Artificial Intelligence for Bio-medical Applications

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Software Installation

- sudo apt-get install libatlas-base-dev gfortran python-dev
- sudo apt-get install python-pip
- sudo pip install numpy
- sudo pip install scipy
- sudo pip install matplotlib
- Sudo pip install seaborn
- sudo pip install scikit-learn
- sudo pip install tensorflow
- sudo pip install theano
- sudo pip install keras
- sudo pip install pandas
- sudo pip install h5py
- sudo pip install jupyter

Artificial Intelligence (AI) toolkits

Scikit-learn - Python library that implements a comprehensive range of machine learning algorithms.

- easy-to-use, general-purpose toolbox for machine learning in Python.
- supervised and unsupervised machine learning techniques.
- Utilities for common tasks such as model selection, feature extraction, and feature selection.
- Built on NumPy, SciPy, and matplotlib.
- Open source, commercially usable BSD license.

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TensorFlow - library for numerical computation using data flow graphs / deep learning.

- Open source
- By Google
- used for both research and production
- Used widely for deep learning/neural nets
- But not restricted to just deep models
- Multiple GPU Support

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Keras – It is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation.

- Allows for easy and fast prototyping (through user friendliness, modularity, and extensibility).
- Runs seamlessly on CPU and GPU.

Supporting Libraries



NumPy Base N-dimensional array package



SciPy library Fundamental library for scientific computing



Matplotlib Comprehensive 2D Plotting



IPython Enhanced Interactive Console



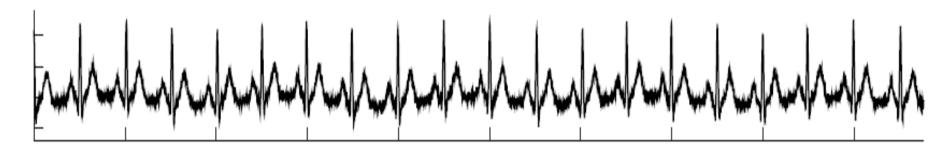
Sympy Symbolic mathematics

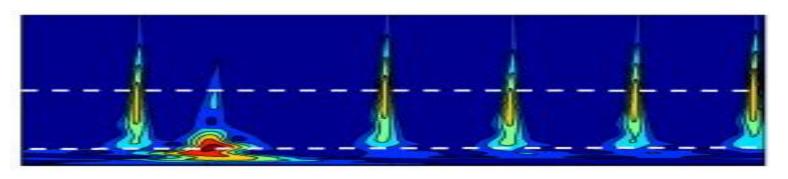


pandas Data structures & analysis

Hands – on tutorial on supporting libraries

ECG Analysis





• An electrocardiogram or ECG signal is a graphical representation which captures the electrical potential changes of the heart

• Electrocardiograph machine is used to obtain ECG signal by capturing the signal through electrodes placed on specific locations on skin of the human body

• For over a period of time, the electrical activity is measured from these leads.

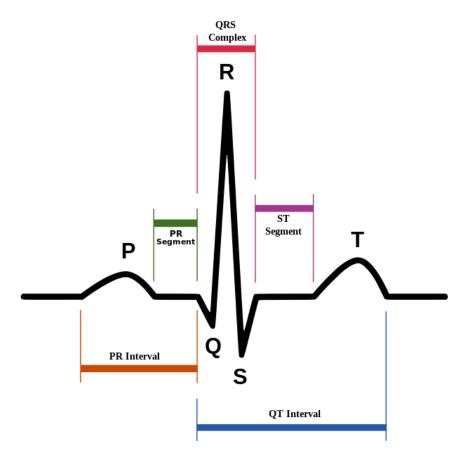
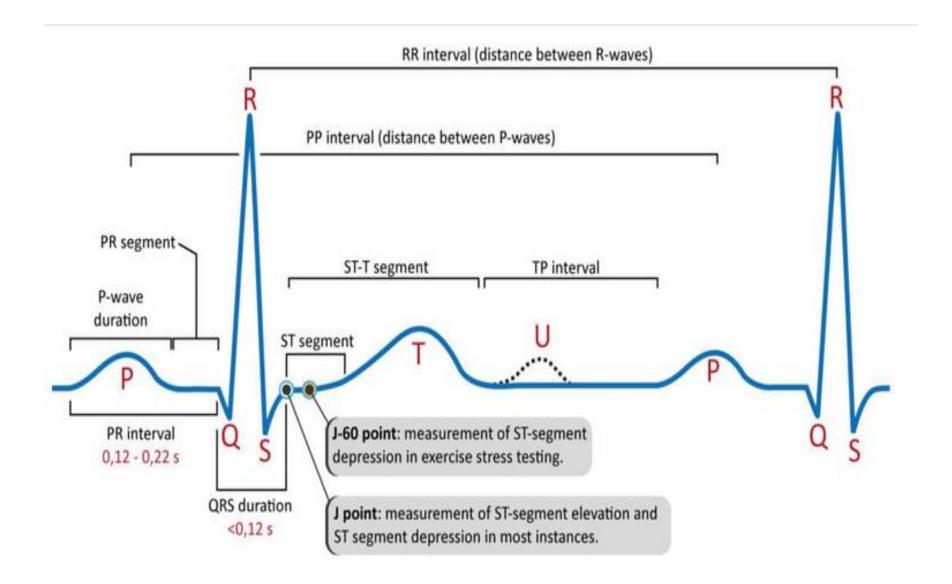
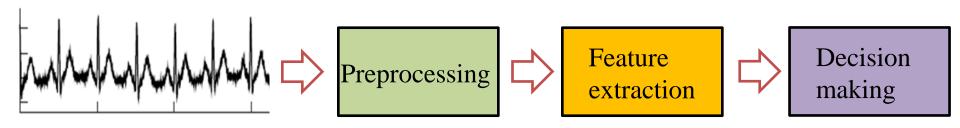


Figure: ECG signal corresponding to normal sinus rhythm [12]



- P wave occurs due to atrial depolarization, QRS complex due to ventricular depolarization and T wave due to ventricular repolarization.
- QRS complex is the most significant and distinctive feature of ECG used to indicate the presence of cardiac cycle.
- After T, U wave is a small rounded upright wave representing repolarization of Purkinje fibers.
- The intervals that occur in ECG wave are PR Interval and QT Interval.
- PR interval is measured from beginning of P wave to start of QRS complex. It measures travel time of depolarization wave from atria to ventricles.
- QT interval is beginning of QRS complex to end of T wave. It reflects total ventricular activity

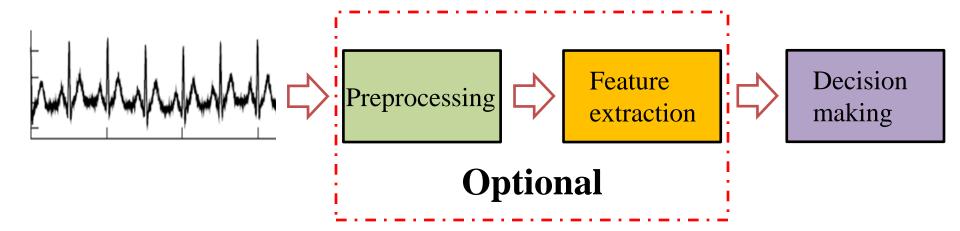
Conventional ECG Analysis



Noises - PLI, muscle artifacts, motion artifacts, baseline wandering and other external interferences

Features - Slope, width and amplitude of QRS complexes, area under the waves etc

Deep Intelligent ECG Analysis



Real-time detection of Atrial Fibrillation from Short time single lead ECG traces using Recurrent neural networks

- Atrial fibrillation (AF) is a disorder of the functioning of the heart's electrical system that is characterized by the irregular/rapid beating of the heart [1].
- Atrial fibrillation (AF) is the predominant type of cardiac arrhythmia affecting more than 45 Million individuals globally.
- It is one of the leading contributors of strokes and hence detecting them in real-time is of paramount importance for early intervention.

Proposed Method

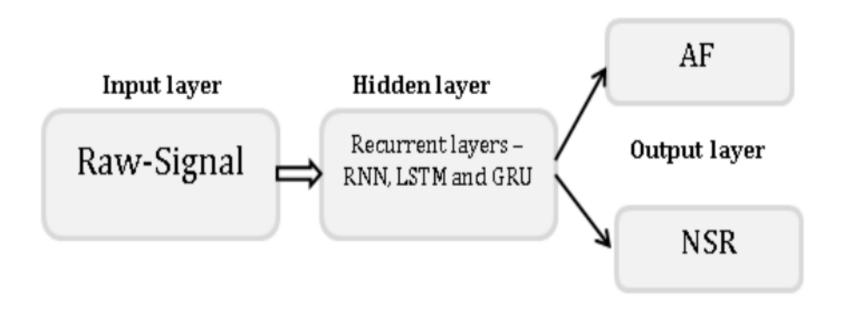
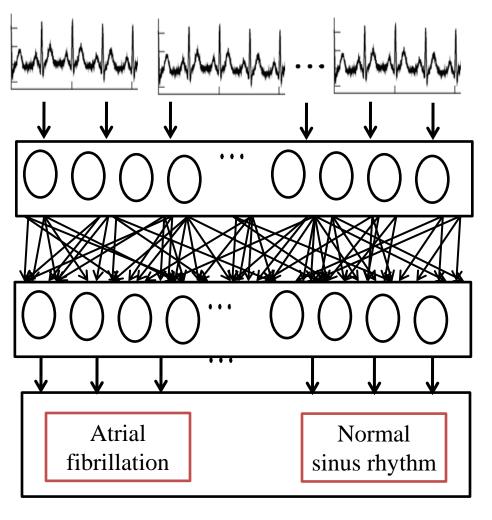


Figure: Architecture of proposed system for normal sinus rhythm and atrial fibrillation.



Raw ECG signals

LSTM recurrent layer with 64 memory blocks

Dense layer with sigmoid activation function

Predicted classes

Description of dataset

Name of signal		
AF	25	(60sec duration)
NSR	25	

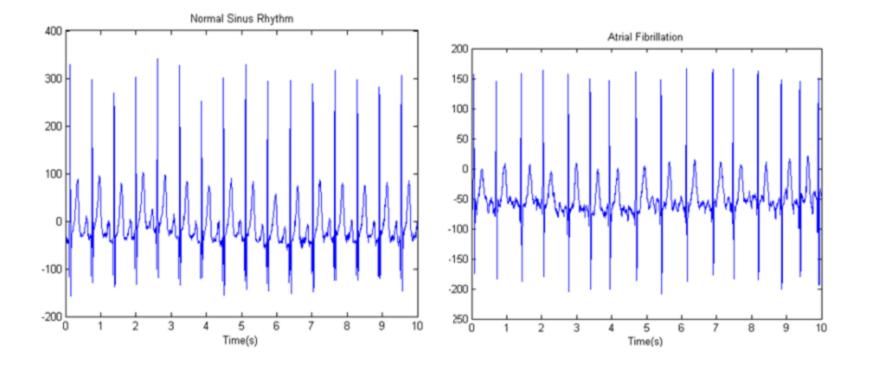


Figure: (a) A single lead ECG wave of normal sinus rhythm,(b) A single lead ECG wave with atrial fibrillation

Results

Algorithm	Accuracy	Precision	Recall	F-score
RNN	0.95	1.00	0.889	0.941
LSTM	1.00	1.00	1.00	1.00
GRU	1.00	1.000	1.00	1.00

The proposed method is considered as more accurate in real-time ECG classification because it doesn't rely on any feature engineering mechanisms.

[1] Sujadevi. V. G, Soman. K. P, Vinaykumar. R, "Real-Time Detection of Atrial Fibrillation from Short Time Single Lead ECG Traces Using Recurrent Neural Networks"- Springer AISC series proceedings of the International Symposium on Intelligent Systems Technologies and Applications 2017.

Sleep Apnea Diagnosis using Deep Learning

- A potentially serious sleep disorder in which breathing repeatedly stops and starts (interruption of breath during sleep).
- Untreated prolonged sleep apnea is directly related to atrial fibrillation, which could later lead to serious conditions such as heart failure and stroke
- Sleep apnea is a medically significant disease condition affecting as much as 24% of men and 9% of women in US population.

Description of dataset

Physionet Computing in Cardiology (CinC) Sleep Apnea Challenge database.

8-hour ECG readings from 35 patients

It includes three different groups; class A with 20 patient records having very severe sleep apnea incidence, class B with 5 patient records with borderline apnea incidence, and class C with 10 patient records that have less than 5% apnea annotated signals.

Furthermore, for analyzing the accuracy of sleep apnea classification among arrhythmia patients we obtained 45 ambulatory ECG recordings from MIT BIH Arrhythmia database

Proposed Method

- The records are taken as length of 60 sec.
- Raw data are processed to extract instantaneous heart rate (IHR), which helps to identify the heart rate variability (HRV) and blood oxygen saturation (SpO2)
- Trained and tested using LSTM/RNN network

Computational flow . . . Normal Sleep Apnea sinus rhythm

Input signals

LSTM layer with 32 memory blocks

LSTM layer with 32 memory blocks

Dense layer with sigmoid activation function

Predicted output

Results

TABLE I.	ACCURACY AND F1 SCORE ON TEST DATASETS.			
Dataset	Apnea minutes	Non-Apnea minutes	Accuracy of classification	
Class A&C	3060	2622	1.0	1.0
Class B	198	1897	1.0	1.0
Arrhythmia	0	1242	0.999	0.999

Pathinarupothi RK, Vinaykumar R, Rangan E, Gopalakrishnan E, Soman KP. Instantaneous heart rate as a robust feature for sleep apnea severity detection using deep learning. In Biomedical & Health Informatics (BHI), 2017 IEEE EMBS International Conference on 2017 Feb 16 (pp. 293-296). IEEE.

Results

TABLE II. ACCURACY, PRECISION AND RECALL OF STACKED LSTM-RNN USING SPO2, IHR AND COMBINATION OF BOTH

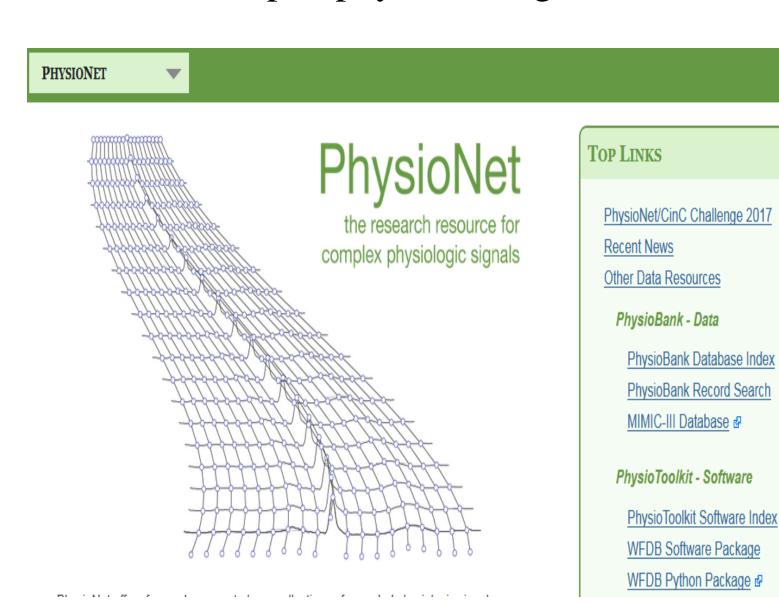
Parameter	Accuracy (%)	Precision (%)	Recall (%)
SpO2	95.5	99.2	92.9
IHR	89.0	82.4	99.4
SpO2-IHR	92.1	99.5	84.7

Pathinarupothi RK, Rangan ES, Gopalakrishnan EA, Vinaykumar R, Soman KP. Single Sensor Techniques for Sleep Apnea Diagnosis Using Deep Learning. InHealthcare Informatics (ICHI), 2017 IEEE International Conference on 2017 Aug 23 (pp. 524-529). IEEE.

Disturbed sleep, daytime sleepiness, snoring chronic obstructive pulmonary disease, acute type 2 respiratory failure Symptoms documented hypertension, history of stroke, signs of right heart failure. Overnight ambulatory recording of SpO2 and IHR Sensing Detection of apnea minutes from SpO2 and IHR data using trained S-LSTM-RNN classification algorithm Analyze Calculation of mean sum of apnea minutes per hour which corresponds to AHI Summarize Confirm OSA diagnosis if number of apnea minutes per hour exceeds 15 in both SpO2 and IHR data. Diagnose Treat

Figure 9: LSTM based new clinical diagnosis protocol for OSA

https://physionet.org/



Thanks for listening:

Questions?

References

- [1] Sujadevi, V. G., Soman, K. P., & Vinayakumar, R. (2017, September). Real-Time Detection of Atrial Fibrillation from Short Time Single Lead ECG Traces Using Recurrent Neural Networks. In The International Symposium on Intelligent Systems Technologies and Applications (pp. 212-221). Springer, Cham.
- [2] Pathinarupothi, R. K., Rangan, E. S., Gopalakrishnan, E. A., Vinaykumar, R., & Soman, K. P. (2017, August). Single Sensor Techniques for Sleep Apnea Diagnosis using Deep Learning. In Healthcare Informatics (ICHI), 2017 IEEE International Conference on (pp. 524-529). IEEE.
- [3] Pathinarupothi, R. K., Vinaykumar, R., Rangan, E., Gopalakrishnan, E., & Soman, K. P. (2017, February). Instantaneous heart rate as a robust feature for sleep apnea severity detection using deep learning. In Biomedical & Health Informatics (BHI), 2017 IEEE EMBS International Conference on (pp. 293-296). IEEE.

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