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Robust and Efficient ECG Classification with Privacy Preservation using LSTM+CNN and Adaptive Least Signal Bit

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Abstract

Maintaining patient data privacy is a critical concern in the medical domain. However, safeguarding crucial information during data transmission presents significant challenges for healthcare professionals and organizations. Additionally, the accurate classification of electrocardiogram (ECG) signals is hindered by the need for supplementary information to ensure precise examinations and accurate diagnoses. This paper introduces a novel hybrid framework that addresses both ECG classification challenges and privacy preservation. The proposed framework consists of two main phases. In the first phase, a combination of Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) with an attention gate is employed for ECG classification. This phase enhances the accuracy of ECG signal classification by incorporating deep learning techniques. The second phase of the framework utilizes adaptive least signal bit with neutrosophic logic to conceal critical medical data during transmission. Neutrosophic sets, which represent data as degrees of truth, falsehood, and indeterminacy, are leveraged and passed through an embedding layer. In the sender part, important data is converted into three degrees and embedded within the ECG signal using true and false degrees. An intermediate set acts as a shared dynamic key between the sender and receiver. The receiver can reconstruct the important data using either the shared dynamic key or the intermediate set. The experiments done prove the efficiency of different parts of the framework; the augmentation model archives 14.67 and 37.89 for the inception score and freshet inception distance, respectively. The hybrid approach also achieves 99.01 and 99.12 for dice score and accuracy, respectively.

Keywords: Adaptive LSB, Neutrosophic, Steganography, ECG, CNN, Attention Gate, LSTM, Latent Diffusion Model.

1. Introduction

Electrocardiogram (ECG) is a fundamental diagnostic tool widely used in the field of cardiology to assess the electrical activity of the heart. It records the electrical signals generated by the heart as it contracts and relaxes, providing valuable insights into the heart's rhythm, rate, and overall cardiac health. The ECG waveform, consisting of P, QRS, and T waves, represents the depolarization and repolarization phases of the cardiac cycle [1-3] with the advancements in technology and the widespread availability of Portable ECG devices, the use of ECG has expanded beyond clinical settings. It has found applications in telemedicine, remote patient monitoring, fitness tracking, and early detection of cardiac abnormalities. However, the increasing utilization of ECG data in various domains raises concerns regarding privacy and data security. [4, 5].

Patient data privacy is of utmost importance in healthcare, as it involves sensitive personal information and medical records. ECG signals, being a direct reflection of a person's cardiac health, contain confidential information that must be safeguarded during transmission, storage, and analysis. Unauthorized access or manipulation of ECG data can lead to privacy breaches, identity theft, or misuse of sensitive medical information.

To address these privacy concerns, researchers have focused on developing techniques and frameworks that ensure the confidentiality and integrity of ECG data while maintaining its clinical utility. These techniques encompass a range of approaches, including encryption, anonymization, access control, and steganography. Each approach aims to strike a balance between privacy preservation and the seamless utilization of ECG data for accurate diagnosis and treatment [6, 7].

This paper aims to contribute to the field of ECG privacy preservation by investigating the integration of ECG signals with steganography techniques. Steganography, the art of hiding information within other data, offers a unique approach to conceal sensitive medical information within the ECG waveform itself. By embedding confidential data within the ECG signals, unauthorized individuals or systems would not be able to detect or access the concealed information. The paper also presents a deep learning hybrid model to combines between argumentation and classification of ECG after extracting the secret message or secret data from the ECG.

The integration of neutrosophic-based steganography techniques with ECG signals offers several advantages. It allows for the concealment of confidential medical information within the ECG waveform while preserving the overall integrity and diagnostic value of the signal. Neutrosophic sets can be utilized to represent the degrees of truth and falsehood associated with the concealed data, ensuring that the embedded information remains Undetectable to unauthorized individuals or systems. [8-11].

In the context of ECG steganography, the embedding process involves converting the important medical data into degrees of truth and falsehood and embedding them within the ECG signal using appropriate techniques such as least significant bit (LSB) substitution or frequency domain encoding. The choice of embedding method is crucial to maintain imperceptibility and minimize distortion to the original ECG waveform, ensuring accurate diagnosis and analysis [12]. The receiver, equipped with the appropriate decoding algorithm, can reconstruct the concealed information using the shared dynamic key or intermediate sets derived from neutrosophic logic. This approach enables authorized individuals to access the hidden data while preserving patient privacy and ensuring the confidentiality of sensitive medical information during transmission and storage. [13].

The second phase of the framework is about augmentation and classification of the ECG after extraction process of the secret message from the ECG. ECG classification plays a crucial role in diagnosing various cardiac conditions and monitoring the overall health of the heart. With the increasing availability of large-scale ECG datasets, deep learning techniques have emerged as powerful tools for accurate and automated ECG analysis. Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated remarkable success in ECG classification tasks, surpassing traditional machine learning approaches [15].

However, deep learning models often require a substantial amount of labeled data for training, which may be limited in the healthcare domain, particularly for rare cardiac conditions. Data augmentation techniques have emerged as effective strategies to address this challenge by artificially increasing the size and diversity of the training dataset. Augmentation methods generate new synthetic samples by applying transformations, such as scaling, rotation, noise addition, or signal manipulation, to the existing ECG data [16]. The augmentation of ECG using various versions of Generative Adversarial Networks (GANs) has gained significant attention in recent research. Several studies have explored the application of GAN-based methods to generate synthetic ECG signals that can be used for data augmentation and improving the performance of ECG analysis algorithms.

The combination of deep learning and data augmentation techniques offers several advantages for ECG classification. Firstly, deep learning models can automatically learn relevant features from augmented data, enhancing their ability to generalize and classify unseen ECG signals accurately. Secondly, data augmentation mitigates the problem of limited labeled data, allowing the model to learn from a larger and more diverse dataset, thus reducing overfitting and improving model performance. Lastly, data augmentation can increase the robustness of the model by exposing it to a broader range of ECG signal variations [17, 18].

The main contribution of the paper is as following;

1. The framework combines effective classification using a hybrid (CNN+LSTM+AG) with modified GAN and steganography using neutrosophic
2. The framework introduces a method based on neutrosophics and embedding for hiding data; this method produces effective steganography results.
3. The framework achieves efficient results in augmentation, classification, and steganography when compared with other methods.
4. The used latent diffusion model overcome many problems such as mode collapse and vanishing gradient problem in traditional versions of GAN.

The remaining parts of the paper are organized as following:

Section 2 discusses the related work in steganography, classification, and augmentation; Section 3 The proposed Method, which discusses the augmentation step, classification, and steganography; Section 4 introduces the experimental results and discussion; and Section 5 introduces the conclusion, future work, and limitations.

2. Related work

The related work presents recent methods of steganography using ECG, classification of ECG based on deep learning and the methods of augmentation the ECG images.

Steganography is the practice of concealing information within a carrier medium, such as an image, audio file, or text, in such a way that it is hidden and can only be extracted by the intended recipient. Embedding information inside ECG signals is an emerging field of research with potential applications in secure medical data transmission and authentication. A framework for recovering both the lost block feature and the lost secret information was described by Girish [17] A supervised long-short term memory (Su-LSTM) recurrent neural network (RNN) was also created, and it successfully predicted the missing signal. The method's distortion error after encryption was found to be rather low when it was tested on a range of ECG, PPG, and EEG data. The inaccuracy was further reduced after data extraction (percent root mean squared difference less than 0.01%), leading to a technique that was only partially irreversible.

N. Duda-Mróz [١٨] proposed a steganographic technique based on dynamic time warping (DTW) to embed secret messages within the ECG signal. The authors used DTW to find similar segments in the ECG signal and modified the amplitude of these segments to carry the hidden information.

The approach provided by S. E. Jero [١٩] embeds a secret authentication message as an error inside several bio signals, including ECG, PPG, and EEG. In order to retrieve the hidden message and recreate the original bio signal, an Extended Binary Golay Code-based error correcting algorithm is employed.

Neutrosophic set theory is an extension of fuzzy set theory that introduces a third indeterminate component, called indeterminacy, in addition to truth and falsehood. Applying neutrosophic set theory in steganography within ECG signals can offer several advantages, Neutrosophic set theory allows for a more flexible representation of uncertainty compared to traditional binary approaches. By incorporating the indeterminate component, it becomes possible to embed more information in the ECG signal without significantly affecting its perceptual quality. Neutrosophic steganography can improve the security of hidden information within ECG signals. By leveraging the indeterminate component, it becomes more challenging for potential attackers to detect and extract the hidden message. Neutrosophic steganography techniques can exploit the uncertain nature of the indeterminate component to spread the hidden information across multiple parts of the ECG signal, making it more resilient to attacks such as noise addition, filtering, or compression.

Convolutional Neural Networks (CNNs) have been widely used for the classification of ECG signals due to their ability to automatically learn hierarchical features from the data.

ECG Classification with a Convolutional Recurrent Neural Network by V. Sankari [20] proposed a CNN-RNN hybrid model for ECG classification. The authors combined the strengths of both CNNs and RNNs to capture both local and temporal dependencies in the ECG signals. The model achieved competitive results on a benchmark dataset for arrhythmia classification. ECG Arrhythmia Classification Using a 2-D Convolutional

Neural Network This work proposed a 2-D CNN architecture for ECG arrhythmia classification. Instead of considering the ECG signal as a 1-D time series, the authors converted it into a 2-D image representation and applied CNNs to extract relevant features. The model achieved high accuracy in classifying different arrhythmias.

In order to extract ECG characteristics, M. Chourasia, A. Thakur, S. Gupta and A. Singh [21] suggested using a 21-layer 1D convolutional recurrent neural network. He also suggested expanding the convolution filter to enhance local awareness and using residual connection, normalisation, and other techniques to increase the efficiency of the algorithm. Teijeiro extracts a collection of ECG signal features using the consensus-cantive framework to explain the morphological properties of the complete ECG signal. In order to improve the accuracy of recognition and classification, it double marks the ECG recording and works with the recurrent neural network.

K. F. Hossain [22] suggested extracting ECG signal properties using a 13-layer convolutional neural network (CNN) and classifying the results using a softmax classifier. Manuscript Document to see references that are linked, go here. On the ECG data set supplied by the 2021 PhysioNet/CINC challenge, the f1 score was 0.84. This technique requires that the data be segmented first, which obviously adds uncertainty to the segmentation process and the evaluation of the segmentation findings' dependability. On the 2021 PhysioNet/CINC challenge data set, Pyakillya employs a convolutional neural network with a 1D convolutional layer to recognise and categorise ECG events. The learning framework's accuracy in identifying the best data outcomes is 85.5%.

Generative Adversarial Networks (GANs) [23] have shown promise in generating synthetic data that can be used for data augmentation in various domains, including ECG signals. By training GANs on real ECG data, it becomes possible to generate additional synthetic ECG samples that can be used to augment the original dataset. GANs can learn the underlying distribution of the real ECG data and generate diverse synthetic samples that capture different variations and patterns [24]. By using different versions of GANs, such as vanilla GANs, conditional GANs, or Wasserstein GANs, it's possible to explore different modelling techniques and generate augmented data with varying characteristics. This increased data diversity can help improve the generalization and robustness of ECG classification models. ECG Data Augmentation Using Deep Convolutional GAN for Improved Generalization by Y. Li [25]: This study proposed an ECG data augmentation method using a deep convolutional GAN to improve the generalization of ECG classification models. The authors trained the GAN on real ECG data and generated synthetic samples to augment the training set. The augmented data improved the model's ability to generalize to unseen ECG signals and enhanced its performance in classifying various cardiac conditions. ECG Data Augmentation Using Deep Convolutional GANs for Improved Cardiac Arrhythmia Classification by N. Gupta [26]: This research focused on using deep convolutional GANs (DCGANs) to augment ECG data for cardiac arrhythmia classification. The authors trained the DCGAN on real ECG data and used it to generate synthetic samples to augment the original dataset. The augmented data helped improve the classification performance of the deep learning model, especially for minority arrhythmia classes. ECG Data Augmentation Using Conditional Wasserstein Generative Adversarial Networks for Deep QRS Detection" by M. K. H. Almoussawi [27]: This study proposed the use of conditional Wasserstein GANs to augment ECG data specifically for deep QRS detection. The authors trained the GAN on a large dataset of real ECG signals and generated synthetic samples to increase the size of the training set. The augmented data improved the performance of the deep QRS detection algorithm by enhancing its ability to handle variations in QRS complex morphology.

Although there are many different version of GAN augmentation networks, but all of them have different problems such as mode collapse and vanishing gradient problem.

Latent Diffusion Models (LDMs) offer certain advantages over traditional GANs in the context of ECG augmentation. LDMs utilize a progressive generation process, where the generator gradually refines the generated samples from low to high resolutions. Traditional GAN training can be challenging due to issues such as mode collapse, training instability, and vanishing gradients. LDMs address these problems by employing a diffusion process that gradually transforms a simple initial distribution into the desired data distribution. LDMs provide a more structured and controlled exploration of the latent space compared to traditional GANs. LDMs offer greater flexibility in terms of modelling the latent space and adjusting the diffusion process. The diffusion process can be modified to control the level of noise, randomness, or detail in the generated ECG signals.

3. The proposed Method

This hybrid methodology proposed in the paper consists of two parts: a client and a server. The client first converts the patient's data into a neutrosophic set. Then, it hides the neutrosophic set in the ECG signal and sends the signal to the server. The server then decrypts the data from the ECG signal and retrieves the patient's data. The server contains two stages: data augmentation and classification. The data augmentation stage is used to enlarge the dataset by creating new samples from existing ones. Fig. (1) shows the client part, and Fig. (2) shows the receiver part, or the server part. The client starts by generating the ECG signal, data preprocessing, the neutrosophic stage, and then the steganography step. The last step in the client is about pushing data into the transmission medium. The document contains two phases: the first phase is about extracting the secret data, and the second phase is about classifying the ECG using CNN+ LSTM and attention gates. The client also contains the augmentation using latent diffusion model in order to enhance the classification step.

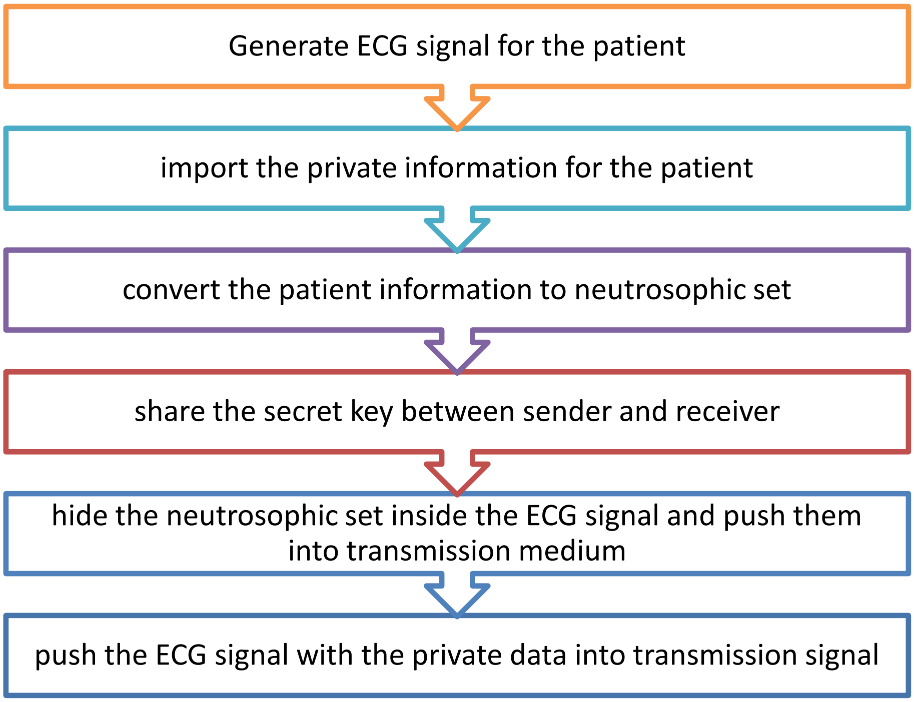

Fig. (1): sender side block diagram.

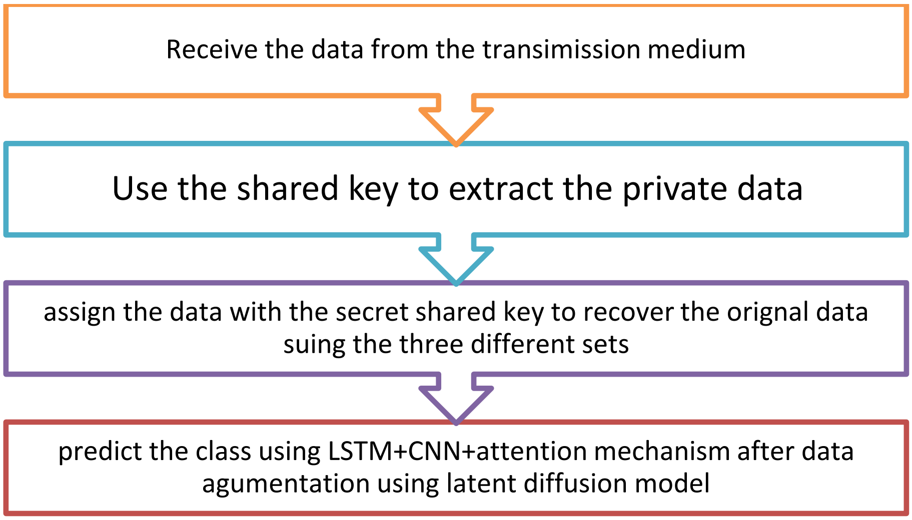

Fig. (2): server side block diagram

3.1 ECG images augmentation using latent diffusion model.

The Latent Diffusion Model (LDM) is a generative model that has been successfully applied to data augmentation tasks, including ECG signals. It provides a framework for learning data distributions and generating diverse, realistic samples that can be used to augment the training dataset. The LDM consists of several steps and architectural components: ECG signal preprocessing involves standardizing the data, removing baseline wander, and resampling to a fixed sampling rate if necessary. This ensures a consistent format and quality across the dataset. The LDM maps the ECG signals to a lower-dimensional latent space representation. This is achieved using an encoder network, such as a convolutional neural network (CNN) or recurrent neural network (RNN), which learns to encode the input ECG signals into a compact latent representation. The diffusion process is a series of steps that gradually transforms a simple distribution (e.g., Gaussian) into the true data distribution. It models the data generation process by iteratively applying diffusion steps. Each diffusion step involves adding noise to the latent space representation and updating the latent variables.

The LDM architecture typically consists of an encoder network, a diffusion process, and a decoder network. Encoder Network: The encoder network takes the input ECG signal and maps it to the latent space representation. It captures the salient features of the ECG signal and encodes them into the latent variables. Diffusion Process: The diffusion process consists of multiple diffusion steps, where noise is gradually added to the latent variables. Each diffusion step updates the latent variables based on the added noise and the previous latent variables. Decoder Network: The decoder network takes the updated latent variables and reconstructs the ECG signal. It learns to generate realistic ECG waveforms based on the latent space representation.

The LDM is trained using a two-step process: pretraining and fine-tuning. Pretraining: In the pretraining phase, the encoder and decoder networks are trained to reconstruct the original ECG signals. This helps to learn an initial mapping between the latent space and the ECG signals. Fine-tuning: After pretraining, the diffusion process is introduced, and the entire model is fine-tuned to perform the diffusion steps. This fine-tuning process optimizes the model to generate diverse and realistic samples during the diffusion process. Once the LDM is trained, it can be used to generate augmented ECG signals. By sampling latent variables from the latent space, the LDM can generate new ECG signals that exhibit similar characteristics to the original dataset. Data augmentation techniques, such as random sampling from the latent space or interpolating between latent variables, can be employed to generate a diverse set of ECG signals.

3.2 Hybrid Classification Model

The CNN+LSTM attention gate model works by first passing the ECG signal through a CNN. The CNN extracts features from the signal, such as the amplitude, frequency, and shape of the waves. The extracted features are then passed to an LSTM. The LSTM captures the temporal dependencies in the signal, such as the way that the waves change over time. The output of the LSTM is then passed to an attention gate. The attention gate decides which parts of the signal are most important for classification. The output of the attention gate is then passed to a classifier, which decides the class of the ECG signal. **The structure of the CNN+LSTM with attention gate can be broken down into several components:**

- Input layer: The input layer receives the ECG signal, which is commonly shown as a time series of voltage values on the screen.
- Convolutional layers: These layers take the input signal's regional characteristics and extract them. They accomplish this by applying a variety of filters to the input signal, producing a number of feature maps.

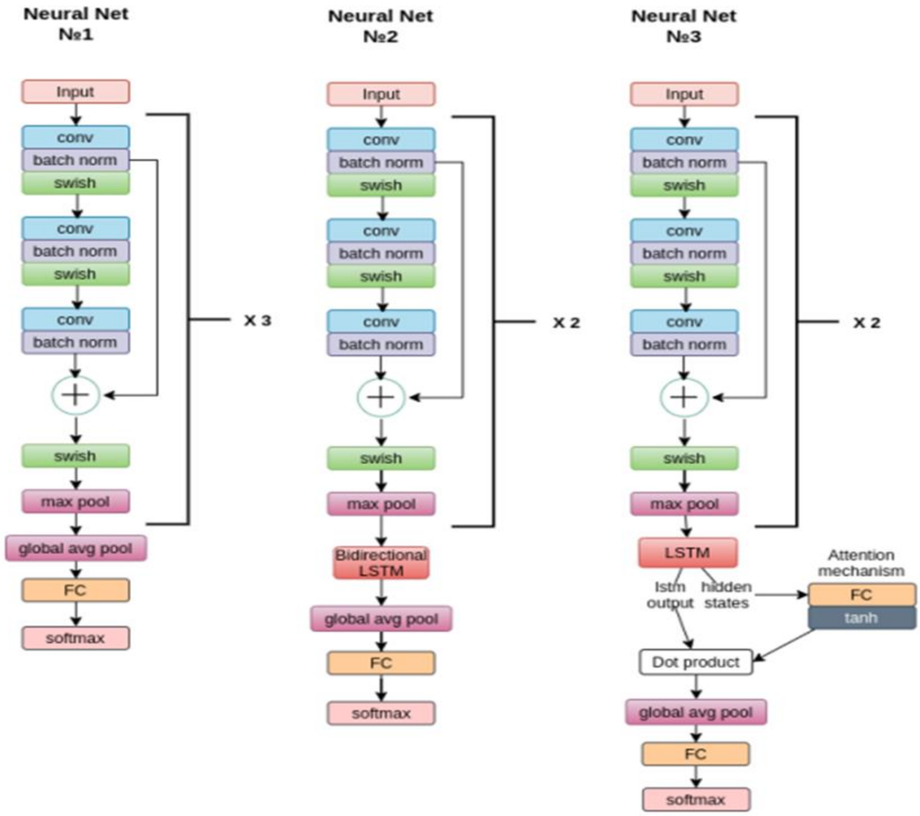

Fig. (3) architecture of the classification model

- Max pooling layers: By down sampling the feature maps, the max pooling layers decrease the dimensionality of the data. As a result, processing the data by the LSTM layers is made simpler.
- LSTM layers: The input signal's temporal relationships are captured by the LSTM layers. They do this by constructing a group of hidden states by sequentially processing the input sequence.
- Attention gate: The attention gate narrows its attention on the input signal's key characteristics. This is accomplished by creating a collection of attention weights from the hidden states in the LSTM layers, which are then utilised to weight the feature maps from the convolutional layers.
- Fully connected layers: The fully connected layers represent the output classes as a map from the output of the attention gate. They frequently have numerous layers with non-linear activations, such sigmoid or ReLU.

The input layer is the first layer in the architecture. It takes in the ECG signal and converts it into a sequence of numbers. The convolutional layers then extract regional features from the input signal. The max pooling layers down sample the feature maps, which reduces the dimensionality of the data. The LSTM layers capture the temporal relationships in the input signal. The attention gate focuses on important features in the input signal. The fully connected layers map the output of the attention gate to the output classes.

CNNs are well-suited for extracting local and spatial features from input data, making them Suitable for analysing the temporal structure of ECG signals. In the context of ECG classification, CNN layers can capture key patterns and local features such as P-waves, QRS complexes, and T-waves. These layers consist of convolutional filters that slide over the ECG signal, convolving the input data with the filters to detect relevant features at different scales and positions. The filters can capture variations in amplitude, frequency, and shape of the ECG waves, encoding important characteristics of the signal.

LSTM is a type of recurrent neural network (RNN) that excels at capturing temporal dependencies and long-term dependencies in sequential data. ECG signals are inherently sequential in nature, with each data point depending on the previous ones. LSTM layers can process the ECG signal over time, taking into account the temporal relationships between different points in the waveform. This enables the network to capture the dynamic patterns and long-term dependencies present in the ECG signal. LSTM layers can learn to recognize complex temporal patterns, such as the relationships between different parts of the waveform and the overall shape of the ECG wave.

Combination of CNN and LSTM layers, the model can leverage the strengths of both architectures. The initial CNN layers extract local features and capture variations in amplitude, frequency, and shape of the ECG waves. The LSTM layers then process the extracted features over time, considering the temporal dynamics and dependencies in the signal. This combination allows the model to capture both local and global patterns, ensuring that the features relevant for classification are effectively extracted.

3.3 Sender Side part

The message is sent to the receiver side, which extracts the message from the ECG, after the sender side has converted the patient data into a neutrosophic set and hidden the data inside the ECG. The proposed technique generates a reversible ECG steganography with a high hiding capacity, enhanced perceived quality, and durability on a 1D FDCT utilizing the adaptive LSB approach. The suggested strategy is accurately applied in two steps. Each input host is assigned to one of four possible bundles using Phase-I to classify the FDCT bundles. Phase-II employs the adaptive LSB approach to embed data bits in the designated coefficients of the categorized bundles in accordance with a preset bit-index table (obtained from phase-I), and also converts it into three neutrosophic sets for added security.

3.3.1 Data Representation into Neutrosophic

A neutrosophic set is a generalization of a fuzzy set that allows for uncertainty. This makes it a good fit for representing secret data, as it allows for some distortion of the data without affecting the quality of the data. To represent secret data as a neutrosophic set, we first need to convert the data into a binary string. This can be done by using a hash function to convert the data into a fixed-length string of bits. Once the data is in binary form, we can then represent it as a neutrosophic set. The membership function of the neutrosophic set will be a function that maps each bit of the binary string to a value between 0 and 1. The value 0 represents a bit that is definitely not part of the secret data, the value 1 represents a bit that is definitely part of the secret data, and the values in between represent bits that are uncertain. The framework converts the secret data into three neutrosophic sets (truth set, intermediate set, and false set). Each set has a degree between 0 and 1. Both sides use the intermediate degree as the shared key between each other. When the receiver extracts the other two degrees, they then use the shared key, which is the intermediate value, to extract the original data.

3.3.2 Hiding data in ECG signal Using LSB

The LSB method is a simple and effective way to hide data in signals, but it can be easily detected by attackers. Adaptive LSB is a more secure variation of the LSB method that uses a statistical model to select the LSBs that are least likely to be detected. To hide secret data using adaptive LSB, the sender first converts the secret data into a binary string. This string is then divided into blocks of bits, each of which is the same length as the ECG signal. The sender then selects the LSBs of each block that are least likely to be detected by an attacker. The selected LSBs are then used to hide the secret data in the ECG signal. The receiver of the ECG signal uses the same statistical model to select the LSBs that are most likely to contain the secret data. The receiver then uses the selected LSBs to recover the secret data. Fig. (5) shows the sender and receiver steps.

Based on the processing of one-dimensional fast discrete cosine transform (1D FDCT) coefficients, the framework offers a successful reversible data hiding strategy for electrocardiogram (ECG) signal processing. The recommended technique is carried out in two phases. With each input bundle being categorized into one of four different bundles, Phase-I's objective is to classify the FDCT (host) bundles. Phase-II's objective is to embed data bits in the selected coefficients of the categorized bundles using the adaptive least significant bit (LSB) technique in line with a given bit-index table (obtained from phase-I). Simulations showed that the original ECG signal could be completely reconstructed and that hidden bits could be retrieved without creating any artefacts. Fig. (5) shows the block diagram of encoding and decoding method.

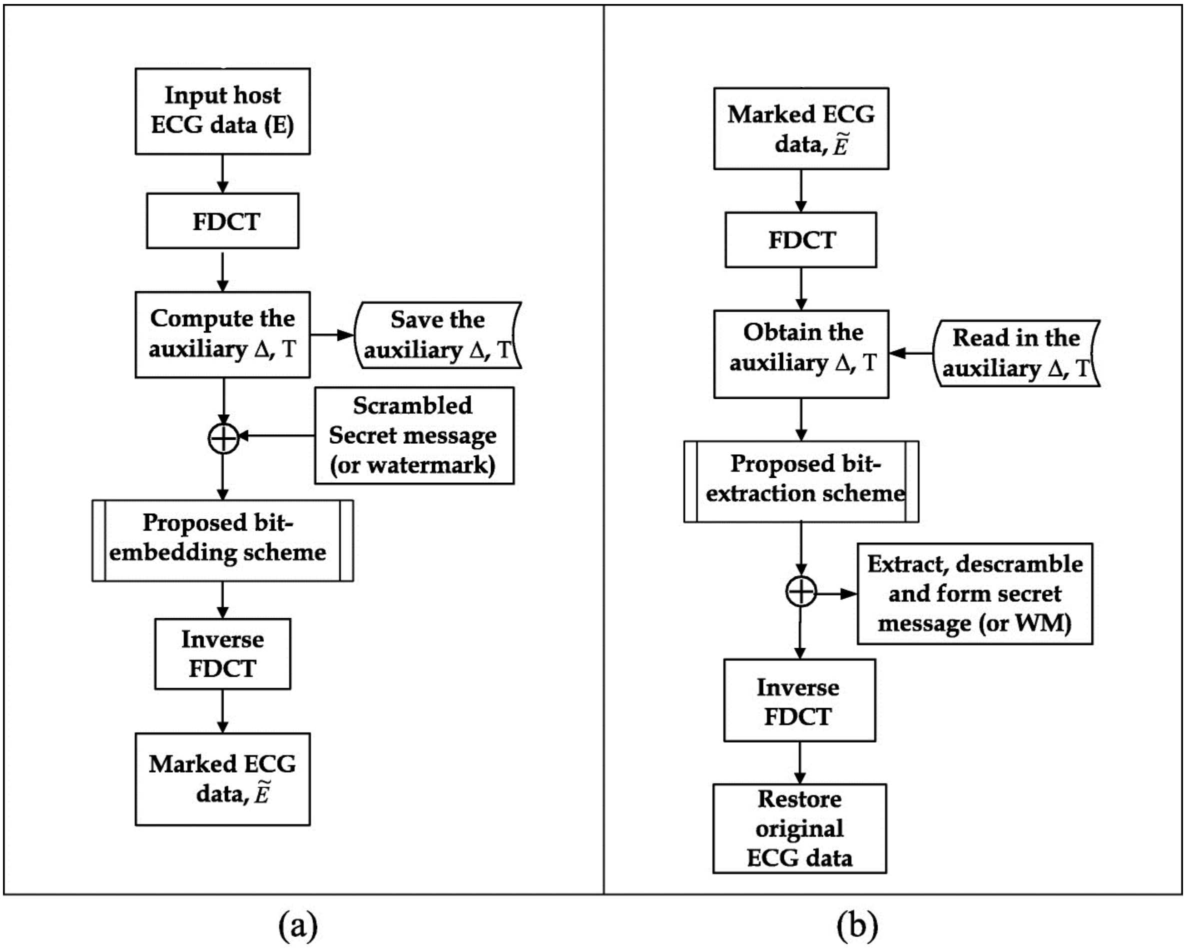

Fig. (4): block diagram of encoding and decoding method: (a): Encoding method and (b): decoding method.

3.4 Accuracy metrices and hyperparameters

The framework uses the following accuracy metrics in the classification process Eqs.(1), (2) and (3). The framework uses the recall accuracy and dice score to compare between different models in classification. All model uses 100 epochs with admax optimizer, learning rate .0001 and cross entropy loss function.

$$Recall = \frac{TP_i}{TP_i + FN_i} \times 100\% \tag{1}$$

$$Accuracy = \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \times 100\% \tag{2}$$

$$Dice\ Score = \frac{2 \times |\ \mathrm{Precision} \times \mathrm{Recall}\ |}{|\ \mathrm{Precision} + \mathrm{Recall}\ |} \times 100\% \tag{3}$$

4. Experimental results and discussion

The MIT-BIH Arrhythmia Dataset [28] and The PTB Diagnostic ECG Database, two well-known datasets in heartbeat classification, are used to create two collections of heartbeat signals that make up this dataset. Both collections include enough samples to allow for the training of a deep neural network.With the use of deep neural network architectures, this dataset has been utilized to investigate the categorization of heartbeats and to examine some of the possibilities of transfer learning. For both the normal case and cases afflicted by various arrhythmias and myocardial infarction, the signals correlate to the ECG varieties of heartbeats. These signals are preprocessed and divided into segments, each of which represents a heartbeat. The Arrhythmia Dataset contains 109446 samples, 5 categories with classes ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4] from Physionet's MIT-BIH Arrhythmia Dataset. The PTB Diagnostic ECG Database contains 14552 with multiple classes or categories from Physionet's PTB Diagnostic Database. All samples are downscaled, cropped, and, if required, padded with "0" to the fixed dimension of 188.

This section introduces the different sections of the paper, such as the payload and SNR/PRD performance of the proposed method, the classification result using the hybrid model, and shows the comparison between the hybrid model and other available models.

The payload and SNR/PRD performances produced by the suggested approach utilising a = 20 and BPS = 1.0 and 2.0, respectively, are shown in tables 1and 2. The tables show that the average payload of the suggested approach at BPS = 2.0 is almost twice as large as it is at BPS = 1.0, while the former's SNR is decreasing by around 10 dB.

Table(1). Payload and SNR/PRD performance of the proposed method in BPS = 1.0

ECG data	Payload	SNR	PRD
Ecg200	34,212	47.9636	0.004586
Ecg201	31,324	47.395	0.004657
Ecg202	33,164	47.236	0.004767
Ecg203	31,342	48.235	0.0041789
Ecg204	28,753	47.253	0.0042871
Ecg211	29,454	48.3265	0.003886
Ecg212	34,457	46.2564	0.0048996
Ecg213	27,436	48.12568	0.003765
Ecg214	28,654	47.2642	0.0038987
Ecg215	34,432	45.16584	0.0005187

Table(2) . Payload and SNR/PRD performance of the proposed method in BPS = 2.0

ECG data	Payload	SNR	PRD
Ecg200	65.236	38.2322	0.013528
Ecg201	61.34655	37.2362	0.014551
Ecg202	63.21654	38.32651	0.014541
Ecg203	61.235	37.2366	0.023594
Ecg204	58,1655	36.7397	0.017521
Ecg205	60,565	36.5714	0.0152671
Ecg206	61,5568	38.2366	0.015359
Ecg207	57.26521	37.23256	0.0153265
Ecg208	61.2695	37.2326	0.0146149
Ecg209	60.26781	38.23658	0.0183564
Ecg210	63.26584	37.2365	0.0142552
Ecg211	58.2689	36.3255	0.0175215
Ecg212	57.26812	37.3521	0.017215
Ecg213	61.23598	38.32654	0.0153245
Ecg214	56.23658	37.23525	0.0183214

Table(3) shows the comparison between the latent diffusion model and different version of the GANs. The results in the table show the efficiency of the latent diffusion model when compared with the different versions of the GANs according the higher value of the inception score and the lower value of the freshet inception distance.

Table(3) . Comparison between latent diffusion model and different version of the GANs in augmentation process

Model	**GAN**	**DCGAN**	**Identity GAN**	**Ultra GAN**	Proposed
Inception score	11.43	13.11	13.36	13.69	14.67
Freshet inception distance	42.53	46.46	44.66	42.26	37.89

Table(4). shows the results of classification before augmentation process and Fig. (5) shows the comparison between the model and other models in the classification process.

Table(4) Results of classification before augmentation

Model	Dice Score %	Accuracy %	Recall %
CNN	94.23	94.36	94.36
RNN	95.26	94.36	95.27
CNN+LSTM	94.36	94.39	94.89
CNN+LSTM+AG	95.36	95.67	94.36

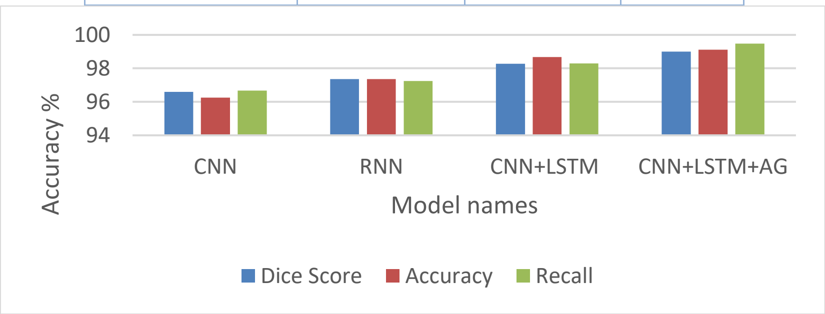

Fig. (5): comparison chart before augmentation process

Table(5). shows the comparison between the modified frameworks after augmentation when compared with other model for classification. The results shows the efficiency of the modified model when compared with other model according different metrics. Fig. (6) shows the chart of comparison between the used model and other available model in the classification of ECG. The chart shows the efficiency of the model when compared with other models.

Table(5) Results of classification after augmentation

Model	Dice Score %	Accuracy %	Recall %
CNN	96.59	96.25	96.68
RNN	97.36	97.36	97.25
CNN+LSTM	98.28	98.68	98.29
CNN+LSTM+AG	99.01	99.12	99.48

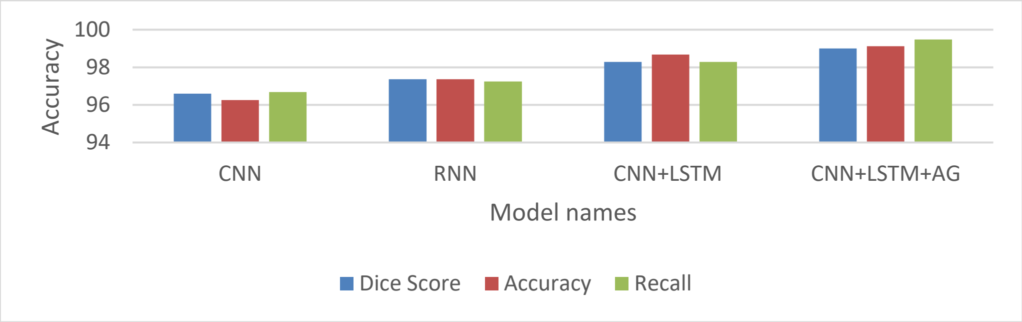

Fig. (6): comparison chart after augmentation process

Fig. (7) shows the loss function of the CNN+LSTM in the classification and Fig. (8) shows the loss function of the model during training and metrics during training in CNN+LSTM+AG.

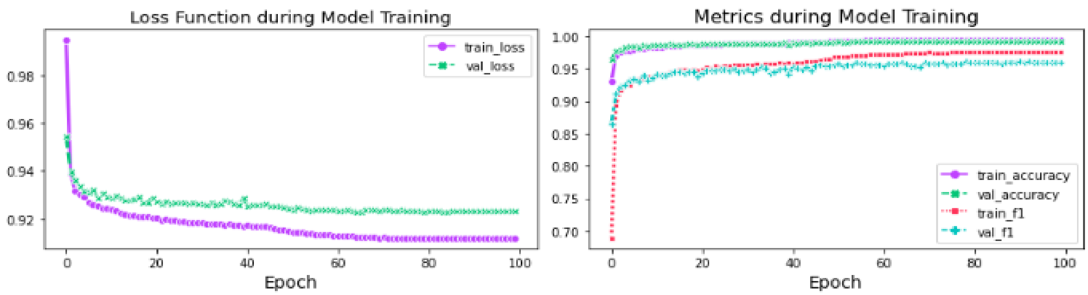

Fig. (7): Loss function of CNN+LSTM

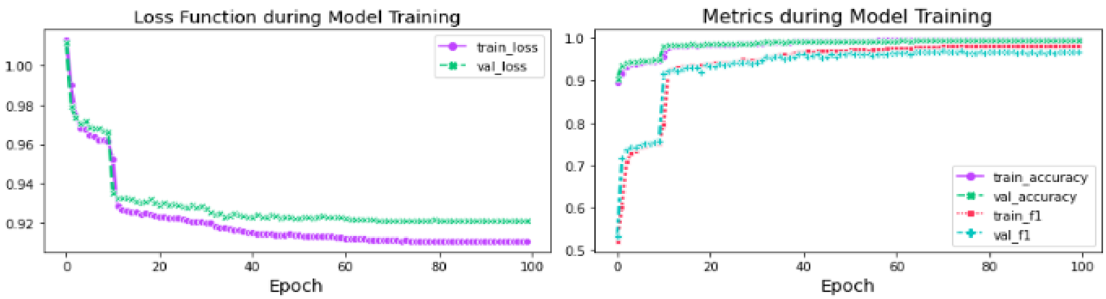

Fig. (8): Loss function of CNN+LSTM+AG

The combination of CNN+LSTM+AG (Attention Gate) with the Latent Diffusion model demonstrates high efficiency and superiority compared to other models in ECG classification. The CNN+LSTM architecture effectively captures local and temporal features, allowing it to extract crucial information such as amplitude, frequency, and shape of ECG waves. The addition of the AG mechanism enhances the model's ability to focus on relevant regions of the ECG signal, further improving feature extraction and classification accuracy. Moreover, the integration of the Latent Diffusion model provides additional benefits. The Latent Diffusion model leverages diffusion processes to learn latent representations of the ECG data, enabling the model to capture intricate patterns and complex dependencies. This latent representation enhances the model's ability to discriminate between different ECG classes and improves the overall classification performance. the CNN+LSTM+AG model with Latent Diffusion demonstrates high efficiency and outperforms other models in ECG classification tasks. Its ability to capture local features, temporal dependencies, and intricate patterns, along with the attention mechanism and the Latent Diffusion model, results in superior classification accuracy and contributes to more reliable and effective ECG analysis.

5. Conclusion

The research introduced a novel approach that combines ECG signal processing and steganography techniques to address privacy concerns in healthcare applications. The integration of these fields offers promising avenues for secure data transmission while preserving the diagnostic integrity of ECG signals. The proposed framework contributes to the advancement of privacy-preserving techniques in healthcare and sets the stage for further research in this emerging field. This paper introduced a framework that contained two different phases: the first phase for hiding the secret message inside the ECG to preserve the privacy of patients using the neutrosophic, and the second phase for classifying the ECG effectively. The framework used the neutrosophic for the steganography process and CNN+LSTM with attention gate with latent diffusion model in the classification and augmentation processes. The framework achieved effective results in augmentation, classification, and steganography compared to other methods. The framework achieved efficient recall, accuracy, and precision when compared with other classification processes, an efficient inception score, and a fresh inception distance. Although the framework achieved efficient results in augmentation, classification, and steganography, there are some limitations, such as the mode collapse problem during the augmentation process using the latent diffusion model, the complexity of the neutrosophic-based method in steganography, and the high probability of losing part of the data during the extraction process.

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