Point of Care Device for measurement and analysis of vital parameters

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7th Semester – Final Year Major Project

Outline

- Introduction
- Literature Survey
- Proposed Methods
- Performance Analysis
- Conclusion
- References

Introduction

- As we know, whenever a patient goes to a doctor with slightly off the charts symptoms, the most common advice that is being given to them is to perform all the vital related tests like ECG, Heart Rate, Blood Pressure and Oxygen Level, etc.

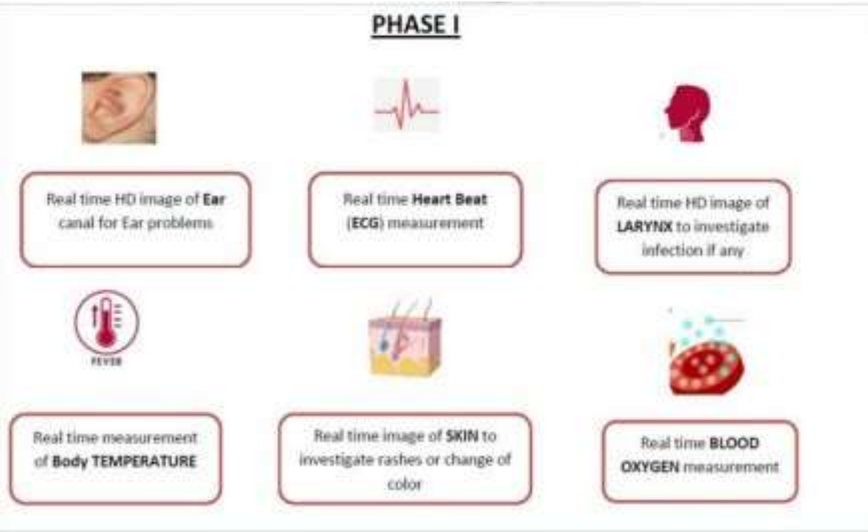
- Many a times, patient in rural areas travel to urban areas for their check up and cannot afford these costly tests.

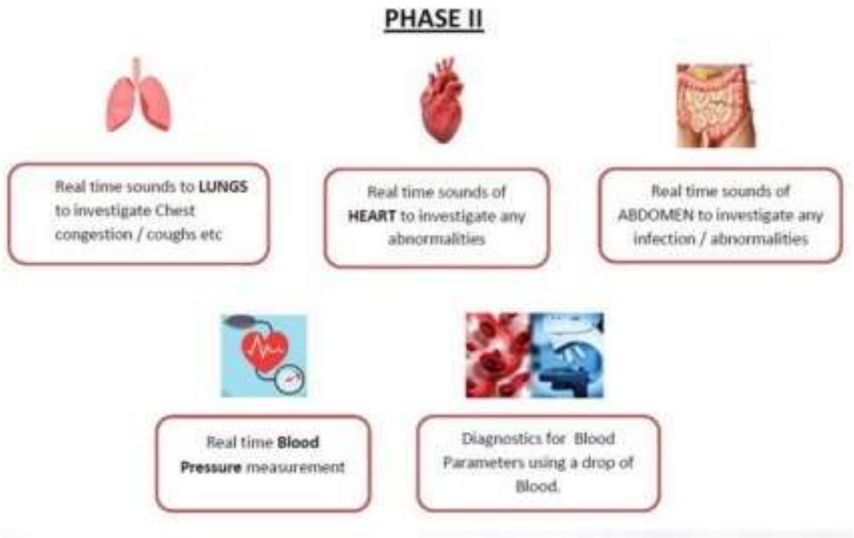
- Also, even if they visit the local clinics in sub-urban areas, they do not have these facilities and do not provide accurate results.

Objectives

- Hence, to solve this issue, we tend to develop a device, which is capable of measuring several vital parameters like : ECG, Heart Rate, SpO2 , Blood Pressure, Monitoring of several body parts like ear canal, eye pupil, skin rash, etc.
- We aim to provide all these functionalities into a single device with high accuracy.
- Secondly, we aim to achieve high portability in our device, which would be handy and easy to carry. For this, we will be designing our hardware in as much low form factor as possible.
- Also, we wish to develop a mobile application as well as an online website to store all the details related to patients, so that they can connect with doctors for further diagnosis and medications, ultimately establishing an online practo-service.
- Several parameters, will be calculated in a non-invasive way, via implementing several algorithms.
- Additionally, we wish to implement several machine learning algorithms to perform certain predictions, based on patient history.

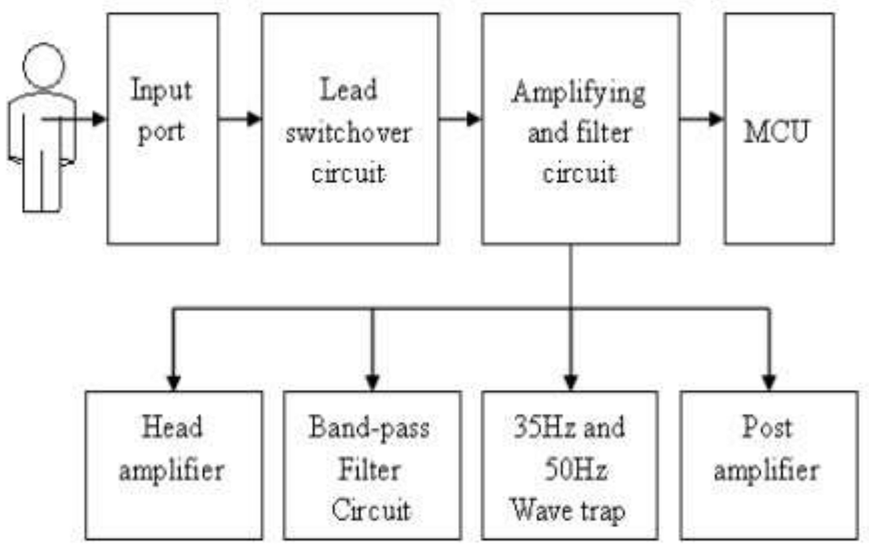
Objectives


PHASE I
Real time HD image of Ear canal for Ear problems
Real time Heart Beat (ECG) measurement
Real time HD image of LARYNX to investigate infection if any
FEVER
Real time measurement of Body TEMPERATURE
Real time image of SKIN to investigate rashes or change of color
Real time BLOOD OXYGEN measurement


PHASE II
Real time sounds to LUNGS to investigate Chest congestion / coughs etc
Real time sounds of HEART to investigate any abnormalities
Real time sounds of ABDOMEN to investigate any infection / abnormalities
Real time Blood Pressure measurement
Diagnostics for Blood Parameters using a drop of Blood.

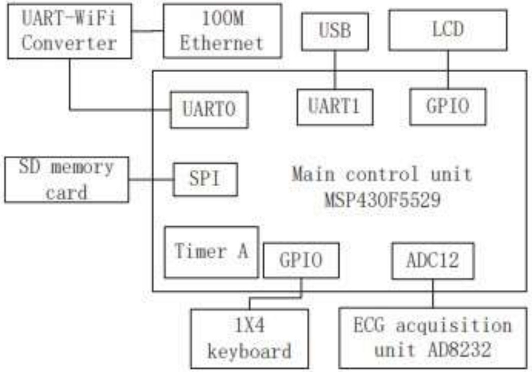
Literature Survey

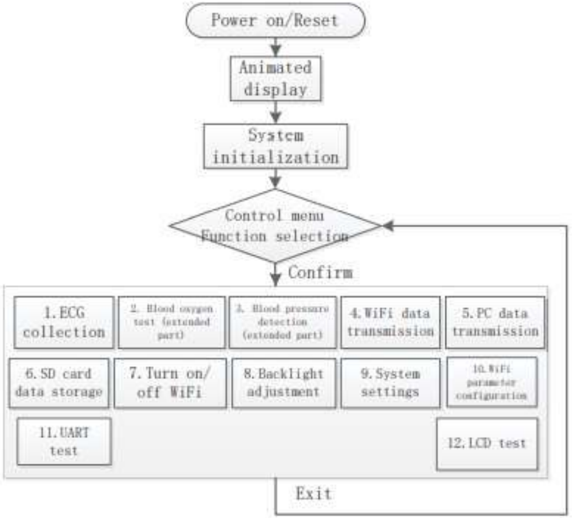
- Portable ECG Monitoring System with USB Host Interface (2010 IEEE-EMB)

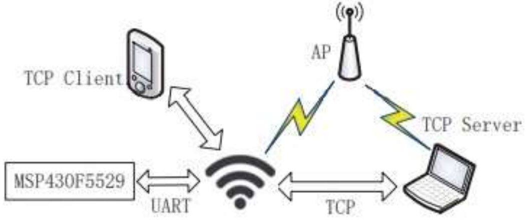


Literature Survey

- Portable ECG Monitoring System Design (IEEE 2019)

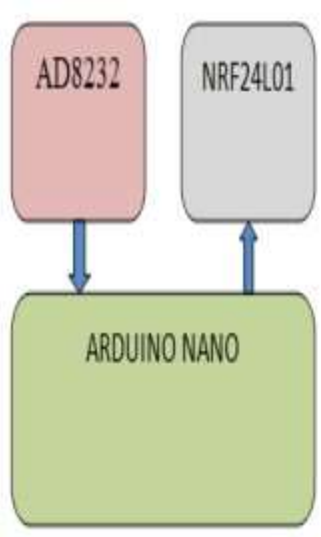


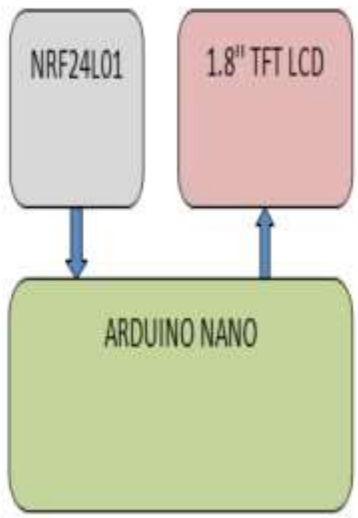


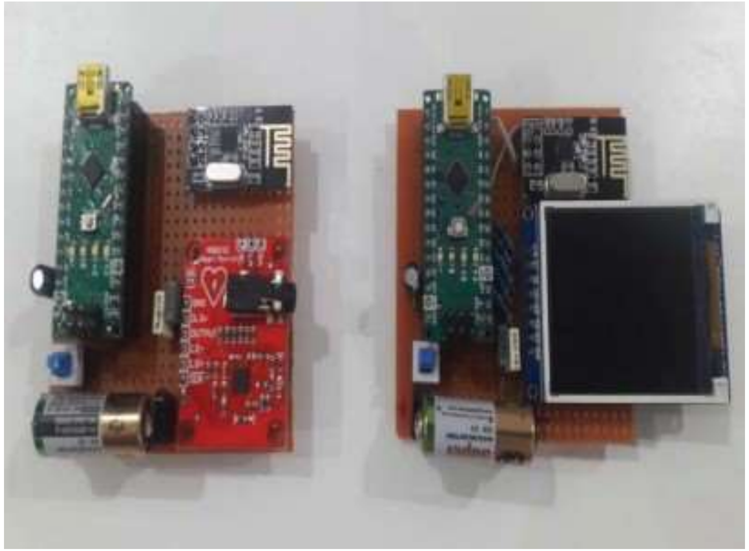


Literature Survey

- ECG Monitoring Device Based On Arduino (IEEE 2020)

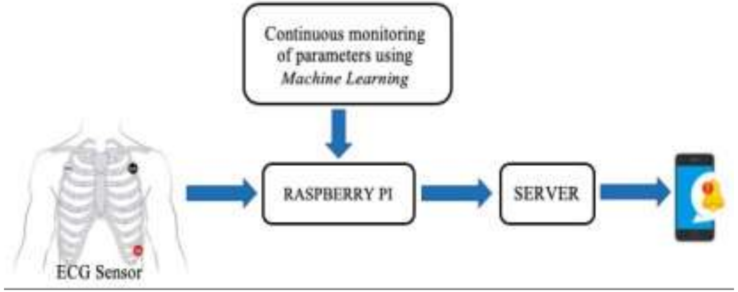


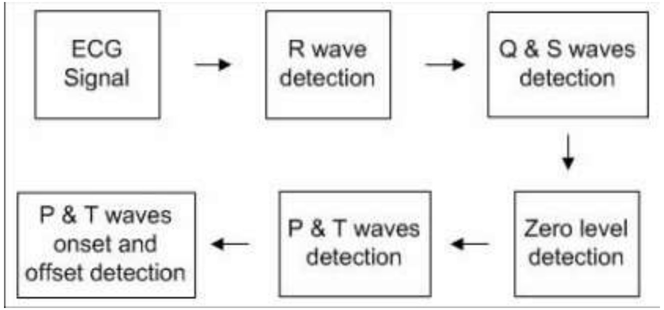




Literature Survey

- Portable ECG Device for Remote Monitoring and Detection of Onset of Arrhythmia (IEEE 2020)

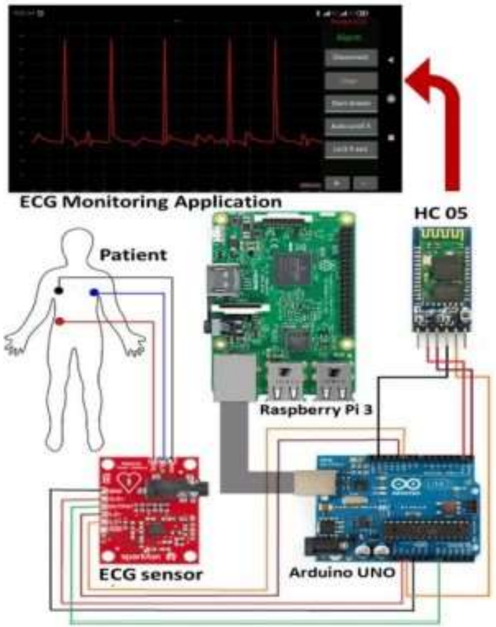


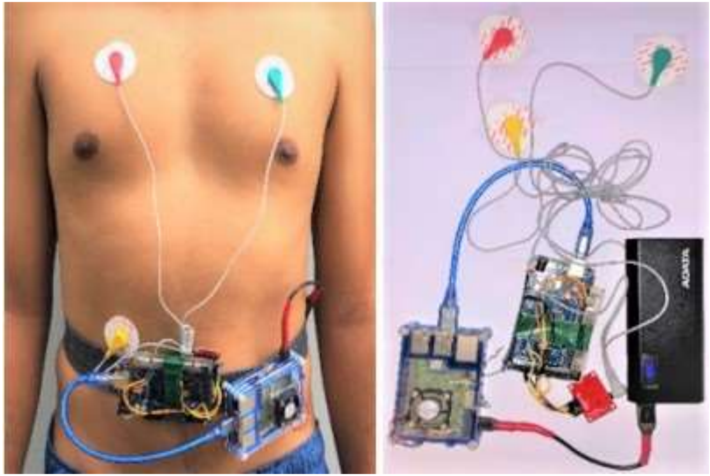


Algorithm	Decision tree	SVM	Naïve Bayes	KNN	MLP
Accuracy	65.51%	98%	69%	65.51%	72.41%
F1 score	0.62	0.98	0.69	0.66	0.72

Literature Survey

- Low Cost, Portable ECG Monitoring and Alarming System Based on Deep Learning (IEEE 2020)





Name	Value
Classification rate for train data	99%
Classification rate for test data	97%
Overall model accuracy	97.57%
Model loss	0.01%
Total root mean square error	0.004

Literature Survey

- Machine Learning in Electrocardiogram Diagnosis (IEEE 2009)

Author(s)	Feature extraction/reduction method	Classification model	Accuracy (%)
Y. zbay et al. [37]	Segments of arrhythmia.	MLP-BB+FCNN*	98.9 for ANN 99.9for FCNN
A. Sengur et al.[38]	Wavelet transforms and short time Fourier transform	AIS based fuzzy k-NN**	95.9 sensitivity# 96specificity# #
Z. Dokur et al. [39]	Fourier and wavelet analyses	ANN+GAs	96
K. Lewenstein et al. [40]	Segment of QRS complex, P and T wave	ANN + Expert System	92.5 sensitivity 96.7specificity
C-W. CHU et al. [41]	Moving average and differential equation approach	ANN and CBR	very high clustering performance
R. Ceylan et al. [42]	Segments of arrhythmia	T2FCM+ANN***	99
R. U. Acharya et al. [17, 18]	Spectral entropy	ANN + Fuzzy	80-85

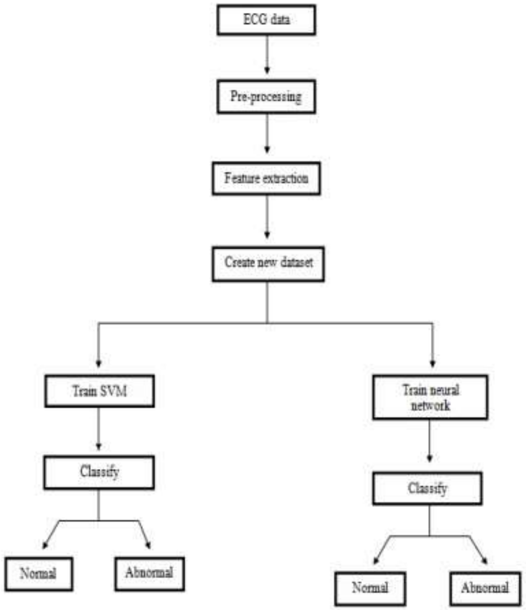
Literature Survey

- A Survey : Classification of ECG Signals using Machine Learning Techniques (IEEE 2015)

Researchers	No. of features	ECG Features	Preprocessing Technique	Database	Modeling Technique	Performance Measures	Accuracy (%)
R.Ceylan et al. (2008)	1	RR interval	Feature extraction: DWT	MIT-BIH arrhythmias	3-layered FFNN, T2FCNN, fuzzy clustering neural network	Sensitivity, Specificity, Average detection rate	96.7 100 98.35
J.Wang et al. (2012)	2	R peak, RR interval	Feature normalization: Z score, Feature reduction: PCA and LDA	MIT-BIH arrhythmias	PNN classifier with probability density function (pdf) as training rule	Sensitivity, Specificity, Accuracy	97.98 99.10 99.71
V.Kumari and P.Kumar (2013)	1	RR interval	Feature extraction: Symlets, CWT, Feature reduction: Symmetric uncertainty	MIT-BIH and UCI arrhythmia	Modular neural network – MLPNN	Precision , Recall, Root MSE	95.1 95.1 0.1765
S.Jadhav et al. (2012)	1	RR interval	Feature extraction: DWT	UCI arrhythmia	MLPNN, Generalized FFNN, Modular neural network	Sensitivity, Specificity, Accuracy	93.75 93.1 86.67
A.Dallali et al. (2011)	1	RR interval	Feature normalization: Z score, Denoised: Baseline adjustment, Feature extraction: DWT	MIT-BIH arrhythmias database	FCM and heart rate variability (HRV)	Accuracy	99.05
M.Vijayavanan et al. (2014)	12	Peaks-R, Q, S, P, T, Intervals- RR, PR, QT, ST, QRS duration, Segments- ST, PR	Feature extraction: DWT level-8, Remove baseline wander	MIT-BIH arrhythmias	Feed forward PNN classifier Trained with extracted features	Accuracy	96.5
A.Dallali et al. (2011)	2	RR interval R point location	Feature extraction: DWT using Daubechies wavelet Of order 3	MIT-BIH arrhythmias	Pre-classification: FCM, Final classification: MLPNN	Accuracy	99.99

Literature Survey

- Application of Machine Learning on ECG Signal Classification Using Morphological Features (IEEE 2020)

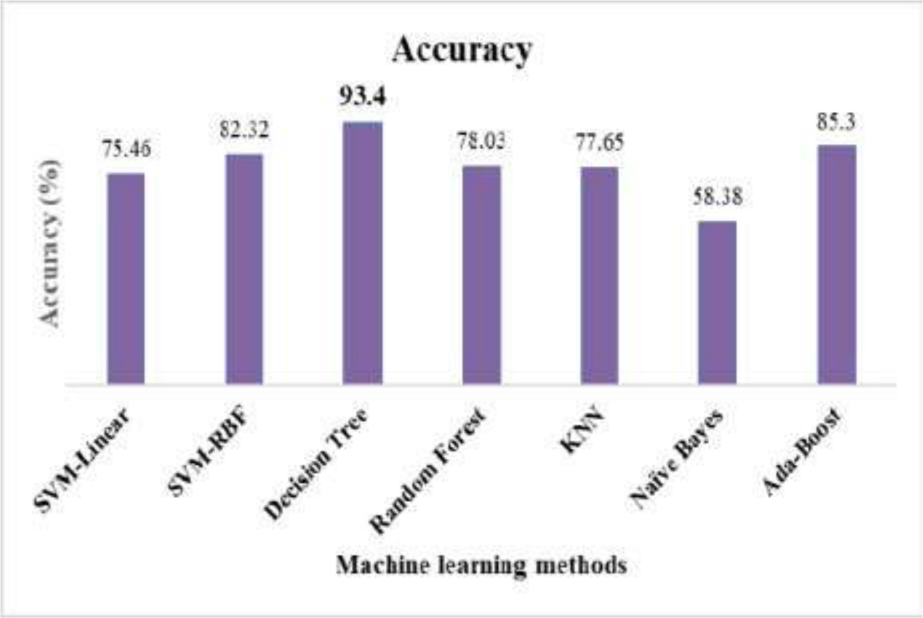


# Hidden Neurons	ANN Classifier's Performance			
	Training	Validation	Test	All
10	TP=34.3%, TN=42.4%, FP=18.6%, FN=5.7%, Accuracy=75.7%	TP=33.3%, TN=53.3%, FP=0%, FN=13.3%, Accuracy=86.7%	TP=33.3%, TN=26.7%, FP=20%, FN=20%, Accuracy=60%	TP=34%, TN=41%, FP=16%, FN=9%, Accuracy=75%
14	TP=42.9%, TN=44.3%, FP=7.1%, FN=5.7%, Accuracy=87.1%	TP=46.7%, TN=33.3%, FP=6.7%, FN=13.3%, Accuracy=80%	TP=40%, TN=46.7%, FP=6.7%, FN=6.7%, Accuracy=86.7%	TP=43%, TN=43%, FP=7%, FN=7%, Accuracy=75.7%
22	TP=40%, TN=50%, FP=7.1%, FN=2.9%, Accuracy=90%	TP=53.3%, TN=46.7%, FP=0%, FN=0%, Accuracy=100%	TP=60%, TN=33.3%, FP=0%, FN=6.7%, Accuracy=93.3%	TP=45%, TN=47%, FP=5%, FN=3%, Accuracy=92%
28	TP=12.9%, TN=45.7%, FP=40%, FN=1.4%, Accuracy=58.6%	TP=6.7%, TN=66.7%, FP=26.7%, FN=0%, Accuracy=73.3%	TP=20%, TN=46.7%, FP=33.3%, FN=0%, Accuracy=66.7%	TP=49%, TN=13%, FP=37%, FN=1%, Accuracy=62%

Literature Survey

- Classification and Detection of Arrhythmia in ECG Signal Using Machine Learning Techniques (IEEE 2019)

Machine learning methods	Training sample	Test sample	Sensitivity (%)	Specificity (%)	Accuracy (%)
SVM-Linear	84148	21037	86.16	53.21	75.46
SVM-RBF	84148	21037	96.62	49.64	82.32
Decision Tree	**84148**	**21037**	**97.34**	**68.24**	**93.40**
Random Forest	84148	21037	94.91	47.66	78.03
KNN	84148	21037	85.82	52.26	77.65
Naïve Bayes	84148	21037	55.34	63.72	58.38
Ada-Boost	84148	21037	87.32	82.57	85.30



Literature Survey

- Estimation Of Blood Pressure by using Electrocardiogram(ECG) and Photo-plethysmogram(PPG) (IEEE 2015)

- In this study, we found the relationship between blood pressure (BP) and pulse transit time (PTT).
- After measuring ECG and photo-plethysmogram, the PTT was calculated from the acquired signals.
- Blood pressure (BP) , the pressure exerted by circulating blood upon the walls of blood vessels, is an important physiological parameter and can provide some information forpersonal healthcare.
- Pulse transit time is the time taken for the arterial pulse Pressure wave to travel from the aortic valve to a peripheral site.
- It is usually measured from the R wave on the electrocardiogram to a photoplethysmography signal. PTT is inversely proportional to blood pressure.
- The mean error are 0.29 mmHg for SBP and 0.1mmHg for DBP.
- These results are satisfied with the regulation of ANSI/AAMI for certification of sphygmomanometer that real measurement error value should be within the mean error of ±5mmHg

Literature Survey

- ECG Heartbeat Classification Using Multimodal Fusion (IEEE 2021)

Categories	Annotations
N	Normal Left/Right bundle branch block Atrial escape Nodal escape
S	Atrial Premature Aberrant atrial premature Nodal premature Supra-ventricular premature
V	Premature ventricular contraction Ventricular escape
F	Fusion of ventricular and normal
Q	Paced Fusion of paced and normal Unclassifiable

Literature Survey

- ECG Heartbeat Classification Using Multimodal Fusion (IEEE 2021)

TABLE 5. Experimental results of MIT-BIH dataset using AlexNet.

Modalities	Accuracies%	Precision%	Recall%
GAF Images only	97.3	85	91
RP Images only	97.2	82	93
MTF Images only	91.5	86	89
Concatenation Fusion	97	82	91
Average Fusion	98.5	95	93.1
Proposed MIF	98.6	93	92
Proposed MFF	99.7	98	98

TABLE 6. Experimental results of MIT-BIH dataset using simpler CNN of Fig. 4.

Modalities	Accuracies%	Precision%	Recall%
GAF Images(gray scale)	94.2	74.2	91
RP Images(gray scale)	96.3	80	90
MTF Images(gray scale)	94	72	86
Concatenation Fusion	94.6	80.4	84
Average Fusion	97.6	87	92
Proposed MFF	98.3	90.5	93

TABLE 7. Experimental results of PTB dataset using AlexNet.

Modalities	Accuracies%	Precision%	Recall%
GAF Images only	98.4	98	96
RP Images only	98	98	94
MTF Images only	95.3	94	89
Concatenation Fusion	97.4	95	95
Average Fusion	98.5	97	98
Proposed MIF	98.4	98	94
Proposed MFF	99.2	98	98

TABLE 8. Experimental results of PTB dataset using simpler CNN of Fig. 4.

Modalities	Accuracies%	Precision%	Recall%
GAF Images (gray scale)	94.7	91	90
RP Images (gray scale)	95.1	95	87
MTF Images(gray scale)	86.6	80	69
Concatenation Fusion	92.2	88	84
Average Fusion	96.3	91	94
Proposed MFF	96.5	94	93

TABLE 9. Comparison of heart beat classification results of MITBIH dataset with previous methods.

Previous Methods	Accuracies%	Precision%	Recall%
Izci et al. [43]	97.96	-	-
Dang et al. [23]	95.48	96.53	87.74
Li et al. [47]	99.5	97.3	98.1
Zhao et al. [49]	98.25	-	-
Oliveria et al. [37]	95.3	-	-
Huang et al. [21]	99	-	-
Shaker et al. [32]	98	90	97.7
Kachuee et al. [28]	93.4	-	-
Xu et al. [66]	95.9	-	-
He et al. [67]	98.3	-	-
Qiao et al. [68]	99.3	-	-
Proposed MIF	**98.6**	**93**	**92**
Proposed MFF	**99.7**	**98**	**98**

TABLE 10. Comparison of MI classification results of PTB dataset with previous methods.

Previous Methods	Accuracies%	Precision%	Recall%
Dicker et al. [39]	83.82	82	95
Acharya et al. [27]	95.22	95.49	94.19
Kojuri et al. [69]	95.6	97.9	93.3
Kachuee et al. [28]	95.9	95.2	95.1
Liu et al. [40]	96	97.37	95.4
Sharma et al. [12]	96	99	93
Chen et al. [31]	96.18	97.32	93.67
Cao et al. [70]	96.65	-	-
Ahamed et al. [71]	97.66	-	-
Proposed MIF	**98.4**	**98**	**94**
Proposed MFF	**99.2**	**98**	**98**

TABLE 11. Comparison of computational cost of AlexNet and CNN of Fig. 4 using MFF framework on MIT-BIH dataset.

CNN Model	Fusion Framework	Training Parameters
AlexNet	MFF	9259427
AlexNet	MIF	3086475
CNN of Fig. 4	MFF	612069

Literature Survey

Sr. No.	Title	Indexing and Year of Publication	Remarks
1	Portable ECG Monitoring System with USB Host Interface (2010 IEEE-EMB)	2010 3rd International Conference on Biomedical Engineering and Informatics.	Only a theoretical explanation of how the required system can be developed is explained. System developed on a 8051 MCU variant. Only ECG transfer and display process and no analysis performed.
2	Portable ECG Monitoring System Design (IEEE 2019)	2019 3rd International Conference on Electronic Information Technology and Computer Engineering (EITCE).	Concerned only with how ECG can be acquired via sensors and main focus is on data transfer and display of data via Wi-Fi and development of UI on Android. No analysis of ECG is performed.
3	ECG Monitoring Device Based On Arduino (IEEE 2020)	2020 Medical Technologies Congress (TIPTEKNO).	Concerned with developing of a low cost simple system working of Arduino, which receives ECG signal and displays on a monitor. No analysis is performed.
4	Portable ECG Device for Remote Monitoring and Detection of Onset of Arrhythmia (IEEE 2020)	2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT).	Developed a complete system on R-pi along with analysis of ECG signals.

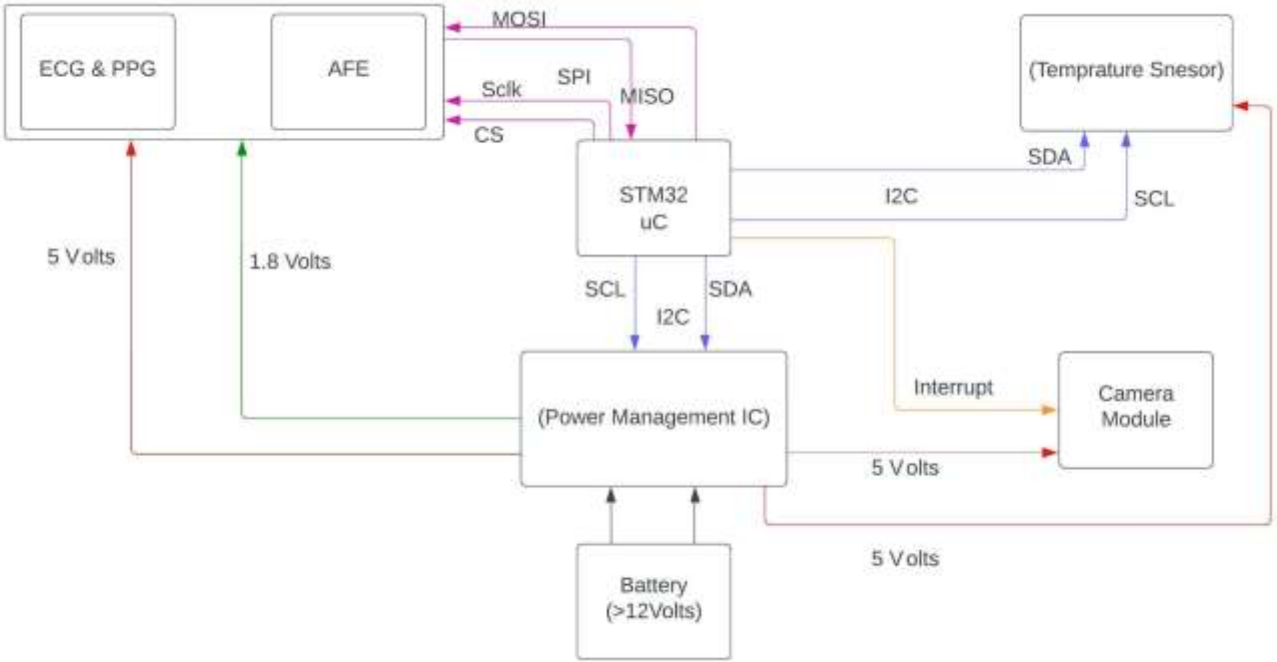
Literature Survey

Sr. No.	Title	Indexing and Year of Publication	Remarks
5	Low Cost, Portable ECG Monitoring and Alarming System Based on Deep Learning (IEEE 2020)	2020 IEEE Region 10 Symposium (TENSYMP).	Complete End-to-End system for ECG acquisition and analysis done via ML algorithm. However, hardware is bulky and should be changed.
6	Machine Learning in Electrocardiogram Diagnosis (IEEE 2009)	2009 International Multiconference on Computer Science and Information Technology.	A survey is carried out on several ML algorithms for ECG diagnosis and their comparison has been done.
7	A Survey : Classification of ECG Signals using Machine Learning Techniques (IEEE 2015)	2015 International Conference on Advances in Computer Engineering and Applications.	A survey is carried out on several ML algorithms for ECG diagnosis and their comparison has been done.
8	Application of Machine Learning on ECG Signal Classification Using Morphological Features (IEEE 2020)	2020 IEEE Region 10 Symposium (TENSYMP).	ML model based on neural networks is explained and a methodology is defined to classify and perform analysis of ECG into normal and abnormal category.
9	Classification and Detection of Arrhythmia in ECG Signal Using Machine Learning Techniques (IEEE 2019)	2019 16th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON).	Several ML techniques are applied on ECG signals and their comparison is made to find which technique is best.

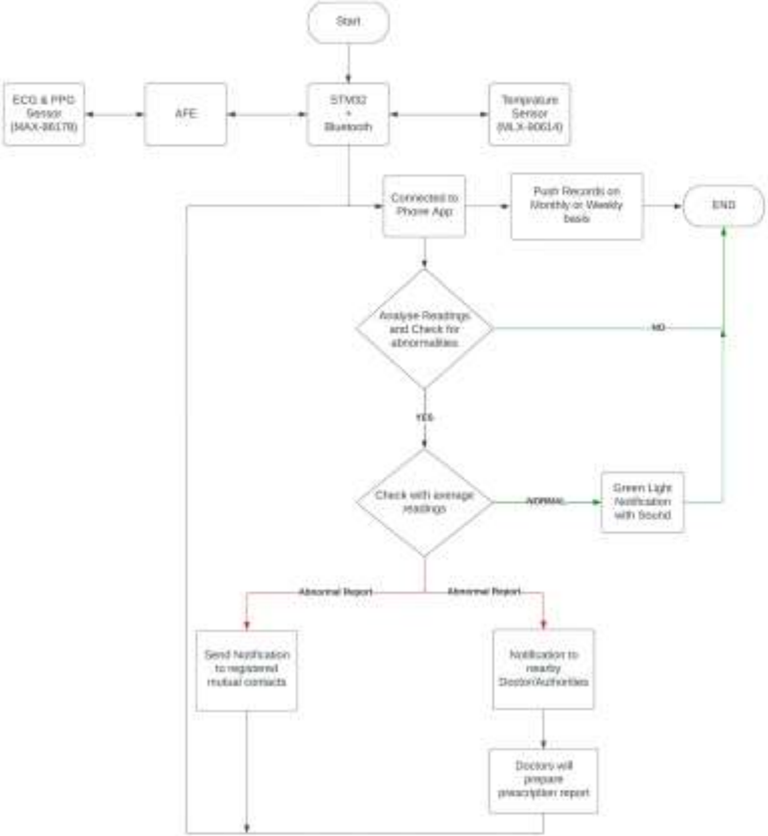
Literature Survey

Sr. No.	Title	Indexing and Year of Publication	Remarks
10	Estimation Of Blood Pressure by using Electrocardiogram(ECG) and Photo-plethysmogram(PPG) (IEEE 2015)	2015 Fifth International Conference on Communication Systems and Network Technologies.	Discussed techniques and algorithms, by the help of which, we can accurately predict the blood-pressure from ECG and PPG.
11	ECG Heartbeat Classification Using Multimodal Fusion (IEEE 2021)	IEEE Access, 9, 100615–100626.	Concerned with analysis of ECG signals and classification of Heart beat into several categories.

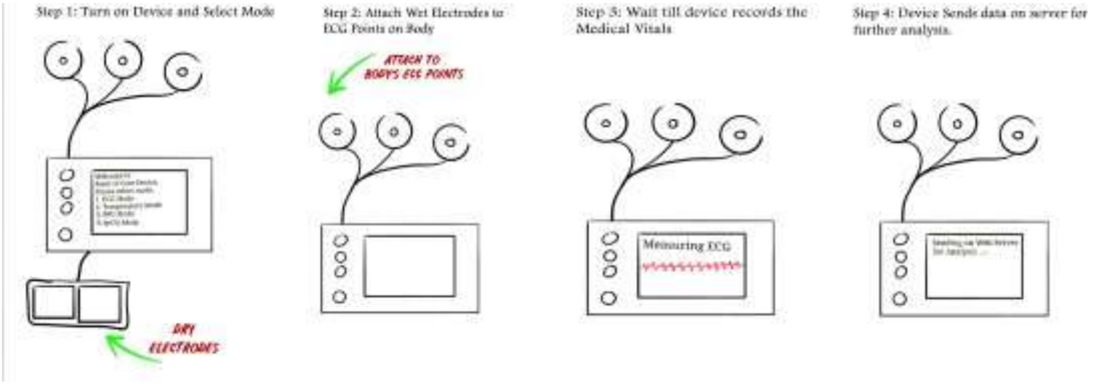
Generalized Block Diagram



Proposed Method

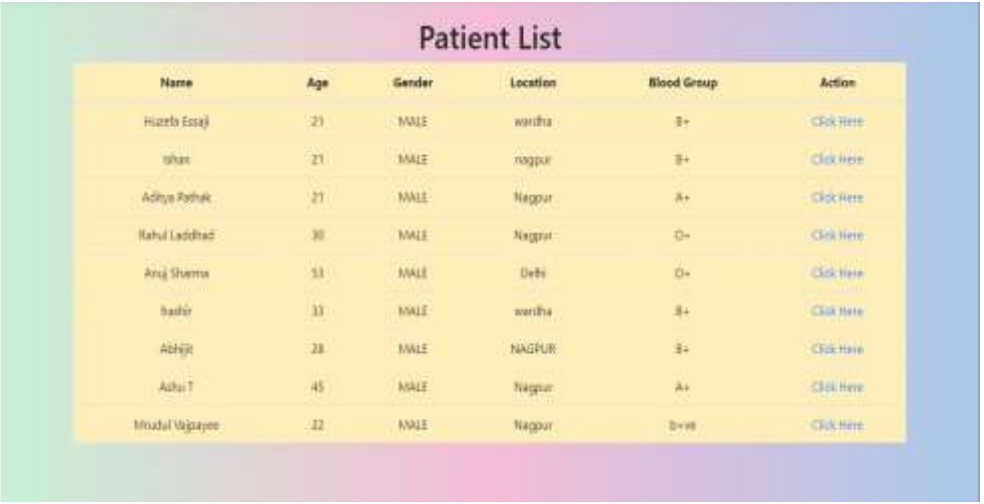


Proposed Method



The Proposed Device is centered around a dedicated micro processor which will be able to acquire the Analog signals, convert them into Digital data and through use of the algorithms. AI process the same to give digital outputs as per the medical templates required. Since the microprocessor and other components are mass produced the reliability and repeatability in the devices is assured.

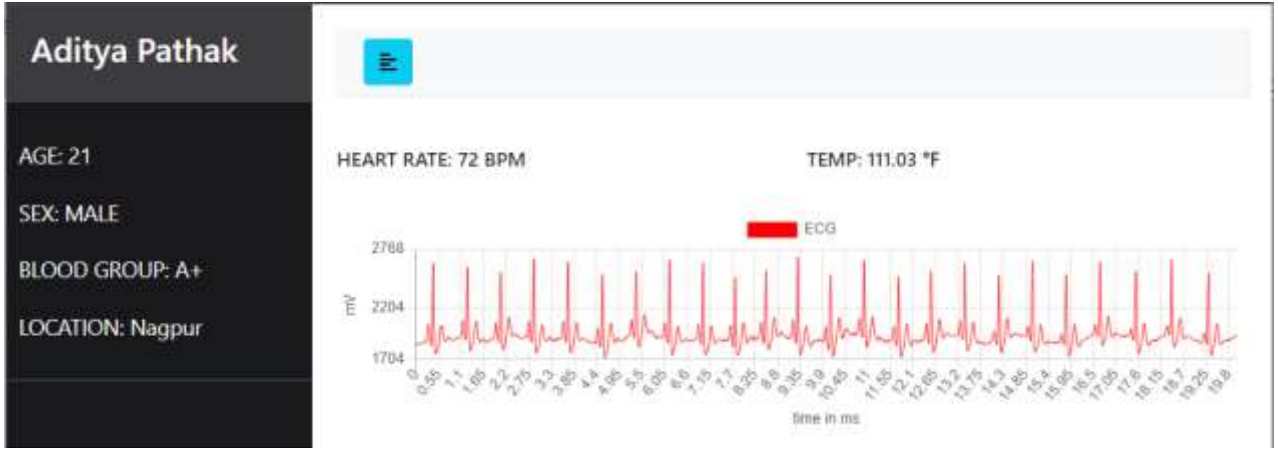
Performance Analysis



Patient List

Name	Age	Gender	Location	Blood Group	Action
Huzefa Essaji	21	MALE	wardha	B+	Click Here
ishan	21	MALE	nagpur	B+	Click Here
Aditya Pathak	21	MALE	Nagpur	A+	Click Here
Rahul Laddhad	30	MALE	Nagpur	O+	Click Here
Anuj Sharma	53	MALE	Delhi	O+	Click Here
bashir	33	MALE	wardha	B+	Click Here
Abhijit	28	MALE	NAGPUR	B+	Click Here
Ashu T	45	MALE	Nagpur	A+	Click Here
Mrudul Vajpayee	22	MALE	Nagpur	b+ve	Click Here

Performance Analysis



Performance Analysis

Performance Analysis

Hearth Disease Prediction

Personal Informations

Name: Can
Sex: Male
Age: 18-24
Race: White
Height: 185
Weight: 70

General Information

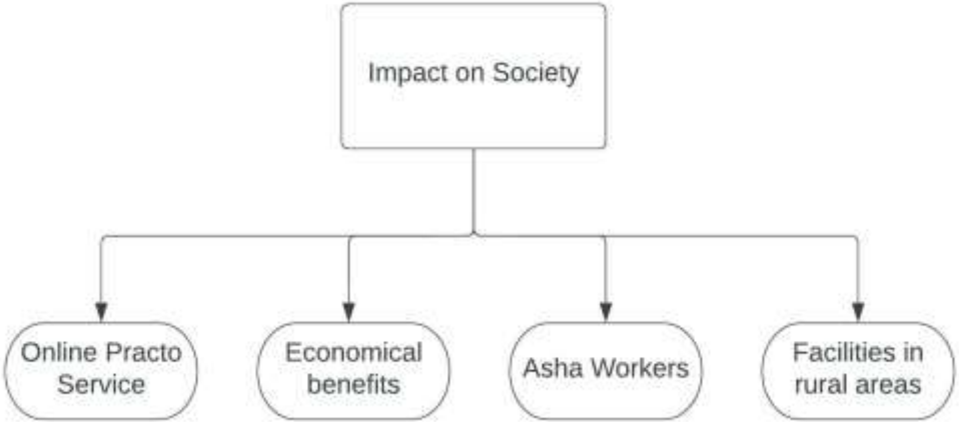
Have you smoked at least 100 cigarettes in your entire life? Yes
Heavy alcohol drinkers (Male: >14 drinks & Female: >7 drinks per week) Yes
Would you say that in general your health is.. Fair
On average, how many hours of sleep do you get in a 24-hour period? 3
How many days during the past 30 days was your mental health not good? 15
How many days during the past 30 days was your physical health not good? 15

Health Information

Did you do exercise during the past 30 days other than their regular job? Yes
Do you have serious difficulty walking or climbing stairs? Yes
Have you ever had a stroke? Yes
Have you ever had a diabetes? Yes
Have you ever had an asthma? Yes
Have you ever had a skin cancer? Yes
Have you ever had a kidney disease? Yes

Submit

Impact Of Project



Conclusion

- ✓ With the proposed device a person doesn’t require to visit hospital and can eventually test for the required parameters using wearable medical device at home.
- ✓ Wearable medical device can provide regular records of these tests to doctors.
- ✓ The complete system is user friendly and easy to use.
- ✓ With the advances in this wearable medical device, we can help many patients by saving their time and money, along with connecting them with doctors remotely.

References

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- Portable ECG Device for Remote Monitoring and Detection of Onset of Arrhythmia (IEEE 2020), 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT).
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- Estimation Of Blood Pressure by using Electrocardiogram(ECG) and Photo-plethysmogram(PPG) (IEEE 2015), 2015 Fifth International Conference on Communication Systems and Network Technologies.
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