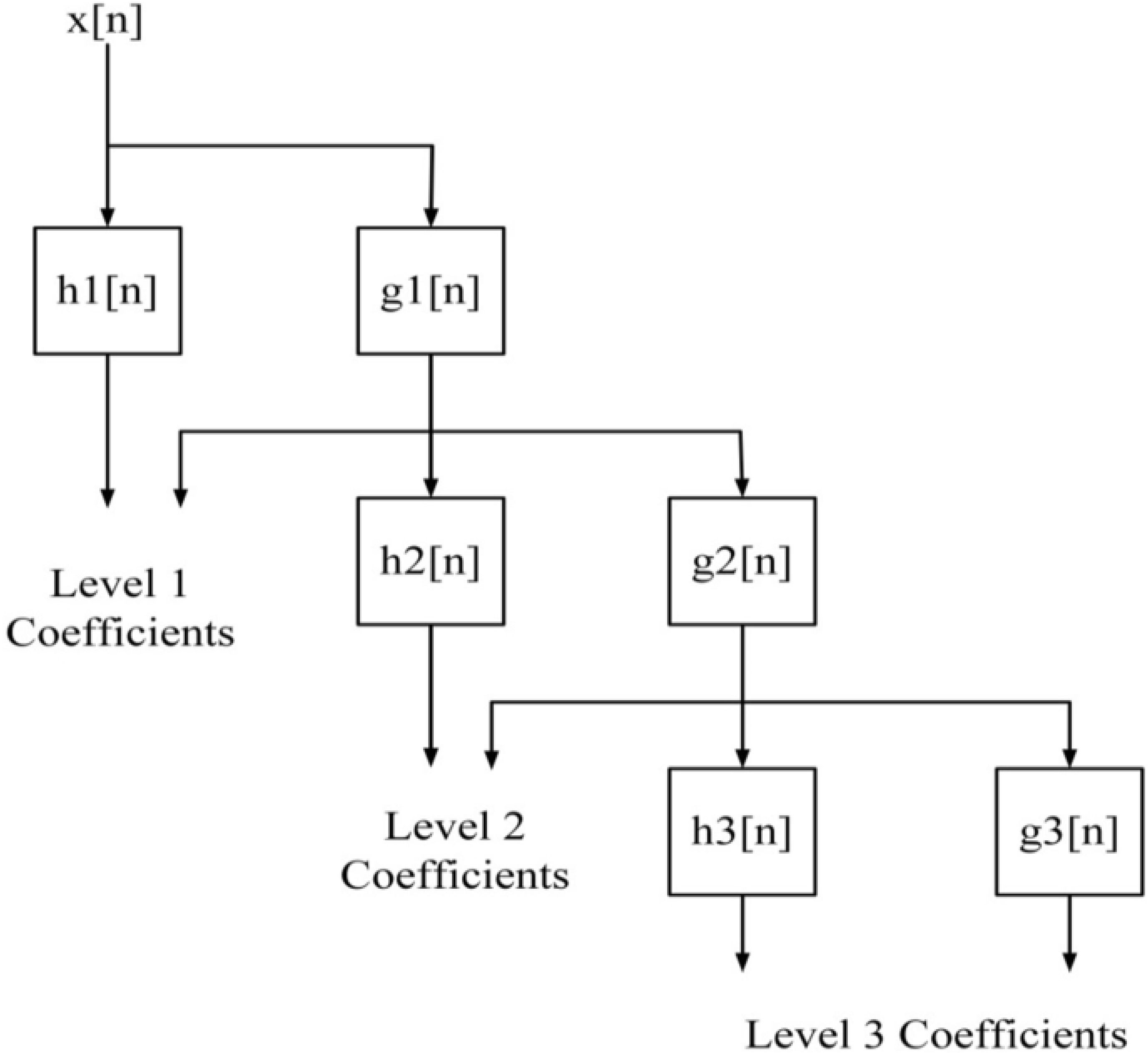
Figure 3 illustrates how well the ECG signal is handled by UDWT and IUDWT for noise reduction during data normalization. The ECG signal, which travels to many regions of the body, creates the electrical potential of the cardiac. It includes three essential pulses named P wave, T wave, and QRS complex. Individual ECG signals may contain a variety of background noise from numerous sources. The main sources of noise are power line disturbance, electrodes contacting disturbance, muscle contractions, and baseline drifting. In order to better classify heart activity, ECG processing is essential for reducing impulse sounds. Preprocessing of the electrocardiogram (ECG) signal is done to get rid of noise and other disturbances in the raw data. Noises in the wireless channel are a common problem in telemedicine applications involving the transmission of electrocardiogram (ECG) signals. To eliminate the disturbances and prevent a waveform distortion in the signal, a filtration approach is used. Due to the successful capture and depiction of the signal's high-frequency transient conditions as well as its low-frequency elements, DWT-based processing approaches are seen as a potential option for ECG data (Martis et al. 2013); (Li and Zhou 2016). Yet, shifting variability is a concern for the DWT technique. In this study, the preprocessing phases of the ECG are done using UDWT, as shown in Fig. 4. In contrast with the DWT, the UDWT strikes a good balance among smooth and reliability by excluding downwards sampling procedures.

Fig. 3



UDWT-based preprocessing

Fig. 4



UDWT multi-level decomposition

The ECG and heart rhythms file retrieved from the database was processed using MATLAB's signal processing capabilities. A user-friendly interface was used to build the tools for the examination of the various filters, making it very easy to use. To extract the signal's UWT parameters, perform the UWT transformation on the tainted signal. Lower value factors often correlate to the signal's distortion. To reduce the UWT transformation coefficients to rates close to zero, choose an acceptable cutoff. The threshold value may be chosen autonomously using MATLAB's techniques. The maximum level of noise that may be reduced with this approach is 3 dB. In order to obtain greater effectiveness removing the noise of the signal, the study may pick a threshold individually. Use the UWT inverse transform to reconstruct the signals. Figure 4 displays a multi-level decomposed depending on UDWT. In the case of computing the UDWT signals as $x(n)$ utilizing filtering sequence, $h(n)$ is the high-pass operational signal, and $g(n)$ denotes the impulse response. Each stage in UWT estimates the parameters of the upstream samples based on low-pass and high-pass filters.

The following Eq. (1) can be used to determine a signal's wavelet coefficient matrix "w"

$$ w = W(X) = W(S) + W(\sigma N) $$

(1)

where S is the underlying functional derived from noisy data, and W is the wavelet transform. The noise level is σ, and N is randomly initialized. The signal's changed coefficient is defined as following Eq. (2).

$$ \hat{w} = w $$

(2)

Using the inverse transform of the updated detailed parameter, the signal's denoised coefficients are determined as following Eq. (3).

$$ \hat{S} = W^{ - 1} (\hat{w}) $$

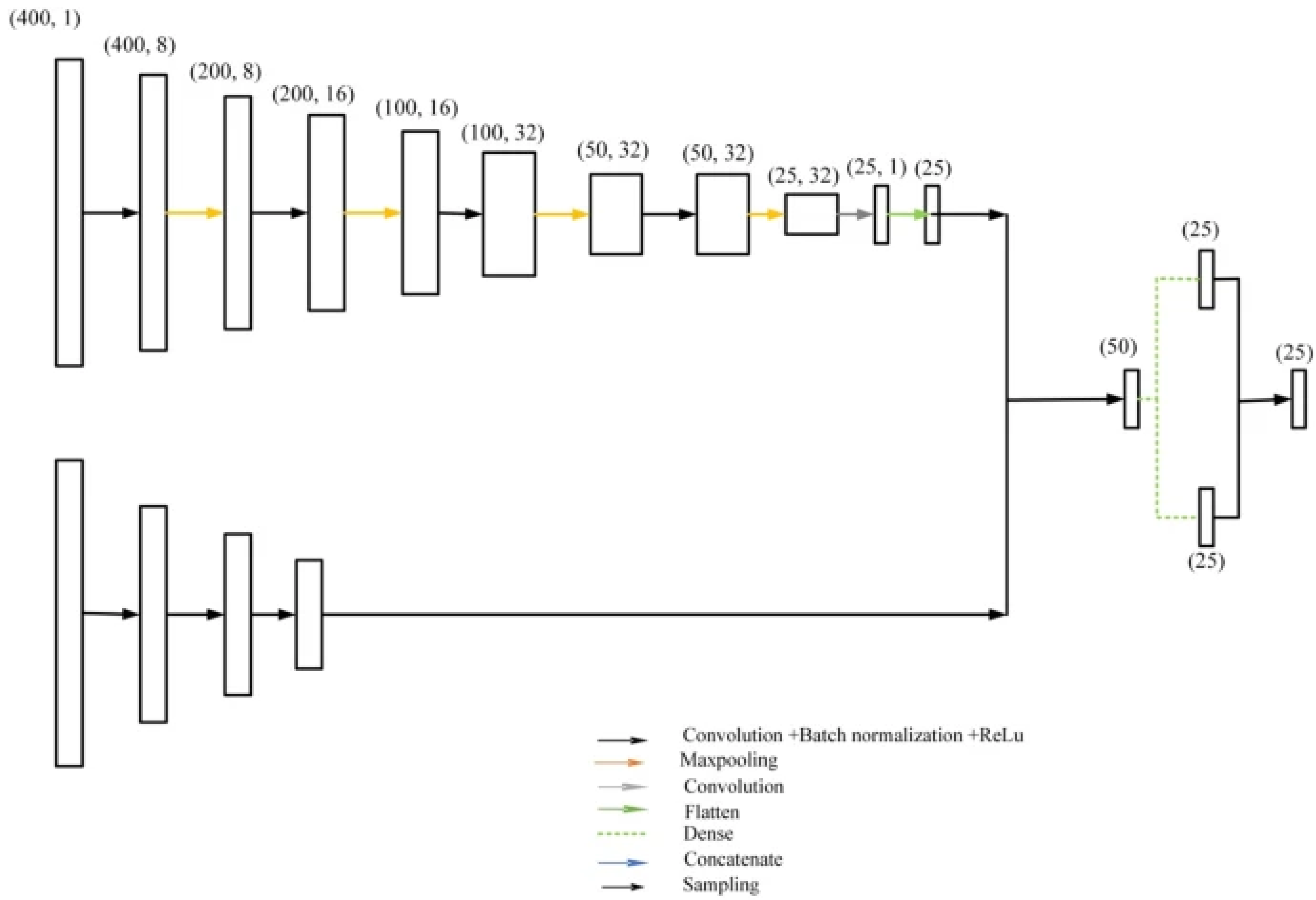
(3)

The shrinking procedure in UDWT in this case takes the distortion out of the noisy signal. The soft thresholding approach is used in the shrinking stage to denoise ECG data. Maximum signals and heart rates are computed following IUDWT for further analysis.

3.3 Feature extraction using auto encoder

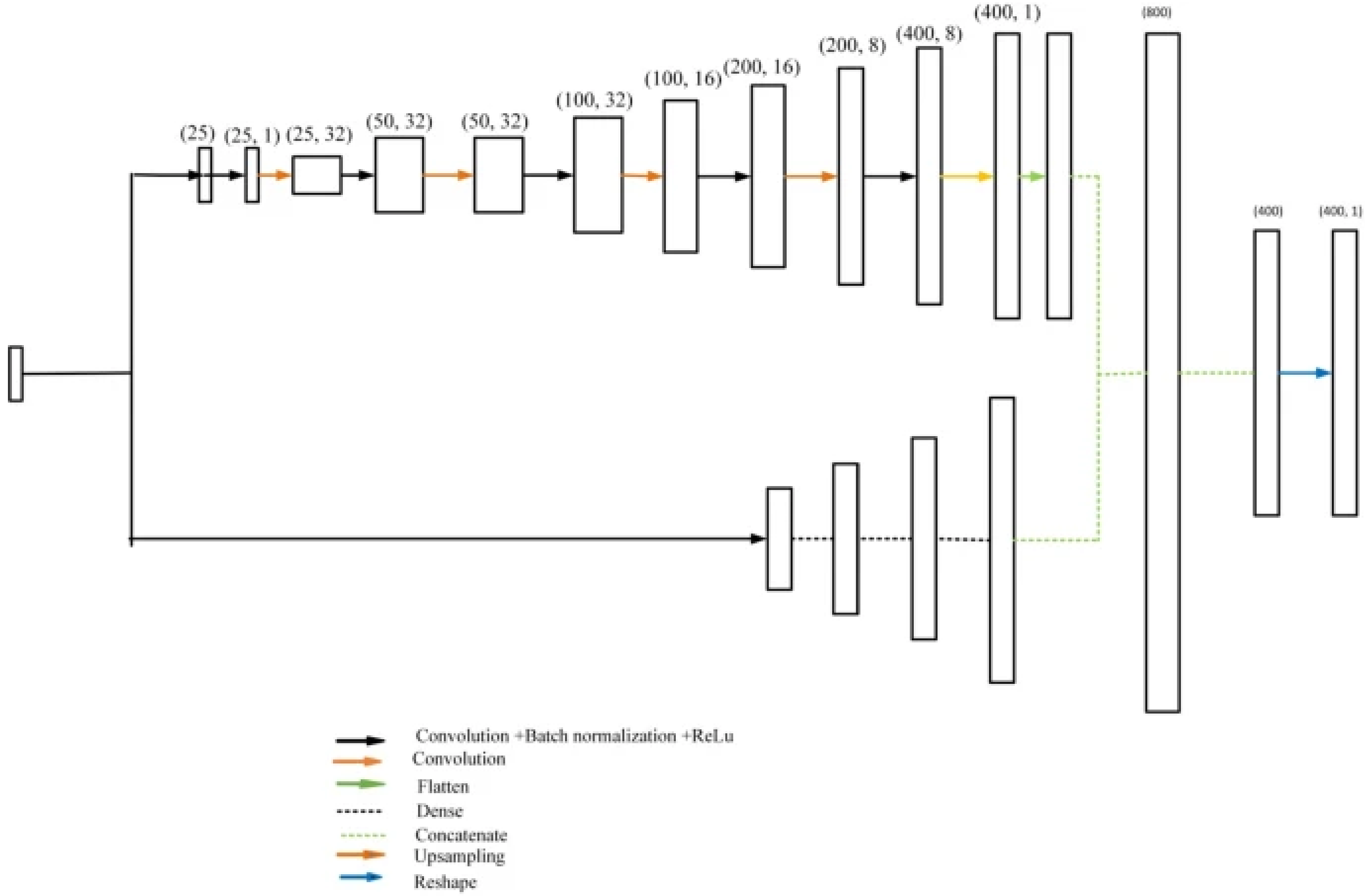
Auto encoders are among the most beneficial applications because they can automatically provide valuable qualities from raw source data. With a nonlinear activation function and several layers, an auto encoder may learn nonlinear transformations. Auto encoder training is more time-efficient than principal component analysis (PCA) training since it focuses on learning numerous layers. A feed-forward neural network with all of its connections is an auto encoder. Depending on unsupervised learning, it operates. It is an automated system that produces certain representations of the data. Information that will be utilized for categorization is preprocessed. Making inputs unlabeled data equivalent to data output is the aim of an auto encoder. In this type of network, the encode and decode stages should be differentiated. Encoders and decoders are grouped in a symmetrical configuration for single-layer auto encoder. It can be utilized to features extracted from unprocessed input and is dependent on a neural network (NN). For compressing and reconstructing the input, an auto encoder comprises an encoder and a decoder (Vančura and Kordík 2021). Whenever the instruction is finished, the decoding is thrown away. In order to get additional information from the input signals and improve the categorization, a varied auto encoder was utilized in this study. Figures 5 and 6 depict the decoder and encoder's architectural layout.

Fig. 5



Encoder structure

Fig. 6



Decoder structure

Convolution, max-pooling, and concatenated layers make up the encoding concept. The encoder takes a 400-point vector as input and generates 25 neurons as outcome. Fifty neurons are outcome from the concatenated layer, which mixes information from higher and lower levels. Twenty-five neurons are produced by the output layer after evaluating 510 neurons with predetermined averages and variability. By assuming that this vectors of 25 dimensions has sufficient new characteristics to identify a signals.

The Kullback–Leibler distances may be applied as follows to determine the loss function using Eq. (4)

$$ D_{{{\text{kl}}}} (P{\text{||Q)}} = \int\limits_{{\text{x}}} {{\text{plog}}\frac{{\text{p}}}{{\text{q}}}} {\text{d}}\mu $$

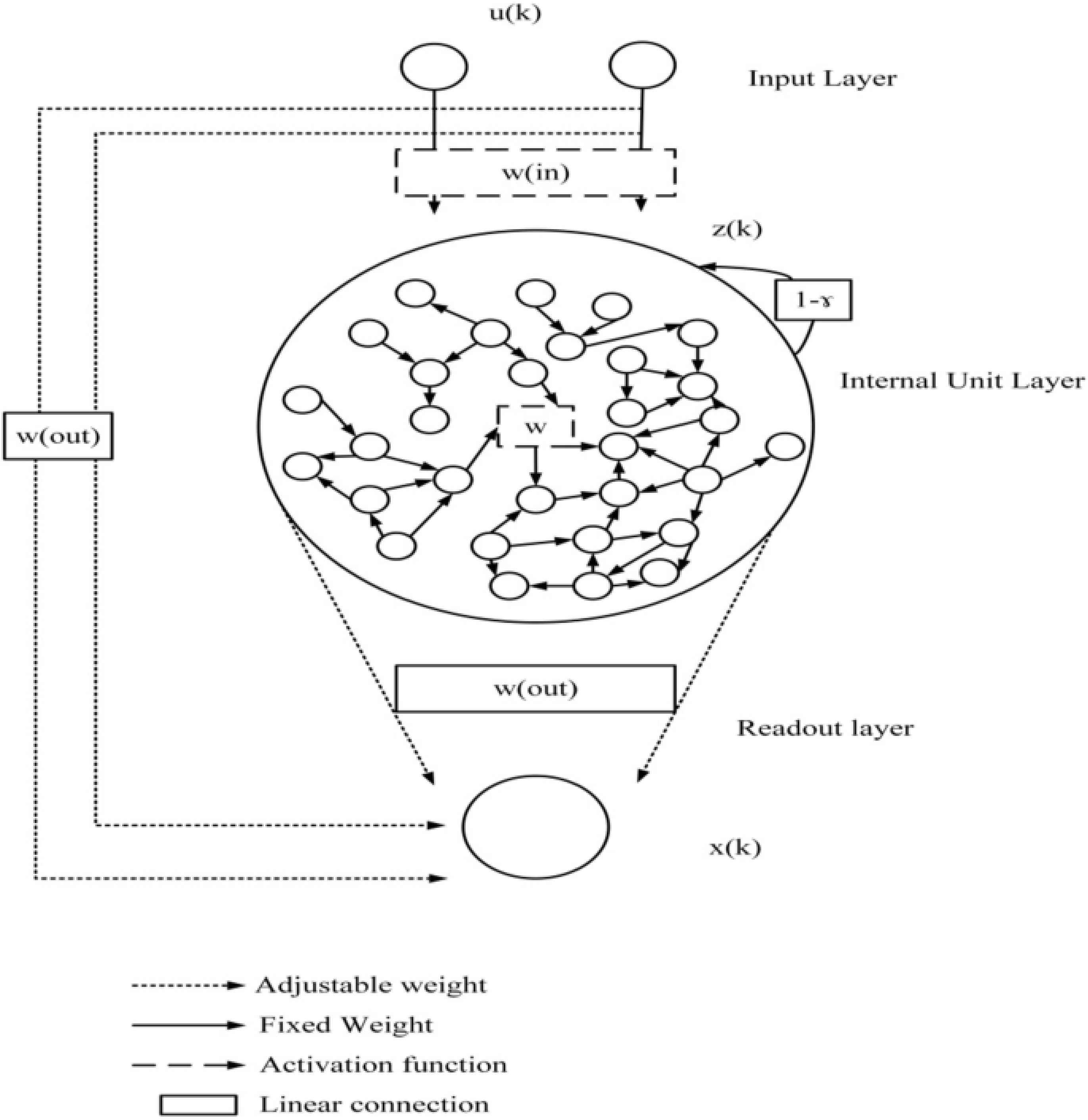
(4)

where Q stands for the newly acquired distributed, and P stands for the initial distribution. A novel measurement is x.

3.4 An optimized ESN-based classifier

The reservoirs computation (RC) model, in which the recurring layers is depicted as a reservoirs of randomly linked hidden layers and the training set is restricted to the weights of a linear memory-less readout layer, was realized with the introduction of echo state networks (ESNs). The framework demonstrates the characteristics of the ESN system for storing, retaining, accessing, and discarding information in a way comparable to how the brain functions. A randomized RNN with sparse connections termed reservoirs serves as the brain of an ESN. Every neuron in the reservoirs produces its own nonlinear modification of the input signals whenever triggered by incoming signal. Just the reading weights of the ESN are customized for a classification assignment; the interconnectivity weights in the reservoir are not. As a result, ESNs provide a low-cost computing method for predicting time series, and over the past 20 years, they have been used to simulate and forecast nonlinear time sequence. The input layer, internal unit layer, and readout layer made up the ESN in this investigation, as shown in Fig. 7. At first, the internal units' layer's weights were configured with sparse and erratic connection. It is possible to adjust the weights of each link to the reading (outcome) layer of the brain in order to produce particular temporal variations.

Fig. 7



The structure of the echo state network (ESN)

Due to the recurrent properties of the internal unit layer, RNNs, especially ESNs, exhibit fading or short-term memory. The below formula (5) describes the condition of the internal unit, $x(t)$:

$$ z(k) = (1 - \gamma) \cdot z(k - 1) + \gamma \cdot F(w_{{{\text{in}}}} \cdot u(k) + w \cdot z(k - 1)) $$

(5)

wherein W_{in}, the weighting matrix among the input and internal unit, is applied to $u(k)$, an input vectors at time interval t. The interior units with w, the weighted matrix within interior units, were in the vectors $z(k-1)$ prior phase. The fact that w is generated randomly and fixed throughout training makes ESNs stand out from traditional RNNs the most. The reservoir's leakage rate is Υ, and function F is the activation function. As the activation function in this investigation, the hyperbolic tangent (tanh) functional was employed. In accordance with the subsequent formula (6), the reading layer's units were modified:

$$ x(k) = w_{{{\text{out}}}} (u(k) \cdot z(k)) $$

(6)

wherein $(u(k), z(k))$ represents the union of the interior units and the input units. While consideration may be given to the following internal data $z(k+1)$ and output $x(k+1)$, the response from the prior output $x(k)$ was not utilized for this investigation. Incoming streams were used to frequently upgrade the echoing level, which represented the internal unit layer's current condition. The echoing phase was most affected by the most recently input, and the impact of each input diminished with time. ESNs are especially helpful for the forecasting of complicated, nonlinear time sequences because of this repeating characteristic of the "reservoir." Therefore, a classifier for loneliness recognition is an echoing phase networks. ESNs categorization performance is largely influenced by the model's construction variables. In this research, we treat ESN tuning as an optimization issue and find the optimal solution with the help of the Tasmanian devil (TDO). Tasmanian devil behavior has inspired a novel bio-inspired metaheuristic algorithm named TDO. TDO's primary motivation comes from trying to mimic the eating habits of the Tasmanian devil, which may either attack its victim while it is still alive or consume its meal after it has already died.

3.4.1 Tasmanian devil optimization (TDO)

The approach used to solve issues in the actual world is optimizing. Because of their efficacy and avoidance of local optima, metaheuristics methods have drawn increased attention in optimization techniques. Exploring and exploiting are two aspects a metaheuristic system must have in order to function well. Exploring is the procedure of doing a broad search and identifying the best location for the issue. Exploit is the local search procedure utilized to assess the optimum way to resolve a problem. As comparing to other optimization methods, TDO is a metaheuristic optimizing that offers extremely strong exploratory and exploitative features (Dehghani et al. 2022). TDO is inspired by a Tasmanian devil's need to find food in order to survive. The Tasmanian devil typically uses one of two strategies to get food: either hunting live prey or consuming the flesh of deceased animals. In order to identify answers to the issue, the procedure of locating sources of food is computationally analyzed. Initializing, hunting living prey, and consuming the flesh of deceased animals are the three stages of TDO optimization and finally predict the fitness value for optimized results.

3.4.1.1 Initialization

The suggested TDO uses a population-based stochastic method with Tasmanian devils as its finder agents. These agents' initialization is produced at randomly using the problem's limitations. Depending on where they are in the search area, members of a population of TDO who are problem solvers offer potential solutions to the variables in the issue. As a result, every person in a community may be thought of mathematically as a vector whose constituents are equivalent to the amount of factors in the issue. Components of the initialization are described using the following matrix after being produced at randomness.

$$ {\text{P}}\, = \,\left| {\begin{array}{*{20}c} {P_{1} } \\ . \\ . \\ {P_{i} } \\ . \\ . \\ {P_{N} } \\ \end{array} } \right| = \left[{\begin{array}{*{20}c} {p_{1,1} } & . & . & {p_{1,j} } & . & . & {p_{1,m} } \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ {p_{i,1} } & . & . & {p_{i,j} } & . & . & {p_{i,m} } \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ {p_{N,1} } & . & . & {p_{N,j} } & . & . & {p_{N,m} } \\ \end{array} } \right] $$

(7)

wherein N stands for the quantity of searches, and P stands for the amount of Tasmanian devils. By entering every potential solution into the values of the target function's parameters, the objective function of the issue may be calculated. The problem's objective function is described by Eq. (8):

$$ {\text{F}} = \left| {\begin{array}{*{20}c} {F_{1} } \\ . \\ . \\ {F_{i} } \\ . \\ . \\ {F_{N} } \\ \end{array} } \right| = \left| {\begin{array}{*{20}c} {F(P_{1})} \\ . \\ . \\ {F(P_{i})} \\ . \\ . \\ {F(P_{{\text{N}}})} \\ \end{array} } \right| $$

(8)

where F is the problem's vector value.

The potential solutions' effectiveness is shown by a study of the values produced for the objective function. The greatest individual in a population is the candidate solution that results in the computation of the best rates for the objective function. Every cycle updates the population's greatest membership depending on new data. Two Tasmanian devil feeding techniques are used as models for the population update process in TDO. Each Tasmanian devil has the ability to consume carrion or seek for food. In TDO, it is presummated that there is a 50% chance that one of these tactics will be chosen. As per this idea, just one of these two procedures is used to upgrade every Tasmanian devil in a TDO cycle.

3.4.1.2 Meats of dead animals—exploration stage

The Tasmanian devil, who does not usually like hunting, occasionally consumes the flesh of dead animals. Utilizing systematic modeling of the searching behavioral of the deceased animals as an exploration stage, it is possible to calculate how the Tasmanian devil advances toward food in the following ways:

$$ c_{i,j} = P_{k} $$

(9)

wherein $c_{i,j}$ stands for the chosen dead animal chosen by the kth Tasmanian Devil.

$$ p_{i,j}^{{{\text{new}},s1}} = \left\{ {\begin{array}{*{20}c} {p_{i,j} + {\text{rand}}*\left({c_{i,j} - R*c_{i,j} } \right), \;\; {\text{Fc}}_{i} < F_{i} ;} \\ {p_{i,j} + {\text{rand}}*\left({p_{i,j} - c_{i,j} } \right), \;\; {\text{otherwise}}} \\ \end{array} } \right. $$

(10)

$$ P_{i} = \left\{ {\begin{array}{*{20}c} {P_{i}^{new,S1} F_{i}^{new,S1} < F_{i} ;} \\ {P_{i} , otherwise} \\ \end{array} } \right. $$

(11)

$P_{i}^{{{\text{new}},S1}}$ stands for a devil's new location in relation to $F_{i}^{{{\text{new}},S1}}$ be the objective function. The random number, R, is either one or two. Within 0 and 1, the term "random" refers to a number.

3.4.1.3 Hunting living prey—exploitation stage

The Tasmanian devil hunts for prey in the intended region during this stage. It involves two phases: hunting for prey in a manner identical to the preceding step, then giving up and eating. Modeling of the Tasmanian devil's updated position according to the location of the prey in a target region looks like this:

$$ {\text{pr}}_{i,j} = p_{k} $$

(12)

where Pr is chosen prey for eating

$$ p_{i,j}^{{{\text{new}},s2}} = \left\{ {\begin{array}{*{20}c} {p_{i,j} + {\text{rand}}*\left({{\text{pr}}_{i,j} - R*p_{i,j} } \right), \;\; {\text{Fpr}}_{i} < F_{i} ;} \\ {p_{i,j} + {\text{rand}}*\left({p_{i,j} - pr_{i,j} } \right), \;\;{\text{otherwise}}} \\ \end{array} } \right. $$

(13)

$$ P_{i} = \left\{ {\begin{array}{*{20}c} {P_{i}^{new,S2} F_{i}^{new,S2} < F_{i} ;} \\ {P_{i} , otherwise} \\ \end{array} } \right. $$

(14)

$P_{i}^{{{\text{new}},S2}}$ stands for a devil's new location in relation to $F_{i}^{{{\text{new}},S2}}$ objective function. The random number, *R*, is either one or two. Rand denotes a quantity randomly selected from 0 to 1.

Fitness computation: The fitness level was then determined for each solution; the one with the lowest number was designated as the best option, and the fitness level was assessed using Eq. (15).

$$ f(k) = \frac{1}{N}\sum\limits_{k = 1}^{N} {\left({\hat{O}_{t} - O_{t} } \right)}^{2} $$

(15)

where O_t stands for categorized output, *N* stands for entire specimens, and $\hat{O}_{t}$ symbolizes the goal output.

4 Results and discussion

The dataset was collected from Thiru Arutprakasa vallalar old age charitable trust in Salem. The proposed work is implemented by MATLAB on Windows 10 platform. The accuracy of the proposed model is tested using 96 ECG signals records collected from 48 patients. The different waves of the heart signal are used for this experiment. These signals are tested in the system followed by preprocessing operation that removes noises present in the signal. The noise-free signal is fed into variable auto encoder for feature extraction then the TDO-based ESN approach classifies the loneliness. With excellent prediction accuracy, the proposed methodology (VAE-OESN) improved the classification outcomes. In terms of performance indicators such as accuracy, sensitivity, and specificity, the effectiveness of the proposed study is validated using existing methods.

The effectiveness of the suggested system is assessed using the metrics listed below: The letters T_p stand for properly forecasted loneliness cases, F_p for normal cases that the suggested technique incorrectly identified as loneliness, T_n for correctly identified normal symptoms, and F_n for loneliness instances that were mistakenly labeled as normal or abnormal cases.

$$ {\text{Accuracy}} = \frac{{T_{p} + T_{n} }}{{T_{p} + T_{n} + F_{n} + F_{p} }} $$

(16)

The percentage of actual positive instances that were correctly predicted is determined by sensitivity. This model's capacity for forecasting is assessed by this measure. The following expression can be used to determine the sensitivity:

$$ {\text{Sensitivity}} = \frac{{T_{p} }}{{T_{p} + F_{n} }} $$

(17)

This was anticipated accurately to employ specificity to define the percentage of real negative situations. A model's capability to forecast true-negative instances of a certain group is measured using the statistic known as specificity. Therefore, these measures were used to analyze the results of each classification model. The following is the formula for determining specificity:

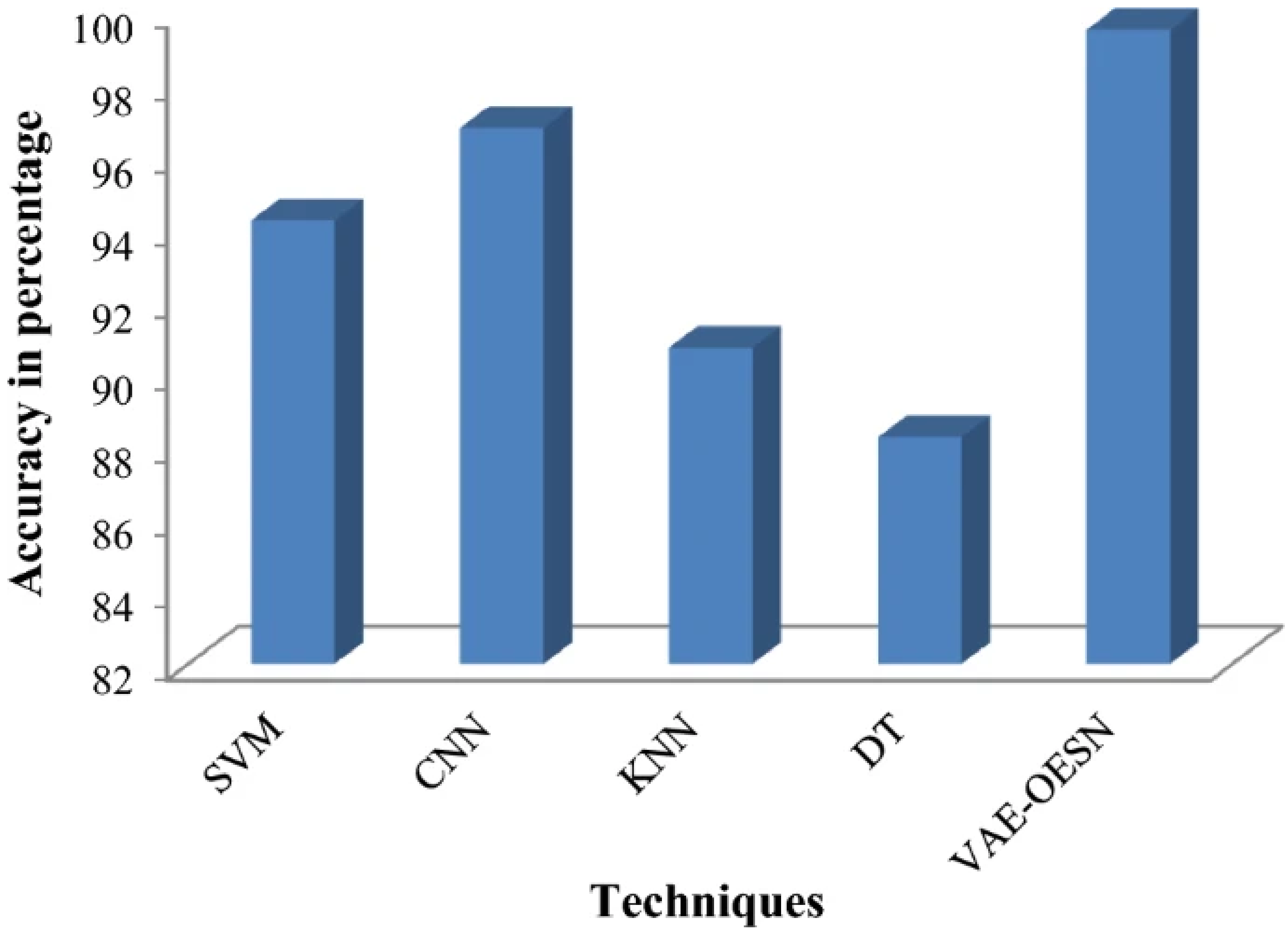
$$ {\text{Specificity}} = \frac{{T_{n} }}{{F_{p} + T_{n} }} $$

(18)

An evaluation of VAE-OESN models with SVM, CNN, KNN, and DT was done in order to assess the effectiveness of the suggested techniques. Table 2 represents the performance comparison of proposed system with other existing approach. Figures 8, 9, and 10 depict the performance evaluation in terms of accuracy, sensitivity, and specificity. These figures show that the proposed VAE-OESN models outperformed other conventional models in terms of the classification results. The findings demonstrated that the VAE-OESN model had the greatest performance of the classifier, with accuracy, sensitivities, and specificity scores for the loneliness, correspondingly, of 99.50%, 98.95%, and 98.99%. As a result, it was determined that these proposed techniques can effectively predict loneliness.

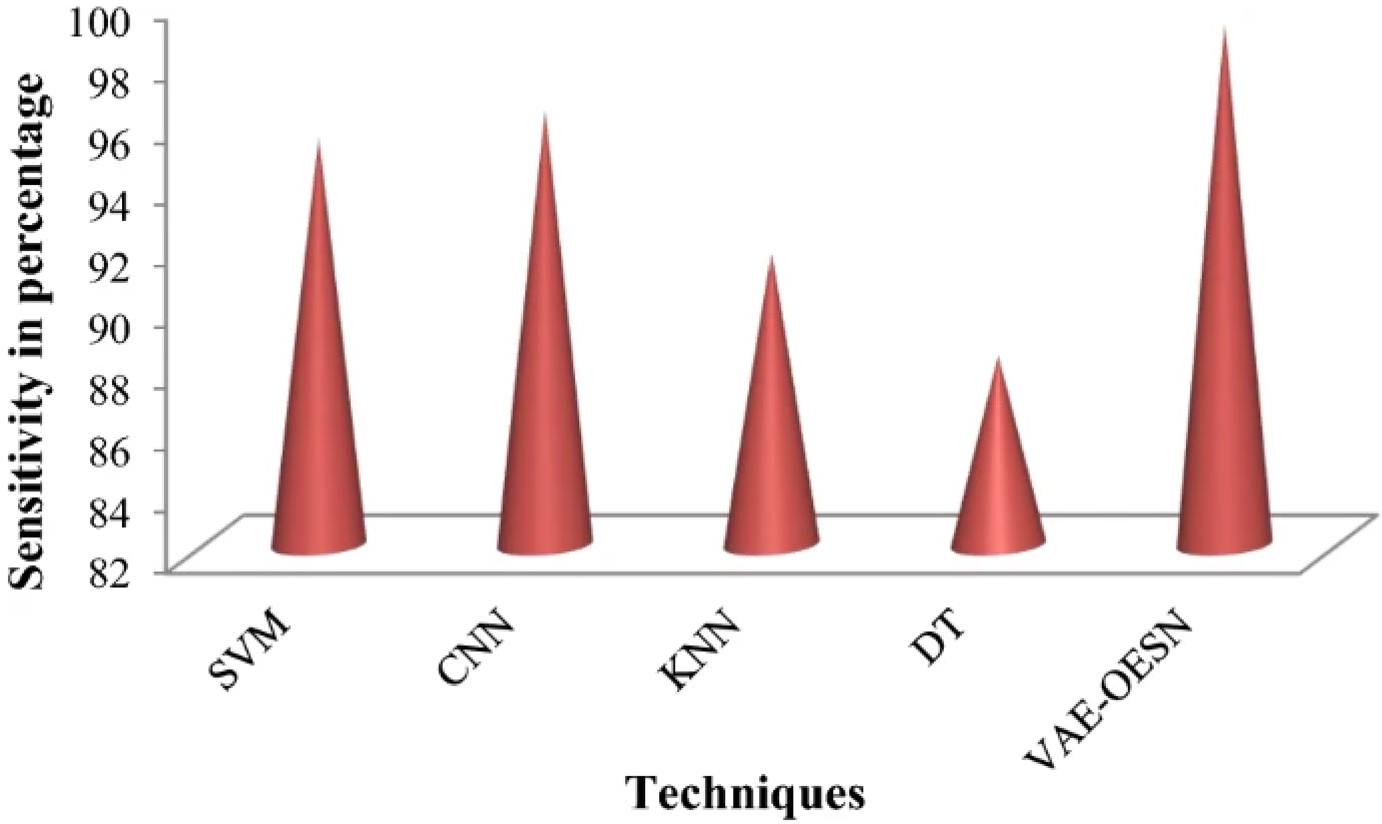
Table 2 Performance comparison of proposed system with other conventional approaches

Fig. 8



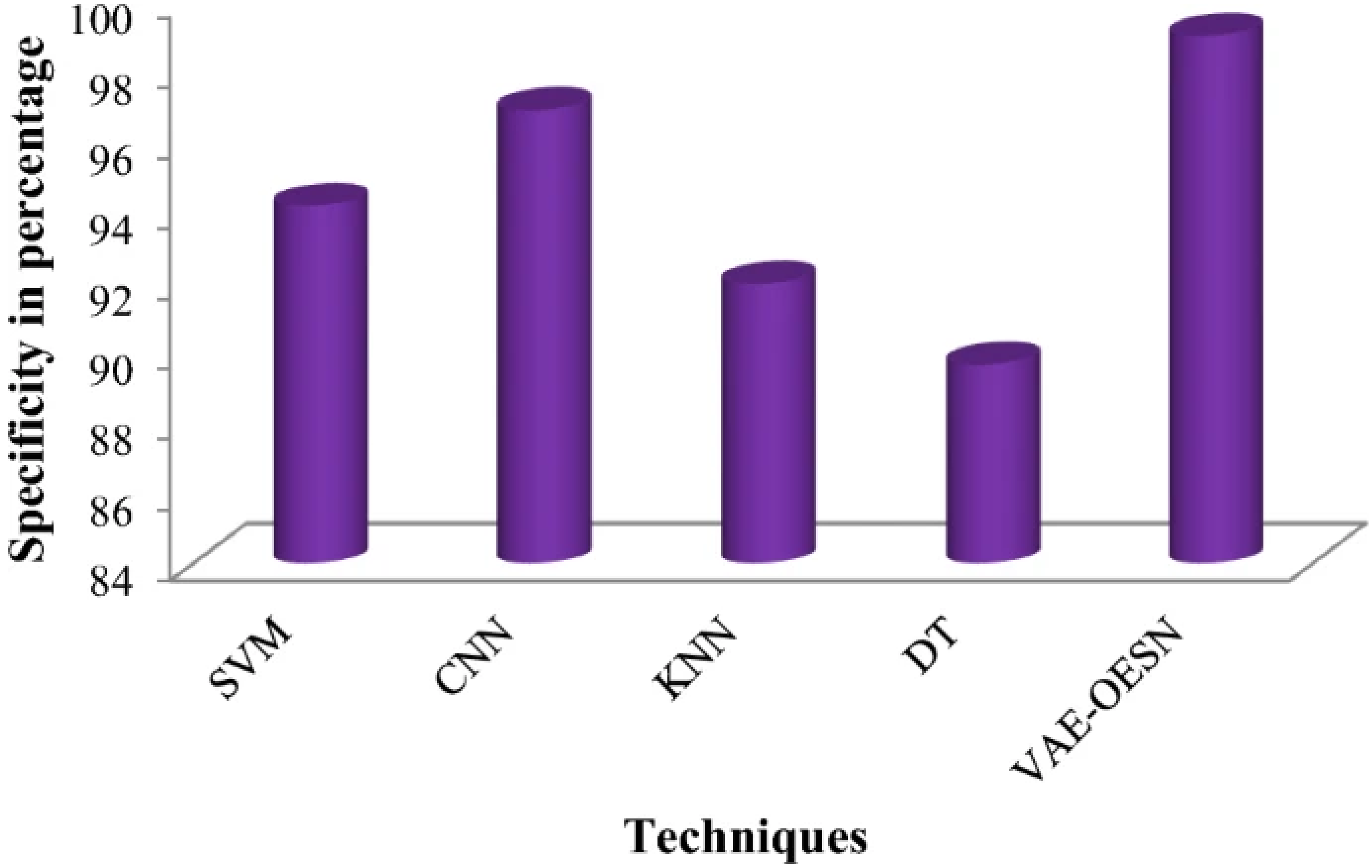
Performance evaluation in terms of accuracy

Fig. 9



Performance evaluation in terms of sensitivity

Fig. 10



Performance evaluation in terms of specificity

Having a single metric to evaluate the system's performance across all phases (learning, cross-validation, and monitoring) is really beneficial. Absolute accuracy in predicting a response variable's value is measured by the root-mean-squared error (RMSE), while the predictor variables' ability to explain that variance is measured by the R-squared statistic. The RMSE is one of the most popular measures for this. It is a suitable scoring system that is easy to understand and consistent with a number of the most commonly used statistical assumptions. RMSE, sometimes referred to as root-mean-square deviance, is one of the techniques most regularly used to evaluate the accuracy of predictions. It displays the Euclidean separation among predictions and measured actual values. To calculate the RMSE, calculate the residual (difference between prediction and reality) for each data point, in addition to the standard, average, and square root. RMSE is widely used in supervised learning situations since it needs and makes use of actual measurements at every predicted data point. Table 3 depicts the error prediction of proposed system with other existing system, and its performance evaluation is represented as Fig. 11. For expressing root-mean-square error as follows

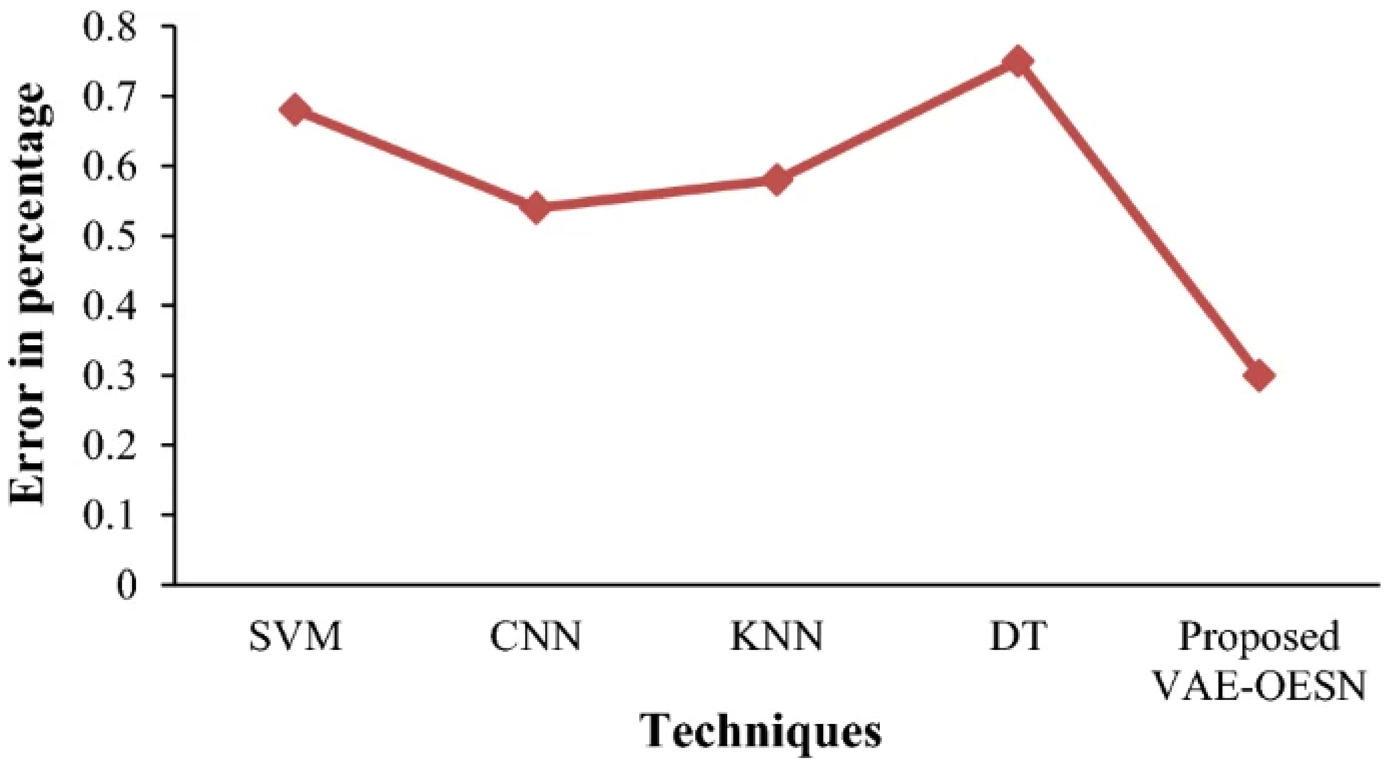
$$ {\text{RMSE}} = \sqrt {\frac{{\sum\nolimits_{k = 1}^{n} {\left| {Z(k) - \left. {Z^{\prime}(k)} \right|^{2} } \right.} }}{n}} $$

(19)

where $Z(k)$ is the k-th measurement, and $Z^{\prime}(k)$ is its corresponding prediction, and n is the number of data points.

Table 3 Error prediction of proposed system with other existing system

Fig. 11

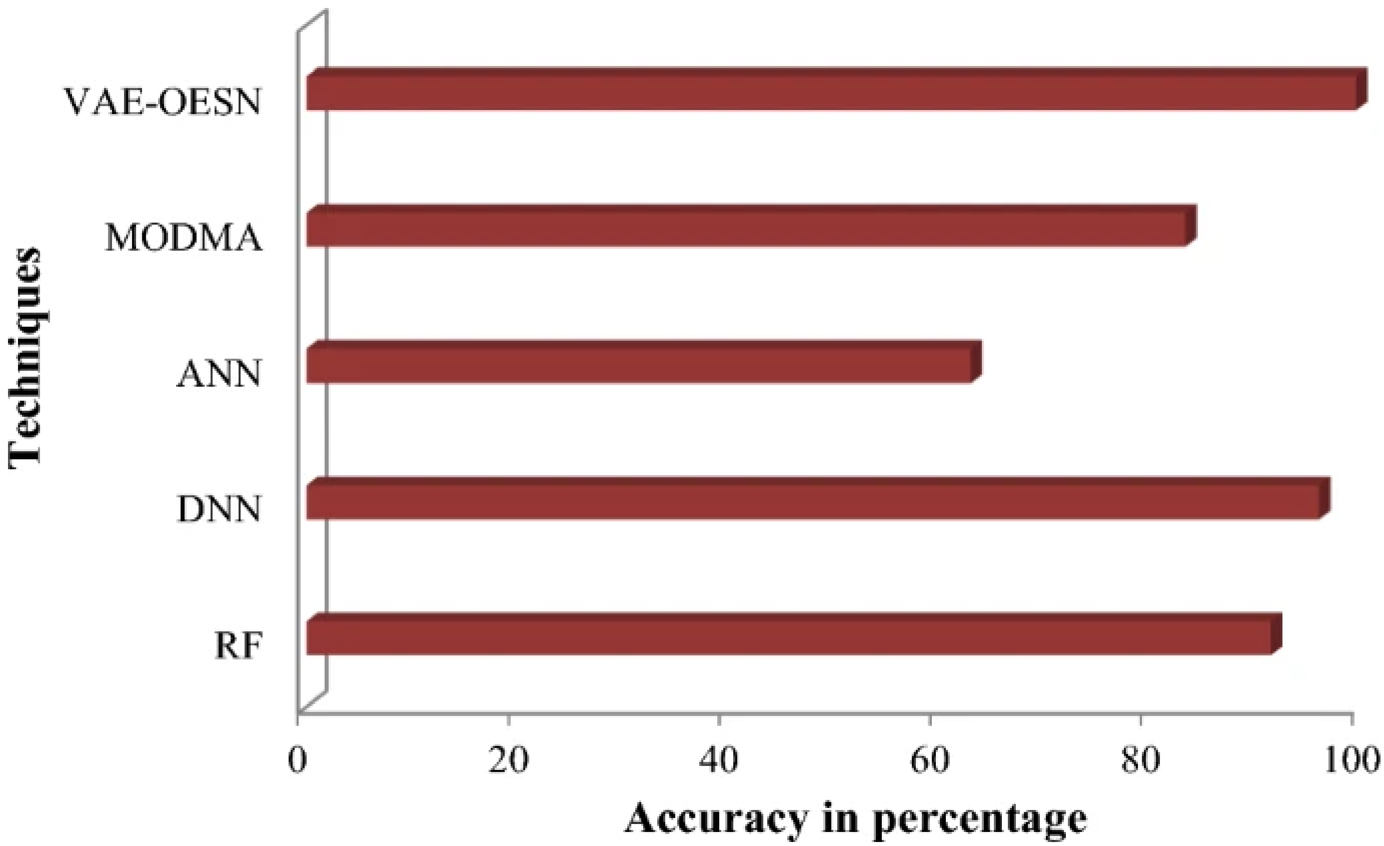


Proposed system error performance evaluation with other techniques

To identify the effectiveness of the proposed VAE-OESN technique which is compared to the recent research techniques such as RF, DNN, ANN, and MODMA which is represented in Table 4, the performance evaluation of graphical representation is depicted in Fig. 12.

Table 4 Comparison of proposed VAE-OESN with other current approaches

Fig. 12



Performance evaluation in terms of accuracy

From Fig. 12, it is proved that the accuracy of VAE-OESN approach is higher than all other models; secondly, DNN technique is superior to other techniques such as RF, ANN, and MODMA. ANN approach has lower accuracy and recall value compared to all other techniques.

5 Conclusions

Elderly adults who are lonely or socially isolated pose major health concerns to the public, increasing their likelihood of developing dementia, and other deadly illnesses. Earlier loneliness identification helps people prevent heart-related problems. This study also includes representations of the findings from the previous study and an evaluation of the current models. This study put out a deep learning framework depending on echo state networks for the precise identification of loneliness. Undecimated discrete wavelet transform methods are used to properly manage the noise and interference inherent in the ECG signal. Auto coders are used to retrieve the characteristics needed for categorization. In order to categorize the normal and lonely stages of ageing, the Tasmanian devil optimization-based ESN is used. The suggested model beats the current hybrid models when different performance measures such as accuracy and recall are compared and evaluated. The small sample size of VAE-OESN is still a difficult challenge. The future research direction can be effectively solved by expanding the sample size.

Data availability

Enquiries about data availability should be directed to the authors.

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