Advancements in ECG Signal Processing: Compression, Generation, and Prediction Techniques

Abstract—**In emergency situations, patients frequently require immediate medical care, which can be difficult to provide while transporting them to a healthcare facility. This difficulty is particularly significant when patients are severely injured and require immediate medical care. Historically, nurses have provided rudimentary medical care during ambulance transport, but their scope of practise is limited. We propose a method that enables physicians to remotely monitor patient vitals and provide quality medical care to a patient in an ambulance from a hospital hundreds of kilometres away. The system enables doctors to provide timely and accurate diagnoses and treatment recommendations, thereby reducing the risk of transport complications. In addition, the system assures continuity of care by allowing physicians to begin treatment before the patient arrives at the hospital, resulting in better outcomes.**

Index Terms—**Machine Learning, Wavelet Transforms, Time Series Forecasting, ECG, Signal Processing, Remote Monitoring**

I. Introduction

In our research, we investigated numerous time series methods and methodologies for predicting ECG signals. Initially, we endeavoured to distinguish between the P, Q, R, S, and T peaks and use their cyclical patterns to predict forthcoming waves. However, this strategy proved ineffective for arrhythmia patients. Then, we investigated alternative techniques, such as Fourier analysis, wavelet analysis, and neural networks, for generating more precise predictions. By analysing the ECG signals in a variety of ways, we intended to gain a deeper understanding of the signals' underlying patterns and behaviors, which would ultimately result in more accurate predictions and diagnoses of cardiac conditions.

In addition, we investigate the use of wavelet transforms for ECG signal compression. This method facilitates the transmission of ECG signals over mobile networks to hospitals, where they can be analysed. The compressed ECG signals can be transmitted rapidly, allowing for surveillance and diagnosis in real time. Nonetheless, in instances where signal transmission is lost, our proposed signal prediction model is utilised. The model employs machine learning techniques to predict the ECG signal until the transmission of the original signal resumes. This strategy assures continuity of care, even in instances where the signal may be temporarily interrupted. Our proposed system represents a significant advancement in the remote surveillance and diagnosis of ECG signals, resulting in improved patient outcomes and enhanced emergency medical care efficiency.

II. Data

The MIT-BIH Arrhythmia Database [12] is a collection of electrocardiogram (ECG) recordings obtained from patients with diverse types of arrhythmia. The database contains 48 half-hour ECG recordings sampled at 360 Hz with two leads per subject. It has become a popular resource for the development and evaluation of arrhythmia detection algorithms and other signal-processing techniques. The dataset contains annotations indicating the location and nature of each heartbeat, making it a useful resource for training and evaluating machine learning models for ECG analysis.

We also use the Physiobank [6] database to source our data. Specifically, we use the Biometric human identification ECG database (ecgiddb). The database contains 310 ECG recordings obtained from 90 different individuals, representing a wide variety of data. Each recording consists of a 500 Hz, 12-bit digitization of a 20-second I-lead ECG signal. An automated detector was used to annotate the R- and T-wave maxima of 10 beats in each recording. The number of records for each individual ranges from 2 to 20, collected either in a single day or intermittently over a period of 6 months, and each recording is accompanied by age, gender, and recording date information.

The recordings' unprocessed data is quite chaotic and includes both high- and low-frequency noise components. In order to counteract this, each recording incorporates raw and filtered signals, with Column 0 representing the raw signal and Column 1 representing the filtered signal. The dataset was acquired from students, colleagues, and acquaintances, with

44 men and 46 women ranging in age from 13 to 75 years old, providing a wide variety of data for analysis. Overall, this database is a useful tool for analysing ECG signals and cardiac conditions.

III. Related Work

Studies on peak detection, ECG signal generation, and wavelet transforms all pertain to the analysis and interpretation of ECG signals. Peak detection is crucial for identifying critical points in the ECG signal, whereas ECG signal generation can be used to evaluate the performance of ECG devices and algorithms. Wavelet transforms, on the other hand, are a potent mathematical instrument for analysing signals in both the time and frequency domains, and can be used in a variety of applications, such as ECG analysis. These studies have contributed to a greater comprehension of ECG signals and their potential medical applications.

GeM-REM [13] proposes a generative model-driven resource-efficient ECG monitoring system for body sensor networks that uses a deep generative model to reconstruct absent ECG signals and achieves greater accuracy with fewer resources than conventional methods. Proposed is a two-module system in which a base module, M_{BS}, and a sensor module, $M_{LIT\ E}$, work in tandem to generate accurate ECG signals. The most important aspects of this paper are that it proposes a QRS detection algorithm for use in $M_{LIT\ E}$ and that data is transmitted from $M_{LIT\ E}$ to M_{BS} only if the generated ECG and the actual ECG are more dissimilar than a predetermined threshold.

Separately, [1] proposed a dynamical model for synthesising ECG signals that captures the heart's underlying dynamics. This model generates realistic ECG signals for use in training and testing machine learning models for ECG signal processing tasks, such as cardiac condition prediction and diagnosis. It is founded on a mathematical analysis involving the solution of three coupled ordinary differential equations. This makes it less resilient to the anticipated rapid variations in heartbeat patterns in an ambulance setting.

As mentioned in [4] and [5], the generation of ECG signals using GANs is a promising area of research. Although these techniques can be beneficial for generating data, they are incapable of predicting future ECG signals. GANs rely on capturing and replicating patterns in the training data, but they may struggle to accurately capture the dynamic complexity of ECG signals. In addition, GANs are frequently employed in unsupervised learning, making it difficult to ensure that the generated signals align with clinical expectations and diagnostic criteria. GANs may not be the most effective method for anticipating future ECG signals in clinical settings, despite their utility in ECG signal analysis.

A mathematical instrument for analysing the peaks associated with a pulse is proposed in [11] . To achieve this, the authors separate the QRS peaks from the ECG signal using band-pass filters. The wave is then amplified to distinguish the T peak from the wave. This allows them to analyse the QRS complex and identify the Q, R, and S peaks associated with a single pulse. In order to pinpoint these peaks more precisely, the authors employ a set of thresholds. These thresholds enable a more accurate determination of the locations of each peak in the QRS complex, which can be useful for diagnosing cardiac conditions.

Transmitting ECG signals over a narrow bandwidth is a difficult task that calls for compression techniques. Various compression techniques for ECG signals have been the subject of multiple studies. Transform-based methods, such as wavelet transform, Fourier transform, and discrete cosine transform (DCT), and prediction-based methods are the most frequently employed techniques. [7] proposed a compression method based on discrete wavelet transform (DWT). The DWT compresses signal energy into a smaller data change and has perfect frequency and time localization capabilities. The DWT threshold has been chosen to perform for DWT coefficients based on the Energy Packing Efficiency of the signal (EPE). The selected DWT coefficient has been encoded with a Huffman encoder. In addition, [16] proposes a coding algorithm for compressing ECG signals following DWT preprocessing. The DWT coefficients are separated into three groups, and each group is thresholded based on the desired energy-packing efficiency. A binary significance map is then generated by scanning the coefficients of wavelet decomposition and outputting a binary one if the coefficient is significant and a binary zero if it is insignificant. Compression is achieved by compressing the significance map with a variable length code based on run length encoding and then representing significant coefficients with direct binary representation.

There are no benchmarks for predicting the future ECG signals of patients because it is a fairly complex task to capture the sudden, abrupt rise in signal amplitudes and the non-regular position of signal peaks. SOTA papers on time series forecasting do provide some promising results. [15] discusses the application of FFNN for predicting simulated ECG signals via the window shifting method. Replacing FFNN with a 1-dimensional CNN, as described in [14], can significantly improve the results because CNNs are superior at extracting features. LSTM [8] architectures are widely used for time-series forecasting tasks because they can retain the characteristics of past data points. For precipitation nowcasting, [17] introduced a novel architecture that combines the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs). Multiple CNN layers are followed by multiple LSTM layers, with skip connections between the CNN and LSTM layers. The skip connections allow the network to propagate low-level features learned by CNNs directly to the LSTM layers while avoiding the problem of vanishing gradients that can occur in deep neural networks.

Since the introduction of transformer architectures [19], this has been the standard architecture for time series forecasting, according to a survey on Transformers in Time Series published in [20]. Among those architectures, Temporal Fusion Transformers [9] and Deep Transformer Models [21] contributed to the SOTA results.

IV. Methodology

A. Feature Extraction

The concept of extraction is derived from the framework presented in [13]. The peaks of the ECG, which are the most prominent features in defining the signal, receive the initial focus. The reference [10] discusses an algorithmic method for detecting the R-peaks in an ECG signal. We went a bit further by locating local maximas and local minimas in close proximity to R-peaks in order to identify additional peaks among PQRST.

Taking advantage of the fact that the height and width of PQRTS peaks have a significant effect on the shape of the ECG signal, [2] discusses using the gaussian bell curve to regenerate the ECG signal from the detected peak positions. The objective is to generate Gaussian bell curves for each peak with a height equal to that of the peak and a width equal to the x-intercept at half of the peak's height. Now, they combine all the bell curves to produce an ECG signal comprised of all the peaks. This method performs better near the peaks as the curves are influenced by the height of the bell; however, in regions with few peaks, this method depicts a pronounced shift. We improved this approach by reducing the shift by skewing the bell curve in regions with few peaks.

B. Wavelet Transforms

Investigated various methods under wavelet transforms like Fourier transforms, DWT(discrete wavelet transforms). The data was taken from MIT-BIH Arrhythmia Database [12]. We used various wavelets like HAAR wavelet, DB4(daubechies), BIOR4.4 to compress the ECG signal. DWT was applied on the ECG signal and coefficients for various levels of decomposition were obtained. In signal compression, thresholding of a certain decomposition band is done by eliminating all coefficients that are smaller than a threshold . This introduces distortion in a certain aspect of the reconstructed signal. Thresholding does not create significant distortion because of energy invariance property as explained in [16]. The compression ratio obtained using this method was 7:1. We further tried to increase the compression ratio by equating the high frequency coefficients to zero. This does not distort the signal much as the high frequency coefficients correspond to the noise in the signal. Further, the signal is smoothed. Compression ratio obtained was 17:1.

Additionally, we explored the creation of custom wavelet for better compression. When a signal has a repeating pattern, a wavelet that has scaling function similar to the shape of the repeating pattern can give better compression ratio. To do this we define the desired scaling function that we want to match. We approximate the continuous scaling function with a discrete set of coefficients using numerical methods such as the least squares method. Using the wavelet filter bank theory, we computed the filter coefficients for the low pass filter. This involves computing the scaling coefficients and wavelet coefficients for the filter bank. We used the pywt library in python for all the above stated experiments.

C. Signal Prediction

We began by drawing ideas from the window-shifting technique described in [15]. We can use the previous 32 or 64 ECG signal values to predict the next one and assess which combination gives the best result. For the frameworks and architectures we tested, the most effective combination was using the previous 128 value to predict the next value. In retrospect, we determined that 128 ECG signal values correspond to 300–350 milliseconds of continuous signals, which is the average duration of time encompassing all peaks of the PQRTS complex. We began with arrays of ECG signals and used the window shifting method to generate an array with 129 columns, where each row represents a timestep. The first row, for instance, depicts the timestep t=0, as shown in fig[1]. The first 128 values will be used by the model as historical data, which means they will be inputted into the model, and the 129^{th} value will be the target variable that the model will predict.

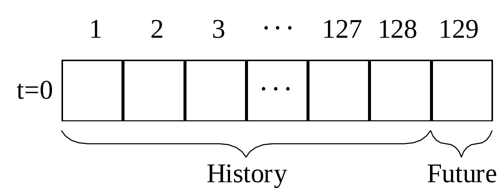

Fig. 1. timestep t=0

For the second time step, we will shift the window by 1 value and will use these new 128 values to predict the next 129^{th} value as shown in fig[2]. Similarly, we inputted the value of each time step in the model as shown in fig[3]

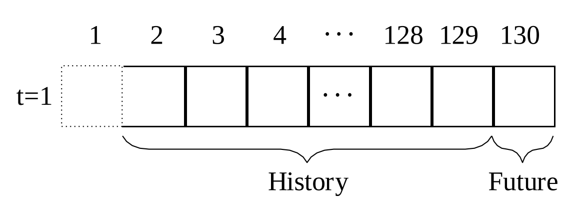

Fig. 2. timestep t=1

As mentioned about the window shifting method discussed in [15], we also start with their baseline of Feed Forward Neural Network(FNNN). We started with Dense Layer

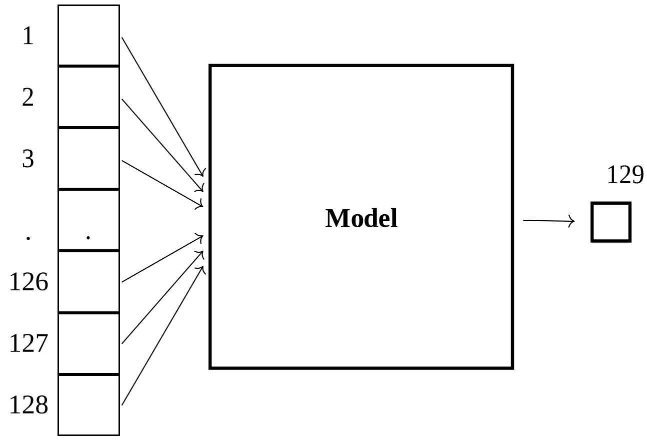

Fig. 3. Model Pipeline

architecture, as shown in fig [4], taking the 128 values and then predicting the next value. Then we tried CONV1D to predict the with the same window combination because they are better at low-level feature extraction as described by [3]. Then we stacked CNNs over LSTMs for the same window combination, and at last, we tried CNNs stacked over LSTMs with weak skip connections as shown here in fig[5]. We tried both **tanh** and **relu** as the activation function in all of our architectures and settled for the best activation at a certain layer level for each architecture.

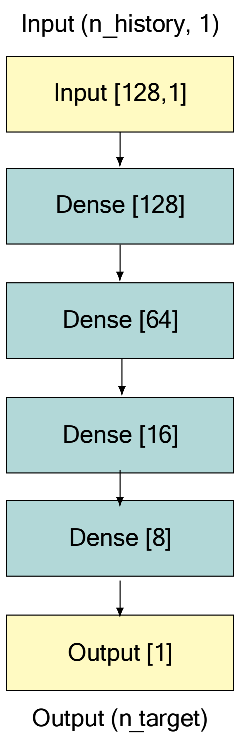

Fig. 4. Architecture: FFNN with Dense layers

TFTS [18] introduces a Python library named TensorFlow Time Series which facilitates easy-to-use function calls to implement SOTA in time series forecasting very conveniently. We implemented BERT, sequence2sequence, RNN, and transformer from that library and assessed how differently they work on this task than the standard architectures implemented initially.

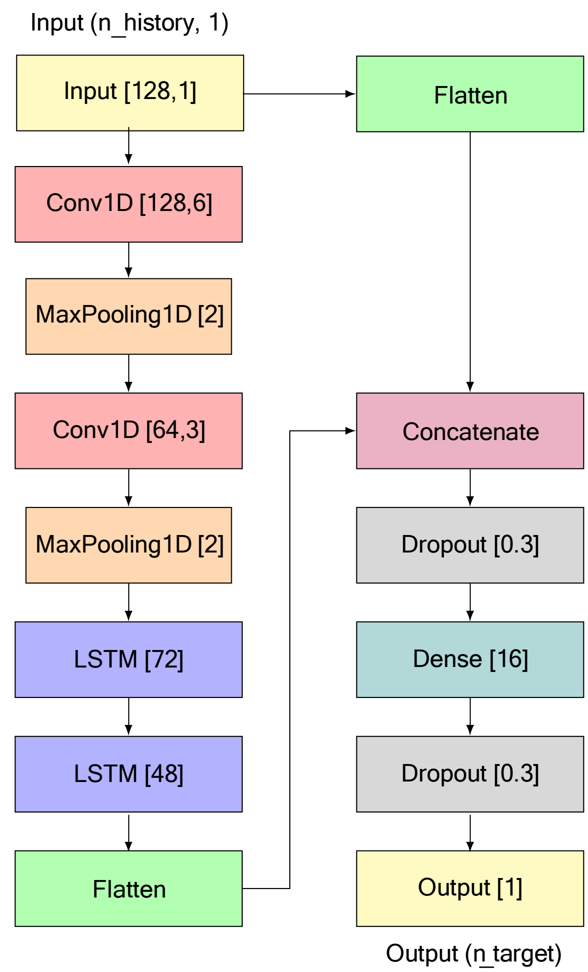

Fig. 5. Architecture: CNNs stacked over LSTMs with skip connections

V. Experiments and Results

A. Feature extraction

The method discussed in IV-A results in the successful detection of all the peaks comprising in PQRTS complex in the case of a normal heart patient, as shown in fig[6]. In the case of abnormal patients, the ECG signal shows no regular pattern in such a way that peaks can not be identified even manually; hence our improved algorithm also fails in this case. The improvement in the Gaussian method we discussed gives a significant improvement in the regenerated curve both metrically and visually. Fig[7] denotes the generated black curves before biasing, and fig[8] denotes the same after biasing.

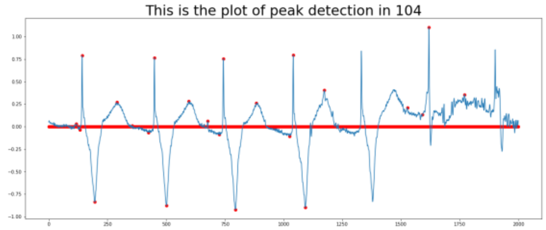

Fig. 6. Red dot represents the peaks

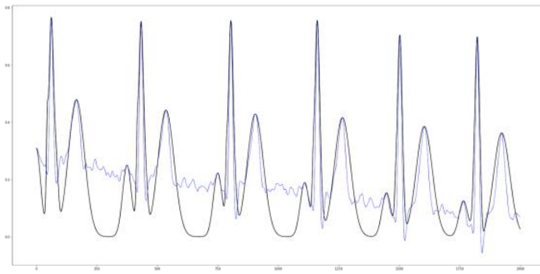

Fig. 7. Regeneration by biasing before biasing

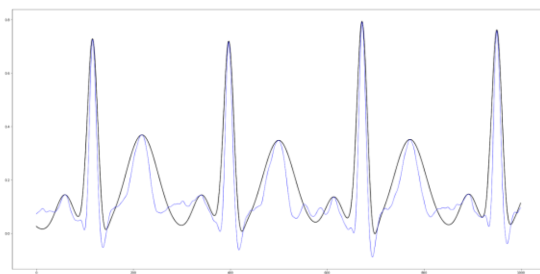

Fig. 8. Regeneration by biasing after biasing

B. Signal Compression

Figures [9], [10], and [11] include some snapshots of reconstructed waves after compression. The wavees were taken from the MIT-BIH dataset [12].

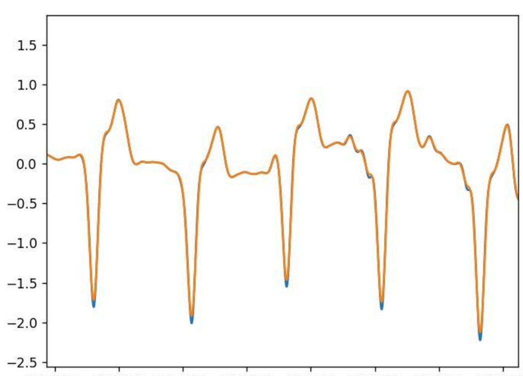

Fig. 9. Prefect reconstruction without compression

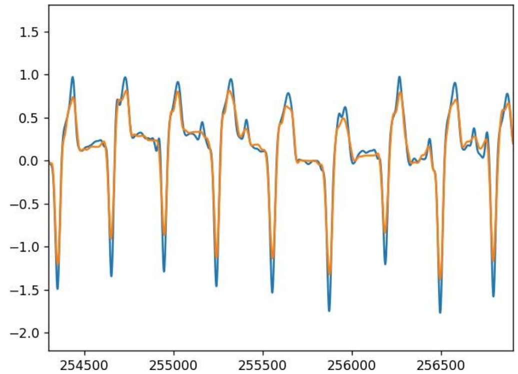

Fig. 10. Reconstruction after thresholding CR=7:1

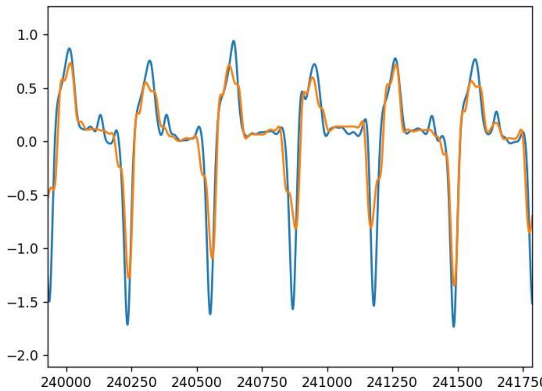

Fig. 11. Reconstruction after removing high-frequency coefficients CR 17:1

C. Signal Prediction

The methods discussed in (IV-C) were implemented with hyperparameter tuning being experimented on them while training. These waves were taken from the Physiobank dataset [6].

The orange lines represent the predicted signals, while the blue lines represent the original signals. Chronologically, some milestone architectures have been implemented, and their results are as follows:

1) **Dense** (Fig 12)

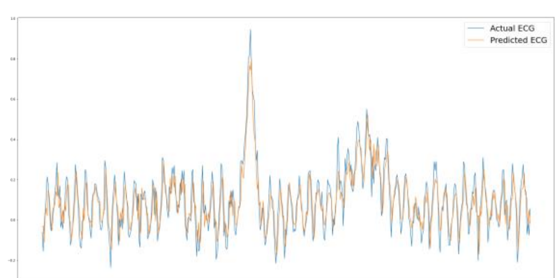

Fig. 12. Prediction by FFNN(Dense layers)

2) **CNNs stacked over LSTMs** (Fig 13)

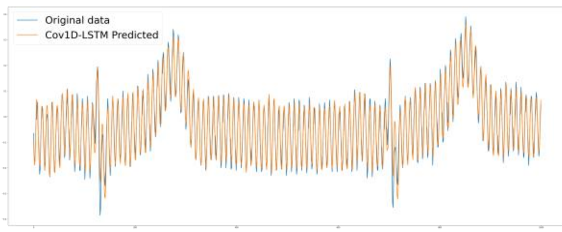

Fig. 13. Prediction by LSTM stacked CNNs

3) **CNNs-LSTMS with Skip Connections** (Fig 14)
During the implementation of this architecture, we conducted experiments to predict multiple values of an ECG signal by considering a significant number of historical data points. In addition to our standard window combination of $128 : 1$, we tried using $720 : 360$. This means that we can predict the ECG signal continuously for one second, as 360 values roughly correspond to one second.

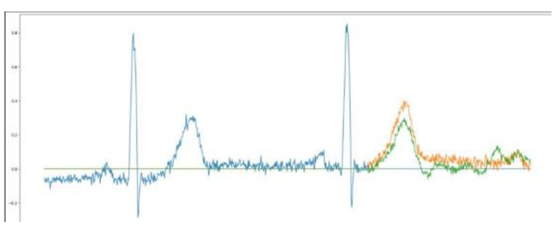

Fig. 14. Prediction by LSTM stacked CNNs with skip connections

4) **TFTS BERT** (Fig 15)

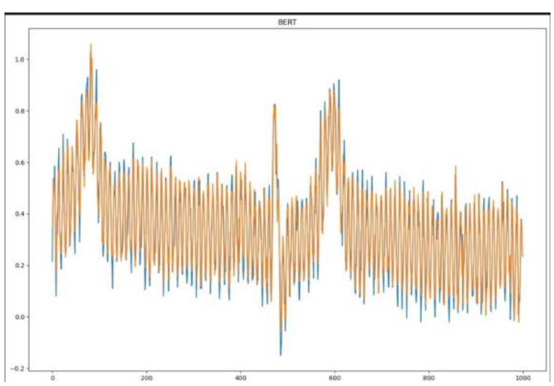

Fig. 15. Prediction by TFTS BERT

The Conv1D-LSTM(skip)$*$ model in Table I is for predicting the signals one second (360 values) in the future while the other models are used to predict just one value in the future ($1/360^{th}$ of a second).

VI. Future Work

We plan on developing a wavelet for common types of arrhythmia. A simple classifier will decide which type of

Model	R2 Score
Dense	0.87 ± 0.03
Conv1D	0.95 ± 0.02
LSTM	0.96 ± 0.02
Conv1D-LSTM	0.97 ± 0.01
Conv1D-LSTM(skip)	0.99 ± 0.008
Conv1D-LSTM(skip)$*$	0.76 ± 0.8

TABLE I
Standard Architectures

Model	R2 Score
BERT	0.84 ± 0.03
RNN	0.94 ± 0.02
seq2seq	0.92 ± 0.02
Transformer	0.89 ± 0.02

TABLE II
TFTS Models

arrhythmia is present, and we will appropriately compress the waves. If the wave doesn't match any of the predefined types, we will create a wavelet on the fly and compress the wave using that to achieve maximum compression ratio.

In addition to developing a wavelet for arrhythmia detection and compression, we also plan on using an ensemble model to improve our ability to predict future ECG signals. The ensemble model will consist of multiple individual models, each trained to predict a specific type of arrhythmia. By combining the outputs of these models, we can create a more accurate and robust prediction of future ECG signals, even when dealing with complex arrhythmias. This approach will help us to understand the underlying patterns in ECG signals better and improve our ability to diagnose and treat cardiac conditions. We are excited about the potential of this ensemble model to enhance our existing technology and contribute to better patient outcomes in the field of cardiology.

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