iKardo: An Intelligent ECG Device for Automatic Critical Beat Identification for Smart Healthcare

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***Abstract*—In medical practices, the detection of diseases highly depends on different medical tests. Electrocardiogram (ECG) technique is commonly used for heart disease diagnosis. Doctors can measure pulse and other heart boundaries with the aid of it. Fast and precise detection of forms of arrhythmia is critical while identifying heart disease. In this work, we proposed an intelligent ECG device (called iKardo) with the built-in automatic capability to classify into critical and non-critical data from an imbalanced ECG dataset for the smart IoT or Internet of Things based smart healthcare device. Particular emphasis is given to the reduction of data misclassification by converting imbalanced data into a balanced dataset using necessary techniques. This proposed iKardo helps in the accurate detection of critical ECG beats with an accuracy of 99.58% and result in a smart healthcare monitoring device that would make the disease detection fast and precise.**

***Index Terms*—ECG signals, Machine learning, Smart healthcare, Critical signal beats, Imbalanced data**

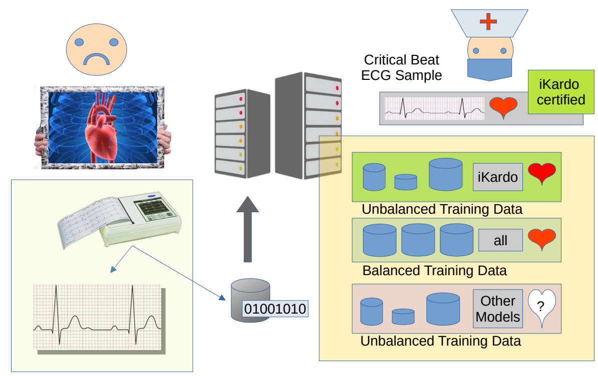

Fig. 1. A Smart Healthcare Framework for Automatic Heart Monitoring

I. Introduction

An efficient IoT-based smart ECG monitoring device can revolutionize the healthcare system. Electrocardiogram (ECG) analyses the tiny electrical impulses produced by the heart. An ECG system shows the electrical activity data as a graph with clear traces. A medical professional interprets the data afterwards. The ECG helps to detect irregular heart rhythm (cardiac) anomalies.

A smart and remote ECG monitoring system is more effective when identifying critical signal beats within the device itself. This may be realized with the application of machine learning-based approaches. A healthcare program built on the Internet of Things (IoT) may track individuals' ECG signals remotely and accurately with proposed *iKardo* over an extended period. IoT guided WBAN or wireless body area network based smart ECG monitoring system will dramatically improve the safety and well-being, especially by monitoring the patient's ECG signal automatically, feeding it to the relevant classifier. It is found by adequately classifying the ECG data monitored [1]. In this context, it is crucial to find a simple and less resource-consuming machine learning based device capable of identifying critical and non-critical signals accurately and consumes less power. Our aim is to provide the best possible hardware-based machine learning model for ECG beat recognition and in Fig. 1 we show the proposed model of a smart healthcare system.

The classification of ECG signals with the help of machine learning techniques have some vital issues [2]. For example, the lack of proper guidelines and imbalanced nature of present standard database,the task is more complicated but in iKardo we are able to overcome most of these issues. Medical practitioners' observations differ a great extent on the same ECG signal reading i.e. individuals are generally incapable of perceiving the morphological changes of ECG signals without specialized aids [3].The salient contributions of this paper are discussed in the novelty section. The remainder of the paper is arranged as follows: Section II discusses related prior work,the problem addressed in ECG beat classification in Section III, smart IoT based healthcare device is discussed in Section IV, Section V describes machine learning modeling, Section VI contains experimental validation of the results, concluded by Section VII.

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II. Related Prior Work

Rapid Advancement in technology and health awareness resulted a massive growth in smart healthcare system and by the end of 2020 it reached above 809 million, that can discussed in [4]. Multi feature ECG classification proposed in [5] using Distance weighted k nearest neighbour (DWKNN) by dividing the data set into two categories: V-type and S-type with up-to 99% average accuracy. In [6] proposed a convolutional neural network and multi-layer perceptron based ECG classification with focal loss and 96.27% accuracy. A wavelet based Arrhythmia Monitoring System proposed in [7] with chip fabrication and tested on human body achieved 95.83% accuracy for arrhythmia detection.In [8] a health monitoring system was proposed for ECG of elder people when they are in outdoor using multi-thread method and GPS to locate that person when there is any detection of falling event. They were able to decrease the detection time by 38%. A wearable diabetes care device [9] was proposed using PPG signal by random forest and adaboost regression models and achieved 90% accuracy in glucose prediction. In [10] the authors proposed an automated IoMT based seizure detection system from EEG signal using SRA (Signal Rejection Algorithm) and VLD (Voltage Level Detector) and achieved sensitivity and specificity of 96.9% and 97.5% respectively. A deep learning neural network (DNN) based stress level detection device was proposed in [11] They were able to achieve a 99.7% accuracy rate, which was proved to be beneficial to schizophrenia patients. In [12] a long term ECG monitoring considered with general regression neural network (GRNN) model with accuracy 89%. A cellphone-based healthcare wireless framework was created in [13]for providing continuous online data about anatomical states of a patient.

An algorithm trained with the patient's heart rate, EEG, temperature information being forwarded to a mobile application. However, deep learning based algorithms are not utilized in [14]. In [15] Ahmad, discussed beat classification in multiple classes using waveform and RR interval by wavelet-based classification in MIT/BIH dataset with 97.52% accuracy without consulting the problem of imbalanced nature of data. They introduced an IoT-based health observation framework with Wavelet for removing highlights, and group the ECG beats alongside PCA (Principal Component Analysis) in [16], [17].

In [18],they implement ECG classification based on HHT (Hilbert-Huang Transform) for pre-processing and statistical features with multi-class SVM proposed and got results up to 98.8%. Among the algorithms, SVM has performed truly well in this regard for multi-class and binary characterization alongside the KNN (K-nearest neighbour) algorithm in [19], [20]. Brain-inspired AI approach is utilized for wireless wearable devices for ECG monitoring. In MIT/BIH dataset, they had a positive prediction rate of 86.1% [21].

SMOTE was used for detecting breast cancer [22] [23] where it is used to manage missing data and the imbalanced nature of the dataset and improved the accuracy from 97.4% to 98.1%. In [24] they proposed a automatic body vital monitoring wearable garments with average accuracy of 96.9%. In [25], a new bidirectional deep LSTM network-based wavelet sequences(DBLSTM-WS) model was deployed for classification of ECG signals. However, target application is not mentioned. The results of 5 types of heartbeats collected from the MIT-BIH arrhythmia database are evaluated with a performance of 99.39%.

III. Contribution of the Work

The main favourable circumstances in smart health care system are the checking, investigation, finding, and monitoring of patients' symptoms by IoT based health monitoring device. The primary motivation of this proposed model is to support medical practitioners in the diagnosis of patient health using ECG signals. The proposed iKardo is an IoT-based health monitoring device. Therefore, power consumption is an important issue to extend its battery life. An adaptive power management technique has been explored. The proposed health monitoring device works with the ECG signals received from the sensor present in the patient's body. Firstly, the outputs of the sensors are connected with the computation unit. The outputs of the computation unit are connected with the classifier. Then received signals are classified using our proposed classifier model in terms of critical and non-critical signals. Apart from the power-aware device, another important contribution of this work is to achieve accuracy, which is significant over the existing works. We explore a ResNet residual CNN (Convolution Neural Network) stack method for various machine learning approaches for classification, which outperformed individual algorithms. One of the major issues with ECG signal classification is the imbalanced nature of the standard datasets. In the case of an imbalanced dataset, the number of non-critical data is larger than the critical data. Due to this lots of misclassifications take place. Hence, this affects the performance of the applied machine learning model. As a consequence, the diagnosis of patient health may be wrong. To address this bottleneck, we explore two well-known techniques SMOTE and BIRCH for healthcare applications. In comparison to the state-of-the-art, we improve the iKardo device's performance in terms of power consumption using adaptive power-saving method, and accuracy by reducing misclassifications. Table I shows that the state-of-the-art has primarily focused on classification or as a health monitoring device. We took into account the dataset's imbalanced nature as well as the power consumption. The proposed work addressed both the problem and presented a better solution. Fig. 1 and Fig. 2 depicted the framework and illustration of the proposed new generation health monitoring device, iKardo.

A. Problems Addressed in the current work

In Table I, we compare iKardo to the state of the art and highlighted our contributions in terms of accuracy precision, and adaptive power management scheme. The existing works are entirely focused on improving classification accuracy for health monitoring, however, the issues associated with the imbalanced nature of ECG dataset have not discussed. In addition to that, power consumption has become a major issue at ultra-submicron technology node which is also explored. To improve the performance of a healthcare device, the proposed work focused on both accuracy and power management

The proposed iKardo can accurately determine whether an incoming ECG signal packet is critical or non-critical using

TABLE I
SUMMARY OF THE RELATED WORKS

Ref	Dataset Used	Approach	Accuracy	Remarks
Ji [5]	MIT/BIH	DWKNN	96%	V-type and S-type data considered
Wang [6]	MIT/BIH	CNN with MLP	96.27%	Morphological features used
Lee [7]	MIT/BIH	Wavelet based Classification	95.83%	Chip fabricated and Tested
Li [12]	MIT/BIH	GRNN	89%	Long term ECG monitoring
Khoureich [15]	MIT/BIH	Wavelet based Classification	97.52%	Classify six types of heart beats
Sharma [18]	MIT/BIH	HHT	98.8%	Statistical Features used
Alfaras [21]	MIT/BIH	Brain Inspired AI	86.1%	Wireless wearable Device
Fallahi [22]	Wisconsin	SMOTE	98.1%	Breast cancer detection
Sethuraman [24]	MIT/BIH	DNN	96.9%	Wearable garments for body vital monitoring
Yildirim Özal [25]	MIT/BIH	LSTM	99.39%	Bidirectional deep LSTM network-based wavelet sequence model
iKardo (Proposed)	MIT/BIH	SMOTE and BIRCH with ResNet residual CNN stack	99.58%	Adaptive power management scheme has been introduced

a trained model and respond accordingly. If the incoming ECG signal packet is critical, the adaptive power management technique activates the subsystems and transmits the data to its intended location before returning to sleep mode; if signal is not critical, the subsystems enter into sleep mode or power saving mode and wait for the next signal. In addition to Table I, we compared our proposed device to the existing devices in Table II. Summary of proposed and existing devices are shown in Table II. Our proposed iKardo device is capable of improving further in terms of accuracy as well as power consumption.

B. *Solution Proposed*

A significant amount of power consumption is one of the major bottlenecks in IoT. Hence, there is a great need to explore radical alternatives and architectural innovations for sustaining the IoT for the long term. We explore the power consumption issue as well as accuracy which is the most crucial parameter for any healthcare device. We proposed effective solutions to overcome the potential problems.

The imbalanced nature of the data is a major challenge for ECG and it has been resolved by a combination of two methods: SMOTE and BIRCH to perform a comparative study.We randomly initialized Residual Network (ResNet) CNN stacking instead and the results are then compared with some well known classification algorithm (SVM, RF, and BN) and to come up with the best possible solution.

C. *Novelty of the Work*

The proposed solution has been applied to get the desired results and the salient contributions of this paper are:

- A device to help medical practitioners in the analysis and diagnosis of pathologies through ECG signal processing
- Adaptive power management techniques for power-aware healthcare devices. It improves the life of the device in terms of usage and power consumption.
- Improvement of the performance of the applied ResNet residual CNN stack model by handling imbalanced data using BIRCH and SMOTE and identifying each category with the reduction of misclassified data.
- Machine learning-based intelligent ECG signal classification system suitable for IoT-based smart ECG monitoring device iKardo.

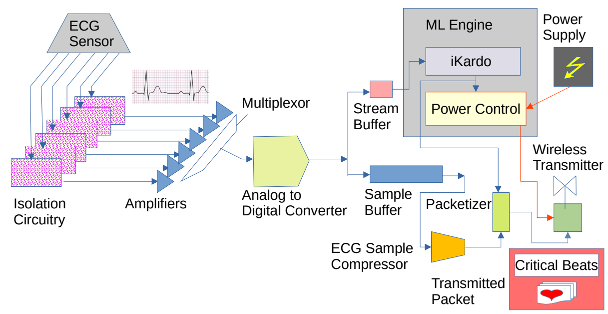

Fig. 2. Illustration of new generation ECG device, iKardo

IV. IOT BASED SMART HEALTHCARE DEVICE FOR ECG MONITORING

A. *WBAN and Smart Healthcare*

IoT technology has made possible the perception of an intelligent, automated, and remotely real-time healthcare network. Wireless Body Area Network (WBAN), with IoT, will attach wearable sensor devices to track signals for an intelligent healthcare system. As in [27] IoT-based WBAN sensor nodes have four major units: body sensor unit, power unit, a communication unit, and a processing unit. The sensor unit receives ECG signal packets from ECG sensors. Microcontroller Unit processes the ECG signal packets by sampling with integrated Analog to Digital Converter. The digital samples are identified as non-critical and critical classes and proposed iKardo belongs to ML engine improved the overall classification accuracy. The Power Management Controller (PMC) reduces power consumption adaptively with the help of power saving

TABLE II
COMPARISON WITH EXISTING CONSUMER ELECTRONICS DEVICE

Ref	Approach	Accuracy	Medical Data Used	Remarks
Tsai [9]	Random Forest Adaboost Regression	90%	PPG	Self-generated data without imbalance nature, Power related issues not discussed
Sayeed [10]	SRA and IoMT Adaboost Regression	97.5%	EEG	Imbalance Nature not in consideration however, total power consumption is mentioned
Raj [26]	LSTSVM and Bee colony optimization	96.14%	ECG	The imbalanced nature of the ECG dataset and Power related issues are not discussed
iKardo (Proposed)	ResNet Residual CNN Stack	99.58%	ECG	Imbalance problem discussed and resolved and adaptive power management scheme has been introduced

techniques. The structural diagram of new generation ECG device is shown in Fig. 2.

B. Power Management

To improve the lifetime of IoT-WBAN, a crucial design criterion is power management. In [28] a flexible power-saving technique is used to maximize the effectiveness of the ECG monitoring system by a adaptive power management scheme. It monitors power utilization based on battery energy level and non-critical or critical data by transmitting the alert signal only when it is critical and saves power consumption. Therefore, it is imperative for the healthcare system to accurately identify critical signals to produce an efficient performance in adverse situations. Machine learning-based approaches seem to be the feasible solution to this issue. The detailed implementation of adaptive power management scheme discussed in Algorithm 1 along with walkthrough example. The flowchart for the power management is shown in Fig. 3.

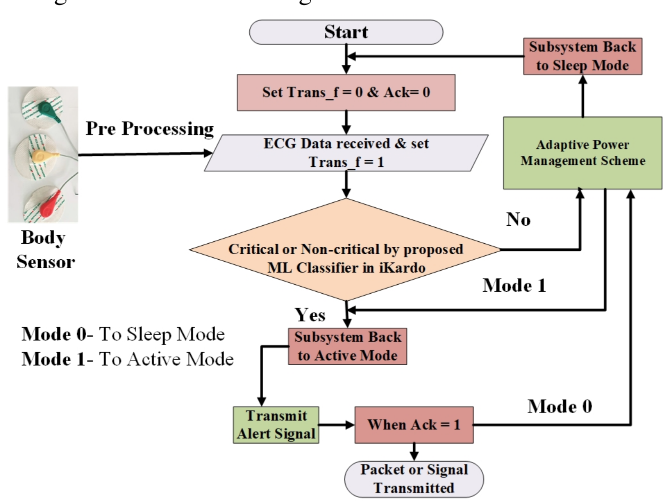

Fig. 3. Flow Chart for Power Management Controller

1) Walkthrough Example: Suppose an ECG signal data is received by a node ‘m’ at time t. The flag for the transmitter, ‘Trans_f’ (transmitter power flag) will be 1 (High) on receiving of the packet which was initially 0 (Low). Each subunit S has a power consumption of P. The transition period from active to sleep is t_1 is ignored, as it is very small. The raw ECG packet data transfer time is t_2, while the warning signal data transmission time is t_3. The received ECG signal is preprocessed and to check it is critical or not by the proposed ML classifier model in iKardo the ‘Trans_f’ is set to 1. If the ECG data is judged to be critical, the adaptive power model active the subsystems and sent alert signals to the destination, otherwise the subsystems are going to be in sleep mode. The power saving strategy is based on the employment of all subunits engaged in signal transmission. The user will get the packet at time t + t_3. The acknowledgment, ‘Ack’ is altered from ‘0’ to ‘1’, which indicates, that data transmitted successfully.

Algorithm 1 Adaptive Power Management

[1] $Initialized$ Trans_f = 0 and Ack = 0
(where Trans_f is Transmitter power flag and Ack for Acknowledgement)
[2] $While$ ECG packets are available go through all the steps
[3] Set Trans_f = 1
[4] $Received$ ECG signal processed and input to classifier in iKardo for classification
[5] If Input ECG packet is Critical then $goto\ step6$ otherwise $goto\ step7$
[6] $Supply$ All units Vdd i.e. Active Mode (mode 1)
To transmit an alert signal, use adaptive voltage scaling.
Set Ack = 1 when transmission completed and $goto\ step7$
[7] $Supply$ all units $0V$;i.e. Sleep Mode (mode 0)
[8] $Loop$ back to $step2$

C. Proposed Deep Learning Model for ECG Classification

Accessible ECG signals are grouped into two basic classes: critical class and non-critical class, as indicated by AAMI recommended practice [29]. From the required signal, highlights are determined, and their qualities are contrasted with the estimations of typical ECG signals to decide whether the signal is critical. Significant highlights of ECG and their characteristic ranges are shown in Table III [29]. By the AAMI recommendations, two types of labels are there for representing various types of ECG signal as described in Table IV [28]. According to the MIT labels, ECG signals are classified into several classes. But due to the research purpose, those are combined into non-critical and critical classes i.e., in 2 classes, as shown in Table V [30].

D. Dataset Overview and Feature Description

This experiment is performed by utilizing the information of the MIT/BIH arrhythmia database by Dr Surekha Pal Reddy.

TABLE III
PARAMETERS OF ECG SIGNAL WITH NORMAL RANGE

PARAMETERS	NORMAL RANGE
RR(Time Between 2 successive R waves) interval	0.6s-1s
PR (P to QRS Complex) interval	0.12s-0.2s
ST(QRS Complex to Starting of T) interval	0.08s-0.12s

TABLE IV
TWO TYPES OF BEAT LABELS USED IN THIS MM(AAMI RECOMMENDATE BEAT LABEL)

N	Beats that do not belong to the normal beats(V), super ventricular ectopic beats (F), or Others (Q)
V	The ventricular premature beat,Ron-T ventricular premature beat, or ventricular escape beat (ventricular ectopic beats (VEB))

TABLE V
ACCORDING TO AAMI RECOMMENDATIONS MIT/BIH DATABASE BEATS WITH TWO CATEGORIES

Description of BEAT	MIT label	Test label
Normal	1	1
Left Bundle Branch Block	2	1
Right Bundle Branch Block	3	1
Bundle Branch Block(Unspecified)	25	1
Nodal (Junctional) Premature	7	1
Article Premature	8	1
Supra Ventricular Premature (Atrial OR Nodal)	9	1
Aberrated Atrial Premature	4	1
Nodal (Junctional) Escape	11	1
Atrial Escape	34	1
Ventricular Premature	5	2
R-on-T Ventricular Premature	41	2
Ventricular Escape	10	2

The first database has 48 records, each of which is 30 min long. Thirty three out of 48 records contain the ordinary beats and untimely ventricular withdrawals. Premature ventricular contractions (PVC) are utilized for this investigation. In the dataset, in the 10^{th} column, the initial four feature components are temporal parameters (e.g. the R–R intervals), which are determined as the duration between the two successive QRS peaks. It contains names (1 for non-critical and 2 for critical). The initial 9 sections include all the highlights separated in the MIT/BIH dataset for characterizing the ECG signals in ordinary and basic classes. The rest five feature components are separated according to morphology.

The fifth feature is the relationship with the past beat and the sixth feature is the connection beat with the next. These are separated for all the beats in the database, and the feature represents one except for the first and last beat in a record.

The last three features depend on the rate span of the waveform above certain given thresholds. Since the standardized waveform lies somewhere in the range of 0 and 1, three limits are selected that are 0.2, 0.5, and 0.8. These features have great discriminate force for PVCs as they are commonly wide complexes compared to sharp ordinary beats.

There is an imbalance in the dataset i.e., Out of the 74,000 plus beats only 6612 beats have been labelled as 2 (i.e. they are critical), and the rest are labelled as 1 (Non-critical). The presence of such imbalance in the dataset can create a large amount of bias in the performance of the applied machine learning model. This issue needs to be addressed. We fixed the same using two different ways, i.e. SMOTE (Synthetic Minority Oversampling Technique) & BIRCH (Balanced Iterative Reducing and Clustering produces aggregated data from massive databases).

V. PROPOSED MACHINE LEARNING MODELING FOR ECG CLASSIFICATION

A. Proposed Methods for Managing ECG Data Imbalance

The imbalance nature of the dataset have been solved by resampling of data,with two common approaches broadly upsampling and downsampling. In most of the cases the upsampling is preferred over the downsampling method.We used both the methods to handle the imbalance nature of the dataset.

The first approach is to downsample the set of non-critical ECG signal beats to a size comparable to that of the set of critical ECG signal beats with the implementation parameters includes, number of cluster i.e. 6612 and threshold 0.12 which indicate the radius of the subcluster by merging new sample and the nearest subcluster must be lesser than that. However, it is necessary to retain the distribution of the original dataset as much as possible in the downsampled dataset. For this purpose, the BIRCH algorithm is applied to get a dataset of non-critical ECG signal beats of length around 6800. This is combined with the set of critical ECG signal beats and then shuffled to prepare a balanced dataset for training and testing the proposed machine-learning model.Fig. 4 shows the BIRCH method.

Another balanced dataset is created with the application of oversampling method SMOTE [31].It maintained the binary class distribution of 1:1. It selects the minority class and find its nearest neighbors by KNN (k=5 default value) and draw a line between them.Choose any one of the neighbor and place

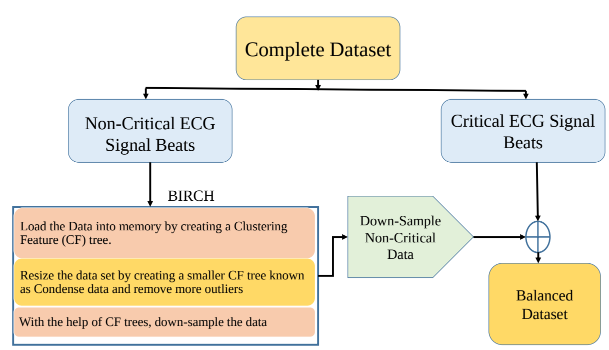

Fig. 4. Balanced dataset generation using BIRCH Algorithm

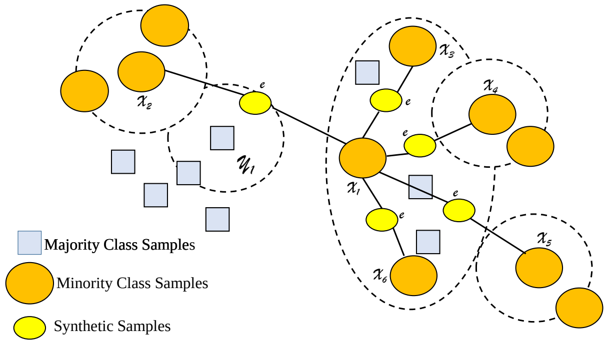

Fig. 5. SMOTE method

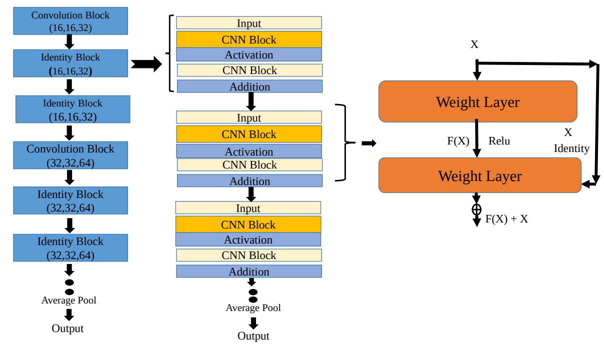

Fig. 7. ResNet Residual Block Architechture

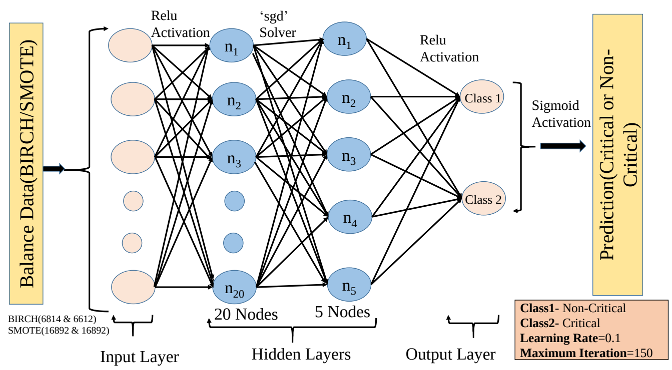

Fig. 6. MLP model

a synthetic point on that line and oversampling the minority class.Working process of SMOTE is in Fig. 5.This dataset is larger with each of the classes consisting of samples 16892 in number and details are shown in Table VI. All the experiments have been performed on both the datasets separately and achieved results are compared in the result section.

B. Proposed Method for ECG Data Classification

Instead of using very deep neural networks or pre-trained models, we have experimented with default and randomly initialized Residual Network (ResNet) stacking, instead the results are then compared to a well-known classification algorithm (SVM, RF, and BN) to come up with the best possible solution.

TABLE VI
BALANCE DATASET

	Class 1 (Non-Critical)	Class 2 (Critical)
Before Balancing	67570	6612
After Balancing (BIRCH)	6814	6612
After Balancing (SMOTE)	16892	16892

1) Classification Algorithms: Different standard machine learning algorithms have been deployed. The algorithms are: KNN,Logistic Regression,SVM,Gaussian Naive and Random Forest. The MLP, a feed forward ANN with minimum three number of layers namely input layer, hidden layer and an output layer with activation function in each node except the input layer nodes is used along with ResNet on the ECG dataset.the performance is noted for both. For internal layers, ReLu activation is considered in ResNet. We have used Adam optimizer and binary cross-entropy loss function. The Structure of the MLP model is shown in Fig. 6.

2) ResNet: The infamous vanishing gradient problem makes training deep network models difficult. The core idea of ResNet is applying a so-called“Identity shortcut connection,“ which skips for one or more layers, as shown in Fig. 7. We can characterize a residual neural network (ResNet) as an artificial neural network (ANN) of a kind that depends on pyramidal cells construction in the cerebral cortex. Regular ResNet models are executed with 2 fold or 3 layer skips with non-linearities (ReLU) and normalization between batches.

VI. EXPERIMENTAL VALIDATION OF IKARDO

In this experimental setup, the dataset prepared by SMOTE and BIRCH algorithm is explored. A power management algorithm has been proposed and implemented in WBAN to control the operating voltage in order to implement adaptive power savings.

A. Simulation Setup

The experiments have been carried out using Python 3.7 and Keras with Tensorflow 2.0 backend. SKLearn library has been used for the application of machine learning algorithms. We also look after the binary cross-entropy loss or Sigmoid Cross-Entropy loss. It used the Sigmoid activation function, which is not independent of all vector components like Softmax loss, which means the loss calculated for every CNN output vector element is not affected by other values. Adam Optimizer is used to optimize that loss which is predefined in TensorFlow Model. In different classification algorithm, parametric changes are incorporated for random forest 65% data for training. Rest are used for testing purpose with the estimator size 100, (implies 100 numbers of different decision trees in the forest), logistic regression used 'lbfgs' solver. It performs gradient evaluation and saves memory by reducing the last few steps only. SVM used with linear kernel and C value is 10 that tells the SVM classifier how much it avoids misclassifying the training set. The larger value of C chooses a small-margin hyperplane, and for the smaller value, it chooses a large-margin hyper plane, and in KNN, we consider K=4 after performing some operations with other values of K (The no. of nearest neighbours to include in the majority). Reduction of power consumption considered only the critical data transmission with available energy from source was implemented using Cadence tools to obtain power,area, and delay of sleep transistors and Synopsis Design Controller with 65nm and 28nm technology node with default parameters.

TABLE VII
COMPARISON FOR RESNET WITH BIRCH

Classifier	Accuracy	Labels	Precision	Recall	F1 Score
KNN	0.97	1	0.97	0.97	0.97
		2	0.97	0.97	0.97
Logistic	0.89	1	0.90	0.88	0.89
Regression		2	0.88	0.90	0.89
	0.95	1	0.96	0.94	0.95
SVM		2	0.94	0.96	0.95
Gaussian	0.90	1	0.90	0.89	0.90
NB		2	0.89	0.90	0.90
Random	0.93	1	0.94	0.93	0.93
Forest Classifier		2	0.93	0.94	0.93
MLP	0.9884	1	0.99	0.98	0.98
		2	0.98	0.99	0.98
ResNet	0.995	1	1.00	0.99	1.00
		2	0.92	1.00	0.95

TABLE VIII
COMPARISON FOR RESNET WITH SMOTE

Classifier	Accuracy	Labels	Precision	Recall	F1 Score
KNN	0.99	1	1.00	0.99	0.99
		2	0.99	1.00	0.99
Logistic	0.95	1	0.95	0.94	0.95
Regression		2	0.95	0.94	0.95
	0.98	1	0.98	0.98	0.98
SVM		2	0.98	0.98	0.98
Gaussian	0.90	1	0.86	0.95	0.90
NB		2	0.94	0.85	0.89
Random	0.93	1	0.97	0.98	0.98
Forest Classifier		2	0.98	0.97	0.97
MLP	0.9914	1	1.00	0.99	0.99
		2	0.98	0.97	0.97
ResNet	0.9958	1	1.00	0.99	0.99
		2	0.97	0.99	0.99

B. Metrics used for Evaluation

Classification algorithms usually suffer from the over fitting or under fitting problem. To measure any ML model's performance, accuracy may not be the only metric to look after always and to validate the model's precision, Recall and F1 score metrics have an equally vital role to validate any model.

Precision provides the rate of correctly positive predicted values over the total positive predicted values (True Positive/ (True positive + False Positive)) where Recall is used to measure correctly positive predicted values overall predicted values(True Positive/ (True positive + False Negative)), as we discussed precision and recall we have to consider F1 score because it makes a balance between them and it is calculated weighted average and can be a good measure when the distribution of classes is uneven.

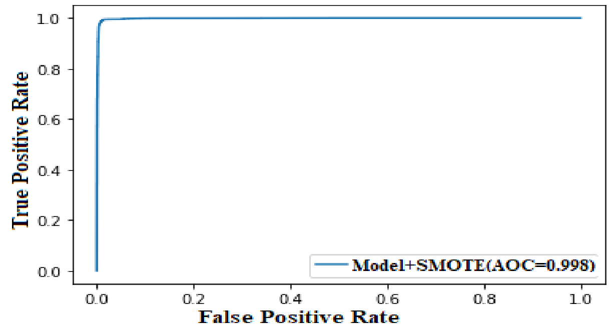

Fig. 8. ROC curve using SMOTE with ResNet

C. Results and Discussion

We have experimented with different standard algorithms on our balanced (using BIRCH with threshold 0.12 and SMOTE) dataset and achieved promising results, as shown in the tables. The performance of each one of these algorithms reaches a level of saturation quite early, as suggested by the corresponding ROC curves. The high value of the area under the curve in every case is a sign of employed algorithms' good performance. However, considering the importance of accurate classification of ECG signals in the field of healthcare, this performance is not sufficient. To achieve better performance, the stacking approach using ResNet architecture has been followed, and achieved better result.

1) Result with BIRCH: Table VII clearly shows that ResNet gives the highest accuracy for both the classes in the BIRCH model. With accuracy, we can also observe the other metrics like precision, recall, and F1 scores with values 1, 0.99, and 1, respectively, where MLP and KNN are just after it with the 0.97, 0.98, 0.97 for other matrices with an accuracy of 0.98 and 0.97 respectively. ResNet module used two no of dense block and four no of ResNet block (RNB0 to RNB3). Initial dense block activated using Relu activation, and last dense block had sigmoidal activation function. The dense layers belong to Keras API and with binary cross-entropy and Adam optimizer.

2) Result with SMOTE: Table VIII shows the best results for both MLP and ResNet using SMOTE Model. Not only in terms of accuracy, and it has demonstrated the other matrices with 0.97, 0.99, and 0.98 for precision, recall, and F1 score respectively. ResNet module had the same setup as used in BIRCH, and for MLP, two hidden layers are considered with several hidden nodes 20 and 5 respectively with 'sgd'(stochastic gradient descent) solver and 150 iterations. The F1 score for the ResNet model shown that the problem of uneven distribution or imbalanced nature of the dataset is addressed as the value of it up to 0.99. Although the performance of ResNet is slightly increases for smote in terms of accuracy, and the ROC curve, which indicates the true positive rate of SMOTE with ResNet stack in Fig. 8.

3) Power Overhead: State of the art smart healthcare devices consumes significance amount of power. Fig. 9 depicts the distribution of power consumption by subsystem in terms of percentage of total power. We observed that a significant portion of the power is involved in the communication subsys-

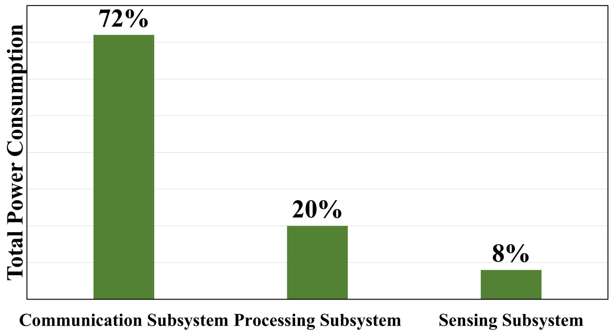

Fig. 9. Power/energy used by different units

tem [32]. In order to serve PMC with adaptive voltage scaling, the independent component-wise voltage must be supplied to the respective components. The voltage levels should change quickly depending on the type of data packet received. To provide different voltage levels, a voltage regulator based on a switched capacitor and a switched inductor is used, which is adopted from [28]. The regulator's output voltage levels are V_1, V_2, V_3, and V_4 with 1V, 0.9V, 0.8V, and 0V, respectively, which are used when communicating ECG data and critical data. The voltage regulator unit (VRU) regulates the four different output voltage levels based on the signal supplied by the PMC.

The component voltage is switched to the desired voltage level at each transmission.Because the voltage level changes dynamically during each ECG packet transmission, a level shifter is included to handle voltage transitions from one level to another. Depending on the signal received from the PMC, transmission gates pass various voltage levels V_1, V_2, V_3, and V_4 as Vout. As a result, the output voltage Vout has switched adaptively for that particular instance for different components of a specific subunit.

The power consumption involved in Communication Unit for WBAN architecture goes to inactive mode instantly, if identified ECG signal is non-critical. The major share of ECG signals is classified as noncritical, which contributes to 87% of power saving for the current application of WBAN. Again, if iKardo finds a critical, it sends a low bandwidth alert signal rather than sending raw ECG data. It saves 70% power in raw ECG data transfer and 74% power saving when working with the critical signal. The controller consumed 0.24nW power. The area occupied is 10.17 μm^2 by the single controller and area overhead 36.5 μm^2 for the level shifter with a power consumption of $6 \times 10^3 \mu$W. The voltage monitor has an area of 0.033 mm^2 that consumes 0.058 W power. We achieved a gain of 27% power saving over the conventional method.

We mainly emphasize on the classification of critical data labelled as 2 in table V. From the above tables and metrics, we make a precise observation of 99.58 % accuracy with 27% power savings and successfully addressed the contribution that is a ML-based power-aware intelligent ECG signal classification system suitable for IoT-based smart ECG monitoring device iKardo, and we are able to achieve efficient results in comparison with other works shown in Table I and II.

VII. Conclusion

This work proposes an intelligent ECG device for automatic critical beat identification using a machine learning-based approach for smart healthcare applications, iKardo, to alleviate the major issues associated with an imbalanced dataset, using IoT and WBAN frameworks. In addition to that, the proposed model also reduces power consumption significantly. Based on the observation, it is found that iKardo is a suitable candidate for consumer electronics applications with the help of a machine learning approach. The proposed model reduces the detection timing, memory utilization, and power consumption significantly over the existing models.

Implemented fine-tuned ResNet model has outperformed compared to the existing methods. During the experiments, special attention is given to identify the critical ECG signal beats. This work can be further extended the boundary of ML approaches for several biomedical applications. With proper optimization, it would be possible to identify a particular category of signals accurately. The proposed work may be extended even for multi-class classification tasks.

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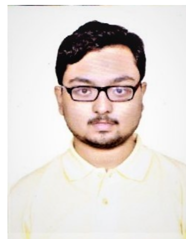

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