**Use of artificial intelligence in detection of arrhythmia from electrocardiograms**

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# Abstract

Arrhythmias are a common cardiovascular disease afflicting primarily the elderly population which often have severe symptoms including death. As populations age, the case count of arrhythmias are expected to rise and the primary method of detecting them, manual electrocardiogram interpretation, may require large amounts of resources dedicated that may be better allocated elsewhere in the healthcare system. Therefore, it is pertinent to provide an alternative method of interpreting electrocardiograms that is more automated and still maintains high standards of care. In this work, we provide our ideal solution. Herein, we describe the creation, testing, and use simulation of a multilayer perceptron deep-learning artificial intelligence model for the detection and characterization of arrhythmias based on standard ECG measurement data provided by MIT. Two models were created, with 94% and 96% accuracy rates on detecting and identifying ventricular ectopic beats arrhythmia and supraventricular ectopic beats arrhythmia. A facile and accessible data input methodology was developed for the trained model and a use case simulation using 100 datapoints was conducted, which yielded 98% accuracy.

**Keywords:** A.I.-detection, ECG, arrhythmia, cardiovascular disease

**Introduction**

Cardiovascular diseases (CVDs) are the leading cause of death in the world, eclipsing even cancer-caused mortality [1]. Age is, in a way, the primary risk factor for CVDs with over 80% of CVDs related deaths occurring in those aged over 65, where over 40% of the population have deaths attributed to CVDs [2], consequently detection of CVDs is important to the general health of those ageing populations. A common specific group of CVDs are arrhythmias. Arrhythmias are a type of CVD characterized by abnormal rhythms in the heartbeat outside the normal, which can be in either rate (outside the expected range of 60-100 beats per minute) or irregular activations of certain attributes of a heartbeat [3]. Arrhythmias encompass a large number of specific conditions of which some are benign and others are more severe, often depending on other abnormalities, often physical, of the heart [3]. One common method of detecting and characterizing specific arrhythmias is using electrocardiograms (ECGs) to determine abnormalities in attributes of the electrical activity of the cardiac muscle cells, or cardiomyocytes. An ECG is generally designated into PQRST, and occasionally U, markers which represent the normal stages of a heartbeat [4]. This method of ‘breaking up’ an ECG into sections such as ST-interval or T-peak is useful for clinical practices as it is clear and easy to identify specific abnormalities by manual inspection [5]. However, manual inspection is limited in multiple ways, such as the ability of the healthcare professional and the availability of labour and time. Additionally, ECGs are standardized measurements, and specific arrhythmias will have unique attributes of their ECG affected, which is how arrhythmias are identified, which makes them identifiable by patterns and potentially artificial intelligence (A.I.). These factors make the use of A.I. for interpreting ECGs a valuable potential pathway for increasing the rates of non-normal patient ECGs to be identified, as it can facilitate manual inspection more as the ‘normal’ ECGs may be screened off by the A.I. model and the manual inspection can allocate more resources towards ECGs that are more likely to be important overall. A.I. models require extensive amounts of data to be trained on, and fortunately, there are databases such as the MIT-BIH Arrhythmia Database [6] presenting the required data for A.I. models to be trained on.

While there are many types of arrhythmias, as described in the supplementary information, the MIT-BIH database only has useful amounts of data regarding VEB and SVEB arrhythmias, consequently, models developed using the database can only be trained to those arrhythmias.

In the following work, we describe the creation and testing of two A.I. models (herein referred simply to as ‘models’) both trained and tested on the MIT-BIH Arrhythmia Database to a high degree of accuracy (>94%) alongside the creation of a simple user-input application to run their own ECGs through the models. This is in a goal to understand to what extend can a machine learning model, trained on a large-scale ECG database, accurately identify and characterize different arrhythmias. While helpful for any age demographic, this is especially important to the elderly and aging population as those are who suffer the most from arrhythmias.

# Methods

## Biological basis for using MIT ECG datapoints for diagnosing arrhythmias

All arrhythmias present on ECGs by variations in certain attributes of the ECG. In the MIT data, ECGs are categorized into 16 attributes over two heart beats. For example, with VEB there are 14 attributes of the ECG that are affected [7–14], which are listed in the supplementary information. In the database, there are 5 groups, 1 of which is normal (‘N’) and 4 of which are arrhythmias (ventricular ectopic beats (‘VEB’), supraventricular ectopic beats (‘SVEB’), fusion (‘F’), and unknown beat (‘Q’)), though this does not represent the full set of arrhythmias, which we have included in the supplementary information. Because ECG attributes are affected in unique ways for each arrhythmia, it is possible to both identify an arrhythmia and to characterize it as a specific arrhythmia using purely patterns in ECG data attributes. A.I. deep-learning models can determine the complex and non-linear relationships between the attributes to predict arrhythmias.

## Model development

The model created is a multilayer perceptron (MLP). MLPs are a type of artificial neural network that enforces layered structures, which are complex equations also known as hidden layers, to learn from complex, non-linear data and predict outcomes based on a series of inputs and outputs, simplified seen below in Figure 1 [15]. These hidden layers were obtained from the PyTorch framework, further elaborated in the supplementary information. The inputs to the model are the 32 attributes of an ECG and the output is one of N, VEB, or SVEB. The model uses three hidden layers, with further increases in hidden layers tested instead showing decreased accuracy.

A diagram of a network

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Figure 1: Simplified diagram of a MLP model

The MIT-BIH dataset is heavily weighted towards N compared to VEB and SVEB data points (90000, 7000, and 3000 in count respectively). However, we could not use the dataset in its entirety due to the over-biased nature of the model. This would result in the model overly predicting the majority (N), creating high overall accuracy but low rates of VEB and SVEB detection. To prevent this outcome, the dataset was randomly subset according to predefined weight distributions with respect to arrhythmia types using a random seed generator. From the total number of data points within the original dataset, a subset of 10000 entries – 5000 N, 2500 VEB, 2500 SVEB – were extracted and saved as a balanced dataset. While the MIT-BIH dataset does include two more types for arrhythmia classification, F and Q, this was ignored due to low data availability.

To determine the ideal architecture for our MLP model, two distinct model structures were explored to determine optimal trade-off. The first model employed two hidden layers with dimensions of 128 and 64 neurons each. This is the most common structure for simple MLP models in which it contains a funnel-shaped structure in layers which converges quickly. The second model employed three hidden layers with dimensions of 128, 128, and 64 neurons each. The structure of this model also represents a funnel shape with an additional layer of neurons for enhanced processing power and added complexity. From the total balanced subset with 10000 data points, a setup ratio of 8:1:1 was enforced with respect to training, validating, and testing the overall performance of the model. Primary outcomes of this process include loss in training and accuracy in validation. Both models were trained on this dataset with equal learning rates, epoch counts of 1000, and batch sizes to ensure training conditions remained the same. The models were then evaluated on precision, accuracy, recall, and F-1 score.

To test the trained models, the balanced dataset was re-randomized with another random seed and saved as a fully labeled CSV file. Subsequently, the "type” and “record” columns were then removed from the dataset, which now comprises only 32 standardized predictor variables. From this new set, 500 observations were drawn to serve as an out-of-sample test panel. These observations were then propagated through the model where outputs were compared against the labeled CSV to determine overall accuracy.

# Results

Model 1, with 2 hidden layers, had an accuracy of 94%, while Model 2, with 3 hidden layers, had an accuracy of 96%. 500 random datapoints were used as blind inputs into the model which yielded 98% accuracy. Losses decreased rapidly as additional epochs were ran, though this effected slowed as additional epochs were conducted, as seen below in Figure 2 and Figure 3, and consequently accuracy increased. When a third model was attempted, with a fourth hidden layer, accuracy dropped significantly, and this was not investigated further.

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AI-generated content may be incorrect.Figure 2: Model 1 Training Loss (left) and Accuracy (right) over 1000 epochs

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Figure 3: Model 2 Training Loss (left) and Accuracy (right) over 1000 epochs

# Discussion

The accuracy rate of both models increased as additional epochs were conducted, which is logical as the additional learning cycles should make the models better at identifying arrhythmias. However, the rate of gain plateaus rather quickly, and additional epoch gain becomes more similar. Additional epochs invokes an additional risk of ‘overtraining data’, in that the model becomes trained so closely to the data that it cannot effectively identify arrhythmias on any data that is not part of the model- such as those from a real input ECG, therefore it is not reasonable to simply run the model for an arbitrarily large number of epochs to achieve a high, yet less useful, accuracy. Instead of additional training on the same data, which would carry the risk aforementioned, training on *additional* data would be greatly beneficial in both increasing the accuracy *and* expanding the breadth of the model to identify arrhythmias in a real patient that may be naturally more variable than the patients recorded in the MIT-BIH study.

The high accuracy rate of both models and the input tests present a significant finding, especially on such a preliminary model, and with further research – which is elaborated on below – the accuracy rate has the potential of increasing. This research therefore has the potential to aid significantly in reducing the volume of ECGs physicians need to interpret to only the ones identified as VEB or SVEB. This can facilitate more ECG testing, as physicians will only need to review the arrhythmia identified ones, which overall increases the chance that an arrhythmia could be identified, diagnosed, and treated. With an aging population, the models have the potential to increase local community health and alleviate healthcare resources to other sectors.

There are limitations to these models and other similar models used in healthcare as a whole, despite the relatively high accuracy rate. As the accuracy rate is not 100%, not that that is ever feasible, physicians will still need to maintain awareness towards populations with high prevalences of arrhythmias and conduct occasional manual ECG interpretation to ensure that the models do not fail to identify an arrhythmia owing to their potential severity when undiagnosed. Physicians must also be aware that the model diagnosing an arrhythmia may be incorrect, especially if two arrhythmias present very similar ECG readings. Individual variation in ECGs and other health conditions must be considered as well in using these models as they can cause either the model to not identify an arrhythmia when the patient is suffering from one, or, to misdiagnose one arrhythmia as another. Hence, there is significant work still to be done before these, or other similar models, can be safely integrated into the healthcare system.

Additional research might involve, with larger data bases, the training of the models on individual patients (in the MIT-BIH model, ‘records’) to correct for more specific individual-individual differences with average heartbeat attributes. Larger databases would also facilitate the expansion of types of arrhythmias the models can be trained on with minimal changes to the model as all arrhythmias would have unique attributes to their ECGs the models can be trained on.

Integration with constant, wearable ECG measurement devices might allow for long-term identification of elusive and other hard to diagnose arrhythmias.

# Conclusion

In this work we created and tested two A.I. deep-learning models for identifying and characterizing arrhythmias based on ECG data provided by MIT [6]. The models we used are based on multilayer perceptron models, using either 2 or 3 hidden layers. Data from MIT was extracted and balanced before being trained and tested over 1000 epochs to yield final models with 94% and 96% accuracy in identifying and characterizing VEB and SVEB arrhythmias from normal. We also developed a method for either manual or automatic input of ECG data into the model so that a third party may run their ECG through the model to test it. This work is vital in aiding an aging population, as older populations will suffer more from arrhythmias compared to a younger population. These models facilitate physicians to spend their time more effectively in only interpreting problematic ECGs and it also allows for more ECG surveillance in general. Further extensions on this work, especially with data from more types of arrhythmias, will allow for these models to extend beyond simply VEB and SVEB arrhythmias. Additional work needs to be conducted before a model like this is put into practice for safety and practicality reasons as well as further policy guidelines to prevent overreliance on models such as these without adequate understanding of the limitations of such models.

# Acknowledgements

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# Supplementary information

Models (and details related to models as referred to in the main paper) stored on Github at: <https://github.com/dmchxng448/Arrhythmia-Prediction-MLP>

ECG attributes affected by the following arrhythmias:

VEB: pPeak, Pq\_interval, pre-RR, post-RR, rPeak, Qrs\_interval, Qt\_interval, QRS\_morph0-4, sPeak, qPeak

SVEB: pPeak, Pq\_interval, pre-RR, post-RR, rPeak, Qrs\_interval, tPeak, Qt\_interval, Qrs\_morph0-4

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| --- | --- | --- | --- | --- | --- |
| Arrhythmia Category | Arrhythmia Type | Characterization | | | |
| Heart Rate | Origin Source | Common Afflicted Populations | Severity |
| Supraventricular Arrhythmias | Sinus bradycardia | slow heart rate (<60 bpm) | SA node | Athletes, sleep, vagal tone, medication users (e.g., beta-blockers) | Usually benign unless symptomatic (e.g., dizziness, syncope) |
| Sinus tachycardia | fast heart rate (>100 bpm) | SA node | response to stress, fever, pain, or dehydration | Benign when physiologic; investigate underlying cause |
| Atrial fibrillation | Variable (typically 100–175 bpm ventricular rate) | Multiple atrial foci (esp. pulmonary veins) | Elderly, hypertensive, valvular heart disease, hyperthyroidism | Moderate to high — increased stroke and heart failure risk |
| Atrial flutter | Atrial 250–350 bpm; ventricular ~150 bpm | Single reentry circuit in right atrium | Older adults, post-cardiac surgery, structural heart disease | Moderate — stroke risk, can deteriorate into AFib |
| Paroxysmal supraventricular | 150–250 bpm | Atria or AV node (reentry) | Young, healthy adults, anxiety, caffeine/alcohol users | Usually benign but uncomfortable (palpitations) |
| AV Nodal Reentrant Tachycardia (AVNRT) | 150–250 bpm | AV node (dual pathways) | Females > males, teens to middle-aged adults | Low risk but may require ablation for symptom control |
| AV Reentrant Tachycardia (AVRT) | 150–250 bpm | Reentry via accessory pathway (bypasses AV node) | Young adults; inherited WPW syndrome | Risk of sudden cardiac death if triggers AFib → VF |
| Multifocal Atrial Tachycardia | 100–150 bpm | Multiple ectopic atrial pacemakers | Elderly, COPD patients, electrolyte imbalances | Moderate — often indicates significant underlying illness |
| Premature Atrial Contractions (PACs) | Normal sinus interrupted by early beat | Ectopic atrial focus | All ages; stress, fatigue, stimulants | Benign; may signal atrial irritability if frequent |
| Ventricular Arrhythmias | Premature Ventricular Contractions (PVCs) | Underlying rhythm with early wide QRS | Ectopic focus in ventricles | Healthy individuals, ischemic heart disease, hypoxia | Usually benign if isolated; more serious in structural heart disease |
| Ventricular Tachycardia (VT) | >100 bpm (often 120–250) | Ventricular focus (often scar tissue post-MI) | Prior MI, cardiomyopathy, electrolyte imbalance | High — risk of progression to VF, sudden death |
| Torsades de Pointes | 150–250 bpm, polymorphic | Ventricular; triggered by prolonged QT | Drug-induced QT prolongation, hypokalemia, congenital LQTS | Very high — often degenerates into VF |
| Ventricular Fibrillation (VF) | Disorganized; no effective output | Multiple ventricular foci | Acute MI, cardiac arrest, electrolyte imbalance | LETHAL — requires immediate defibrillation |
| Accelerated Idioventricular Rhythm (AIVR) | 40–100 bpm | Ventricular automaticity focus | Post-reperfusion in MI, digitalis toxicity | Usually benign; self-limited |
| Conduction and Other Rhythm Disturbances | First-degree AV Block | Normal | Delayed conduction in AV node | Athletes, beta-blockers, normal variant | Benign |
| Second-Degree AV Block Type I (Wenckbach) | Usually normal or slightly slow | AV node | Athletes, increased vagal tone, medication | Benign if asymptomatic |
| Second-Degree AV Block Type II (Mobitz II) | Slow (due to dropped beats) | Below AV node (His-Purkinje system) | Ischemic heart disease, fibrosis | High — can progress to complete heart block |
| Third-Degree AV Block (Complete Heart Block) | Slow (20–40 bpm) | Atria and ventricles beat independently | Fibrosis, MI, Lyme disease | Very high — requires pacemaker |
| Bundle Branch Blocks (LBBB, RBBB) | Normal | Block in left or right bundle | Aging, hypertension, ischemia | Variable; LBBB often indicates underlying heart disease |
| Escape Rhythms (Atrial, Junctional, Ventricular) | Atrial: 60–80 bpm  Junctional: 40–60 bpm  Ventricular: 20–40 bpm | Backup pacemakers (atria, AV junction, ventricles) | Sinus arrest, AV block | Moderate — reflects underlying bradyarrhythmia or failure of SA node |

Table S1: Total forms of arrhythmia