A MAJOR PROJECT II REPORT

ON

ANXIETY LEVEL PREDICTION USING PHYSIOLOGICAL DATA FROM WRIST-WORN WEARABLE DEVICE

Submitted in Partial Fulfillment of the Requirements for the
Award of the Degree of

MASTER OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

Submitted By

ALANKRITA SINGH

2K22/CSE/01

Under the Supervision of

DR. VINOD KUMAR

PROFESSOR

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)
Main Bawana Road, Delhi-110042

MAY, 2024

Delhi Technological University

(Formerly Delhi College of Engineering)

Shahbad daulatpur, main bawana road, delhi-110042

CANDIDATE'S DECLARATION

I, Alankrita Singh hereby certify that the work which is being presented in the report entitled "Anxiety Level Prediction Using Physiological Data From Wrist-Worn Wearable Device" in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Computer Science and Engineering, Delhi Technological University is an authentic record of my own work carried out under the supervision of Dr. Vinod Kumar.

The matter presented in the report has not been submitted by me for the award of any other degree of this or any other Institute.

Place: Delhi — Alankrita Singh

Date: May, 2024 — 2K22/CSE/01

Delhi Technological University
(Formerly Delhi College of Engineering)
Shahbad daulatpur, main bawana road, delhi-110042

CERTIFICATE

Certified that Alankrita Singh (2K22/CSE/01) has carried out their search work presented in this report entitled "Anxiety Level Prediction Using Physiological Data From Wrist-Worn Wearable Device" in partial fulfillment of the requirements for the award of the Degree of Master of Technology, submitted in the Department of Computer Science and Engineering, Delhi Technological University, under my supervision. The report embodies results of original work, and studies are carried out by the student herself and the contents of the report do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other Institution.

Dr. Vinod Kumar
Professor
Department of CSE,
Delhi Technological University

Place: Delhi
Date: May, 2024

ABSTRACT

Anxiety disorders form a group of mental disorders which are quite common and have been shown to affect millions of people around the world. There are a number of traditional approaches to assessment of anxiety, and typically they are based on the subject's questionnaires. This report outlines a new solution that is based on the accurate calculation of anxiety levels based on physiological parameters collected by wrist-worn devices.

Here, the following study is proposed to employ a broad dataset that includes physiological data with citizens wearing wrist-worn gadgets. Five ML algorithms are employed for anxiety level prediction: K-Nearest Neighbors, Support Vector Machines, Decision trees, Random forests, Histogram Based Gradient Boosting etc. As for the validation of these models, cross-validation of the k-fold type is used to increase the model's reliability and to make it as universal as possible.

As it will be shown next, the proposed approach has promising applications for refining the evaluation and treatment of anxiety. As such, the present research aims to extend the existing literature on self-report measures for anxiety levels and offer an actual physiological perspective by using only basic physiological data and applying the sophisticated methods of AI. The results of this study might positively influence the creation of online surveillance programs and appropriate strategies for proactive treatment of anxiety disorders that would improve the subjects' quality of life.

This study helps to advance the area of affective computing to uncover how analysis of physiological data, machine learning algorithms, and mental health can all be connected. Among the possibilities, further developments of the current models can be mentioned as well as the promoted cooperation between disciplines and the investigation of the bodily expressions of anxiety.

ACKNOWLEDGEMENTS

On the very outset of this report, I would like to extend my sincere and heartfelt gratitude towards all luminaries who have helped us directly or indirectly in this project.

I are ineffably thankful and pay my sincere gratitude to my supervisor Dr. Vinod Kumar, Head of Department, Department of Computer Science and Engineering, Delhi Technological University, Delhi for his helpful information, keen interest, valuable guidance, constructive criticism, and insightful advice at various stages of my training period.

I would also like to thank Dr. R. K. Yadav, Department of Computer Science and Engineering, Delhi Technological University, Delhi and the project monitoring committee members for delivering the guidelines and organizing the presentations composedly with time and ease.

Finally, I would like to wind up by paying my heartfelt thanks to my supportive family and friends for motivating me for the project.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

ML	Machine Learning
AI	Artificial Intelligence
NN	Neural Networks
SVM	Support Vector Machine
KNN	K-Nearest Neighbors
DT	Decision Trees
RF	Random forest
HR	Heart Rate
ST	Skin Temperature
EDA	Electrodermal Activity
&	And

CHAPTER 1

INTRODUCTION

This chapter is a theoretical component that discusses the topic of anxiety disorders. This topic is chosen due to its significance for the understanding of anxiety disorders. The flow goes through the physical element of anxiety – getting specific on heart rate, skin temperature, and electrodermal activity. The study outlines the engineering applications of wearable technology in tracking these indicators and the future usage of ML models for forecasting anxiety states.

1.1 Anxiety Disorders: A Growing Concern

Anxiety disorders are a set of mental illnesses that involve constant worry, fear, or anxiety that inhibits people's daily living [1]. That is why these disorders are not uncommon anymore as WHO stated in 2019 that 301 million people worldwide have been struggling with anxiety [2].

Anxiety disorders are classified into a number of separate categories and each of these has its own peculiar set of symptomatic features and predictors. Fear Generalized anxiety disorder (GAD) is characterized by excessive and persistent concerns about many events and aspects of life, including work, health, and interpersonal relationships [1][3]. It is a disorder of Panic when a person gets severe frights or panics or terror random associated with activation or arousal [1][4]. Social anxiety disorder the diagnostic and statistical manual of mental disorder 5th edition describes social anxiety disorder as an anxiety that is caused by the fear of being judged or embarrassed by other people in social situations [1][2].

Anxiety disorder commonly occurs during pre-adolescence or adolescence and persists into adulthood if not treated [4]. Mendelian genetics in which these disorders arise as a result of an inherent neurological defect, as well as environmental factors which expose the brain to adverse conditions that may manifest in these disorders [3]. Anxiety disorders in women are more common than in men, this may be due to hormonal variations or they may simply be more susceptible to seek for help for the condition [3].

Main symptoms of anxiety disorder may be physical and cognitive. The physical symptoms include muscle tension, migraine headaches, fatigue, indigestion and tiredness [1][3]. Psychological symptoms can include excessive worry, difficulty in concentrating, restlessness and psychomotor agitation and feeling of being depressed or despairing [1][5].

However, since there are effective treatments already available, the majority of the people experiencing several anxiety disorders refuses to receive the proper care. Another investigation by WHO indicates that only 27% of the population afflicted by any form of Anxiety disorder receives treatment [2]. Another reason for the shortage of getting care is unawareness of being treatable; lack of adequate services dedicated to certain mental disorders and social discredit [2].

Medication and psychotherapy are combined in the most cases for this disorder's treatment. CBT is one of the most effective and popular types of psychotherapy that helps identify and change negatively expressed thoughts and ineffective behaviors [3]. In addition, such prescriptions may be provided to address symptoms through the use of antidepressants and anxiety medications [3].

Many more nowadays appreciate the importance of addressing such conditions such as anxiety disorders. But much more also has to be done in the way of education regarding mental illness and the removal of stigma and the establishment of access to treatment for all who require it. That is why promoting mental to incorporate evidence-based approaches will ensure more people gain healthier lives living with different forms of anxiety disorders.

1.2 The Body Speaks: Unveiling Anxiety's Physiological Fingerprint

Experiencing an emotional stressor activates the fight or flee mechanism response preparing the body to take an action. This ancient survival tactic, critical for survival in dangerous circumstances may become activated by the everyday stressors that characterize nervousness and anxiety disorders. The primary function of anxiety is to elicit changes in the body that help the individual maintain balance and homeostasis during threatening events.

Among the early symptoms of anxiety are elevated heart rate and increased blood pressure which can be related to fight-or-flight response of the human body. Moreover, during an episode of anxiety, the sympathetic nervous system causes an acute increase in heart rate to ensure the body is ready to fight. Also, it worth mention that heart rate variability (HRV) is widely a used tool to understanding of stress and resilience. This was also the case in the study by this author that revealed that lower values of HRV are associated with anxiety disorders so as to identify an individual's physiological response to stress.

Another physiological change in those who undergo anxiety is the change in temperature of their skin. The body responds to anxiety by redirecting blood to its inner organs, reducing their temperature which in turn causes vasoconstriction in the hands and feet. Checking skin temperature is another vital way of ensuring the individual knows how far the anxiety has progressed, which enables him or her to better discriminate between levels of anxiety.

EDA is an important variable in this study because it is a measure of skin conductance and offers insight into the amount of sweat the body produces when an individual is anxious. The problems obtained results from enhanced sweating due to anxiety which leads to changes in skin conductibility and which can be registered with the aid of EDA. The EDA value can increase in anxiety related scenarios and thus using wearable devices stress can be measured through direct physiological changes in the body as through increased sweat production.

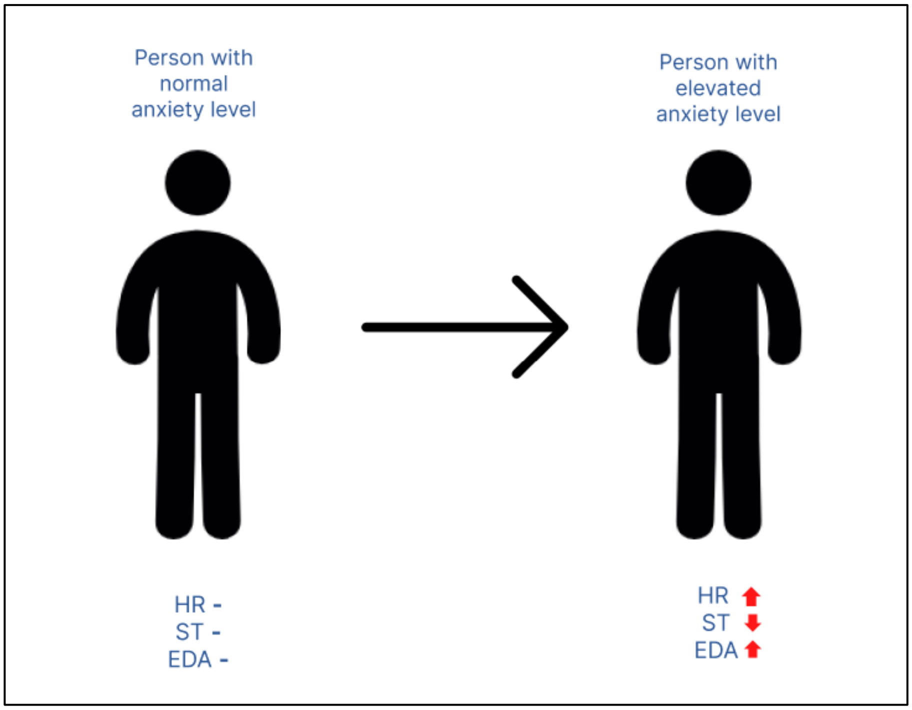

Fig 1.1: Physiological Levels

As a whole current technologies that could be used for wearable devices provide a snap shot of the physiological variation of anxiety in terms of HR, ST changes and EDA. Thus these physiological indicators can be of immense help to an individual to understand his or her levels of anxiety and the extent to which the condition could be treated periodically to avoid further complications.

1.3 Technology as an Ally: Harnessing Wearables for Anxiety Detection

Mental health represents a constantly changing and challenging domain wherein technology is particularly effective in the battle against anxiety disorders. Smart watches and similar devices are arguably the perfect technological solution to control, monitor or even prevent anxiety attacks in the future. The continuous monitoring of the individual's physiological changes induces by anxiety will allow such unobtrusive tools to enable the affected person a greater understanding of the situation and provide them with the means to actively learn to control their mental health.

Wrist-worn wearables are especially suitable for the detection of anxiety as they allow analyzing a large set of indicators in real-time. Such gadgets can monitor HRV – fluctuations in the period between consecutive heart pulses that are considered to correlate with anxiety. Wearables can also note shifts in HRV and recognize changes that might precede an anxiety attack. Moreover, wearables have got sensors which are able to monitor skin temperature and EDA which both changes in response to anxiety in the body.

Wearables are preferable for anxiety detection thanks to their non-intrusive nature. In contrast to the electrocardiograms or the skin conductance sensor methods, wearable technology is intentionally designed to be felt on the body through the day, and as such, wearers do not have to adapt to its presence for most of the day in order to monitor their health. This can be easily done during real-time investigations to provide valuable insight to the causes and trends in a person's anxiousness thereby helping to develop better coping mechanisms and sooner seek treatment if necessary.

Also, detecting anxiety using wearables is significant because it can lead to early intervention. These gadgets can help in the detection of changes in physiological signals before the individual experiences an anxiety episode and thus suggests prevention methods such as the use of relaxation techniques or seeking mental health experts. This proactive advent is likely to reduce the intensity and frequency of occurrence of anxiety attacks hence improving the quality of life of individuals suffering from anxiety disorders.

But wearable technology and mental health tracking raise several ethical concerns. These gadgets collate personal information that must be protected; as such privacy and usage concerns are important. Those who are developing the software or providing the healthcare services need to ensure that the information is collected, stored, and transferred in an open and protected manner following the protocols for user consent. Moreover, while incorporating wearable data in treating mental health conditions, the inclusion of a licensed mental health specialist is crucial to ensure that the data are used in an appropriate clinical context.

In summary, it is strongly believed that wearables have great potential as a tool for combating anxiety disorders. These devices are small and inconspicuous and allow individuals to gain a clearer picture of their anxiety levels and other aspects of the illness by providing people with on-going information about their physical health. It is essential that it is made sure that most of the tools that are used for this are used in the right way to promote better mental health and that is why developers and healthcare professionals need to prioritize the privacy, permission, and integration into clinical practice as the area of wearable technology develops further.

1.4 Machine Learning: Decoding the Body's Language

ML is similar to how people learn through experience. Like we can learn to recognize someone's face or predict certain outcomes based on historical data, ML systems are used to detect patterns and determine outcomes. In the context of mental health, ML gives an avenue through which the body can be interpreted into physical language equivalent to the physiological manifestation of anxiety.

The process of analyzing the patients as individuals with complex physiological profiles is significantly easier thanks to the ML algorithms and the physiological data that the researchers and professionals have. They can systematically analyze a great deal of physiological data to identify actions that may help to analyze anxiety levels. Such algorithms can then be trained using datasets of labeled anxiety and will learn different patterns associated with anxiety that may not be detected by the human senses.

The use of ML in analyzing the presence and severity of anxiety has the numerous benefits. Its first benefit is the potential for unaided detection of anxiety levels using the physiological variables, which made it easier and faster to diagnose anxiety disorders among healthcare workers scale. Second, ML evaluates anxiety in an objective way to avoid any prejudice associated with the traditional methods. It can guarantee more reliable and fair assessments of individuals' psychological well-being.

In addition, ML has the capacity to offer treatment plans that will specifically address patients' unique physiologies. Based on the factors that characterize each individual's anxiety, machine learning models can make suggestions regarding the best way of managing anxiety. This personalized advent has the potential to improve treatments and to improve the quality of lives of individuals with anxiety disorders.

These algorithms are the ones used in predicting anxiety; some of the algorithms are SVM, KNN, Decision Trees and Random Forest. SVM is also thought to be good with the complex data and the decision boundaries that are good and thus appropriate for multidimensional physiological data that pertain to anxiety. KNN can find the relationship between data points based on their proximity; thus, it can be used to determine the influence of anxiety on the physiological state of the body. Both Decision Trees and Random Forest are better at processing large datasets and relationship interdependency and therefore better suited to predict anxiety based on multi-modal physiological data.

To sum up, ML has the potential to be a tool for demystifying the language of the body and understanding the physiological markers of anxiety. Using ML algorithms for the prediction of anxiety will help us to better understand and manage mental health conditions and with this we will pave the way towards more personalized treatment options in the field of anxiety disorders.

1.5 Problem Statement

Mental anxiety disorders are a major problem in the current world, and they impact millions of people across the globe. Managing anxiety requires early identification of the disorder and early intervention and prevention – but the current methods of identifying anxiety are often dependent on self-assessment or clinical assessment which are both slow and subjective. Wearable technology presents the best option for addressing this issue as it can be used to monitor physiological data and predict anxiety throughout the day.

The objective of this research work is to build a forecasting framework for anxiety using physiologic data collected from wrist-worn wearables using a machine learning approach. The focus is on three key physiological variables: such measures of anxiety, such as heart rate, skin temperature, and electrodermal activity. In using the five algorithms of ML-SVM, KNN, Decision Trees, Random Forest and HistGradient Boosting – this study aims to identify the most accurate and reliable way to predict anxiety levels.

Using wearable devices for anxiety detection has several advantages: they can be non-invasive and continuous; can provide objective assessment; and might enable earlier intervention. But at the same time, due to the complexity of the physiological data analysis, the development of the accurate prediction models must be approached cautiously. This work deals with the tasks of feature selection, model selection, and performance measurement as an end-to-end methodology for the development of a reliable anxiety level prediction device.

The proposed system would have a positive impact on mental health care since patients will easily monitor their condition and take timely decisions for help when they are experiencing stress. The use of ML and wearable technology employed in this study thus contributes in the formulation of solutions in the diagnosis and prevention of anxiety management.

In conclusion, this chapter has reinforced the potential of wearable technology in monitoring biological markers of anxiety through analysis of HR, ST, and EDA. The examination of applying ML algorithms for predicting anxiety levels shows that the current discussion builds on a promising area of personalized and objective anxiety assessment. This chapter also introduces the aim of the subsequent research in which it is important to develop a prediction model based on the physiological data by the wrist worn wearables accurately and reliably. The use of wearable technology and ML has a high potential for improving the field of mental healthcare and improving the well-being of those suffering from anxiety.

CHAPTER 2

LITERATURE REVIEW

One of the recent inventions that have continued to revolutionize the monitoring of healthcare is the use of wearable technology. Wrist-worn devices are beneficial for gathering data continuously in a non-invasive manner and can be used to monitor physiological reactions. These gadgets can have the capability to capture signs related to anxiety attacks when it comes to anxiety disorders in real time. However, to achieve this promise, there is a need for intensive research on ML algorithms for predicting anxiety through data obtained from wearing wrist wear. This literature review analyzes current research related to the effectiveness of this approach and possible areas for future research.

2.1 Physiological Markers of Anxiety

The paper "Physiological Detection of Anxiety" by Adheena M A et.al [6] provides a comprehensive review of the literature that attempts to use physiological variables to describe, model, analyze, or predict anxiety. The authors emphasize the importance of mathematical and statistical methods in this area of research.

The review emphasizes the importance of mental stress in the development and progression of anxiety disorders by disrupting the equilibrium between the sympathetic and parasympathetic nervous systems. Anxiety symptoms include pounding or increased heart rate, perspiration, body tremors, and elevated blood pressure.

The development of non-intrusive and wearable sensors ensures the measurement of physiological variables such as heart rate pulse, heart rate variability, electrodermal activity, and blood pressure. Such technologies would allow the creation of capabilities for anxiety detection and concern with physiology and its correlates. The authors of this paper undertook a scoping review to determine the current knowledge of how the body responds to anxiety and the information knowledge gaps. They sought out research articles in peer-reviewed journals using physiological variables to describe, measure, predict, or model anxiety, with an emphasis on mathematical and statistical methods.

The review also stresses on the importance of physiological variables and the use of machine learning methods to infer anxiety. But the authors mention that the obtained results depend significantly on the type of anxiety and the approach used for prediction. They propose that further studies may even attain higher accuracy rates in order to better support patients with anxiety disorder.

The article by Khullar et al. al [7] explores the prediction of anxiety levels in Asia countries as accurately as possible by means of a Fuzzy Expert System. The study is useful because it uses physiological variables to build a predictive model for the task of anxiety detection and highlights how machine learning can benefit this endeavor. Primarily, the authors use an ensemble machine learning technique to interpret physiological signals and diagnose anxiety with high levels of accuracy. This study aims to investigate the application of ML algorithms with physiological data to improve the forecasting of anxiety, especially in Asian culture. These results reaffirm the importance of using highly effective computational methods to accurately and efficiently detect anxiety –an area where machine learning models are promising solutions.

2.2 Wearable Technology for Anxiety Detection

The paper "Wearable Artificial Intelligence for Detecting Anxiety: Systematic Review and Meta-Analysis” by Abd-alrazaq A et al [8] explores the use of the wearable for identification of anxiety. It establishes the concept of the objective and timely management of anxiety, taking into consideration the fact that subjective assessment is not enough. The purpose of the study is to improve further increases in automation and possibility to predict the anxiety using AI with the help of wearable devices. The work shall seek to evaluate the effectiveness of wearable AI in identifying and clinicians anxiety disorders through systematic review and meta analysis.

As highlighted here, smartwatch or wristband integrated with AI algorithms can be applied for various aspects of health about anxiety such as activity, pulse, sleep, SpO2, and the rates of breathing. These devices would also help those individuals with anxiety to easily and effectively assess their anxiety level and other useful health information that may be important for diagnosis of anxiety disorders. Drawing insights from studies of wearable AI for the detection of anxiety, this systematic review and meta-analysis has significant implications that can be applied to formulate approaches to further enhance the agenda of utilizing wearable devices for personal mental health assessment and intervention.

2.3 Use of Machine Learning for Anxiety Detection

Shruti Garg [9] had undertaken a study in which to determine the level of stress, anxiety and depression, with the help of five ML algorithms, KNN, DT, RFT, Naïve Bayes and SVM. In a way, Naive Bayes was considered to be the most accurate model despite the fact that Random Forest was the best model. The imbalanced partitioning results in unequal classes thus the best model was determined using f1 score.

Arfan Ahmed's work [10] employed PRISMA principles in conjunction with ML models to identify anxiety and depression on social media platforms such as Twitter, Facebook, Reddit, and Weibo. The accuracy, f1 score, and outcome were used to evaluate the data.

In a research by Jan Gross [11], models that use frontal asymmetry brain activity to diagnose anxiety were examined in relation to suggested machine learning techniques. The Random Forest classification showed a good accuracy of 80.71 percent and a balanced accuracy of about 81.25 percent when used to distinguish between people suffering from low and high levels of trait anxiety. The study also evaluated typical brain activity using the mean of the FAI values.

Adolescent anxiety and depression were predicted by ML analysis of multi-wave longitudinal data in a study led by Mariah T. Hawes [12]. In order to assess the elements that went into making the predictions based on data collected at various stages of development, ablation analysis was done. The results demonstrated that anxiety concerns can be successfully screened for as early as age three.

Data from the Netherlands Study of Depression and Anxiety was used in a study by Wessel A. van Eeden [13] which compared the predicting abilities of automated ML with basic probabilistic machine learning techniques. The study examined the predictive abilities of the naïve Bayes classifier, logistic regression, and Auto-sklearn in relation to anxiety diagnoses over a range of time intervals. It found that auto-sklearn performed better than the other two in analyzing a more complicated dataset with individual item scores.

Eight ML algorithms were used to forecast psychological diseases like sadness and anxiety in the work conducted by Prince Kumar [14]. After classifying the algorithms into groups of hybrid and single algorithms, it was discovered that the hybrid algorithms' accuracy was higher than the single algorithms', indicating that NN outperformed the other types of algorithms. In a study published in 2010, Astha Singh reviewed the literature on stress detection and the connection between psychological practices and various physical symptoms. She also talked about the use of AI to diagnose SAD and the application of ML models to classify cases of this kind.

In a paper written by Walid Yassin [15], classifiers for differentiating between ASD and schizophrenia were compared, built, and their effectiveness evaluated using information gathered from patients at risk and in the early stages of the condition. The best-performing and most accurate classifier, according to the results, was the linear regression model. According to a journal article by Kristin Mitte [16], the majority of documented studies had suggested otherwise, despite the fact that certain theories contend that people with anxiety selectively recall dangerous events. 165 studies with 9,046 participants (clinical and nonclinical samples) were quantitatively integrated to ascertain whether a memory bias exists and which moderator variables influence its extent. Nevertheless, effect sizes did not show that anxiety had a significant influence on implicit memory or recognition.

Work carried out by Abdul Rehman et.al [17] includes a chapter on machine learning's application in the early detection of autism in children through emotion recognition. LSVM classification for emotion classification guarantees area- and energy-optimized hardware realization because of the reduced computational complexity. The binary categorization is used to assess the emotional state. Fourfold cross-validation was used to evaluate the outcomes and determine the overall accuracies. ML was utilized in a work by Silvan Hornstein [18] to forecast the course of therapy in a digital mental health intervention for anxiety and depression. The study's findings shed light on how little research had been done on the subject of machine learning's potential to anticipate digital mental health therapies. This was accomplished by employing a random forest classifier and training multiple algorithms.

In an article by Iuliia Pavlova [19], ML was used to identify the aspects that cause anxiety in young men who face the possibility of being drafted into the military. A sample of conscripted Ukrainian men participated in a survey that used k-means algorithm and the random forest algorithm were used to validate the model and make additional forecast. In doing so, three subgroups were found, and it became evident that anxiety levels were not significantly correlated with the experience or proximity of military operations.

In a review, Danilo Bzodok [20] calls on academics and medical professionals to look for ways to integrate ML into the realm of psychiatric practice. Classes of ML techniques were presented together with their objectives, potential applications in psychotherapy, and opportunities that arise from machine learning's prediction-focused approach. The study also outlined a few potential difficulties with machine learning, including data availability, management, and reproducibility. The study's conclusion suggested that using cutting-edge statistical technologies like machine learning could improve the effectiveness of our approach to mental health.

Deep learning algorithms were utilized in a study by Jina Kim [21] to identify mental illness from user posts on social media. This was accomplished by compiling postings from Reddit forums pertaining to mental health. Six subreddits were used to gather the data: r/depression, r/anxiety, r/bipolar, r/BPD, r/schizophrenia, and r/autism. A large number of postings about mental health and mental disease were also gathered. In general, CNN models outperformed XGBoost models in terms of accuracy. It was suggested to use numerous ML algorithms to assess a person's mental health in an article by M. Srividya [24] that examines behavioral modeling for mental health utilizing these algorithms. First, the responses to the questionnaire that was developed were subjected to unsupervised learning techniques. To confirm the labels that the clustering produced, the Mean Opinion Score was computed. After that, classifiers were developed to ascertain an individual's mental health based on these cluster labels.

Hierarchical CNN models with multimodal fusions were used to detect stress in a recent study by Radhika Kuttala [22]. In order to achieve this two physiological signals which were multimodal – Electrocardiogram and Electrodermal activity were used. Multiple levels of CNN features were stacked to form a hierarchical feature set for each modality that offered higher performance than previous models by tackling frequency bands. Abdulhakim Al-Ezzi [23] also used machine learning algorithms to investigate the EEG data to determine the features of social anxiety disorder complexity in patients. A classification test on Naive Bayes (NB) revealed that the proposed method is superior to the existing methods with 86%. 93% accuracy, 92. 46% sensitivity, and 95. 32% specificity.

Overall, there is rising interest in ML's increasing potential in predicting and analyzing anxiety. The outcomes of these studies also explain a possibility of prediction for positive effect of ML on the enhancement of patient care and support of patient with anxiety disorders or possibility of utilizing ML to make beneficial changes in patient care and mental health treatment programs and its influence on the patients care.

CHAPTER 3

METHODOLOGY

The approach for this study involves data collected from the wearable technology, and applying the ML algorithm that helps in estimating the level of anxiety of the person. The research procedures are a series of activities to collect data from the participants' wrist worn devices that monitor the bodily parameters including HR, ST, and EDA. Next the collected data goes through preprocessing stage to remove noise and achieve data consistency before feature extraction. SVM, KNN, Decision trees, Random forests and Histogram based Gradient boosting methods are used further to analyze the features and predict anxiety levels precisely.

3. 1 Workflow

The process of conducting this study is presented in the form of a workflow, which focuses on the ML algorithms to predict anxiety levels through physiological data. The workflow consists of four key phases:

3.1.1 Data Collection

The collected data is based on 12 participants, six males and six females, of age varying between 18 and 25 years old. Each participant has contributed to about 10,000 data points to the dataset. The dataset incorporates the following physiological metrics:

1.	Heart Rate
2.	Skin Temperature
3.	Electrodermal Activity

Table 3.1 Physiological Variables

These devices are worn by the participants on a continuous basis in order to capture real-time information on physiological parameters. These parameters give a broader perspective of the physiological state of the participants. Information like this is necessary to comprehend how stress and emotional states evolve, and it relates to research in areas like mental health, stress control, and forecasting. This process of inclusion of both genders and a specified age range allows the dataset to be applied to a wider scope. Continuous data collection allows the acquisition of a more complete picture of the participants' physiological reactions that include not only the baseline levels of anxiety but also the varying degrees.

3.1.2 Data Analysis and Pre-Processing

The data collected from various physiological sensors is statistically evaluated and pre-processed using different statistical and ML approaches to find out correlations and dependencies regarding anxiety levels. The process is carried out through data preparation and feature engineering as well as the use of multiple ML algorithms such as Support Vector Machines, K-Nearest Neighbors, Decision Trees, HistGradient Boosting, and Random Forest to make accurate predictions of anxiety levels.

3.1.3 Model Building

Building an effective model for the prediction of anxiety levels based on physiological data collected from wearable devices, the following models were built:

Support Vector Machine

SVMs are ultimate supervised ML models for classification and regression problems. The basic SVM model aims to find a hyperplane that can distinguish between different categories of data as well as maximizing the distance between these categories. This margin is the distance between the hyperplane and the vectors of nearest samples of each class – support vectors.

For instances in 2D space, the hyperplane is a line that separates the data space into two halves or classes. The kernel trick is aimed at retrieving the hyperplane which not only optimally separates the given classes but also generalizes well on test input. Particular to the idea the ability of the model to accurately classify new data if the data lies on a hyperplane that contributes towards maximizing the margin is a crucial concept.

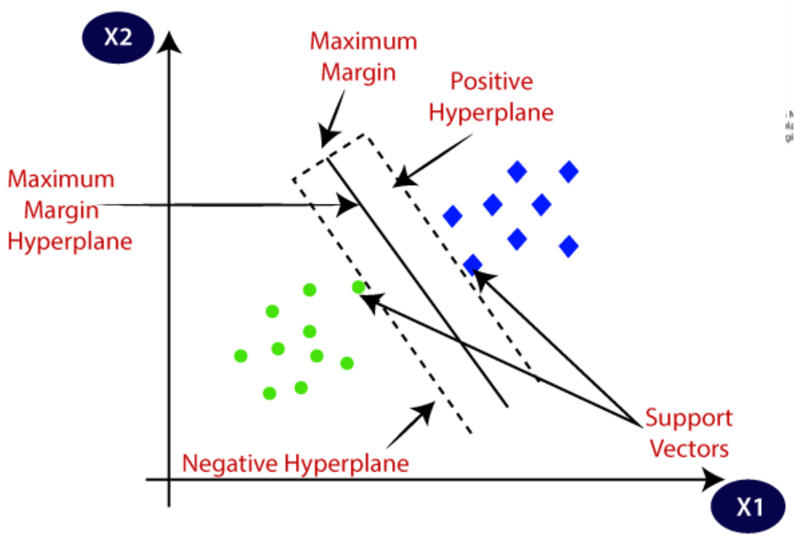

Fig 3.1 SVM Classifier

SVMs are also effective in solving non-linear classification tasks using some kernel tricks as which map the data provided in a higher space in order to linearly separate them. Some of the common types of kernel functions include: linear kernel for linear classification regions; polynomial kernel for nonlinear boundaries and the radial basis function (RBF) for more complex shapes.

While SVMs are widely used and they produce good results, there are some issues associated with this method such as the necessity to choose optimal values for parameters including regularization parameter and kernel function type. They are suitable when dealing with high dimensional object and when the size of the data is small to medium large though computational problems may arise when using large data sets. SVM is used in the various fields in image recognition, text classification and even in docking molecular and protein in bioinformatics to show the ability and the potential of these machines based on the different algorithms.

K-Nearest Neighbors

K-nearest neighbors (KNN) is a classification algorithm which is one of the fastest growing simple and most comprehensible classification algorithms in the field of machine learning. KNN on the other hand is one of the classification algorithms that classifies a given data point with the help of its neighbors and is far based on the notion of similarity. It is also able to compute the distance of an unseen data point from their K nearest Neighbor based on a distance such as Manhattan distance or Euclidean distance.

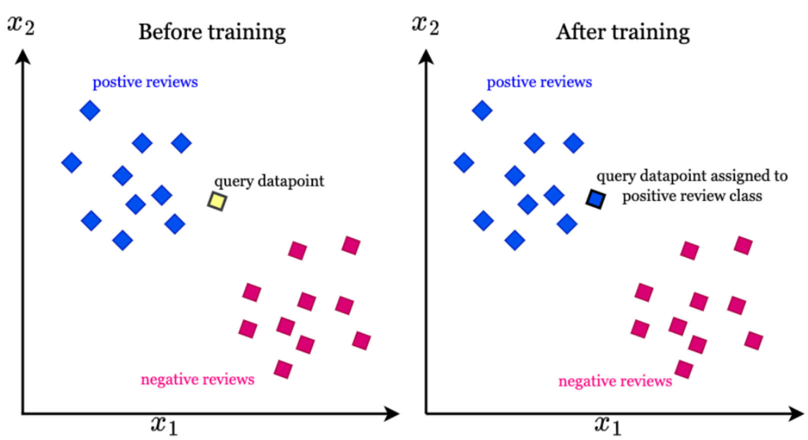

Fig 3.2 KNN Classifier

KNN can be a perfect choice for classification tasks of many kinds because it is easy to apply and does not require developing complicated algorithms for classification. It works excellently where a complex boundary cannot be clearly and distinctly defined using a linear approach. KNN is non-parametric algorithm and can therefore manage flexibility of different datasets as it doesn't entail presuppositions about the origins of underlying data. KNN is a non-parametric algorithm which enables it to handle a variety of datasets with extreme flexibility as it does not make and presumptions about the distribution of the data under consideration.

The second aspect of KNN that one can admire about this algorithm is that it adapts to variations in the data condition since unlike some algorithms, it does not need new training. This feature makes KNN applicable for further incremental learning and those tasks in which the data is distributed dynamically.

Yet, one should also take into account that the val of k used and the distance metric impact the performance of KNN. However, larger values of k can create a more smoothed-up boundary but also lead to over-simplification of the model, meanwhile smaller values of k could create a boundary that is noisy-sensitive.

Decision Tree

Decision Tree is a very popular algorithm which is used in classification and one of the most widely used algorithm in ML. It gives a simple and clear outline that makes it easier to create visual representations for complicated decision-making processes. The technique works by recursively splitting the dataset based on feature values for each node to create a tree-like structure where the parent node indicates the choice of sub-tree for a given set of parameters. The root node indicates the feature that best classifies the data separability and maximizes the class separation.

A second way is based on additional features added at each of the following nodes to better classify the data. Until some predefined condition of stopping criteria such as a specific depth or a purity is not met the decision rule is then applied again. Therefore, leave nodes represent the process of final classification.

Decision trees have several positive aspects, for instance, they are robust against outliers, they can be easily interpreted, and they are easy to implement. The advantage of using the data is that it is extremely useful in various applications due to the way in which it can deal with numerical as well as categorical data. Moreover, the most informative features required to categorize the set of retrieved data are also identified during the process of decision trees deployment therefore making it an option that is powerful enough in feature selection also known as feature extraction.

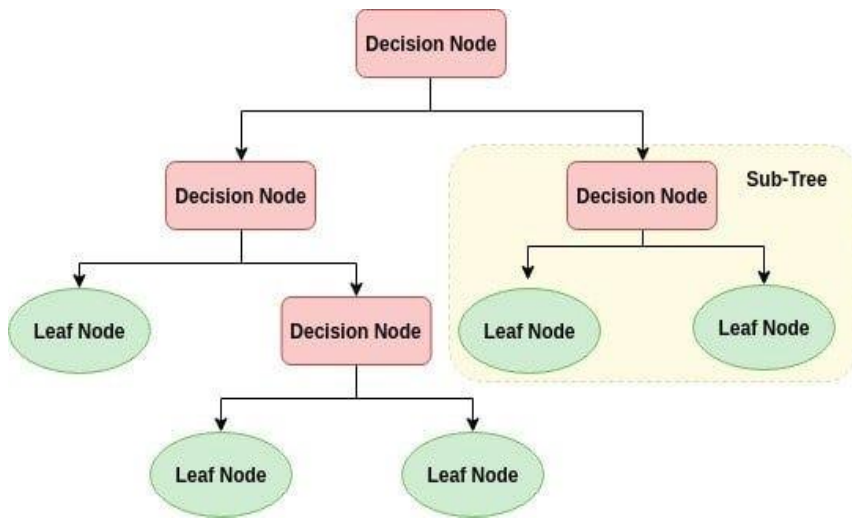

Fig 3.3 Decision Tree Classifier

But, Decision Trees are inadequate in predicting new datasets since they overfit easily in the training data and pick up noise in the training set. This limitation is overcome by use of techniques such as pruning, restricting the depth of the tree or using an ensemble techniques such as Random Forests.

Random Forest

One of the most useful ways to use ensemble learning to improve machine learning classification is termed random forest. Random Forest is applied as an ensemble technique that transforms the results of many decision trees into one prediction for the generalized model improvement. In each forest, a given subset of the dataset is used to train several decision trees which then independently calculate their own predictions. The same is true for each tree; it develops an output for categorizing the data while the voting option is used to make a forecast with respect to the final forecast.

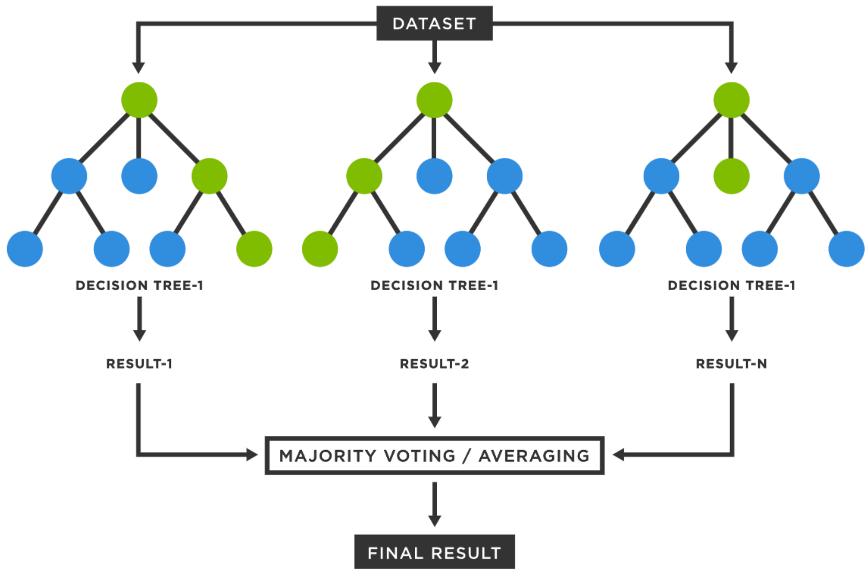

Fig 3.4 Random Forest Classifier

A strong positive about the Random Forest is its ability to reduce the occurrence of overfitting which is a particular weakness of decision trees. Random Forest increases the performance of a classifier and reduces the variance of the error by providing diverse results from numerous decision trees. With the help of the algorithmic structure, the randomness is achieved by applying different subsets of features to different trees and data to increase the diversity between the individual classifiers. It is for this reason that random forests are applicable to any type of dataset for the simple fact that they are able to handle both numerical and categorical information. They also provide feature ranking information which is helpful in determining the priority of different features based on their contribution towards classification.

Random forests are also capable of providing accurate results with little hyperparameter tuning and even can be scaled for use cases where decision trees cannot. Nevertheless, their efficiency and scalability make them a common choice for classification work across multiple domains, including financials, healthcare, and image processing. On the one hand, Random Forest appears to be an excellent choice that provides accurate classification and robustness.

Histogram Based Gradient Boosting

Gradient boosting is a type of boosting with iconic characteristics. Histogram-based gradient boosting may be considered a special case of gradient boosting. This is usually applied in supervised ML tasks like classification and regression with classification boosting as a kind of decision tree boosting in deciding model performance and training process acceleration.

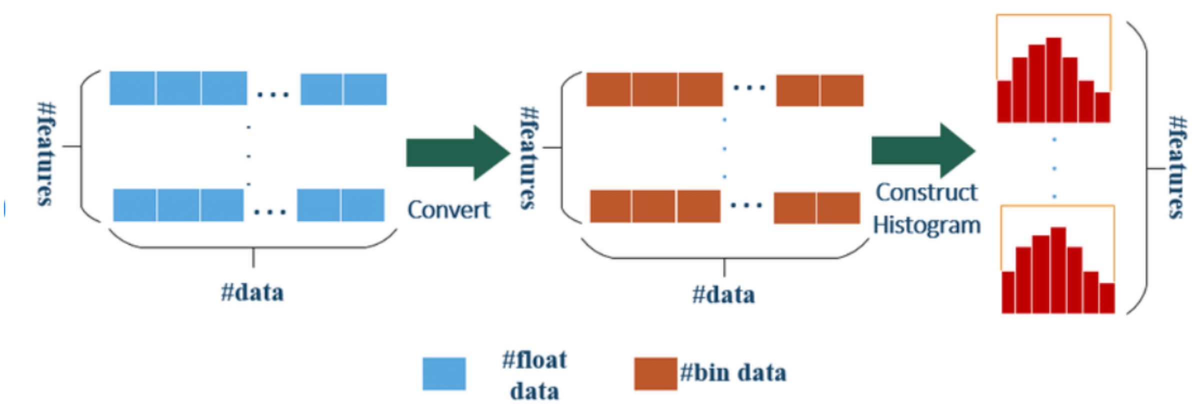

Fig 3.5 HistGradient Boosting Classifier

At each step, rather than seeking a split point for each feature extracted from the features, Histogram based Gradient boosting divide the discrete feature value interval into bins and describe the distribution of features in the sample, which can also describe the characteristics of categorical features and reduce the computational burden for seeking the best split point.

The main phases or stages of Histogram-based Gradient Boosting are; Define hyperparameters and variables and histograms: The training stage of building the decision trees that use the histogram to identify the optimal point to split: The iteration phase to update the model with new trees: The prediction stage to estimate the prediction for a given input. The leaf-wise growth strategy in this technique produces more deep trees capable of identifying complex relationships in the given data and information.

K-fold Cross Validation

This paper aims to explain the method of K-fold cross-validation which is a resample analysis used in ML to evaluate predictive models accuracy. The approach implies that the dataset is divided into several subsets or folds of approximately equal size. These 1-k folds are trained and 1 fold is validated in each iteration. This is repeated for k times such that the hold-out set becomes the validation set for exactly one fold. This allows grouping the performance metrics per each iteration and to calculate the average performance metrics for the model.

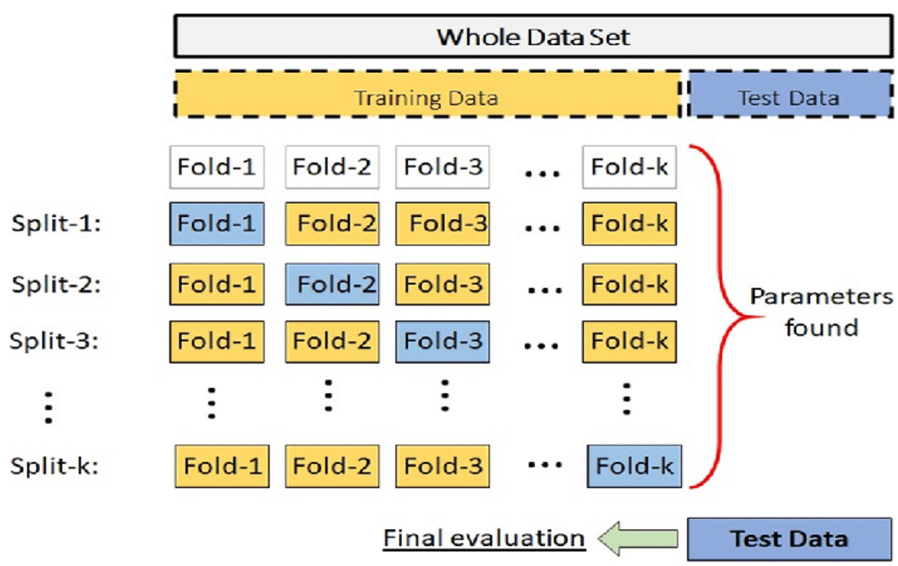

Fig 3.6 K-fold Cross Validation

Cross-validation has several benefits, with better performance and testing characteristics of the model compared to the standard train-test split. With the help of many data splits, k-fold cross-validation is a more reliable estimate that shows how the model works on the data that was not used to train the system. It is useful in identifying overfitting problems since it allows testing of the competency of the model on different samples of the data. Moreover, K-fold cross-validation is quite efficient for a limited dataset because it addresses the issue of obtaining compatible training and validation datasets.

The selection of k values for k-fold cross-validation is critical and is often reported to be set at 5 or 10. A smaller value of k would correspond to greater variance in the performance estimate while at the same time requiring more computational time for the algorithm to converge whereas a large value of k would lead to greater computational efficiency but estimation variance may suffer. From the above, we see that k-fold cross-validation shows how important it is for an ML model to maintain its performance consistently on new data from the real world.

3.1.4 Comparison of Models

A custom function has been created to compare all the models that were prepared in order to calculate the anxiety levels. This function obtains the number of folds from the user as input and then calculates the mean accuracy after training, the time taken for training the model, and the mean standard deviation. Function under ideal conditions is implemented using k-fold cross validation thereby offering a comprehensive evaluation of each model's predictive performance and any potential deviations in the model arising from changes in the training/validation set.

The output comprehensively includes a boxplot that highlights the rate at which accuracy scores are distributed for each model and provides predictions on the overall consistency of performance metrics. Furthermore the tabular type of representation provides the mean accuracy, training time and standard deviation values so that accurate appraisal of the model and comparison of efficiency can be achieved. This systemic strategy allows us to compare the ability of various models in predicting levels of anxiety through an overall evaluation of their accuracy consistency and computational resource demand for training.

The entire workflow process for the project is represented by the flowchart given below:

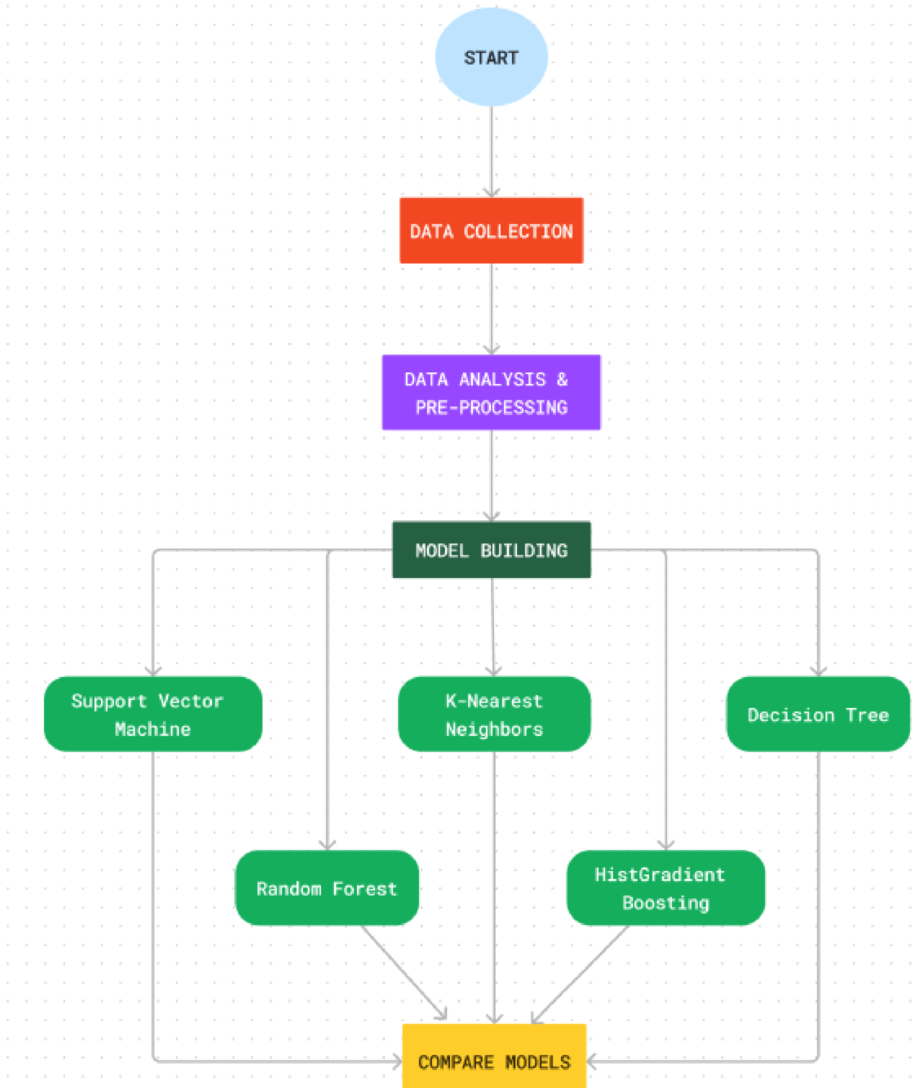

Fig 3.7 Flowchart of Methodology

3.2 Tools and Libraries Used

The various tools and technologies that have been utilized to create the project are described in this section.

3.2.1 Python

Python is a robust high-level computer language commonly applied in ML because it is simple, transparent, and has multifaceted libraries. Python thus plays a role a major foundational tool for data manipulation, for definitions of models, and for implementing models. They are well-supported by libraries like NumPy, SciPy, Pandas, and Scikit-learn for tasks like data preparation, data analysis, and by virtue of which supporting implementation of ML algorithms. The syntax of the language is similar to English and also promotes learning of individuals since it is ideal for machine learning custom applications where the design can be tried out and then done on a different platform. Moreover, the ability to use Python on other systems, such as Windows, can improve the portability of Python applications on various platforms. As Python is easy to use, well supported with such extensive library collections as among its community contributions, and can be effectively utilized by the ML practitioners for their everyday model building, training of the machine learning models for various and specific tasks.

3.2.2 Anaconda Navigator and Jupyter Notebook

There are other products like the Anaconda Navigator and the Jupyter Notebook that are popular in ML workflows. Anaconda Navigator provides a simple GUI for applications that manage environments, packages, and other projects that allow the user to set up the ML environments. Users can also install, update, and manage packages using R with minimal effort and is thus a suitable option for ML practitioners. On the other hand, Jupyter Notebooks provide a collaborative, highly interactive, and fully interactive platform for computing and creating other computational documents such as code, visualizations, and explanations in a notebook. In ML, Jupyter Notebooks are majorly used as a tool for data analytics task, model creation and delivery and sharing of insights into other stakeholders. They enable the creation of reusable tasks to write code, view results, and create documents efficiently for ML professionals. Anaconda Navigator eliminates much of the pain associated with the development of ML projects as it incorporates all the necessary components involved in the development of ML projects, including interacting notebooks for easy data manipulation and training, and the easy sharing and collaboration for ML projects. These are graphical user interfaces that provide a suitable platform for ML developers who want to develop and use versatile interaction functions for ML models.

3.2.3 NumPy

NumPy is a crucial module for numerical calculations in Python, which handles arrays and matrices with high-dimensional data solely. It has a large collection of mathematical operations and functions that render it as the best tool for mathematic manipulation and calculations in machine learning. NumPy's array operations and broadcasting functionality help in performing multiple mathematical manipulations in lesser time and thus improving the overall performance of ML algorithms.

3.2.3 Pandas

Data in ML projects may often be in the form of structured data which can be best exploited using libraries such as Pandas that offer data manipulation and analysis libraries and data structures such as DataFrames and Series. It is really helpful in case you need to do works with datasets such as data cleaning, transformation and onwards: indexing, merging and reshaping. The fact that pandas offers a straight-forward language for expressing data pre-processing tasks, combining its simplicity and functionality makes it ideal for solving problems involved in the pre-processing of data in ML.

3.2.4 Matplotlib

Matplotlib is a well-designed library of tools to create many different types of graph with its line plot and scatter plot as well as histogram. It is used in the visualization of the data that is being used in a ML project for easy exploration and on communication of the results. Matplotlib is unique for its ability to customize plots as well as control the user’s interaction with the plots and the data to generate plots that are necessary in analyzing and representing ML results.

3.2.5 Seaborn

Matplotlib is a graphing library for Python which includes a wide variety of common plotting functions while seaborn is a Python visualization library based on matplotlib that’s used for exploratory data analysis using enhanced aesthetics and more plotting functions. It simplifies the generation of scenarios like heat, paireg, and violin plots so as to improve the quality of data being presented in terms of ML analyses. Pandas and NumPY are Open-Source Python libraries that Seaborn supports and integrate with to allow the creation of visually appealing plots used to infer patterns and possibly causal mechanisms in data.

3.2.6 Statistics

Python has a statistics module that offers a built-in function for statistics such as mean median mode variance standard deviation. It can help evaluate descriptive statistics and data distributions in machine learning tasks. The statistics module is important in data analysis since it provides some functions that are not offered by other libraries such as NumPy and Pandas, which can be used for summarizing and identifying characteristics of a dataset.

3.2.7 Decimal

Python’s Decimal module is used to avoid approximate decimal numbers as it provides accurate division of decimals. It is useful for applications that include a lot of precision calculations like financial modelling or scientific computations. The Decimals module is used to work with decimal numbers because when doing numerical operations in ML with numbers the accuracy must increase to make the calculations more precise and reliable.

3.2.8 Time

A portion of the time module helps to calculate time taken for any execution, introduce delays and manipulate time stamps. It is useful for performance analaysis, benchmarks, and timing in ML scripts. The number of years the time module can be used to ensure that the algorithms that are conducted in the field of ML become fast and efficient in terms of time used and management of the resources used in the process.

3.2.9 Scikit-Learn Packages for ML

Simple and efficient tools for ML in Python – Scikit-Learn is an open-source ML library in the Python language used to implement different algorithms and tools for model selection. The packages imported include:

- SVM

It can be imported as “from sklearn import svm”. SVM is a ML algorithm that is used for classification and regression tasks.

- RandomForestClassifier

It can be imported as “from sklearn.ensemble import RandomForestClassifier”. It is an ensemble learning model that is mostly used for classification tasks.

- KNeighborsClassifier

It can be imported as “from sklearn.neighbors import KNeighborsClassifier”. It is widely used ML algorithm to perform classification tasks.

- DecisionTreeClassifier

It can be imported as “from sklearn.tree import DecisionTreeClassifier”. It is a classifier for problems that are generally classification in nature.

- HistGradientBoostingClassifier

It can be imported as “from sklearn.ensemble import HistGradientBoostingClassifier”. The scikit-learn library also provides a gradient boosting for the categorical variable and numerical variable target of the article.

- Metrics

It is imported using “from sklearn import metrics”. It is primarily used when working with certain metrics relevant to model assessment in ML.

- Preprocessing

It is imported as ‘‘from sklearn import preprocessing”. Preprocessing and normalizing techniques are used in assembling and handling feature set for data sets using ML libraries. The Scikit-Learn library has several built-in functions within the preprocessing module for learning and modifying the data for use in ML featuring standardization, imputation, and feature extraction.

In conclusion, the research methodology for data collection and data analysis that is advanced in this study offers a cumulative approach to using wearable technology and ML to estimate anxiety levels. The physiological data and different ML models and algorithms demonstrate that the study presents a thorough approach and an ideal platform toward anxiety detection. This cross-validation technique makes sure the viability and efficiency of the model that is deployed and this research contributes knowledge and findings in the field of mental health screening and strategies related to its prevention.

CHAPTER 4

RESULTS AND DISCUSSIONS

In this chapter, an overview of how the anxiety levels could be forecasted by using the physiological data obtained from the wrist worn devices are presented. Various machine learning algorithms like the SVM, Random Forest, KNN, Decision Trees, and Histogram-based gradient Boosting are employed for this purpose. The results highlight the ways of utilizing wearable technologies in predicting the anxiety levels.

4.1 Data Description

A descriptive statistics of the dataset containing the physiological variables HR, ST and EDA along with the labels is presented below:

Some descriptive statistics extracted from the combined experiment

	HR	ST	EDA	Labels
count	61012.000000	61012.000000	61012.000000	61012.000000
mean	87.726116	31.358579	0.358737	0.613453
std	14.538783	1.611184	0.270503	0.486962
min	52.043333	28.858000	0.000229	0.000000
25%	79.732222	29.957667	0.118689	0.000000
50%	88.650000	31.484667	0.322676	1.000000
75%	94.920278	32.891333	0.566445	1.000000
max	147.584444	34.566000	1.000244	1.000000

Fig 4.1 Data Description

A correlation matrix of the physiological data is shown in the figure below:

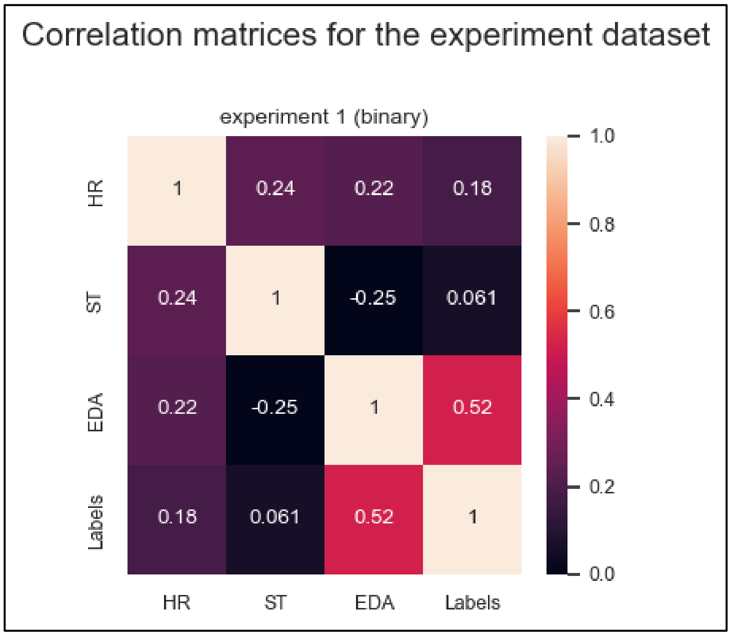

Fig 4.2 Correlation Matrix

The graphs below illustrates the variations in the HR, ST and EDA parameters, shedding light on the body's physiological fingerprint of anxiety:

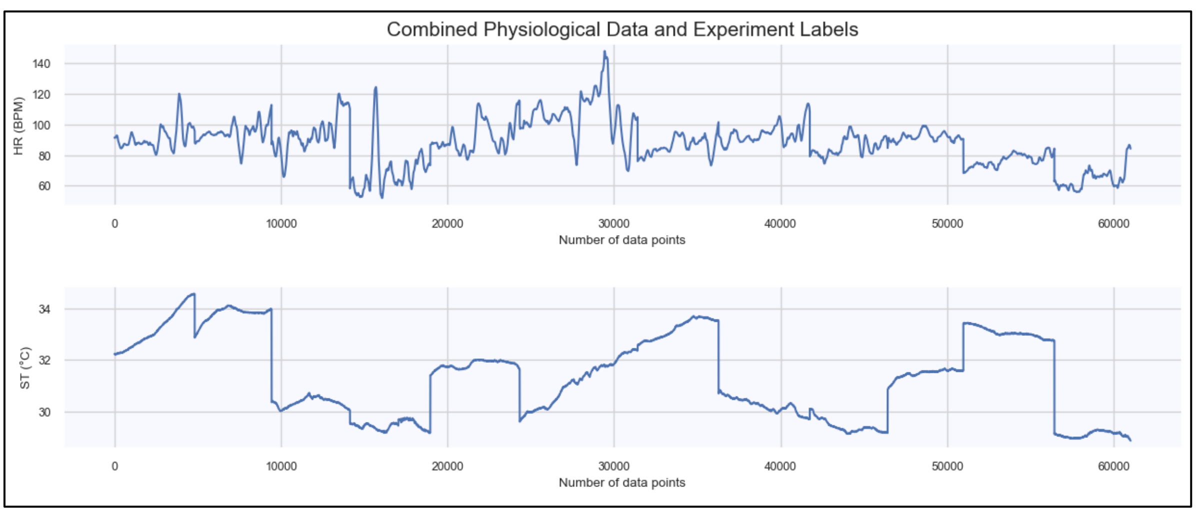

Fig 4.3 HR and ST data

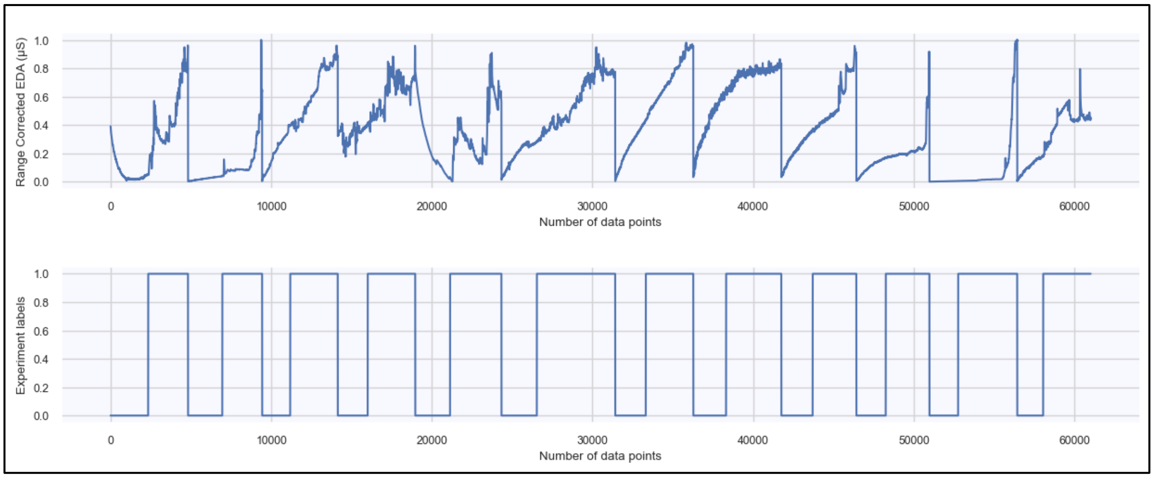

Fig 4.4 EDA and Labels data

4.2 K-fold Cross Validation Results

Now, k-fold cross-validation gives a good indication as to how well the machine learning model performs in terms of its accuracy, how stable the results are, as well as how well the model can generalize across several folds. The function has been created to use k-fold cross validation to assess the models and takes the number of folds, the model type, and boolean for random data as argument and returns confusion matrix for each iteration, the mean of the model scores and the standard deviation of the model scores.

4.2.1 3-fold Cross Validation

These results are obtained by passing value 3 to the cross validation function. The results of the 5 ML algorithms are displayed below:

- **SVM**

  The results obtained when svm.SVC(kernel='rbf', C = 1000, gamma = 1) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[ 7794    51]
 [   73 12419]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[ 7825    38]
 [   79 12395]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[ 7809    66]
 [   54 12408]]
------------------------------------------------------------------------------------------
Mean score for 3-fold cross validation is 99.41 and standard deviation is 0.017
------------------------------------------------------------------------------------------
Classifier: SVC(C=1000, gamma=1)
```

Fig 4.5 3-fold SVM

- **KNN**

  The results obtained when KNeighborsClassifier(n_neighbors=50) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[ 7766    79]
 [  174 12318]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[ 7783    80]
 [  180 12294]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[ 7780    95]
 [  141 12321]]
------------------------------------------------------------------------------------------
Mean score for 3-fold cross validation is 98.77 and standard deviation is 0.061
------------------------------------------------------------------------------------------
Classifier: KNeighborsClassifier(n_neighbors=50)
```

Fig 4.6 3-fold KNN

- **Decision Tree**

  The results obtained when DecisionTreeClassifier(criterion = 'gini', max_depth = 8) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[ 7804    41]
 [  453 12039]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[ 7694   169]
 [  381 12093]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[ 7725   150]
 [  434 12028]]
------------------------------------------------------------------------------------------
Mean score for 3-fold cross validation is 97.33 and standard deviation is 0.223
------------------------------------------------------------------------------------------
Classifier: DecisionTreeClassifier(max_depth=8)
```

Fig 4.7 3-fold Decision Tree

- **Random Forest**

  The results obtained when RandomForestClassifier(n_estimators= 400, min_samples_split = 2, min_samples_leaf = 1, max_depth = 8, bootstrap = False) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[ 7790    55]
 [  348 12144]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[ 7801    62]
 [  307 12167]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[ 7821    54]
 [  357 12105]]
------------------------------------------------------------------------------------------
Mean score for 3-fold cross validation is 98.06 and standard deviation is 0.110
------------------------------------------------------------------------------------------
Classifier: RandomForestClassifier(bootstrap=False, max_depth=8, n_estimators=400)
```

Fig 4.8 3-fold Random Forest

- **Histogram based Gradient Boosting**

  The results obtained when HistGradientBoostingClassifier(learning_rate=0.01, min_samples_leaf=1) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[ 7595   250]
 [  195 12297]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[ 7611   252]
 [  164 12310]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[ 7550   325]
 [  139 12323]]
------------------------------------------------------------------------------------------
Mean score for 3-fold cross validation is 97.83 and standard deviation is 0.119
------------------------------------------------------------------------------------------
Classifier: HistGradientBoostingClassifier(learning_rate=0.01, min_samples_leaf=1)
```

Fig 4.9 3-fold HistGradient Boosting

4.2.2 5-fold Cross Validation

These results are obtained by passing value 5 to the cross validation function. The results of the 5 ML algorithms are displayed below:

- **SVM**

  The results obtained when svm.SVC(kernel='rbf', C = 1000, gamma = 1) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[4637   28]
 [  43 7494]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[4730   33]
 [  29 7410]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[4730   23]
 [  39 7410]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 4
[[4667   18]
 [  47 7470]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 5
[[4673   44]
 [  32 7453]]
------------------------------------------------------------------------------------------
Mean score for 5-fold cross validation is 99.45 and standard deviation is 0.050
------------------------------------------------------------------------------------------
Classifier: SVC(C=1000, gamma=1)
```

Fig 4.10 5-fold SVM

- **KNN**

The results obtained when KNeighborsClassifier(n_neighbors=50) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[4633   32]
 [  77 7460]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[4714   49]
 [  89 7350]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[4702   51]
 [  78 7371]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 4
[[4651   34]
 [  93 7424]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 5
[[4653   64]
 [  67 7418]]
------------------------------------------------------------------------------------------
Mean score for 5-fold cross validation is 98.96 and standard deviation is 0.088
------------------------------------------------------------------------------------------
Classifier: KNeighborsClassifier(n_neighbors=50)
```

Fig 4.11 5-fold KNN

- **Decision Tree**

  The results obtained when DecisionTreeClassifier(criterion = 'gini', max_depth = 8) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[4572   93]
 [ 243 7294]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[4737   26]
 [ 271 7168]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[4639  114]
 [ 209 7240]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 4
[[4609   76]
 [ 267 7250]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 5
[[4689   28]
 [ 240 7245]]
------------------------------------------------------------------------------------------
Mean score for 5-fold cross validation is 97.43 and standard deviation is 0.253
------------------------------------------------------------------------------------------
Classifier: DecisionTreeClassifier(max_depth=8)
```

Fig 4.12 5-fold Decision Tree

- **Random Forest**

The results obtained when RandomForestClassifier(n_estimators= 400, min_samples_split = 2, min_samples_leaf = 1, max_depth = 8, bootstrap = False) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[4628   37]
 [ 200 7337]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[4717   46]
 [ 181 7258]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[4720   33]
 [ 167 7282]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 4
[[4647   38]
 [ 251 7266]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 5
[[4671   46]
 [ 214 7271]]
--------------------------------------------------------------------------------
Mean score for 5-fold cross validation is 98.01 and standard deviation is 0.276
--------------------------------------------------------------------------------
Classifier: RandomForestClassifier(bootstrap=False, max_depth=8, n_estimators=400)
```

Fig 4.13 5-fold Random Forest

- **Histogram based Gradient Boosting**

The results obtained when HistGradientBoostingClassifier(learning_rate=0.01, min_samples_leaf=1) is passed in the function are displayed below.

```
Confusion matrix, for iteration 1
[[4454  211]
 [ 153 7384]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 2
[[4538  225]
 [ 103 7336]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 3
[[4545  208]
 [   73 7376]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 4
[[4512  173]
 [ 165 7352]]
--------------------------------------------------------------------------------
Confusion matrix, for iteration 5
[[4504  213]
 [   74 7411]]
--------------------------------------------------------------------------------
Mean score for 5-fold cross validation is 97.38 and standard deviation is 0.288
--------------------------------------------------------------------------------
Classifier: HistGradientBoostingClassifier(learning_rate=0.01, min_samples_leaf=1)
```

Fig 4.14 5-fold HistGradient Boosting

4.2.3 10-fold Cross Validation

These results are obtained by passing value 10 to the cross validation function. The results of the 5 ML algorithms are displayed below:

- **SVM**

  The results obtained when svm.SVC(kernel='rbf', C = 1000, gamma = 1) is passed in the function are displayed below.

```
Confusion matrix, for iteration 6
[[2397   11]
 [  15 3678]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 7
[[2333    8]
 [  24 3736]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 8
[[2332   12]
 [  17 3740]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 9
[[2348   18]
 [  21 3714]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 10
[[2330   21]
 [  10 3740]]
-------------------------------------------------------------------------------------------
Mean score for 10-fold cross validation is 99.48 and standard deviation is 0.084
-------------------------------------------------------------------------------------------
Classifier: SVC(C=1000, gamma=1)
```

Fig 4.15 10-fold SVM

- **KNN**

  The results obtained when KNeighborsClassifier(n_neighbors=50) is passed in the function are displayed below.

```
Confusion matrix, for iteration 7
[[2325   16]
 [  50 3710]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 8
[[2324   20]
 [  28 3729]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 9
[[2340   26]
 [  33 3702]]
-------------------------------------------------------------------------------------------
Confusion matrix, for iteration 10
[[2324   27]
 [  26 3724]]
-------------------------------------------------------------------------------------------
Mean score for 10-fold cross validation is 99.08 and standard deviation is 0.105
-------------------------------------------------------------------------------------------
Classifier: KNeighborsClassifier(n_neighbors=50)
```

Fig 4.16 10-fold KNN

- **Decision Tree**

  The results obtained when DecisionTreeClassifier(criterion = 'gini', max_depth = 8) is passed in the function are displayed below.

```
Confusion matrix, for iteration 6
[[2361   47]
 [ 109 3584]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 7
[[2331   10]
 [ 134 3626]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 8
[[2314   30]
 [ 141 3616]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 9
[[2357    9]
 [ 133 3602]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 10
[[2343    8]
 [ 113 3637]]
--------------------------------------------------------------------------------------------
Mean score for 10-fold cross validation is 97.54 and standard deviation is 0.290
--------------------------------------------------------------------------------------------
Classifier: DecisionTreeClassifier(max_depth=8)
```

Fig 4.17 10-fold Decision Tree

- **Random Forest**

  The results obtained when RandomForestClassifier(n_estimators= 400, min_samples_split = 2, min_samples_leaf = 1, max_depth = 8, bootstrap = False) is passed in the function are displayed below.

```
Confusion matrix, for iteration 7
[[2327   14]
 [ 132 3628]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 8
[[2330   14]
 [ 111 3646]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 9
[[2351   15]
 [ 117 3618]]
--------------------------------------------------------------------------------------------
Confusion matrix, for iteration 10
[[2333   18]
 [  74 3676]]
--------------------------------------------------------------------------------------------
Mean score for 10-fold cross validation is 97.96 and standard deviation is 0.343
--------------------------------------------------------------------------------------------
Classifier: RandomForestClassifier(bootstrap=False, max_depth=8, n_estimators=400)
```

Fig 4.18 10-fold Random Forest

- **Histogram based Gradient Boosting**

  The results obtained when HistGradientBoostingClassifier(learning_rate=0.01, min_samples_leaf=1) is passed in the function are displayed below.

```
Confusion matrix, for iteration 4
[[2295   94]
 [  43 3669]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 5
[[2258   87]
 [  42 3714]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 6
[[2310   98]
 [  34 3659]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 7
[[2263   78]
 [ 101 3659]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 8
[[2255   89]
 [  68 3689]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 9
[[2265  101]
 [  52 3683]]
------------------------------------------------------------------------------------------
Confusion matrix, for iteration 10
[[2246  105]
 [  37 3713]]
------------------------------------------------------------------------------------------
Mean score for 10-fold cross validation is 97.59 and standard deviation is 0.296
------------------------------------------------------------------------------------------
Classifier: HistGradientBoostingClassifier(learning_rate=0.01, min_samples_leaf=1)
```

Fig 4.19 10-fold HistGradient Boosting

4.3 Comparison of Models

The results of the ML models prepared for anxiety prediction are presented in the following table, showcasing the mean accuracy and mean standard deviation across the 3-fold cross-validation, 5-fold cross-validation and 10-fold cross-validation. The table compares the performance of SVM, KNN, Random Forest, Decision Trees and Histogram based gradient boosting algorithm.

Algorithm	Folds	Mean Accuracy	Mean Standard Deviation
SVM	3-fold	99.41%	1.7%
	5-fold	99.45%	5.0%
	10-fold	99.48%	8.4%
KNN	3-fold	98.77%	6.1%
	5-fold	98.96%	8.8%
	10-fold	99.08%	10.5%
Decision Tree	3-fold	97.33%	22.3%
	5-fold	97.43%	25.3%
	10-fold	97.54%	29.0%
Random Forest	3-fold	98.06%	11.0%
	5-fold	98.01%	27.6%
	10-fold	97.96%	34.3%
HistGradient Boosting	3-fold	97.83%	11.9%
	5-fold	97.38%	28.8%
	10-fold	97.59%	29.6%

Table 4.1 Comparison of Models

A comparison function is created that takes the number of folds as an input and produces a box-plot graph along with a table that displays the total time consumed, the mean accuracy and the standard deviation of the models. The results of the same are shown below:

- **10-fold Results**

  These results are calculated by passing the value 10 to the function.

	Mean Cross Validation Accuracy	Standard Deviation	Time Elapsed (sec)
SVM	99.475496	0.083933	226
KNN	99.078840	0.105037	6
Decision Tree	97.536469	0.289936	2
Random Forest	97.980659	0.366329	355
HistGradient Boosting	97.498771	0.178585	8

Fig 4.20 10-fold Compare data

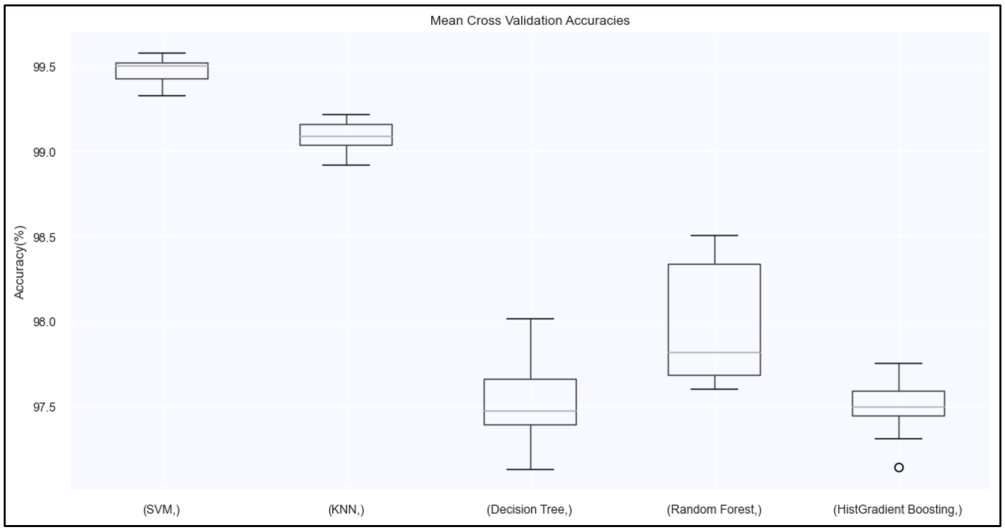

Fig 4.21 10-fold Box-plot

- ### 5-fold Results

These results are calculated by passing the value 5 to the function.

	Mean Cross Validation Accuracy	Standard Deviation	Time Elapsed (sec)
SVM	99.449271	0.050320	78
KNN	98.960826	0.088343	5
Decision Tree	97.428290	0.246911	1
Random Forest	97.951156	0.360643	268
HistGradient Boosting	97.402065	0.309477	5

Fig 4.22 5-fold Compare data

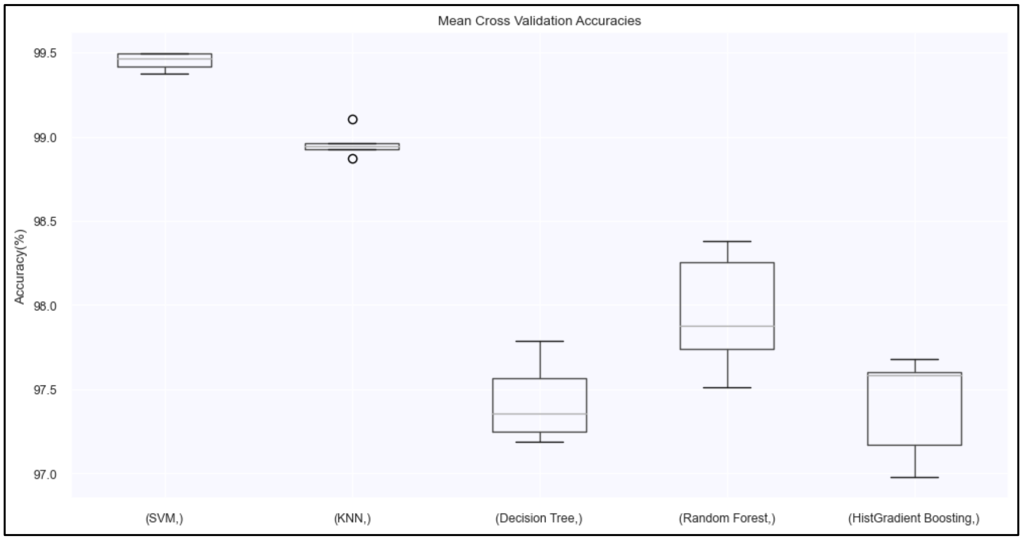

Fig 4.23 5-fold Box-Plot

In summary, the results of ML models for anxiety prediction show that the combination of wearable devices and advanced algorithms can effectively help in the prediction of anxiety development among people. The comparison of SVM, Random Forest, KNN, Decision Trees and HistGradient Boosting shows that the mean accuracy for SVMs was highest at 99.47% while the mean accuracy for HistGradient Boosting was the lowest at 97.49%. The training time for the models are also reasonable with Decision Tree taking 2 seconds and KNN taking 6 seconds on 10-fold cross validation.

In conclusion, the implications of these findings indicate that using the AI in wearable devices can be beneficial for early detection of anxiety disorders with an objective and unbiased approach. Many models are trained using physiological data that can reveal small fluctuations that correlate directly with anxiety manifestations and are detected by wearable sensors including the heart rate, skin conductivity, and respiration rates. The non-invasive nature of this method coupled with its continuous nature ensures early detection of potentially dangerous behavior as well as proper management of anxiety related conditions.

CHAPTER 5

CONCLUSION AND FUTURE WORKS

5.1 Conclusion

The study has shown the potential for analyzing physiological data using wearable sensors combined with advanced ML algorithms for predicting and monitoring anxiety. The study gathered information from heart rate and skin temperature and electrodermal activities, wearable devices, which were used to accurately model anxiety through models such as support vector machines, k-nearest neighbors, decision trees, random forest, and histogram gradient boosting.

The rigorous evaluation approach using k-fold cross-validation showed that the support vector machine model was able to demonstrate extremely high mean accuracies as high as 99%. With an accuracy of 99% across 10 folds, there was no major variance across the models and the balance across folds shows 8.4% mean standard deviation. The KNN model also showed good results as evidenced at 99. 08% mean accuracy. These results provide strong evidence indicating that machine learning combined with wearable sensor data has tremendous potential for advancing mental health diagnosis and therapy.

There are many future avenues of research that can be contemplated to further explore this topic. It is much easier to evolve the models further to allow calculating the anxiety score in real-time based on data from wearable sensors. There was potential for the development of easy-to-use mobile applications with notification systems that could empower users utilizing this tool to self-manage their diseases. The use of the technology in conjunction with healthcare professionals could make it even easier to monitor patients and implement evidence-based therapeutic strategies.

Overall, the integration of wearables with physiological signals as well as machine learning paves the way for personalized mental care for impending and precise mental illnesses. Using these technologies allows us to measure these physical symptoms of anxiety quantitatively and to detect any anxiety issues at an early stage and provide a person with complete and individual care. This paradigm shift has the potential to de-stigmatize and improve the means through which prevention, detection, and managing anxiety disorders becomes possible for millions of people around the world.

5.2 Future Works

This work has further opened the path towards using ML models and wearable sensing measurements to assess and monitor anxiety. However, there are several promising avenues to further enhance and expand the capabilities of this system:

5.2.1 Real-time anxiety calculation

Enabling real-time anxiety calculation directly from data streams obtained from smartwatches or other wearable devices would allow for continuous, uninterrupted monitoring of an individual's mental state. This would help ensure access to treatment and care at any time when heightened anxiety levels are observed.

5.2.2 User friendly Application Development

The development of a user friendly mobile application can offer crucial advantages. It can help people in tracking their own anxiety levels with the help of the anxiety prediction system. The application will enable the user to enter their personal information, monitor anxiety levels and receive alerts in case of regularly elevated anxiety levels.

5.2.3 Integration with healthcare providers

Integration with healthcare providers can pose a great opportunity for exploration. The synergy between the system and medical practitioners could facilitate in remote monitoring the status of the patient by trained professionals. Considering the anxiety predictions, specific adjustments can be made by the healthcare provider for the individual to get better therapy and medication.

5.2.4 Expansion to other mental health conditions

Moreover, developing the machine learning models to be able to recognize and diagnose other mental illnesses in-addition to anxiety will extend the use of the system. The establishment of a multimodal screening tool for multiple disorders may drastically transform the field of mental health by allowing for swift screening of patients for an extensive array of psychological illnesses.

Lastly, as more data is accumulated in database then the models can be further improved, fine-tuned and researched, enriched new sensing modalities and as well as enhanced algorithms, which may pave way to the next generation of mental health technology and potentially its predictive power or outcome. By building on these potential future lines of research, the anxiety prediction system would become a highly effective, user-focused tool to offer support for each individual, care takers, as well as healthcare providers in their quest for the better mental health state.

Due to constant exploration of technological advancement and incorporation of design for humanity principles this work creates a realistic picture of anxiety disorder and other disorders to remove stigma and find solutions to eradicate them. It also acts as a guide or light therefore supporting the development of people and societies by incorporating care for mental health.

REFERENCES

[1] Kristen Mitchell, “Anxiety Disorders”, [Online] Available: https://www.webmd.com/anxiety-panic/anxiety-disorders, Accessed: 19 May 2024

[2] WHO, “Anxiety Disorders”, [Online] Available: https://www.who.int/news-room/fact-sheets/detail/anxiety-disorders, Accessed: 19 May 2024

[3] Cleveland Clinic, “Anxiety Disorders”, [Online] Available: https://my.clevelandclinic.org/health/diseases/9536-anxiety-disorders, Accessed: 19 May 2024

[4] Mayo Clinic, “Anxiety Disorders”, [Online] Available: https://www.mayoclinic.org/diseases-conditions/anxiety/symptoms-causes/syc-20350961, Accessed: 19 May 2024

[5] National Institute of Mental Health, “Anxiety Disorders”, [Online] Available: https://www.nimh.nih.gov/health/topics/anxiety-disorders, Accessed: 19 May 2024

[6] M a, Adheena & Naroli, Sindhu & Selvaraj, Jerritta, “Physiological Detection of Anxiety”, 1-5. 10.1109/ICCSDET.2018.8821162, 2018.

[7] Khullar, V., Tiwari, R.G., Agarwal, A.K., Dutta, S., “Physiological Signals Based Anxiety Detection Using Ensemble Machine Learning”, Cyber Intelligence and Information Retrieval. Lecture Notes in Networks and Systems, vol 291. Springer, Singapore, 2022.

[8] Abd-Alrazaq A, AlSaad R, Harfouche M, Aziz S, Ahmed A, Damseh R, Sheikh J., “Wearable Artificial Intelligence for Detecting Anxiety: Systematic Review and Meta-Analysis.”, doi: 10.2196/48754. PMID: 37938883; PMCID: PMC10666012, 2023.

[9] Priya, Anu & Garg, Shruti & Tigga, Neha, “Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms”, Procedia Computer Science. 167. 1258-1267. 10.1016/j.procs.2020.03.442., 2020.

[10] Ahmed A, Aziz S, Toro CT, Alzubaidi M, Irshaidat S, Serhan HA, Abd-Alrazaq AA, Househ M., “Machine learning models to detect anxiety and depression through social media: A scoping review”, Comput Methods Programs Biomed Update, 2022.

[11] Priya, Anu & Garg, Shruti & Tigga, Neha, “Predicting Anxiety, Depression and Stress in Modern Life using Machine Learning Algorithms”, Procedia Computer Science. 167. 1258-1267. 10.1016/j.procs.2020.03.442, 2020.

[12] Hawes MT, Schwartz HA, Son Y, Klein DN, “Predicting adolescent depression and anxiety from multi-wave longitudinal data using machine learning”, Psychol Med. 2023 Oct;53(13):6205-6211. doi: 10.1017/S0033291722003452. Epub 2022 Nov 15. PMID: 36377499, 2022.

[13] Wessel A. van Eeden, Chuan Luo, Albert M. van Hemert, Ingrid V.E. Carlier, Brenda W. Penninx, Klaas J. Wardenaar, Holger Hoos, Erik J. Giltay, “Predicting the 9-year course of mood and anxiety disorders with automated machine learning: A comparison between auto-sklearn, naïve Bayes classifier, and traditional logistic regression”, Psychiatry Research,Volume 299, ISSN 0165-1781, https://doi.org/10.1016/j.psychres.2021.113823, 2021.

[14] Prince Kuma,Shruti Garg,Birla, Mesra Ashwani Garg, “Assessment of Anxiety, Depression and Stress using Machine Learning Models”, 10.1016/j.procs.2020.04.213, 2020.

[15] Yassin W, Nakatani H, Zhu Y, Kojima M, Owada K, Kuwabara H, Gonoi W, Aoki Y, Takao H, Natsubori T, Iwashiro N, Kasai K, Kano Y, Abe O, Yamasue H, Koike S., “Machine-learning classification using neuroimaging data in schizophrenia, autism, ultra-high risk and first-episode psychosis”, Transl Psychiatry. 2020 Aug 17;10(1):278. doi: 10.1038/s41398-020-00965-5. PMID: 32801298; PMCID: PMC7429957, 2020.

[16] Mitte, K., “Memory bias for threatening information in anxiety and anxiety disorders: A meta-analytic review”, Psychological Bulletin, 134(6), 886–911. https://doi.org/10.1037/a0013343, 2008.

[17] Aslam, Abdul Rehman & Altaf, Muhammad Awais Bin, “Machine learning–based patient-specific processor for the early intervention in autistic children through emotion detection”, 10.1016/B978-0-12-822822-7.00014-4, 2021.

[18] Hornstein S, Forman-Hoffman V, Nazander A, Ranta K, Hilbert K., “Predicting therapy outcome in a digital mental health intervention for depression and anxiety: A machine learning approach”, Digit Health. 2021 Nov doi: 10.1177/20552076211060659, PMCID: PMC8637697, 2021.

[19] Pavlova I, Zikrach D, Mosler D, Ortenburger D, Góra T, Wąsik J., “Determinants of anxiety levels among young males in a threat of experiencing military conflict-Applying a machine-learning algorithm in a psychosociological study”, PLoS One. 2020 Oct 7;15(10):e0239749. doi: 10.1371/journal.pone.0239749, PMCID: PMC7540846, 2020.

[20] Danilo Bzdok a b e, Andreas Meyer-Lindenberg c d, “Machine Learning for Precision Psychiatry: Opportunities and Challenges”, doi.org/10.1016/j.bpsc.2017.11.007, 2018.

[21] Kim, Jina & Lee, Jieon & Park, Eunil & Han, Jinyoung, “A deep learning model for detecting mental illness from user content on social media”, Scientific Reports. 10. 10.1038/s41598-020-68764-y, 2020.

[22] R. Kuttala, R. Subramanian and V. R. M. Oruganti, "Multimodal Hierarchical CNN Feature Fusion for Stress Detection," in IEEE Access, vol. 11, pp. 6867-6878, doi: 10.1109/ACCESS.2023.3237545, 2023.

[23] A. Al-Ezzi, A. A. Al-Shargabi, F. Al-Shargie and A. T. Zahary, "Complexity Analysis of EEG in Patients With Social Anxiety Disorder Using Fuzzy Entropy and Machine Learning Techniques," in IEEE Access, vol. 10, pp. 39926-39938, doi: 10.1109/ACCESS.2022.3165199, 2022.

LIST OF PUBLICATIONS

Paper 1: Navigating the Smart Landscape: A Comparative Analysis of Operating Systems for Wearable IoT Devices

Index: Scopus

NATIONAL CONFERENCE

NCACSI - 24

NATIONAL CONFERENCE ON ADVANCED COMPUTER SCIENCE AND INFORMATION TECHNOLOGY (NCACSI - 24)

19th May 2024 Guwahati, India

Acceptance Letter

Authors Name: Alankrita Singh, Vinod Kumar

Dear Authors,
We are pleased to inform you that your paper has been accepted by the review committee for Oral / Poster Presentation at the **NATIONAL CONFERENCE ON ADVANCED COMPUTER SCIENCE AND INFORMATION TECHNOLOGY (NCACSI - 24)**

Article Title: **Navigating the Smart Landscape: A Comparative Analysis of Operating Systems for Wearable IoT Devices**

Paper ID: **National Conference_5196832**

This conference will be held on **19th May 2024 in Guwahati, India**

Your paper will be published in the conference proceeding and Well reputed journal after registration.

Please register as soon as possible in order to secure your participation:
https://www.nationalconference.in/event/registration.php?id=2481785

You are requested to release the payment and mail us the screen of successful payment release with your name and title of paper to confirm your registration.

Sincerely,

NATIONAL CONFERENCE NC

Dr. Tara Srivastava
National Conference

+91 96770 07228 info@nationalconference.in www.nationalconference.in

Gmail Alankrita Singh <alankrita.aparna@gmail.com>

Transaction Acknowledgment - Successful Payment

National Conference <info@nationalconference.in> Sat, May 11, 2024 at 4:34 PM
Reply-To: National Conference <info@nationalconference.in>
To: Alankrita Singh <alankrita.aparna@gmail.com>

Dear Alankrita Singh,

We are pleased to inform you that your online payment transaction has been successfully processed. The details of your payment are as follows:

Order ID: 663f5013f1329

Reference ID: 113284056428

Amount: 4875.00 INR

Name: Alankrita Singh

Email ID: alankrita.aparna@gmail.com

Phone Number: 8126704585

Thank you for choosing **National Conference**
. We appreciate your prompt payment.

For assistance or inquiries, feel free to reach out to us at **info@nationalconference.in** or **+91 9677007228**.

Best Regards,
National Conference
info@nationalconference.in
+91 9677007228

Paper 2: Anxiety Level Prediction Based on Physiological Variables using Adaptive Neuro Fuzzy Inference System

Index: Scopus

NATIONAL CONFERENCE

NCACSI - 24

NATIONAL CONFERENCE ON ADVANCED COMPUTER SCIENCE AND INFORMATION TECHNOLOGY (NCACSI - 24)

18th May 2024 Udaipur, India

Acceptance Letter

Authors Name: Alankrita Singh, Vinod Kumar

Dear Authors,
We are pleased to inform you that your paper has been accepted by the review committee for Oral / Poster Presentation at the **NATIONAL CONFERENCE ON ADVANCED COMPUTER SCIENCE AND INFORMATION TECHNOLOGY (NCACSI - 24)**

Article Title: **Anxiety Level Prediction Based on Physiological Variables using Adaptive Neuro Fuzzy Inference Syste**

Paper ID: **National Conference_2849630**

This conference will be held on **18th May 2024 in Udaipur, India**

Your paper will be published in the conference proceeding and Well reputed journal after registration.

Please register as soon as possible in order to secure your participation:

https://www.nationalconference.in/event/registration.php?id=2481806

You are requested to release the payment and mail us the screen of successful payment release with your name and title of paper to confirm your registration.

Sincerely,

NATIONAL CONFERENCE NC

Dr. Tara Srivastava
National Conference

+91 96770 07228 info@nationalconference.in www.nationalconference.in

Gmail

Alankrita Singh <alankrita.aparna@gmail.com>

Transaction Acknowledgment - Successful Payment

National Conference <info@nationalconference.in>
Reply-To: National Conference <info@nationalconference.in>
To: Alankrita Singh <alankrita.aparna@gmail.com>

Sat, May 11, 2024 at 9:01 PM

Dear Alankrita Singh,

We are pleased to inform you that your online payment transaction has been successfully processed. The details of your payment are as follows:

Order ID: 343f5263d9306

Reference ID: 209284055009

Amount: 4875.00 INR

Name: Alankrita Singh

Email ID: alankrita.aparna@gmail.com

Phone Number: 8126704585

Thank you for choosing **National Conference**
. We appreciate your prompt payment.

For assistance or inquiries, feel free to reach out to us at **info@nationalconference.in** or **+91 9677007228**.

Best Regards,
National Conference
info@nationalconference.in
+91 9677007228

PLAGIARISM REPORT

Source: TurnitIn

Similarity Report

PAPER NAME
removed_ai.docx

WORD COUNT **9697 Words**	CHARACTER COUNT **54116 Characters**
PAGE COUNT **47 Pages**	FILE SIZE **1.5MB**
SUBMISSION DATE **May 27, 2024 10:22 AM GMT+5:30**	REPORT DATE **May 27, 2024 10:24 AM GMT+5:30**

6% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

- 3% Internet database
- 3% Publications database
- Crossref database
- Crossref Posted Content database
- 3% Submitted Works database

Excluded from Similarity Report

- Bibliographic material
- Cited material
- Small Matches (Less then 8 words)

Summary