SEIZURE DETECTION USING WEARABLE DEVICE

A PROJECT REPORT

Submitted by

DIPIN RAJ (21BCS6729)

JEEVAN A.J (21BCS6589)

RASHAZ RAFEEQUE (21BCS6634)

AKSHAY S (21BCS5849)

RHISHITHA T.S (21BCS6272)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

IN

COMPUTER ENGINEERING

Chandigarh University

MAY 2023

BONAFIDE CERTIFICATE

Certified that this project report "SEIZURE DETECTION USING WEARABLE DEVICE" is the bonafide work of "Dipin Raj, Jeevan A.J, Rashaz Rafeeque, Akshay S, Rhishitha T.S" who carried out the project work under our supervisor.

SIGNATURE	SIGNATURE
SUPERVISOR	HEAD OF THE DEPARTMENT

Submitted for the project viva-voce examination held on ________________

INTERNAL EXAMINER	EXTERNAL EXAMINER

ACKNOWLEDGEMENT

We would like to extend our heartfelt gratitude to our Project Supervisor ‘Ms. Merry K P’, who gave us the golden opportunity to do this project on “Seizure Detection Using Wearable Device”.

We would also like to thank our friends and families, who helped us in finalizing and completing this project with their constant encouragement and understanding.

TABLES OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

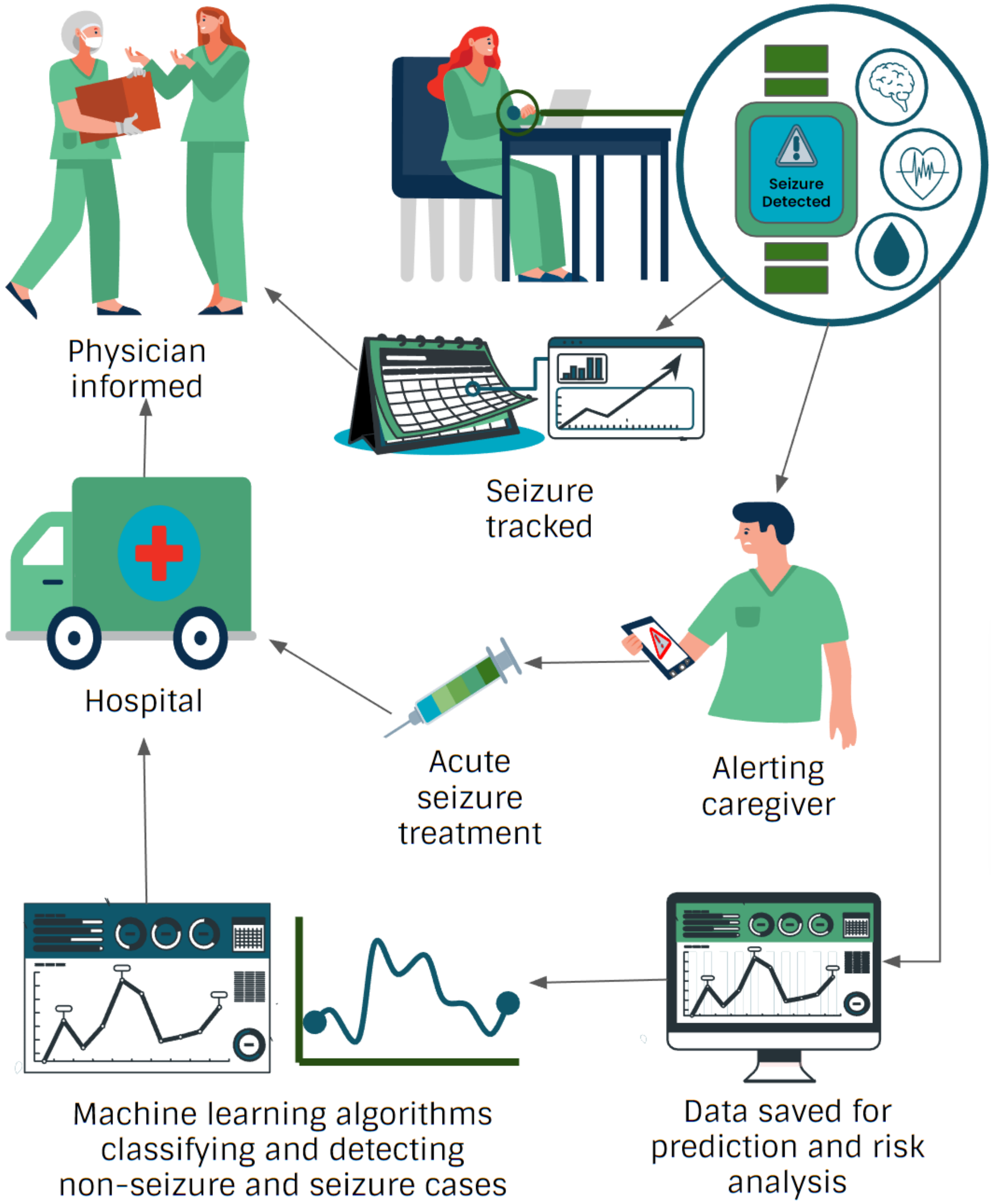
ABSTRACT

Sudden Unexpected Death in Epilepsy (SUDEP) is one of the most common syndromes shown by epileptic patients. With regard to neurological diseases' impact on mortality, SUDEP comes in second. According to studies, having a companionship reduces the incidence of SUDEP, and medical equipment that can detect or anticipate seizures is crucial in helping epileptic people live longer and healthier lives. The development of wearable technologies that can automatically detect and forecast seizures might revolutionize the lives of epileptic seizure victims. These tools can provide continuous seizure monitoring and seizure detection.

This project aims to produce a portable wearable device that can detect and monitor seizures. Accurate seizure detection is possible with the aid of multimodal sensors like the Accelerometer (ACC) and Electrodermal Activity (EDA). The device can examine skin conductivity and erratic heartbeats that can portend an imminent seizure. The device will also have the unique capability of real-time location monitoring, which will enable emergency contacts like carers, guardians, and physicians to be informed of the patient's precise locations during an episode. The project also features a thorough log system that keeps track of the seizures' frequency and specifics, which can help with patient monitoring and tailored care.

Overall, the project aims to demonstrate the potential of wearable technology in enhancing seizure management and improving patient outcomes.

GRAPHICAL ABSTRACT



ABBREVATIONS

ABBREVATION	MEANING
SUDEP	Sudden Unexpected Death in Epilepsy
ACC	Accelerometer
EDA	Electrodermal Activity
HR Sensor	Heart Rate Sensor
BVP	Blood Volume Pulse
EEG	Electroencephalogram
ECG	Electrocardiogram
PCG	Phonocardiography
EMG	Electromyography
SVM	Support Vector Machine
KNN	K-Nearest Neighbor
GNB	Gaussian Naïve Bayes
MLP	Multi-layer Perceptron
AUC	Area under Curve
ROC	Receiver Operating Characteristic Curve

CHAPTER – 1
INTRODUCTION

1.1. Problem Identification

Seizure detection using wearable devices is a technology whose purpose is to detect and alert when a person is experiencing a seizure episode. It seeks for easier detection of seizures and prevention of SUDEP with a system that makes use of sensors such as EDA and ACC. It also involves the use of various machine learning algorithms to provide the most efficient result.

This technology seeks to address the problem of untimely detection of seizures, which can prove fatal at times. Seizures are proven to have various consequences, leading to injuries and, in some cases, death. Hence, detecting seizures early and taking the necessary precautions would prove useful in increasing the quality of life for a person diagnosed with epilepsy.

There are various challenges to accurately detecting seizures, as we need to differentiate day-to-day activities such as exercising and sleeping from actual seizures. Therefore, using sensors and algorithms that provide the highest accuracy is important.

1.2. Seizures & its Types

Seizures can be defined as sudden and uncontrollable movements of a person caused by an uncontrollable electrical disturbance in the brain. Seizures can result in changes in behaviour, movements, feelings, and levels of consciousness. The cause of seizures can vary from brain injury to genetic conditions or even side effects from medicines. There are mainly two types of seizures,namely Generalized Seizure & Focal Seizure which have other types branching off from them.

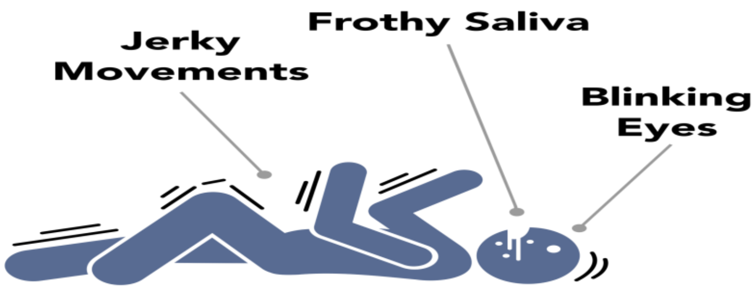


Fig 1.1: Seizure

1.2.1. Generalized Seizures

Generalised seizures are a type of seizure in which brain activity happens in both hemispheres of the brain at the same time. There are various types of seizures that fall under the category of generalised seizures.

1.2.1.1. Absence Seizures

Absence seizures are ones that involve a brief loss of consciousness.The loss of consciousness usually lasts for a few seconds. During this, the person might stare blankly without any response to stimuli.

1.2.1.2. Tonic-Clonic Seizures

Tonic-clonic seizures involve the loss of consciousness while having convulsive movements and stiffening of the body. These are also known as grand mal seizures.

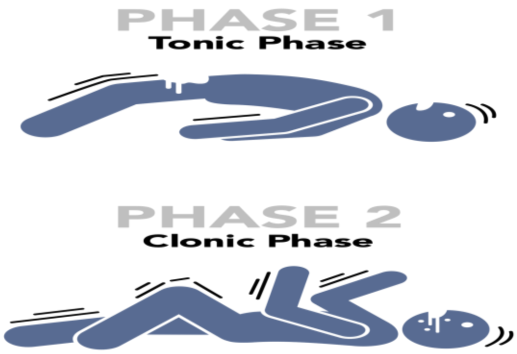


fig 1.2: Tonic-Clonic Seizure

1.2.1.3. Myoclonic Seizures

Myoclonic seizures involve muscle jerks that are sudden and brief. It can affect more than one part of the body.

1.2.1.4. Atonic Seizures

Atonic seizures involve the sudden loss of muscle tone, which can result in the person collapsing.

1.2.1.5. Clonic Seizures

Clonic seizures involve rhythmic and jerking muscle movements that can affect body parts such as the face, neck, and arms.

1.2.2. Focal Seizures

Focal seizures are a type of seizure that focuses on one hemisphere of the brain. These seizures can end up affecting different regions of the brain, and the symptoms can vary depending on the location and extent of the seizure. There are mainly two types of focal seizures.

1.2.2.1. Focal Seizure without loss of consciousness

These seizures do not cause any loss of consciousness but end up causing sensory, motor, or autonomic symptoms. The person experiencing it might have tingling or numbness in parts of the body, visual and auditory hallucinations, and muscle twitching or jerking.

1.2.2.2. Focal Seizure with impaired consciousness

These seizures can cause loss of consciousness and may or may not include chewing, lip-smacking or walking in repetitive pattern.

1.3. Sensors

To accurately detect seizures and differentiate between actual seizures and pseudo-seizures, we need to use a wide variety of sensors. These sensors include EDA, ACC, HR, BVP, EEG, ECG.

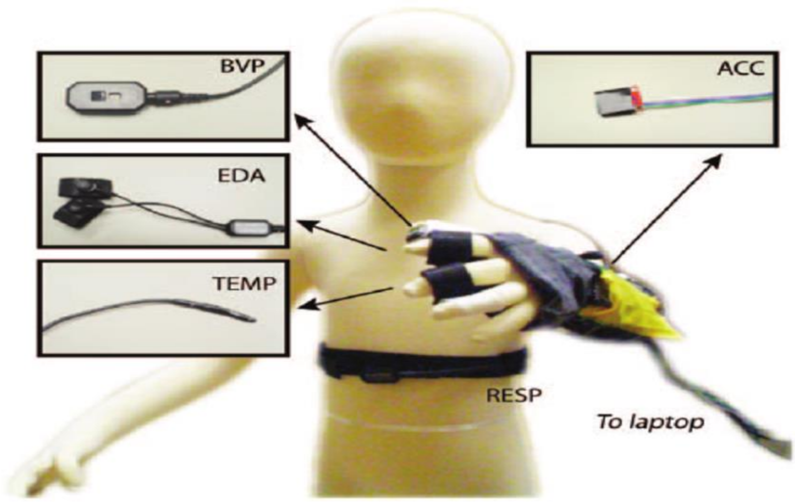


Fig 1.3: Different Sensors

1.3.1. EDA

EDA sensors stand for electrodermal activity sensors, and they are devices that measure the electrical conductivity of skin. Electrical conductivity is produced by the sweat glands in the skin, and they are controlled by the autonomous nervous system. EDA sensors can be used to detect changes in the skin's electrical conductivity, which can be caused by emotional arousal or stress. Detecting these changes can provide useful insight into a person's emotional state. Hence, these sensors can help in detecting changes in emotional arousal in a person before an episode of seizure.

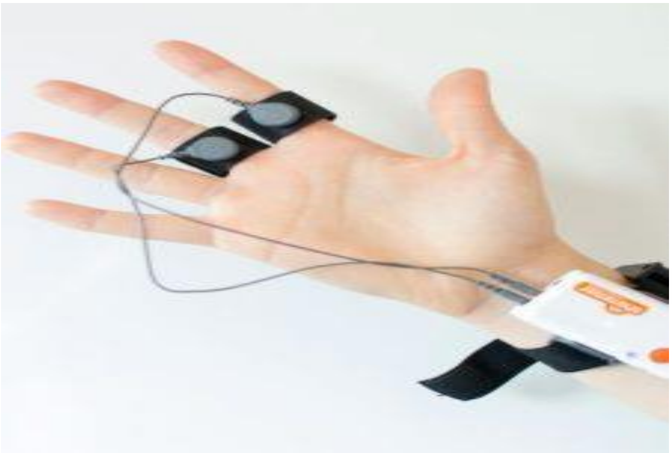


Fig 1.4: EDA Sensor

1.3.2. **ACC**

ACC sensors, or accelerometers, help in measuring the acceleration or movement of a muscle at the time of seizure activity. A person diagnosed with seizures will have movements that happen during seizures and movements that happen during exercise or other day-to-day activities. The data collected from ACC sensors can be incorporated with other data to accurately differentiate between actual seizures and false seizures.

1.3.3. **EEG**

EEG sensors stand for electroencephalogram sensors and are commonly used in the diagnosis of epilepsy and other neurological disorders. EEG detects the electrical activity produced at the time of communication between neurons and converts it into a digital signal that can be analysed and interpreted by a computer.

They can be used to provide vital information about the frequency, duration, and location of the abnormal brain activity, which can be used to identify the type of seizure and prepare accordingly.

1.3.4. ECG

Electrocardiogram sensors are devices that can be used to detect and record the electrical activity happening inside the heart. ECG sensors can be used to detect changes in electrical activity of heart, which might sometimes be a sign of an imminent seizure.

1.3.5. HR

Heart rate sensors can be used to measure a person's heart rate per minute. At the time of an impending seizure, HR sensors can detect changes in a person's heartbeats per minute. These changes can be used to detect seizure more easily.

1.3.6. BVP

BVP stands for blood volume pulse sensors and are devices which are used to measure changes in blood volume of the skin. They emit light onto the skin and measure the amount of light reflected back. As blood absorbs some of the light, there will be variations in the light which is reflected back. At the time of seizure, there will be changes in blood volume and blood flow of the body. By monitoring these changes, the system can detect the occurrence of a seizure and alert medical professionals.

1.4. Machine Learning Algorithms

In order to accurately differentiate between true seizures and false seizures and to detect them using the values from the sensors mentioned above, machine learning algorithms can be used. Various machine learning algorithms can be selected for this experiment, but selecting the one with the best possible result will provide the most efficient result. Some machine learning algorithms used are KNN, SVM, Logistic Regression, MLP, Random Forest, Gradient Boosting.

CHAPTER – 2
LITERATURE REVIEW

- SEIZURE AND ITS CLASSIFICATIONS:

The use of sensors and machine learning classifiers for identifying and categorising various types of epileptic episodes is covered in the article. Recurrent seizures are a hallmark of the neurological condition epilepsy, and proper classification and localization of these seizures is essential for successful diagnosis and therapy.

The classification system for seizures used by the International League Against Epilepsy (ILAE) has recently been modified, and now there are four primary categories: focal seizures, generalised seizures, combined generalised and focal seizures, and unknown seizures. Both focal aware seizures and focal impaired awareness seizures are referred to as focal seizures because they start in a particular region of the brain. On the other hand, generalised seizures affect both sides of the brain and can be further divided into six categories based on their unique characteristics.

Sensors can be used to assess physical or chemical characteristics connected to the epileptic episode in order to identify and categorise seizures. The analysis and interpretation of this data using machine learning classifiers enables precise seizure location and identification. These techniques help medical practitioners comprehend the nature of the seizures and create individualised treatment programmes for their patients.

Overall, the research emphasises the value of precisely identifying seizure types and locations in the diagnosis and management of epilepsy, as well as how sensors and machine learning classifiers might facilitate this process.[12]

- SENSORS

The study article covers the application of sensors to identify and quantify the physical or chemical characteristics connected to epileptic episodes. The bodily alterations and motions that are symptomatic of seizures are recognised using these sensors. Accelerometers, for instance, can be used to identify sudden movements or convulsions, while electroencephalography (EEG) sensors can gauge the electrical activity of the brain.

A key component of controlling epilepsy is seizure detection, which can be aided by technology like sensors and machine learning algorithms. Algorithms for machine learning can be trained to analyse sensor data and spot patterns that point to the onset of a seizure. This enables medical personnel to act fast and offer the right care.

Electrodermal activity (EDA) is one particular indicator of physical characteristic changes that is mentioned in the article. The evaluation of fluctuations in skin's electrical conductivity, which may serve as a sign of shifting mental or physical states, is referred to here. Skin conductance sensors can detect EDA, which has been used in studies to examine the connection between seizures and emotional stress.

In general, the diagnosis and management of epileptic episodes can benefit from the use of sensors and other detection technologies, such as machine learning algorithms and EDA measurement. These technologies allow medical personnel to better care for epilepsy patients and enhance their quality of life.[7][9][17]

- MACHINE LEARNING CLASSIFIERS:

The application of machine learning classifiers for seizure detection and localization is the main topic of the study paper. The physical or chemical characteristics connected to epileptic episodes serve as the input features for these algorithms, which are utilised to classify or categorise data. Decision forests and black-box classifiers are just a couple of the machine learning classifiers that are examined in this paper.

Machine learning techniques like decision forests can be applied to classification and regression issues. They function by integrating the predictions of various decision trees to increase the final result's accuracy. On the other hand, black-box classifiers are a sort of machine learning model that are challenging to comprehend or explain. When the data analysed is complicated for people to fully comprehend, they are frequently deployed.

During epileptic seizures, seizure detection is evaluated, and wearable gadgets with built-in biosensors and machine learning algorithms are utilised to track and monitor them. In order to find trends and categorise the different types of seizures, machine learning algorithms can be used to analyse the real-time data that these sensors can provide on the physical and chemical changes connected to seizures.

Overall, seizure detection and localisation using machine learning classifiers has the potential to significantly increase the precision and efficiency of epilepsy diagnosis and treatment. Healthcare practitioners can better monitor and track seizures with the use of wearable devices with embedded biosensors and machine learning algorithms, which will result in more effective management of the illness.[1][3][14]

- SEIZURE DETECTION:

A fast-expanding field of study is the use of technology, such as sensors and machine learning algorithms, in the detection of epileptic seizures. The study covered in the article used biosensors built into wearable technology along with machine learning algorithms to identify seizures. Acceleration (ACC), phonocardiography (PCG), and electrodermal activity (EDA) are only a few examples of the physical and chemical characteristics that the sensors recorded.

The capacity to offer real-time seizure monitoring is one of the key advantages of using technology in seizure detection. This may make it easier for medical staff to act promptly and offer the right care, lowering the possibility of problems and enhancing patient outcomes. Technology can also help to increase seizure detection accuracy, lowering the chance of a mistake or an underdiagnosis.

The use of biosensors and wearable technology in the treatment of epilepsy and other neurological diseases is becoming more and more crucial. Healthcare practitioners can better understand the underlying causes of the disorder and create more effective treatment plans by monitoring and tracking seizure activity. Wearable technology can also provide useful information for research, advancing our knowledge of epilepsy and other neurological conditions.

Finally, seizure detection technologies can enhance both the quality of life for epilepsy sufferers and those who provide care for them. Wearable technology can assist in lowering the stress and worry related to having epilepsy by offering real-time monitoring and alert systems. Biosensors and wearable technology may become even more important instruments in the treatment of epilepsy and other neurological diseases with additional research and development.[8][10][14][17][20]

- ELECTRODERMAL ACTIVITY (EDA):

The electrical conductivity of the skin is measured as electrodermal activity (EDA), which can reveal details about both mental and physical states. EDA sensors have been used to track alterations in physiological responses in a number of disciplines, including psychology and neuroscience. EDA was assessed during epileptic convulsions in the study article's context to better understand their physiological effects.

In both the ictal and postictal phases of seizures, the study saw a rising EDA response. This shows that EDA might be a helpful tool for identifying and tracking seizures, possibly allowing medical providers to offer patients more effective treatments. However, the study also found that compared to other forms of seizures, focal seizures had a weaker EDA response, which may restrict the utility of EDA sensors.

The use of EDA sensors for seizure detection still has a lot of problems that need to be fixed. Sweat, for instance, and movement can influence skin conductance, which could lead to readings that are either falsely positive or falsely negative. Further study and development will be needed to create EDA sensors that are more accurate and dependable.

Despite these difficulties, EDA sensors show promise as a seizure detection and monitoring tool, and additional study in this field may result in more potent treatment approaches for epilepsy and other neurological conditions.[18][23]

- WEARABLE HEALTH CARE DEVICES USING AI:

In recent years, the notion of monitoring and tracking epilepsy patients using wearable technology embedded with biosensors and machine learning algorithms has gained popularity. The application of these tools for seizure detection and classification was covered in the study publication. Wearable technology can help medical professionals and carers by gathering data on the bodily alterations and movements linked to epileptic episodes.

The data gathered by the wearable sensors is categorised using machine learning algorithms, which also find patterns connected to various types of seizures. This makes it possible to detect seizures more precisely and quickly, which might be essential for avoiding harm and delivering quick care.

AI technology is also utilised to predict prognoses and choose the most effective therapy for each patient, in addition to seizure detection. Machine learning algorithms can offer individualised therapy recommendations that take into account each patient's particular needs and circumstances by analysing data on seizure frequency, severity, and other aspects.

Last but not least, wearable gadgets with integrated biosensors and AI technology can also be used to alert loved ones and medical personnel when a seizure has happened. This can guarantee that patients get prompt medical care and that family members' carers are aware of their status.

Overall, the lives of persons with epilepsy and those who care for them could be considerably improved by the deployment of wearable technology with embedded biosensors and machine learning algorithms. This technology has the potential to completely change how epilepsy and other neurological disorders are treated by enabling more precise and rapid seizure detection, personalised therapy suggestions, and real-time notifications.[10][20]

- AI-BASED TREATMENT PLANS FOR SEIZURES:

A potential area of research involves the automated diagnosis and prognosis forecasting of certain epilepsy patients using AI technology. Healthcare providers can gain a more precise and thorough grasp of each patient's condition by using AI and machine learning approaches to computer research.

The creation of individualised treatment plans is a significant application of AI technology in the treatment of epilepsy. In order to choose the best suitable course of therapy for each patient, machine learning algorithms can analyse data on the frequency, severity, and other aspects of their seizures. This individualised strategy may lead to better therapeutic results while lowering the chance of problems and side effects.

The computerised diagnosis of epilepsy is a significant use of AI technology. Machine learning algorithms are capable of correctly diagnosing epilepsy in a patient by examining EEG data and other clinical markers. When symptoms are ambiguous or individuals have trouble describing their experiences, this can be especially helpful.

Last but not least, epilepsy prognosis predictions can also be done using AI technology. Machine learning systems can forecast the risk of future seizures and other issues by examining data on patient outcomes over time. This can assist medical practitioners in creating treatment regimens that are more successful and in providing patients with greater care and support.

Overall, using AI technology to the treatment of epilepsy has the potential to transform the industry and enhance patient outcomes. Healthcare workers may improve care for and support people with epilepsy by using AI and machine learning techniques to deliver personalised treatment regimens, accurate diagnoses, and prognosis predictions.[6]

- ALERTING THE CARERS AT THE NEED OF TIME:

This concept emphasises the significance of creating an alert system for epilepsy patients so they may promptly warn their loved ones and medical personnel when they have a seizure. For patients who live alone or who have a high risk of damage from seizures, this technology is very important. In the study paper, it is discussed how fall detection algorithms and motion sensors can be used to create an alert system that can swiftly inform loved ones and medical personnel to a seizure by sending an SOS siren, a call, an SMS, and a GPS location. The fall detection algorithms are made to recognise abrupt changes in motion, as those brought on by a seizure, and to send out an alert. The motion sensors can also monitor the patient's motions and provide alarms if they stop moving normally or stop responding.

With peace of mind and the assurance to live independently, this alert system can considerably increase the safety and well-being of epilepsy patients. Additionally, it helps ease the strain on carers who could be tasked with watching over patients round-the-clock. However, there are possible drawbacks to using these technologies, such as the possibility of false alarms or the requirement for routine maintenance to guarantee the system is operating effectively. Overall, the study article proposes that further research and development should be done on the use of technology to create an alert system for epilepsy patients in order to maximise patient outcomes.[5]

2.1. LITERATURE REVIEW SUMMARY TABLE

Year and Citation	Article/ Author	Tools/ Software	Technique	Source	Evaluation Parameter
Regalia, G., Onorati, F., Lai, M., Caborni, C. and Picard, R.W., 2019. Multimodal wrist-worn devices for seizure detection and advancing research: focus on the Empatica wristbands. Epilepsy research, 153, pp.79-82.	Regalia, Onorati, Lai, Caborni and Picard	Multimodal Sensors (EDA, ACC)	Machine Learning	Science Direct	Furthermore, research is still needed to reduce the FAR and improve the accuracy of seizure detection using multimodal sensors.
Ortega, M.C., Bruno, E. and Richardson, M.P., 2022. Electrodermal activity response during seizures: A systematic review and meta-analysis. Epilepsy & Behaviour, 134, p.108864.	Ortega, M.C., Bruno, E. and Richardson	Electroderm al Activity Sensor	Machine Learning	Science Direct	Further research is indeed needed deep understanding EDA response during epileptic seizures.
Tang, J., El Atrache, R., Yu, S., Asif, U., Jackson, M., Roy, S., Mirmomeni, M., Cantley, S., Sheehan, T., Schubach, S. and Ufongene, C., 2021. Seizure detection using wearable sensors and machine learning: Setting a benchmark. Epilepsia, 62(8), pp.1807-1819.	Tang, J., El Atrache, R., Yu, S., Asif, Jackson, M., and Ufongee	ACC, EDA, PCG	Machine Learning	Epileps ia	The use of ML algorithms and biosensors would be of great help in determining the type of seizure a patient is having.
Zangróniz, R., Martínez Rodrigo, A., Pastor, J.M., López, M.T. and Fernández-Caballero, A., 2017. Electrodermal activity sensor for classification of calm/distress condition. Sensors, 17(10), p.2324.	Zangróniz, R., Martínez-Rodrigo, A., Pastor, J.M., López, M.T. and Fernández-Caballer	Electrodermal Activity Sensor	Machine Learning	MDPI	The usage of EDA sensors in wearable devices turned out to be of great importance in the health industry, notably in the epilepsy section.

Humairah Tabasum, Nikita Gill, Rahul Mishra and Saifullah Lone. Wearable microfluidic- based eskin sweat sensors – Article.	Humairah Tabasum, Nikita Gill, Rahul Mishra and Saifullah Lone	Electrodermal Activity Sensor (EDA)	Machine Learning	Royal Society of Chemistry	Developing new cell subtypes, organ-specific microbiomes, biochemical and biophysical gradients across organ & mimicking physiological responses are crucial.
Xu Zeng, Hai-Tao Deng, Dan- Liang Wen, Yao-Yao Li, Li Xu and Xiao-Sheng Zhang.Wearable Multi-Functional Sensing Technology for Healthcare Smart Detection –Article.	Xu Zeng, Hai-Tao Deng, Dan-Liang Wen, Yao-Yao Li, Li Xu and Xiao-Sheng	Accelerometer (ACC)	Machine Learning	MDPI	Wearable sensor has made sprogress but still face challenges such as high integration, fitting human skin, achieving high resolution.
Rosales, M.A., Bandala, A.A., Vicerra, R.R. and Dadios, E.P., 2019, November. Physiological Based Smart Stress Detector using Machine Learning Algorithms. In 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM) (pp. 1-6). IEEE.	Rosales, M.A., Bandala, A.A., Vicerra, R.R. and Dadios	Galvanic Skin Response	Machine Learning, SVM classifiers	IEEE	The GSR sensor can detect changes in sweat gland activity that are reflective of the intensity of the person’s emotional state.
Adwitiya, A.Y., Hareva, D.H. and Lazarusli, I.A., 2017, September. Epileptic Alert System on Smartphone. In 2017 International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT) (pp. 288- 291). IEEE.	Adwitiya, A.Y., Hareva, D.H. and Lazarusli	Accelerometer (ACC)	Fall Detection Algorithm	IEEE	The research consists of negatives such as the placement of smartphones, as it is not convenient to place the device on the upper arm or the head.

Sarmast, S.T., Abdullahi, A.M. and Jahan, N., 2020. Current classification of seizures and epilepsies: scope, limitations and recommendations for future action. Cureus, 12(9).	Sarmast, S.T., Abdullahi, A.M. and Jahan	-	-	Cureus	The classification system can help patients understand their condition and describe their symptoms to healthcare providers very easily which helps in better communication.
Siddiqui, M.K., Morales-Menendez, R., Huang, X. and Hussain, N., 2020. A review of epileptic seizure detection using machine learning classifiers. Brain informatics, 7(1), pp.1-18.	Siddiqui, M.K., Morales-Menendez, R., Huang, X. and Hussain	Electroencephalogram (EEG), Electrocorticography (ECoG)	Machine Learning classifiers Blackbox and non-Blackbox methods	Brain Informatics	Black-box classifiers may achieve high predictive accuracy, but they cannot generate interpretable logic rules. Detecting seizures from large volumes of EEG data is a major challenge in epilepsy diagnosis.
Beniczky, S., Wiebe, S., Jeppesen, J., Tatum, W.O., Brazdil, M., Wang, Y., Herman, S.T. and Ryvlin, P., 2021. Automated seizure detection using wearable devices: A clinical practice guideline of the International League Against Epilepsy and the International Federation of Clinical Neurophysiology. Clinical Neurophysiology, 132(5), pp.1173-1184.	Beniczky, S., Wiebe, S., Jeppesen, J., Tatum, W.O., Brazdil, M., Wang, Y., Herman, S.T. and Ryvlin, P.	-	-	Science Direct	Furthermore, the growth in this research field can result in precise and accurate detection of epileptic seizures, which can effectively support patience with epilepsy.
Chen, F., Chen, I., Zafar, M., Sinha, S.R. and Hu, X., 2022. Seizures detection using multimodal signals: a scoping review. Physiological Measurement.	Chen, F., Chen, I., Zafar, M., Sinha, S.R. and Hu, X.	Multimodal sensors	Machine Learning, SVM Classifiers, Random Forest	PubMed	Furthermore, research is indeed needed to rectify the FAR signals.

Falco-Walter, J.J., Scheffer, I.E. and Fisher, R.S., 2018. The new definition and classification of seizures and epilepsy. Epilepsy research, 139, pp.73-79.	Falco-Walter, J.J., Scheffer, I.E. and Fisher, R.S.	Electroence phalogram (EEG)	Machine Learning	Science Direct	Research in artificial intelligence and machine learning can help improve imaging of EEGs, resulting in better understanding and diagnosis of epileptic seizures.
An, S., Kang, C. and Lee, H.W., 2020. Artificial intelligence and computational approaches for epilepsy. Journal of epilepsy research, 10(1), p.8.	An, S., Kang, C. and Lee, H.W.	-	Machine Learning	Researc hGate	For improved performance and successful clinical application of developed computational systems, close cooperation in various fields such as medicine, neuroscience, computer science and engineering is crucial.
Posada-Quintero, H.F. and Chon, K.H., 2020. Innovations in electrodermal activity data collection and signal processing: A systematic review. Sensors, 20(2), p.479.	Posada-Quintero, H.F. and Chon, K.H.	Electrodermal activity (EDA)	Machine Learning	Researc hGate	There are tools available for detecting and removing corrupted signals of EDA, but their sensitivity is a factor that needs to be further evaluated.
Van Andel, J., Ungureanu, C., Aarts, R., Leijten, F. and Arends, J., 2015. Using photoplethysmography in heart rate monitoring of patients with epilepsy. Epilepsy & Behavior, 45, pp.142-145.	Van Andel, J., Ungureanu, C., Aarts, R., Leijten, F. and Arends, J.	Photoplethy smography(PCG)	Machine learning	PubMe d	In ambulatory heart rate monitoring of patients diagnosed with epilepsy, the heart rate measured with OHR sensor seemed to be equivalent to the heart rate received from automatic ECG analysis.

Mustafa Halimeh, Yonghua Yang, Theodore Sheehan, Solveig Viieluf, Michele Jackson, Tobias Loddenkemper, Christian Meisel. Wearable device assessments of antiseizure medication effects on diurnal patterns of electrodermal activity, heart rate, and heart rate variability - Article preview.	Mustafa Halimeh, Yonghua Yang, Theodore Sheehan, Solveig Viieluf, Michele Jackson, Tobias Loddenkemper,Christian Meisel.	Electrodermal Activity (EDA)	Machine Learning	Science Direct	The multimodal assessment of different data modalities provided by wearable devices may offer a more comprehensive evaluation of antiseizure medications' effects on the ANS, leading to better seizure detection, forecasting, and treatment monitoring in the ambulatory setting.
Jonas Munch Nielsen, Ivan C. Zibrandtsen, Paolo Masulli, Torben Lykke Sørensen, Tobias S. Andersen, Troels Wesenberg Kjær. Towards a wearable multi-modal seizure detection system in epilepsy: A pilot study.	Jonas Munch Nielsen, Ivan C. Zibrandtsen, Paolo Masulli, Torben Lykke Sørensen, Tobias S. Andersen, Troels Wesenberg Kjær.	Electroencephalogram (EEG), Electrocardiogram (ECG), Accelerometer (ACC)	Machine Learning	Science Direct	Visualizations of EEG and ECG features were found to be useful for supplementing manual data review.
Lockman J, Fisher RS, Olson DM. Detection of seizure-like movements using a wrist accelerometer. Epilepsy Behav. 2011 Apr;20(4):638-41. Doi: 10.1016/j.yebeh.2011.01.019. Epub 2011 Mar 29. PMID: 21450533.	Lockman J, Fisher RS, Olson DM.	Accelerometer (ACC)	-	Science Direct	This study shows tonic–clonic seizure detection based on wrist-worn motion detector with a Bluetooth link to a computer.

Affanni, A., 2020. Wireless sensors system for stress detection by means of ECG and EDA acquisition. Sensors, 20(7), p.2026.	Affanni, A.	Electrodermal activity (EDA) sensor Electrocardiogram (ECG) sensor	Machine Learning, SVM Classifier	ResearchGate	The researchers designed a wearable sensors system for measuring two channels SPR (Skin Potential Response) from the hands and two channels ECG from chest.
Majumder, A.K.M., ElSaadany, Y.A., Young, R. and Ucci, D.R., 2019. An energy efficient wearable smart IoT system to predict cardiac arrest. Advances in Human-Computer Interaction, 2019.	Majumder, A.K.M., ElSaadany, Y.A., Young, R. and Ucci, D.R.	Heart Rate, Body Temperatures	IoT System	ResearchGate	In this paper, researchers designed and developed an integrated smart IoT system to predict and monitor heart abnormality in patients.
Moodbidri, A. and Shahnasser, H., 2017, January. Child safety wearable device. In 2017 International Conference on Information Networking (ICOIN) (pp. 438-444). IEEE.	Moodbidri, A. and Shahnasser, H.	Real-time location, surrounding temperature, UV radiation index, Distress alarm buzzer	IoT System	ResearchGate	It provides parents with the real-time location, surrounding temperature, UV radiation index and Distress alarm buzzer functionality locate their child or alert bystanders to rescue or comfort the child.
Chen, Y.H., Chiou, H.Y., Lin, H.C. and Lin, H.L., 2009. Affect of seizures during gestation on pregnancy outcomes in women with epilepsy. Archives of neurology, 66(8), pp.979-984.	Chen, Y.H., Chiou, H.Y., Lin, H.C. and Lin, H.L.	-	-	PubMed	The paper found that women who had seizures during pregnancy had higher odds of preterm birth, LBW, and SGA infants than women without epilepsy.
Bornoiu, I.V. and Grigore, O., 2013, May. A study about feature extraction for stress detection. In 2013 8th International Symposium on Advanced Topics in Electrical Engineering (ATEE) (pp. 1-4). IEEE.	Bornoiu, I.V. and Grigore, O	Heart Rate, Electromyography (EMG), Electrocardiogram (ECG), Electroencephalogram (EEG)	-	Semantic Scholar	Overall, it seems like this paper may be of interest to researchers studying EDA signals and their relationship to stress and other physiological responses.

Sai Manohar Beeraka, Abhash Kumar, Mustafa Sameer, Sanchita Ghosh, Bharat Gupta. Accuracy Enhancement of Epileptic Seizure Detection: A Deep Learning Approach with Hardware Realization of STFT.	Sai Manohar Beeraka, Abhash Kumar, Mustafa Sameer, Sanchita Ghosh, Bharat Gupta.	Electroencephalogram (EEG)	Deep Learning models STFT, CNN, Bi-LSTM	ResearchGate	The study demonstrates the potential of deep learning-based approaches for EEG analysis and seizure detection, providing a promising direction for future research in this field.

Table 2.1: Literature Survey Summary Table

2.2. EXISTING SYSTEM

For people who experience epileptic seizures, wearable technologies that automatically detect and forecast seizures could be a game-changer. Embrace E4 watches can identify seizures well in advance of their beginning. Using features like electrodermal activity (EDA), For people who experience epileptic seizures, wearable technologies that automatically detect and forecast seizures could be a game-changer. Embrace E4 watches can identify seizures well in advance of their beginning. Using features like electrodermal activity (EDA), heart rate, blood pressure, and acceleration, it learns and evaluates using sophisticated machine learning techniques. These gadgets make use of machine learning techniques that perform analysis of a person's sensor responses and seizure frequency. The sensor responses were improved by the data availability, leading to very low false alarm rates. With the help of the Embrace E4 watches, GTCS was successfully detected. EDA, ACC, and BVP sensors are used. The watch's success rates ranged from 92% to 100%, whereas the watch's percentage of false alarms varied from 0.1% to 2%. As the sensitivity is nearly 100 %, this device can reduce the risk of SUDEP by predicting the seizure. It also has an added location feature that can alert the caregivers when the patients have a possible epileptic seizure. But still the False Alarm Rate (FRA) was higher than expected. Therefore, machine learning algorithms can be used to differentiate between a seizure and a false seizure. This could help patients and could be used for monitoring and further understanding of epileptic seizures.

Fig 2.1: Empatica E4 Wristband

2.3. PROBLEM FORMULATION

A seizure is a neurological condition developed by an abrupt burst of electrical activity in the brain. Epilepsy is a condition caused by frequent seizures due to unknown triggers. It affects about 50 million individuals, making it one of the most prevalent neurological conditions worldwide. Both the person having the seizure and others nearby find it frightening and unsettling. These are typically non-life-threatening, and, with proper care and assistance, many sufferers can have a healthy life.

There have been many approaches to developing systems that can monitor seizure patients and detect seizures. Seizures can be easily identified by ECG or EEG waves. But the sensors and systems that can detect ECG and EEG waves are not portable or convenient to use. Then came the idea of using a wrist-worn device like a watch, which is mobile and conveniently sized for this purpose.

To make the model viable, we need sensors that need to be attached to a device that can detect seizures. This cannot be made possible with any one sensor, thus the use multimodal sensor approach. The most practical sensors applicable for this are the ACC and EDA sensors. The Accelerometery (ACC) sensor can pinpoint the position of the device and track sudden movements. Electrodermal activity (EDA) sensor measures the variations in skin conductivity brought on by an increase in sweat gland activity.

Machine learning algorithms can be used to train the model using data acquired from the sensors, we can develop a model that can detect seizures. Further, we can improve this model and implement it on the wristwear device, which will have the functionality of alerting the connected carers when seizures are detected.

2.4. PROPOSED SYSTEM

The proposed system is a machine learning model that can accurately detect seizures in individuals with epilepsy. The system involves using wearable sensors to collect data on movement, heart rate, and other physiological parameters. The main goal of the system is to develop a highly sensitive and specific machine learning model that can accurately detect seizures in real-time. The model should be trained on a large dataset of labelled seizure and non-seizure data to enable it to learn the complex patterns and characteristics associated with seizures. Improving the overall performance of the model will be a critical objective of the research, thereby increasing the model's accuracy. By developing a machine learning model to detect seizures, individuals with epilepsy can benefit from timely interventions that reduce the risk of injury or other serious consequences. Additionally, this technology can provide caregivers and medical professionals with valuable information that can inform treatment decisions and improve the overall management of epilepsy.

2.5. OBJECTIVES

- **To develop accurate seizure detection algorithm using wearable devices.**
- **To evaluate the performance of the seizure detection system.**
- **To validate the seizure detection system.**
- **To optimize the wearable device.**
- **To understand the clinical application of the seizure detection system.**

CHAPTER – 3
DESIGN FLOW / METHODOLOGY

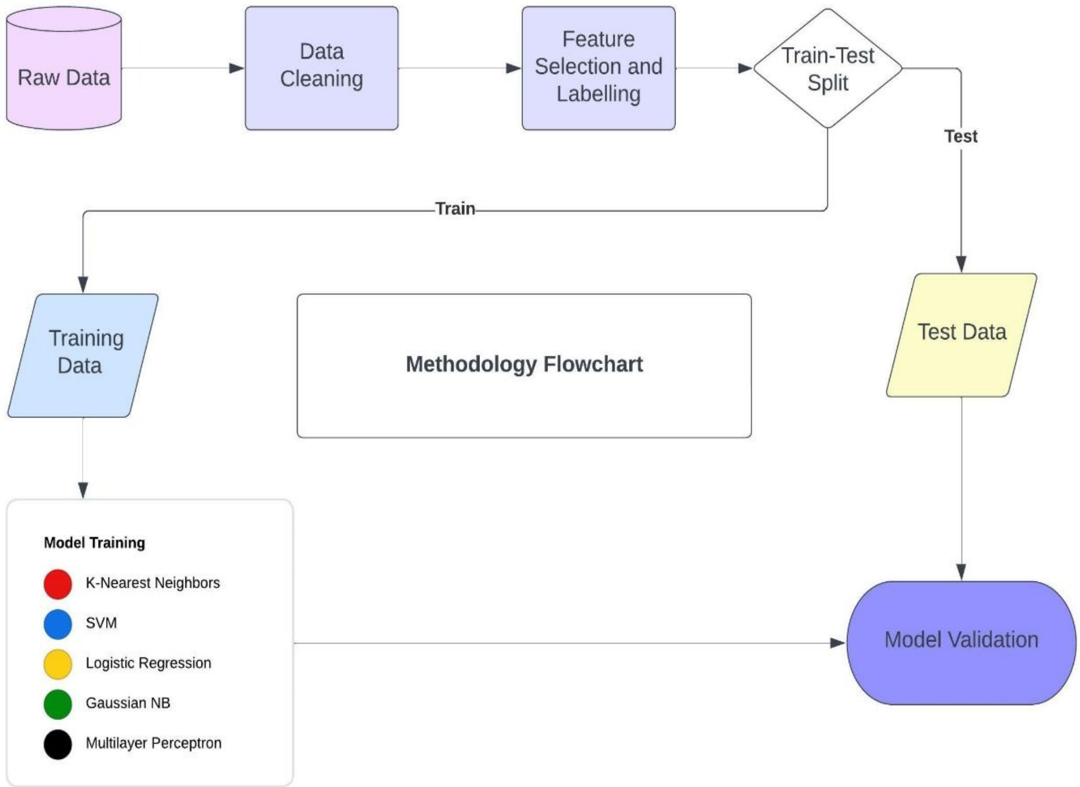


Fig 3.1: Methodology Flowchart

In order to work with the dataset, necessary libraries were imported. The CSV file was read and stored in a variable to progress with the work. The raw dataset is then sliced into a smaller dataset of 25,000 rows. The features in the multimodal data are: accelerometery ACC (x-axis, y-axis, z-axis, and magnitude), heart rate variability (HR), blood volume pulse (BVP) and electrodermal activity (EDA). Firstly, the data was cleaned, and null or error values were replaced and fixed. The ACC values were highly correlated. By plotting the EDA and HR values, we recognised a variation and pattern in the data points. Accordingly, we set the threshold values and classified the data as 1 for the rows where thresholds were less than the actual data value and 0 for the rest. After that, the data were separated into training and testing sets. Then, to use the dataset, the machine learning algorithms were imported and put into use. The performance metrics and ROC curves of the machine learning algorithms were obtained.

Classification algorithms used:

The dataset was processed using the following machine learning algorithms: Logistic Regression, Random Forest Classifier, Gradient Boosting Classifier, SVM, KNN, GNB, and MLP.

- Logistic Regression:

A common statistical analysis technique for estimating the likelihood of an occurrence or result based on a set of independent variables is logistic regression. It can be used in medical research to estimate the probability of an event, like seizures, depending on a number of characteristics or independent variables, such age, gender, and medical history.

The result or dependent variable in logistic regression is binary, which means it might have one of two possible values, such as seizure or no seizure. The dependent variable's likelihood of taking on the value of either of the independent factors is predicted using the independent variables.

The logistic curve that results from logistic regression demonstrates the connection between the independent factors and the likelihood of the dependent variable occurring. When given a set of values for the independent variables, the curve is used to calculate the likelihood that an event will occur. As the value of the independent variable rises, the curve gradually rises from 0 on the y-axis to 1 on the y-axis.

A probabilistic value, which is a continuous value ranging from 0 to 1, is the result of logistic regression. This number shows the likelihood that an event, such a seizure, will occur. While numbers closer to 0 or 1 imply a stronger possibility of one outcome over the other, a value of 0.5 indicates that the event is equally likely to occur or not.

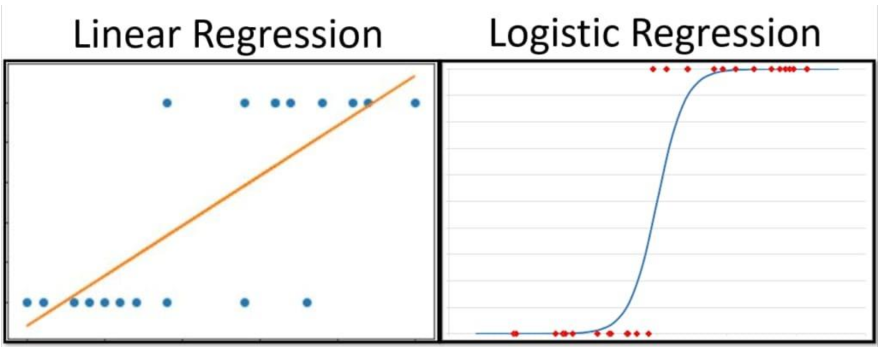


Fig 3.2: Logistic Regression

- Random Forest:

A machine learning system called Random Forest combines the results of various decision trees. There are two main steps to the algorithm.

Making the decision trees is the initial step. The algorithm randomly chooses K data points from the training set with replacement in order to construct the trees. Each decision tree is trained using the K data points that were used. The approach lessens the possibility of overfitting to the training data by building each tree from a random subset of the training data.

Recursive partitioning is a technique used to create the decision trees. Based on the values of the independent variables, the algorithm divides the data into smaller subsets in this procedure. The objective is to build tree branches that maximise the distance between data points with various values for the dependent variable. A stopping criterion, such as a minimum number of data points in a subset or a maximum depth of the tree, is reached when this procedure is still ongoing.

The predictions for each of the trees are made in the second stage of the algorithm. The method uses the mean of all the predictions from all the decision trees to produce a forecast. The accuracy of the entire model is improved and the variation in the predictions is reduced as a result of this approach.

- Gradient Boosting Classifier:

The ensemble method family of machine learning algorithms, which combines several weak models to create a stronger one, includes the gradient boosting classifier. The approach works by focusing on the incorrectly categorised instances while iteratively adding additional weak predictors to the model and changing the weights of the training examples. This method is known as boosting.

On the whole training dataset, the algorithm trains a weak model in the first iteration, which is often a decision tree with low depth. Although this weak model can produce predictions, its accuracy is likely to be low since it might not be able to fully capture the many relationships in the data.

The method adds new trees in successive iterations in an effort to strengthen the weak model. The residual mistakes of the prior model are used to train each new tree. This method keeps going until a predetermined stopping criterion is satisfied, such as the maximum number of trees or the minimum accuracy improvement.
In order to best utilise the loss function, which gauges the discrepancy between anticipated and actual values, additional trees are incorporated into the model. The algorithm adjusts the weights of the training instances based on the inaccuracy of the prior model to obtain the ideal weights for the new trees using a gradient descent approach.

By incrementally enhancing the prior models, the gradient boosting classifier combines weak models to create a strong one in this manner. Every new model concentrates on the flaws of the preceding model and makes an effort to fix them. Even if the individual predictors have low accuracy, this method aids in improving the model's accuracy.

- Support Vector Machine (SVM):

For classification and regression analysis, machine learning algorithms called Support Vector Machines (SVMs) are used. The SVM algorithm searches for a hyperplane in n-dimensional space that may divide the data points into distinct classes when used for classification. A decision boundary called a hyperplane maximises the margin, or the distance between it and the closest data points for each class.

The SVM technique first converts the input data points from their original n-dimensional space to a higher-dimensional space, where a hyperplane may be more easily drawn to divide the data points apart. Utilising a kernel function, which compares two data points in the original space and maps them to a new space, accomplishes this.

Support vectors are the data points that are most closely located to the hyperplane, or the line dividing the classes. The risk of overfitting to the training data is decreased by selecting the hyperplane to maximise the margin between the support vectors from each class.

The SVM algorithm may categorise fresh and incoming datasets by mapping them to the same higher-dimensional space and determining which side of the hyperplane they fall on once the hyperplane has been established. A new data point is categorised as belonging to one class if it falls on one side of the hyperplane, and to another class if it falls on the opposite side.

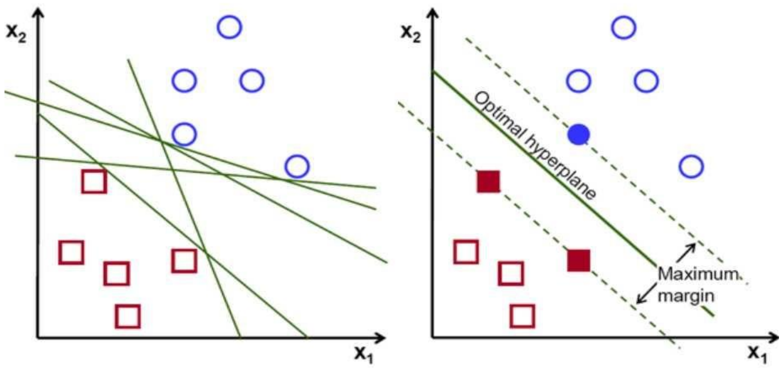


Fig 3.3: SVM

- K-Nearest Neighbors (KNN):

Machine learning algorithms like the KNN (K-Nearest Neighbours) algorithm are typically utilised for classification and regression analysis. It operates by presuming that new data and existing data are similar, and then assigning the new data to the class that is most similar to the existing data.

The dataset is saved for later use during the training phase of the KNN algorithm. When new data is received, the algorithm first chooses the K neighbours in the feature space that are closest to the new data point. K is a hyperparameter that the user sets to indicate how many nearest neighbours should be taken into account.

The programme then determines the Euclidean separation between each of the new data point's K neighbours and it. The Euclidean distance, which is determined as the square root of the sum of the squared differences between each coordinate of the two points, is a unit used to describe the separation between two points in a multidimensional space.

The algorithm places the new data point in the class that is most prevalent among its K neighbours after measuring the distances between it and each of its K neighbours. This indicates that the new data point is allocated to a class if the majority of the neighbours are members of that class.

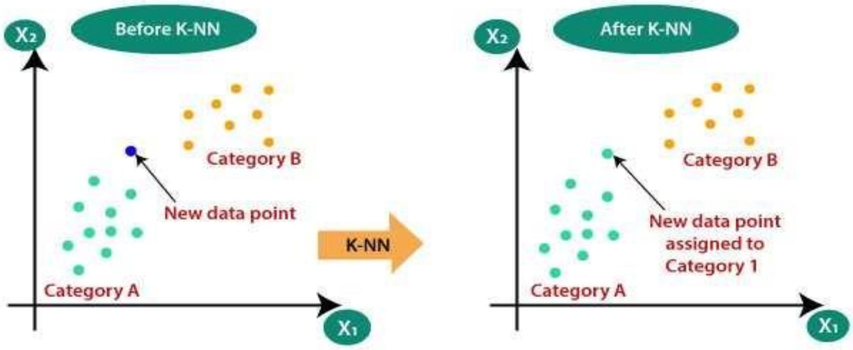


Fig 3.4: KNN

- Gaussian Naïve Bayes:

A well-liked machine learning approach for classification tasks is the Naive Bayes algorithm. It is based on the Bayes theorem, a mathematical formula that determines the likelihood of a hypothesis (or occurrence) in light of previously collected data or other supporting information.

According to the Bayes theorem, the likelihood of a hypothesis H given evidence E is equal to the likelihood of the evidence given the hypothesis multiplied by the likelihood of the hypothesis prior divided by the likelihood of the evidence.

The Naive Bayes approach converts the dataset into frequency tables by creating likelihood tables using the probabilities of the supplied characteristics. This method is referred to as "Naive" since it is predicated on the notion of feature independence.
Following the creation of the frequency tables, the posterior probability is computed utilising the Bayes theorem. The likelihood divided by the posterior probability, which is the product of the prior probability and the likelihood, is the probability of the hypothesis given the evidence.

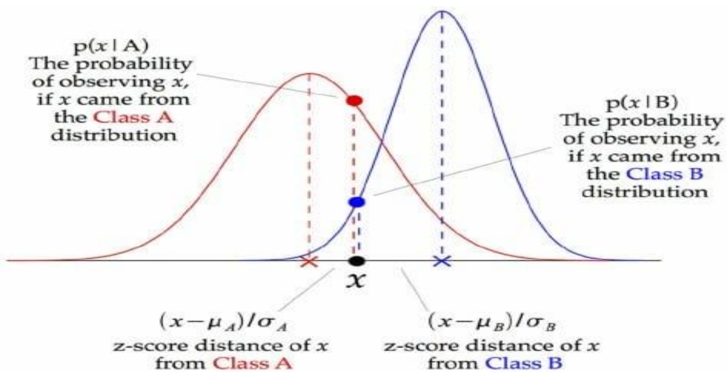


Fig 3.5: GNB

- Multi-Layer Perceptron:

The capability of the TensorFlow library to modify input dimensions using a neural network with several layers appears to be described in the text.

A well-liked open-source package for deep learning and machine learning tasks is called TensorFlow. Building and training deep neural networks, which are made up of numerous layers of interconnected nodes, is one of TensorFlow's core characteristics. These networks are employed for a variety of applications, including natural language processing, picture and audio recognition, and many others.

Deep neural networks have the benefit of being able to automatically train to extract meaningful features from unprocessed input data, such as photos or audio signals. Before the input data can be used as input to a neural network, it frequently needs to be converted and preprocessed.

This is where TensorFlow's capability to modify the input dimension is useful. For preprocessing and manipulating data, TensorFlow offers a range of tools and functions, including tools for bending input dimensions. For applications like image classification or natural language processing, it is possible to shift input data from one dimension to another by employing a neural network with multiple layers.

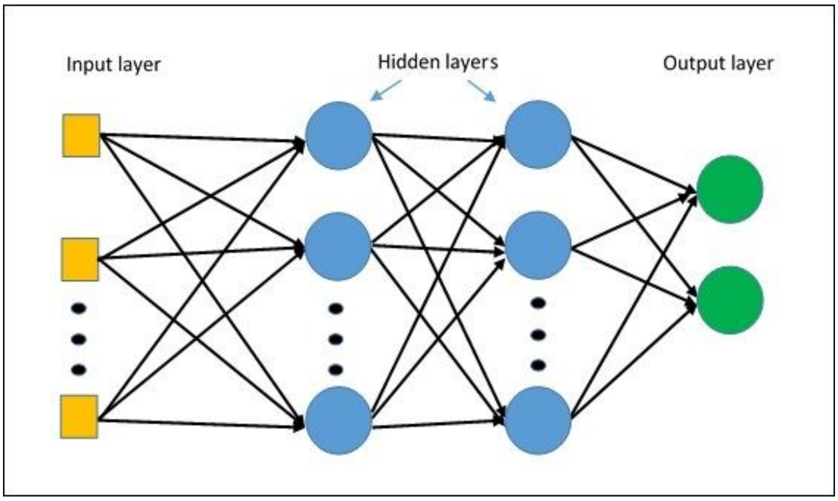


Fig 3.6: MLP

3.1. IMPLEMENTATION

```
[1] import pandas as pd
```

```
[3] dfa = pd.read_csv('/content/extracted_data.csv')
    dfa
```

	utc_timestamp	acc_x	acc_y	acc_z	acc_mag	bvp	eda	hr	temp
0	1582878000	19.002142	20.001913	-57.99558	63.221635	18.143450	0.438182	59.053240	35.250505
1	1582878000	19.002142	20.001913	-57.99558	63.221635	17.434694	0.438182	59.053240	35.250505
2	1582878000	19.002142	20.001913	-57.99558	63.221635	16.637344	0.438182	59.055033	35.250505
3	1582878000	19.002142	20.001913	-57.99558	63.221635	15.839994	0.438182	59.056827	35.250505
4	1582878000	19.002142	20.001913	-57.99558	63.221635	15.042643	0.438182	59.058620	35.250505
...	...	...	...	...	...	...	...	...	...
24995	1582878195	18.032975	20.001913	-57.99558	62.946187	19.738151	0.233303	44.950617	35.212704
24996	1582878195	18.282918	20.001913	-57.99558	63.012499	18.409233	0.233303	44.950617	35.212704
24997	1582878195	18.532861	20.001913	-57.99558	63.089012	17.080316	0.233303	44.950617	35.212704
24998	1582878195	18.782804	20.001913	-57.99558	63.160424	15.839994	0.233303	44.950617	35.212704
24999	1582878195	18.971536	20.001913	-57.99558	63.211433	14.688265	0.233303	44.950617	35.212704

25000 rows × 9 columns

Fig 3.7: Raw Data

```
[ ] import matplotlib.pyplot as plt
```

```
plt.plot(dfa.index,dfa.eda)
```

```
[<matplotlib.lines.Line2D at 0x7f1101e2e0e0>]
```

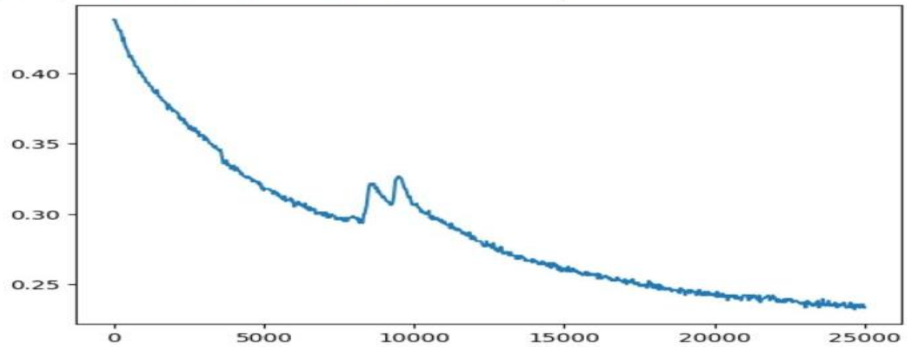


Fig 3.8

```
plt.plot(dfa.eda,dfa.hr)
plt.xlabel("EDA")
plt.ylabel("HR")
```

```
Text(0, 0.5, 'HR')
```

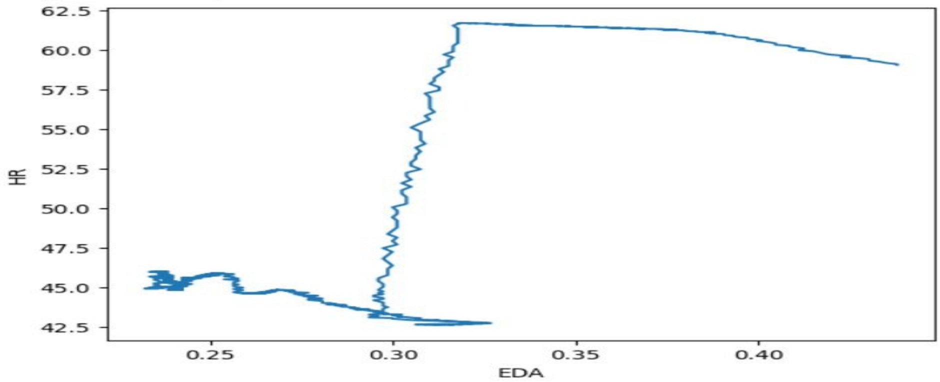


Fig 3.9

```
[ ] threshold1 = 0.33
    threshold2 = 58.6
    dfa['target'] = ((dfa['eda'] >= threshold1) & (dfa['hr'] >= threshold2)).astype(int)
```

```
dfa
```

	utc_timestamp	acc_x	acc_y	acc_z	acc_mag	bvp	eda	hr	temp	target
0	1582878000	19.002142	20.001913	-57.99558	63.221635	18.143450	0.438182	59.053240	35.250505	1
1	1582878000	19.002142	20.001913	-57.99558	63.221635	17.434694	0.438182	59.053240	35.250505	1
2	1582878000	19.002142	20.001913	-57.99558	63.221635	16.637344	0.438182	59.055033	35.250505	1
3	1582878000	19.002142	20.001913	-57.99558	63.221635	15.839994	0.438182	59.056827	35.250505	1
4	1582878000	19.002142	20.001913	-57.99558	63.221635	15.042643	0.438182	59.058620	35.250505	1
...	...	...	...	...	...	...	...	...	...	...
24995	1582878195	18.032975	20.001913	-57.99558	62.946187	19.738151	0.233303	44.950617	35.212704	0
24996	1582878195	18.282918	20.001913	-57.99558	63.012499	18.409233	0.233303	44.950617	35.212704	0
24997	1582878195	18.532861	20.001913	-57.99558	63.089012	17.080316	0.233303	44.950617	35.212704	0
24998	1582878195	18.782804	20.001913	-57.99558	63.160424	15.839994	0.233303	44.950617	35.212704	0
24999	1582878195	18.971536	20.001913	-57.99558	63.211433	14.688265	0.233303	44.950617	35.212704	0

25000 rows × 10 columns

Fig 3.10

```
columns_to_drop = ['acc_mag','utc_timestamp']
dfa.drop(columns_to_drop, axis=1, inplace=True)
print(dfa)
```

```
           acc_x      acc_y      acc_z        bvp       eda         hr  \
0      19.002142  20.001913 -57.99558  18.143450  0.438182  59.053240
1      19.002142  20.001913 -57.99558  17.434694  0.438182  59.053240
2      19.002142  20.001913 -57.99558  16.637344  0.438182  59.055033
3      19.002142  20.001913 -57.99558  15.839994  0.438182  59.056827
4      19.002142  20.001913 -57.99558  15.042643  0.438182  59.058620
...          ...        ...       ...        ...       ...        ...
24995  18.032975  20.001913 -57.99558  19.738151  0.233303  44.950617
24996  18.282918  20.001913 -57.99558  18.409233  0.233303  44.950617
24997  18.532861  20.001913 -57.99558  17.080316  0.233303  44.950617
24998  18.782804  20.001913 -57.99558  15.839994  0.233303  44.950617
24999  18.971536  20.001913 -57.99558  14.688265  0.233303  44.950617

            temp
0      35.250505
1      35.250505
2      35.250505
3      35.250505
4      35.250505
...          ...
24995  35.212704
24996  35.212704
24997  35.212704
24998  35.212704
24999  35.212704

[25000 rows x 7 columns]
```

Fig 3.11

```
x = dfa.iloc[:,0:7]
x
```

	acc_x	acc_y	acc_z	bvp	eda	hr	temp
0	19.002142	20.001913	-57.99558	18.143450	0.438182	59.053240	35.250505
1	19.002142	20.001913	-57.99558	17.434694	0.438182	59.053240	35.250505
2	19.002142	20.001913	-57.99558	16.637344	0.438182	59.055033	35.250505
3	19.002142	20.001913	-57.99558	15.839994	0.438182	59.056827	35.250505
4	19.002142	20.001913	-57.99558	15.042643	0.438182	59.058620	35.250505
...	...	...	...	...	...	...	...
24995	18.032975	20.001913	-57.99558	19.738151	0.233303	44.950617	35.212704
24996	18.282918	20.001913	-57.99558	18.409233	0.233303	44.950617	35.212704
24997	18.532861	20.001913	-57.99558	17.080316	0.233303	44.950617	35.212704
24998	18.782804	20.001913	-57.99558	15.839994	0.233303	44.950617	35.212704
24999	18.971536	20.001913	-57.99558	14.688265	0.233303	44.950617	35.212704

25000 rows × 7 columns

Fig 3.12

```
y = dfa.target
y
```

```
0        1
1        1
2        1
3        1
4        1
        ..
24995    0
24996    0
24997    0
24998    0
24999    0
Name: target, Length: 25000, dtype: int64
```

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.25, random_state=1)
```

Fig 3.13

```
from sklearn.neighbors import KNeighborsClassifier
knn= KNeighborsClassifier(n_neighbors=1800)
knn.fit(x_train, y_train)
```

```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=1800)
```

```
y_pred= knn.predict(x_test)
```

```
from sklearn.metrics import confusion_matrix
cm1= confusion_matrix(y_test, y_pred)
cm1
```

```
array([[5075,   80],
       [ 150,  945]])
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      5155
           1       0.92      0.86      0.89      1095

    accuracy                           0.96      6250
   macro avg       0.95      0.92      0.93      6250
weighted avg       0.96      0.96      0.96      6250
```

Fig 3.14: KNN

```
[ ]  from sklearn.svm import SVC
```

```
svc_model = SVC(C=.15, kernel='linear', gamma=2)
svc_model.fit(x_train, y_train)

prediction = svc_model .predict(x_test)
y_pred2= svc_model.predict(x_test)
```

```
[ ]  from sklearn.metrics import confusion_matrix
     cm2= confusion_matrix(y_test, y_pred2)
     cm2

     array([[5053,  102],
            [  73, 1022]])
```

```
[ ]  from sklearn.metrics import classification_report
     print(classification_report(y_test,y_pred2))

                  precision    recall  f1-score   support

               0       0.99      0.98      0.98      5155
               1       0.91      0.93      0.92      1095

        accuracy                           0.97      6250
       macro avg       0.95      0.96      0.95      6250
    weighted avg       0.97      0.97      0.97      6250
```

Fig 3.15: SVM

```
[ ]  from sklearn.linear_model import LogisticRegression
     lr = LogisticRegression()
     lr.fit(x_train, y_train)
     y_pred3= lr.predict(x_test)
```

```
[ ]  from sklearn.metrics import confusion_matrix
     cm3= confusion_matrix(y_test, y_pred3)
     cm3

     array([[5053,  102],
            [  67, 1028]])
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred3))

              precision    recall  f1-score   support

           0       0.99      0.98      0.98      5155
           1       0.91      0.94      0.92      1095

    accuracy                           0.97      6250
   macro avg       0.95      0.96      0.95      6250
weighted avg       0.97      0.97      0.97      6250
```

Fig 3.16: Logistic Regression

```
[ ] from sklearn.naive_bayes import GaussianNB
    nb = GaussianNB()
    nb.fit(x_train,y_train)
    y_pred4= nb.predict(x_test)
```

```
[ ] from sklearn.metrics import confusion_matrix
    cm4= confusion_matrix(y_test, y_pred4)
    cm4

    array([[4947,  208],
           [   1, 1094]])
```

```
from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred4))

              precision    recall  f1-score   support

           0       1.00      0.96      0.98      5155
           1       0.84      1.00      0.91      1095

    accuracy                           0.97      6250
   macro avg       0.92      0.98      0.95      6250
weighted avg       0.97      0.97      0.97      6250
```

Fig 3.17: Naïve Bayes

```
[ ] from sklearn.neural_network import MLPClassifier
    mlp = MLPClassifier()
    mlp.fit(x_train,y_train)
    y_pred7= mlp.predict(x_test)
```

```
from sklearn.metrics import confusion_matrix
cm5= confusion_matrix(y_test, y_pred7)
cm5

array([[5049,  106],
       [  54, 1041]])
```

```
[ ] from sklearn.metrics import classification_report
    print(classification_report(y_test,y_pred7))

              precision    recall  f1-score   support

           0       0.99      0.98      0.98      5155
           1       0.91      0.95      0.93      1095

    accuracy                           0.97      6250
   macro avg       0.95      0.97      0.96      6250
weighted avg       0.98      0.97      0.97      6250
```

Fig 3.18: MLP Classifier

```
[ ] from sklearn.metrics import confusion_matrix, accuracy_score, log_loss, precision_score, recall_score, f1_score, roc_auc_score
    import seaborn as sns
    from sklearn.metrics import roc_curve, auc
```

```
print("KNN")
print(" accuracy = ",accuracy_score(y_test, y_pred),
      "\n precision = ", precision_score(y_test, y_pred, average = 'macro'),
      "\n recall = ", recall_score(y_test, y_pred, average = 'macro'),
      "\n f_score = ", f1_score(y_test, y_pred, average = 'macro'))
print(cm1)


test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred)

plt.grid()

plt.plot(test_fpr, test_tpr, label=" AUC TEST ="+str(auc(test_fpr, test_tpr)))
plt.plot([0,1],[0,1],'g--')
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("AUC(ROC curve)")
plt.grid(color='black', linestyle='-', linewidth=0.5)
plt.show()
```

Fig 3.19

```
print("Log Regression")
print(" accuracy = ",accuracy_score(y_test, y_pred3),
      "\n precision = ", precision_score(y_test, y_pred3, average = 'macro'),
      "\n recall = ", recall_score(y_test, y_pred3, average = 'macro'),
      "\n f_score = ", f1_score(y_test, y_pred3, average = 'macro'))
print(cm3)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred3)

plt.grid()

plt.plot(test_fpr, test_tpr, label=" AUC TEST ="+str(auc(test_fpr, test_tpr)))
plt.plot([0,1],[0,1],'g--')
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("AUC(ROC curve)")
plt.grid(color='black', linestyle='-', linewidth=0.5)
plt.show()
```

Fig 3.20

```
print("SVM")
print(" accuracy = ",accuracy_score(y_test, y_pred2),
      "\n precision = ", precision_score(y_test, y_pred2, average = 'macro'),
      "\n recall = ", recall_score(y_test, y_pred2, average = 'macro'),
      "\n f_score = ", f1_score(y_test, y_pred2, average = 'macro'))
print(cm2)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred2)

plt.grid()

plt.plot(test_fpr, test_tpr, label=" AUC TEST ="+str(auc(test_fpr, test_tpr)))
plt.plot([0,1],[0,1],'g--')
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("AUC(ROC curve)")
plt.grid(color='black', linestyle='-', linewidth=0.5)
plt.show()
```

Fig 3.21

```
[ ] print("Naive Bayes")
    print(" accuracy = ",accuracy_score(y_test, y_pred4),
          "\n precision = ", precision_score(y_test, y_pred4, average = 'macro'),
          "\n recall = ", recall_score(y_test, y_pred4, average = 'macro'),
          "\n f_score = ", f1_score(y_test, y_pred4, average = 'macro'))
    print(cm4)
    test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred4)

    plt.grid()

    plt.plot(test_fpr, test_tpr, label=" AUC TEST ="+str(auc(test_fpr, test_tpr)))
    plt.plot([0,1],[0,1],'g--')
    plt.legend()
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("AUC(ROC curve)")
    plt.grid(color='black', linestyle='-', linewidth=0.5)
    plt.show()
```

Fig 3.22

```
print("MLP")
print(" accuracy = ",accuracy_score(y_test, y_pred7),
      "\n precision = ", precision_score(y_test, y_pred7, average = 'macro'),
      "\n recall = ", recall_score(y_test, y_pred7, average = 'macro'),
      "\n f_score = ", f1_score(y_test, y_pred7, average = 'macro'))
print(cm5)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_pred7)

plt.grid()

plt.plot(test_fpr, test_tpr, label=" AUC TEST ="+str(auc(test_fpr, test_tpr)))
plt.plot([0,1],[0,1],'g--')
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("AUC(ROC curve)")
plt.grid(color='black', linestyle='-', linewidth=0.5)
plt.show()
```

Fig 3.23

CHAPTER – 4
RESULT ANALYSIS

Utilising the multimodal data gathered from wearable devices, various machine learning algorithms' performance was assessed for identifying seizures. In this research Logistic Regression, Support Vector Machine, K-Nearest Neighbors, Naive Bayes, and Multilayer Perceptron, was evaluated and compared using the perfomance metrics . The results are based on raw unlabeled data consisting of Accelerometer (ACC), Heart Rate (HR), Electrodermal Activity (EDA), Blood Volume Pulse (BVP) and Temperature of one patient recorded for 6 hours consisting of approximately 32 Lakh rows of data points which was then cut into smaller data of 25,000 data points.

The procedure of labelling the data presented the project's biggest hurdle. This required recognising the occurrence of erroneous values and comprehending the fluctuations present in sensor signals. The existence of strongly correlated features, notably the "acc_magnitude" feature, was one concern that came up. The decision was made to remove this feature from the dataset since it was generating issues and introducing errors. The remaining features were utilised to assess the model after the problematic feature was removed. Also, a variety of tree-based classification methods were used. However, the noise levels that these algorithms were creating overfitting.

Machine Learning Algorithms	Accuracy	Precision	Recall	F_Score
Logistic Regression	97.2%	94.8%	95.9%	95.3%
Support Vector Machine	97.2%	94.7%	95.6%	95.2%
K-Nearest Neighbors	96.3%	94.6%	92.3%	93.4%
Naive Bayes	96.6%	92%	97.9%	94.6%
Multilayer Perceptron	97.4%	94.8%	96.5%	95.6%

Table 4.1: Performance Metrics

```
KNN
 accuracy =  0.9632
 precision =  0.9466215427704516
 recall =  0.9237473924770472
 f_score =  0.9346757189079143
[[5075   80]
 [ 150  945]]
```

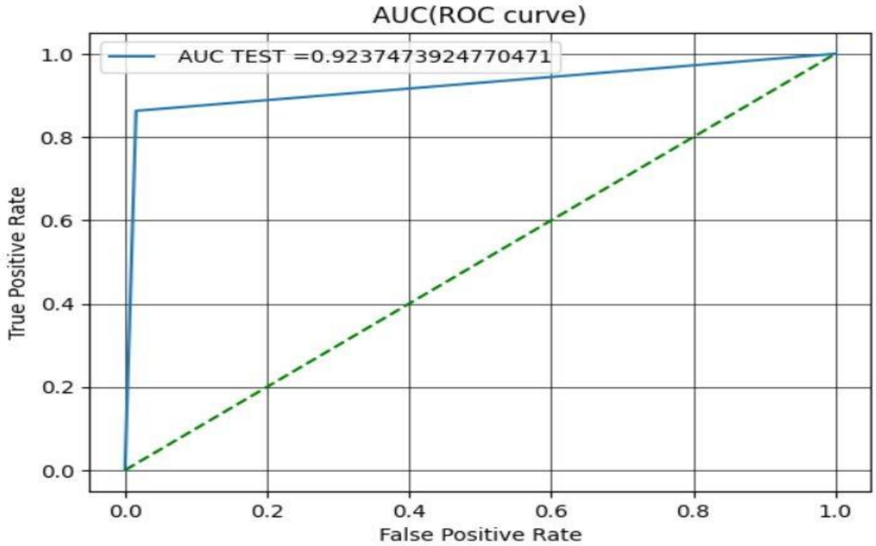


Fig 4.1: KNN – ROC

Confusion Matrix of KNN

	Predicted: NO	Predicted: YES
Actual: NO	5075	80
Actual: YES	150	945

Fig 4.2: KNN- Confusion Matrix

```
Log Regression
 accuracy =  0.97296
 precision =  0.9483242878871682
 recall =  0.9595130852255866
 f_score =  0.9537986276278739
[[5053  102]
 [  67 1028]]
```

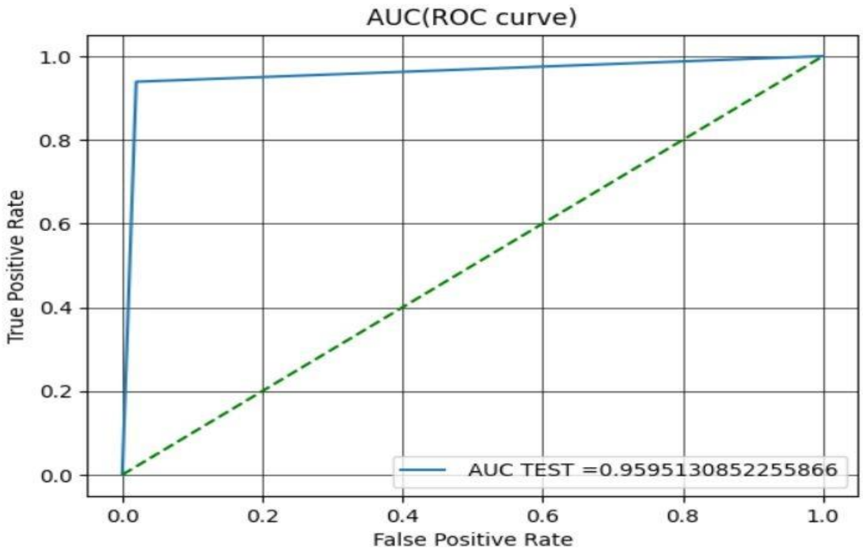


Fig 4.3: Logistic Regression - ROC

Confusion Matrix of Logistic Regression

	Predicted: NO	Predicted: YES
Actual: NO	5053	102
Actual: YES	67	1028

Fig 4.4: Logistic Regression – Confusion Matrix

```
SVM
 accuracy =  0.972
 precision =  0.9475057726779811
 recall =  0.9567733591981895
 f_score =  0.9520569780953319
[[5053  102]
 [  73 1022]]
```

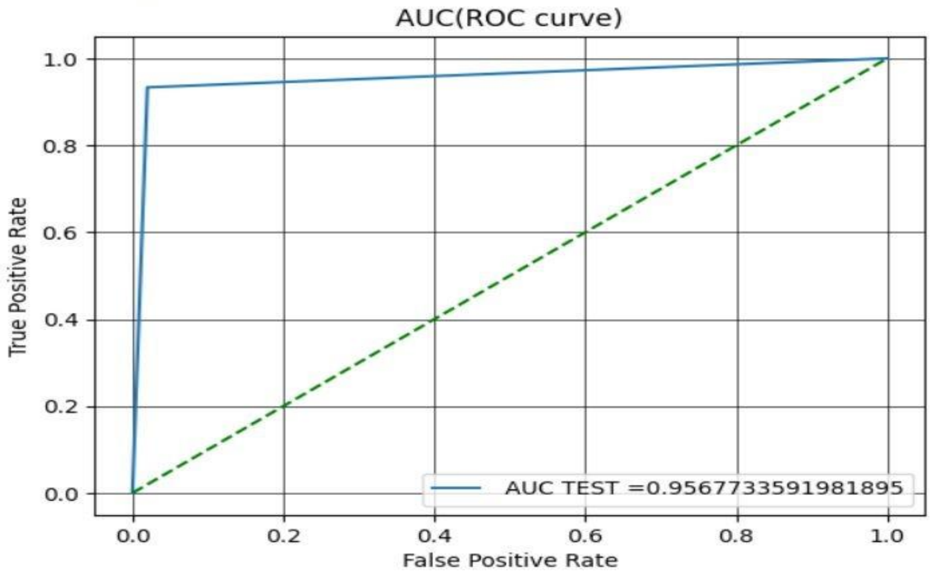


Fig 4.5: SVM – ROC

Confusion Matrix of SVM

	Predicted: NO	**Predicted: YES**
Actual: NO	5053	102
Actual: YES	73	1022

Fig 4.6: SVM – Confusion Matrix

```
Naive Bayes
 accuracy =  0.96656
 precision =  0.9200218369351547
 recall =  0.9793687912165783
 f_score =  0.9460603757930777
[[4947  208]
 [   1 1094]]
```

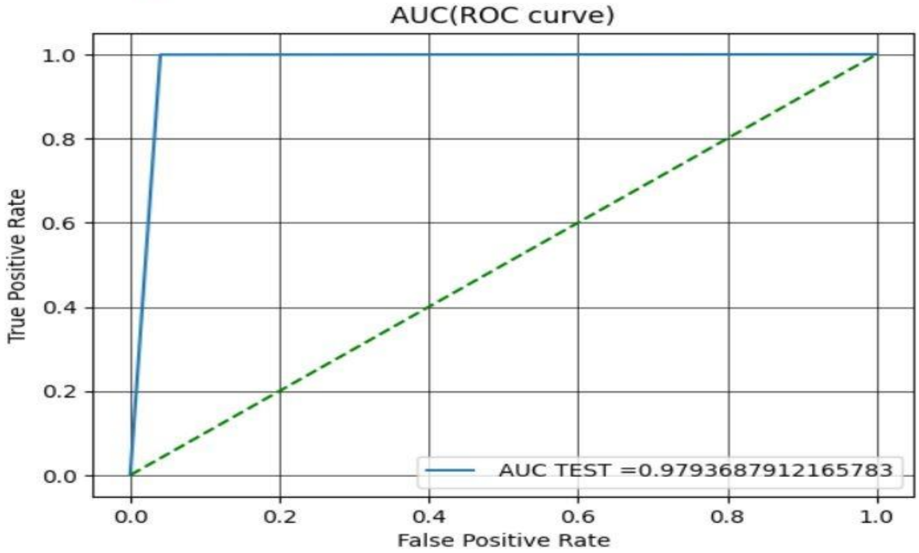


Fig 4.7: Naïve Bayes – ROC

Confusion Matrix of Naive Bayes

	Predicted: NO	**Predicted: YES**
Actual: NO	4947	208
Actual: YES	1	1094

Fig 4.8: Naïve Bayes – Confusion Matrix

```
MLP
 accuracy =  0.9744
 precision =  0.9485014968885936
 recall =  0.9650611854430464
 f_score =  0.9565187824076384
[[5049  106]
 [  54 1041]]
```

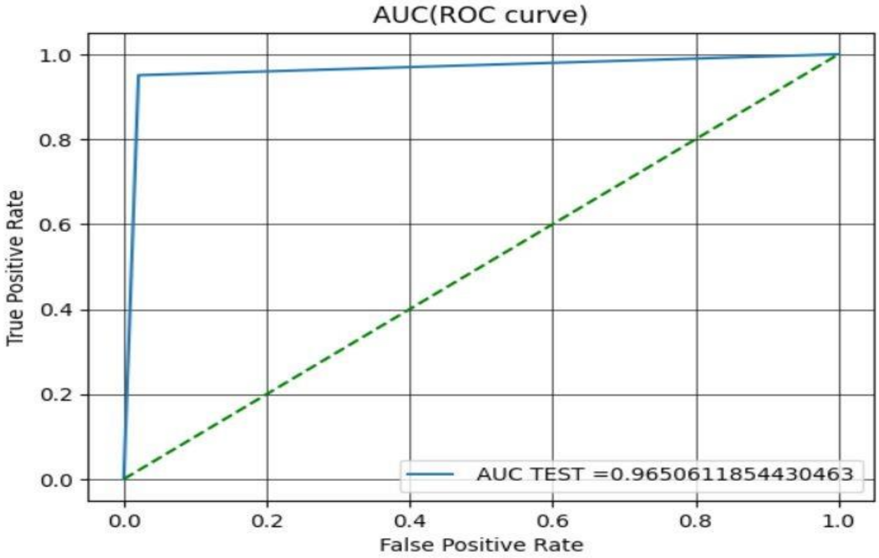


Fig 4.9: MLP - ROC

Confusion Matrix of MLP

	Predicted: NO	Predicted: YES
Actual: NO	5049	106
Actual: YES	54	1041

Fig 4.10: MLP – Confusion Matrix

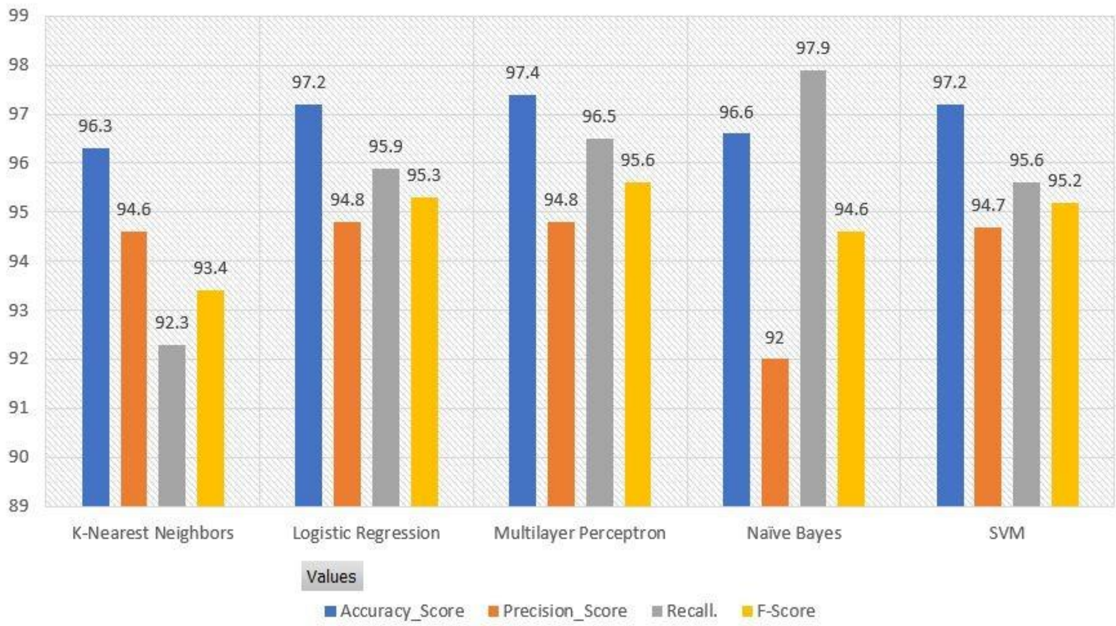


Fig 4.11: Performance Metrics

Negatives of Tree Classifiers on Binary Classification

Tree classifiers have several potential drawbacks in binary classification:

1. Overfitting: Tree classifiers have a tendency to overfit the training data, especially if the tree is allowed to grow to a large depth. This can result in a model that performs well on the training data but poorly on new data.
2. Bias and Variance: Tree classifiers can suffer from both bias and variance problems. A tree with a small depth may have high bias, meaning it may oversimplify the relationship between the features and the target variable, while a deep tree may have high variance, meaning it may be too sensitive to noise in the data.
3. Limited expressive power: Tree classifiers have limited expressive power when compared to other machine learning models. This is because trees can only represent linear decision boundaries, whereas other models, such as neural networks, can represent more complex non-linear relationships.
4. Imbalanced classes: Tree classifiers may struggle with imbalanced classes, where one class has significantly fewer observations than the other. This can result in a model that is biased towards the majority class.

Overall, while tree classifiers can be useful for binary classification problems, they do have some potential drawbacks that should be taken into consideration when deciding whether to use them for a particular problem.

CHAPTER – 5

CONCLUSION & FUTURE SCOPE

4.1. CONCLUSION

In conclusion, the research on the use of multimodal datasets and machine learning algorithms to detect seizures has shed light on the potential of wearable technology and biosensors for reliably detecting seizures. In terms of accuracy, precision, recall, and F-score, the findings show that the Multilayer Perceptron (MLP) classifier performed better than other classifiers. It achieved an amazing accuracy rate of 97.4%, precision of 94.8%, recall of 96.8%, and F-score of 95.6%. With a precision, recall, and F-score that were all in balance and an accuracy rate of 97.2%, the Logistic Regression technique also performed well.

The results demonstrate how machine learning algorithms are successful at managing multimodal datasets and their capacity to detect non-linear interactions between the target variable (seizure incidence) and the attributes acquired from wearable device data. A good option for seizure detection systems using wearable technology is the MLP classifier, which in particular shows its capacity to handle complicated patterns and interactions within the data.

The study's findings offer positive proof that seizure detection using data from wearable devices is possible and has the potential to enhance epilepsy treatment. Wearable technology may precisely measure physiological variables including acceleration, phonocardiogram, and electrodermal activity by utilizing machine learning algorithms, allowing for the quick identification and monitoring of seizures. By allowing for immediate medical intervention and aid, this timely diagnosis helps to reduce the dangers and effects of seizures.

However, further study is required to confirm and generalize these findings. To evaluate the algorithms' effectiveness in various demographics and seizure kinds, larger and more varied datasets must be examined. Furthermore, it is important to assess the viability and usefulness of real-time seizure detection systems employing wearable technology in clinical settings.

Wearable seizure detection devices have many uses beyond only reliable seizure detection. Wearable technology's continuous monitoring capabilities allow for long-term data gathering and extensive study of seizure patterns, triggers, and therapeutic response. Personalized treatment regimens, risk prediction algorithms, and improved understanding of epilepsy care can all benefit from this plethora of data.

In conclusion, the work provides strong evidence that wearable device data may be used to accurately predict seizures using machine learning techniques, specifically the MLP classifier and Logistic Regression. This discovery has the potential to revolutionize the area of managing epilepsy by providing immediate monitoring and empowerment for those who have epilepsy and their careers. Wearable seizure detection devices can help patients receive better care, contribute to more individualized and targeted treatment plans, and improve the quality of life for people with epilepsy with further development and integration with healthcare systems.

4.2. DISCUSSION

The study report examined multimodal datasets collected from wearable devices to examine the performance of machine learning algorithms in identifying seizures. The study shed important light on the potential of biosensors and wearable technologies to enhance epilepsy care. We will examine potential directions for future study in this discussion as well as go into further detail on the implications and restrictions of the research findings.

According to the study's findings, the Multilayer Perceptron (MLP) classifier excels in correctly identifying seizures because of its high accuracy, precision, recall, and F-score. The MLP classifier beat the other classifiers tested in the study with accuracy rates of 97.4%, precision of 94.8%, recall of 96.8%, and an F-score of 95.6%. This demonstrates how the MLP classifier can accurately detect seizures by capturing complex patterns and non-linear correlations in multimodal datasets.

Additionally, the Logistic Regression method performed well, with a 97.2% accuracy rate and balanced precision, recall, and F-score. The outcome of this research further establishes the effectiveness of the Logistic Regression technique for seizure detection using wearable device data. This algorithm has been utilized for a long time in other classification applications.

The results of this study have important ramifications for managing epilepsy, highlighting the need of prompt and precise seizure identification as a means of enhancing patient outcomes. Healthcare providers can get important information regarding seizure patterns and treatment response through the use of wearable technology and machine learning algorithms. The development of personalized strategies for managing epilepsy can benefit patient care and wellbeing by using this information.

However, it's crucial to recognize the study's limitations. The study employed a particular dataset and concentrated on a small number of machine learning techniques. Although the MLP classifier and Logistic Regression demonstrated excellent performance, it is necessary to examine if these results apply to bigger and more varied datasets. The study also did not explore the real-time application and usability of wearable seizure detection devices in clinical settings. To determine the viability, user acceptability, and integration of wearable devices into current healthcare systems, more study is required.

Future studies should address these issues and consider different approaches to improving seizure detection with wearable technology. The performance of the algorithms in various demographics and seizure kinds might be better understood with the inclusion of more and more varied datasets. Incorporating real-time monitoring and assessing the practical use of wearable seizure detection technologies would also be beneficial to the research.

In conclusion, the study offers important insights into how well machine learning algorithms can identify seizures from wearable device data. The study emphasizes how well the Multilayer Perceptron and Logistic Regression algorithms recognize seizures, potentially improving epilepsy care. It is crucial to recognize the study's limitations and the need for more research in order to confirm and generalize the results. The practical integration of wearable seizure detection systems requires doing research on bigger and more varied datasets, investigating real-time deployment in clinical settings, and assessing user satisfaction.

4.3. FUTURE SCOPE

The future scope provides opportunities for further improving the project. To enhance the analysis of multimodal data, the following scopes can be considered:

1. Our study used a small dataset to evaluate the performance of the classifiers. Future research can use a larger dataset to evaluate the generalisation of the model.
2. By using different techniques, we can tune the hyperparameters, which play a critical role in the performance of the machine learning models.
3. Proper feature engineering should be done on the data to identify important features, define thresholds, and select algorithms that perform better on the data.
4. Using deep learning techniques like neural networks, we can extract more complex patterns from the data and perform better analysis.
5. Future research can investigate the usability of wearable devices with seizure detection systems in clinical settings.

A wristwatch with crucial sensors including ACC, EDA, HR, and BVP would be the best wearable device for seizure detection. The wristwatch should be able to recognise input signals and identify seizures with accuracy using the trained model. In order to allow for a more thorough investigation of the event, it should also be able to continue collecting sensor data and documenting seizure activity while the patient is having a seizure.

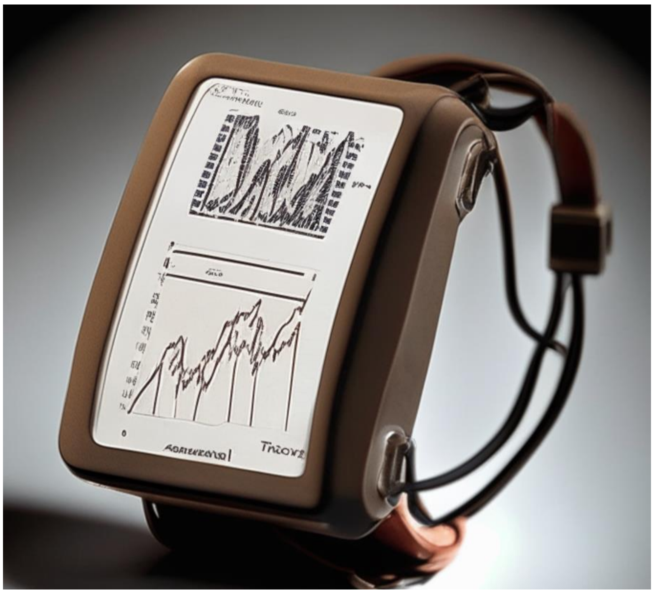


Fig 5.1

The wristwatch should include Bluetooth, Wi-Fi, and GPS capabilities to make sure that relatives and medical experts are promptly informed about seizure activity. This would allow for quick action, if necessary, by enabling connected devices to receive notifications and the wearer's present location. The smartwatch should also be made with an easy-to-use interface in order to make it accessible and user-friendly. Caretakers and medical experts should be able to easily evaluate the results if the sensor data is given in a clear and straightforward way.

REFERENCES

[1] Alazzam, M.B., Alassery, F. and Almulihi, A., 2021. A novel smart healthcare monitoring system using machine learning and the Internet of Things. Wireless Communications and Mobile Computing, 2021, pp.1-7.

[2] Moodbidri, A. and Shahnasser, H., 2017, January. Child safety wearable device. In 2017 International Conference on Information Networking (ICOIN) (pp. 438-444). IEEE.

[3] Rosales, M.A., Bandala, A.A., Vicerra, R.R. and Dadios, E.P., 2019, November. Physiological-Based Smart Stress Detector using Machine Learning Algorithms. In 2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM) (pp. 1-6). IEEE.

[4] Lockman J, Fisher RS, Olson DM. Detection of seizure-like movements using a wrist accelerometer. Epilepsy Behav. 2011 Apr;20(4):63841. doi: 10.1016/j.yebeh.2011.01.019. Epub 2011 Mar 29.

[5] Adwitiya, A.Y., Hareva, D.H. and Lazarusli, I.A., 2017, September. Epileptic Alert System on Smartphone. In 2017 International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT) (pp. 288- 291). IEEE.

[6] Mustafa Halimeh, Yonghua Yang, Theodore Sheehan, Solveig Viieluf, Michele Jackson, Tobias Loddenkemper, Christian Meisel. Wearable device assessments of antiseizure medication effects on diurnal patterns of electrodermal activity, heart rate, and heart rate variability.

[7] Humairah Tabasum, Nikita Gill, Rahul Mishra and Saifullah Lone. Wearable microfluidic-based e-skin sweat sensors.

[8] Jonas Munch Nielsen, Ivan C. Zibrandtsen, Paolo Masulli, Torben Lykke Sørensen, Tobias S. Andersen, Troels Wesenberg Kjær. Towards a wearable multi-modal seizure detection system in epilepsy.

[9] Xu Zeng, Hai-Tao Deng, Dan-Liang Wen, Yao-Yao Li, Li Xu and Xiao-Sheng Zhang. Wearable Multi-Functional Sensing Technology for Healthcare Smart Detection.

[10] Sai Manohar Beeraka, Abhash Kumar, Mustafa Sameer, Sanchita Ghosh, Bharat Gupta. Accuracy Enhancement of Epileptic Seizure Detection: A Deep Learning Approach with Hardware Realization of STFT.

[11] Majumder, A.K.M., ElSaadany, Y.A., Young, R. and Ucci, D.R., 2019. An energy efficient wearable smart IoT system to predict cardiac arrest. Advances in Human-Computer Interaction, 2019.

[12] Sarmast, S.T., Abdullahi, A.M. and Jahan, N., 2020. Current classification of seizures and epilepsies:scope, limitations and recommendations for future action. Cureus, 12(9).

[13] Bornoiu, I.V. and Grigore, O., 2013, May. A study about feature extraction for stress detection. In 2013 8th International Symposium on Advanced Topics in Electrical Engineering (ATEE) (pp. 1-4). IEEE.

[14] Siddiqui, M.K., Morales-Menendez, R., Huang, X. and Hussain, N., 2020. A review of epileptic seizure detection using machine learning classifiers. Brain informatics, 7(1), pp.1-18.

[15] Chen, Y.H., Chiou, H.Y., Lin, H.C. and Lin, H.L., 2009. Affect of seizures during gestation on pregnancy outcomes in women with epilepsy. Archives of neurology, 66(8), pp.979-984.

[16] Beniczky, S., Wiebe, S., Jeppesen, J., Tatum, W.O., Brazdil, M., Wang, Y., Herman, S.T. and Ryvlin, P., 2021. Automated seizure detection using wearable devices: A clinical practice guideline of the International League Against Epilepsy and the International Federation of Clinical Neurophysiology. Clinical Neurophysiology, 132(5), pp.1173-1184.

[17] Chen, F., Chen, I., Zafar, M., Sinha, S.R. and Hu, X., 2022. Seizures detection using multimodal signals: a scoping review. Physiological Measurement.

[18] Ortega, M.C., Bruno, E. and Richardson, M.P., 2022. Electrodermal activity response during seizures:A systematic review and meta-analysis. Epilepsy & Behavior, 134, p.108864.
[19] Falco-Walter, J.J., Scheffer, I.E. and Fisher, R.S., 2018. The new definition and classification of seizures and epilepsy. Epilepsy research, 139, pp.73-79.
[20] Regalia, G., Onorati, F., Lai, M., Caborni, C. and Picard, R.W., 2019. Multimodal wrist-worn devices for seizure detection and advancing research: focus on the Empatica wristbands. Epilepsy research, 153, pp.79-82.
[21] An, S., Kang, C. and Lee, H.W., 2020. Artificial intelligence and computational approaches for epilepsy. Journal of epilepsy research, 10(1), p.8.
[22] Zangróniz, R., Martínez-Rodrigo, A., Pastor, J.M., López, M.T. and Fernández-Caballero, A., 2017. Electrodermal activity sensor for classification of calm/distress condition. Sensors, 17(10), p.2324.
[23] Posada-Quintero, H.F. and Chon, K.H., 2020. Innovations in electrodermal activity data collection and signal processing: A systematic review. Sensors, 20(2), p.479.
[24] Van Andel, J., Ungureanu, C., Aarts, R., Leijten, F. and Arends, J., 2015. Using photoplethysmography in heart rate monitoring of patients with epilepsy. Epilepsy & Behavior, 45, pp.142-145.
[25] Tang, J., El Atrache, R., Yu, S., Asif, U., Jackson, M., Roy, S., Mirmomeni, M., Cantley, S., Sheehan, T., Schubach, S. and Ufongene, C., 2021. Seizure detection using wearable sensors and machine learning: Setting a benchmark. Epilepsia, 62(8), pp.1807-1819.
[26] Nasseri, M., Pal Attia, T., Joseph, B., Gregg, N.M., Nurse, E.S., Viana, P.F., Worrell, G., Dümpelmann, M., Richardson, M.P., Freestone, D.R. and Brinkmann, B.H., 2021. Ambulatory seizure forecasting with a wrist-worn device using long-short term memory deep learning. Scientific reports, 11(1), p.21935.