CHAPTER 6

CONCLUSIONS AND FUTURE SCOPE

The presented research work presents a novel way of dealing with the problem of smoothing noised ECG signals and classification using deep learner CNNs and secure transmission. A detailed flow scheme for the elimination of baseline wanders and high-frequency noise, features extraction, classification encryption, and authentication are explained in this research. In this flow, the data is first loaded from the MIT-BIH database, and then the down-sampling procedure is employed for the sampled data; for reduction of baseline wander, the output is further given to Savitzky-Golay (SG) filter to reduce the noise present in the ECG information. After that, the Maximal overlap wavelet packet transform (MOWPT) is employed to remove high-frequency noises. Following pre-processing, the wavelet transform is used to retrieve features, and the number of features is provided before the information is sent to the channel, which uses a cryptographic authenticity mechanism to achieve security. The next step is to encrypt the data using the cypher-block-chaining (CBC) mode of the triple data encryption standard (3-DES) method. This transmission method sends cypher text together by a verification identifier that enables the recipient to validate the validity of the data. Private data, a security key, and an IV key are the three inputs needed for data encryption in the CBC manner. As a result, the water cycle optimization (WCO) method is used to determine the initialization vector key. The digitized ECG data is then separated into distinct blocks (64 bits). Then, for encryption purposes, the block data information is supplied to the triple data encryption standard (3-DES) algorithm with the IV and key.

For each block, the encryption process is used again to receive encrypted data. Aside from that, the encrypted data in the final block serves as an authentication tag, allowing the receiver to verify the authenticity of the data. To assess security, various criteria are employed for the performance of data encryption. ThingSpeak uploads encrypted data and authentication tags on the cloud channel in the third stage. The user and IV keys are also sent to the receiver over a secure channel. On the receiver side, the receiver receives the encrypted data and the authentication tag from the cloud.

In the same way, the user key and IV key are recovered from the secure channel. The secret data is presented in the output when the decryption algorithm gets the encrypted data, user key, and IV key. After recovering the secret data, the receiver generates an authentication tag using the same CBC mode as the transmitter. After that, the authentication tags are compared. Authentication was successful if the authentication tags had identical values; otherwise, it failed. Post-processing is used to request it to resend the information. The triple data encryption standard (3-DES) was used for encryption, and the water cycle optimization (WCO) method was used for authentication. Then, using ThingSpeak, an Internet of Things (IoT) platform, encrypted and authenticated ECG characteristics are sent to a cardiologist for examination.

For the MIT-BIH database, we identified five categories of arrhythmias in our proposed work. Five of its heartbeats are annotated and identified using the labels N, S, V, F, and Q, which are indexed as class 0, class 1, class 2, class 3, and class 4 respectively. The label N represents non-ectopic beat, the label S represents supraventricular ectopic beat, the label V represents ventricular ectopic beat, the label F represents fusion beats, and the label Q represents unknown beats. The research work collected total number of 87554 ECG beats. The non-ectopic heartbeat data is 72471, the supraventricular ectopic heartbeat data is 6431, the ventricular ectopic heartbeat data is 5788, the fusion heartbeat data is 2223, and the unknown heartbeat data is 611. The QRS waveform of the synthesized ECG data is identical to that of the original ECG waveform by expending the total number of samples of each class. The S-type heartbeat data is expanded to 26431. The V-type heartbeat data is expanded to 25788. The F-type heartbeat data is expanded to 22223. The Q-type heartbeat data is expanded to 20611. The suggested deep learner convolution Neural network (CNN) classification divides the data into 5 categories of arrhythmias with an average accuracy of 98%. The identification and detection of cardiac arrhythmia is integrated with the Internet of medical things (IoT), allowing users to monitor their health during daily activities like walking and jogging. Future development of the proposed research work includes implementation of another existing encryption technique and better machine learning-based classification for different cardiac conditions in telecardiology.

Future scope

For real-time applications in diagnosing cardiac arrhythmias, automatic heartbeat classification is essential. This thesis highlights the promising potential for future advancements in automated ECG classification systems. The systems must encompass four key processes: pre-processing, QRS complex recognition, feature extraction, and heartbeat classification. Future research should prioritize developing novel techniques for feature extraction and classification. The following suggestions could guide these advancements:

1. The features that could increase the classification accuracy can be extracted using a variety of additional transformations, including the discrete cosine transform (DCT) and other time-frequency approaches.

2. Variable ECG beat length may be selected for feature extraction and classification to increase the detection rate.

3. To improve the classifier's classification accuracy compared to the current heartbeat classifiers.

4. Additional dimensionality reduction approaches can be carried out as a future path as an extension of the three-feature selection method.

5. The unsupervised methods may be modified for classifying real-time data analysis since the supervised classification system is employed for ECG beat identification.

6. This thesis suggests five methods for categorizing ECG beats, each producing different misclassification patterns in a supervised classification system. Therefore, integrating all these methods can be adjusted to improve system performance by reducing misclassification.

7. Now a days, machine learning (ML) techniques are widely employed to classified ECG data. However, using heuristic features with low-feature learning architectures is the fundamental drawback of these ML outcomes. An alternative strategy emphasizes using deep learning architectures for selecting the final ECG class. This deep learning architecture method

simplifies creating new feature extractors for each issue. Artificial neural networks, which are used in learning algorithms, are inspired by the organization and operation of the brain. Deep learning classifiers are in high demand because of these benefits and may be employed in classifying ECG beats.