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Adaptive ECG Leads Selection for Low-Power ECG Monitoring Systems Using Multi-class Classification

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Abstract—**The computer-aided interpretation of ECG signals has become a pivotal tool for physicians in the clinical assessment of cardiovascular diseases during the last decade. Therefore, computerized diagnosis systems depend heavily on machine learning and deep learning models to guarantee high classification accuracy. However, a large amount of power is consumed due to the need for heavy computations to handle the classification tasks which act as a barrier to maintain continuous ECG monitoring. Hence, this work targets energy saving in the constrained embedded environment on a Texas Instruments CC2650 Micro-controller Unit (MCU). We provide a new approach to support energy-efficient ECG monitoring in real-time through the adaptive selection of ECG leads after applying multi-class classification on the raw ECG signals. We deploy two different CNN model scenarios on MIT-BIH and CODE-test datasets, and adjust the number of ECG streamed channels to 1,4, and 8, based on the detected cardiac abnormalities, such as arrhythmias and heart blocks. The adaptive selection of ECG channels achieves 77.7% power saving in the normal cardiac condition and up to 55.5% for the heart blocks, sinus bradycardia, and sinus tachycardia.**

1. Introduction

During the last 30 years, cardiovascular diseases are the dominant cause of mortality in more than 195 countries worldwide [1]. Thus, the ECG diagnosis tools are vital for clinical assessment and early medical intervention. The recent Internet of Things (IoT) technologies have a significant impact on the rapid evolution of commercial ECG monitoring systems [2] [3]. Accordingly, a wide range of cardiac solutions is released to facilitate different diagnosis applications, like arrhythmias and heart blocks detection or heart attack early prediction. Therefore, ECG signals classification with high accuracy are highly demanded in the ECG monitoring platforms, especially after the new era of deep learning (DL) techniques. The deep learning models have a big advantage of recognizing the various patterns by extracting meaningful features from input data without extensive feature engineering. Moreover, the performance of neural networks increases if we use huge training data which is essential for real-time ECG streaming that generates a large volume of ECG raw data. Although there are multiple existed efforts in the literature concerning the deep learning effect on the accurate diagnosis of ECG abnormalities, the power consumption evaluation in the low-power ECG monitoring systems that utilize DL models is still underexplored.

In this paper, we aim to fill the research gaps by answering the following questions: How to control the power consumption of ECG patch using multi-class classification with DL models? How could we facilitate the adaptive selection of ECG leads? What is the effect of adaptive leads selection on the ECG patch battery within our real-time constrained embedded platform?

Based on the medical literature, the cardiovascular risks could be categorized into: Arrhythmias [4], Myocardial Infarction [5], Heart Blocks [6]. The ECG abnormalities could be diagnosed using a varied number of ECG leads based on the cardiac risk category. Energy saving on the low-power ECC systems could be achieved by adjusting the number of streamed ECG channels according to the detected cardiac class by the multi-class classifier. By deploying a smart decision maker to select the corresponding number of ECG leads, we will control the ECG patch mode of operation efficiently without the need for full mode (i.e., 12 leads streaming).

Through this study, we are targeting 3 main objectives to expand the battery life of ECG patch in the constrained real-time ECG platform. First, To evaluate the performance of the commonly used neural models in literature within the real-time environment. Second, to adjust the number of ECG leads and manipulate the mode of operation on the ECG patch based on the identified cardiac abnormality from the classifier. Third, to minimize the total power consumption of the ECG patch using the adaptive leads selection.

Towards satisfying system objectives, we propose two multi-classification scenarios using a single lead and 12 leads and compare two existing neural network models in the literature in terms of the output classes, the required number of channels for each class, and accuracy. Afterwards, we will measure the impact of multi-class classification and the flexible choice of leads selection on the energy saving of the ECG patch.

The remainder of this paper is organized as follows: In section 2, we demonstrate previous work in using deep learning models for ECG diagnosis. Section 3 describes the system architecture and the scenario of deploying deep neural networks models. The experimental setup is explained in Section 4 concerning the methodology, the neural network architecture, and the used dataset. In section 5, we evaluate each DL model in terms of power consumption and the amount of energy saving. The conclusion and future directions are illustrated in Section 6.

2. Background

The ECG monitoring systems have witnessed a significant improvement after emerging deep learning techniques. The deep neural networks play a vital role in providing accurate and fast diagnosis for a wide range of cardiac diseases. Accurate ECG classification is clinically essential to predict and control cardiac patients before suffering from critical side effects and deterioration. Unlike the traditional machine learning algorithms, the deep learning algorithms could handle data pre-processing, feature extraction and classification efficiently on large data volumes.

In the literature, many efforts are introduced to support ECG diagnosis using deep learning [7] [8]. The existed solutions for abnormal ECG detection differ in terms of: the diagnosis type, DL algorithm, and the used datasets. There are different types of diagnosis applications that rely on DL models. As an example, myocardial infarction detection, arrhythmias detection, irregular heart rhythm classification, and coronary artery classification are different ECG diagnosis types. The convolutional neural network (CNN) and recurrent neural networks (RNN) are the commonly used DL algorithms in diagnosis applications. The used datasets vary between the MIT-BIH dataset, PTB-XL dataset, PhysioNet Cardiology Challenge 2017 dataset, European ST-T dataset, INCART dataset, and Self-constructed datasets.

Some of the existed solutions focus on the type of hardware used in training the neural networks. For instance, Wu et al. [9] introduce a lightweight neural network-based ECG classification algorithm with high recognition accuracy by combining both the Bi-directional Long Short-Term Memory (BLSTM) and convolutional neural networks (CNN). The authors utilize a high degree of similarity between successive heartbeats to achieve computation reuse on hardware architecture which speeds up the network inference and improves the energy efficiency. However, the proposed processor is not for continuous ECG monitoring. Although they reuse the repeated cardiac cycles to minimize the computational power and save energy, this technique could lead to additional delay which contradicts real-time ECG streaming. Correspondingly, Janveja et al. [10] propose an initial prototype for wearable ECG monitoring. They fabricate an additional processor unit to handle multi-class classification using DNN and MIT-BIH dataset. The Co-Processor consists of 2 main blocks: Pre-processing with beat extraction block and classification block. They minimize the computational complexity by reducing the total number of input and hidden layers which leads to minimizing the power consumption. Despite the main goal of using the energy-efficient processor, the energy-saving analysis for the different classified classes using the customized co-processor is missing. Corradi et al. [11] introduce a method for encoding and compressing ECG signals into a stream of asynchronous digital events. The compressed ECG signals can be correctly classified into one of 18 classes after a dimensionality expansion performed by RNN. The authors use a software simulation that is compatible with a digital embedded implementation. After the simulation results, they fabricate a custom mixed-signal analog/digital neuromorphic processor to implement the recurrent SNN. The authors aim to reduce the power consumption during training the RNN using the VLSI neuromorphic processor, but there is no explanation of the way they used to evaluate or reduce the power consumption. According to the work proposed by Monedero [12], a functional ECG diagnosis system could perform an accurate medical assessment by following the approach of a specialist. The author uses a set of rules in the system to differentiate 13 diseases with a high-reliability rate. Five leads (I, II, V1, V5, and V6) are used instead of a standard 12-lead ECG to perform the diagnosis. A novel noise indicator is deployed to measure the quality of the acquired ECG signals which allows repeating the ECG recording if the noise level is high and cannot be filtered. Furthermore, signal processing techniques are applied to captured signals for wave identification and CHAID (Chi-squares Automatic Interaction Detection) model detects 13 cardiac risks. As the proposed system depends on signal processing techniques, it will need large memory to store records besides the high computational delays which act as a barrier to supporting real-time ECG monitoring. Hybrid architectures, such as Long Short Term Memory (LSTM) cells and Multi-Layer Perceptrons (MLP) are merged in [13] for ECG anomaly detection on the MIT-BIH dataset. Sivapalan et al. recommend data augmentation using Synthetic Minority Oversampling TEchnique (SMOTE) to solve the unbalanced classes in the dataset. Energy saving is achieved according to the following scenario: Once an ECG beat is identified to be anomalous, the wireless transmission will be enabled and thus sensor power consumption can be reduced. One of the ANN technique drawbacks is the large amount of power consumption during execution. In addition, the continuous real-time ECG transmission is not supported as ECG readings are only transmitted if an anomalous beat is detected.

3. System Design

3.1. System Architecture

Figure 1 shows the system architecture of our real-time platform with the adaptive leads selection scenario based on the multi-class classification output. The captured raw signals are transmitted to the gateway device that contains the pre-trained CNN model. According to the detected ECG class from the multi-class classification, the ECG patch operation mode will be changed.

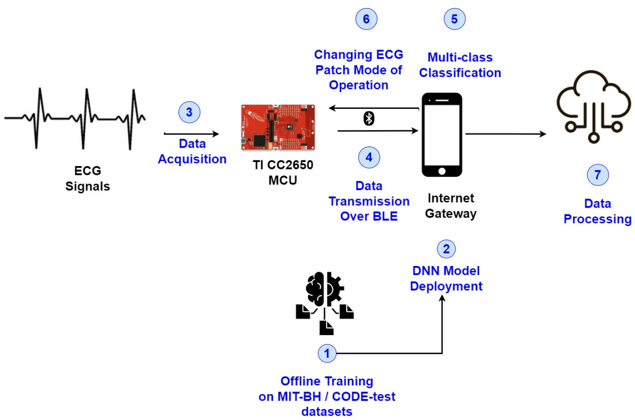

Figure 1. System architecture of real-time ECG monitoring platform

3.2. System Objectives

Our proposed system has 2 main goals to optimize the power consumption as follows:
(1) To control the number of streamed ECG channels based on the recent cardiac status instead of sending the 8 channels continuously.
(2) To maximize ECG patch battery life time and total number of operational hours.

4. Experimental Setup

In light of the promising results of energy saving using the binary classification approach [14], we investigate the possibility of changing the number of required ECG leads used to diagnose specific cardiac abnormalities by using multi-class classification. The alteration of the ECG patch mode of operation (i.e., changing the number of ECG channels) will affect the total power needed to transmit the ECG data over BLE to the internet gateway device. In this section, we will compare the popular existing deep learning models that work on single lead or 12 leads datasets to classify irregular cardiovascular rhythms, and discuss the impact of applying these models on the total energy saving of our real-time ECG platform.

4.1. Multi-class classification using single ECG lead

Hannun et al. [15] introduce a cardiologist-level arrhythmia detection to classify 12 rhythm classes using a single lead ambulatory ECG. The authors aim to classify a wide range of distinct arrhythmias with high diagnostic performance similar to the level of ECG evaluation from expert cardiologists. Our proposed scenario is to operate the ECG patch on the single lead as a default operation mode. The streamed data from the single lead will be classified using a multi-class classification model. Based on the detected ECG class, we will change the number of streamed ECG channels to assure effective medical evaluation for the cardiologist at the healthcare centers. The ECG patch operation mode would reset to single lead mode after 30 minutes of streaming the required channels.

4.1.1. Dataset. The authors in the original work [15] collect a large, novel ECG dataset [16]which is annotated by a group of cardiologists using Zio monitor. We target deploying the DNN introduced by Hannun et al. using the MIT-BIH dataset to assure the diversity of cardiac risks between arrhythmias and heart blocks.

4.1.2. Deep Neural Network Architecture. Hannun et al. propose a Deep Neural Network (DNN) which accepts ECG raw signal sampled at 200 Hz as an input for the 1st convolutional layer. The DNN contains 33 convolutional layers total followed by a linear output layer to one of 12 rhythm classes. Additionally, 16 residual blocks act as short connections for fast back-propagation. The output of the dense layer will be the input of the softmax activation function that produces a vector to represent the probability distributions of the 12 rhythm classes.

4.1.3. Methodology. The training was applied offline before model deployment on the gateway device. We select 80: 20 as a ratio between the training set and testing set. The multi-class classification with MIT-BIH dataset produces 7 cardiac classes, such as Normal Beat (N), Premature Ventricular Contraction (V), Left Bundle Branch Block Beat (L), Right Bundle Branch Block Beat (R), Paced Beat (/), Supraventricular premature (S), Atrial premature beat (A).

We utilize the DNN architecture and initialize the Adam optimizer with the following parameters: $\beta 1 = 0.9, \beta 2 = 0.999, LearningRate = 0.001, BatchSize = 128$.

4.2. Multi-class classification using 12 ECG leads

In the previous section, we evaluated the power consumption using the open source single lead DNN model provided by Hannun et al., and we will discuss it's effect on the total power consumption in the results section. However, we found the power consumption evaluation is still largely unexplored for the constrained environments using 12 Leads datasets with DNN models. We will deploy the open-source DNN model proposed by Ribeiro et al. [17] to measure the impact of their 12-leads classifier on the ECG patch power consumption.

4.2.1. Dataset. The authors in [17] create a large annotated ECG dataset called CODE-test [18]that contains 2,322,513 ECG records from 1,676,384 different patients of 811 counties in the state of Minas Gerais/Brazil. Ribeiro et al. release 827 ECG tracings from the total dataset records for public usage. All the records are annotated by cardiologists, residents and medical students. The CODE-test dataset includes 6 different rhythmic and morphologic ECG abnormalities.

4.2.2. Deep Neural Network Architecture. Ribeiro et al. propose a Deep Neural Network (DNN) based on the previous work of Hannun et al. with less number of convolutional layers. The modified DNN accepts ECG raw signal sampled at 400 Hz as an input for the 1st convolutional layer followed by 4 residual blocks. The convolutional layers have 64 filters with a length of 16 for the first convolutional layer and residual block and increasing the number of filters by 64 every second residual block. The output of the last residual block is an input for the Dense layer with a Sigmoid activation function as some records have intersected classes.

4.2.3. Methodology. We target deploying the DNN introduced by Ribeiro et al. using the CODE-test dataset to evaluate the power consumption with a different set of cardiac irregularities. As we have done before, the training was applied offline before model deployment on the gateway device. We select 80: 20 as a ratio between the training set and testing set. The multi-class classification with CODE-test dataset produces 6 cardiac classes as follows: 1st Degree AV Block (1dAVb), Sinus Bradycardia (SB), Left Bundle Branch Block Beat (LBBB), Right Bundle Branch Block Beat (RBBB), Atrial Fibrillation (AF), Sinus Tachycardia (ST). We reproduce the implementation of the DNN architecture [17], and initialize the Adam optimizer with the following parameters: $\beta1 = 0.9, \beta2 = 0.999, LearningRate = 0.001, BatchSize = 64$.

5. Results and Discussion

The single lead and 12 leads neural models are evaluated in terms of: the output classes, the classification accuracy, the performance metrics, the total power consumption for each cardiac class, and the amount of saved energy after applying the adaptive leads selection.

5.1. Evaluation of multi-class classification with single-lead DNN

After training and testing the single lead DNN model on the MIT-BIH dataset, we found that the DNN model achieves 99% accuracy to classify the raw ECG signals into 7 different classes. To obtain valuable insights about the DNN predictions, we visualize the true positives, true negatives, false positives, and false negatives using the confusion matrix as shown in Figure 2.

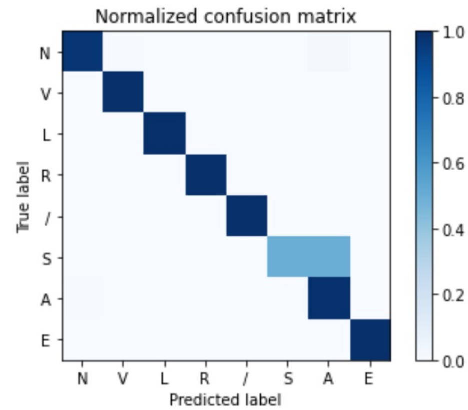

Figure 2. Confusion matrix of the single-lead DNN model

In Table 1, We evaluate the single lead DNN model in terms of precision, recall, and F1-score for each ECG class. The both types of heart blocks and paced beat have the maximum precision, recall, and F1-scores. On the other hand, the Supraventricular premature class has the minimum recall, and F1-scores values.

TABLE 1. EVALUATION REPORT FOR MULTI-CLASS CLASSIFICATION WITH MIT-BIH DATASET

	Precision	Recall	F1-Score
N	0.99	0.98	0.98
V	1.00	0.99	0.99
L	1.00	1.00	1.00
R	1.00	1.00	1.00
/	1.00	1.00	1.00
S	1.00	0.5	0.67
A	0.83	0.99	0.90

5.2. Power consumption analysis using single-lead DNN

In this scenario, the number of required ECG leads varies between 1, 4, and 12 leads based on the detected ECG class. For instance, The normal and paced classes will only need 1 lead. Both right and left bundle heart blocks need 4 leads (V1, V2, V5, V6) to be diagnosed [19] while the premature ventricular contraction, the Supraventricular premature, and the atrial premature beat will need 12 leads for efficient medical evaluation. The commercial ECG monitoring devices are released with a different number of channels between 1 and 8 channels where 1 channel could be represented by a single lead, 3 channels are represented with 3 or 4 leads, and 8 ECG channels mean 12 leads...etc. Given 24 bits of data for each channel, and 24 bits for channel status, the data size produced by 1 ECG channel at 500 sampling rate for 2 Sec is 6 KB compared to 15 KB and 27 KB for the 4 channels and 8 channels respectively. Table 2 shows the number of ECG channels needed for each cardiac class resulting from the single lead DNN besides the total data size streamed from these channels at a 500 sampling rate.

TABLE 2. ECG CHANNELS FOR EACH CARDIAC CLASS OF THE SINGLE-LEAD DNN

ECG Class	# of Required Leads	# of Required Channels	Data Size for (N) Channels (Bits)	Data Size at 500 Sampling Rate (kB)
N	1	1	48	3
V	12	8	216	13.5
L	4	3	96	6
R	4	3	96	6
/	1	1	48	3
S	12	8	216	13.5
A	12	8	216	13.5

Power consumption measurements for TI CC2650 MCU are calculated using equations (1) and (2) given the base current values in [20], 500 samples/sec as a sampling rate and a minimum 2-sec duration to capture the full cardiac cycle.

$$\text{Airtime to transmit ECG data} = \frac{\text{Size of transmitted ECG data}}{251} * 1.4 \quad (1)$$

$$\text{Total Energy} = \text{Airtime } (T_{\text{Air}}) * (I_{\text{Tx}} + I_{\text{Core}} + I_{\text{Peri-RF Core}} + I_{\text{Peri-Power Domain}} + I_{\text{Peri-DMA}}) + \text{Processing time } (T_{\text{Proc}}) * (I_{\text{Core}} + I_{\text{Peri-RF Core}} + I_{\text{Peri-Power Domain}} + I_{\text{Peri-DMA}} + I_{\text{Peri-SPI}}) \quad (2)$$

The energy saving is achieved by changing the mode of operation for the ECG patch based on the detected ECG class and eliminating the need of streaming the 12 ECG leads all the time which drains the patch battery. In Table 3, we demonstrate the power consumption before (i.e., 12 leads streaming) and after (i.e., streaming with a varied number of leads) the multi-class classification. We reach the maximum energy saving in single lead and 4 leads scenarios with 77.7% and 55.5% respectively.

TABLE 3. POWER CONSUMPTION AND ENERGY SAVING AFTER USING SINGLE LEAD DNN

ECG Class	Power Consumption Using 12 Leads (mJ)	Power Consumption Using Adaptive Leads Selection (mJ)	Power Saving (%)
N	1706	379.1	77.7
V	1706	1706	-
L	1706	758.2	55.5
R	1706	758.2	55.5
/	1706	397.1	77.7
S	1706	1706	-
A	1706	1706	-

5.3. Evaluation of mutli-class classification using 12-lead DNN

After training and testing the 12-lead DNN model on the CODE-test dataset, we found that the DNN model achieves 99.5% accuracy to classify the raw ECG signals into 5 different classes We visualize the true positives, true negatives, false positives, and false negatives using the confusion matrix as shown in Figure 3 to obtain valuable insights about the DNN predictions.

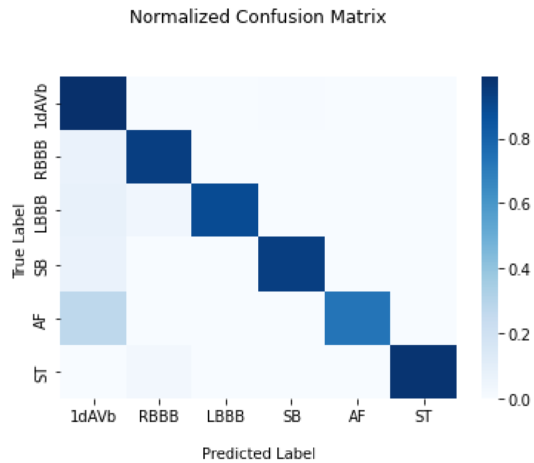

Figure 3. Confusion matrix of the 12-leads DNN model

In Table 4, we evaluate the 12-lead DNN model in terms of precision, recall, and F1-score for each ECG class. The resultant scores from the reproducible implementation and the paper results are the same. left bundle block and atrial fibrillation classes have the maximum precision scores. The left and right heart blocks classes achieve the highest recall scores while the left bundle and sinus tachycardia are the top F1 scores.

TABLE 4. EVALUATION REPORT FOR MULTI-CLASS CLASSIFICATION WITH CODE-TEST DATASET

	Precision	Recall	F1-Score
1dAVb	0.86	0.92	0.89
RBB	0.89	1.00	0.94
LBB	1.00	1.00	1.00
SB	0.833	0.93	0.88
AF	1.00	0.76	0.87
ST	0.94	0.97	0.96

5.4. Power consumption analysis using 12-lead DNN

In this scenario, the number of required ECG leads varies between 3, 4, and 12 leads for the abnormal ECG signals and 1 lead for the normal condition. As an example, sinus bradycardia needs 3 leads (II, III and aVF) to be diagnosed [19] while sinus tachycardia requires 4 leads (V1, V2, V5, V6) for the accurate medical evaluation [21]. Furthermore, both right and left bundle heart blocks need 4 leads (V1, V2, V5, V6) to be diagnosed [19]. The 1dAVB and the atrial fibrillation are under the arrhythmias category where 12 leads are crucial to maintain an effective diagnosis.

Table 5 shows the number of ECG channels needed for each cardiac class resulted from the 12 leads DNN besides the total data size streamed from these channels at 500 sampling rate using equations (1) and (2) on each ECG class.

TABLE 5. ECG CHANNELS FOR EACH CARDIAC CLASS OF THE 12 LEADS DNN

ECG Class	# of Required Leads	# of Required Channels	Data Size for (N) Channels (Bits)	Data Size at 500 Sampling Rate (kB)
1dAVB	12	8	216	13.5
RBB	4	3	96	6
LBB	4	3	96	6
SB	3	3	96	6
AF	12	8	216	13.5
ST	4	3	96	6

Similarly to the single lead DNN, the power consumption measurements are calculated. In Table 6, we demonstrate the power consumption before and after applying the multi-class classification. As a result, we get the maximum energy saving in 3 and 4 leads scenarios with 55.5%.

TABLE 6. POWER CONSUMPTION AND ENERGY SAVING AFTER USING 12 LEADS DNN

ECG Class	Power Consumption Using 12 Leads (mJ)	Power Consumption Using Adaptive Leads Selection (mJ)	Power Saving (%)
1dAVB	1706	1706	-
RBB	1706	758.2	55.5
LBB	1706	758.2	55.5
SB	1706	758.2	55.5
AF	1706	1706	-
ST	1706	758.2	55.5

6. Conclusion

This study evaluates the impact of adaptive ECG leads selection on the power consumption of real-time cardiac event monitoring within the constrained embedded environment of TI-CC2650 MCU. The flexible choice of ECG channels depends on the cardiac classes output from two varied CNN models that are deployed on single-lead and 12-leads datasets. Based on the detected cardiac class, we change the ECG patch mode of operation which in return expands the battery lifetime and preserve continuous ECG evaluation. The adaptive leads selection technique saves 77.7% of the total power consumption in the normal ECG status compared to 55.5% energy saving in the abnormal ECG conditions. In the future, we plan to apply the adaptive ECG channels selection as a bench-marking approach to a wide range of cardiovascular diseases datasets to expand the operational hours of the low-powered ECG diagnosis platforms.

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