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Automated detection of atrial fibrillation based on vocal features analysis

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Abstract

Introduction: Early detection of atrial fibrillation (AF) is desirable but challenging due to the often-asymptomatic nature of AF. Known screening methods are limited and most of them depend of electrocardiography or other techniques with direct contact with the skin. Analysis of voice signals from natural speech has been reported for several applications in medicine.

The study goal was to evaluate the usefulness of vocal features analysis for the detection of AF.

Methods: This prospective study was performed in two medical centers. Patients with persistent AF admitted for cardioversion were enrolled. The patients pronounced the vowels “Ahh” and “Ohh” were recorded synchronously with an ECG tracing. An algorithm was developed to provide an “AF indicator” for detection of AF from the speech signal.

Results: A total of 158 patients were recruited. The final analysis of “Ahh” and “Ohh” syllables was performed on 143 and 142 patients, respectively. The mean age was 71.4 ± 9.3 and 43% of patients were females. The developed AF indicator was reliable. Its numerical value decreased significantly in sinus rhythm (SR) after the cardioversion (“Ahh”: from 13.98 ± 3.10 to 7.49 ± 1.58; “Ohh”: from 11.39 ± 2.99 to 2.99 ± 1.61). The values at SR were significantly more homogenous compared to AF as indicated by a lower standard deviation. The area under the receiver operating characteristic curve was >0.98 and >0.89 (“Ahh” and “Ohh,” respectively, $p < .001$). The AF indicator sensitivity is 95% with 82% specificity.

Conclusion: This study is the first report to demonstrate feasibility and reliability of the identification of AF episodes using voice analysis with acceptable accuracy, within the identified limitations of our study methods. The developed AF indicator has higher accuracy using the “Ahh” syllable versus “Ohh.”

KEYWORDS

atrial fibrillation diagnosis, atrial fibrillation screening, vocal features, voice analysis

Michael Glikson and Gregory Golovchiner contributed equally to this study.

1 | INTRODUCTION

Atrial fibrillation (AF) is the most common persistent cardiac arrhythmia, affecting almost 40 million adults worldwide,[1–4] and is expected to double in prevalence within the next four decades.[5,6] Its prevalence increases with age.[4–6] Several complications are associated with AF, including disabling complications such as stroke.[1] Twenty to thirty percent of all ischemic strokes are associated with AF[1] and 10% are associated with previously undiagnosed AF. This chronic condition poses a growing economic and clinical burden for healthcare systems worldwide.[7,8]

Early detection of AF before the occurrence of complications may result in effective treatment that may decrease stroke rate by more than 60%, and has been a long-standing clinical challenge.[9] However, due to the often-asymptomatic nature of AF this has remained an unmet goal. While guidelines recommend opportunistic screening of patients >65-year-old using pulse palpation followed by confirmatory 12-lead ECG[1] and screening of patients >75 year old by systematic ECG, the low accuracy of pulse palpation and logistic hurdles involved in ECG recording prevent this recommendation from becoming an effective modality for long-term, large population screening.[10]

New monitoring methods and devices have been introduced and presented in literature in recent years for the detection of AF. Their importance is well recognized today and discussed in guidelines.[1,11] These include wristband devices,[12] smartphone applications,[13–15] and smart-watches features[16] and are based on ECG signal recording, finger pulsatile photo-plethysmographic signals, and facial video monitoring.[17] All these methods, whether involving skin contact with a device or not, require active initiation by the patient, and may not be practically applied in a continuous mode.[9]

Analysis of voice signals from natural speech has been reported to enable estimation of heart rate,[18–22] and specific frequency-related characteristics of the voice signal have been associated with coronary artery disease.[23]

However, no practical method for the detection of AF, based on analysis of vocal parameters, has been reported so far.

The primary goal of this study was to evaluate the usefulness of vocal feature analysis for the detection of AF and for discriminating between sinus rhythm (SR) and AF. This type of detection may enable monitoring for AF in a long-term "passive" noncontact modality, and may serve as a screening tool for wide population.

2 | METHODS

This prospective study was performed in two medical centers. Consecutive patients with persistent AF, admitted to the intensive cardiac care units between August 1, 2016 and June 10, 2020 at Rabin Medical center (Beilinson campus) and Kaplan Medical center for the purpose of AF cardioversion, were enrolled. The study protocol was approved by the institutional review boards of both medical centers, and all the participants signed informed consent according to good clinical practice requirements.

The inclusion criteria were: Persistent AF documented by ECG, in a patient between ages 35 and 85 scheduled to undergo nonurgent cardioversion.

Exclusion criteria included: Inability to provide informed consent, hemodynamic instability, and speech disturbances.

The patients were asked to pronounce specific vowels ("Ahh"; "Ohh") for at least 4 s at maximum volume. Each vowel was pronounced three times with a waiting period between the recordings based on patient's comfort (minimum 1 min, not exceeding 3 min). These speech recordings were synchronized to a simultaneously recorded ECG. The synchronization with ECG was used for confirmation of the rhythm at the exact time of the speech recording during postprocessing.

The recordings were performed before the cardioversion and then repeated following successful cardioversion. To avoid the impact of sedation and other factors related to the procedure, the second recording was performed after the patient completely recovered from sedation, before discharge with SR confirmed. The voice was recorded using a Shure WH20LR microphone and Focusrite Scarlett 2i2 sound card. The sampling rate was 16 KHz with 24-bit resolution. The ECG signals were recorded using a regular ECG recorder or Attys portable biological data acquisition device. Cardioversion was performed, using a Lifepak 20e defibrillator (Physio-Control) connected to the patient by Quick-Combo electrodes, using a biphasic shock of between 200 and 360 joules.

2.1 | Diagnostic algorithm

A "Speaker Dependent" algorithm was developed to provide an "AF indicator" for detection of AF from recorded speech.

The algorithm is based on detecting changes in a specific set of vocal features. This set was based on common features used in voice analysis: Mel-frequency cepstral coefficient, pitch, glottal pulse, linear prediction coefficient.[24,25]

The algorithm's main stages are: (Figure 1)

I. At first stage a "SR model" for each patient was created (Figure 2).

(1) Detecting the vowel part. Silent parts, before and after the vowel, were removed.
(2) Dividing speech signals into frames. Due to the stationary properties of the speech signal the analysis was performed on frames of 40 ms each. A "Hanning" window was applied for each frame.[26] The signal was normalized by subtracting the mean value and dividing by the root mean square value.
(3) The predefined set of vocal features was calculated per frame.
(4) Feature matrix. A feature matrix was obtained by sequencing all the calculated features sets.
(5) Patient specific model (training). For the obtained feature matrix from SR recordings of each patient, the K-means ($K = 8$)

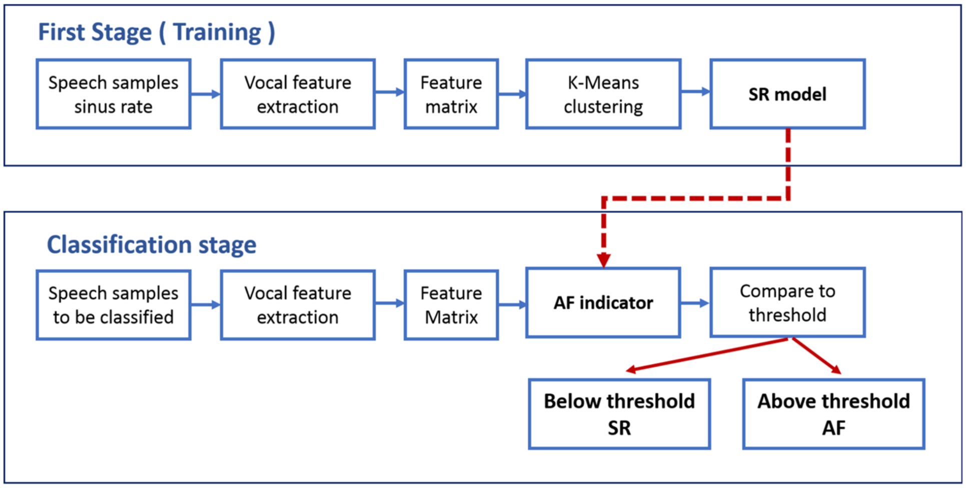

FIGURE 1 Diagnostic algorithm. AF, atrial fibrillation; SR, sinus rhythm.

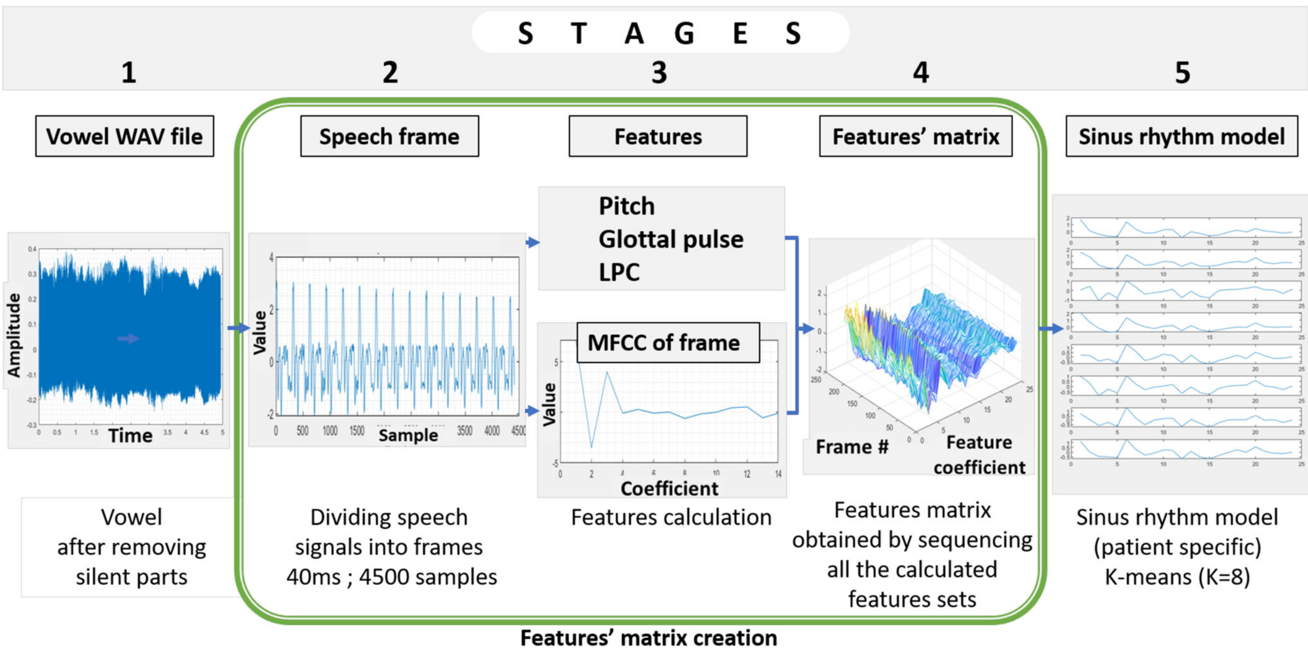

FIGURE 2 Creation of the "sinus rhythm model." The patient sinus rhythm specific model was created in five stages using sinus rhythm recordings. LPC, linear prediction coefficient.

clustering method was applied[27] to build a model of *K* centroids that represented the SR voice feature of individual patient.

II. Classification. To classify the patient recording between SR and AF the following steps were used (Figure 3):

(1) Analysis of the AF and SR recording using the above-mentioned stages 1–4.
(2) Calculation of distance (i.e., difference) between the result and the SR model.
(3) The "AF indicator" was calculated as the distance (difference) between the resulting feature matrix and the SR model. If the average distance exceeds a predefined threshold (see below), the recording is classified as Afib. If not, it is classified as SR.
(3a) Threshold calculation:

(1) A training set consisting 30% of the frames in the SR and AF recordings was randomly selected. SR model is calculated using K-means method applied on the SR recordings in the set.
(2) All distance (difference) values were calculated for the training set.
(3) Threshold value was defined as the distance value which yielded maximal clinical accuracy (true positive + true negative/all cases) across the training set.

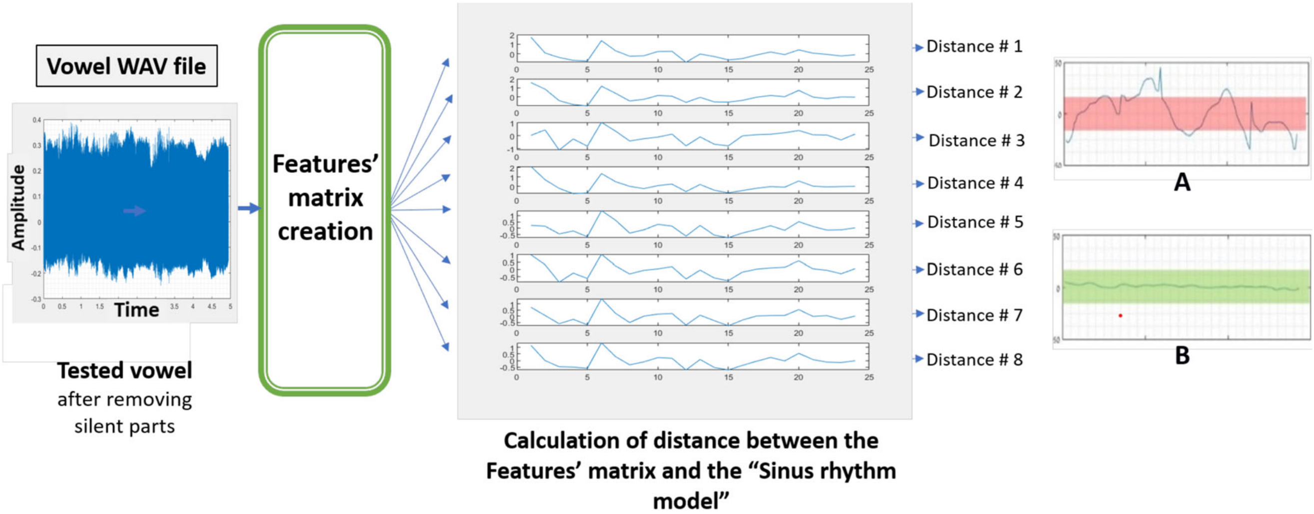

FIGURE 3 Classification. To classify the patient recording between sinus rhythm (SR) and atrial fibrillation (AF) the tested vowel has been processed. First Features' matrix has been created (Stages 1–4 as in "SR model"). Then distance between the tested vowel Features' matrix and "SR model" was calculated. If average distance exceeds a predefined threshold (A in the higher right panel), the recording is classified as AF. If not, it is classified as SR (B in the lower right panel).

2.2 | Statistical analysis

(1) Reliability of the developed indicator was assessed using internal consistency, producing Cronbach's α coefficients for AF and SR.
(2) Discriminant analysis was performed to assess predictive discriminant power of the indicator to classify patients into groups (AF vs. SR). An receiver operating characteristic (ROC) curve was calculated.
(3) To test the predictive ability of the diagnostic algorithm, a cross-validation model was used. Thirty five percent of cases were assigned to a training data set to build a reference model. All other cases were assigned to a testing data set.

To test classification success, we compared the classification accuracy between the training and testing datasets using the χ^2 method.

3 | RESULTS

3.1 | Patients

A total of 158 patients were recruited for the study. One hundred fifty-six patients had successful cardioversions along with recordings during AF and in SR. Of these 156 patients, 13 patients were excluded from the "Ahh" vowel analysis due to poor voice quality or technical error. An additional patient was excluded from the "Ohh" vowel analysis due to poor voice signals (Figure 4).

The final analysis of "Ahh" and "Ohh" syllables of 143 and 142 patients, respectively, is presented. Baseline characteristics of the patients are presented in Table 1.

No statistically significant differences in patients' characteristics was found between the group excluded from final analysis ($n = 13$) compared to the general study population.

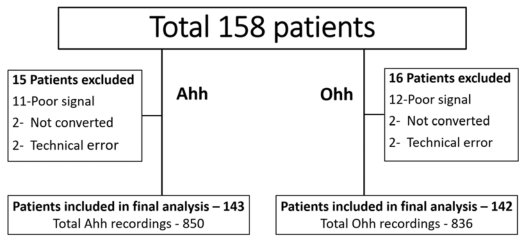

FIGURE 4 Patients flowchart

3.2 | Reliability

Reliability of the "AF indicator," estimated by internal consistency analysis using Cronbach's α coefficient, is shown in Table 2, showing that the AF indicator is reliable. The results of the comparison between AF indicator values before and after cardioversion are shown in Table 3. This value decreased significantly after cardioversion. In addition, values at SR are significantly more homogenous compared to values at AF, as indicated by a lower standard deviation. These results show that the indicator can predict classification of rhythm between AF and SR.

3.3 | ROC curve

The ROC curve (Figure 5) shows the classification performance: The area under the curve is above 0.98 for the verb "Ahh" and above 0.89 for the verb "Ohh" with a $p < .001$.

The sensitivity and specificity of the data is shown in Figure 6.

TABLE 1 Patients' characteristics

Demographic data (*N* = 158)	
Age (years; mean ± SD)	71.4 ± 9.3
Female (*N* [%])	68 (43.0%)
BMI (kg/m^2; mean ± SD)	30.0 ± 5.6
LA diameter (mm)	44.8 ± 7.6
Medical history (%)	
Diabetes mellitus	28.6
Hypertension	77.6
Coronary artery disease	10.2
Valvular disease	7.5
Congestive heart failure	21.4
Stroke history	6.8
Smoking history	10.2
Medical therapy (%)	
Oral anticoagulant	94.6
Antiarrhythmic drugs	33.3
Beta-blockers	78.9
Ca-channel blockers	22.4

Abbreviations: BMI, body mass index; LA, left atrium; SD, standard deviation.

TABLE 2 Alpha Cronbach coefficients before and after cardioversion

	Average distances to sinus rhythm (SR) model[a]	
Syllable	**Before (AF)**	**After (SR)**
Ahh	0.892	0.719
Ohh	0.845	0.915

Abbreviation: AF, atrial fibrillation.

[a]See test for details.

TABLE 3 Means, standard deviations, and effect sizes of distances from reference model, before and after cardioversion

	Before (AF)		After (SR)				
Vowel	***M***	**SD**	***M***	**SD**	***T***	***p***	**Cohen's *d***
Ahh	13.98	3.10	7.49	1.58	24.20	<.001	2.63
Ohh	11.39	2.99	7.09	1.61	18.34	<.001	1.79

Abbreviations: AF, atrial fibrillation; SD, standard deviation; SR, sinus rhythm.

3.4 | Cross-validation model

For the training data set, the model identified 90.5% true positive cases, 93.2% true negative cases, 6.8% false positive cases, and 9.5% false negative cases ($\chi^2 = 64.80$, $p < .001$, $\varphi = 0.834$).

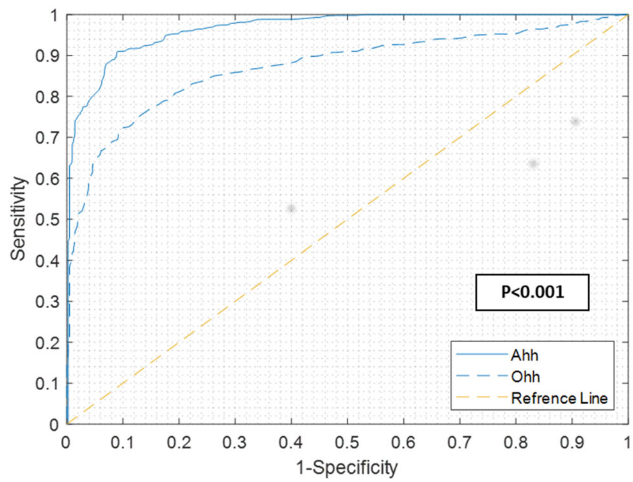

FIGURE 5 The receiver operating characteristic curve. The area under the curve is above 0.98 for the verb "Ahh" and above 0.89 for the verb "Ohh" with a $p < .001$.

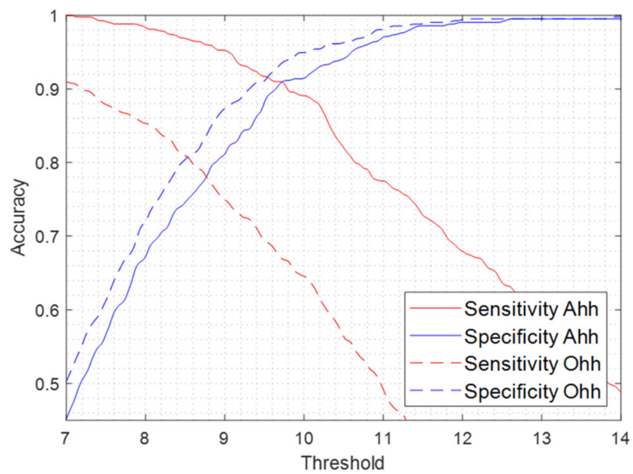

FIGURE 6 Sensitivity and specificity curves. The curves show sensitivity and specificity values for each vowel (Ahh and Ohh) as a function of threshold settings.

For the testing data set, the model identified 89.7% true positive cases, 91.6% true negative cases, 8.4% false positive cases, and 10.3% false negative cases ($\chi^2 = 126.81$, $p < .001$, $\varphi = 0.813$).

The odds ratio (OR) of cohort membership in the training data set (OR = 0.231, 95% confidence interval [CI]: 0.105–0.496) was similar to the OR of the testing data set (OR = 0.267, 95% CI: 0.177–0.405). These results imply that the "AF indicator" has a high prediction value for discrimination between AF and SR.

4 | DISCUSSION

This study demonstrates the feasibility and reliability of AF detection using voice analysis. The developed indicator has a higher accuracy for the "Ahh" vowel than for the "Ohh."

The sensitivity and specificity of the analysis can be adjusted to the desirable values by choosing the appropriate settings, as shown in Figure 7. This graph (Figure 7) demonstrates working points for two different scenarios (for the "Ahh" syllable).

If a higher specificity is desired, for example for widespread screening of a healthy population, then analysis based on the parameters corresponding to the second point in the graph could be chosen. When higher sensitivity is imperative, for example in high-risk population such as post-stroke patients, then analysis corresponding to the first point on the graph can be used.

What is the physiologic background underlying the findings of this study? Speech signal contains information related to the heartbeat. In fact, heartbeats impact the voice production mechanism, affecting the acoustic properties of speech. There are two different mechanisms that contribute to the link between the speech signal and the heartbeat. The first mechanism, described in several studies,[18–22] is based on the periodic influence of the blood pulse on the vocal cords and the larynx ("voice box"), two vital organs for voice production. Each heartbeat initiates a blood pulse at the larynx and the vocal cord muscles, changing their mass periodically. These temporal changes of the vocal cords' mass produce slight changes of the voice pitch. The second mechanism is the mechanical effect of heart contractions on the air flowing through the vocal cords. Due to the heart's location inside the chest cavity, in close contact with the lungs and respiratory tract, heart contractions change the dynamics of air flow through the vocal cords. These periodic changes of the air flow affect the spectral properties of the voice signal. Irregular heart contraction, such as that occurs during AF episodes, is expected to modulate voice signals differently than a regular heart contraction.

Screening for AF is useful and cost-effective in older patients (>65 years old) and other high-risk population[28-30] and is a class I recommendation in current practice guidelines.[1] The diagnosis of AF requires its demonstration on an ECG with at least one cardiac lead.[1] Due to the nature of paroxysmal AF, especially in those patients with short or asymptomatic episodes, establishing the diagnosis by an ECG may be challenging. Simple and effective detection methods for AF are desired.

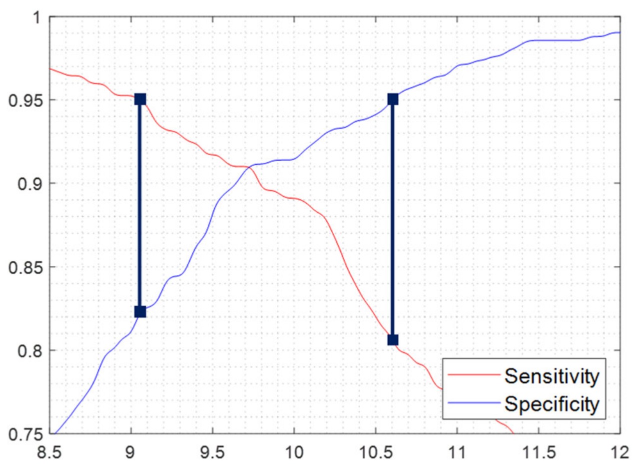

FIGURE 7 Sensitivity and specificity (Ahh vowel) as a function of threshold. Examples of two different points dependent on "AF indicator" threshold. Threshold selection for higher sensitivity is shown with the left line. Right line showing the results for threshold selected for higher specificity. First point is with higher sensitivity of 95% and corresponding specificity of 82%. Second point with specificity of 95% and corresponding sensitivity of 81%. AF, atrial fibrillation.

In recent years, novel methods have been developed for both short and long-term rhythm monitoring and AF diagnosis without the necessity of a 12-lead ECG, although the ECG is always used for confirmation. These include wristband devices and smart-watches,[11,12] and are based on ECG signal recording, finger pulsatile photo-plethysmographic signals, and facial video monitoring.[15,16] However, while some of these technologies have been found effective in identifying AF, there are limitations to most of these devices.[9] The less intrusive of these devices have inherently limited monitoring periods, and some of the simple, portable, and user-initiated models may not provide reliable and easily interpretable monitoring signals. The more durable and longer-term devices may provide easily interpretable signals but can be either invasive[31] or bulky. External devices that harness a device that the user may be already wearing require at least some skin contact with a device,[14] and usually a user-initiated monitoring period.[12,13] Additionally, adoption of smartwatch-driven AF monitors by the over 65-year-old population is rather limited.[32] Voice analysis has been used as a monitoring tool for various medical conditions[33] and has been reported to enable estimation of heart rate.[18-22]

In this study we found that voice analysis is feasible for automatic recognition of AF.

The advantage of voice-based screening and monitoring of AF is that it is contactless, sensor-free, and may be easily implemented using wide-spread voice-related infrastructure and devices such as telephones, cellular phones, smart speakers, and so forth, as it is a postprocessing algorithm-based modality. Additionally, dependent on the population for which its use is intended, it may not require the end user to initiate a monitoring session. This can be of particular value in large high-risk populations, such as those with a recent cryptogenic stroke, as the symptoms of AF may be elusive, and user-initiated monitoring may not be done in correlation with symptoms or may be challenging for a post-stroke patient.

The performance of the method presented here depends on factors that have been optimized in this study, including the choice of vowels used for the training of the model and the level of training.

The method presented was examined separately for two pronounced vowels ("Ahh" and "Ohh") used for training and testing the model. A combined model based on "fused analysis" of both "Ahh" and "Ohh" recordings may boost the accuracy and may serve as a most relevant direction for future studies, paving the way for a free-speech model.

4.1 | Study limitations

The study was conducted in an intensive cardiac care unit and the results may not be replicable in every-day situations with different background noises. Currently, further studies are underway to check the developed algorithms in a regular, nonhospital environment. In the beginning of the study, some voice recordings were of poor quality, and so technical adjustments were made that resulted in better interpretations of the recordings. The analysis in this study was limited to specific vowels; fluent speech has yet to be analyzed. The “Ahh” and “Ohh” vowels were chosen as they are frequent in fluent speech. Further studies should check the usefulness of these vowels in predicting AF when analyzed from fluent speech.

This study presents a model trained on both AF and sinus recordings. Models trained on pre–post cardioversion conditions usually demonstrated reduced performance in real-life situations.[16,34,35] Generalizing the model to perform well without pretraining for AF, for a specific patient, may need further study on a larger cohort.

Potential false positive burden poses a limitation that should be addressed, in view of multiple recordings and especially if actual specificity is lower in real-life conditions. The model demonstrated here may not reach same accuracy levels in free speech modality, which is much preferred, which is another limitation.

5 | CONCLUSION

This study confirms the hypothesis that AF results in changes in vocal features that can be analyzed. An “AF indicator” based on this analysis was developed and showed statistically significant differences in AF and SR. Thus the “AF indicator” can be a useful tool in detecting AF. This opens horizons for noninvasive, low-cost, age-friendly, prolonged, and systematic AF monitoring. Diagnostic tools supported by this technology could be used for rhythm monitoring in patients with known AF as well as for screening for AF in populations at risk. Further studies are needed to test the use of this technology in outpatient setup with paroxysmal short term AF episodes

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