# AIoT BASED AUGMENTED REMOTE HEALTH PREDICTION SYSTEM-Predictive Healthcare at Your Fingertips

**Dr.G.HainathaReddy[1], Thejaswini[2], Sai Vinoothna[3], Tejaswini[4], Susmitha[5]**
[1]*Professor & HOD*, [2,3,4,5]*Student*
*Department of Electronics & Communication Engineering*,N.B.K.R Institute of Science and Technology ,Andhra Pradesh

***Abstract – The main aim of this project is to develop a Machine Learning model capable of predicting Physical activity as well as the Respiratory health of an individual enabling the doctor to monitor the person remotely. In order to develop a such model, we have used machine learning algorithms like Robust Scalar & Random Forest classifiers and MFCC & LSTM for physical activity and respiratory health prediction respectively. In addition to this, we have also designed a Hardware kit capable of calculating an individual's heart rate and temperature. These readings can be accessible to the person with the help of a mobile application developed by using React Native platform.***

***Index Terms: Machine Learning*, Robust Scaler, Random Forest Classifier, Mel Frequency Cepstral Coefficients (MFCC), Long Short-Term Memory (LSTM)**

## 1. INTRODUCTION

Regular physical activity plays a vital role in improving the health of individuals, whether it is a child under 5 or an elderly above 65. Physical activity has well-documented health benefits and can extensively improve the health and well-being of individuals and reduce the risks of non-communicable diseases. Both moderate- and vigorous-intensity physical activity improves health. Physical inactivity increases the risk of noncommunicable disease mortality and puts inactive people at a 20–30% higher risk of death in comparison to physically active people. Physical inactivity is among the leading factors which cause mortality and is estimated to contribute to 6% of worldwide deaths. Therefore, World Health Organization (WHO) also recommends people of all ages indulge in physical activity and recommends the duration and intensity of physical activity for different age groups. It has been noted that physical activity improves muscular and cardiorespiratory fitness, bone health, and mental fitness while reducing the risk of heart disease, diabetes, hypertension, obesity, and fractures.

Physical activity and the promotion of healthy living can significantly lower the risks of non-communicable diseases. It also serves as the best remedy for obesity. Obesity is one of the major chronic illnesses and increases the risk of developing many serious comorbidities, such as hypertension, sleep apnea, type 2 diabetes, depression, etc. Furthermore, obesity is becoming an increasingly prevalent issue. Obesity has become a global epidemic, with global stats suggesting nearly one-third of the world population is obese or overweight. Obesity has also added a significant burden to healthcare services, with nearly 10% of the medical costs in the US being spent on obesity-related issues. It also has been among the major causes of death in the US. Similarly, in Saudi Arabia, with 36% of the population being obese and 69% being categorized as overweight, nearly 20,000 lives are claimed to obesity each year. Therefore, under such circumstances, providing physical activity (PA) to control obesity has become increasingly important.

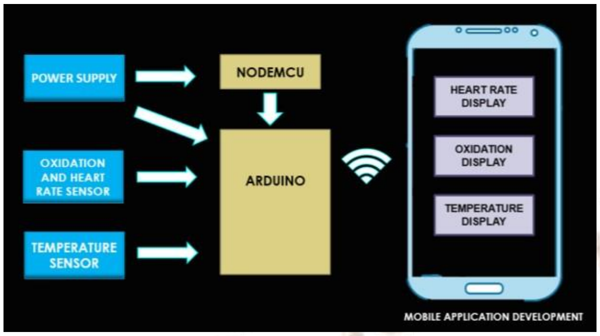
Obesity is one of the prevailing problems responsible for several health issues and medical conditions. Weight loss surgery, also referred to as bariatric or metabolic surgery, is one of the possible solutions for extremely overweight people. While the surgery can result in significant weight loss, it is still nottermed a cure for obesity. Obesity is not a matter of concern only for younger and older adults as it has also become very common in children. Therefore, suitable lifestyle changes should be introduced to avoid regainingweight. Patients who have undergone weight loss surgeryneed a balanced diet and regular exercise once they haverecovered. They also need to maintain a regular appointment schedule to keep everything in check. It is therefore important that a technology-driven framework for long-term support is developed to assist these patientsin prolonging their healthy living choices and balancing exercise and diet accordingly.

To help an individual in all these aspects we have developed a few models in this project.

**Technologies used**: Machine Learning – Supervised IoT, React Native

# 2. HARDWARE BLOCK DIAGRAM

The Block Diagram shown below depicts the architecture of the device(kit) which we have designed to calculate the readings from an individual,




## 2.1 Hardware Requirements

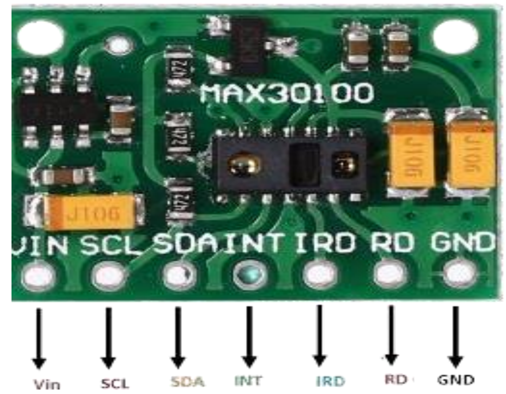
- **Power Supply:**

The power supply circuit consists of a step-down transformer which is 230v step down to 12v.In this circuit, 4diodes are used to form a bridge rectifier which delivers pulsating dc voltage & then fed to the capacitor filter the output voltage from the rectifier is fed to the filter to eliminate any A.C components present even after rectification.

Due to the advantages of the bridge rectifier over the half and full wave rectifier, the bridge rectifier is frequently used for converting AC to DC.

- **OXIDATION SENSOR :**

MAX30100 is an integrated pulse oximeter and heart-rate monitor sensor solution. It's an optical sensor that derives its readings from emitting two wavelengths of light from two LEDs – a red and an infrared one – then measuring the absorbance of pulsing blood through a photodetector. This particular LED color combination is optimized for reading the data through the tip of one's finger. It has an I2C digital interface to communicate with a host microcontroller.




The MAX30100 operates from 1.8V and 3.3V power supplies and can be powered down through software withnegligible standby current, permitting the power supply to remain connected at all times.

- **NODE MCU / ESP 8266 :**

NodeMCU is a microcontroller developmentboard with wifi capability.

It uses an ESP8266 microcontroller chip, a low-cost Wi-Fi chip with a full TCP/IP stack. The working voltage is5V and the current is 250mA. The successor to these microcontroller chips is the ESP32.

- **TEMPERATURE SENSOR :**


The DHT11 is a basic, ultra-low-cost digital temperature and humidity sensor. It uses a capacitive humidity sensor and a thermistor to measure the surrounding air and spits a digital signal on the data pin (no analog input pins are needed). It's fairly simple to usebut requires careful timing to grab data.

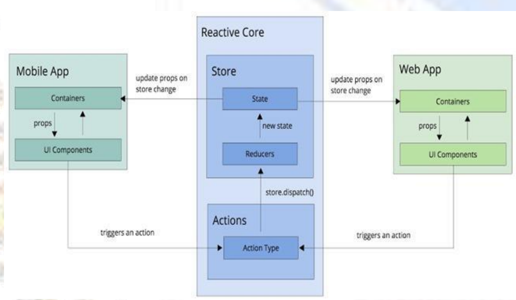
- **Arduino:**

Arduino is an open-source electronics platform that creates cost-effective medical devices and systems. It can be used in various medical applications, from monitoring vital signs to developing assistive devices. It also detects the body condition and location of the patients and helps in dealing with ill people or theelderly at your home.

We have used ARDUINO IDE software in order to dump the code into our Arduino board in such a way that it can read the data from the respective sensors like DHT11 & MAX30100 etc... and is connected to the NODE MCU to display the readings via the internet through the mobile app.

- **App Development:**

We have used React Native Framework to develop an application using a VISUAL STUDIO CODE platform. Visual Studio Code combines the simplicity of a source code editor with powerful developer tooling, like IntelliSense code completion and debugging. VS Code includes enriched built-in support for Node.js development with JavaScript and TypeScript, powered by the same underlying technologies that drive Visual Studio. VS Code also includes great tooling for web technologies such as JSX/React, HTML, CSS, SCSS, Less, and JSON. Architecturally, Visual Studio Code combines the best of web, native, and language-specific technologies. Using Electron, VS Code combines web technologies such as JavaScript and Node.js with the speed and flexibility of native apps.




Mobile Application Development

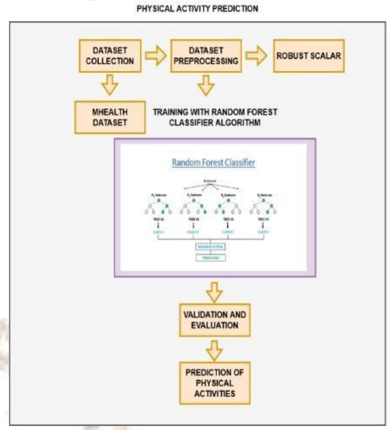
React Native is written with a mixture of JavaScript and JXL, a special markup code resemblant of XML. The framework has the ability to communicate with both realms – JavaScript-based threads and existent,native app threads.

## 3. SOFTWARE ARCHITECTURE

Our project consists of two software modules for Physical Activity Prediction and Cough &Healthy Prediction.

### SYSTEM ANALYSIS:

The Architecture of Physical Activity Prediction software can be represented as follows,




### 3.1 ACTIVITY PREDICTING SOFTWAREMODULE DESCRIPTION:

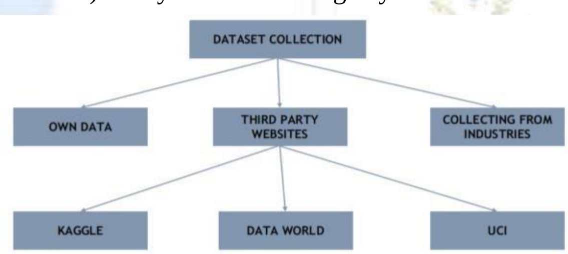
The Physical activity prediction module consists of thefollowing sequence of steps they are,

- Dataset Collection
- Dataset Pre-processing
- Training using a machine learning algorithm
- Validation and Prediction of Physical

ActivityEach of the above steps can be explained

as follows, **Dataset Collection:**

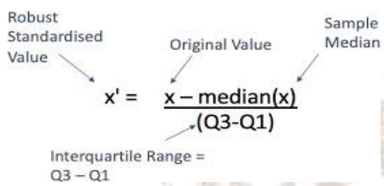
In this project, we are going to collect the dataset and it will be fed for training with the machine learning algorithms. Increasing the amount of dataset increases the accuracy. It's definitely by far the best-performing method for prediction tasks. These machine-learning machines that have been working so well need fuel lots offuel; that fuel is data. The more labeled data available, thebetter our model performs. This labeled data can be collected (i.e., Dataset collection) in any of the followingways.




Here in our project, we have collected MHEALTH (Mobile HEALTH) dataset from the Kaggle website.

### Dataset pre-processing:

Data preprocessing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine-learning model. Data preprocessing is a required task for cleaning the data and making it suitable for a machine learning model which also increases the accuracy and efficiency of a machine learning model (i.e., it converts the data gathered from different sources it is collected in raw format which is not feasible for the analysis).Robust Scaler transforms the feature vector by subtracting the median and then dividing by the interquartile range (75% value — 25% value). Like Min-Max Scalar, our feature with large values — normal-big — is now of a similar scale to the other features.



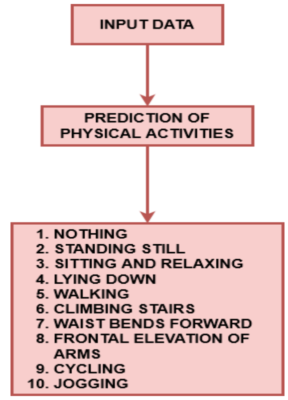

### Training using machine learning algorithm:

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset". Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, predicts the final output.


The greater number of trees in the forest leads to higheraccuracy and prevents the problem of overfitting.

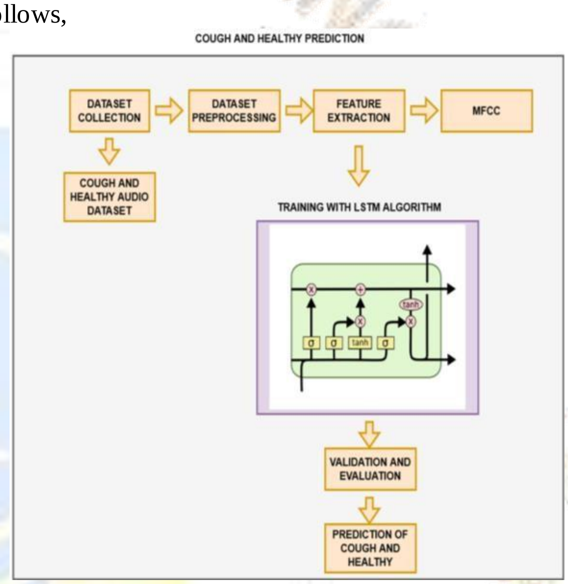
### Validation and Prediction of Physical Activity:

After training with a machine learning algorithm, it will validate and evaluate the datasets. Validation in machine learning is like authorization or authentication of the prediction done by a trained model. When input data is given for the prediction process, it caneffectively detect physical activities. Thus, this project provides an effective solution to classifying daily life activities such as Standing still, Sitting and relaxing, lying down, etc.




### 3.2 COUGH PREDICTING SOFTWAREMODULE DESCRIPTION:

The Architecture of Cough & Healthy Predictionsoftware can be represented as follows,




The Cough prediction module consists of the followingsequence of steps they are,

- Dataset Collection
- Dataset Preprocessing
- Feature Extraction
- Training using a machine learning algorithm
- Validation and Prediction of Cough andHealthy

The Dataset can be collected and pre-processed in the same way as we have done for physical activity prediction. But here we have collected the cough and healthy audio dataset from the Kaggle website.

**Feature extraction:**

In this project, the MFCC technique is used for feature extraction. The Mel frequency cepstral coefficients (MFCCs) of a signal are a small set of features (usually about 10-20) that concisely describe the overall shape of a spectral envelope. In sound processing, the mel-frequency cepstrum (MFC) is a representation of the short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear mel scale of frequency. Mel-frequency cepstral coefficients (MFCCs) are coefficients that collectively make up an MFC. They are derived from a type of cepstral representation of the audio clip (a nonlinear "spectrum-of-a-spectrum"). MFCCs are popularfeatures extracted from speech signals for use in recognition tasks. In the source-filter model of speech, MFCC is understood to represent the filter (vocal tract). The frequency response of the vocal tract is relatively smooth, whereas the source of voiced speech can be modeled as an impulse train.

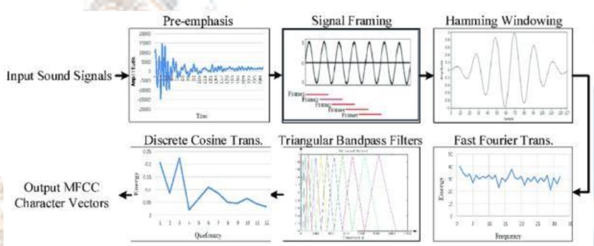



Fig: MFCC feature extraction

**Training using a machine learning algorithm:**

After the dataset is collected and preprocessed, it will be fed for training with the machine learning algorithm such as LSTM. Long short-term memory (LSTM) is an artificial Recurrent Neural Network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can process not only single data points (such as images) but also entire sequences of data (such as speech or video).

The LSTM algorithm is well adapted to categorize, analyze, and predict time series of uncertain duration. A sequence of repeating neural network modules makes up all recurrent neural networks. This repeating module in traditional RNNs will have a simplestructure, such as a single tanh layer. The output of the current time step becomes the input for the following time step, which is referred to as Recurrent. At each element of the sequence, the model examines not just thecurrent input, but also what it knows about the prior ones.

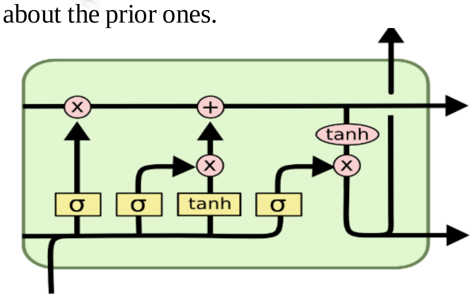



**Fig:** LSTM algorithm

**Validation and Prediction of Cough andHealthy:**

After training with the machine learning algorithm, it will validate and evaluate the datasets. When input data is given for the prediction process, it caneffectively detect normal and abnormal coughs. Thus, this project provides an effective solution to determine whether the patient is breathing normally or having a cough with higher accuracy than the existing models.

We have used Google Colab in order to run these software modules.

## 4. RESULTS

The hardware kit we have made is shown below,

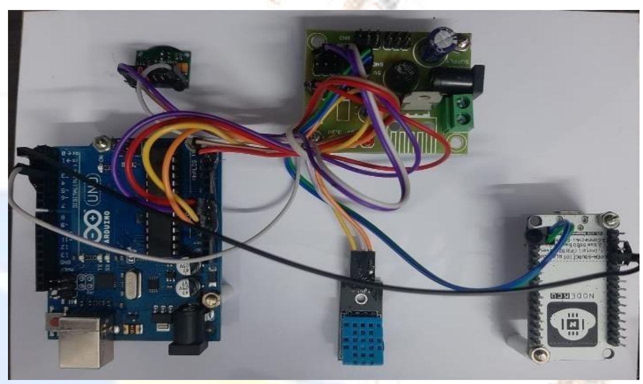
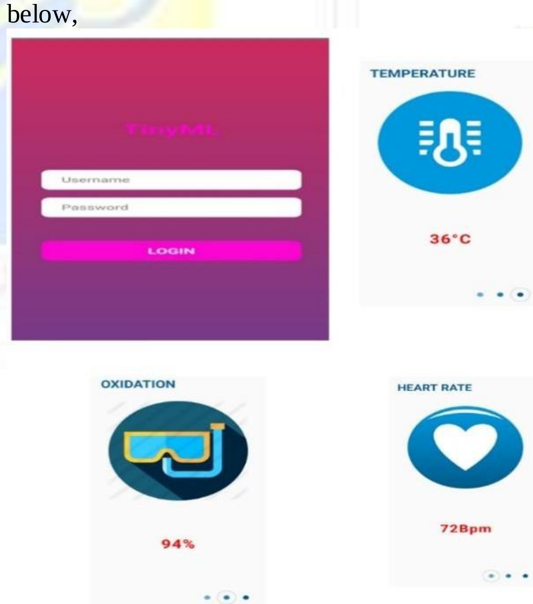


**Fig**: Hardware kit

A mobile application is developed using reactjsto display the parameters of patient conditions such as oxidation, heart rate, and temperature**.**

The login, Heart rate, Oxidation, and temperature level pages will be as seen in the figure below,




In Physical Activity Prediction, the test dataset taken from the Kaggle website yields the following Classification Report,

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Nothing | 0.98 | 0.91 | 0.94 | 7646 |
| Standing still | 0.99 | 1.00 | 0.99 | 7663 |
| Sitting and relaxing | 0.97 | 1.00 | 0.98 | 7647 |
| Lying down | 0.98 | 1.00 | 0.99 | 7641 |
| Walking | 0.97 | 0.99 | 0.98 | 7581 |
| Climbing stairs | 0.99 | 0.99 | 0.99 | 7768 |
| Waist bends forward | 0.98 | 1.00 | 0.99 | 7141 |
| Frontal elevation of arms | 1.00 | 1.00 | 1.00 | 7342 |
| Knees bending (crouching) | 1.00 | 0.99 | 0.99 | 7354 |
| Cycling | 1.00 | 1.00 | 1.00 | 7658 |
| Jogging | 0.97 | 0.97 | 0.97 | 7660 |
| Running | 0.96 | 0.98 | 0.97 | 7768 |
| Jump front & back | 0.99 | 0.91 | 0.95 | 2610 |
| accuracy | | | 0.98 | 93479 |
| macro avg | 0.98 | 0.98 | 0.98 | 93479 |
| weighted avg | 0.98 | 0.98 | 0.98 | 93479 |

**Fig**: Classification Report (obtained from Random Forest Classifier)

Once the model is trained its accuracy is tested with the help of the confusion matrix and the model is tested by using the test input, the resultant output would be,

```
input_data = [0.7268399999999999,-9.5552,1.9845,0.31169,-0.6041300000000001,0.62868,-1.7145,-9.2012,2.8837,-0.056863,-0.64271,0.96767,7.0]
input_data = np.array(input_data).reshape(1,-1)
robust_weight = pickle.load(open("/content/gdrive/MyDrive/physical_activity/robust_weight.p","rb"))
preprocessed_data = robust_weight.transform(input_data)
rf_model = pickle.load(open("/content/gdrive/MyDrive/physical_activity/rf_weight.p","rb"))
predictions = rf_model.predict(preprocessed_data)
print("predicted activity is:",labels[predictions[0]])

predicted activity is: Waist_bends_forward
```

Similarly, for cough and healthy prediction, the Classification Report is obtained as,

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| Cough | 0.86 | 1.00 | 0.92 | 6 |
| Healthy | 1.00 | 0.96 | 0.98 | 28 |
| accuracy | | | 0.97 | 34 |
| macro avg | 0.93 | 0.98 | 0.95 | 34 |
| weighted avg | 0.97 | 0.97 | 0.97 | 34 |

**Fig**: Classification Report

And when the trained model is tested against the test data (i.e., input) the resultant output of the model wouldbe,

```
input_df = pd.read_csv('data_new_extended.csv', index_col=None)
input_df.drop("label",axis=1,inplace = True)
input_df.drop("filename",axis=1,inplace = True)
input_data = input_df.dropna(axis='columns')
scaler_weight = pickle.load(open("/content/gdrive/MyDrive/physical_activity/scaler_weight.p","rb"))
scaled_data = scaler_weight.transform(input_data.values)
model = load_model("/content/gdrive/MyDrive/physical_activity/lstm_weight.h5")
predict = model.predict(scaled_data)
target_names = ["Cough","Healthy"]
print("predicted label is",target_names[predict.argmax()])

1/1 [==============================] - 0s 449ms/step
predicted label is Healthy
```

## 5. CONCLUSION

The project has been successfully implemented to provide a solution for patients' physical activities such as Standing still, Sitting, relaxing, etc., and the conditionof whether the person coughs or is healthy using machine learning algorithms. The algorithms such as random forest and LSTM are used to determine the physical activities and the presence of cough. A mobile application is developed using reactjs to display the parameters of patient conditions. Multiple sensors such as oxidation, temperature, and heart rate are used for monitoring the patient's health condition. Moreover, thissystem can be utilized for monitoring patients remotely and is also very promising for real-time applicationsbecause of the fast-processing time. It is also very usefulfor diseased patients.

## 6. REFERENCES


[1] Chakraborty, C. and Kishor, A. (2022). Artificial Intelligence of Things- (AIoT-) Based Patient Activity Tracking System for Remote Patient Monitoring. Journal of Healthcare Engineering, doi.org/10.1155/2022/8732213.

[2] Fasih Haider, Member, IEEE, Sofifia de la Fuente andSaturnino Luz, Member, IEEE,"An Assessment of Paralinguistic Acoustic Features for Alzheimer's Cardiomyopathy Recognition in Spontaneous Speech",IEEE Journal of Selected Topics in Signal Processing,Vol. 14, No. 8, August 2016.

[3] Hui Yang, Peter A. Bath," The Use of Data Mining Methods for the Prediction of Cardiomyopathy: Evidence from the English Longitudinal Study of Aging", IEEE Journal of Biomedical and Health Informatics, Vol.2168-2194, 2019.

[4] Kishore, P. V. V., Kumar, D. A., Sastry, A. S. C. S., & Kumar, E. K. (2018). Motion lets Matching With Adaptive Kernels for 3-D Indian Sign Language Recognition. IEEE Sensors Journal, 18(8), 3327–3337. doi:10.1109/jsen.2018.2810449

[5] Lu, J. and Tong, K.-Y. (2019). Robust Single Accelerometer-Based Activity Recognition Using Modified Recurrence Plot. IEEE Sensors Journal, 19(15), pp.6317–6324.

[6] Pholpat Durongbhan, Yifan Zhao, Senior Member,

IEEE, Liangyu Chen, Panagiotis Zis, Matteo De ,Marco, Sheng Li, Yitian Zhao, Daniel J.Blackburn, and Ptolemaios G. Sarrigiannis,"A Cardiomyopathy Classification Framework using Frequency and Time-frequency Features based on EEG signals",, IEEE Transactions on Neural Systems and Rehabilitation Engineering,Vol. 1534-4320,2019.

[7] Savvaki, S., Tsagkatakis, G., Panousopoulou, A. and Tsakalides, P. (2017). Matrix and Tensor Completion on a Human Activity Recognition Framework. IEEE Journal of Biomedical and Health Informatics, 21(6), pp.1554–1561.

[8] Tao, D., Jin, L., Yuan, Y., & Xue, Y. (2016). Ensemble Manifold Rank Preserving for Acceleration-Based Human Activity Recognition. IEEE Transactions on Neural Networks and Learning Systems, 27(6), 1392–1404. doi:10.1109/tnnls .2014.2357794

[9] Ting-Ying Li, Yi-Wei Chien, Chi-Chun Chou, Chun-Feng Liao, Member, IEEE, Wen-Ting Cheah, Li-Chen Fu, Fellow, IEEE, Cheryl Chia-Hui Chen, Chun-Chen Chou, and I-An Chen," A Fast and Low-Cost Repetitive Movement Pattern Indicator for Massive Cardiomyopathy Screening", IEEE Transactions On Automation Science And Engineering, Vol. 1545-5955,2019.

[10] Wang, L., Zhao, X., Si, Y., Cao, L., & Liu, Y. (2017). Context-Associative Hierarchical Memory Model for Human Activity Recognition and Prediction. IEEE Transactions on Multimedia, 19(3), 646–659. doi:10.1109/tmm.2016.2617079

[11] Wang, Z., Wu, D., Chen, J., Ghoneim, A., & Hossain, M. A. (2016). A Triaxial Accelerometer-Based

Human Activity Recognition via EEMD-Based Features and Game-Theory-Based Feature Selection. IEEE Sensors Journal, 16(9), 3198–3207.doi:10.1109/jsen.2016.2519679

[12] Wei-Hsin Wang1, Yu-Liang Hsu, Member, IEEE, Pau-Choo (Julia) Chung, Fellow, IEEE, and MingChyi Pai,” Predictive Models for Evaluating CognitiveAbility in Cardiomyopathy Diagnosis Applications Based on Inertia- and Gait-related Parameters”, IEEE Sensors Journal,Vol. 1558-1748,2018.

[13] Xu, W., Miao, Z., Zhang, X.-P., and Tian, Y. (2017). A Hierarchical Spatio-Temporal Model for Human Activity Recognition. IEEE Transactions on Multimedia, 19(7), pp.1494–1509.

[14] Zhang, H., Zhou, W., & Parker, L. E. (2015). Fuzzy Temporal Segmentation and Probabilistic Recognition of Continuous Human Daily Activities. IEEE Transactions on Human-Machine Systems, 45(5), 598–611. doi:10.1109/thms.2015.2443037

[15] Nazabal, A., Garcia-Moreno, P., Artes-Rodriguez, A., & Ghahramani, Z. (2016). Human Activity Recognition by Combining a Small Number of Classifiers. IEEE Journal of Biomedical and Health Informatics, 20(5), 1342–1351. doi:10.1109/jbhi.2015.2458274

## AUTHOR’S DETAILS:

**1.**

Dr.G. Harinatha Reddy Guide,
Professor & HOD,
Department of ECE,
NBKR Institute of Science andTechnology,
Vidyanagar.

**2.**

R.Thejaswini,
Student,
Department of ECE,
NBKR Institute of Science andTechnology,
Vidyanagar.

**3.**

V.Sai Vinoothna,
Student,
Department of ECE,
NBKR Institute of Science andTechnology,
Vidyanagar.

**4.**

T.Tejaswini,
Student,
Department of ECE,
NBKR Institute of Science andTechnology,
Vidyanagar.

**5.**

B.Susmitha,
Student,
Department of ECE,
NBKR Institute of Science andTechnology,
Vidyanagar.