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Prediction of paroxysmal atrial fibrillation using a convolutional neural network and electrocardiogram signals

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ABSTRACT

Atrial fibrillation (AF) is the most clinically diagnosed arrhythmia in cardiac pathology. The incidence of AF begins at a very early age and its initial state is paroxysmal atrial fibrillation (PAF). This type of heart disease can be detected and predicted by analyzing the spectrogram of a surface electrocardiogram (ECG) signal. In many studies, different ECG signal formats and convolutional neural network (CNN) architectures have been used. However, the lack of good signal preprocessing or signal adequacy may have affected the accuracy, especially on short-term ECG signals. In this study, we analyzed a preprocessed ECG signal, determined the optimal set to predict PAF, and evaluated the accuracy using ECG signals of different durations. The PAF Prediction Challenge–PhysioNet database was used to extract spectrograms in 30 sec and 5 sec windows for two classes (Normal, PAF) and 3 classes (Normal, Close-AF, Distant-AF). Then, the AlexNet architecture was used. The proposed method achieved a two-class accuracy of 99.92% with a 30 sec window and 99.42% with a 5 sec window, improving the PAF prediction performance compared with similar works. In addition, the three-class accuracies were 96.92% and 97.43% with windows of 30 sec, and 5 sec, respectively. These results prove the efficacy of the method for the early diagnosis of PAF, even based on short-term ECG signals.

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1. INTRODUCTION

Atrial fibrillation (AF) is one of the most clinically diagnosed cardiac arrhythmias. This pathology usually triggers hemodynamic disorders that can generate strokes and even death. The severity of an AF increases as the person ages. Despite the effects of this progression being reflected in a rise in incidence and prevalence of the disease from its first stage (paroxysmal atrial fibrillation (PAF)) to its last stages (permanent or persistent), its indicators have not been fully identified. Therefore, predicting AF in its early form is essential to avoid the risks of stroke, heart failure, and mortality [1].

The process of predicting AF is performed manually by a cardiologist or electrophysiologist by interpreting electrocardiogram (ECG) records. This process is highly demanding due to both the number of records to be analyzed and the fact that sometimes it is necessary to examine each heartbeat individually to ensure the correct identification of the cardiac pathology [2]. Thus, a good method for predicting AF would improve its diagnosis and prevention [3], [4]. To date, methods for predicting PAF based on an ECG signal have been proposed in different studies. These methods include using P-wave features [5]–[7], RR intervals [8], [9], or both [10], [11] to extract the features that indicate AF episodes.

Then, the extracted features were used in different classifiers, such as support vector machines (SVMs), random forest (RF), and feedforward neural networks, and an algorithm was also used to predict and/or diagnose AF. The parameters and functions related to AF were obtained with a particular method for each of the features. Finally, in some studies, the short-term ECG signal (2 min) was analyzed [12]; the results from these studies were satisfactory compared to those achieved by other authors. The convolutional neural network (CNN) method is the best-known deep learning architecture. Currently, its applications in biomedical engineering, include medical imaging [13] and sleep apnea detection [14], among others. CNN can analyze morphological characteristics and learn the slit variation of an input signal during a short-term ECG [15]. We propose a method for the automatic prediction of AF based on an AlexNet CNN model architecture that uses a normal short-term ECG signal that, through preprocessing, becomes the spectrograms that will be the input of AlexNet-CNN as shown in Figure 1. The proposed method can predict whether the subject is a Normal or AF patient using 5 sec or 30 sec segments of ECG signal for these two classes. It can also predict whether the subject is a Normal, Close-AF, or Distant-AF patient using 5 sec or 30 sec segments of the ECG signals for these three classes. Finally, the results of the evaluation performance for the proposed AlexNet-CNN model will be compared with those of conventional methods and those existing with CNN for PAF prediction.

2. METHOD

The proposed methodology is divided into 8 stages as shown in Figure 1. The first stage is the ECG signal acquisition stage, which is followed by 4 preprocessing stages where the signal is transformed into spectrogram images. The database acts as input to the CNN to predict PAF.

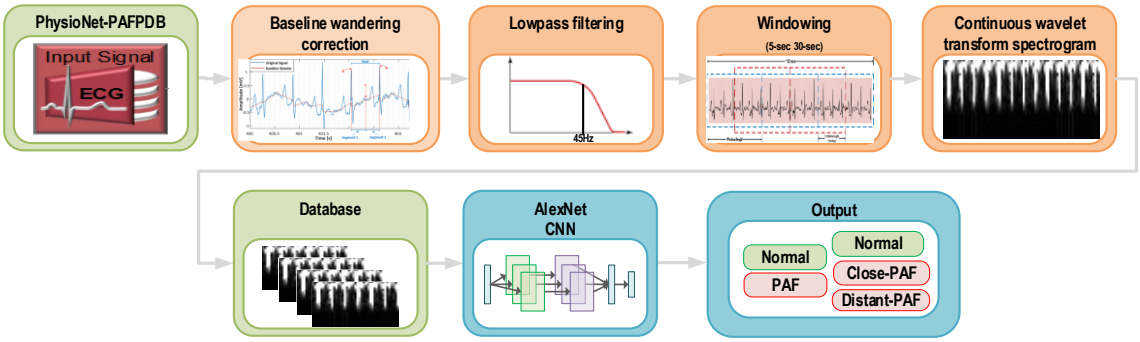

Figure 1. Proposed methodology

2.1. ECG signal acquisition

In this paper, single-channel ECG signals are obtained from PhysioNet's PAFPDB [16] which contains a total of 100 records: 50 records of normal subjects (Normal), those who have never had PAF, and 50 records of subjects who have experienced PAF. These last 50 records are further divided into two classes: 25 records that precede the immediate appearance of PAF (Close-PAF) and 25 records that do not have PAF 45 minutes after its termination or 45 minutes before its start (Distant-PAF).

2.2. Baseline wandering correction

In this stage, baseline wandering is removed from the ECG signal to avoid unwanted frequencies in the spectrogram that need to be extracted at a later stage. In this paper, we use beat-to-beat piecewise linear interpolation with three reference points: two located at the peaks of two consecutive R-waves and one located at half the distance between them. Two regression lines are estimated and subtracted from each corresponding beat [17]. Figure 2 shows the raw ECG signal obtained from the database in Figure 2(a) and the corrected ECG signal after baseline wandering removal in Figure 2(b). Algorithm 1 describes this process.

2.3. Low-pass filtering

The ECG signal is the sum of the cardiac activity with frequencies ranging between 2.5 and 45 Hz, baseline noise, electrical noise, and white noise [18]. This signal is described in (1). Baseline noise is eliminated in the previous stage, thus, to isolate the cardiac activity it is necessary to apply a low-pass filter with a cut-off frequency of 45 Hz.

$$x(n) = y(n) + r(n) + b(n) \quad (1)$$

where, $x(n)$ is ECG signal from a database, $y(n)$ is the filtered ECG signal (2.5 and 45 Hz), $r(n)$ is electrical and white noise, $b(n)$ is the baseline wandering.

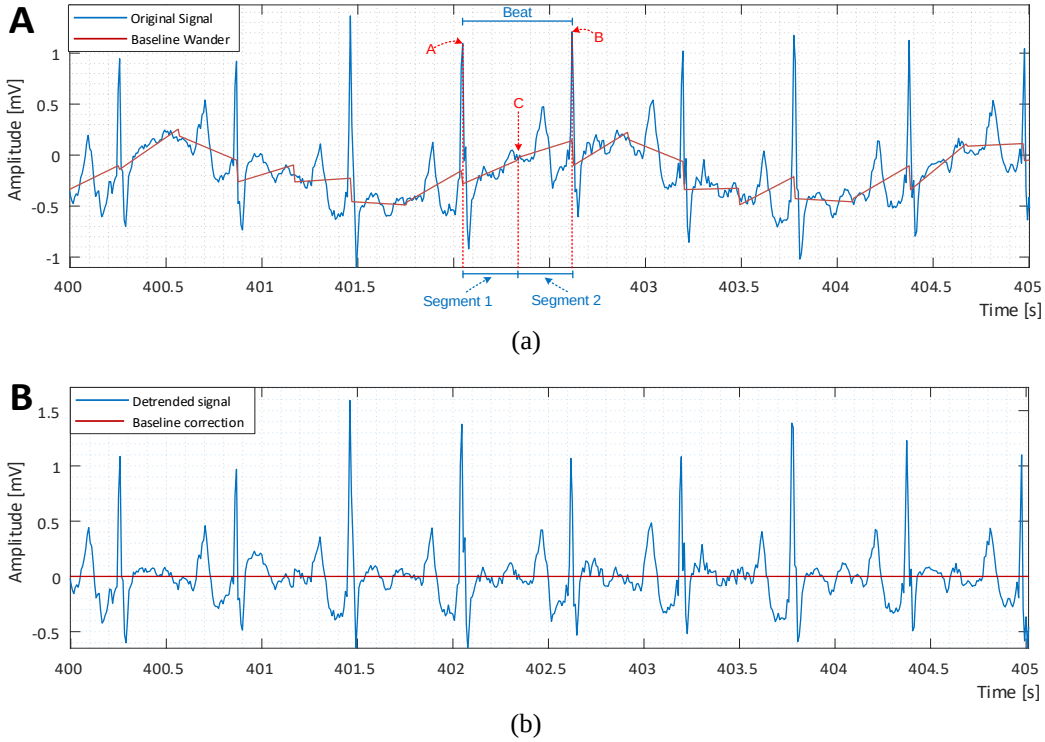

Figure 2. Baseline wandering correction: (a) raw ECG signal and (b) corrected ECG signal

Algorithm 1. Baseline wandering correction

```
ECG // Raw ECG signal
fitLM() // Linear regression method
t  // Time instant of each sample (x Axis)
R_peaks // R peaks location
for n from 0 to length(R_peaks)-1
     start  ← R_peaks[n]
     middle ← R_peaks[n]+(R_peaks[n+1]-R_peaks[n])/2
     end ← R_peaks[n+1]-1
     base_line[start:middle] ← fitLM(t[start:middle], ECG[start:middle])
     base_line[middle+1:end] ← fitLM(t[middle+1:end], ECG[middle+1:end])
end
ECG_detendred ← ECG - base_line // Corrected ECG signal
```

2.4. Windowing

In this stage, the filtered ECG signal obtained is segmented into smaller signals of 5 sec or 30 sec. These windows length was chosen to compare the results obtained by this study with previous work done by other authors. Figure 3 and Algorithm 2 describe this process.

2.5. Continuous wavelet transform of the spectrogram

This is the last stage of preprocessing. ECG spectral analysis through wavelet transform is used to separate the signal by amplitude and scaling to simultaneously analyze the time and frequency domains [19]. In this study, a Morlet mother wavelet is used to obtain a spectrogram whose magnitude is normalized between 0 and 65,535. The Morlet wavelet is very similar to the ECG signal and produces a very sharp time-frequency Image [20]. The spectrogram of each smaller signal obtained in the windowing stage for a 30 sec window is represented by a 3,840×91×1 grey-scale image with 16-bit depth and for a 5 sec window by a 640×91×1 grey-scale image.

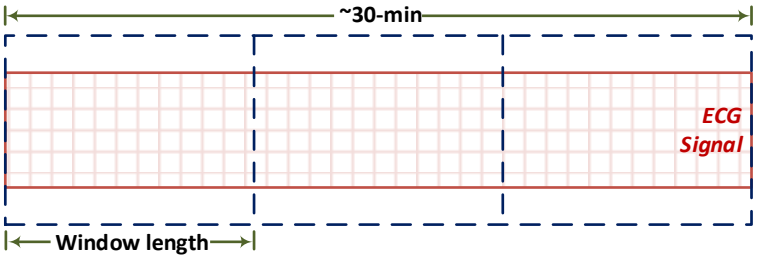

Figure 3. Windowing of the ECG signal

Algorithm 2. Windowing process

```
ECG_filter // ECG signal
windowSize // Window size in seconds
nWindow ← RoundDown(length(ECG)/windowSize) // Number of windows
for w from 0 to nWindow-1
     ECG_window[w] ← ECG_filter[t>=w*windowSize and t<(w+1)*windowSize]
end
```

2.6. Input database

In this stage, a new database is formed using the images obtained from the spectrograms of all windowed signals from PhysioNet's PAF database. This new database acts as input to train, validate, and test the CNN that predicts PAF. The number of images in the database is 36,000 for 5 sec signals and 6,000 for 30 sec signals. These images were divided into training (60%), validation (20%), and testing (20%).

2.7. CNN

In this study, AlexNet is used with modified input and output for PAF prediction. Due to this, no knowledge transfer took place and the network was trained initially using random weights. This type of CNN has been previously used in the classification of arrhythmia [21], and recognition [22], [23]. AlexNet contains eight layers of which 5 are convolutional and 3 are fully connected [24]. AlexNet uses a ReLU activation function and some pooling layers as shown in Figure 4. The input layer is modified to receive 3,840×91×1 or 640×91×1 images and the output layer is changed to 2 or 3 neurons for prediction.

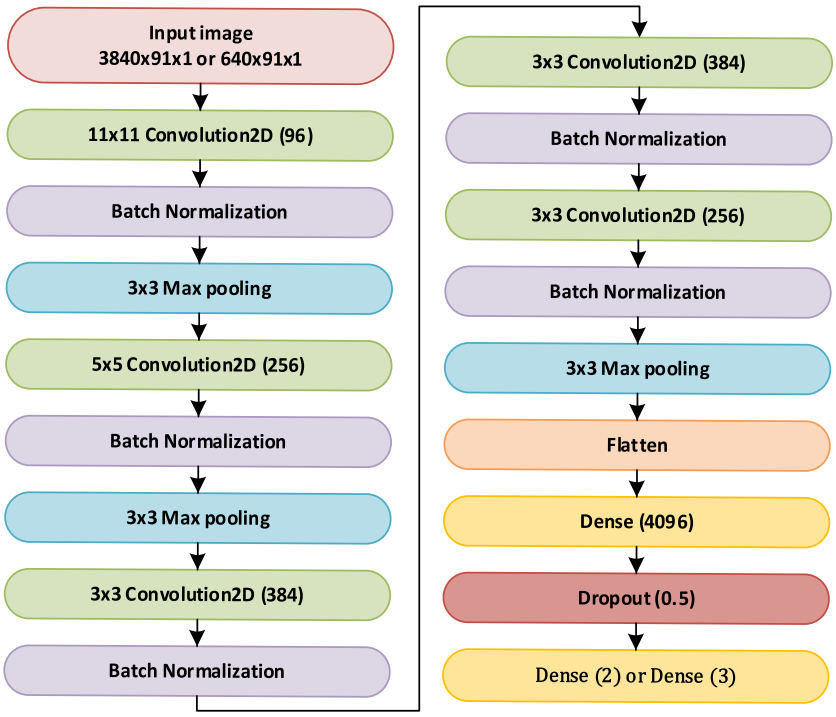

Figure 4. AlexNet architecture

2.8. Output

Using the information from PhysioNet's PAF database the CNN results are classified into two or three classes. Which changes the size of the dense layer to 2 or 3 neurons. In the case of using three classes, we used the same labeling as in PhysioNet's database (Normal, Close-PAF, and Distant-PAF). In the case of two classes, Close-PAF and Distant-PAF are merged into a single class.

3. RESULTS

The performance of the proposed methodology for the prediction of atrial fibrillation based on the AlexNet architecture is presented. In the case using two classes, the AlexNet architecture was trained with 30 sec ECG signal segments, as illustrated in the confusion matrices in Figure 5, and 5 sec segments, as shown in Figure 6. In the case using three classes, training was performed with 30 sec ECG signal segments, as illustrated by the confusion matrices in Figure 7, and 5 sec segments, as shown in Figure 8. The results show an accuracy greater than 99% for the 30 sec and 5 sec segments in the two classes case and greater than 97% for the 30 sec and 5 sec segments in the three classes case.

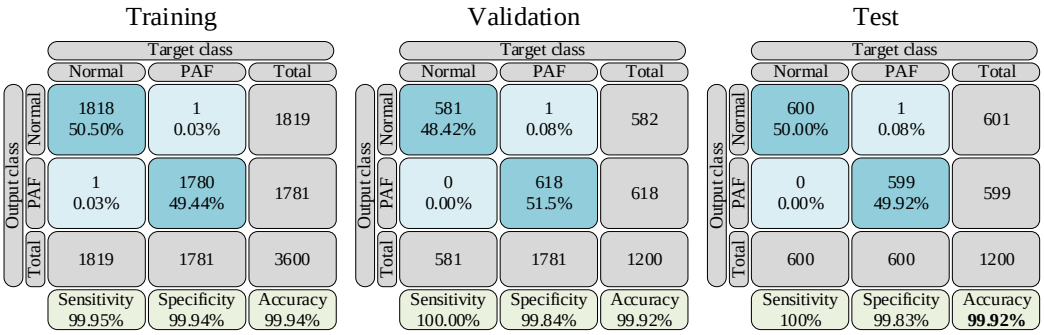

Figure 5. Training, validation, and test confusion matrices for 2 classes and a 30 sec window

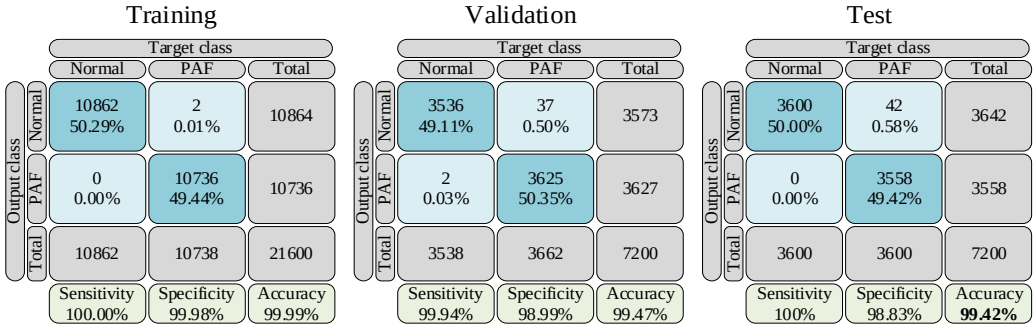

Figure 6. Training, validation, and test confusion matrices for 2 classes and a 5 sec window

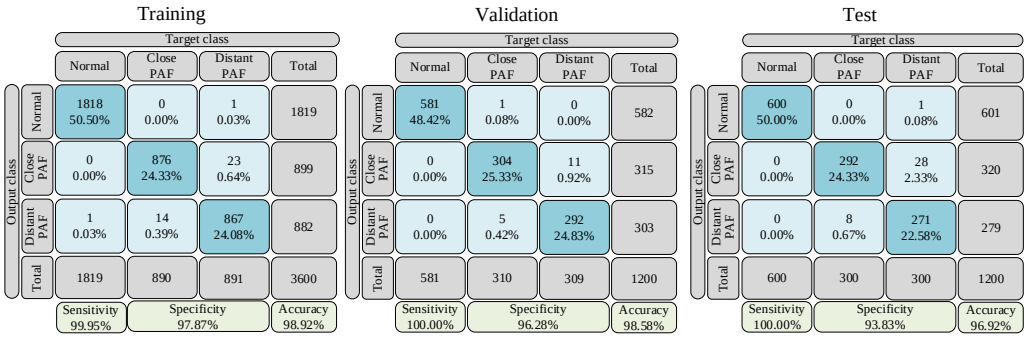

Figure 7. Training, validation, and test confusion matrices for 3 classes and a 30 sec window

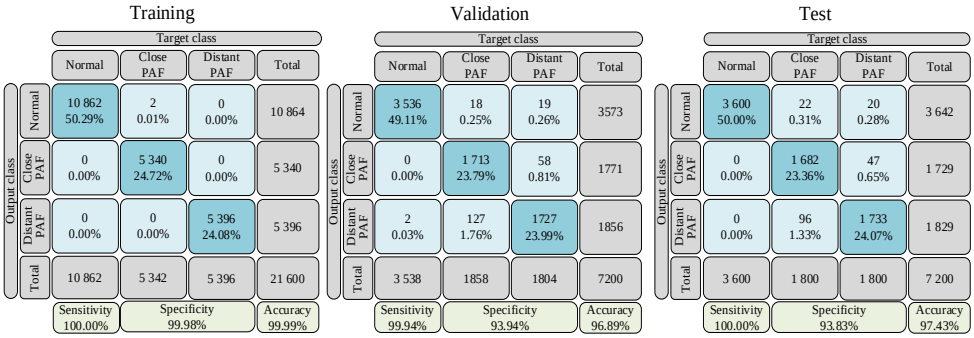

Figure 8. Training, validation, and test confusion matrices for 3 classes and a 5 sec window

4. DISCUSSION

In this investigation, a method based on the AlexNet architecture was used for the prediction of PAF using a short segment of an ECG signal. A PhysioNet PAF Prediction Challenge database signal was applied to the proposed AlexNet architecture for different segment lengths (30 sec and 5 sec segments) and different prediction classes (2 classes: normal and PAF and 3 classes: normal, Close-AF, and Distant-AF). For the automatic prediction of PAF, the following accuracy values were obtained: 99.92% for 30 sec segments and 2 classes, 99.42% for 5 sec segments and 2 classes, 96.92%, for 30 sec segments and 3 classes, and 97.43% for 5 sec segments and 3 classes. The efficiency of the AlexNet model for the prediction and detection of PAF can be observed.

Parameters or characteristics related to the ECG signal, including the P wave, heart rate variability (HRV), RR interval, and QR electrical alternans, have been analyzed in different studies. In most studies, HRV obtained from a signal from a lead was analyzed. Table 1 shows the comparative performance between methods proposed in different studies for the prediction of PAF. In one study [25] atrial fibrillation was predicted using a 7-layer architecture of the proposed CNN model and a short-term normal ECG signal with a segment length of 30 sec; values of 98.7%, 98.6%, and 98.7% were obtained for the sensitivity, specificity, and accuracy, respectively.

Table 1. Performance comparison between the proposed method and those from previous studies

Study	Method	Classes	Duration	Sensitivity (%)	Specificity (%)	Accuracy (%)
Boon *et al.* [26]	HRV[1] features, SVM[2]	2	15 min	85.20	82.10	83.90
			30 min	96.40	71.40	83.90
Mohebbi *et al.* [27]	HRV features, SVM	2	30 min	96.20	93.10	94.50
			10 min	75.10	64.30	69.60
Thong *et al.* [28]	PACs[3] analysis	2	30 min	89.0	91.0	90.0
Zhou *et al.* [29]	HRV features	2	15,000 min	96.89	98.25	97.67
Limam *et al.* [30]	CRNN, SVM	2	60 sec	82.50	98.70	90.60
Runnan *et al.* [31]	CNN[4]	2	6 sec	99.41	98.90	99.16
Ross *et al.* [32]	Spectrogram + DenseNet + SVM	2	600 min	88.38	95.14	92.18
	Spectrogram + ConvNet	2	600 min	98.33	89.74	93.16
Erdenebayar et al. [25]	CNN	2	30 sec	98.70	98.60	98.70
This study 2022	CNN-AlexNet	2	30 sec	100	99.83	**99.92**
			5 sec	100	98.83	**99.42**
		3	30 sec	100	93.83	**96.92**
			5 sec	100	94.86	**97.43**

[1]HRV = heart-rate variability, [2]SVM = support vector machine, [3]PACs = premature atrial complexes,
[4]CNN = convolutional neural network

In another study [31], 6-s ECG signals based on continuous wavelet transform and a 2D convolutional network were analyzed to detect AF episodes. The time-frequency characteristics of the ECG signal were analyzed instead of isolated atrial or ventricular signals. The 2D CNN model was trained for AF detection using the MIT-BIH database. In contrast, the results obtained using the proposed AlexNet architecture were superior to the results obtained in previous studies in terms of both the duration of the signal and the number of classes. A high prediction accuracy of 99.92% was obtained using a time window of 30 sec and two classes, and an accuracy of 99.42% was obtained using a time window of 5 sec and two classes. In addition, the present approach can be used to predict pathology using three classes with an accuracy of 96.92% using a 30 sec time segment and 97.43% using a 5 sec time segment.

5. CONCLUSION

In this paper, we evaluated the accuracy of the AlexNet architecture for PAF prediction using 5 sec and 30 sec ECG signals as input data. The results showed that this method achieved higher accuracy than other methods with an accuracy of 99.92% for 2 classes and 97.43% for 3 classes. Furthermore, the length of signal needed was always lower than those in previous studies. Additionally, this method achieved a sensitivity of 100% in all tests performed. This shows a clear tendency to correctly identify a normal subject. According to these results, the combination of a spectrogram and AlexNet is a good alternative for close and distant PAF prediction.

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