# Risk Prediction of Atrial Fibrillation Using the 12 lead Electrocardiogram and Deep Neural Networks

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**Abstract**
Please use no more than 300 words and avoid mathematics or complex script.

*Dedicated to all hard-working*
*doctoral and master students at Uppsala University*

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# 1. Introduction

Heart diseases are among the major causes of death for humanity. In 2017, it has been reported that an estimated 17.8 million people died due to cardiovascular diseases worldwide [21]. Among them, approximately 287 thousand cases were linked to atrial fibrillation (AF) and flutter, and nearly 6.17 million to stroke. Atrial fibrillation is a serious heart condition characterised by cardiac rhythm disturbance, in which the heart's upper chambers (the atria) beat irregularly and out of sync with the lower chambers (the ventricles) of the heart [14]. AF may be asymptomatic for some patients or may cause among others a fast, pounding heartbeat, shortness of breath or weakness for others. Previous studies have found a close link between atrial fibrillation and increased risk of stroke [32, 20], which is a medical condition determined by blockage or poor blood circulation to the brain leading to cell death [1]. At the most basic level, stroke can be classified into ischemic and hemorrhagic stroke. Ischemic stroke is caused by interruption of the blood flow, while hemorrhagic stroke is due to rupture of a blood vessel or an anomalous vascular structure [1]. Both result in loss of function to some parts of the brain.

One way to diagnose AF is to take an electrocardiogram (ECG) exam. This tool has been used since the beginning of the 20th century [25] as a recording of the heart's electrical activity [6]. Several cardiac abnormalities result in changes in the normal ECG pattern, allowing the identification of a particular condition [18]. ECG is a convenient, fast and affordable option used at many hospitals, clinics and primary health centres to diagnose many types of cardiovascular diseases. However, its proper and accurate analysis require an expert in electrocardiography in order to determine the type of heart condition. Doctors with such an expertise are not always found at each health facility, which may require some exams to be transferred to a nearby expert or to be analysed by a general practitioner. The former option may lead to delays in having the results, while the later possess some risks of misdiagnosis [23, 3]. In addition, certain patients with normal ECG may present, as studies have shown, higher risks of developing a cardiovascular disease in the future, such as people with elevated low-density lipoprotein or high blood pressure [33].

[1] Anon, Stroke. National Heart Lung and Blood Institute. Available at: https://www.nhlbi.nih.gov/health-topics/stroke [Accessed January 26, 2022]

## 1.1 Motivation

Accuracy and speed in manual diagnosis of cardiovascular diseases and their prediction and prevention have been some of the issues that led many researchers to try alternative solutions. Many previous studies have opted to automatic tools that can analyse ECG exam and detect a patient heart condition, such as cardiac arrhythmia, or even predict the risk of having an imminent disease in case of normal results or some abnormalities are found [27, 15, 28]. Deep Neural Network (DNN) is a sub-category of the machine learning techniques that have been experimented and which has given promising results in detecting some abnormalities in ECG [20]. DNN deals with algorithms that are inspired by the human brainâs biological structure and functioning to aid machines with intelligence [19]. A DNN is composed of multiple layers between the input and output layers [2], an architecture that resulted in outstanding ability to model complex non-linear relationships. Hence, DNN has been widely applied in medical field and has achieved a series of remarkable results in recent years [23, 16, 10].

Knowing the amount of time it would take for a normal person or a patient to be under the threat of a new health condition is a useful information in disease prevention and patient management. An analytical study that has as outcome the time until an occurrence of event is referred to as survival analysis, which is a subfield of statistics. The time that would pass before an event occurs is denoted as survival time. Survival analysis methods can be subdivided into two main categories: statistical methods and machine learning based methods. Statistical methods have as target to predict the survival time and the survival probability at the estimated survival time. They focus more on producing survival curves and characterising the distributions of the event times [31]. Cox model [5], Kaplan-Meier method [12], Tobit model [30] are among the most popular statistical methods in survivor analysis problems. Machine learning methods share the same goal as statistical counterparts, but they mostly focus on prediction of an occurrence of event at a given time point. The advantage of machine learning methods is that they incorporate machine learning and optimisation techniques with statistical methods, and are best suited for high-dimensional data. Artificial neural networks [26], survival trees [7], Bayesian methods [13] and support vector machines [29] have been among the most popular machine learning methods in recent years. This research work used DNN to make survival analysis by predicting the risk of developing AF and the time to the AF condition for a normal person.

## 1.2 Aim

The aim of this study was to predict the imminent risk of developing atrial fibrillation, and how long it might take for the event to occur using Deep Neural Network. This had been approached by first training DNN models to distinguish between ECGs of patients presenting AF condition and normal ECGs, then determine if an individual having a normal ECG may be at risk of developing AF in the future. After that, a survivor model had been developed to find out when the event of having AF is likely to occur since the date an ECG exam is taken. In the end, the study had applied different performance metrics to access the accuracy of the models and their usability on a different dataset. This made it possible to highlight the robustness of DNN models for the task of risk prediction and disease prevention for cardiovascular abnormalities.

## 1.3 Research questions

This research work had as objective to answer the following questions.

**Q1:** How a DNN algorithm perform in discriminating a normal ECG against an ECG presenting AF condition?

This was a preliminary task as the model was presented with ECGs tracings from normal patients, or patients who do not have AF at the time of the exam, and patients who already present the condition. A good performance of the model at this stage was very important to make the following steps meaningful.

**Q2:** Can DNN be useful in predicting whether a person with normal ECG will develop AF in the future, and if yes, what performance it can achieve?

The normal ECG exams had been classified into two categories depending on whether a patient had never presented AF condition or whether a patient was once normal but later developed AF condition. Different performance metrics that are common for classification tasks had been used to assess the usefulness of the model.

**Q3:** In case a patient might develop AF, how long the event might occur from the moment an ECG exam is taken?

## 1.4 Related work

Many studies that employ deep neural networks and ECG tracings have been conducted to diagnose or predict the risks of different heart conditions. In terms of relevant literature, surveys conducted by authors in [27, 15, 28] have found that many approaches based on DNN have emerged popularly during the last decade for the automatic and early diagnosis of cardiovascular diseases using ECG signals. A preliminary study based on DNNs for ECG analysis was presented in [9]. In this work, DNNs were used to analyse single-lead ECGs and when trained on a large enough dataset, the models showed superior performance compared to practising cardiologists. Authors in [23] developed an end-to-end DNN to analyse the short-duration, standard, 12-lead ECG exams and detect six abnormalities. Their model reached a diagnostic performance comparable or superior to medical residents and students. The study presented in [11] designed a convolutional neural network for predicting eight types of arrhythmia using 2D time-frequency feature map from standard 12-lead ECG. The algorithm showed high performance in classifying persistent cardiac arrhythmias, but relatively lower performance in classifying episodic arrhythmias.

Gustafsson et al. [8] developed a deep neural network for ECG diagnosis of myocardial infarction in high-risk emergency department patients. This model showed fair precision in discriminating ST-elevation myocardial infarction (STEMI), but the classification of non-STEMI was poor. The authors in [3] presented a model that used digital biomarkers and deep representation learning to predict the risk of AF. The model combined random forest classifier for prediction and DNN for features generation. A model combining features from all modalities considered in this work had the best performance and the findings suggested that structural changes in the 12-lead ECG are associated with existing or impending AF. However, medical doctors who were consulted suggested that the method used in this study was less obvious, a more apparent way would be applying DNN directly on ECG signals, excluding digital biomarkers. The models mentioned above were claimed to have value in decision support during clinical process by serving as auxiliary device for diagnosing cardiac arrhythmias, and to assist in the management of cardiovascular diseases.

Several research works have also focused on the application of survival modelling in the medical domain. Mariani et al. assessed the prognostic factors for the recurrence of breast cancer using the neural network method and the standard cox model [17]. Authors in [4] used Random Forests, Gradient Boosting, and SVM radial as machine learning methods, serum creatinine and ejection fraction as features to develop models that predict survival of patients with heart failure. DNN and Cox proportional-hazard model were developed in [22] to predict an important future clinical event and 1-year all-cause mortality using 12-lead electrocardiogram voltage data. The findings in these studies proved having the potential to provide substantial prognostic information that are useful for clinicians during patient management process.

# 2. Theory

## 2.1 Electrocardiogram

To be edited soon

## 2.2 Deep Neural Networks

To be edited soon

### 2.2.1 Concepts

### 2.2.2 Training

### 2.2.3 Cost function

### 2.2.4 Convolutional Neural Network

To be edited

## 2.3 Risk prediction – Survival modeling

# 3. Method

To be edited

## 3.1 Dataset

### 3.1.1 Data exploration

## 3.2 Problem formulation

## 3.3 DNN architecture and training

## 3.4 Weights and Hyperparameter tuning

## 3.5 Performance evaluation methods

## 3.6 AF risk prediction – Survival modeling

# 4. Results

To be edited

## 4.1 Automatic AF diagnosis

### 4.1.1 Performance evaluation and testing

## 4.2 AF Risk prediction

# 5. Discussion

To be edited

# 6. Conclusion

To be edited

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