THE IMPACT OF DIGITAL TECHNOLOGY ADDICTION ON MENTAL HEALTH AND WELL-BEING

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled “THE IMPACT OF DIGITAL TECHNOLOGY ADDICTION ON MENTAL HEALTH AND WELL-BEING”, submitted by Mahmudul Hasan Raihan to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 01-06-2024.

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We hereby declare that this project has been done by us under the supervision of **Dr. S. M. Aminul Haque, Professor and Associate Head, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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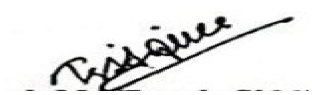

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ABSTRACT

Addiction to digital technology has become a major issue in modern culture, affecting mental health and wellbeing in a variety of intricate ways. On the one hand, excessive screen time and technology use can cause a number of negative effects, such as worsening attention-deficit symptoms, lowering social and emotional intelligence, developing a technology addiction, and isolating oneself from others. Notable side effects include disturbed sleep patterns and a deterioration in psychological well-being, which are made worse by less social interactions, a rise in hopelessness and loneliness, and a drop in self-worth. Moreover, there is a negative relationship between internet addiction and subjective well-being, which includes good emotions and life satisfaction. The significance of processing capacity, data storage, and reliable networking gear as hardware requirements for managing sizable datasets and executing complex machine learning algorithms is highlighted by this study. The process includes gathering a lot of data via questionnaires, interviews, and surveys. Metrics like the F1 score are used in performance assessment and are especially useful for skewed datasets. The investigation of several machine learning models, such as Decision Trees, Support Vector Machines, K-Nearest Neighbors, Logistic Regression, Random Forest, Gradient Boosting, XGBoost, CatBoost, Neural Network, and XGBoost3, reveals the effectiveness of these models in predicting the impact of digital technology addiction on mental health. Of these, Gradient Boosting and Neural Network models demonstrated the highest accuracy in modeling the complex relationships between digital technology use and mental health outcomes. On the other hand, the study recognizes the potential for digital technology to influence behavioral issues and disorders, such as ADHD. This research offers insights into the possible advantages and disadvantages of using digital technology, as well as a thorough review of the effects of addiction to digital technology on mental health and wellbeing.

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CHAPTER 1

Introduction

1.1 Overview

In the era of digitalization, technology has permeated every aspect of our life, changing the ways in which we interact, collaborate, learn, and pass the time. Digital technology addiction is a new problem that has emerged along with the many advantages of digital technology. This condition, which is typified by obsessive and excessive use of digital platforms and gadgets, has gained substantial attention due to its potential effects on mental health and general wellbeing. This essay explores the causes, impacts, and ramifications of digital technology addiction for both people and society as a whole. It is a complex topic. Digital technology addiction includes a variety of behaviors that make it difficult for a person to go about their everyday life regularly. It is not only about spending excessive amounts of time online. Compulsive internet use, excessive gaming, a fascination with social media, and even an addiction to certain apps or digital services are examples of these behaviors. These technologies are inherently addictive because of the way they are designed, which makes use of psychological concepts to keep users interested and coming back for more. This may result in a vicious cycle of reliance where the person is driven to utilize the technology even when it has drawbacks.

Addiction to digital technology has a significant and complex effect on mental health. Numerous mental health conditions, such as anxiety, sadness, and stress disorders, can result from it. Constant information overload and the need to always be connected can worsen loneliness and isolation, which lowers one's sense of value and self-worth. In addition, a sedentary lifestyle brought on by excessive screen time and a lack of physical activity can be harmful to one's physical health, which exacerbates mental health issues. Comfort, health, and happiness are common definitions of well-being, which is another important factor impacted by addiction to digital technology. Compulsive digital gadget use can harm relationships, interfere with sleep, and lower productivity. One's sense of purpose and fulfilment might be undermined by an ongoing state of distraction and an inability to concentrate on interactions with others in the actual world. An all-encompassing strategy that incorporates policy interventions, education, and awareness raising is needed to address the problem of digital technology addiction. Promoting healthy behaviors and thoughtful technology use on an individual basis can help reduce the hazards related to digital technology addiction.

1.2 Background and Present State

The increasing body of research on the effects of digital technology addiction on mental health and overall wellbeing is a testament to the difficulty of the problem and the pressing need for workable solutions. In addition to examining the psychological and sociodemographic consequences of digital technology addiction, recent research has also probed the neurological foundations of this problem.

For instance, by mapping changes in brain activity linked to excessive screen time, researchers are beginning to investigate the neural mechanisms associated with digital technology addiction. In order to develop more individualized treatment plans, this field of study seeks to understand the neurobiological underpinnings of digital technology addiction [e.g., Small et al., 2020]. [1]

In addition, there is increasing interest in the use of artificial intelligence (AI) and machine learning in the diagnosis and treatment of addiction to digital technology. AI algorithms have the potential to identify individuals at risk of developing problematic digital technology use patterns earlier than traditional methods allow, allowing for more timely intervention and possibly lessening the severity of addiction outcomes [e.g., Gross et al., 2020]. AI algorithms analyze patterns in user behavior and physiological responses.

An important topic of research is the connection between digital technology addiction and other mental health conditions. Studies are investigating the connection between the usage of digital technology and co-occurring mental health problems such as depression and anxiety. Finding out whether digital platforms or material are most likely to induce or exacerbate these diseases is the aim. This information may help with the creation of treatments that deal with co-occurring mental health disorders and addiction at the same time (Lebni et al., 2020).

Researchers are also focusing on policy and regulatory interventions, as they investigate how laws and regulations might be used to encourage better digital technology usage behaviors. This involves assessing the efficacy of age limitations, parental controls, and educational initiatives designed to improve young users' critical thinking and digital literacy [e.g., Giles et al., 2011].

Even with these developments, it is still difficult to completely comprehend and treat digital technology addiction. Longitudinal studies are still required to monitor the long-term impacts of digital technology use on mental health and well-being in various demographic groups. Furthermore, additional study is required to assess the effectiveness of currently available therapies and to provide fresh, cutting-edge methods for diagnosing, treating, and preventing digital technology addiction.

In conclusion, research on the effects of addiction to digital technology on mental health and wellbeing is still in its early stages and represents a vibrant area of study. As the knowledge grows, so too does the possibility of creating practical solutions to lessen the negative effects of excessive use of digital technology, eventually enhancing people's mental health and general wellbeing around the globe.

1.3 Problem Statement

As Digital Technology spread out all over the world. So, every step in the world there is the term off digital technology-

Effect on Mental Health: Examining the relationship between addiction to digital technology and mental health conditions such stress, anxiety, and depression.

Patterns of Technology Usage: investigating the relative contributions of various digital device and social media usage patterns to negative versus positive effects on mental health. Understanding the diagnostic criteria for digital technology addiction, such as the digital platforms involved and the intensity of addictive behavior, is essential to defining the term.

1.4 Objectives

It aims to explore the profound effects that excessive use of digital technology has on individuals' mental health and overall well-being.

Recognizing the Digital Age: The way we work, communicate, and pass our leisure time has changed dramatically as a result of the digital age. But there are drawbacks to this change as well, such as the possibility of digital technology addiction. It is crucial to comprehend these effects in order to successfully navigate the digital terrain.

Mental Health Concerns: Excessive use of digital technology has been connected to mental health problems like stress, anxiety, and depression. This research aims to shed light on the mechanisms via which digital technology use influences mental health outcomes by examining the effects of addiction to digital technology on mental health.

Development of Policies and Interventions: Knowledge gathered from this research may help shape the creation of programs and policies meant to lessen the harmful effects of addiction to digital technology. This covers methods for encouraging better digital behaviors and helping people who are battling addiction.

Well-being and Quality of Life: Addiction to digital technology can have negative effects on one's physical and general well-being in addition to their mental health. The purpose of this research is to examine the effects of digital technology addiction on dimensions of well-being, including social contacts, physical activity levels, and sleep patterns.

Raising Awareness and Educating: It's critical to educate people about the possible dangers of digital technology addiction for individuals, families, and communities. This study adds to larger educational initiatives that support appropriate use of digital technologies.

1.5 Scope and Limitations

Concerning the impact of digital technology addiction on mental health and well-being is vast and multifaceted, encompassing various dimensions of individual and societal well-being. It is crucial to spread knowledge about the potential dangers of digital technology addiction. Individuals and families may make educated decisions about their digital usage with the aid of education and preventative initiatives. Teenagers as well as other people are already addicted to technology, to get rid of the issues and disorder, we are working through the study.

Different people may display varying degrees of dependency on different types of technology, making it difficult to develop interventions or treatments that are universally applicable. The measurement of digital technology addiction presents its own set of challenges, as well. It is difficult to define "addiction" in the context of digital technology because it involves differentiating between problematic behavior and healthy use. This ambiguity can limit the effectiveness of diagnostic tools and the accuracy of research findings.

1.6 Summary

In the digital age, while technology enhances our lives, it also leads to digital addiction, characterized by compulsive use of digital platforms. This addiction negatively impacts mental health, causing anxiety, depression, and stress, and affects physical health. Addressing this issue requires comprehensive strategies, including policy interventions, education, and awareness. Research is focusing on the neural mechanisms of addiction, AI's role in diagnosis and treatment, and its connection with other mental health conditions, along with policy measures to promote healthier digital habits. However, challenges remain in defining and treating digital addiction, necessitating further research to understand its relationship with mental health and develop effective interventions.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

In today's digital age, technology profoundly influences how we interact, work, and spend our time. However, it has also led to digital technology addiction, characterized by excessive and compulsive use of digital devices and platforms. This addiction has significant impacts on mental health and well-being, including anxiety, depression, and stress. It also contributes to physical health issues due to a sedentary lifestyle.

Digital technology addiction disrupts daily life, affecting sleep, relationships, and productivity. Addressing this issue requires comprehensive strategies, including policy interventions, education, and awareness campaigns, to promote healthier and more mindful use of technology.

2.2 Related Works

Recently, there is several related works on the basis of digital technology addiction and the effects of more using digital technology.

Anju Singh, et al. [1] works with digital addiction based where they present per sequences and future abstract as well. They have used the classifier to get the best accuracy on the basis of the result.

The study from J. Y. Lebni and et al. [2] had 447 individuals, with a mean age of 23.47 years, mostly from Iranian universities. Most of the participants were pursuing bachelor's degrees, mostly in medical, and were unmarried. According to the survey, 45.9% of participants utilized the internet while living in dorms, while 79.6% of participants had computers. The main motivations for using the internet were to communicate with loved ones.

Another paper by I. M. Talha, et al. [3] which has worked on human behavior impact by smartphones on the basis of Naive Bayesian algorithms to model the relationships between smartphone use and behavioral outcomes, potentially identifying trends or predicting the likelihood of certain behaviors based on smartphone usage.

Jan Gross, Ricardo Buettner, and Hermann Baumgartl [4] also utilized the Internet Addiction Test (IAT) in their study, achieving a high accuracy of 94.17%.

T. Ramayah, T. Rabaya, S. Saparya, I. Mahmud, and S. Rawshon [5] applied Partial Least Squares (PLS) in their research, which yielded an accuracy of 37.9%.

Mark A. Bellis, Catherine A. Sharp, Karen Hughes, and Alisha R. Davies [6] used Logistic Regression in their study, achieving an accuracy of 75.4%.

Gary W. Small, Jooyeon Lee, Aaron Kaufman, Jason Jalil, Prabha Siddarth, Himaja Gaddipati, Teena D. Moody, and Susan Y. Bookheimer [7] also used the Naïve Bayes algorithm in their research, achieving an accuracy of 47%.

2.3 Comparison between existing works

Related several works in the comparison of my study, maximum of them has the main things which is related to digital technology addiction. Several of them has same algorithm but don't have the better accuracy. Some of them has better accuracy according to their algorithm. By comparing on my study, there is multiple different things which is I am going to work on the basis of uses of device on different ages and according to their base sleeping hour. Tough it's quite difficult, but I am going to use different classifier and model on the work.

Table 2.3.1. Comparative analysis with previous work

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Anju Singh & Sakshi Babbar [1]	Naïve Bayes	89%
2.	J. Y. Lebni and et al. [2]	Random Sampling, IAT	82.10%
3.	Jan Gross, Ricardo Buettner, Hermann Baumgartl [4]	IAT	94.17%
4.	T. Ramayah, T. Rabaya, S. Saparya, I.Mahmud, S.Rawshon [5]	PLS	37.9%

5.	Mark A. Bellis, Catherine A. Sharp, Karen Hughes, Alisha R. Davies [6]	Logistic regression	75.4%
6.	Iftakhar Mohammad Talha, Imrus Salehin, Susanta Chandra Debnath, Mohd. Saifuzzaman , Nazmun Nessa Moon , Fernaz Narin Nur [3]	Naïve Bayes	71%
7.	Gary W. Small, Jooyeon Lee, Aaron Kaufman, Jason Jalil, Prabha Siddarth, Himaja Gaddipati, Teena D. Moody, Susan Y. Bookheimer [7]	Naïve Bayes	47%

2.4 Open Issues

The many problems that digital technology addiction presents for mental health and wellbeing require a diverse strategy that addresses a number of unresolved concerns. Treating the negative impacts of digital technology addiction on mental health and wellbeing can be challenging in a number of ways.

Intentional Technology Use: People who use technology mindfully must establish clear guidelines for their online conduct. For example, they should only check in on social media or send emails during specific times. Achieving this degree of self-awareness and control, meanwhile, is difficult for many people since it requires willpower to ignore the allure of digital distractions all the time.

Social Interactions in Person: Another crucial problem is promoting in-person relationships over internet ones. Real human interactions outside of digital spaces should be prioritized. This requires a conscious and consistent effort, which can be difficult in a time when technology is ingrained in nearly every element of everyday life. It may be challenging for people to develop and sustain deep in-person connections because of the ease and speed of digital contacts, which frequently eclipse the richness and depth of in-person interactions.

Work-Life Balance: As people juggle many online platforms for both personal and professional objectives, finding a balance between work and personal life becomes more and more difficult. Constant connectedness can cause stress, which can have a detrimental effect on mental health. the fuzziness of the boundaries between work and play.

2.5 Summary

In today's digital age, technology has greatly influenced our daily lives, but it has also led to digital technology addiction. This addiction, characterized by excessive use of digital devices, negatively impacts mental health, causing anxiety, depression, and stress, and leads to physical health issues due to a sedentary lifestyle. It disrupts sleep, relationships, and productivity, necessitating comprehensive strategies like policy interventions, education, and awareness campaigns. Most studies use similar algorithms but vary in accuracy. The current study will explore device usage across different ages and its impact on sleep, using various classifiers and models. Addressing digital technology addiction is complex, involving challenges such as promoting mindful technology use, prioritizing in-person social interactions, and balancing work and personal life. These require self-awareness, consistent effort, and strategies to manage constant connectivity and its mental health impacts.

CHAPTER 3
METHODOLOGY

3.1 Overview

Clearly define the parameters of addiction by taking into account elements such as frequency, length, and influence on day-to-day functioning. Think about the various digital technologies at play, such as communication apps, games, and social networking. the precise mental health outcomes such as anxiety, depression, quality of sleep, and general wellbeing—that you would like to gauge. Questionnaires to determine how participants use digital technology, how they believe it affects their mental health, and whether they have any concerns or challenges. Information about the real-time usage durations, engagement trends, and associations with mental health markers. Self-judgment and interviews will be another instrumentation from the research.

3.2 Proposed Methodology

This research study will be the through of preprocessing and other algorithm. And there will be some train and test data for implementation by dependency and non-dependent data. Several model like Logistic Regression, Random Forest for getting the better accuracy from the directed data. As there will be new models if we needed to get better outcome with some good values.

Accuracy:

One statistic for classifying models is accuracy, which can be defined as the percentage of correctly categorized photos to total samples, the accuracy equation, or the model's anticipated percentage.

Accuracy=(TP+TN)/(TP+TN+FP+FN

Precision:

Accuracy is the probability of a positive label and the number of positive labels. The precision indicates the number of positively predicted cases with accuracy. It is useful to be precise when FP is more important than FN. This equation represents it mathematically:

Precision=TP/(TP+FP)

Recall:

The number of correctly categorized positive predicted events is measured by recall or sensitivity. Recall is a useful statistic in cases where FN outperforms FP. An further statistic for classification accuracy that accounts for both recall and precision is the F1-score. Since recall and accuracy are harmonic means, a thorough comprehension of these two metrics may be obtained from the F1 score. When Precision and Recall are equal, it performs best. Utilize the following equation to calculate it:

Recall=TP/(TP+FN)

F-1 Score:

The F1 score combines precision and recall, two important measures for assessing model performance, in a way that creates a comprehensive assessment of categorization accuracy. The precision of the model's positive identifications is a measure of how many of the projected positives turn out to be real positives. On the other hand, recall indicates the percentage of true positives that were accurately detected by gauging the model's capacity to locate all pertinent examples. The harmonic mean of recall and precision is used to compute the F1 score, which yields a single number that represents the harmony between these two factors.

F-1 Score=2*(Precision*Recall)/(Precision+Recall)

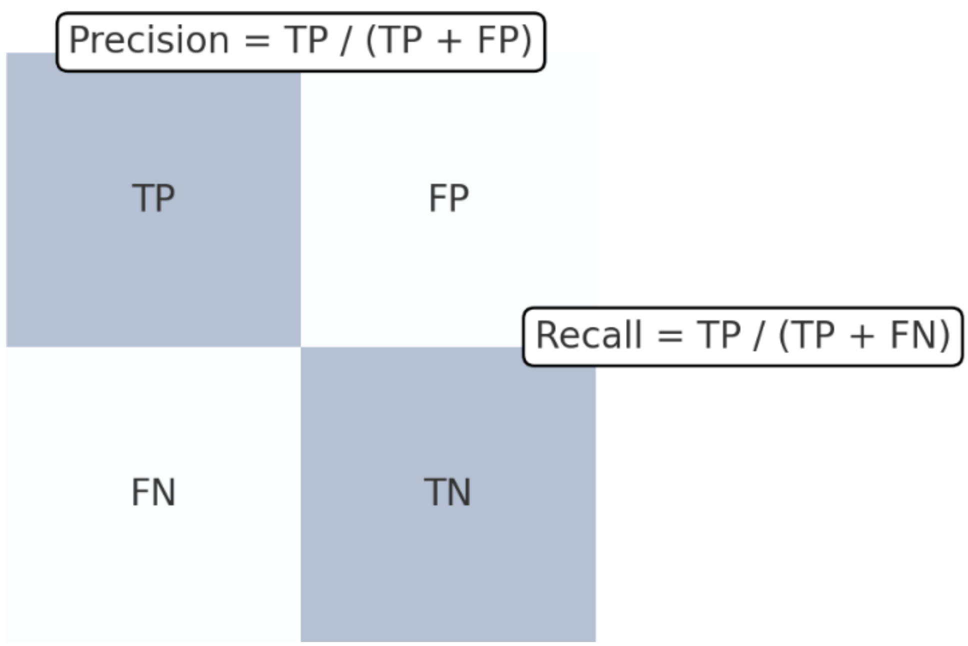

Figure 3.2.1: Method of Confusion Matrix

Figure Explanation

True Positives (TP): Correctly predicted positive cases.

True Negatives (TN): Correctly predicted negative cases.

False Positives (FP): Incorrectly predicted positive cases.

False Negatives (FN): Incorrectly predicted negative cases.

3.3 Hardware and Software Requirement

Hardware Requirement:

Computational Power: The ability to handle huge datasets and run machine learning algorithms effectively using high-performance computer resources.

Data Storage: Sufficient storage space for gathering, archiving, and organizing enormous volumes of data produced by several sources, including questionnaires, interviews, and the monitoring of online activity.

Networking Equipment: Sturdy networking framework for transferring and collecting data in real time.

Software Requirement:

Programming Languages: Python and machine learning are two programming languages, and libraries like scikit-learn are used to create models.

Systems for managing databases: various databases, such as Google Sheets (csv or excel).

Tools for Data Visualization: Use packages like Matplotlib, Seaborn, or pandas to create informative graphics that effectively communicate research findings.

3.4 Project Management and Financial Analysis

First of all, I have started working with a google from to collect the data. The google form on the basis of those question which are related to my work. I have collected the required data from different persons of different age.

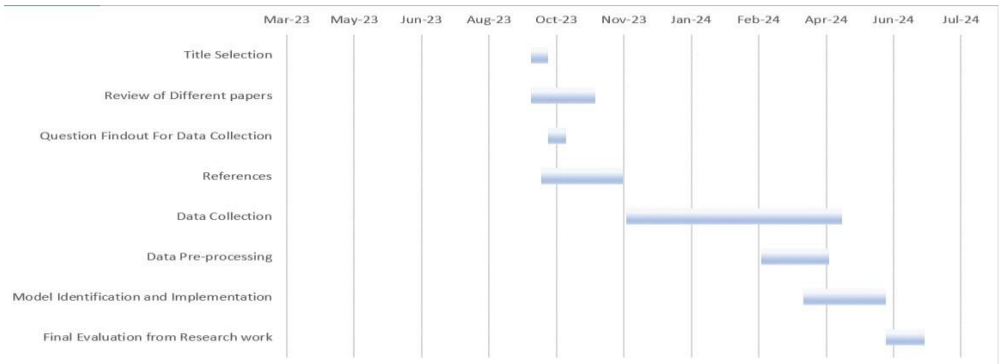

Figure 3.4.1: Project Management

Finance: To get the work successfully, there is several type costings like copying cost, transport cos. And I have made those cost from self-funded.

Table 3.4.1: Financial Analysis

SL NO	Costing Spaces	Cost
1	Data Collection	25000-27000 BDT
2	Copy for Dataset	12000-15000 BDT
3	Instrument(Hardware)	50000-52000 BDT
4	Instrument(Software)	11000-14000 BDT
5	Stakeholder visiting	8000-10000 BDT
6	Transport	6000-9000 BDT
7	Communication Cost	7000-10000 BDT
	Total Estimated Cost	120000-150000 BDT

3.5 Summary

The research aims to define digital technology addiction by examining frequency, duration, and daily life impact. It will assess communication apps, games, and social networks on mental health, including anxiety, depression, sleep quality, and well-being. Data will be collected via questionnaires, real-time monitoring, self-assessments, and interviews. The methodology involves preprocessing data and using algorithms like Logistic Regression and Random Forest, with metrics such as accuracy, precision, recall, and F1 score for evaluation. Necessary resources include high-performance computing, data storage, networking equipment, Python, scikit-learn, database systems, and visualization tools. The estimated budget is 120,000 to 150,000 BDT, funded personally.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In today's technologically advanced society, digital technology addiction is a serious issue that may have a profound impact on one's mental and overall wellbeing. This abstract describes an implementation overview that combines sophisticated analytical approaches, hardware and software requirements, and data gathering strategies to address the complexity of digital technology addiction through a multidisciplinary approach. In order to effectively handle and analyze massive volumes of data gathered from diverse sources, such as surveys, interviews, and internet activity monitoring, the project highlights the need for processing power, data storage, and reliable networking technology. To create prediction models, the project's software mostly uses Python and machine learning tools like scikit-learn. The gathered data is organized, stored, and visually represented using database management systems and data visualization tools, such as Google Sheets, Matplotlib, Seaborn, and pandas. This allows for a deeper understanding of the connections between the use of digital technology and outcomes related to mental health. In-depth qualitative interviews as well as the development and dissemination of surveys and questionnaires are two methods used in data collecting. By obtaining thorough insights into people's digital technology usage patterns, demographic data, and mental health state, these techniques hope to produce a rich dataset for study. The project's main objectives are performance evaluation, model selection, and feature engineering. By transforming unstructured data into relevant features, feature engineering may effectively convey the essence of digital technology addiction and its detrimental effects on mental health. The task's requirements determine which model is best, with Random Forest and Logistic Regression classification models being especially well-suited for forecasting the effects of digital engagement on mental health.

4.2 Train Model

To train a model effectively, there is a systematic approach that involves selecting the right algorithm based on the problem requirements, preparing the data, tuning the model, and finally evaluating its performance.

Decision Tree: In situations where interpretability is essential, like credit scoring or medical diagnosis, decision trees are frequently utilized despite their propensity to overfit. While maintaining its interpretability, techniques like pruning—which eliminates superfluous branches—or employing ensemble techniques like Random Forests can assist enhance its generalization performance.

Support Vector Machine (SVM): Are adaptable and have applications in bioinformatics, image recognition, text categorization, and other fields. Because of the kernel method, which enables SVMs to handle non-linear decision boundaries, they work well in situations when the data is not linearly separable. On the other hand, choosing the right kernel function and adjusting the hyperparameters can be difficult and need domain knowledge.

K-Nearest Neighbors (KNN): When the decision boundary is irregular or nonlinear, KNN is especially helpful. Recommendation systems, anomaly detection, and grouping tasks are among its frequent uses. Even though KNN is straightforward, it may yield competitive outcomes, particularly when paired with feature selection techniques or dimensionality reduction approaches like PCA.

Logistic Regression: In domains including as healthcare, finance, and marketing, logistic regression is extensively employed for binary classification problems, such forecasting client attrition or diagnosing a specific illness in a patient. Because it offers comprehensible coefficients, practitioners are able to comprehend how each parameter affects the anticipated result.

Random Forest: Random forests are renowned for their resilience and capacity to manage large, multi feature, high-dimensional data sets. They are employed in many different applications, such as recommendation engines, fraud detection, and client segmentation. In order to determine which features in the dataset have the most influence, Random Forests can also yield feature importances.

Gradient Boosting: Because of its great prediction accuracy, Gradient Boosting is frequently utilized in both real-world and Kaggle contests. It works well in situations where optimizing prediction performance takes precedence above interpretability, such algorithmic trading. Gradient Boosting model training, however, may be computationally costly, particularly when dealing with big datasets.

XGBoost: Because of its efficiency and speed, XGBoost is now the recommended method for structured and tabular data. It is commonly used for tasks like credit risk assessment, product suggestion, and illness prediction in industries including banking, e-commerce, and healthcare. XGBoost is appropriate for real-world datasets with noisy or partial information because of its capacity to manage missing values and outliers.

CatBoost: In sectors like advertising where categorical variables like user IDs or product categories are common, CatBoost is the go-to option because to its ability to handle categorical features without the need for human preprocessing. Performance is enhanced by its feature ordering method, particularly in situations when there are a lot of categorical variables

Neural Network: In a number of fields, such as computer vision, natural language processing, and autonomous driving, neural networks have demonstrated cutting-edge performance. Applications such as speech recognition, machine translation, and picture categorization employ them. Training deep neural networks is now possible, even with large-scale datasets, thanks to developments in deep learning frameworks and hardware acceleration.

XGBoost3: Although specifics regarding XGBoost3 are not given, it is most likely the result of continuous research and development aimed at improving the XGBoost algorithm even further. This might entail adaptations to accommodate new kinds of data or learning tasks, improvements in memory use and scalability, or optimizations for certain hardware architectures. XGBoost and other algorithms need to be continuously innovated in order to advance the field of machine learning and artificial intelligence.

4.3 System Testing

A few essential actions and factors must be taken into account in order to properly assess a machine learning model's effectiveness. In order to comprehend the model's potential and constraints, these procedures entail choosing the appropriate assessment metrics, properly preparing the data, and interpreting the findings. Let's see evaluation:

Accuracy: The percentage of accurate forecasts among all predictions is known as accuracy. For datasets that are balanced, it works.

Precision: The precise ratio represents the difference between the total number of true positives and erroneous positives. Low false-positive rates are indicative of high precision.

Recall: The ratio of true positives to the total of true positives and false negatives is known as recall (sensitivity). Reduced false-negative rates are indicated by high recall.

F1 Score: The harmonic mean that strikes a balance between recall and precision. When false positives and false negatives are significant, it is helpful.

Confusion Matrix: Displays true positives, true negatives, false positives, and false negatives as well as an overview of the model's performance.

Data Splitting: Separate the dataset into sets for testing, validation, and training. The model is trained using training data, parameters are adjusted with the help of validation data, and the final model is assessed with test data.

Feature engineering: To enhance model performance, add new features or alter current ones.

Managing Data Inequalities: Class imbalance can be addressed by employing strategies such as SMOTE, undersampling, and oversampling.

Hyperparameter tuning: To maximize performance, change the model's parameters. Random or grid search are other viable tactics.

Analysis of the Findings: Examine the selected metrics in order to determine the advantages and disadvantages of the model. Think about the cost of false positives or negatives and the business context.

4.4 Summary

A methodical strategy that includes choosing the best algorithm based on the needs of the task, preparing the data, fine-tuning the model, and assessing its performance is necessary to train a model successfully. Different algorithms are better at different things. For example, Decision Trees are good at being interpretable in critical fields; Support Vector Machines are good at handling non-linear decision boundaries; K-Nearest Neighbors are good at handling irregular or non-linear decision boundaries; Logistic Regression is good at binary classification problems; Random Forests are good at handling large, multi-feature datasets; Gradient Boosting is good at making accurate predictions; XGBoost is good at handling structured and tabular data; CatBoost is excellent at handling categorical features. Along with crucial processes like data collection, key performance measures include recall, accuracy, precision, F1 score, and confusion matrix.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The evaluation compares several machine learning models such as SVM, Gradient Boosting, Neural Network, and others on their accuracy in predicting the effects of digital technology addiction on mental health. SVM, Gradient Boosting, and Neural Network perform best with 61% accuracy, highlighting their suitability for high-precision applications. Logistic Regression and Random Forest show moderate accuracy, while KNN performs less effectively at 53%. Detailed metrics reveal strengths and weaknesses in classifying different outcomes, emphasizing areas for model refinement to better understand and address digital addiction's impact on well-being.

5.2 Experimental Result

The works on model which is Decision Trees, Support Vector Machines, K-Nearest Neighbors, Logistic Regression, Random Forest, Gradient Boosting, XGBoost, CatBoost, Neural Network, and XGBoost3, reveals the effectiveness of these models in predicting the impact of digital technology addiction on mental health.

Table 5.2.1: Accuracy according to Models

Model	**Accuracy (%)**
Decision Tree	56%
Support Vector Machine	61%
K-Nearest Neighbors	53%
Logistic Regression	55%
Random Forest	56%
Gradient Boosting	61%
XGBoost	58%
CatBoost	56%
Neural Network	61%
XGBoost3	59%

With accuracy ratings of 0.61, the Support Vector Machine, Gradient Boosting, and Neural Network models have great predictive skills and could be chosen for applications where high accuracy is essential. With an accuracy of 0.56, Decision Tree demonstrated its mediocre performance in tasks requiring prediction. With a comparatively high accuracy of 0.61, Support Vector Machine proved to be useful in producing precise predictions. With an accuracy score of 0.53, K-Nearest Neighbors may not outperform other models in classification tests. With an accuracy of 0.55, logistic regression was shown to be rather useful in making predictions. With an accuracy of 0.56, Random Forest's performance was equivalent to Decision Trees. Both Neural Network and Gradient Boosting attained a high accuracy of 0.61, demonstrating their potent predicting powers. With a noteworthy accuracy score of 0.58, XGBoost demonstrated its potency in categorization tests. CatBoost's accuracy of 0.56 was comparable to that of Decision Tree and Random Forest. With XGBoost3's impressive accuracy score of 0.59, it was evident how well it could make predictions.

5.3 Performance Analysis

The accuracy obtained from the Neural Network model evaluation was around 61.21%. Out of all the examples analyzed, this accuracy shows the percentage of correctly categorized instances.

```
Evaluating Neural Network...
Accuracy: 0.6121212121212121
Confusion Matrix:
 [[22 14  3]
 [ 6 49 13]
 [12 16 30]]
Classification Report:
              precision    recall  f1-score   support

           0       0.55      0.56      0.56        39
           1       0.62      0.72      0.67        68
           2       0.65      0.52      0.58        58

    accuracy                           0.61       165
   macro avg       0.61      0.60      0.60       165
weighted avg       0.61      0.61      0.61       165
```

Figure 5.3.1: Neural Network Evaluation

The model's performance across several classes is broken down in depth by the confusion matrix. The projected class labels are represented by each column, while the actual class labels are represented by each row. The matrix displays the number of times the model successfully predicted each class—22 for class 0, 49 for class 1, and 30 for class 2. However, as the off-diagonal parts show, it misclassified certain cases.

```
Evaluating Support Vector Machine...
Accuracy: 0.6060606060606061
Confusion Matrix:
 [[19 19  1]
 [ 6 52 10]
 [ 9 20 29]]
Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.49      0.52        39
           1       0.57      0.76      0.65        68
           2       0.72      0.50      0.59        58

    accuracy                           0.61       165
   macro avg       0.62      0.58      0.59       165
weighted avg       0.62      0.61      0.60       165
```

Figure 5.3.2: Support Vector Machine Evaluation

The SVM model's total accuracy is 60.61%. This indicates that for around 61% of the dataset's cases, the model predicted the class label accurately.

Class 0: Of the 19 examples that the model accurately identified, 19 were wrongly classified as Class 0, while 1 instance was incorrectly classified as Class 1.

Class 1: Of the 52 occurrences that the model properly identified, six were wrongly labeled as Class 1 and ten were incorrectly classified as Class 2.

Class 2: Of the examples categorized by the model, 29 were correctly classified, 9 were wrongly classified as Class 2, and 20 instances were incorrectly classified as Class 1.

The percentage of true positives among all positive predictions given for a class is measured by precision. Class 0 precision values are 0.56, whereas Class 2 precision values are 0.72. The percentage of true positives among all real positives for a class is measured by recall. Class 0 recall scores are 0.49, whereas Class 1 recall values are 0.76. The F1-Score offers a fair assessment of a model's performance by integrating recall and accuracy into a single statistic. Class 0 F1-scores are 0.52 to Class 2 F1-scores of 0.59. Support shows how many examples of each class are included in the dataset.

```
Evaluating Gradient Boosting...
Accuracy: 0.6060606060606061
Confusion Matrix:
 [[20 16  3]
 [ 6 51 11]
 [ 9 20 29]]
Classification Report:
              precision    recall  f1-score   support

           0       0.57      0.51      0.54        39
           1       0.59      0.75      0.66        68
           2       0.67      0.50      0.57        58

    accuracy                           0.61       165
   macro avg       0.61      0.59      0.59       165
weighted avg       0.61      0.61      0.60       165
```

Figure 5.3.3: Gradient Boosting Evaluation

The Gradient Boosting model has an estimated accuracy of 0.61. This suggests that around 61% of the model's predictions based on the test data are accurate.

Confusion Chart:

The model's performance across many classes is broken out in depth by the confusion matrix:

Class 0:

True Positives: 20

False Negatives: 19

False Positives: 15

Class 1:

True Positives in : 51

False Positives : 36

False Negatives : 17

Class 2:

True Positives: 29

False Negatives : 29

False Positives: 14

Class 0:

Precision: 0.57 (out of all instances predicted as class 0, 57% were actually class 0)

Recall: 0.51 (out of all actual instances of class 0, 51% were correctly identified)

F1-Score: 0.54 (harmonic mean of precision and recall)

Support: 39 (number of true instances in the dataset)

Class 1:

Precision: 0.59 (out of all instances predicted as class 1, 59% were actually class 1)

Recall: 0.75 (out of all actual instances of class 1, 75% were correctly identified)

F1-Score: 0.66 (harmonic mean of precision and recall)

Support: 68 (number of true instances in the dataset)

Class 2:

Precision: 0.67 (out of all instances predicted as class 2, 67% were actually class 2)

Recall: 0.50 (out of all actual instances of class 2, 50% were correctly identified)

F1-Score: 0.57 (harmonic mean of precision and recall)

Support: 58 (number of true instances in the dataset)

Additional metrics like accuracy, recall, and F1-score are provided for each class in the classification report. Recall is the percentage of genuine positives that the model accurately detected out of all actual positives. In this instance, the model accurately recognized a sizable fraction of cases belonging to class 1, as seen by its relatively high accuracy and recall for class 1. For classes 0 and 2, on the other hand, it did significantly worse, with lower accuracy and recall values.

All classes' aggregated scores are provided via the weighted-average and macro-average measures.

The macro-average assigns equal weight to each class by first calculating the metric individually for each class and then taking the average. The weighted-average, on the other hand, gives classes with more support more weight by taking into account the number of occurrences in each class.

The assessment metrics as a whole show that the Neural Network model performs rather well in categorizing cases into the three classifications. There is still space for development, especially in terms of strengthening the model's capacity to accurately identify examples across all classes and lowering the number of misclassifications. The model's performance may be enhanced.

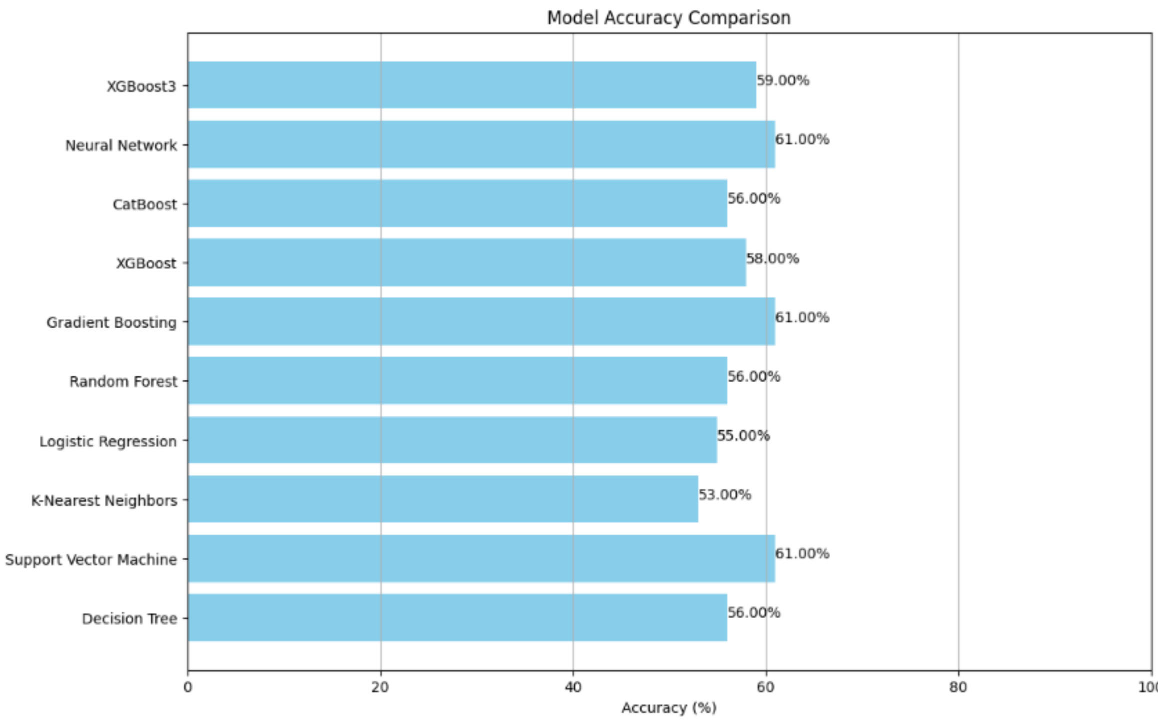

Figure 5.3.4: Accuracy comparison in Different ways and by ensembling models.

5.4 Summary

Addressing this part, it shows that the Neural Network model performs well across a range of criteria, particularly in classifying cases into three groups. But there's still potential for improvement, especially when it comes to improving the model's capacity to correctly recognize instances in all classes by adjusting hyperparameters or training approaches. Support Vector Machine, Gradient Boosting, and Neural Network stand out among the assessed models with high accuracy scores, demonstrating their applicability for applications requiring exact predictions. On the other hand, K-Nearest Neighbors and models with moderate accuracy, like Decision Tree, Random Forest, XGBoost, CatBoost, and XGBoost3, show different degrees of efficacy. This emphasizes how crucial it is to choose the best algorithm depending on the particular needs of a task.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Addiction to digital technology has a major negative influence on mental health and wellbeing, which affects many facets of life. Due to its widespread use, technology is incorporated into almost every facet of our everyday lives, including communication, work, play, and education. Although there are numerous advantages to this integration, it may also result in problematic use habits that hinder a person's capacity to perform well in both their personal and professional spheres. The continual barrage of information and the urge to be active on social media can exacerbate conditions like anxiety and depression. Physical health is also impacted; signs and symptoms could include headaches and eyestrain, as well as more serious ailments including sleep disturbances.

6.2 Impact on Society & Environment

Impact on Society

A comprehensive strategy encompassing people, communities, and policy makers is needed to address the societal ramifications of digital technology addiction:

Education and Awareness: Educating people about the dangers of digital technology addiction through campaigns and educational programs can give them the power to choose wisely when it comes to their usage of digital media.

Support Networks: Fostering the growth of support networks in families, schools, and workplaces can give people the tools they need to properly regulate their use of digital devices.

Policy Interventions: Governments and organizations can enact laws that support sensible digital behavior. Some examples of these laws are those that restrict screen time, make mental health services accessible, and promote outdoor recreation.

Technological Solutions: App developers may create features like timers for app usage, alerts about excessive screen time, and the incorporation of mindfulness activities into digital platforms to promote healthy digital habits.

Research and Innovation: Funding studies to determine the long-term consequences of addiction to digital technologies and creating creative ways to lessen its effects can help to provide the groundwork for later remedies.

Impact on Environment

To address these multifaceted issues, a comprehensive approach involving technological, educational, and policy interventions is required:

Technological Interventions: Create hardware and software features, such screen time limits, break reminders, and tools for distraction management, that promote healthy usage habits. Promote the use of environmentally friendly procedures in the production and disposal of devices.

Educational Initiatives: Put programs in place in communities and schools to raise awareness of the possible dangers of digital addiction and to encourage safe online conduct. This involves promoting offline activities that improve interpersonal skills.

6.3 Ethical Aspects

Individual autonomy is one of the core ethical precepts at issue in the research of digital technology addiction. The right to make educated judgments about one's own life and to be in charge of one's own actions and choices is known as autonomy. Data security and privacy are issues related to addiction to digital technology. Addiction to digital technology has many ethical ramifications for mental health and wellbeing, including concerns about privacy, equality, autonomy, and social responsibility. Upholding ethical norms and values that prioritize the rights and dignity of individuals while working to solve the larger social and structural causes that lead to technology addiction is crucial as researchers and practitioners continue to investigate this phenomena.

6.4 Sustainability Plan

The sustainability plan for the research on "THE IMPACT OF DIGITAL TECHNOLOGY ADDICTION ON MENTAL HEALTH AND WELL-BEING" can contribute to a more resilient, equitable, and effective mental health system that leverages the full potential of digital technologies. Encourage ongoing research into new digital technologies and interventions, focusing on those that demonstrate promise in improving mental health outcomes.

6.5 Summary

The impact of digital technology addiction on society, environment, and sustainability is profound and multifaceted. It significantly affects mental health, leading to issues like anxiety and sleep disturbances, while also influencing personal and professional performance negatively. Societally, education, support networks, policy interventions, and technological solutions are crucial to mitigate these effects. Ethically, it raises concerns about autonomy, privacy, and social responsibility. A sustainability plan includes ongoing research and innovative digital interventions aimed at improving mental health outcomes while promoting responsible digital usage and environmental stewardship.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

The research on the effects of addiction to digital technology on mental health and well-being highlights several key conclusions and implications. It emphasizes the intricate relationship between digital technology use and mental health outcomes, noting that while digital technology offers numerous benefits, its misuse or overuse can adversely affect mental health. Different digital activities, such as social media use, gaming, and web browsing, have varying impacts on mental health depending on usage patterns and individual characteristics. Factors like age and cultural background significantly shape the association between digital technology use and mental health, with adolescents, for example, being more susceptible to the negative effects of excessive screen time. This underscores the need for tailored interventions. Future research should employ robust methodologies, including longitudinal studies, diverse sample populations, and comprehensive mental health assessments, to gain a thorough understanding of these phenomena. Combining quantitative and qualitative measures will further enrich this understanding.

Additionally, recognizing the benefits of digital technology and identifying specific risk factors can help balance the positive and negative aspects, leading to personalized intervention strategies that cater to individual needs and circumstances. Research should also explore the impact of digital detoxes and intermittent technology use, examining both short-term and long-term effects on mental health, productivity, and social interactions. Effective strategies for reducing digital consumption, such as scheduled breaks and technology-free zones, should be identified and promoted. Socio-demographic variations, including age, cultural background, socioeconomic status, and gender, should be carefully considered to develop more inclusive and equitable mental health interventions. Furthermore, promoting digital literacy and integrating digital well-being education into curriculums can empower users to manage their technology use more effectively. Finally, addressing ethical and policy considerations, such as privacy and data security, and fostering interdisciplinary collaboration will be crucial in creating comprehensive strategies to manage digital technology use and its impacts on mental health.

7.2 Further Suggested Works

Comprehensive Behavioral Examination:

Improved Definitions of Digital Technology Use: Future studies should focus on providing a more accurate definition and distinction between various forms of digital technology use. To further understand the differing effects of particular activities on mental health, studies might focus on particular behaviors like passive consumption (scrolling) versus active involvement (commenting, generating content) on social media.

Extended Measures of Mental Health:

Comprehensive Mental Health Assessment: Make use of a greater range of mental health metrics, such as tests for social well-being, anxiety, depression, stress, and sleep quality. A more comprehensive understanding of the effects on mental health may be obtained by combining both quantitative and qualitative data.

Hedonic and Eudaimonic Well-Being: Keep measuring the emotional (hedonic) and meaningful life (eudaimonic) dimensions of well-being. Additional investigation into the ways in which various digital actions affect these characteristics may provide insightful information.

Advanced Methods of Analysis:

Machine Learning and Predictive Analytics: Use increasingly sophisticated algorithms for machine learning and data analytics to forecast a person's vulnerability to addiction to digital technology and the effects it may have on their mental health. Interventions based on prediction models may be more successful if they are personalized.

Real-Time Data collecting: To obtain more precise and context-specific information on the usage of digital technology and its direct consequences on mental health, employ real-time data collecting techniques like wearable technology and ecological momentary assessments (EMAs).

Emerging Technologies' Effects:

Examine Emerging Digital Trends: As technology advances, new platforms for digital interaction—like augmented and virtual reality—appear. To fully comprehend these phenomena' distinct effects on mental health and wellbeing, research needs to keep up with them.

Digital Tools for Better Well-Being: Examine the efficacy of digital tools and applications for better well-being, such as those that measure and limit screen time, encourage mindfulness, or offer mental health resources.

7.3 Limitations

The study on digital technology addiction and its impact on mental health and well-being faces several limitations. One significant challenge is the varied degrees of dependency individuals exhibit on different types of technology, which complicates the development of universally applicable interventions or treatments. Additionally, defining "addiction" in the context of digital technology is complex, involving the distinction between problematic behavior and healthy use, thus limiting the effectiveness of diagnostic tools and the accuracy of research findings. The vast and multifaceted nature of this issue makes it difficult to comprehensively address all dimensions in a single study. Individual differences in susceptibility to addiction, coping mechanisms, and the impact on mental health further complicate the research. Moreover, the rapid evolution of technology and the emergence of new digital platforms can quickly render some findings outdated. The study's reliance on self-reported data introduces potential biases and inaccuracies. Finally, cultural differences in attitudes towards technology use may affect the generalizability of the findings across different populations and region.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title:
THE IMPACT OF DIGITAL TECHNOLOGY ADDICTION ON MENTAL HEALTH AND WELL-BEING.

Student ID: 202-15-3852

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**

CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by the employment of Different Models and way like XG Boost and so on. The project demonstrates **specialist knowledge (K4)** by implementing KNN, Random Forest, Decision Tree, Logistic Regression on the Dataset.	**Page no:** [10-12] **Section:** [3.2] **Page no:** [19-24] **Section:** [5.2-5.3]
				In this portion the work is gone through some preprocessing where I need to use different required things and it's have design portion as well **K5**. Over this place, I have worked with social impact as well. As digital technology harming on different spaces like sleep habit, food habit etc. So my work will make some improvement social side which belongs to	**Page no:** [10-12] **Section:** [3.2]

				K7.	**Page no:** [25-26] **Section:** [6.1-6.4]
				This project ensures to **K8 (Research Literature),** Here I have talk about the works which previously done related to me. Those works neither related to topic model or health beings.	**Page no:** [6-7] **Section:** [2.2]
2.	**EP2: Range of Conflicti ng Require ments**	Yes	CO2, and CO7	Basic challenges is data collection from the youth and different generation. The approval from the specialist is another level of challenge. The comparative analysis shows the main fact and challenge of the work over here.	**Page no:** [26] **Section:** [6.3]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project will be gone trough multiple model from ML like Naive Bayes, SVM, Random Forest as well for the better solution. It's have Gradient Boosting, Neural Network for better accuracy.	**Page no:** [19] **Section:** [5.1]
4.	**EP4: Familiari ty of Issues**	Yes	CO8	The work is not only full basis in CSE, it will be gone through health issues as well. As this work is machine learning model based mental health checking.	**Page no:** [3-4] **Section:** [1.4]

5.	**EP5: Extends of applicati on codes**	No	CO5	N/A	N/A
6.	**EP6: Ext ends of stakehol ders involved and conflictin g requirem ents**	No	CO8	Here I have to take the suggestion from the phycologist and Doctor as well. And different type users suggestion according to their usability.	
7.	**EP7: Interdep endence**	Yes	CO5	Over the problem, we have different subworks on the basis of model which I have done in Jupyter by python and implementation of translated sub data which ensures **EP-7**.	**Page no:** [7-8] **Section:** [2.3]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	In our project, there is the multiple performances of machine learning included some artificial intelligence value. The annotated dataset has is the main source for the implementation.	**Page no:** [10-12] **Section:** [3.2]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This initiative benefits society by advancing healthcare with sophisticated pneumonia detection techniques, supporting environmental sustainability through the use of effective computational resources, and upholding moral standards for patient privacy.	**Page no:** [25-26] **Section:** [6.1-6.2]

5.	**EA-5: Familiarit y**	Yes		There is some new according to the previous familiarity where there is the uses of machine learning with the habit.	**Page no:** [26] **Section:** [6.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [12-13] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [28-29] **Section:** [7.1-7.2]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [10-12] **Section:** [3.2]

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