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# A MACHINE LEARNING FRAMEWORK FOR ECG-BASED BIOMETRIC AUTHENTICATION

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## ABSTRACT

This project introduces a framework for appropriately adapting and adjusting machine learning (ML) techniques used to construct electrocardiogram (ECG)-based biometric authentication schemes. It can help define the boundaries of required datasets and get training data with good quality. Use case analysis is adopted to determine the boundaries of datasets. Based on various application scenarios on ECG-based authentication, three different use cases are developed. With more qualified training data given to corresponding machine learning schemes, the precision on ML-based ECG biometric authentication mechanisms are increased in consequence. The ECG time slicing technique with the R-peak anchoring is utilized in this framework to acquire ML training data with good quality. In the proposed framework four new measure metrics are introduced to evaluate the quality of the ML training and testing data. In addition, a MATLAB toolbox, containing all proposed mechanisms, metrics, and sample data with demonstrations using various ML techniques, is developed. For developing ML-based ECG biometric authentication, the proposed framework can guide researchers to prepare the proper ML setups and the ML training datasets along with three identified user case scenarios.

INDEX TERMS: Authentication, ECG Time Slicing, ECG Biometric Authentication, Machine Learning, R-peak Anchoring.

## INTRODUCTION

Because most application systems support Internet access for general users, identifying persons with their own body has become the trend for users to access application systems. In consequence, biometric authentication has become a hot research topic in recent years. Among various biometric authentication schemes such as fingerprint scanning and facial recognition, electrocardiogram authentication has the advantage of adopting live user body signals during authentication. In general, machine learning techniques are adopted to construct a verification model for user identification by getting user's live ECG data. Recently there are a number of state-of-art literatures on ECG based biometrics. However, several ECG biometrics challenges still require further investigation such as authentication categorization, pre-processing for data quality enhancement, data acquisitions, selection on Deep Learning (DL) and other Machine Learning classification approaches.

This project introduces a ML framework for ECG based biometric authentication in order to mitigate identified challenges on ECG authentication. To better understand potential application environments for ECG authentication, it is necessary to identify basic application scenarios through use cases. In the proposed framework, application scenarios using ECG authentication are categorized into three general use cases: Hospital (HOS), Security Check (SCK) and Wearable Devices (WD). Furthermore, new data preprocessing techniques including the baseline adjustment of frequency artifacts in the ECG, the ECG data noise removal technique for Power Line Interference (PLI), and flipping mechanism for ECG signal due to the wrong placement of electrodes, are proposed. In addition, time slicing techniques are introduced in the framework to prepare ML-based training datasets along with new measure metrics developed for authentication precision evaluation. Four new measure metrics for data quality are introduced in the proposed framework. They are Mean Absolute Error Rate (MAER), Upper/Lower Range Control Limits (UCL/LCL), Accuracy Percentage within Ranges (APR), and Accuracy per UCL (APU).

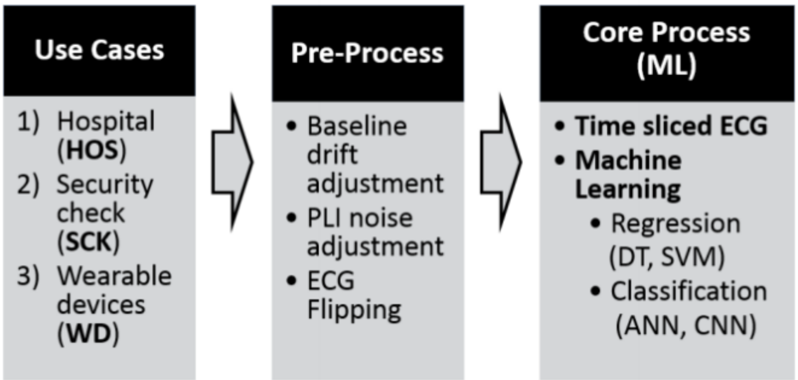


Fig: Overview of the New Framework Model for ECG based Biometric Authentication

Figure illustrates an overview of the new framework model for ML-based ECG biometric authentication. Within the core process portion, several ML techniques are adopted: Decision Tree (DT) and Support Vector Machine (SVM) for regression approach, and Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) for classification approach. In addition, time slicing technique for ECG data is developed and associated with the core process.

## LITERATURE SURVEY

### Heart-ID: A multiresolution convolutional neural network for ECG-based biometric human identification in smart health applications

Body area networks, including smart sensors, are widely reshaping health applications in the new era of smart cities. To meet increasing security and privacy requirements, physiological signal based biometric human identification is gaining tremendous attention. This paper focuses on two major impediments: the signal processing technique is usually both complicated and data-dependent and the feature engineering is time-consuming and can fit only specific datasets. To enable a data-independent and highly generalizable signal processing and feature learning process, a novel wavelet domain multiresolution convolutional neural network is proposed. Specifically, it allows for blindly selecting a physiological signal segment for identification purpose, avoiding the complicated signal fiducial characteristics extraction process. To enrich the data representation, the random chosen signal segment is then transformed to the wavelet domain, where multiresolution time-frequency representation is achieved. An auto-correlation operation is applied to the transformed data to remove the phase difference as the result of the blind segmentation operation. Afterward, a multiresolution 1-D-convolutional neural network (1-D-CNN) is introduced to automatically learn the intrinsic hierarchical features from the wavelet domain raw data without data dependent and heavy feature engineering, and perform the user identification task. The effectiveness of the proposed algorithm is thoroughly evaluated on eight electrocardiogram datasets with diverse behaviors, such as with or without severe heart diseases, and with different sensor placement methods. Our evaluation is much more extensive than the state-of-the-art works, and an average identification rate of 93.5% is achieved. The proposed multiresolution 1-D-CNN algorithm can effectively identify human subjects, even from randomly selected signal segments and without heavy feature engineering. This paper is expected to demonstrate the feasibility and effectiveness of applying the blind signal processing and deep learning techniques to biometric human identification, to enable a low algorithm engineering effort and also a high generalization ability.

**Evolution, current challenges, and future possibilities in ECG biometrics**

Face and fingerprint are, currently, the most thoroughly explored biometric traits, promising reliable recognition in diverse applications. Commercial products using these traits for biometric identification or authentication are increasingly widespread, from smartphones to border control. However, increasingly smart techniques to counterfeit such traits raise the need for traits that are less vulnerable to stealthy trait measurement or spoofing attacks. This has sparked interest in the electrocardiogram (ECG), most commonly associated with medical diagnosis, whose hidden nature and inherent liveness information make it highly resistant to attacks. In the last years, the topic of ECG-based biometrics has quickly evolved toward the commercial applications, mainly by addressing the reduced acceptability and comfort by proposing new off-the-person, wearable, and seamless acquisition settings. Furthermore, researchers have recently started to address the issues of spoofing prevention and data security in ECG biometrics, as well as the potential of deep learning methodologies to enhance the recognition accuracy and robustness. In this paper, we conduct a deep review and discussion of 93 state-of-the-art publications on their proposed methods, signal datasets, and publicly available ECG collections. The extracted knowledge is used to present the fundamentals and the evolution of ECG biometrics, describe the current state of the art, and draw conclusions on prior art approaches and current challenges. With this paper, we aim to delve into the current opportunities as well as inspire and guide future research in ECG biometrics.

**Learning deep off-the-person heart biometrics representations**

Since the beginning of the new millennium, the electrocardiogram (ECG) has been studied as a biometric trait for security systems and other applications. Recently, with devices such as smartphones and tablets, the acquisition of ECG signal in the off-the-person category has made this biometric signal suitable for real scenarios. In this paper, we introduce the usage of deep learning techniques, specifically convolutional networks, for extracting useful representation for heart biometrics recognition. Particularly, we investigate the learning of feature representations for heart biometrics through two sources: on the raw heartbeat signal and on the heartbeat spectrogram. We also introduce heartbeat data augmentation techniques, which are very important to generalization in the context of deep learning approaches. Using the same experimental setup for six methods in the literature, we show that our proposal achieves state-of-the-art results in the two off-the-person publicly available databases.

**Cancelable ECG biometrics using compressive sensing-generalized likelihood ratio test**

Electrocardiogram (ECG) has been investigated as promising biometrics, but it cannot be canceled and re-used once compromised just like other biometrics. We propose methods to overcome the issue of irrevocability in ECG biometrics without compromising performance. Our proposed cancelable user authentication uses a generalized likelihood ratio test (GLRT) based on a composite hypothesis testing in compressive sensing (CS) domain. We also propose a permutation-based revocation method for CS-based cancelable biometrics so that it becomes resilient to record multiplicity attack. In addition, to compensate for inevitable performance degradation due to cancelable schemes, we also propose two performance improvement methods without undermining cancelable schemes: a self-guided ECG filtering and a T-wave shift model in our CS-GLRT. Finally, our proposed methods were evaluated for various cancelable biometrics criteria with the public ECG-ID data (89 subjects). Our cancelable ECG biometric methods yielded up to 93.0% detection probability at 2.0% false alarm ratio (PD*) and 3.8% equal error rate (EER), which are comparable to or even better than non-cancelable baseline with 93.2% PD* and 4.8% EER for challenging single-pulse ECG authentication, respectively. Our proposed methods met all cancelable biometrics criteria theoretically or empirically. Our cancelable secure user template with our novel revocation process is practically non-invertible and robust to record multiplicity attacks.

## Machine learning and deep learning methods for cyber security

With the development of the Internet, cyber-attacks are changing rapidly and the cyber security situation is not optimistic. This survey report describes key literature surveys on machine learning (ML) and deep learning (DL) methods for network analysis of intrusion detection and provides a brief tutorial description of each ML/DL method. Papers representing each method were indexed, read, and summarized based on their temporal or thermal correlations. Because data are so important in ML/DL methods, we describe some of the commonly used network datasets used in ML/DL, discuss the challenges of using ML/DL for cybersecurity and provide suggestions for research directions.

## Comparison of baseline wander removal techniques considering the preservation of ST changes in the ischemic ECG: A simulation study

The most important ECG marker for the diagnosis of ischemia or infarction is a change in the ST segment. Baseline wander is a typical artifact that corrupts the recorded ECG and can hinder the correct diagnosis of such diseases. For the purpose of finding the best suited filter for the removal of baseline wander, the ground truth about the ST change prior to the corrupting artifact and the subsequent filtering process is needed. In order to create the desired reference, we used a large simulation study that allowed us to represent the ischemic heart at a multiscale level from the cardiac myocyte to the surface ECG. We also created a realistic model of baseline wander to evaluate five filtering techniques commonly used in literature. In the simulation study, we included a total of 5.5 million signals coming from 765 electrophysiological setups. We found that the best performing method was the wavelet-based baseline cancellation. However, for medical applications, the Butterworth high-pass filter is the better choice because it is computationally cheap and almost as accurate. Even though all methods modify the ST segment up to some extent, they were all proved to be better than leaving baseline wander unfiltered.

# EXISTING SYSTEM

## 3.1 EXISTING SYSTEM

In our exist system is explain the biometric authentication system generally authentication is checks if your correct user or not so based on data system will check your credentials and give access so in this scenario every person will give their credentials after that he will get access some companies have more than 500 its check on by one so it will take so much time.

**DISADVANTAGES:**

- More time required
- More resources required
- Cost effective

## 3.2 PROPOSED SYSTEM

Our proposed System introduces a framework for how to appropriately adapt and adjust machine learning (ML) techniques used to construct electrocardiogram (ECG)-based biometric authentication schemes. The proposed framework can help investigators and developers on ECG-based biometric authentication mechanisms define the boundaries of required datasets and get training data with good quality. To determine the boundaries of datasets, use case analysis is adopted. Based on various application scenarios on ECG-based authentication, three distinct use cases (or authentication categories) are developed.

**ADVANTAGES:**

- Easy to maintain
- Fast tracking
- Less effective

# SYSTEM REQUIREMENTS

## 4.1 HARDWARE CONFIGURATION

- Processor - Intel i3 or above
- Speed - 1.1 GHz
- RAM - 4 GB
- Hard Disk - 20 GB(min)
- Key Board - Standard Windows Keyboard
- Mouse - Two or Three Button Mouse

## 4.2 SOFTWARE CONFIGURATION

- Operating System : Windows 10
- Programming Language : Python

# MODULES

## 5.1 PRE-PROCESS FOR ECG DATA QUALITY ENHANCEMENT

The pre-process is about adjusting data before starting the core process (i.e., machine learning process). The signal processing techniques have been widely applied into adjusting ECG data since ECG data could be considered as signals. Many applications in the signal processing including the filter designs and the Fourier Transforms are applied for enhancing the ECG recognition. Although many pre-processes are adopted for enhancing signals, three processes are recommended for enhancing ECG data before starting the machine learning process.

### 5.1.1 BASELINE ADJUSTMENT

The baseline drift (also called the baseline wander) is a low frequency artifact in the ECG that arises from breathing, electrically charged electrodes. Baseline adjustment process is removing the baseline wander. Typically, a complete baseline wander removal requires that the cut-off frequency of the high-pass filter be set higher than the lowest frequency in the signal. The majority of baseline wander removal techniques have in common that they cancel the low frequency components of the signal. The frequency of the baseline wander high-pass filter is usually set slightly below 0.5 Hz. Although these techniques are well studied and widely used, the proper frequency for the baseline drift removal should be determined in advance. In case of dealing with ECG data gathering, the baseline drift could also happen by certain movement of an applicant, not by low frequency noise. Therefore, these filtering techniques may not be useful if we do not know the proper indicator of the cut-off frequency or expecting certain movement of an applicant (HOS case).

### 5.1.2 POWER LINE INTERFERENCE NOISE REMOVAL

There are several types of noise signals including the baseline wander and the noise from the PLI which is coupled to signal carrying cables is particularly troublesome in medical equipment is also commonly happened in a hospital (HOS case) when cables carrying signals from the examination room to the monitoring equipment are prone to electromagnetic interference (EMI) of frequency by seamless supply lines. Electromagnetic fields caused by a power line represent a common noise source in the ECG that is characterized by 50 or 60 Hz sinusoidal interference, possibly accompanied by a number of harmonics. Such narrow band noise causes problems interpreting low amplitude waves because it introduces unreliable and spurious waveforms. The Infinite Impulse Response (IIR) notch filter is widely applied to remove PLI noise. A notch filter rejects or attenuates signals in a specific frequency band called the stop band frequency range and passes the signals above and below this band. These types of the filter could be applied to remove the baseline wander but a proper target frequency should be determined before applying the filters. On the other hand, removing abnormal peak points in the frequency domain provides similar effects by using a notch filter without determining the target frequency in advance.

The Fourier Transform has been used to find abnormal peak points in the frequency domain. The abnormal peak points (typically 50-150 times higher than an average magnitude) in the frequency domain including PLI frequencies could be considered as a noise and these peak points are subject to removal for enhancing the original ECG data. Alternatively, the specific frequencies which occur noises could be removed. As it mentioned above, the 50 Hz frequency occurs the PLI and the 1 Hz frequency occurs the baseline wander. The ECG data could be improved by removing these frequencies by using the Fourier Transform even without using filters.

### 5.1.3 FLIPPING SIGNAL

The medical machines including an electrocardiograph typically require professionals to set up and measure ECG signals. But even professionals make mistakes including wrong placement of electrodes. Flipping an ECG signal is a typical situation by mistaking operators in hospitals. Therefore, it is better to check whether a target ECG data (either training or testing phases) is flipped or not. This pre-process adjusts the flipped ECG data if an original data is flipped (if it is not, an adjusted data is the same as original data). The simplified way of flipping ECG data is determining the flipping status by checking the mean of small portions of the data instead of checking a whole data.

## 5.2 TIME SLICING AND MACHINE LEARNING

The time slicing technique is considered for building up the dataset of the machine learning training. This approach is especially applicable for building up the machine learning training data. The ECG data are sliced based on a slice (window) time (typically known as a sliding window) with the R-peak anchoring. This method could generate enough data samples and each sliced data becomes a sample input for the machine learning training. The time sliced ECG dataset is very flexible not only to mix with other training inputs but also to apply various ML training methods.

### 5.2.1 TIME SLICED ECG DATA FOR MACHINE LEARNING

The QRS complex is the combination of three of the graphical deflections seen on a typical ECG which is usually the central and most visually obvious part of the tracing. An R-peak which is the maximum of a QRS complex. It indicates one heartbeat and the moment of the R-peak is commonly used for the anchor of the QRS complex including the R-peak detection and optimizing the sliding window time. Time slicing, which is basically slicing ECG data in the time domain, is targeted for chopping the ECG signal from an R-peak moment to the sliding window period and layering these pieces based on the R-peak moment (i.e., R-peak anchoring). Each slicing peace based on the R-peak anchoring in Figure 6 becomes sample inputs for the machine learning training. In this paper, the average minimum of a heartbeat interval from atypical heart rate is chosen as a slicing time (i.e., sliding window) which is 0.6 seconds which is equivalent with 100 bps heartbeat rate. The optimized sliced window time depends on the purpose of ECG based projects and some performance measures for the machine learning are somewhat depending on the ECG slicing time.

### 5.2.2 MACHINE LEARNING PROCESS FOR TRAINING DATA

Machine learning is a subset of artificial intelligence (AI) which computer systems use to effectively perform a specific task without using explicit instructions. Machine learning algorithms build a mathematical model of training data to make predictions (regressions) or decisions (classification/ pattern recognition) without being explicitly programmed. It has been widely studied for analyzing ECG data by using AI techniques.

#### 5.2.2.1 MACHINE LEARNING FOR REGRESSION APPROACH

A multi-variable regression is a data mining task of predicting a value of the target by building a model based on multiple variables. The Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating pattern. This technique has been applied for regression since the 1990s. The Decision Tree (DT) could also build a regression model in the forms of a tree structure. It breaks down a dataset into smaller subsets while at the same time an associated decision tree is incremented.

#### 5.2.2.2 MACHINE LEARNING FOR CLASSIFICATION APPROACH

Classification is targeted to identify a set of categories on the basis of a training set of data containing observations. The set of the identification is considered as a set of categories and each identification becomes each category in the set. In this paper, neural network (NN) models (Artificial Neural Networks or Convolutional Neural Networks) are proposed for identifying persons by using the time sliced ECG dataset as the inputs.

### 5.3 DATA QUALITY MEASURES

Evaluating your machine learning algorithm is an essential part of any ML projects and delivering the good quality of samples is vital for evaluating the ML system. Some performance measures (evaluation metrics) are the values of evaluation results of sample data qualities and regression approaches based authentication systems. Typical data quality measures and performance measures for a regression approach are as follows:

- Sum of Squares Error
- Sum of Squares Total
- Mean Squared Error
- Mean Absolute Error

Besides typical quality measures, additional new measurement factors are introduced in the project. These quality measures are not only applied for evaluating regression approached machine learning systems but also applied for the criteria of validating samples. The new data quality measures are as follows:

- Mean Absolute Error Rate
- Upper and Lower Range Control Limits
- Accuracy Percentage within Ranges
- Accuracy per Upper Control Limit

### 5.4 MATLAB TOOLBOX

The proposed Toolbox for demonstrating the proposed processes and techniques in each section is actually implemented as the functions of the Matlab. The Amgecg Toolbox (Amang ECG Toolbox) which is the set of the Matlab functions which researchers could use for their own ECG authentication projects and this section introduces some of functions in the Toolbox.

#### 5.4.1 TOOLS FOR PRE-PROCESS AND TIME SLICING

Three processes which include the baseline drift adjustment, the noise adjustments and the flipping ECG data have been newly introduced as the pre-process of the Machine Learning adaptations and the Matlab functions in the new Toolbox are as follows:

- baselinedrift
- enhancednoiseadjust
- pseudoflip

### 5.4.2 TOOLS FOR DATA QUALITY

The amgecg Toolbox also contains the functions for analyzing the data quality. The indicators of the data quality that have been mentioned in Section V are provided in the toolbox and the related functions are as follows:

- rangecontrol
- maer
- mseamg
- maerdataqualityengine
- msedataqualityengine

## ARCHITECTURE

### 6.1 SYSTEM ARCHITECTURE

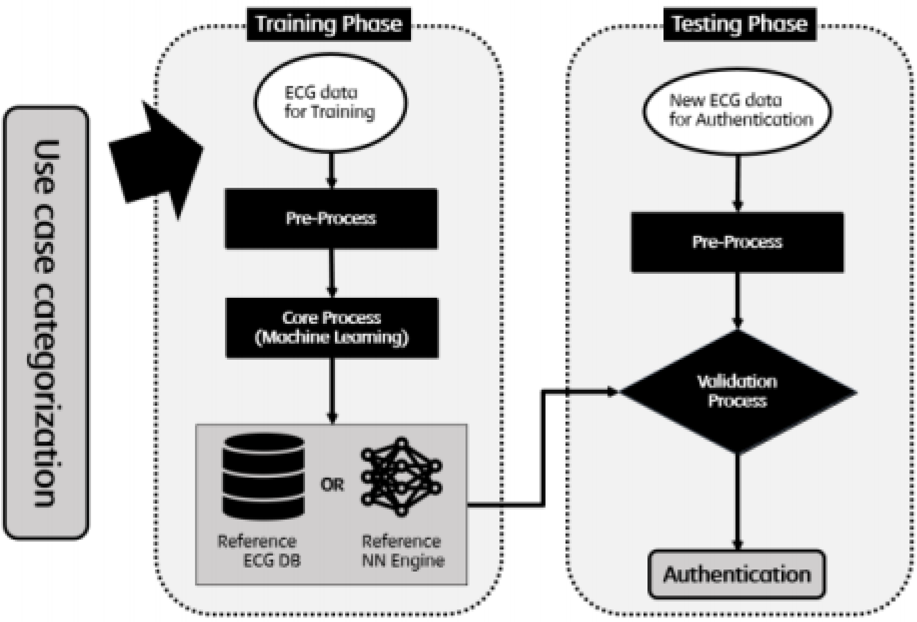


Fig: System Architecture

### 6.2 CLASS DIAGRAM

The class diagram is the main building block of object oriented modeling. It is used both for general conceptual modeling of the systematic of the application, and for detailed modeling translating the models into programming code. Class diagrams can also be used for data modeling. The classes in a class diagram represent both the main objects, interactions in the application and the classes to be programmed. In the diagram, classes are represented with boxes which contain three parts:

- The upper part holds the name of the class
- The middle part contains the attributes of the class
- The bottom part gives the methods or operations the class can take or undertake

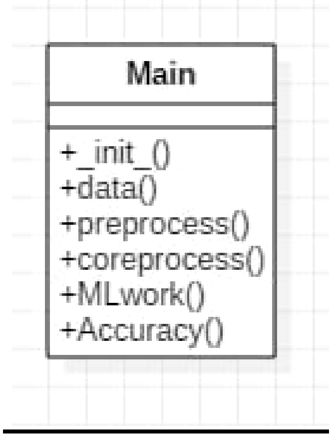


Fig: Class Diagram

### 6.3 USE CASE DIAGRAM

A use case diagram at its simplest is a representation of a user's interaction with the system and depicting the specifications of a use case. A use case diagram can portray the different types of users of a system and the various ways that they interact with the system. This type of diagram is typically used in conjunction with the textual use case and will often be accompanied by other types of diagrams as well.

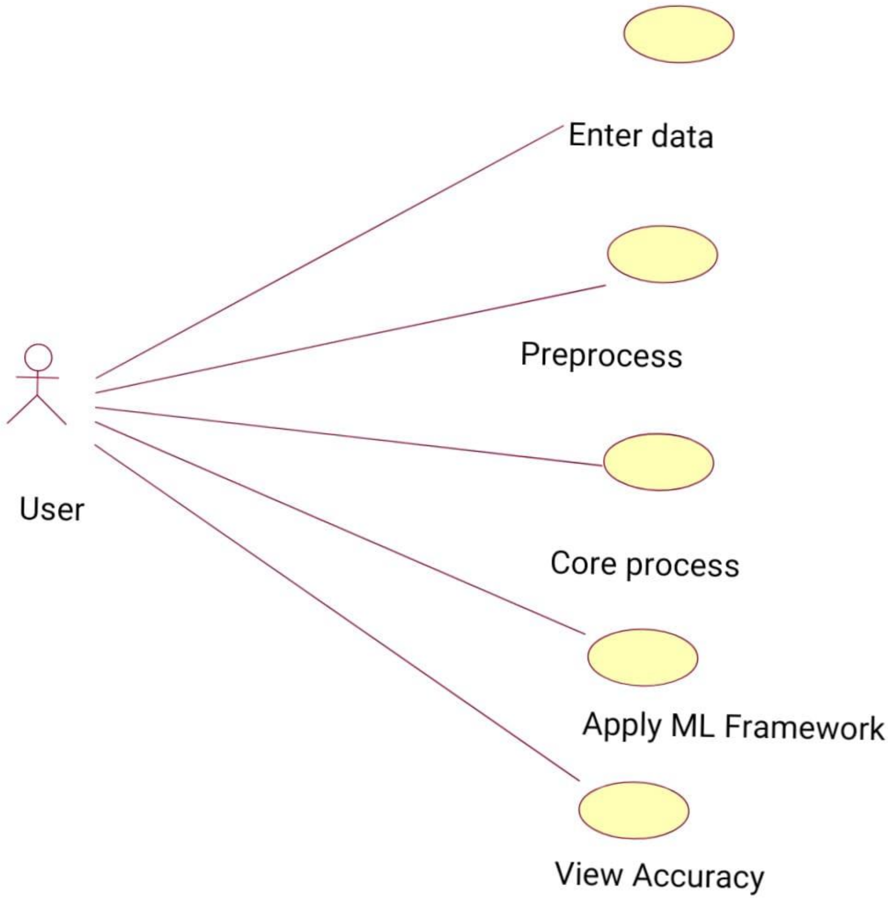


Fig: Use Case Diagram

## 6.4 SEQUENCE DIAGRAM

A sequence diagram is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. A sequence diagram shows object interactions arranged in time sequence. It depicts the objects and classes involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the Logical View of the system under development. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

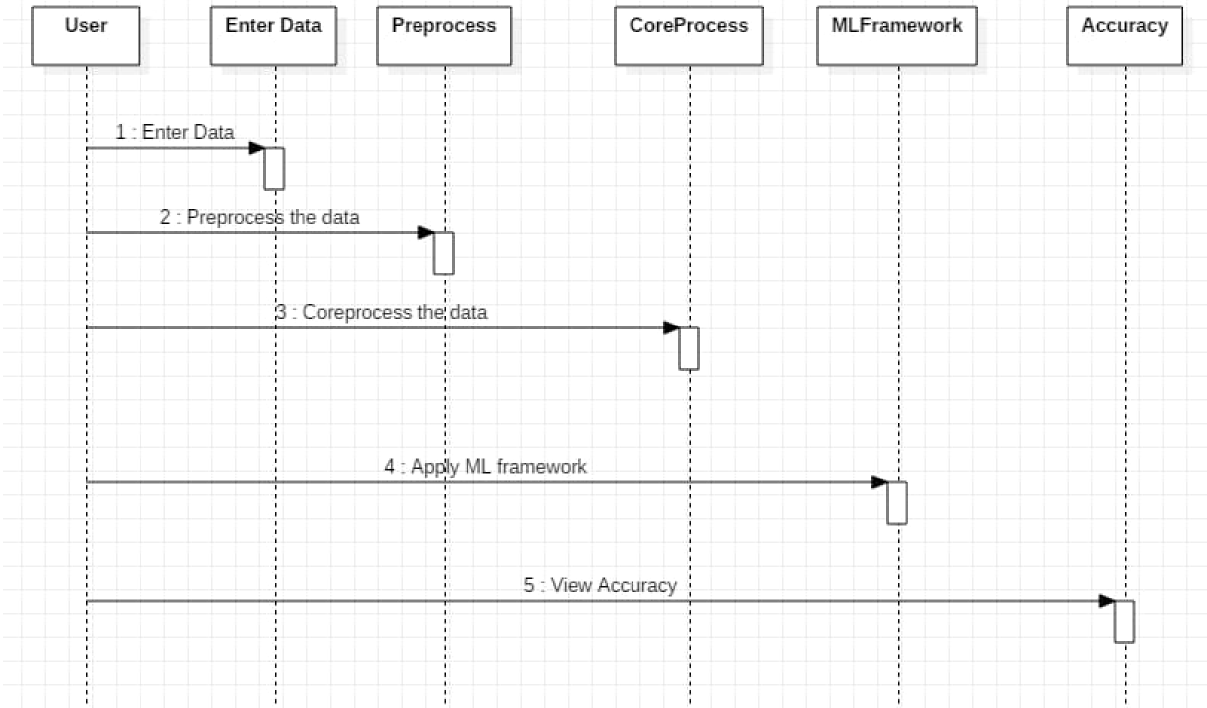


Fig: Sequence Diagram

## 6.5 COMPONENT DIAGRAM

In the Unified Modeling Language, a component diagram depicts how components are wired together to form larger components and or software systems. They are used to illustrate the structure of arbitrarily complex systems.

Components are wired together by using an assembly connector to connect the required interface of one component with the provided interface of another component. This illustrates the service consumer - service provider relationship between the two components.

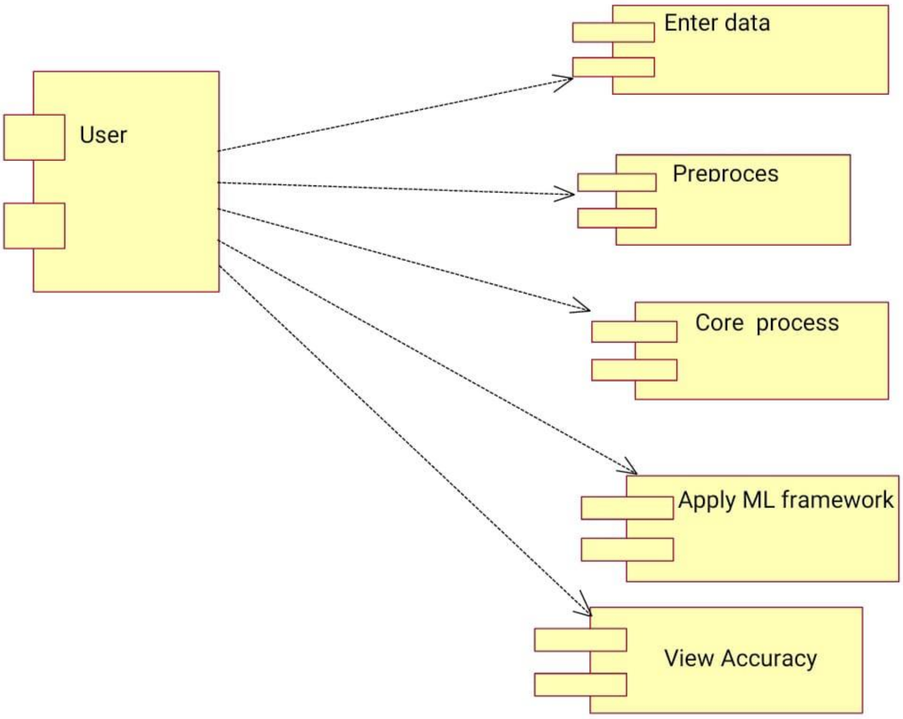


Fig: Component Diagram

## 6.6 DEPLOYMENT DIAGRAM

A deployment diagram in the Unified Modeling Language models the *physical* deployment of artifacts on nodes. To describe a web site, for example, a deployment diagram would show what hardware components ("nodes") exist (e.g., a web server, an application server, and a database server), what software components ("artifacts") run on each node (e.g., web application, database), and how the different pieces are connected (e.g. JDBC, REST, RMI).

The nodes appear as boxes, and the artifacts allocated to each node appear as rectangles within the boxes. Nodes may have sub nodes, which appear as nested boxes. A single node in a deployment diagram may conceptually represent multiple physical nodes, such as a cluster of database servers.

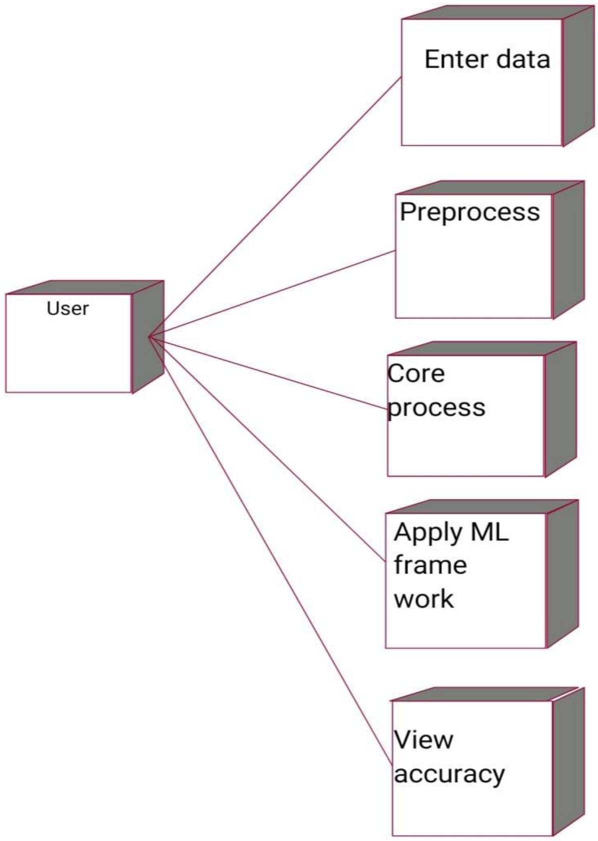


Fig: Deployment Diagram

## 6.7 ACTIVITY DIAGRAM

Activity diagram is another important diagram in UML to describe dynamic aspects of the system. It is basically a flowchart to represent the flow form one activity to another activity. The activity can be described as an operation of the system. So the control flow is drawn from one operation to another. This flow can be sequential, branched or concurrent.

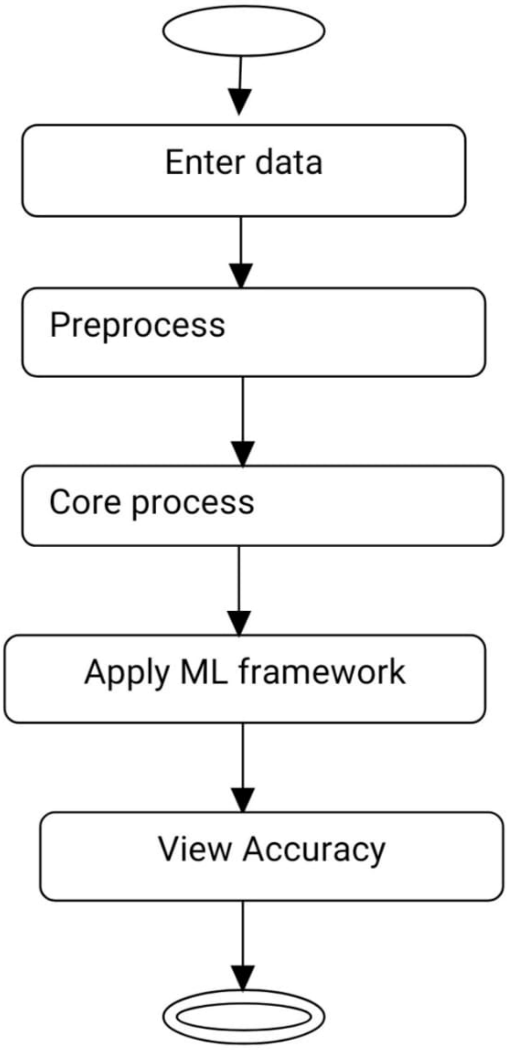


Fig: Activity Diagram

## 6.8 DATA FLOW DIAGRAM

Data flow diagrams illustrate how data is processed by a system in terms of inputs and outputs. Data flow diagrams can be used to provide a clear representation of any business function. The technique starts with an overall picture of the business and continues by analyzing each of the functional areas of interest. This analysis can be carried out in precisely the level of detail required. The technique exploits a method called top-down expansion to conduct the analysis in a targeted way.

As the name suggests, Data Flow Diagram (DFD) is an illustration that explicates the passage of information in a process. A DFD can be easily drawn using simple symbols. Additionally, complicated processes can be easily automated by creating DFDs using easy-to-use, free downloadable diagramming tools. A DFD is a model for constructing and analyzing information processes. DFD illustrates the flow of information in a process depending upon the inputs and outputs. A DFD can also be referred to as a Process Model. A DFD demonstrates a business or technical process with the support of the outside data saved, plus the data flowing from the process to another and the end results.

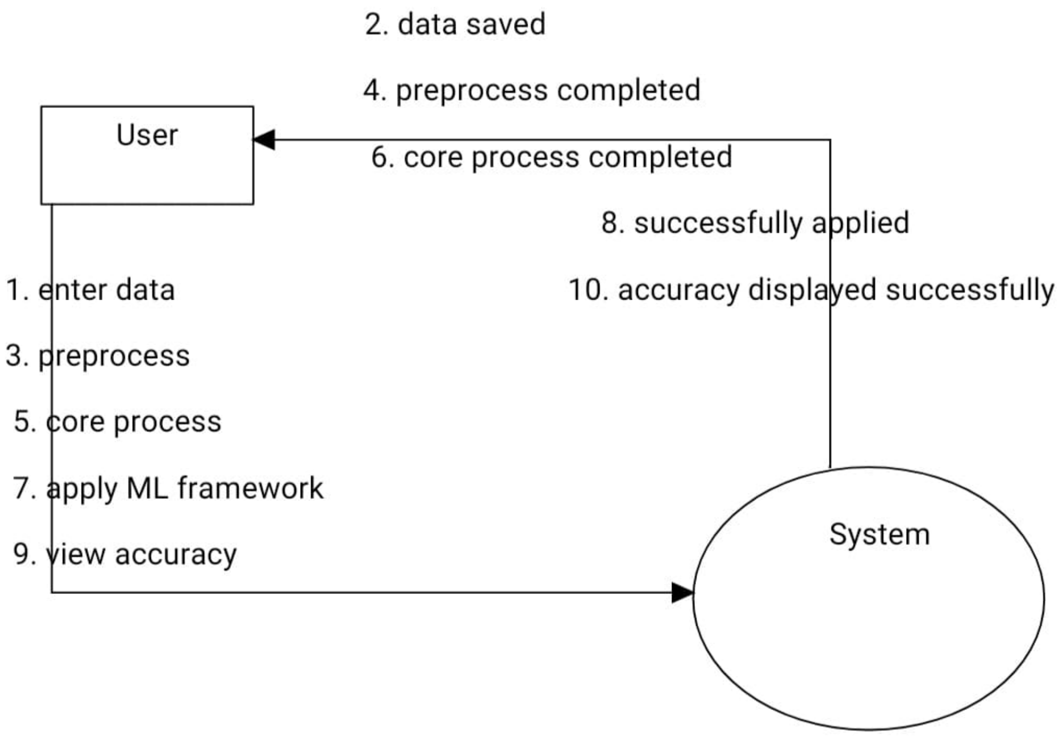


Fig: Data Flow Diagram

## CONCLUSION

As new ECG detection devices become portable, lightweight, embeddable with smartphones and wearable devices, and connectable with remote servers through wireless technologies in the near future, ECG based biometric authentication will be deployed on massive application systems all over the world. To get high accuracy on user authentication, ML techniques are generally adopted to build a more robust evaluation model for ECG based biometric authentication. In this paper a generalized machine learning framework for ECG based biometric authentication is introduced. The proposed framework describes the general data processing flow of a ML-based ECG authentication mechanism along with various function features to help researchers easily design and evaluate a ML-based ECG user authentication scheme. Those functions include three general authentication categories for ECG user authentication, three new data pre-processing techniques, a time slicing technique to generate high quality ECG datasets, four new data quality metrics, and a publicly available Matlab

Toolbox (i.e., amgecg Toolbox). For people using ML technologies to investigate other topics instead of ECG based biometric authentication, several data pre-processing techniques and newly defined measure metrics offered by the proposed framework are still useful and can help researchers accelerate the development of their ML-based schemes.

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