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A Novel and Efficient Framework for Diagnosing ECG Signals Based on the Digital Signal Processing and Optimized Transformer Model

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Abstract: **Heartbeat disorders are considered one of the main maladies that cause mortality. Therefore, their precocious diagnosis via ECG signal is critical for introducing prompt therapy. The advanced automatic classification of ECG signals has the potential to save cardiologists a tremendous amount of time while simultaneously decreasing the chance of misdiagnosis. The dilemma of massive parameters is troubling the current methods of ECG signal classification. Most recent methods exhibit inadequate performance for diagnosing ECG signals in the inter-patient mode. In an attempt to deal with the above limitations, this study offers an innovative, efficient, and end-to-end model. The suggested model uses the optimized transformer framework to classify the heartbeats according to the "Association for the Advancement of Medical Instrumentation, AAMI," and obeys the inter-patient setting. We constructed an efficient architecture called the optimized network to substitute the Self Attention Unit (SAU) in the encoder part of the transformer model. The suggested model, which includes an optimized network, outperforms the SAU-based transformer model and requires fewer computations. A robust embedding architecture based on a Convolutional Neural Network (CNN) with a Squeeze and Excitation (SE) network-based attention scheme that has been used for weighting the Local Heartbeat Shape Pattern (LHSP) features is presented. The introduced model exceeds the state-of-the-art. An extensive test has been done to compare the achievements of the suggested model with those of the cardiologists. The results proved the closeness of their performances.**

Keywords: **End-to-End; ECG Classification; Transformer Architecture; Squeeze and Excitation (SE); Depth Wise Convolution (DWC)**

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1. INTRODUCTION

An Electrocardiogram (ECG) is a popular tool for observing the electrical performance of the heart and is crucial in detecting cardiovascular disorders [1,2]. A typical ECG signal is composed of a series of beats that include a set of sequence waves [3,4]. The medical data of various sections of the heart muscle can be extracted from these waves [5–8]. **Fig. 1** illustrates the standard pattern of the ECG signal. The ECG signal needs to be observed and evaluated by an expert doctor to diagnose heart problems [9]. This aim is difficult to achieve because it requires numerous cardiologists and takes a long time, in addition to the possibility of medical errors in the diagnosis, which may lead to death [10]. To tackle the above challenges, the researchers introduced many advanced automatic heartbeat classifiers. There are two main directions. The first is based on classical methods that use handcrafted features and necessitate manual involvement. Besides, a feature selection process is also required. However, they have limited self-learning and consume time [11–14]. The second depends on Deep Learning (DL) schemes that fuse feature extraction and classification in an end-to-end way [15]. The DL approaches comprise three models: the first is based on CNN [16,17], the second depends on RNN [18,19], and the third is a hybrid that combines CNN and RNN [20,21]. The DL-based techniques, on the other hand, also have certain limitations. For instance, many DL-based schemes necessitate a high number of complicated convolution operations and recurrent architectures; this often yields a series of hidden states, each of which relies on the preceding one. As a result, such architectures have a low level of parallel computing. Currently, a transformer structure that includes a parallel SAU offers faster performance in the field of translation techniques [22,23]. However, the ordinary transformer model has scalable space. In addition to considerable-scale variables for training, the SAU of the transformer contours significant obstacles due to the context dimension, for instance, the quadratic term of the input size [24]. Note that the complicated methods have heavy computations with many variables, consume high power, and require optimization before being implemented on portable, real-time ECG devices. Also, their performance needs to be improved when applied under the AAMI rules and in inter-patient conditions where the training and testing signals are separated. In an attempt to tackle the above problems, this paper suggests a new, end-to-end model based on an adapted and optimized transformer architecture for the ECG signal diagnosis task. The following are our essential contributions:

- We suggest a new, efficient, end-to-end model suitable for ECG devices with limited resources based on a modified and optimized transformer structure. Furthermore, we improve a more abridged and robust framework by employing a dual attention technique. The first is local attention for the ECG input embedding. The second is universal attention based on an optimized network for addressing complicated computations and the high number of variables.
- The outcomes of the introduced model, which complied with AAMI prescripts and inter-patient settings, surpassed the other schemes in the literature.
- This research presented exclusive experiments that included comparing the performance resulting from the suggested model with its counterpart results from the decisions of cardiologists, where the results showed slight excellence of the offered model.

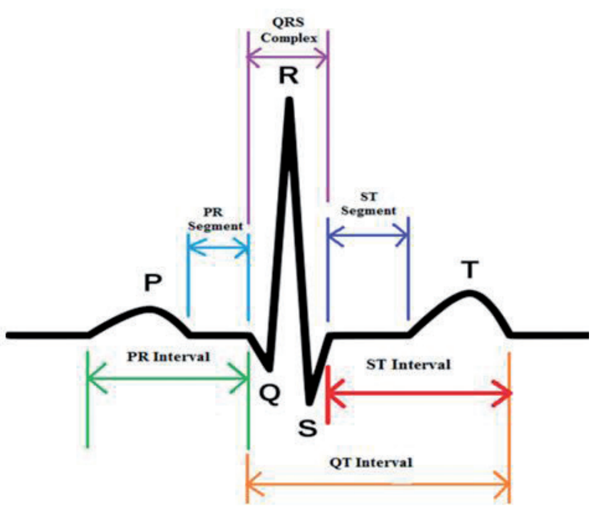

Fig. 1. *The standard pattern of the ECG signal.*

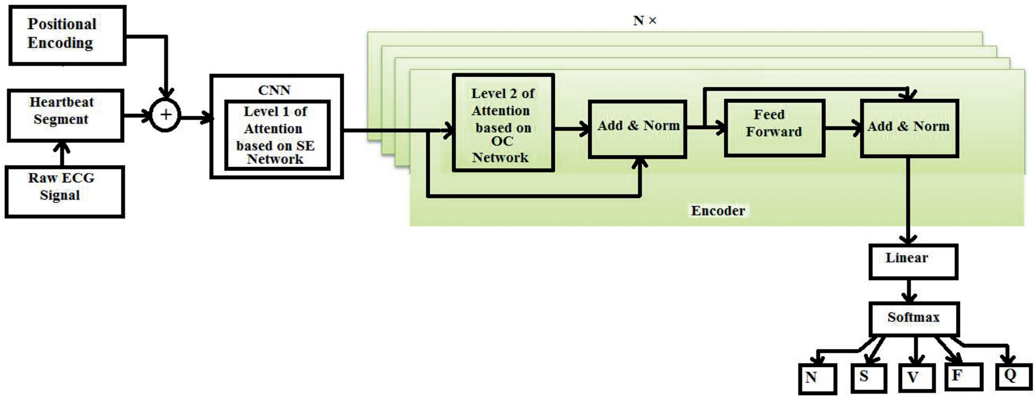

Fig. 2. *The block diagram of the suggested model.*

2. PROPOSED MODEL

After the normalization and R peak detection (based on the method in [25]) for the ECG signal of the MIT-BIH-ARR-DB (MIT-BIH Arrhythmia Database), the heartbeat segmentation is conducted. The length of each beat is 280 samples. The suggested model depends on the transformer framework proposed in [22] for language processing applications. The presented model uses only the encoder portion of the transformer framework, as illustrated in **Fig. 2.** Many modifications and developments to the encoder and input embedding portions have been made. On the input side, we introduce a novel attentional architecture based on CNN and the SE network [26] to strengthen the feature extraction power. To overcome the high number of parameters dilemma, a more effective and robust layout for substituting the SAU of the ordinary model [22] is presented. Furthermore, the offered model includes dual attention techniques, as shown in Fig. 2. Locally, level 1 of attention uses the SE network, and universally level 2 of attention utilizes the optimized network. Let the sequence $Q = (q_1, q_2, \ldots, q_L)$, L is the heartbeat length, then the output of the model $M = (m_1, m_2, m_3, m_4)$, where mj is the probability of Q arbitrated to class j.

2.1 Input Embedding

The primary step in the proposed framework is the embedding of the input. An architecture based on CNNs and SE networks is suggested for strengthening the power of capturing the LHSP features by CNNs and for weighting the LHSP features by the SE network, which represents level 1 of attention, as demonstrated in **Fig. 3**. Every

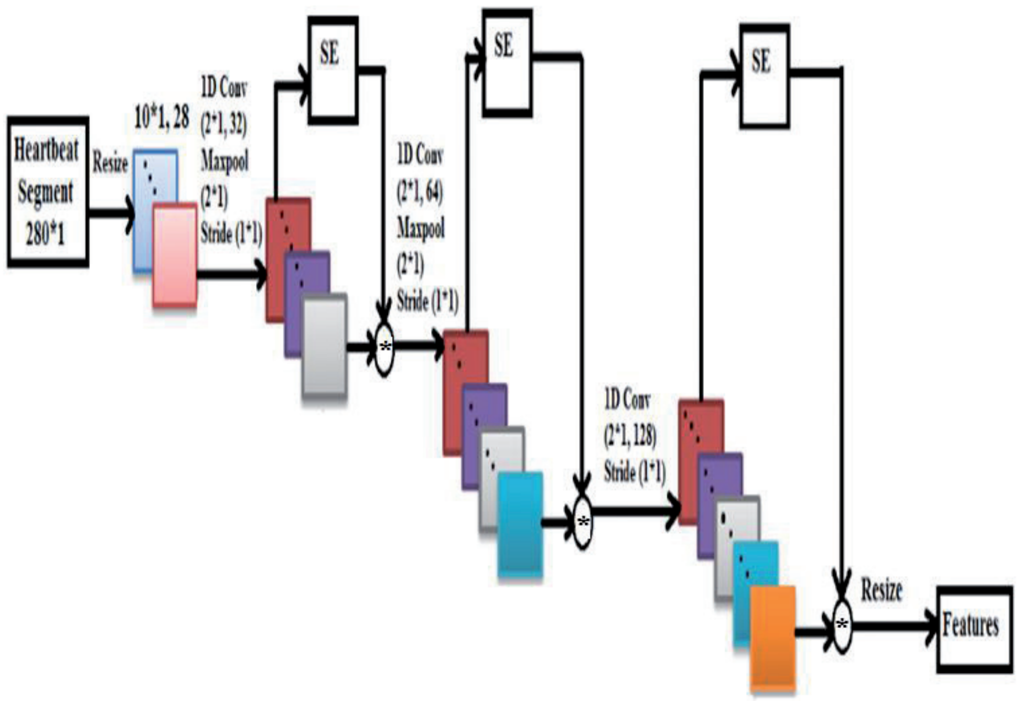

Fig. 3. *The suggested model structure of the input embedding unit.*

heartbeat segment is reconfigured into a feature vector $Q = (q_1, q_2, ..., qL), \in \mathbb{R}^{1\times F\times O}$, where O is the No. channels, the dimension of every channel is $1\times F$. The reconfiguration process includes setting $F = 10$ and $O = 28$. The Q is forwarded to three architectures with level 1 attention successively, and then the output G is a vector with the LHSP feature connection in the beats of the ECG signal. Moreover, the first two architectures comprise one convolution operation, G_{conv}, and one Global Maximum Pooling (GMP) operation, G_{max}. The third architecture does not include the GMP as displayed in Fig. 3. The suggested model implements a sequence of effective processes to increase its power to extract the LHSP features. The SE network is used to re-compute the convolution features and to weight the LHSP features. In other words, to focus on the significant LHSP features and eliminate worthless features such as noise, level 1 attention is used for weighting the LHSP features. This level of attention develops the suggested model's sensitivity to the LHSP information. The SE network consists of a Global Average Pooling Layer (GAPL) and two Fully Connected Layers (FCLs), as shown in **Fig. 4**. After a sequence of processes, the weight $E \in \mathbb{R}^{1+O'}$ of every channel conformable to the feature V', specifies the weight E of the feature V' based on the weighting process. These architectures and processes achieve the weighting of the LHSP features, draw attention to the significant LHSP features, and boost the association between the LHSP features. The

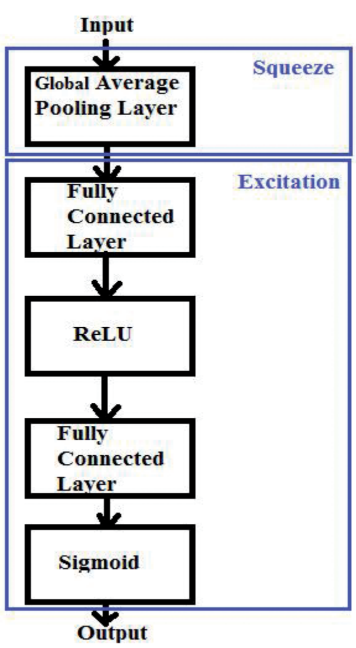

Fig. 4. *The detailed structure of the SE network.*

GAPL is applied to keep associations between the features and to produce the channel features.

$$H = G_{GAPL}(v') = \text{Concat}_{j=1}^{O'}\left(\frac{1}{B}\sum_{a=1}^{B} v'_a\right) \in \mathbb{R}^{1\times O'}. \quad (1)$$

The size of feature H is minimized, and then the size of the features is maximized, where the FCLs configure the $O'H$ for the channels to O'/CoF (CoF is the Compression Factor) to minimize the computations. The values of CoF are specified as 4, 8, and 16, successively.

$$E = sigmoid\left(\omega_2 \operatorname{Re}LU\left(\omega_1 H^T\right)\right) \in \mathbb{R}^{O'\times 1},$$
$$\omega_1 \in \mathbb{R}^{\frac{O'}{CoF}\times O'}, \omega_2 \in \mathbb{R}^{O'\times \frac{O'}{CoF}}. \quad (2)$$

The $ReLU$ is used to capture the non-linear interconnection between the LHSP features of the heartbeat. The sigmoid function is used to capture the relevance between the LHSP features.

$$ReLU(H) = \max(0,H), \quad (3)$$

$$sigmoid(H) = \frac{1}{1+e^{-H}}. \quad (4)$$

The entire equation is given below:

$$V'_a = G_{scale}(V', E) = E \cdot V' \in \mathbb{R}^{O'\times 1\times \frac{F'}{2}}. \quad (5)$$

2.2 Positional Encoding

It is required to pass the positional data of the ECG signal through an encoder and mount it with the provided embedding in the preceding step. The Sinusoidal Position Embedding (SPE) is used since it processes longer sequences with less time in the training stage. The SPE is described by the formulas given below [22]:

$$PoEn(PO, 2n) = \sin\left(PO / 10000^{2n/z_{model}}\right), \quad (6)$$

$$PoEn(PO, 2n+1) = \cos\left(PO / 10000^{2n/z_{model}}\right), \quad (7)$$

where n is the dimension, PO is the position, z_{model} is the dimension of output embedding.

2.3 Level 2 of Attention based on Optimized Network

The application of level 2 attention and the architecture of the optimized network are discussed in this section. A new and optimized architecture is applied to substitute the SAU of the original model presented in [22]. The optimized network mainly depends on the Optimized Convolution (OC). In the beginning, to understand the OC, the

Depth Wise Convolution (DWC) must be explained. The DWC implements the convolution over each channel individually. The number of parameters can be minimized from z^2w to zw, where w is the kernel width. The output $T \in \mathbb{R}^{t\times z}$ (t: is the No. time steps) of a DWC with weight $\omega \in \mathbb{R}^{w\times z}$ for the p^{th} element and o output size can be calculated using Eq. (8).

$$T_{p,o} = Depthwise\ Conv(Q, \omega_o, :, p, o) = \\ = \sum_{a=1}^{w} \omega_{o,a} \cdot Q_{\left(p+a-\frac{[w+1]}{2}\right),\ o}. \quad (8)$$

The OC can be defined using Eq. (9).

$$OC\left(Q, \omega_{\left\lceil \frac{oY}{z} \right\rceil}, :, p, o\right) = \\ = DWC\left(Q\ , soft\max\left(\omega_{\left\lceil \frac{oY}{z} \right\rceil}, :\right), p, o\right). \quad (9)$$

The z channels are segmented into Y sets, and then the parameters of every z/Y channel are combined. Therefore, the No. parameters is minimized to z/Y, for instance, the classical convolution necessitates 1310720 ($z^2 \times w$) weights for z = 512 and w = 5, whereas the DWC has 2560 ($z \times w$) weights, and with the weight sharing property, Y = 8, then we obtain only 40 ($Y \times w$); the weights $\omega \in \mathbb{R}^{Y\times w}$ are normalized using a softmax function.

The OC is a DWC that uses a softmax function to normalize its weights and shares specific output channels. Unlike SAU, the OC has a constant context window and uses weights that do not vary during time steps to evaluate the relevance of context components. **Fig. 5** illustrates the architecture of the SAU, while **Fig. 6** demonstrates the structure of the optimized network. The input of the optimized network is mapped from z to $2z$. After that, the GLU, OC, and SE networks are applied, respectively. The Gated Linear Unit (GLU) utilizes 50% of the inputs as gates using sigmoid modules and then determines the point-wise product with the remaining inputs. DropConnect is considered an efficient regularizer for the OC. Furthermore, DropConnect involves neglecting some of the interim data inside the channel [24]. The optimized network is responsible for catching and weighting the Global Heartbeat (GH) features.

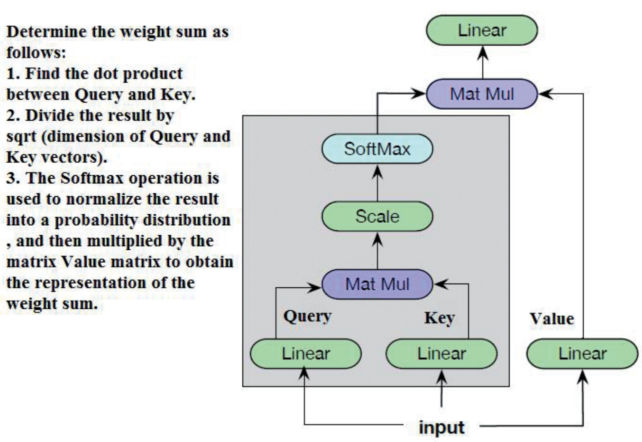

Fig. 5. *The architecture of the SAU.*

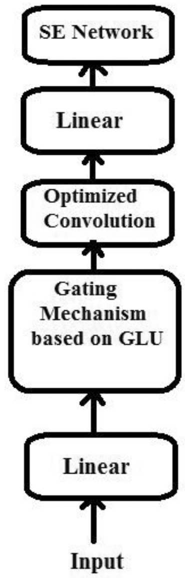

Fig. 6. *The structure of the optimized network.*

3. EXPERIMENTAL SETTINGS

The experiments for this research were carried out using MIT-BIH-ARR-DB [27], following the AAMI guidelines (as illustrated in **Table 1**) and the inter-patient strategy. To meet the inter-patient method, the training-test signal datasets are divided into DS1and DS2, as explained in [28]. DS1 is increased using

Table 1

Relabeling MIT-BIH beats based on the AAMI guidelines

AAMI Classes with Explaination	MIT-BIH Beats with Labels	
Normal beats (N)	N	Normal beat
	L	Left bundle branch block beat
	R	Right bundle branch block beat
	e	Atrial escape beat
	j	Nodal (junctional) escape beat
Supraventricular ectopic beats (SVEB)	A	Atrial premature beat
	a	Aberrated atrial premature beat
	J	Nodal (junctional) premature beat
	S	Supraventricular premature beat
Ventricular ectopic beats (VEB)	V	Premature Ventricular contraction
	E	Ventricular escape beat
Fusion beats (F)	F	Fusion of ventricular and normal beat
Unknown beats (Q)	/	Paced beat
	f	Fusion of paced and normal beat
	Q	Unclassified beat

Table 2

The optimal fusion of variables for the suggested model

Variables	Numerical Value
Dimension of output Embedding (z_{model})	64
Attention Layers	7
Batch Size (BS)	64
No. OC in Every Head	7
The Output Size of Linear Module (z_{inner})	512

SMOTE [29] to treat the dilemma of imbalanced data.

In order to identify the optimal variables for the model, we employ the control variable approach. The search focuses on four crucial variables, namely: z_{model}, Attention Layers, No. OC in Every Head, and z_{inner}. While three variables remain constant, we investigate the impact of the remaining variables on the outcomes. The optimal combination of variables is shown in **Table 2**.

4. RESULTS AND DISCUSSION

A comparison between the introduced model and the competitor approaches in the literature is presented by determining the following metrics: F1-Score, Positive Predictive Value (PPV), Sensitivity (SEN), and Accuracy (ACC), as stated in Equations 10-13.

$$F1-Score = \frac{2.PPV.SEN}{PPV+SEN}, \tag{10}$$

$$PPV = \frac{TP}{TP+FP}, \tag{11}$$

$$SEN = \frac{TP}{TP+FN}, \tag{12}$$

$$ACC = \frac{TP+TN}{TN+FN+TP+FP}, \tag{13}$$

where *FN*: False Negative, *FP*: False Positive, *TP*: True Positive.

The outcomes of the suggested framework and those of the state-of-the-art in recent literature are shown in **Table 3.** Overall, current techniques offer reasonable achievement in *V*-class identification. But, their accomplishments were noticeably reduced in *S*-class recognition; this is essentially a result of the distinguishable LHSP features for the *V*-category. The *S* class usually has LHSP, which is like the *N* class, making distinguishing between them difficult. The findings show our model surpasses the state-of-the-art, especially in detecting the *S*-class. In all categories, our model outperforms the current methodologies, demonstrating the effectiveness of the presented framework architecture. Referring to [30], which is the finest of the reported studies, our model boosted the F1-Score for both *S* and *V* class detection by 13.67% and 2.78%, respectively. However, the authors in [30] could get optimum PPV and SEN for *V* and *S* classes, but they did so at the expense of reduced SEN for *V* and poor PPV for *S* classes. Also, the approach suggested in [30] is not end-to-end, as our model is. Compared with [35], which is the newest in the reported works, the presented model raised the F1-score for *S, V*, and *N* by 53.93%, 16%, and 6.58%, respectively. Because most prior studies focused on the classification of *N, V*, and *S* classes, the detection of the *F* class in the suggested framework was compared with the results of cardiologists only.

4.1 Effect of Architectural Parts of the Proposed Model

To examine if the introduced structure can boost the detection process, we implemented the following tests: (the results are demonstrated in **Table 4**)

- **Level 2 of attention based on optimized network and level 1 of attention based on SE network (Wi level 2 and Wi level 1)**: The suggested model.

Table 3

Attainment comparison between the presented model and the state-of-the-art.

Reference	N (%)				S (%)				V (%)				Overall (%)
	PPV	SEN	ACC	F1-score	PPV	SEN	ACC	F1-score	PPV	SEN	ACC	F1-score	ACCo
[30]	**99.90**	99.10	-	99.49	75.70	**100**	-	86.16	**100**	95.40	-	97.11	98.10
[31]	98.17	99.42	-	98.79	89.54	74.65	-	81.37	93.25	95.65	-	94.43	-
[32]	98.00	94.00	-	95.96	53.00	62.00	-	57.15	59.40	87.30	-	70.70	-
[19]	97.60	99.80	97.80	98.68	95.70	66.90	98.30	78.74	98.20	92.30	99.20	95.15	98.40
[33]	97.60	97.50	-	97.54	59.40	83.80	-	69.52	90.20	80.40	-	85.01	95.10
[34]	98.50	97.60	96.80	98.64	74.00	76.80	97.50	75.37	92.40	93.80	98.60	93.09	97.60
[35]	93.33	94.54	-	93.33	65.88	35.22	-	45.90	79.86	88.35	-	83.89	88.99
Our model	99.89	**99.93**	**99.76**	**99.91**	**99.79**	99.88	**99.80**	**99.83**	99.85	**99.94**	**99.95**	**99.89**	**99.94**

Table 4

Outcomes of the introduced model with various structures

Architecture	Overall (%)	N (%)				S (%)				V (%)			
	ACC	SEN	PPV	ACC	F1-score	SEN	PPV	ACC	F1-score	SEN	PPV	ACC	F1-score
Wi level 2 and Wi level 1	**99.94**	**99.93**	**99.89**	**99.76**	**99.91**	**99.88**	99.79	**99.80**	**99.83**	99.94	**99.85**	**99.95**	**99.89**
Wi level 2 and Wo level 1	98.72	91.84	99.58	98.63	95.55	90.00	**99.86**	98.59	94.67	98.84	95.83	98.93	97.31
Wo level 2 and Wi level 1	98.82	99.33	99.65	98.48	99.49	91.03	88.18	98.52	89.58	99.96	99.44	98.89	99.70
Typical transformer model	97.53	99.11	99.34	97.42	99.22	85.33	93.21	97.37	89.09	**99.98**	99.73	97.88	99.85

- **Level 2 of attention based on the optimized network only (Wi level 2 and Wo level 1)**: The presented framework without level 1 attention.
- **Level 1 of attention based on the SE network only (Wo level 2 and Wi level 1)**: The suggested model without attention part of the optimized network.
- **Transformer Framework (Typical transformer model):** The typical transformer framework that involves self-attention [22].

The outcomes of the tests have demonstrated that an optimized network can substitute for the self-attention technique. Therefore, a self-attention scheme can be a dispensable architecture. Especially with the use of level 2 of the attention technique, the efficiency of the model has been considerably enhanced, particularly for the *S*-class. The use of the SE network in this architecture has a considerable role in weighting the GH features. The input embedding architecture with level 1 attention can also boost the rhythmic information and thus enhance the performance of the introduced model. We can notice slight developments in both types of beats (*N*-class and *V*-class), particularly in *V*-class, that support our prior estimation since the shape of *V*-class heartbeats varies significantly from those of *N*-class.

4.2 Parameters Reduction

One of our aims is to develop a computationally efficient model for ECG signal classification. For this task, we configure a variable comparison test. **Table 5** illustrates the comparison of No. parameters between the suggested model and the transformer model. Note that the No. of parameters for the overall presented model is 17.79% less than that for the typical transformer framework, while its value for level 2 attention based on the optimized network is 44% less than that for SAU (this is due to the use of OC). As a result, our method yields an excellent result. The offered novel architecture serves as an optimized framework for future real-time ECG signal classification devices. The obtained outcomes show the potential of the transformer framework for processing ECG signals. The presented attention architecture eliminates the drawbacks of the exponential increase in parameters of the SAU and attains a more powerful performance since the introduced model utilizes a hierarchical architecture; this is a significant issue since timing data has a high impact on the rhythm of the heartbeats for a given ECG signal.

Table 5

Comparison of No. parameters between the suggested model and the transformer model

Architecture	No. Parameters	Parameter Decrease (%)
Transformer model	3.26 M	17.79
Presented model	2.68 M	
Only SAU	0.1114 M	44
Only level 2 attention Based on the optimized network	0.0623 M	

4.3 Achievement Comparison between the Introduced Model and Doctors

At the start of this section, it is essential to point out that a team of expert cardiologists debated and marked the heartbeats of the MIT-BIH-ARR-DB by unanimous agreement [36]. We consider this the "Ground Truth Classification" (GTC) for comparing the achievement of the proposed model with that of doctors specializing in cardiology. The testing data of the ECG signals were fed to the model and provided to three separate (with various halls and different workplaces [37,38]) doctors to diagnose the heartbeats. To ensure the identity of the labeling procedure, all medical doctors were given specific orders on the notation style of the transitions between the heartbeats, and then the F1-Score, PPV, SEN, and ACC were computed for both the suggested model and the doctors. In order to determine the doctors' performance, at least two doctors' decisions must match to diagnose

Table 6

Findings of comparison between the achievement of the proposed model and that of cardiologists

	N (%)			S (%)			V (%)			F (%)			Overall (%)
	PPV	SEN	F1-Score	PPV	SEN	F1-Score	PPV	SEN	F1-Score	PPV	SEN	F1-Score	ACCo
Cardiologists	98.97	98.66	98.81	95.13	95.01	95.06	98.18	98.79	98.48	97.88	99.54	98.70	98.92
Our model	**99.89**	**99.93**	**99.91**	**99.79**	**99.88**	**99.83**	**99.85**	**99.94**	**99.89**	**98.65**	**99.61**	**99.12**	**99.94**

Table 7

The division of heartbeats for the intra-patient setting

	N (%)			S (%)			V (%)			F (%)			Overall (%)
	PPV	SEN	F1-Score	PPV	SEN	F1-Score	PPV	SEN	F1-Score	PPV	SEN	F1-Score	ACCo
Presented model	**99.90**	99.95	**99.92**	**98.87**	**97.04**	**97.94**	99.85	**99.95**	**99.99**	**99.93**	**99.97**	**99.95**	**99.96**

Table 8.

The outcomes of the proposed model in an intra-patient setting

	N (%)			S (%)			V (%)			F (%)			Overall (%)
	PPV	SEN	F1-Score	PPV	SEN	F1-Score	PPV	SEN	F1-Score	PPV	SEN	F1-Score	ACCo
Presented model	**99.90**	99.95	**99.92**	**98.87**	**97.04**	**97.94**	99.85	**99.95**	**99.99**	**99.93**	**99.97**	**99.95**	**99.96**

the heartbeat. The findings are shown in **Table 6.** The outcomes illustrate that the proposed model and doctors perform similarly, but the model has a slight boost, particularly in *S*-class detection (4.77%); this could be because of a considerable analogy in morphology between the *N* and *S* classes. Furthermore, the closeness of the outcomes indicates that the offered framework is robust in identifying cardiac disease.

The introduced model can be used in an intra-patient setting and produce outstanding outcomes. The heartbeat allocation is shown in **Table 7**, and the findings are illustrated in **Table 8.** This scheme is less trustworthy, realistic, and generic than the inter-patient setting.

5. CONCLUSIONS

This study introduced an improved, end-to-end, powerful, and computationally efficient transformer model for classifying heart diseases using ECG signals obeying the AAMI standards and the inter-patient mode. The presented framework uses attention techniques. Level 1 of attention involves the use of the SE network, which is responsible for weighting the LHSP features captured by the CNNs. Level 2 of attention includes replacing the SAU of the traditional transformer framework with the suggested optimized network. The optimized network is in charge of weighting the GH features, and it includes the low-cost OC. The results showed that the achievements of the presented model surpassed those of the state-of-the-art and were comparable to those of cardiologists. The future horizon of this work is to implement the proposed model using an FPGA.

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