Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/170509

Neutrosophic Adaptive LSB and Deep Learning Hybrid Framework for ECG Signal Classification

Ahmed S. Sakr[1,2], *H. M. Abdulkader*[2] *and Abdalla Rezk*[3,*]

[1]Cybersecurity Department, Engineering and Information Technology College, Buraydah Private Colleges, Buraydah 51418,SaudiArabia
[2]Department of Information System, Faculty of Computers and Information, Menoufia University, Menoufia, Egypt
[3]Department of Information Technology, Faculty of Industry and Energy Technology, Delta University, Menoufia, Egypt

Received: 22 May 2023, Revised: 22 Jul. 2023, Accepted: 2 Aug. 2023
Published online: 1 Sep. 2023

Abstract: This paper proposes a novel hybrid framework for ECG signal classification and privacy preservation. The framework includes two phases: the first phase uses LSTM+CNN with attention gate for ECG classification, while the second phase utilizes adaptive least signal bit with neutrosophic for hiding important data during transmission. The proposed framework converts data into three sets of degrees (true, false, and intermediate) using neutrosophic and passes them to an embedding layer. In the sender part, the framework hides important data in ECG signal as true and false degrees, using the intermediate set as a shared dynamic key between sender and receiver. The receiver can reconstruct the important data using the shared dynamic key or the intermediate set. The proposed framework is more robust against attacks compared to other methods.

Keywords: LSTM, CNN, ECG, steganography, neutrosophic, adaptive LSB

1 Introduction

The medical test known as an electrocardiogram, or ECG, examines the electrical activity of the heart. Electrodes are applied to the skin of the chest, arms, and legs during this non-invasive examination in order to detect the electrical impulses the heart produces while it beats [**?**]. The ECG test is a quick, painless process that usually only takes a few moments. [1] It is a useful tool for medical practitioners in the diagnosis and treatment of cardiac diseases, and it can enhance the results and quality of life for patients [2,3]. Heart problems including arrhythmia, heart attacks, heart failure, and congenital heart anomalies can all be identified with the ECG test. Additionally, it may be used to track the success of these illnesses' therapies and spot variations in the electrical activity of the heart over time [4].

ECG classification is an important task in the medical field and can be use in detection many heart disorders [5]. By examining the electrical activity of the heart, the ECG classification serves as a tool for the diagnosis and monitoring of cardiac problems. Electrocardiograms, or ECGs, are non-invasive tests that use electrodes applied to the skin to record the electrical activity of the heart. The resultant ECG signal can reveal important details regarding the rhythm, pace, and general operation of the heart. Deep learning presents many models for classification the ECG which has achieved high accuracy in this area [6]. The convolutional neural network (CNN) is one of the deep learning models that may be used to classify ECG data out of the many available models. Data augmentation (producing extra training data through applying transformations to the initial data), dropout (randomly removing some of the neurons during training to prevent overfitting), and transfer learning (using a pre-trained CNN as a starting point and fine-tuning it on the ECG classification task) are some additional methods that can be used to enhance the performance of the CNN. In conclusion, using a CNN for ECG classification can offer a strong and precise way for identifying and keeping track of cardiac problems [7]. Clinicians always need some of additional data behind the ECG signal for the purpose of the accurate analysis, detection and diagnosis, so adding additional challenge inside the ECG signal become a main challenge. The main other challenge for

* Corresponding author e-mail: abdallarezk@gmail.com

the data scientists is about hiding the information inside the ECG signal which is called steganography [8].

Steganography is the method of concealing data in a difficult-to-detect manner within other data. Steganography can be applied in the context of ECG signals to conceal information within the signal itself without impacting the diagnostic information included in the signal. The least significant bit (LSB) method, which substitutes a bit of the hidden message for the least significant bit of each sample in the ECG signal, is one way of ECG steganography [9] . This technique may be used to conceal information within the signal without hurting its diagnostic usefulness because the LSBs of the ECG signal are often not used for diagnostic reasons [10] .

A type of steganography called neutrosophic steganography conceals information under a cover picture or signal by using neutrosophic logic. Fuzzy logic may be generalised into neurosophic logic, which supports the representation of uncertainty, inconsistent data, and partial knowledge [11]. The secret message is first transformed into a neutrosophic representation in neutrosophic steganography. This representation has three parts: a truth component, an indeterminacy component, and a falsity component. These elements stand for the degree of veracity, ambiguity, and dishonesty of each communication component [12]. A steganographic method is then used to insert the neutrosophic representation of the secret message into the cover picture or signal. In the process of embedding, the cover picture or signal is altered in a way that is undetectable to the human eye or ear but enables the eventual extraction of the concealed content [13] .

Neutrosophic steganography is a type of steganography that uses neutrosophic logic to encode and decode hidden information within a cover image or signal. Neutrosophy is a branch of philosophy that deals with concepts that have indeterminate properties or are in a state of indeterminacy, such as truth, falsity, and indeterminacy[14].

In neutrosophic steganography, the information to be concealed is first mapped to a neutrosophic domain, where it can be represented in terms of its degree of truth, falsity, and indeterminacy. The cover image or signal is then modified in a way that minimizes the changes to its perceptual quality while simultaneously embedding the neutrosophic-encoded information [15,16].

Neutrosophic steganography offers several advantages over other steganography techniques. It can handle inconsistencies or missing data, making it a more reliable and secure method of concealing data. Additionally, it can provide a higher level of resilience to attacks while maintaining good hidden storage capacity and perceived quality. However, neutrosophic steganography may require more development time and processing resources than traditional steganography techniques [17,18].

The main contribution of the paper as the follow:

1- Neutrosophic steganography has several advantages over traditional steganography methods. It can handle inconsistencies or missing data, making it a more reliable and secure method of concealing data within a cover image or signal. However, it may require more development time and processing resources than conventional steganography techniques.

2- The framework provides a highly effective reversible ECG steganography technique that can maintain a certain level of resilience while achieving high hidden storage and good perceived quality.

3- The framework achieves high levels of accuracy both in ECG classification and in the steganography process.

4- The framework employs the latent diffusion model to generate new samples and augment the dataset, producing more samples.

5- The framework addresses the issue of mode collapse in the GAN for the augmentation process.

6- The framework utilizes the Attention mechanism in ECG classification to emphasize important features, whether they come from recurrent layers or convolutional layers.

The remaining parts of the paper organized as the follow: Section 2 presents the related work which discuss the previous work about the steganography of the ECG signal, section 3 presents the methodology of the hybrid framework, section 4 presents the results and discussion and section 5 presents the conclusion and the future work.

2 Related Work

ECG signal steganography, which includes concealing information within the signal without impairing its diagnostic usefulness, has been studied in considerable detail. Examples of similar work are shown below:

LSB Substitution and Wavelet Transform for ECG Steganography, S. S. Patil et al. [19]: In order to conceal a hidden message inside the ECG signal, this research suggests a steganography technique that combines LSB replacement with wavelet transform. The technique is assessed using metrics like PSNR and BER, and the findings demonstrate that it is successful in obfuscating the message while preserving the ECG signal's diagnostic significance.

ching et al. [20] described a productive reversible data concealing approach for electrocardiogram (ECG) signal processing based on the processing of one-dimensional fast discrete cosine transform (1D FDCT) coefficients. The authors' suggested strategy is put into practice in two stages. Phase-I's goal is to categorize the FDCT (host) bundles, with each input bundle being assigned to one of four distinct bundles. Phase-II's goal is to use the adaptive least significant bit (LSB) approach to embed data bits in the chosen coefficients of the categorized bundles in accordance with a specified bit-index table (which was obtained from phase-I). Simulations demonstrated that concealed bits could be retrieved without artefacts and that the original ECG signal could be fully restored.

Sendeuya et al. [21] a novel method of ECG steganography for concealing patient data. In this study, encryption was carried out inside the TP-segment of the ECG since steganography causes distortion in the ECG signal that impairs the clinical characteristics. Additionally, data concealment inside typical TP-segments was accomplished via segment categorization and feature extraction, leaving anomalous segments untouched. This approach worked when applied to the mitdb, ptbdb, and European ST-T databases, all of which are accessible through Physionet. The percent root mean square difference (PRD), PRD normalised (PRDN), and signal to noise ratio (SNR) and peak SNR (PSNR) values were all less than 1It was found that, compared to previous frequency domain approaches and recently published publications, this algorithm produced better results.

Jero et al. [22] developed an ECG steganography to conceal patient information based on a continuous ant-colony optimisation approach, discrete wavelet transformations, and singular value decomposition (SVD). To achieve this, a 2D ECG matrix was created by first converting a 1D ECG input. The data bits were then added through SVD and additive quantization techniques to the ECG matrix's desired frequency range. According to simulations, the average percentage residual difference (PRD) and PSNR with a payload size of 0.89 Kbytes were 0.0018 and 63 dB, respectively. However, when the payload size rose, the PSNR performance was noticeably worsened. For instance, the method's average PSNR is about 35 dB when the payload is about 3.1 Kbytes.

A high-capacity ECG steganography was reported by Christian et al. [21] based on the 1D discrete cosine transform (DCT) domain. The perceived quality can be significantly improved by hiding many bits in the second decimal place of the DCT coefficients. Although this approach yields great SNR and payload, the size of a marked ECG was raised by a factor of around two compared to the previous one. This approach can place a heavy demand on portable measuring instruments.

With the use of embedding-then-encryption methods and a fused coupled chaotic map, Pandey et al. [21] developed a practical ECG steganography. Data ciphering, least-significant-bit (LSB) embedding, substitution, and permutation are the four steps of this approach. The average PRD and PSNR, according to simulations, are 0.21 and 57 dB with a payload size of 21 Kbytes (entering all datasets took 30 min). Lead I (or Lead II) may be used to get the average PSNR of 71 (or 70) dB and the average PRD of 0.04 (or 0.05) with a payload size of 2.4 Kbytes.

3 Methodology

This part of the paper shows the different section of the hybrid methodology. The paper contains two ends client and server. The client hide the data of the patient after converting it into neutrosophic set in the ECG signal and then send it to the server. The server side decrypt the data from the received ECG signal. The server contains different stages; the first stage is data augmentation in order to enlarging the dataset. The server uses the CNN + LSTM with a new attention mechanism for multi-classification process. Fig.1 and Fig. 2 shows the client and server block diagram.

3.1 The dataset of ECG The framework uses dataset which is consist of both collections of heartbeat signals derived from both different datasets in heartbeat classification process, the MIT-BIH Arrhythmia Dataset and The PTB Diagnostic ECG Database. Both collections contains enough samples to allow for the training of a DL network. Using deep neural network architectures, the dataset has been used to investigate the categorization of heartbeats and to see some of the potential of transfer learning. For both the normal condition and up-normal cases, the signals correlate to the (ECG) forms of heartbeats. These signals are preprocessed and divided into segments, each of which represents a heartbeat. The main disadvantage of this dataset is the small number of the training sample. Fig.3 shows results of exploration some samples from the ECG dataset. The framework present an augmentation using the latent diffusion model for increasing the number of the training samples.

3.2 Data Preprocessing Using Latent diffusion Model Limited data set or small number of samples affects negatively in the classification accuracy of the ECG. The proposed framework uses the latent diffusion model in the augmentation process in order to increase the number of samples. A generative model called the Latent Diffusion Model (LDM) has been applied to data augmentation of ECG samples. Increasing the amount of a dataset by the creation of new samples that are somewhat comparable to the original samples is a process known as data augmentation. This enables machine learning models to learn from a bigger and more varied set of instances, which can help them perform better. The LDM may be used to create new ECG samples from ECG data that are identical to the original samples but have different timing and waveform shape. With the use of sampling from the learnt distribution, the LDM is a kind of deep generative model that develops a low-dimensional representation of the ECG waveform. An encoder network and a diffusion network make up the majority of the network architecture used for ECG data augmentation utilizing the Latent Diffusion Model (LDM).

The input ECG waveform is mapped using an encoder network to a low-dimensional latent space that captures the waveform's underlying structure. A recurrent neural network (RNN), which can learn to extract characteristics from the ECG data, is commonly used for this. In order to

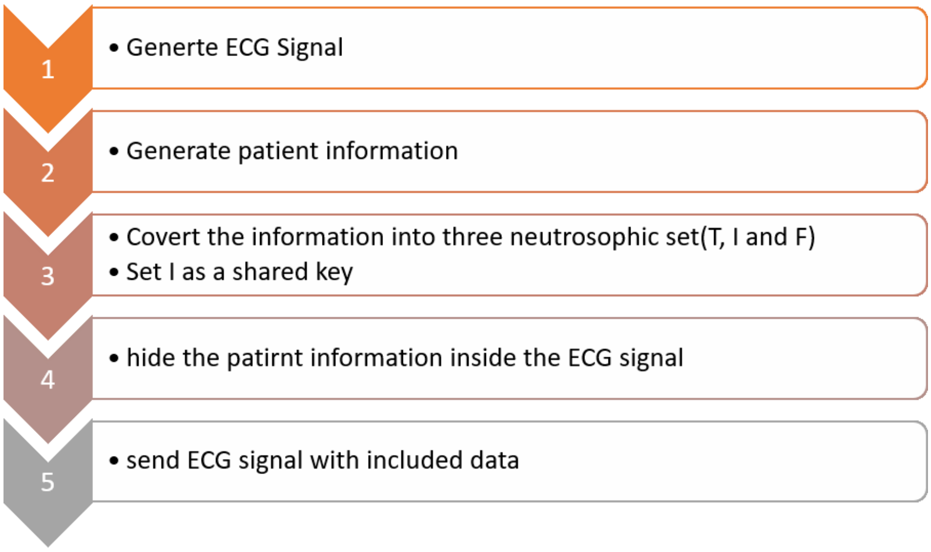

Fig. 1: Sender side block diagram

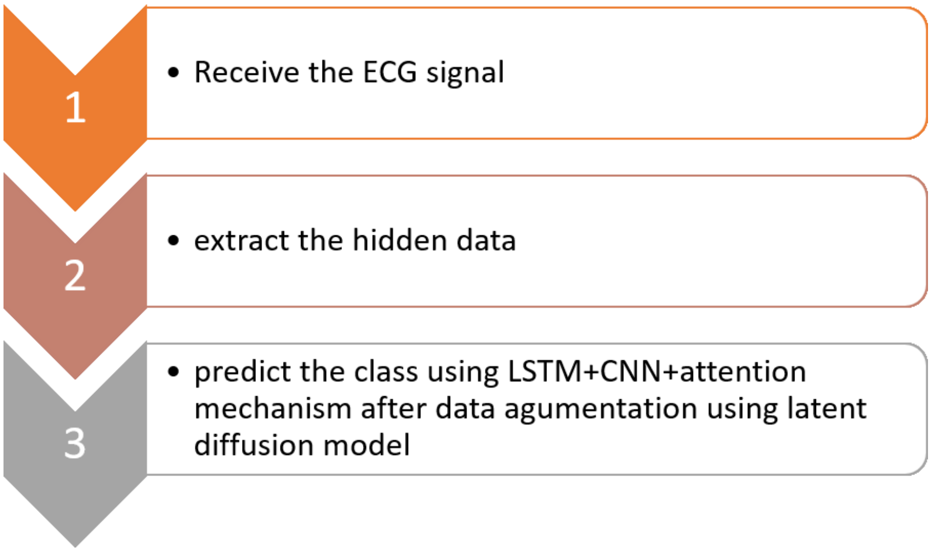

Fig. 2: Server side block diagram

create new ECG waveforms, the diffusion network samples from the latent space's learnt distribution. This is often accomplished by adding noise to the latent space and then allowing it to diffuse through a number of transformations. A decoder network—typically a CNN or RNN that can reconstruct the ECG waveform from the latent space—is then used to map the generated samples back to the original ECG waveform space.

3.3 Classification Model Using Hybrid Model The framework uses the CNN+LSTM with attention mechanism in order to classify the ECG signals. Fig. 4 shows the architecture of the classification model which combine between the CNN, LSTM and the attention mechanism. A well-liked neural network architecture for ECG classification applications is CNN-LSTM with attention gate. It combines the benefits of long short-term memory (LSTM) networks and convolutional neural networks (CNNs), and adds an attention mechanism to concentrate on key elements in the input signal. The structure of the CNN-LSTM with attention gate can be broken down into several components:

1-The ECG signal, which is commonly displayed as a time series of voltage values, is taken in by the input layer.

2. Convolutional layers: The convolutional layers are used to the input signal to extract regional characteristics. They

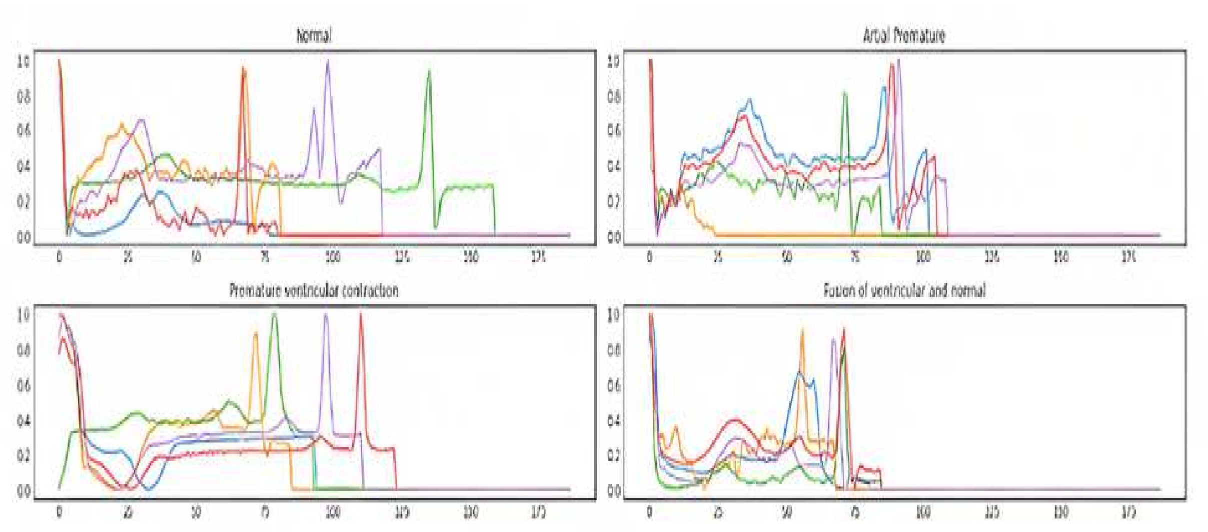

Fig. 3: ECG sample from the dataset

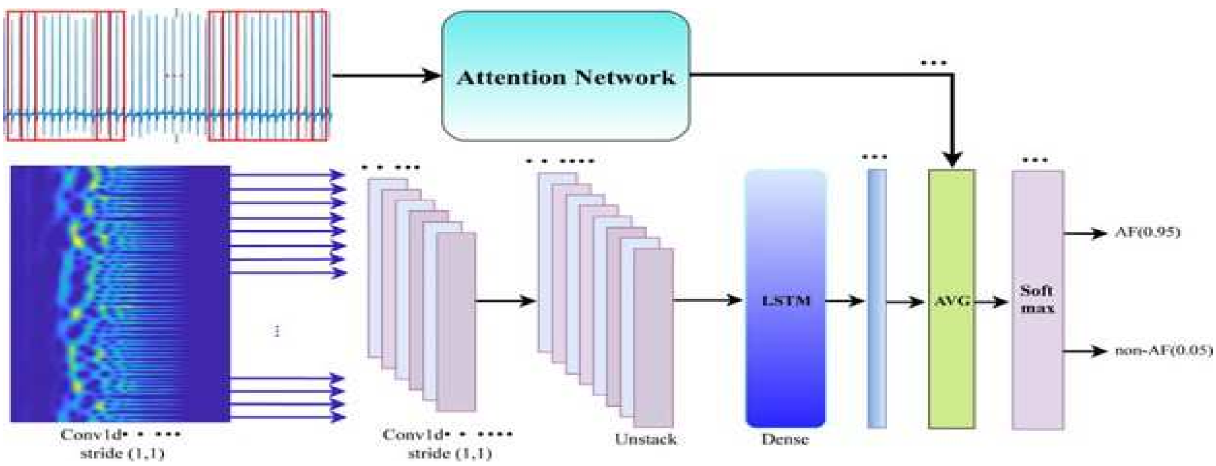

Fig. 4: Architecture of the classification model

generally comprise of a number of filters that are applied successively to the input signal to create a collection of feature maps.
3. Max pooling layers: The LSTM layers' input is dedimensionalized by using the max pooling layers to downsample the feature maps.
4. LSTM layers: The input signal's temporal relationships are captured using LSTM layers. They are made up of a number of LSTM cells, which take the input sequence and process it to create a collection of hidden states.
5. Attention gate: The attention gate is used to focus on important features in the input signal. It takes the hidden states from the LSTM layers and produces a set of attention weights, which are used to weight the feature maps from the convolutional layers.
6. Fully connected layers: The fully connected layers are used to map the output of the attention gate to the output classes. They typically consist of multiple layers with non-linear activations, such as ReLU or sigmoid.

3.4 Sender Side part The sender side part contains converting the patient data into neutrosophic set then hide the data inside the ECG then send the message to receiver part which extract the message from the ECG. The suggested method is carried out on a 1D FDCT using the adaptive LSB methodology to produce a reversible ECG steganography with a large concealing capacity, improved perceived quality, and resilience. The proposed approach is implemented precisely in two stages. Phase-I is used to categorize the FDCT bundles, assigning each input host to one of four different bundles. Phase-II uses the adaptive LSB technique to embed data bits in the chosen

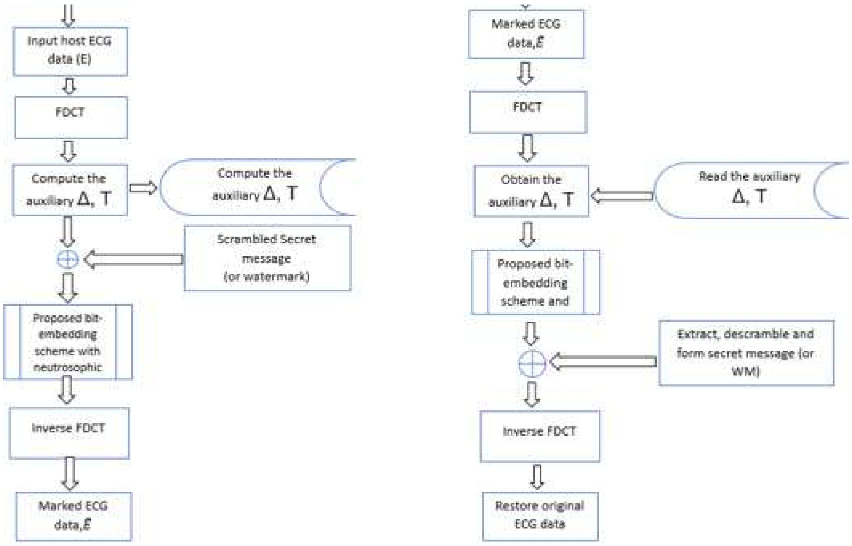

Fig. 5: Block diagram of our proposed method. (a) Sender part and (b) Server part

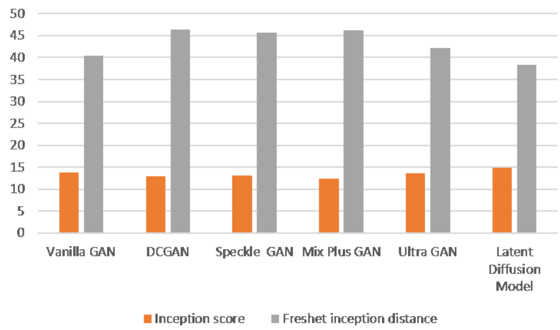

Fig. 6: Comparison between latent diffusion model and other architectures of GANs

coefficients of the classified bundles in accordance with a predetermined bit-index table (obtained from phase-I) and also converting it into three neutrosophic set for more security.

3.4.1 Representing Data into Neutrosophic Converting patient data into neutrosophic sets involves representing the data using neutrosophic logic, which is a mathematical framework that allows for the representation of uncertainty and indeterminacy in data. Neutrosophic sets are a generalization of fuzzy sets, which are commonly used in medical diagnosis and decision-making. To convert patient data into neutrosophic sets, the first step is to identify the variables that are relevant to the diagnosis or decision-making process. These variables could include symptoms, test results, medical history, and other factors that may influence the diagnosis or treatment plan. Once the variables have been identified, they can be represented using neutrosophic sets. A neutrosophic set is defined by three components: the membership function, the non-membership function, and the indeterminacy function. These functions represent the degree to which an element belongs to the set, does not belong to the set, and is indeterminate, respectively. The sender send embedding neutrosophic set(True and False) onto server, the server uses the intermediate set and reverse the process in order to extract the data to the original data.

3.4.2 Adaptive LSB Adaptive LSB (Least Significant Bit) architecture is a stenographic technique used in ECG (Electrocardiogram) signal processing to hide secret information within the ECG signal. It works by modifying the least significant bit of each sample in the ECG signal to encode the secret message. To use Adaptive LSB architecture in ECG steganography, the secret message is first converted into binary format. Then, the LSB of each sample in the ECG signal is replaced with a bit from the secret message. This is done in an adaptive manner, where the number of LSBs modified in each sample is determined based on the characteristics of the ECG signal. In this framework the patient data converted into neutrosophic set then into bit through embedding method as mentioned in FIG.5. The framework describes a productive reversible data concealing approach for electrocardiogram (ECG) signal processing based on the processing of one-dimensional fast discrete cosine transform (1D FDCT) coefficients. Two steps are used to accomplish the suggested strategy. Phase-I's goal is to categorize the FDCT (host) bundles, with each input bundle being assigned to one of four distinct bundles. Phase-II's goal is to use the adaptive least significant bit (LSB) approach to embed data bits in

Table 1: Hardware and software specification

Device	Description
Processors	Intel(R) Core(TM) i7-10750H CPU @ 2.60GHz
Random Access Memory	16.0 GB
Graphical Processing Unit	NVIDIA GeForce RTX 3050Ti
Space	Samsung SSD 970 EVO Plus 2TB
Programming language	Python

the chosen coefficients of the categorized bundles in accordance with a specified bit-index table (which was obtained from phase-I). Simulations demonstrated that concealed bits could be retrieved without artefacts and that the original ECG signal could be fully restored.

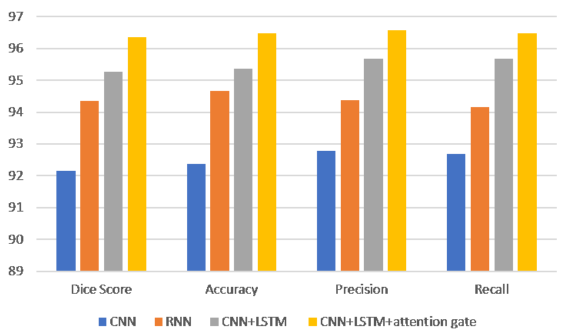

Fig. 7: Comparison between CNN+LSTM+attention gate and other architecture in classification before augmentation

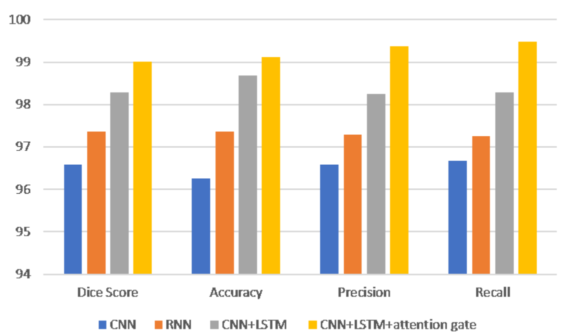

Fig. 8: Comparison between CNN+LSTM+attention gate and other architecture in classification after augmentation

3.5 Hardware and Software specification

Table. 1 shows the hardware and software specification which used by the hybrid framework.

Table 2: Payload and SNR/PRD performance of the proposed method in BPS=1.0

ECG data	Payload	SNR	PRD
ecg100	35,333	46.9636	0.004486
ecg101	30,220	47.395	0.00427
ecg102	33,325	47.1522	0.004397
ecg103	31,650	47.6664	0.004149
ecg104	29,175	47.4548	0.004241
ecg111	28,539	48.2741	0.00386
ecg112	35,114	46.226	0.004896
ecg113	27,692	48.4262	0.003855
ecg114	30,970	47.2325	0.0038565
ecg115	39,455	45.8758	0.005122
ecg121	38,721	48.5214	0.005281
ecg122	30,824	46.7199	0.004128
ecg123	29,826	48.9858	0.004954
ecg124	29,602	45.3035	0.005205
ecg200	23,569	49.9877	0.0033

Table 3: Payload and SNR/PRD performance of the proposed method in BPS=2.0

ECG data	Payload	SNR	PRD
ecg100	64,856	37.3753	0.013528
ecg101	61,494	36.8479	0.019825
ecg102	63,085	37.8017	0.019896
ecg103	61,672	37.4595	0.024478
ecg104	58,206	36.7397	0.019873
ecg111	60,743	36.5714	0.014892
ecg112	61,456	36.6809	0.014798
ecg113	58,234	36.5134	0.014257
ecg114	64,693	36.0326	0.01373
ecg115	62,858	37.6371	0.026179
ecg121	61,714	36.5921	0.058931
ecg122	59,288	35.1828	0.017955
ecg123	59,915	37.3521	0.014869
ecg124	63,221	36.8852	0.014668
ecg200	56,749	36.6153	0.026711

4 Discussion and Results

This part of the paper shows the results of different section of the framework such as augmentation using latent diffusion model, multi classification results using CNN+ LSTM with the attention gate and the relate between SNR and BPS for the used approach based on adaptive LSB with neutrosophic using diverse and five different values of the pattern parameter a and various . It is set to 3 for the parameter. The chart shows that the SNR performance is highest between 0.5 and 1.1 at the BPS-axis when a = 20. Except for when a = 10, the SNR

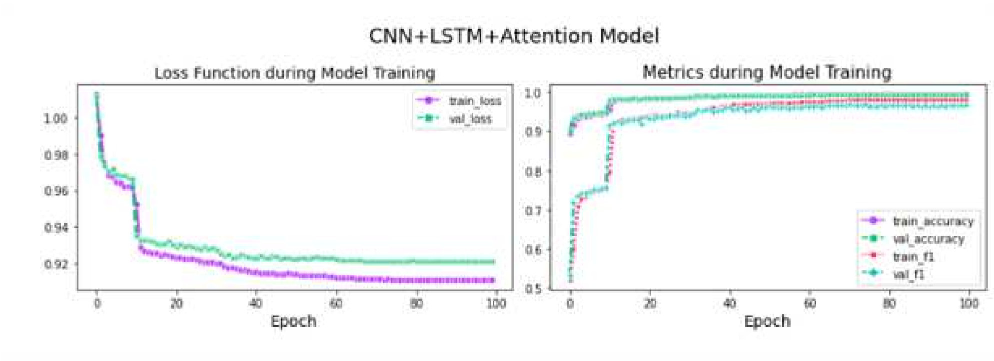

Fig. 9: Loss function and training model

Table 4: Results of the augmentation process using latent diffusion model and different GANs architectures

Model	Vanilla GAN	DCGAN	Speckle GAN	Mix Plus GAN	Ultra GAN	Latent Diffusion Model
Inception score	13.89	13.11	13.21	12.36	13.69	14.67
Freshet inception distance	40.96	46.46	45.26	46.25	42.26	37.89

Table 5: Results of classification before augmentation

Model	Dice Score	Accuracy	Precision	Recall
CNN	92.15	92.36	92.78	92.69
RNN	94.36	94.67	94.37	94.15
CNN+LSTM	95.26	95.36	95.69	95.69
CNN+LSTM+attention gate	96.36	96.47	96.58	96.47

performance of the other four values is comparable as shown in Table.2 and Table.3 respectively.

Table.4 shows the results of comparison between latent diffusion model and other architecture of GANs. The results shows the efficiency of Latent diffusion model when compared with GANs architectures according the values of inception score and freshet inception distance.Fig.6 shows the chart of the comparison.

Table.5 shows the comparison between the modified frameworks before 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 also shows the comparison between CNN+LSTM+attention gate and other architecture in classification before augmentation.

Table.6 shows the results after augmentation process using latent diffusion model. The results in the table also shows the positive efficiency of latent diffusion model in the different architecture of classification. Fig.7 shows the comparison between CNN+LSTM with attention gate after augmentation using latent diffusion model and other architectures in classification. Fig. 8 shows the training model and loss function.

5 Conclusion

ECG is one of most important data for any cardio field. The ECG is also so limited data for any clinicians. Clinicians needs additional data for accurate diagnosis and examination. The privacy of the patient data also become one of the most important challenge in this field. Hiding the patient data inside the ECG signal while transmission. This paper presented a novel framework for steganography the data inside the ECG signal using embedding and neutrosophic set. The paper also present an augmentation method based on latent diffusion model for augmentation the dataset. And also present a CNN+ LSTM with attention mechanism for classification. The experiments done prove the efficiency of the different section of the paper when compared with other methods in the same area.although the proposed framework achieves good results in each parts but there are some of limitation such as mode collapse and vanishing gradient problem. In the future; latent diffusion model will be used in Augmentation part and also we will solve the problem of mode collapse using new loss function such as western function.

Table 6: Results of classification after augmentation

Model	Dice Score	Accuracy	Precision	Recall
CNN	96.59	96.25	96.59	96.68
RNN	97.36	97.36	97.29	97.25
CNN+LSTM	98.28	98.68	98.25	98.29
CNN+LSTM+attention gate	99.01	99.12	99.38	99.48

References

[1] H. Saadi, M. Ferroukhi, Y. L. Elghandja, and F. Lahmari, "Low-cost ecg monitoring system with classification using deep learning," in *2023 International Conference on Advances in Electronics, Control and Communication Systems (ICAECCS)*, pp. 1–6, 2023.

[2] P. Wang, X. Huang, and L. Cui, "Ir-ecg: Invertible reconstruction of ecg," in *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1–5, 2023.

[3] L. N. Thalluri, H. Koripalli, P. K. N. Nukala, V. N. S. R. Mandava, G. Gudapati, and V. V. N. Yaswanth, "Ecg signal classification using deep neural networks with ensemble techniques," in *2022 7th International Conference on Communication and Electronics Systems (ICCES)*, pp. 273–280, 2022.

[4] A. Ukil, L. Marin, and A. J. Jara, "Priv-aug-shap-ecgresnet: Privacy preserving shapley-value attributed augmented resnet for practical single-lead electrocardiogram classification," in *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1–5, 2023.

[5] G. B. Moody and R. G. Mark, "The impact of the mit-bih arrhythmia database," *IEEE engineering in medicine and biology magazine*, vol. 20, no. 3, pp. 45–50, 2001.

[6] J. Mohana, B. Yakkala, S. Vimalnath, P. Benson Mansingh, N. Yuvaraj, K. Srihari, G. Sasikala, V. Mahalakshmi, R. Yasir Abdullah, and V. P. Sundramurthy, "Application of internet of things on the healthcare field using convolutional neural network processing," *Journal of Healthcare Engineering*, vol. 2022, 2022.

[7] A. M. Hilal, I. Issaoui, M. Obayya, F. N. Al-Wesabi, N. Nemri, M. A. Hamza, M. Al Duhayyim, and A. S. Zamani, "Modeling of explainable artificial intelligence for biomedical mental disorder diagnosis," *CMC-COMPUTERS MATERIALS & CONTINUA*, vol. 71, no. 2, pp. 3853–3867, 2022.

[8] I. Azimi, J. Takalo-Mattila, A. Anzanpour, A. M. Rahmani, J.-P. Soininen, and P. Liljeberg, "Empowering healthcare iot systems with hierarchical edge-based deep learning," in *Proceedings of the 2018 IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies*, pp. 63–68, 2018.

[9] G. Xu, "Iot-assisted ecg monitoring framework with secure data transmission for health care applications," *IEEE Access*, vol. 8, pp. 74586–74594, 2020.

[10] U. B. Baloglu, M. Talo, O. Yildirim, R. San Tan, and U. R. Acharya, "Classification of myocardial infarction with multi-lead ecg signals and deep cnn," *Pattern recognition letters*, vol. 122, pp. 23–30, 2019.

[11] R. Shanthapriya and V. Vaithianathan, "Ecg-based secure healthcare monitoring system in body area networks," in *2018 Fourth International Conference on Biosignals, Images and Instrumentation (ICBSII)*, pp. 206–212, IEEE, 2018.

[12] M. Karthikeyan and J. M. L. Manickam, "Ecg-signal based secret key generation (eskg) scheme for wban and hardware implementation," *Wireless Personal Communications*, vol. 106, no. 4, pp. 2037–2052, 2019.

[13] M. Attya, A. S. Sakr, H. Abdulkader, F. Al-Showaikh, and M. K. El-Sayed, "Novel framework for selecting cloud provider using neutrosophic and modified gan," *Appl. Math*, vol. 17, no. 2, pp. 293–307, 2023.

[14] P. Warden and D. Situnayake, *Tinyml: Machine learning with tensorflow lite on arduino and ultra-low-power microcontrollers*. O'Reilly Media, 2019.

[15] S. O. Ooko, D. Mukanyiligira, J. P. Munyampundu, and J. Nsenga, "Edge ai-based respiratory disease recognition from exhaled breath signatures," in *2021 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT)*, pp. 89–94, IEEE, 2021.

[16] S. Celin and K. Vasanth, "Ecg signal classification using various machine learning techniques," *Journal of medical systems*, vol. 42, no. 12, p. 241, 2018.

[17] A. Amirshahi and M. Hashemi, "Ecg classification algorithm based on stdp and r-stdp neural networks for real-time monitoring on ultra low-power personal wearable devices," *IEEE transactions on biomedical circuits and systems*, vol. 13, no. 6, pp. 1483–1493, 2019.

[18] P. Li, Y. Wang, J. He, L. Wang, Y. Tian, T.-s. Zhou, T. Li, and J.-s. Li, "High-performance personalized heartbeat classification model for long-term ecg signal," *IEEE Transactions on Biomedical Engineering*, vol. 64, no. 1, pp. 78–86, 2016.

[19] M. Attya, M. K. El-Sayed, A. Sakr, and H. Ahmed, "An evaluation framework for selecting cloud service provider in neutrosophic environment and modified generative adversarial network," *IJCI. International Journal of Computers and Information*, vol. 10, no. 1, pp. 78–89, 2023.

[20] A. Zand, W. K. van Deen, E. K. Inserra, L. Hall, E. Kane, A. Centeno, J. M. Choi, C. Y. Ha, E. Esrailian, G. R. D'Haens, *et al.*, "Presenteeism in inflammatory bowel diseases: a hidden problem with significant economic impact," *Inflammatory bowel diseases*, vol. 21, no. 7, pp. 1623–1630, 2015.

[21] T. Tuncer, S. Dogan, P. Pławiak, and U. R. Acharya, "Automated arrhythmia detection using novel hexadecimal local pattern and multilevel wavelet transform with ecg signals," *Knowledge-Based Systems*, vol. 186, p. 104923, 2019.

[22] S. Aarthy and J. M. Iqbal, “Retracted article: Time series real time naive bayes electrocardiogram signal classification for efficient disease prediction using fuzzy rules,” *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 5, pp. 5257–5267, 2021.

Abdalla Rizk, He was born in Egypt, in 1998. He received the B.Sc. degree in information system from menoufia university and the M.Sc. degree in information system from menoufia University, Egypt, in 2020 and 2023, respectively. He is currently an Assistant Lecturer of information technology with the Faculty of Industry technology and energy, delta technology University. He has published many research articles published in prestigious international conferences and reputable journals. His current research interests include big data analysis, imagine processing, linked open data, data mining,decision making ,decision support systems and machine learning.

Ahmed Sakr, He received the B.Sc. degree (Hons.) in mathematics and computer science and the M.Sc. degree in computer science from Menoufia University, Egypt, in 2008 and 2013, respectively, and the Ph.D. degree in computer science from Menoufia University, Egypt, in 2016. He is currently an assistant professor at Cybersecurity Department, Engineering and Information Technology College, Buraydah Private Colleges, Buraydah 51418,SaudiArabia and faculty of computers and information at Menoufia University, Menoufia, Egypt. He has authored or co-authored many publications, in ranked journals including refereed IEEE, conference papers. His areas of interests are multimedia content encryption, big data security, secret media sharing, information hiding, cloud computing, bioinformatics and DNA encryption.

Hatem Mohamed, He is a Professor in the Information System and Dean of faculty of computers and information at Menoufia University, Egypt . His research interests include software testing, software engineering, distributed system, cloud computing, IoT, big Data analytics, and bioinformatics.