

Cloud-based ECG Interpretation of Atrial Fibrillation Condition with Deep Learning Technique

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ABSTRACT

The prevalent type of arrhythmia associated with an increased risk of stroke and mortality is atrial fibrillation (AF). It is a known priority to identify AF before the first complication occurs. The limited previous studies have explored the feasibility of conducting AF screening using a deep learning (DL) algorithm (integrated cloud-computing) telehealth surveillance system. Hence, we address this problem. The goal of this research was to determine the feasibility of AF classification with integrated in embedded cloud-computing algorithm. By using a short-term ECG signal in single-lead electrocardiogram (ECG) recorder, we conducted a prospective AF classification study. The ECG measurements were evaluated and interpreted by the cloud-computing algorithm and a cardiologist on the telehealth monitoring system. The initial result found that the proposed DL model of cloud-computing based on Convolutional Neural Network (CNN) architecture produce 99% accuracy, 98% sensitivity, and 99% specificity. The overall satisfaction performance for the process of AF classification, and it is feasible to conduct AF screening by using a telehealth monitoring system containing an embedded cloud-computing algorithm.

Keywords: Telemonitoring, Convolutional Neural Network, Deep Learning, Cloud Computing

1. INTRODUCTION

The introduction of advanced technical capabilities allows physicians to offer treatment beyond the typical face-to-face setting in-office setting. Patients face the burden of social distancing and increased difficulty in finding physicians busy with emergencies under current pandemic conditions. Telehealth has proven to be important in addressing pressing health needs of patients and maintaining good patient-to-clinician dialogue [1]. By using telehealth, Patients increasingly want to be able to receive treatment conveniently, on their own terms, and preferably without the need to drive to a medical office, hospital, or clinic [1][2]. Internet of Things (IoT) for telehealth sector is currently very much needed, especially in developing countries to provide efficiency of health service costs [2]. In developing countries like Indonesia, such a system can reach people in the outermost and border areas, where the availability of health service facilities is not evenly distributed.

With the prevalence and incidence of atrial fibrillation (AF) increasing with age, AF is a rising public health concern. The diagnosis of AF is confirmed based on history and physical examination. Especially from the presence of irregular heart rhythms which are then confirmed by electrocardiogram (ECG) findings that are

irregularly irregular with a narrow complex tachycardia. Patients with AF may have mild or no symptoms, or it could be complaints of heart failure, myocardial infarction, stroke, or hemodynamic disturbances. Because people with AF are at a five-times greater risk of getting a stroke, it is of utmost importance to stick to the drug plans recommended by their doctor [3][4]. It can help to reduce additional health risks to be able to provide people with the support they need to control their AF at home.

Telemedicine is part of telehealth services, improving medication adherence in AF patients has been shown, and research indicates that certain virtual clinics are an important alternative for many patients to the usual treatment model [3][5]. Cloud-based ECG auto-interpretation assures to modernize the health-care sector through continuous, remote and non-invasive monitoring of AF diseases. A cloud-based platform for prediction of AF condition is enabled telemetry system acquires the ECG signal, processes the ECG signal, and alerts physicians for an emergency situation [6]. It is helpful for the physician to analyze the AF condition as early and accurate [5][7][8][9]. To support the telemedicine research, this study develops patient and physician experience with virtual visits in AF prediction, and treatment based on cloud-based ECG auto-interpretation. In this study, deep learning (DL) is proposed as a virtual doctor in a cloud server for AF classification from ECG signal [10]. The DL is chosen, due it allows a large dataset to be easy is trained in cloud computing and it could scale the model efficiently [4][11][12]. The rest of this paper is Section 2 is presented about the research method. Section 3 and 4 describe result and conclusion.

2. RESEARCH METHOD

2.1. CLOUD-BASED ECG INTERPRETATION

In this study, we transformed this story into a timeline that arranged the interrelated behavior that made up the service design to progress with the service design (refer to Figure 1). The timeline and the activities of the cardiologist, patient, and AF detection service are indicated. The timeline starts with a nurse signing up a patient for the AF detection service, and the process of acquisition of patient-led data begins. Cloud technology is used to interact, store and process measurement data. This provides the functionality for AF monitoring. If the processing system detects AF symptoms in the data, the cardiologist is informed. In order to draw a decision, the cardiologist should analyze the data available and fuse this information with experience from personal experiences with the patient. If the results from the AF detection unit are denied by the cardiologist, the monitoring continues. The patient is told if AF is diagnosed, and care will begin. The AF department then tracks the treatment.

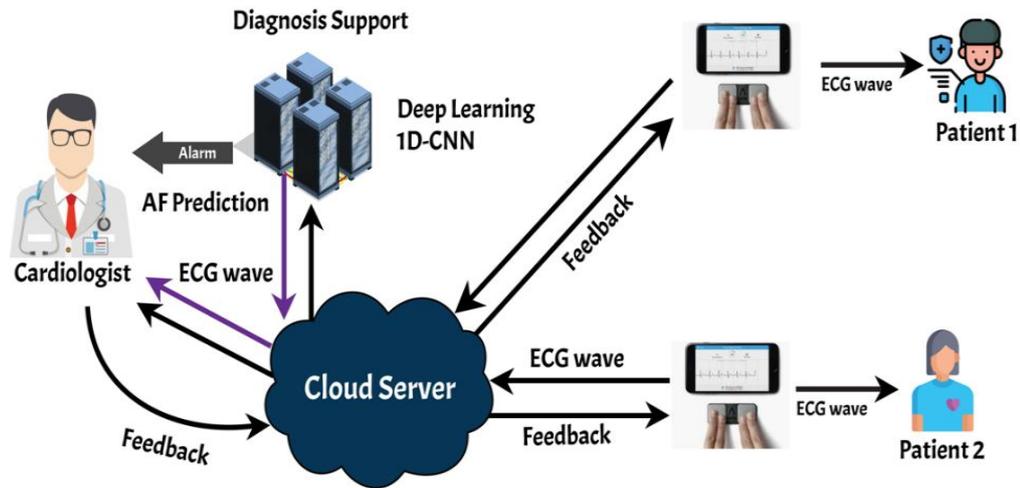


FIGURE 1. Cloud-based AF Interpretation System

Patients cardia mobile with a finger sensor. The sensor communicates the ECG signal via wireless protocol to a mobile device that relays the data to the cloud server. The deep learning model based on CNN, which was validated in this study, analyzes in real-time the incoming ECG waveform signals. A cardiologist is alerted if AF is detected. The cardiologist will review and make a diagnosis of the abnormal ECG signal. As shown in the figure, in the form of a simple traffic light system, the diagnosis can be transmitted to the patients. The dataset for developed DL model is taken from Pysionet in terms of, Normal, and AF signal [13]. The sample of AF signal can be seen in Figure 2.

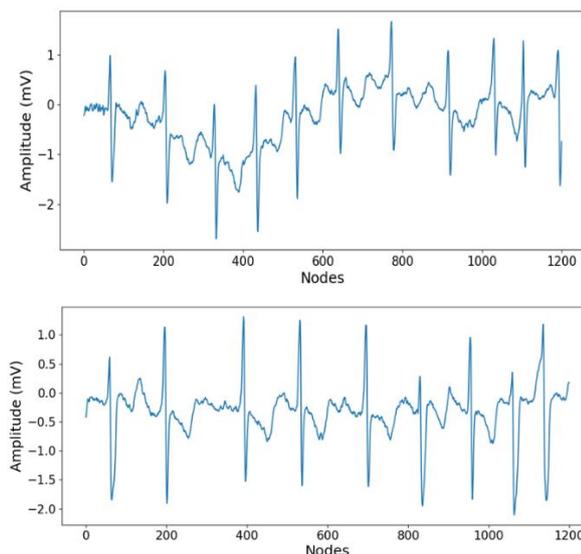


FIGURE 2. The sample of atrial fibrillation signal

2.2. DEEP LEARNING-BASED CLOUD SYSTEM

The stages of the automatic classification process for cloud-based ECG signals can be seen in Figure 3. There are five important processes in the all stages, namely: (i) raw data normalization; (ii) noise removal by using discrete wavelet transform; (iii) ECG signal segmentation for every 2700 nodes; (iv) feature classification with Convolution neural network (CNN) architecture; and (v) evaluation of the proposed CNN model by using five metrics, i.e., accuracy, sensitivity, specificity, precision, and F1-Score. The main features of the ECG waveforms extracted were processed by CNN after eliminating baseline noise by the finite impulse response filter to establish a classification model that can indicate diagnosis. During the analysis, where the detection of Atrial Flutter, Atrial Premature Complex (APC), and Ventricular Premature Complex (VPC) was included an updated ECG interpretation-based cloud-computing algorithm was adopted for determining AF. However, in this study only Normal and Atrial fibrillation is investigated. In the future all these signals will be processed in the cloud, to produce more accurate classifications.

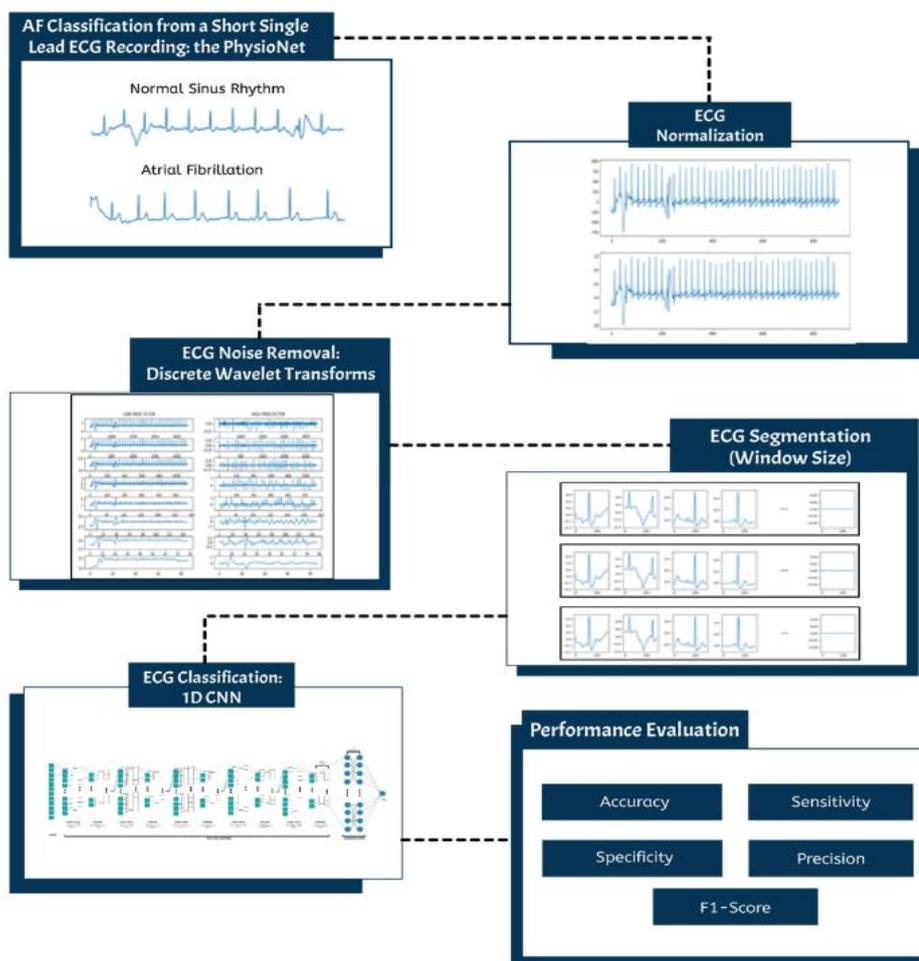


FIGURE 3. The DL Process in Cloud Server

3. RESULTS AND DISCUSSION

This paper describes the validation of a model-based health care framework for deep learning. As such, the DL model was established using the CNN classifier to classify AF episodes. The dataset is taken from a well-known database Physionet for training, and validation. In this study, we validated the initial findings by evaluating the best CNN model built with unknown data from Indonesian Hospital patients. To be precise, we fed the information from 70 subjects to the CNN-based cloud system and compared the results of the classification with the results of the diagnosis shown by human practitioners.

3.1. CLASSIFICATION RESULT

The proposed model was tested with the Physionet Atrial Fibrillation challenge data set and from Indonesian hospital [13]. The CNN model used in as a doctor in the cloud is taken from our previous experiment [14]. Our proposed model in [14] has validated with real datasets from Indonesian Hospital, to ensure the model generalization and robustness. Table 1 indicates the satisfactory performance of the validation result with 99% accuracy, 98% sensitivity, and 99% specificity by using the proposed model. In this study, we use three data slices resources for testing process as unseen data, from Physionet Atrial Fibrillation dataset, MIT-BIH datasets, and Indonesian Hospital respectively. The performance of CNN model is tested by using cloud-based AF interpretation system, and the performance is as depicted in Table 2. All performance still over 85%, specifically when it tested in data patient, the accuracy is 99.5%, sensitivity is 99%, and specificity 99 %. It means our preliminary model has successful to recognize the unseen pattern of ECG signal.

TABLE 1
The Classification Results

	Performance (%)		
	Accuracy	Sensitivity	Specificity
Fold 1	95	83	97
Fold 2	99	97	99
Fold 3	99	98	99
Fold 4	99	99	99
Fold 5	99	99	99
Fold 6	99	99	99
Fold 7	100	100	100
Fold 8	99	99	99
Fold 9	99	99	99
Fold 10	99	99	99
Average	99	98	99

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TABLE 2
The Testing Results

	Performance (%)		
	Accuracy	Sensitivity	Specificity
Testing 1	86.18	87.38	87.38
Testing 2	98.33	98.75	98.75
Testing 3	99.50	99.00	99.00

3.2. CNN-BASED CLOUD COMPUTING VALIDATION

The complexities of the CNN operation are proportional to the total number of links between the convolution layer and the pooling layer. The number of weight parameters, approximately 86 million, 87 million and 45 million respectively, are created in consecutive layers on the basis of such a combination structure. In this research, we assessed the cloud server as a processing time-related physician using the ordinary computer to show that it can process with a satisfactory result. For the CNN implementation, there are two device requirements used. Four-core and eight-core CPU with GPU. The total of 5250 data, with an input shape of 2700 x 1, and 100 epochs. In the Windows 10 operating system environment, Python 3.6 software in the Keras library with a Tensor-Flow history was used to implement the proposed CNN model. Table 3 presents that the processing times of both the training and testing process, with CPU 4 core produce 0.18 seconds, while CPU 8 core produce 0.02 seconds.

These research result suggest that the proposed CNNs model is successfully implemented in AF classification. The CNN can be processed in the cloud system for realistic implementation, due to it must support the practical situation when the patients far from the hospital. However, in the validation stage the ECG data is limited, thus in the future increasing of the data testing is desirable for ensure the robustness. In addition, other cardiac abnormalities should also be considered such as arrhythmias to increase the efficiency of this classification system.

TABLE 3
Processing Time of CNN Results in the Cloud Server

Computer Specification	Training process (seconds)	Testing process (seconds)
CPU: 4 Core, 8 thread, @2.8 GHz Memory: 16Gb, Disk: 1000 Gb GPU: GTX 1050 Ti, 4Gb	6345	Single instance: 0.18 second
CPU: 8 Core, 16 thread, @3.6 GHz Memory: 32Gb, Disk: 1000 Gb GPU: RTX 2080 Ti, 11Gb	1310	Single instance: 0.02 second

4. CONCLUSION

According to contemporary standards, early detection of AF and timely care before first complications arise remain the best practice. In a telemonitoring system, our proposed CNN model was embedded but not in the single-lead ECG units. It allows for a more complete AF detection algorithm. For ECG measurements only the single-lead ECG recorder was used and all measurements were transferred and processed in the cloud. When conducting AF screening in a large population where large quantities of ECG data are needed, there is only a temporary storage requirement, which is a great advantage. AF screening efficiency via the cloud-based DL cloud-computing algorithm is satisfactory, with a high accuracy of about 99%, 98% sensitivity, and 99% specificity. The outcome supports its use in the future for AF screening.

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