10.48047/jocaaa.2024.32.02.30

Chronic Heart Failure Detection Using Recording Feature Aggregate ML Model

Dr.V.ANANTHA KRISHNA [1], SHREYA GANDESIRI[2], KOMAL KUMARI.L[3],K. SRAVANTHI[4]

[1]Professor, Department of Computer Science and Engineering, Sridevi Women's Engineering College, Hyderabad, India
Email: Krishnaananthav@gmail.com,
[2,3,4,]B.Tech Student, Department of Computer Science and Engineering, Sridevi Women's Engineering College, Hyderabad, India

ABSTRACT

The prevalence of chronic heart failure (CHF), which affects over 26 million individuals globally, is rising by 2% a year. Even in the scientific community, approaches for autonomously identifying CHF are surprisingly rare, given the tremendous burden disease CHF poses and the widespread use of sensors in our daily lives. We offer a technique for using heart sounds to detect CHF. End-to-end Deep Learning (DL) and traditional Machine Learning (ML) are combined in this manner. A Spectro-temporal image of the signal is used by the DL to train, while expert features are used by the traditional ML. Using recordings from 947 participants from six datasets that are freely accessible and one CHF sample that was gathered specifically for this study, the approach was assessed. The suggested approach scored 89.3, 9.1 points more than the competition's baseline method, using the exact same evaluation methodology as a previous Phys Net challenge. The method's overall precision is 92.9% (error of 7.1%); although the experimental results cannot be directly compared, this error rate is equivalent to the 9.7% percentage of recordings that experts have classified as "unknown." Ultimately, we discovered 15 expertise features that can be effectively utilized in machine learning models to distinguish between CHF stages (i.e., during hospitalization's decompensated phase and its recompensated stage) with a 93.2% accuracy rate. Promising results are observed with the suggested strategy for both detecting different phases of CHF and differentiating recordings between patients and healthy participants. This could result in the creation of at home CHF monitors to prevent hospital stays and the simpler detection of new CHF patients.

INTRODUCTION

Congestive heart failure, also referred to as chronic ventricular fibrillation

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(CHF), is a medical disorder in which the heart cannot adequately pump blood, resulting in a variety of symptoms and problems. Unlike abrupt heart failure, which happens rapidly, it constitutes an over time or chronic condition. Heart valve problems, hypertension, coronary arteries disease (CAD), cardiomyopathies, and various other heart-related illnesses are some of the underlying causes of congestive heart failure (CHF). Non-cardiac causes like diabetes, renal illness, and lifestyle choices like binge drinking and obesity can also cause it.

Chronic heart failure is usually managed and treated with lifestyle changes, heart function-improving medications, symptom-reduction surgeries, and occasionally heart valve replacement or repair. In extreme circumstances, heart transplantation might be taken into consideration.

Effective management of CHF requires early recognition and routine monitoring of the illness. New technologies are being investigated to help in the early diagnosis and treatment of congestive heart failure (CHF), which can enhance the quality of life for those who have the illness. Examples of these technologies include models based on machine learning and remote monitoring systems.

The incapacity of the heart to provide target tissues and organs with adequate perfusion at physiologic filling levels in order to satisfy their metabolic demands is the hallmark of chronic heart failure (CHF), a progressive and long-lasting syndrome [1]. With its incidence rising by 2% every year, CHF has grown to epidemic size in the population. In developed nations, 1-2% of persons and 10% of those over 65 are affected by CHF.

Currently, 2% of the yearly healthcare expenditure is spent on diagnosing and treating CHF. In 2018 alone, the United States of America spent almost $35 billion USD on CHF treatment; over the next ten years, it is anticipated that these expenses will quadruple [2]. Although medical and device-based therapy options have advanced over the past few decades, the general prognosis for congestive heart failure remains dire, with only around 50% of affected individuals living for five years.

The clinical course of congestive heart failure (CHF) typically involves alternating episodes of paid phases, during which the individual feels well and does not

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exhibit signs and symptoms of excess fluid in the body, and decompensated phases, during which it is easy to see signs and signs of systematic fluid overload, including dyspnea, peripheral swelling, liver congestion, and pulmonary edema. In the later cases, patients frequently need to be admitted to the hospital in order to get intravenous treatment (diuretics, inotropes) in order to successfully achieve an adverse balance of fluids while going back to the compensatory condition.

Early identification of heart failure aggravating would let a treating doctor to promptly modify the patient's outpatient medical care, thereby preventing hospitalization. At this time, a skilled doctor can identify HF worsening through physical examination and distinctive alterations in the patient's heart failure indicators, which are derived from the patient's blood.

Regretfully, when a patient's symptoms intensify, it usually indicates that a full-blown bout of CHF is underway, necessitating hospitalization. Furthermore, phonocardiography can detect distinctive alterations in cardiac sounds that precede the worsening of heart failure in certain patients. Fig. 1 shows an example of a healthy subject's phonocardiogram (PCG) recording. Two heart sounds, known as S1 and S2, are usually audible in healthy individuals.

S1 is brought on by the early systolic closure that occurs in the mitral valve or ventricle wall, while S2 is brought on by the early diastolic closing of the aortic or pulmonary valves. Here, the time between S1 and S2 is referred to as the cardiac cycle's contraction phase, or systole, while the interval among S2 and S1 is referred to as its relaxation phase, or diastole. Some cardiac disorders can produce extra heart sounds (such S3 and S4), which are never considered normal.

When CHF occurs (during decompensation), we frequently detect a third sound (S3), which usually occurs 0.1–0.2 seconds following the second sound, or S2. It has recently been shown that some physiological markers, including the presence of extra heartbeats or elevated blood pressure in the pulmonary circulation, begin to manifest several weeks prior to the development of a decompensation episode that is clinically noticeable in the CHF patient.

Additionally, there is a critical window of opportunity during which outpatient-based treatment approaches might

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stop the progression of CHF and bring the patient back to a compensated state without requiring hospitalization. A number of research conducted recently have suggested using PCG signals captured with an electronic stethoscope to automatically diagnose various cardiac problems using Machine Learning (ML) techniques [1]. However, there aren't many techniques that specifically target CHF detection.

A typical machine learning (ML) pipeline for identifying various heart conditions looks like this: first, the signals are segmented by identifying the "typical" heart sounds (S1 and S2); next, the signals are denoised; next, specific frequency-domain and time-domain features are extracted; and finally, a feature-based ML model is learned (e.g., using ML algorithms, such as Random Forest or Support Vector Machine - SVM) that can distinguish between healthy and unhealthy sounds.

The majority of the features in use today are derived from knowledge of audio and signal processing and medicine. Because different experts may interpret a PCG recording as healthy or unhealthy, clinicians never diagnose CHF patients based solely on cardiac sounds; instead, they use a comprehensive assessment of the patient that includes laboratory testing, blood pressure, complete medical history, and other information.

Because of this uncertainty, experts in the recent Physio Net cardiology challenge [3] actually classified 9.7% of the recordings as "unknown," while classifying the remaining recordings as either healthy or sick. End-to-end learning, or machine learning models that learn straight from the raw data without the requirement for features, may be able to outperform traditional feature-based machine learning, according to recent developments in Deep Learning (DL).

For instance, DL has demonstrated ground-breaking performance in domains like image processing, speech and audio processing, natural language processing, pattern identification, and sensor data processing. A successful mix of end-to-end DL and traditional ML can outperform each approach separately for CHF detection. The DL approach learns from both a temporal plane depiction of the signal (the spectrogram) and a time-domain version of the signal (the raw PCG signal), while the standard ML technique learns from a vast corpus of expert-defined features.

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RELATED WORK

"Chronic heart failure detection from heart sounds using a stack of machine-learning classifiers"

Over 26 million patients worldwide suffer from chronic heart failure, which is a pandemic. It causes more than a million hospital admissions in Europe and the United States each year and plays a significant role in the mortality rate of people with cardiovascular illnesses. The quality of a patient's life can be greatly improved by using methods for detecting chronic heart failure in order to take preventative measures, improve early diagnosis, and avoid hospitalization or even life-threatening situations. We provide a machine-learning approach for the identification of chronic heart failure using cardiac sounds.

The process includes machine learning, feature extraction, segmentation, and filtering. Using information gathered from 122 subjects collected for the study, the procedure was evaluated using a leave-one-subject approach. With an accuracy of 96%, the technique outperformed a majority classifier by 15%. More precisely, it has an 87% precision rate in identifying (calling back) 87% of the people with chronic heart failure. The research verified that chronic heart failure identification may be achieved by using sophisticated machine learning on real-world sounds captured using a discrete digital stethoscope.

"A revaluation of the costs of heart failure and its implications for allocation of health resources in the United States."

Heart failure (HF) is thought to cost $39.2 billion a year. It is known that this understates the actual cost of care. This approach aims to evaluate these expenses more precisely. Data sources that were openly accessible were used. Relevant variables included in the cost calculations were Medicare hospital cost-to-charge ratios, insurance reimbursement from both the public and private sectors, and out-of-pocket expenses. The HF categorization scheme was modified using the Atherosclerosis Risk in Community (ARIC) HF scheme, which was published recently.

The primary diagnostic of heart failure (HF in loneliness, or HFI) or heart failure as one of several diagnoses or a component of an illness milieu (HF condition, or HFS) were used to compute costs. The estimated total direct costs of HF were $115.4 billion (HFS)

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and $60.2 billion (HFI). For both, indirect costs came to $10.6 billion. HF-related expenses can burden US health care far more than is typically mentioned. For policy makers, these altered and higher expenses have consequences.

“Classification of normal/abnormal heart sound recordings: the Physio Net/Computing in Cardiology Challenge 2016,”

Heart sound signals, often known as phonocardiograms or PCGs, have been the subject of extensive research in recent years. In many different clinical contexts, automated heartbeat segmentation and classification methods may be used as a pathology screen. However, the absence of a sizable, publicly accessible database of cardiac recordings has impeded comparison assessments of methods in the literature. In order to address this problem, the Physio Net/Computing in Cardiovascular (Cinch) Challenge 2016 has put together the world's largest public heart sound database, which was compiled from eight sources that were acquired by seven different independent research groups worldwide.

The database has 4,430 recordings from 1,072 participants, which adds up to 233,512 heart sounds from patients with various illnesses such coronary artery disease and cardiac valve disease as well as from healthy subjects. These recordings were made in nonclinical (such in-home visits) settings with a variety of instruments. The recording lasted anything from a few seconds to many minutes. Respondent characteristics (age and gender), recording details (number per cautious, body location, and duration of recording), simultaneously recorded signals (e.g., ECG), sampling frequency, and sensor type utilized are further data supplied.

Classifying recordings as normal, unusual, or unclassifiable (noisy/uncertain) was the task given to participants. A combined specificity and sensitivity score in relation to human expert annotations determined an entry's final score. A synopsis of the fundamental classification technique is given, along with an explanation of the open-source code that has been made available in connection with the Challenge. With Se=0.65 and Spa=0.76, the open-source code produced a score of 0.71. A total of 48 teams filed 348 free submissions during the competition's official phase, with the best score being 0.86 (Se=0.94 Spa=0.78).

RESULT AND DISCUSSION

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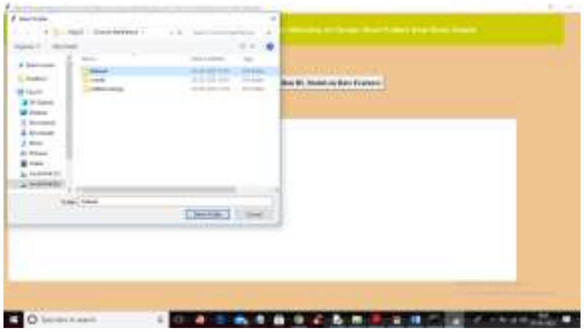

In above screen selecting and uploading 'Dataset' folder and then click on 'Select Folder' button to load dataset and to get below output

In above graph x-axis represents algorithm names and y-axis represents accuracy, sensitivity and specificity and in all algorithm's Recording model has got high accuracy. Now close above graph and then click on 'Predict CHF from Test Sound' button to upload test sound file and get predicted output as Normal or Abnormal

CONCLUSION

In this paper, we provided a novel approach for CHF identification from PCG audio recordings using a combination of classic ML and end-to-end DL, where the DL learns from both the spectral image of the signal and the time-domain (i.e., raw PCG signal) illustration of the signal itself. We evaluated the technique on our own data set for CHF detection and also on six open-access Physio Net datasets utilized for the current Physio Net Cardiology Challenge, which allowed us to thoroughly evaluate the method's performance on similar domains. The findings from the evaluation on all the datasets showed that our method achieves the highest level of performance when compared to the test baseline methods (see the Physio Net

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