



## NOVEL APPROACH TO IDENTIFYING CHF IN PCG RECORDINGS USING MACHINE LEARNING AND END-TO-END DEEP LEARNING

**N.RAJYA LAKSHMI**, MCA, DCA, DVR & Dr.Hima Shekar MIC College of Technology, A.P., India.

**B.MURALI KRISHNA**, Associate Professor, Dept.of AI & IT, DVR & Dr.Hima Shekar MIC college of Technology, A.P., India.

**Abstract**— Chronic heart failure (CHF) is a chronic, progressive condition underscored by the heart's inability to supply enough perfusion to target tissues and organs at the physiological filling pressures to meet their metabolic demands. Chronic heart failure (CHF) affects over 26 million of people worldwide, and its incidence is increasing by 2% annually. Despite the significant burden that CHF poses and despite the ubiquity of sensors in our lives, methods for automatically detecting CHF are surprisingly scarce, even in the research community. We present a method for CHF detection based on heart sounds. The method combines classic Machine-Learning (ML) and end-to-end Deep Learning (DL). The classic ML learns from expert features, and the DL learns from a spectro-temporal representation of the signal. The method

was evaluated on recordings from 947 subjects from six publicly available datasets and one CHF dataset that was collected for this study. Using the same evaluation method as a recent PhysoNet challenge, the proposed method achieved a score of 89.3, which is 9.1 higher than the challenge's baseline method. The method's aggregated accuracy is 92.9% (error of 7.1%); while the experimental results are not directly comparable, this error rate is relatively close to the percentage of recordings labeled as "unknown" by experts (9.7%). Finally, we identified 15 expert features that are useful for building ML models to differentiate between CHF phases (i.e., in the decompensated phase during hospitalization and in the recompensated phase) with an accuracy of 93.2%. The proposed method shows promising results



both for the distinction of recordings between healthy subjects and patients and for the detection of different CHF phases. This may lead to the easier identification of new CHF patients and the development of home-based CHF monitors for avoiding hospitalizations.

### INTRODUCTION

CHF detection based on heart sounds. The method combines classic Machine-Learning (ML) and end-to-end Deep Learning (DL). The classic ML learns from expert features, and the DL learns from a spectro-temporal representation of the signal. The method was evaluated on recordings from 947 subjects from six publicly available datasets and one CHF dataset that was collected for this study. Cardiovascular diseases (CVDs) encompassing heart attacks and chronic heart failure, rheumatic heart disease, acute myocardial ischemia, cerebrovascular disease, arterial hypertension, peripheral artery disease and congenital heart disease, have shown to be the cause of death for 21.5 million people. Chronic heart failure (CHF) is a chronic, progressive condition underscored by the heart's inability to supply enough perfusion to target tissues and organs at the physiological filling pressures to meet their metabolic demands [1]. CHF has reached epidemic proportions in the population,

as its incidence is increasing by 2% annually. In the developed world, CHF affects 1-2% of the total population and 10% of people older than 65 years. Currently, the diagnosis and treatment of CHF uses approximately 2% of the annual healthcare budget. In absolute terms, the USA spent approximately 35 billionUSD to treat CHF in 2018 alone, and the costs are expected to double in the next 10 years [2]. Despite the progress in medical- and device-based treatment approaches in the last decades, the overall prognosis of CHF is still dismal, as 5-year survival rate of this population is only approximately 50%. In the typical clinical course of CHF, we observe alternating episodes of compensated phases, when the patient feels well and does not display symptoms and signs of fluid overload, and decompensated phases, when symptoms and signs of systemic fluid overload (such as breathlessness, orthopnea, peripheral edema, liver congestion, pulmonary edema) can easily be observed. During the latter episodes, patients often require hospital admission to receive treatment with intravenous medications (diuretics, inotropes) to achieve a successful negative fluid balance and return to the compensation state. Early detection of HF worsening would allow a treating physician to adjust the patient's medical management on an outpatient basis in a timely manner and thus avoid



the need for a hospital admission. Currently, an experienced physician can detect the worsening of HF by examining the patient and by characteristic changes in the patient's heart failure biomarkers, which are determined from the patient's blood. Unfortunately, clinical worsening of a CHF patient likely means that we are already dealing with a fully developed CHF episode that will most likely require a hospital admission.

#### LITERATURE REVIEW

Detrano et al. [1], resulting in a 77% accuracy rate. The global evolutionary approach and a features-selection method were used on the Cleveland dataset. Using multi-layer Perceptron and support vector machine (SVM) algorithms, Gudadhe et al. built a diagnosis system for HD categorization and attained an accuracy of 80.41 percent.

Resul et al. [2] created an ANN ensemble-based HD diagnosis system with an accuracy of 89.01%, sensitivity of 80.09%, and specificity of 95.91%. This HD diagnostic system was developed by Akil et al. using machine learning.

Palaniappan et al. [3]. The machine learning predictive models NB, DT, and ANN were employed in the system's creation. Accuracy for NB was 86.12%, accuracy for ANN was 88.12%, and accuracy for DT was 80.4%. By adapting the artificial neural network method, Olaniyi et al. created a three-stage method for HD prediction in angina, which showed an accuracy of 88.89%. For HD diagnosis, Samuel et al. created a unified medical decision support system using artificial neural networks and Fuzzy AHP. The proposed approach achieved an accuracy of 91.10 percent. Using relief and rough set methods, Liu et al. suggested an HD classification system. Overall, the proposed technique was 92.32 percent accurate in its classifications. In this paper, we offer a method for identifying HDs based on the use of feature selection and classification tools. When it comes to choosing which features to use, the Sequential Backward Selection (SBS FS) algorithm is the way to go. K-Nearest Neighbor (K-NN) performance as a classifier has been evaluated using both the entire feature set and a subset of features.



Accuracy was successfully achieved with the proposed strategy.

### PROPOSED SYSTEM

Due to chronic heart failure many peoples are losing their lives worldwide and to reduce this lives lost we need to have expert physicians and sometime if such experts not available then it's difficult to save life. Failure in the presentation of heart sound frequencies and the differentiation between them, the identification of the energy variations, the process of signal de-noising, and the determination of the heart sound components [9] are only few of the issues that the researchers often confront with when analyzing the PCG signals. Some of them we address in the research presented in this paper.

### DISADVANTAGES:

Less accuracy

Need experts

### IMPLEMENTATION

**Upload Physionet Dataset:** using this module we will upload dataset to application

**Dataset Preprocessing:** using this module we will extract audio recording features and systolic and diastolic features from dataset and then normalize values

**Run ML Segmented Model with FE & FS:** using this module we will extract and select systolic and diastolic features from dataset and then train with Random Forest Classic ML model and then apply test data to calculate its prediction accuracy

**Run DL Model on Raw Features:** using this module we will extract RAW features from recording and then train with deep learning model and then this model will be applied on test data to calculate its accuracy

**Run Recording ML Model:** using this module we will extract features from Classic ML model and deep learning model and then



retrain with 3<sup>rd</sup> classifier to get its prediction accuracy

#### **Predict CHF from Test Sound:**

using this module we will upload Test Heart Sound file and then classifier model will predict weather given recording file is Normal or Abnormal

#### **Tensorflow**

TensorFlow is a free and open-source software library for dataflow and differentiable programming across a range of tasks. It is a symbolic math library, and is also used for machine learning applications such as neural networks. It is used for both research and production at Google.

TensorFlow was developed by the Google Brain team for internal Google use. It was released under the Apache 2.0 open-source license on November 9, 2015.

#### **Numpy**

Numpy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

It is the fundamental package for scientific computing with Python. It contains various features including these important ones:

- A powerful N-dimensional array object
- Sophisticated (broadcasting) functions
- Tools for integrating C/C++ and Fortran code
- Useful linear algebra, Fourier transform, and random number capabilities

Besides its obvious scientific uses, Numpy can also be used as an efficient multi-dimensional container of generic data. Arbitrary data-types can be defined using Numpy which allows Numpy to seamlessly and



speedily integrate with a wide variety of databases.

### **Pandas**

Pandas is an open-source Python Library providing high-performance data manipulation and analysis tool using its powerful data structures. Python was majorly used for data munging and preparation. It had very little contribution towards data analysis. Pandas solved this problem. Using Pandas, we can accomplish five typical steps in the processing and analysis of data, regardless of the origin of data load, prepare, manipulate, model, and analyze. Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

### **Matplotlib**

Matplotlib is a Python 2D plotting library which produces publication quality figures in a

variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shells, the Jupyter Notebook, web application servers, and four graphical user interface toolkits. Matplotlib tries to make easy things easy and hard things possible. You can generate plots, histograms, power spectra, bar charts, error charts, scatter plots, etc., with just a few lines of code. For examples, see the sample plots and thumbnail gallery.

For simple plotting the pyplot module provides a MATLAB-like interface, particularly when combined with IPython. For the power user, you have full control of line styles, font properties, axes properties, etc, via an object oriented interface or via a set of functions familiar to MATLAB users.

### **Scikit – learn**



Scikit-learn provides a range of supervised and unsupervised learning algorithms via a consistent interface in Python. It is licensed under a permissive simplified BSD license and is distributed under many Linux distributions, encouraging academic and commercial use. The library is built upon the SciPy (Scientific Python) that must be installed before you can use scikit-learn. This stack that includes:

- **NumPy:** Base n-dimensional array package
- **SciPy:** Fundamental library for scientific computing
- **Matplotlib:** Comprehensive 2D/3D plotting
- **IPython:** Enhanced interactive console

#### **Algorithms used in this project :-**

- **K-means clustering**

- **algorithm :-**

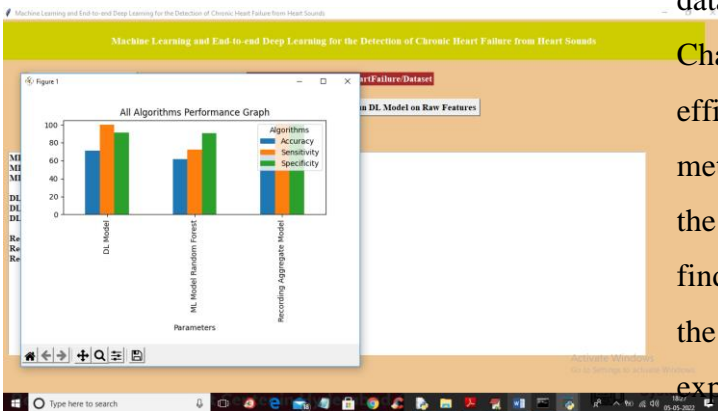
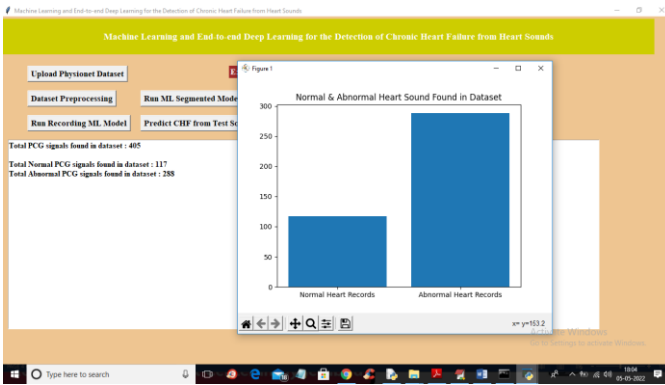
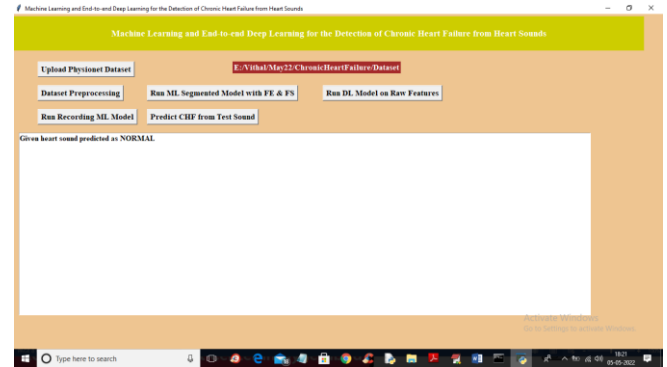
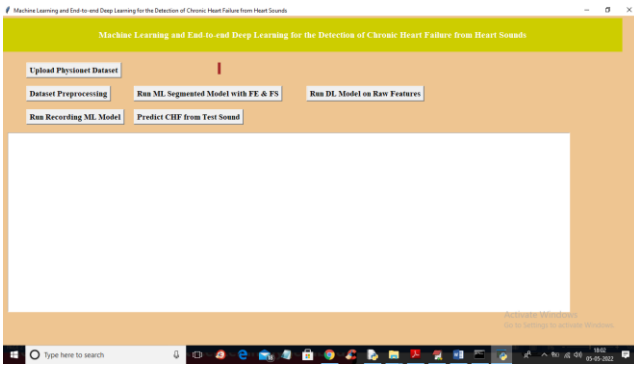
#### **KNN Algorithm:**

- k nearest algorithm combines k nearest points based on their distances and joins them in a cluster and these clusters are then evaluated. .

#### **Artificial neural network :-**

Artificial neural networks are one of the main tools used in machine learning. As the “neural” part of their name suggests, they are brain-inspired systems which are intended to replicate the way that we humans learn. Neural networks consist of input and output layers, as well as (in most cases) a hidden layer consisting of units that transform the input into something that the output layer can use. They are excellent tools for finding patterns which are far too complex or numerous for a human programmer to extract and teach the machine to recognize.

## SAMPLE SCREENSHOTS



## CONCLUSION

In this paper, we propose a novel approach to identifying CHF in PCG recordings. The technique integrates traditional ML with full-stack DL. The time-domain (i.e., the raw PCG signal) and spectral representations of the signal are used by DL for learning, while the classical ML relies on a vast set of features defined by experts. Both our personal dataset for CHF detection and six public PhysioNet datasets used in the recent PhysioNet Cardiology Challenge were utilised to assess the method's efficacy. We were able to thoroughly assess the method's efficacy on analogous domains thanks to the challenge datasets. All dataset evaluation findings demonstrated that our method outperforms the challenge baseline methods (see the PhysioNet experiments section). Given that the PCG audio is recorded from a different body position in most of the datasets (e.g., aortic area, pulmonic area, tricuspid area, and mitral area), and that the datasets





are labelled for different types of heart-related conditions, the proposed method is quite robust and useful for detecting different types of heart-sound classification problems and not just for CHF detection, provided that domain-specific labelled data is available. Finally, we went above and beyond the traditional healthy vs. sick dichotomy and investigated individualised models for recognising the two stages (recompensated and decompensated) of CHF (i.e., when the patient needs medical attention).

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**AUTHOR PROFILES:**

**MR. B.MURALI KRISHNA** completed his Masters in Computer Science and Engineering. He Completed his B.tech in IT, in JNTU-H university. He has published 1 paper in JES journal . Currently working as an Assistant professor in the department of AI and IT at DVR & DR.HS MIC College of Technology (Autonomous), Kanchikacherla, NTR(DT). His areas of interest include C language , Data science and Python.



**Ms. N.Rajya Lakshmi** is MCA Student in the department of IT at DVR & DR.HS MIC College of Techonology (Automonous), Kanchikacherla, NTR(DT). She is Completed Bs.c (Computer

Science ) in Sri Srinivasa Degree College, Vissannapeta, NTR(DT). Her areas of interests are

Machine Learning, Java and Cyber Security.

