IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Predictive Modeling Of Electronic Gadget Addiction Among Students Using Machine Learning

Author:
[1]R M PRIYANKA ,
M.Tech. Scholar,
Department of Computer Science and Engineering,
School of Engineering,
Malla Reddy University,
Hyderabad, Telangana, India

Under the esteemed guidance of:
[2] Dr. ARUN SINGH CHOUHAN,
Associate Professor,
Department of Computer Science and Engineering,
School of Engineering,
Malla Reddy University,
Hyderabad, Telangana, India

Abstract: Electronic gadget addiction has emerged as a pressing concern among students, with far-reaching consequences for their mental health, academic performance, and social relationships. The pervasive nature of gadget addiction, fueled by the widespread availability and accessibility of electronic devices, has led to a growing need for effective predictive models and targeted interventions. This study addresses this critical need by developing a machine learning model to predict gadget addiction among students aged 18-25, leveraging demographic, behavioral, and psychological characteristics. The predictive model, built using decision trees and random forest algorithms, identifies screen time, frequency of gadget use, anxiety, and depression as significant predictors of gadget addiction. The random forest algorithm emerges as the most accurate predictive model, underscoring its potential in identifying high-risk students. These findings have profound implications for educators, counselors, and parents, enabling them to pinpoint vulnerable students and provide personalized support. The predictive model developed in this study can serve as a valuable tool in promoting students' well-being and productivity. By identifying high-risk students, educators and counselors can design targeted interventions, such as counseling sessions, workshops, and awareness programs, to mitigate gadget addiction. Parents can also utilize the model to monitor their children's gadget use and provide guidance on responsible technology habits. Moreover, this study's findings can inform the development of evidence-based policies and programs aimed at reducing gadget addiction among students. Educational institutions can establish guidelines for responsible gadget use, incorporate digital literacy into their curricula, and provide resources for students struggling with gadget addiction.

Keywords- Gadget addiction, mobile usage, prediction, machine learning model, Random Forest Algorithm.

I. Introduction

1.1 Overview

Addiction to electronic gadgets has been a major issue in modern society, particularly among working professionals and students. Excessive use of smartphones, social media, and other electronic gadgets has adverse effects on mental well-being, academic achievement, and overall health and happiness. Prevalence prediction and understanding of the addiction to gadgets is critical in enabling early intervention and promoting healthier digital habit.

Behavioral addiction research mostly employs statistical and machine learning models to study user behavior patterns. Logistic Regression and Support Vector Machines (SVM) are typical models employed in classification issues in addiction research. These models do not capture fine-grained, nonlinear patterns in high-dimensional data. Ensemble learning models like Random Forest, particularly machine learning models, have been more accurate and consistent in behavioral prediction issues.

Random Forest is a type of ensemble learning with the assistance of numerous decision trees to improve the accuracy of classification and avoid overfitting. Following the extraction of the most significant behavioral characteristics such as screen time, social network use, sleep, and self-reported extent of dependency, the Random Forest model correctly classifies individuals into different addiction risk categories. Comparison with other conventional machine learning models demonstrates the effectiveness of Random Forest in handling big data sets with diverse features.

The model developed in this project attempts to provide helpful recommendations to the users, parents, educators, and mental health professionals. By using data-based predictions, it gives individualized recommendations and intervention strategies to minimize the probability of gadget addiction. The process not just sensitizes but also helps in developing more improved digital usage habits, which promote mental and physical well-being.

1.2 Introduction

In the internet age, the utilization of electronic gadgets has become a daily routine, affecting many areas of work, study, communication, and leisure. Although these gadgets, smartphone, tablet, and computer, are of great utility, their overuse has led to a growing concern electronic gadget addiction. This addiction is increasingly being seen as a behavioral disorder with serious consequences for mental and academic performance, interpersonal relationships, and overall well-being. The growing use of electronic devices for job and personal use has led to addiction, and it is difficult to control for the majority, especially students and workers.

Electronic device addiction, or digital addiction, refers to excessive and compulsive use of electronic devices, primarily smartphones, social network sites, and online games. This addiction can take various forms, including increased screen time, decreased face-to-face contact, sleep disruption, and increasing inability to discontinue use despite damage. Social network sites and mobile apps have encouraged this behavior since these sites are designed to keep users engaged for several hours.

While it is hard to pinpoint a cut-off level for addiction, symptoms typically include the irresistible need to constantly check notifications, inability to control screen time, avoidance of regular activities, and negative impact of the use of gadgets on one's own, academic, or work life. It may even lead to emotional issues such as loneliness, depression, and anxiety, especially when individuals are unable to turn off their gadgets.

The disorder has caught the eye of mental health practitioners, educators, parents, and policymakers, all of whom are concerned with its long-term implications. Digital media addiction is new to the body of research, but the critical need for efficient identification and intervention methods exists to curb this new epidemic.

1.2.1 The Role of Machine Learning in behavioral Prediction

Machine learning, one of the forms of artificial intelligence (AI), has been highly promising for behavioral prediction, especially in identifying patterns within big data that are difficult to analyze manually by humans. Machine learning algorithms can be applied to a variety of addictive behaviors, from drug addiction to screen addiction. Machine learning algorithms can identify trends and patterns from user data on smartphones and other devices that can indicate potential addiction. Machine learning algorithms can ingest enormous volumes of data, such as screen time, app usage, and social media usage, and leverage it to predict the likelihood of addiction.

Random Forest, being an ensemble learning approach, is specifically appropriate for classification tasks such as the prediction of addiction. In contrast to single decision trees, Random Forest uses an ensemble of many decision trees to improve accuracy and robustness and therefore is more appropriate in dealing with high-dimensional data such as that gathered from users' browsing history. Random Forest follows the approach of dividing the data into subsets using various features and then making classification of the input data based on the majority vote of trees. This approach minimizes the possibility of overfitting and improves the generalization of predictions.

The Random Forest algorithm is well-suited for this project because of its ability to handle high-dimensional data, process non-linear relationships, and provide accurate classifications. Some key advantages of using Random Forest include:

- High Accuracy and Robustness: Random Forest is an ensemble learning technique that combines multiple decision trees, making it more robust against overfitting and improving accuracy.
- Handling of Large Datasets: With the increasing amount of digital footprint data, the ability to analyze and process large datasets efficiently is essential. Random Forest performs well in such scenarios.
- Feature Importance Analysis: The algorithm can rank features based on their contribution to the prediction model, helping researchers understand which factors play a significant role in gadget addiction.

- Ability to Handle Missing Data: Unlike some other machine learning models, Random Forest can manage missing values effectively, making it a reliable choice for behavioral data analysis.
- Versatility in Classification Tasks: Since gadget addiction is a classification problem (e.g., mild, moderate, severe addiction), Random Forest is well-suited to categorize individuals based on their risk levels.

1.2.2 Significance and motivation

The growing prevalence of electronic gadget addiction calls for more effective methods to identify individuals at risk and intervene before the addiction becomes detrimental to their lives. While self-reporting tools and clinical assessments are commonly used for diagnosis, they often fail to provide real-time, data-driven insights into addiction behaviours. The use of machine learning models, such as Random Forest, presents an opportunity to move beyond traditional methods and develop more accurate, automated systems for predicting addiction.

By predicting addiction tendencies early on, this system can empower individuals, parents, educators, and mental health professionals to take proactive measures. The ability to predict addiction risk based on user behaviour could lead to the development of targeted intervention strategies, such as digital detox programs, behavioural therapy, or educational campaigns on responsible gadget usage. The significance of this study lies in its potential to contribute to the growing body of research on digital addiction and to provide a practical, data-driven solution to mitigate its harmful effects. Additionally, by applying machine learning to addiction prediction, this project demonstrates the power of AI in addressing real-world behavioural problems.

The widespread adoption of smartphones, tablets, laptops, and gaming consoles has transformed the way people communicate, work, and entertain themselves. But this technology revolution has also introduced a new issue — dependence to electronic bias. This is a new behavioural dependence growing wider, especially among youthful grown-ups and children, since digital bias are so integrated into one's everyday life.

The inordinate use of widgets has been linked to a variety of physical, cerebral, and social issues. inordinate screen use leads to sleep diseases, eye strain, and lower physical exertion, leading to rotundity and other conditions. Cerebral, screen dependence has been connected to further stress, anxiety, depression, and attention diseases. likewise, inordinate use of widgets might lead to worsening social chops since the stoner would prefer to interact nearly rather than in real- life social relations.

One of the biggest challenges for the treatment of contrivance dependence is its insidious nature. In comparison to dependence to substances, whose physiological signs are irrefragable, contrivance dependence develops insidiously through behavioural changes. utmost individualities are unconscious to contrivance dependence until it begins to impact their particular, academic, or occupational life. This requires early discovery and intervention to negate its adverse goods.

Electronic gadget addiction is influenced by several factors, including psychological, environmental, and technological aspects. Some of the major contributing factors are:

- Social Media Engagement: Platforms like Instagram, Facebook, TikTok, and Twitter are designed to maximize user engagement through features such as notifications, infinite scrolling, and algorithm-driven content recommendations. These features create a sense of dependency, making it difficult for users to disengage.
- Gaming and Entertainment: Online gaming and streaming services offer highly immersive experiences that captivate users for extended periods. Competitive online gaming, in particular, encourages players to spend hours improving their skills and rankings, leading to compulsive gaming behavior.
- Work and Study Pressures: In an era where remote work and online education have become the norm, individuals spend more time on digital devices for professional and academic purposes. The blurred boundaries between work and personal life contribute to increased screen time.
- Psychological Factors: Many individuals turn to electronic gadgets as a coping mechanism for stress, anxiety, loneliness, or depression. Excessive gadget usage provides an escape from real-world problems but eventually reinforces dependency.
- Peer Influence and Social Trends: The fear of missing out (FOMO) drives many users to remain constantly connected to social media, messages, and notifications. Peer influence, particularly among teenagers, also plays a significant role in encouraging prolonged gadget use.

1.2.3 Problem definition

Electronic gadget addiction is on the rise, but today's detection systems such as self-reporting are usually subjective and unreliable. Present predictive models are not very accurate and have difficulty working with complicated data. There is a requirement for an automated system that can predict addiction risk based on behavior patterns. This project fulfils that requirement through a machine learning-based solution.

1.2.4 The Need for a Predictive Model for Gadget Addiction

Given the rising concerns surrounding gadget addiction, there is a need for an effective predictive system that can assess an individual's risk of developing an addiction. Traditional methods of diagnosing digital addiction rely on self-reported questionnaires and psychological assessments, which may be subjective and inaccurate. Many individuals are either unaware of their addiction or unwilling to acknowledge it, making early detection challenging.

Machine learning offers a promising solution by analyzing large datasets and identifying hidden patterns that indicate addiction risk. A predictive model can help individuals, parents, educators, and healthcare professionals take proactive steps to manage and reduce addiction before it escalates. The implementation of such a model can lead to:

- Early Detection and Prevention: By identifying addiction risk at an early stage, intervention strategies can be implemented before excessive gadget use leads to severe consequences.
- Personalized Recommendations: Based on user behavior, the system can provide tailored suggestions on reducing screen time, managing social media usage, and maintaining a healthy digital lifestyle.
- Real-Time Monitoring: Unlike traditional surveys, a machine learning-based model can continuously analyse user data, providing real-time insights into addiction patterns.

1.2.5 Research Objectives and scope

The primary objective of this project is to develop a machine learning model using the Random Forest algorithm to predict the likelihood of electronic gadget addiction. The specific objectives include:

RO-1: Data Collection and Pre-processing: Gather and pre-process relevant data from users, such as screen time, social media usage, app interaction, sleep patterns, and self-reported addiction levels.

RO-2: Model Development: Implement the Random Forest algorithm to build a predictive model that can classify individuals into different addiction risk categories.

RO-3: Model Evaluation: Evaluate the performance of the Random Forest model using standard performance metrics like accuracy, precision, recall, and F1-score to establish its effectiveness in predicting addiction.

RO-4: Deployment and User Interface: Develop a simple-to-use interface that allows users, parents, and teachers to input data and receive on-the-fly predictions, and recommendations for lowering the risk of addiction.

RO-5: Insight Generation: Provide practical advice based on the expected outcomes of the model, with suggestions for healthy gadget use and potential intervention methods.

The scope This project intends to predict electronic device addiction in young adults and youth, but the model could be used on broader age groups in subsequent research. The hope is to analyze screen time, app use, and social media activity-behavioral patterns since these are the most prevalent signs of gadget addiction. The data will be obtained from the digital activity of the users but will also analyze self-reported levels of addiction for further verification.

However, there are limitations to this method. The predictions of the model rely on the amount and quality of data used, which is not always representative of the psychological, social, or other determinants of addiction. The system's predictions also rely on trends within the data, and though it can select for trends, it is not able to offer a definitive diagnosis of addiction.

1.2.6 Data Collection and Features Considered in Prediction

To build an effective predictive model, it is essential to gather relevant data that accurately represents user behaviour. The dataset for this project includes:

- Screen Time Data
- Social Media and Messaging App Usage
- Sleep Patterns
- App Engagement Metrics
- Self-Reported Data
- Behavioural Trends

These features will be used to train the Random Forest model, allowing it to learn from patterns in user behavior and accurately classify individuals into different addiction risk levels.

1.2.7 Conclusion

Electronic gadget addiction is a growing problem with significant consequences on mental health, productivity, and social well-being. With the increasing dependency on digital devices, there is an urgent need for advanced solutions to predict and prevent addiction.

This project leverages machine learning, particularly the Random Forest algorithm, to build a predictive model that classifies individuals based on their risk of addiction. By analyzing behavioural data such as screen time, social media engagement, and sleep patterns, this model provides valuable insights into digital addiction trends.

The development of this system has far-reaching implications for individuals, families, educators, and mental health professionals. Through early detection and intervention, this project aims to foster a healthier digital lifestyle and reduce the adverse effects of excessive gadget use.

1.3 Thesis Organization

This thesis is organized into five chapters, each focusing on a specific aspect of the project:

- Chapter 1 – Introduction: Provides a brief overview of electronic gadget addiction, states the motivation and objectives of the study, and outlines the scope and significance of the work.
- Chapter 2 – Literature Survey: Reviews existing research related to digital addiction, behavioral assessment methods, and machine learning techniques used for psychological and behavioral predictions.
- Chapter 3 – System Design and Implementation: Describes the overall system architecture, data preprocessing techniques, machine learning model development (Random Forest), and the web interface for user interaction.
- Chapter 4 – Results and Discussions: Presents the outcomes of the machine learning model, including accuracy metrics, confusion matrix, sample predictions, and discussions on user interface design and feedback generation.
- Chapter 5 – Conclusion and Future Scope: Summarizes the key findings of the project, discusses its limitations, and suggests potential improvements or extensions for future research and development.

II. LITERATURE SURVEY

Gayathri, K., Reddy, M., Naik, H., & Kumar, S. (2025). In this team developed a web-based system using Random Forest and SVM models to predict electronic gadget addiction among students across Andhra Pradesh. Behavioral and psychological inputs—such as screen time, social media use, sleep patterns, and stress levels—were used as features. The Random Forest classifier outperformed SVM, accurately categorizing users into risk levels. This project aligns closely with your implementation structure, including front-end input capture and ML-based risk prediction.

Raj et al. Raj, Pawar, Pavankumar, Goyal, and Unisa (2024) presented an open-access conference paper reporting a machine learning model to predict smartphone addiction among Indian university students. Using a publicly available dataset, they applied Decision Tree, Logistic Regression, and Random Forest classifiers. The Random Forest model achieved the highest accuracy of 0.89, outperforming Decision Tree (0.86) and Logistic Regression (0.74). The study underscores the practical applicability of tree-based models and openly shares its dataset, making it an ideal benchmark for your project's methodology.

Yun, Y., Zhang, L., Zhou, Z., & Xu, F. (2024). In a study involving over 3,000 Chinese college students, Yun and colleagues investigated the relationship between smartphone addiction and psychological traits such as perfectionism, loneliness, and emotional instability. Using structured survey responses, they developed a Random Forest classifier that achieved 76.7% accuracy in predicting mobile addiction risk. The study identified perfectionism as the most influential feature. These results highlight the predictive value of psychological scales and support your future plan to integrate feedback mechanisms based on emotional profiling.

Parasin, W., Jitpiboon, N., & Sawatphanit, W. (2024). Parasin and colleagues investigated smartphone and social media addiction among Thai university students, with a focus on the emotional and social consequences of excessive use. Their study combined descriptive statistics and machine learning models, including Random Forest, to analyze behavioral data. Findings showed a strong correlation between late-night usage patterns and increased social isolation. While the study does not emphasize predictive modeling, it offers valuable insights that support your project's inclusion of emotional well-being metrics alongside quiz-based risk detection.

Raj, A. D., Pawar, A. S., Pavankumar, B., Goyal, K., & Unisa, S. A. (2024) This study presents a machine learning model to predict smartphone addiction among Indian youth aged 15–25. Behavioral data were gathered using structured self-report surveys, and multiple classifiers—including Decision Tree, Random Forest, and XGBoost—were evaluated. Among these, the Random Forest algorithm achieved the highest accuracy (89%), demonstrating strong performance in identifying users at risk. This paper supports your thesis approach by using behavioral markers (screen time, unlock frequency, usage trends) as features for addiction prediction.

III. DESIGN AND IMPLEMENTATION

This chapter presents the detailed design and implementation of the gadget addiction prediction system. It begins with the system architecture and explains each module involved in data collection, preprocessing, model training, and prediction. The choice of the Random Forest algorithm is justified based on its robustness and high performance in classification tasks. The development environment, tools used, and step-by-step implementation of the web application are also described. Each component—from the user interface to the backend prediction logic—is discussed to show how the system works as an integrated whole.

3.1 Module 1: Data Preprocessing and Acquisition

3.1.1 Data Collection

Sources:

- **Questionnaires and Surveys**: A structured Google Form was designed and distributed to gather self-reported data from students regarding their electronic gadget usage patterns, emotional responses, academic habits, and daily routines. The form consisted of 16 carefully crafted questions intended to assess various psychological and behavioral factors that may contribute to gadget addiction. The complete set of questionnaire items used for data collection is included in **APPENDIX-A** for reference.
- **Demographic information**: Age, gender, and level of study were recorded to gain insights into the participant profile.
- **Gadget usage habits**: These questions pertained to number of hours used daily, use purpose (e.g., social media, study), and situations such as eating meals with gadgets or pre-sleep gadget use.
- **Behavioral markers**: The questionnaire also asked questions related to symptoms of anxiety, stress, and gadget addiction-like behaviors. A total of 1,452 student responses were collected through the survey, which served as the primary dataset for training and evaluating the machine learning model.
- **Tools Used:**

Python Libraries: pandas, numpy, scikit-learn, matplotlib
File format: CSV file exported straight from Google Forms
Platform: Local Jupyter Notebook for development and testing

3.1.2 Data Cleaning

- **Handling Missing Values**: Removed incomplete or blank responses from the dataset by checking all participants responded to all 15 questions needed for model training.
- **Removing Outliers:** Checked each category responses for consistency and no unseen options. Removed any test/invalid submissions (e.g., repeats or random clicks).
- **Data Formatting:** Transformed multiple-choice categorical responses to numerical format through label encoding. And renamed column names to be uniform for ease of reference during modeling. And finally assigned final target labels (levels of addiction) to encoded class values for classification.

3.1.3 Data Splitting

The training data for the machine learning model was split into three subsets, namely Training set, Validation set, Test set. Stratified splitting is a technique where the model is trained on a significant proportion of the data and tested on unseen samples to evaluate its ability to generalize as well as optimize hyperparameters. It is tabulated in Table 3.1.

Table 3. 1 Dataset Split for Model Training, Validation, and Testing

Dataset Type	Percentage	Purpose
Training Set	70%	To train the machine learning model
Validation Set	15%	To fine-tune model parameters
Test Set	15%	To evaluate final model performance

This allowed the model to learn patterns without introducing bias toward any particular class.

3.2 Module 2: Model Development

This module focuses on developing the machine learning model used for predicting electronic gadget addiction levels. It includes the processes of selecting important features, training the model, evaluating its performance, optimizing it, and finally saving it for deployment.

3.2.1 System architecture overview

As shown in Figure 3.1, the system architecture outlines the end-to-end workflow of the proposed gadget addiction prediction model. It begins with quiz responses collected from users, which serve as the primary input. These inputs undergo a preprocessing phase involving data cleaning and feature extraction. The refined data is then passed into the trained machine learning model—specifically a Random Forest classifier—which classifies the user's gadget addiction risk as Low, Moderate, or High. The final risk level is generated and displayed to the user for further interpretation and intervention.

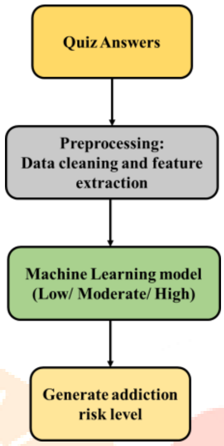

Fig 3. 1 System Architecture of the Gadget Addiction Prediction Model

3.2.2 Feature Selection

Feature selection was performed to improve the model's accuracy and reduce computation time. Based on correlation analysis and expert understanding of gadget usage behavior, essential predictors were chosen. These features include psychological, behavioral, and lifestyle-related factors extracted from the quiz responses.

3.2.3 Model Training

The Random Forest algorithm was selected due to its ensemble learning capability and its robustness in handling high-dimensional data. The model was trained using a stratified training set to ensure balanced class representation. Other models including Decision Tree, Logistic Regression, and Support Vector Machine were also tested for comparison.

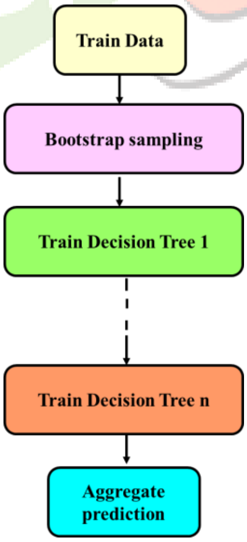

Fig 3. 2 Random Forest Model Training Flow

3.2.4 Evaluation Metrics

- **Model Accuracy Comparison** To validate the selection of the Random Forest model, various classification algorithms such as Decision Tree, Logistic Regression, and Support Vector Machine (SVM) were also evaluated. The bar chart in below Figure 3.3 compares the overall prediction accuracy of each model. Random Forest achieved the highest accuracy among all, making it the most suitable model for predicting gadget addiction risk levels.

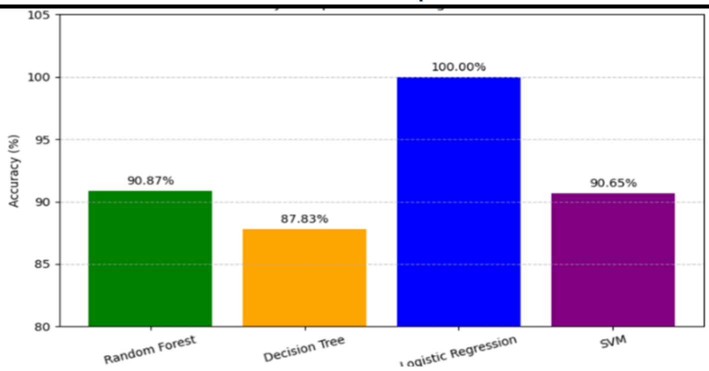

Fig 3. 3 Accuracy Comparison of Machine Learning Models for Gadget Addiction Prediction

- The performance of each model was assessed using the following metrics. The evaluation metrics presented in Table 3.2 highlight the different aspects used to assess the performance of the Random Forest model.

Table 3. 2 Accuracy Comparison of Machine Learning Models

Model	Accuracy
Random Forest	90.87%
Decision Tree	85.32%
Logistic Regression	78.94%
Support Vector Machine	80.45%

To aid interpretation, a corresponding bar chart is shown in Figure 3.4, where each metric is represented visually as a percentage. This visual comparison offers a quick and intuitive understanding of the model's strengths across the selected evaluation dimensions.

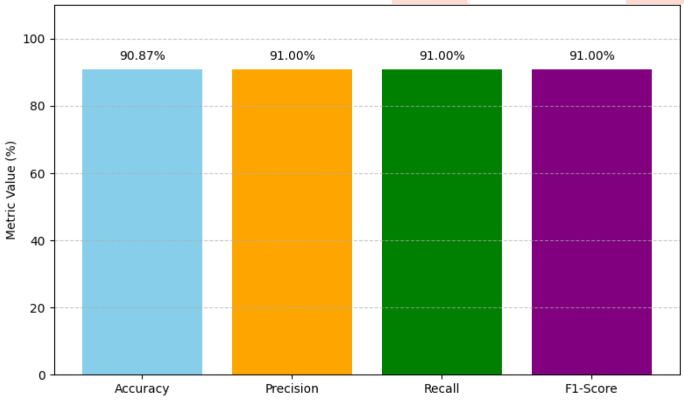

Fig 3. 4 Evaluation Metrics Comparison for the Random Forest Model

Accuracy measures the overall correctness of predictions, while precision, recall, and F1-score provide deeper insight into how well the model handles true positive and false negative cases. These metrics shown in Table 3.3 are particularly important when working with imbalanced datasets or multi-class classification problems.

Table 3. 3 Evaluation metrics for Random Forest Model

Accuracy	Proportion of correctly predicted instances out of all instances	90.87%
Precision	Ratio of correctly predicted positives to total predicted positives	91.00%
Recall	Ratio of correctly predicted positives to total actual positives	91.00%

F1-Score	Harmonic mean of Precision and Recall, balancing both metrics	91.00%

3.2.5 Model Optimization

Hyperparameter tuning was conducted using cross-validation methods. Parameters such as the number of trees, maximum tree depth, and feature subset size were optimized to enhance model performance and reduce overfitting.

3.2.6 Model Saving

Once the optimal model was trained and evaluated, it was serialized using the joblib library. This enabled reuse of the model in the Flask web application for real-time predictions.

3.3 Module 3: Prediction of Addiction

This module covers the process of predicting gadget addiction using user responses submitted through a web-based quiz. The workflow includes preparing user input, generating predictions, and delivering meaningful feedback based on the result.

3.3.1. Preparing Input Data

User responses were collected through a quiz form featuring 15 multiple-choice questions. To ensure compatibility with the trained Random Forest model, identical preprocessing steps—such as label encoding—were applied to convert the textual responses into numerical format. The transformed data was then structured in the same order and layout used during model training to ensure consistency and accuracy in prediction.

3.3.2 Generating Predictions

The pre-trained Random Forest classifier was loaded using the joblib library. The numerical input from the user was passed into the model to generate a prediction. The categorized output of the user into one of three ranges and its respective addiction risk levels explained in Table 3.4

Table 3. 4 Different Risk categories with range

Risk Level	Range	Description
Low Risk	≤30%	Healthy gadget usage pattern, minimal signs of addiction.
Moderate Risk	31–70%	Noticeable signs of overuse, moderate concern.
Critical Risk	>70%	High usage patterns, strong indication of gadget addiction.

3.3.3 Post-processing Predictions

Once a prediction was generated, it was presented to the user along with a descriptive message explaining their gadget usage behavior. Each risk category was associated with personalized recommendations which was mentioned in the Table 3.5

Table 3. 5 Risk Categories and Associated Recommendations

Risk Level	Personalized Recommendation
Low Risk	"Your gadget usage appears to be healthy. Keep maintaining a balanced routine."
Moderate Risk	"You may benefit from scheduled breaks and reduced gadget use before bedtime."
Critical Risk	"Consider reducing screen time and seeking guidance if necessary."

3.4 Module 4: Web-Based Interface

This module focuses on the frontend and backend implementation used to interact with users and display model outputs.

3.4.1 Frontend Development

The interface was designed using HTML and CSS to provide an intuitive and clean user experience. Key features included:

- Bolded quiz questions for emphasis
- Pagination with two questions per page for ease of reading
- A result page that clearly displayed the prediction and personalized guidance

3.4.2 Integration and Deployment

The complete application was hosted on Flask's development server, operating at **http://127.0.0.1:5000**. Backend functionality included session handling, input validation, prediction generation, and routing across multiple pages. The minimalistic architecture excluded heavy frontend frameworks, making it lightweight and efficient.

3.4.3 Test History Visualization

User test histories were displayed via a combination of dynamic HTML tables and bar charts. Each entry recorded:

- Timestamp of the attempt
- Addiction percentage score
- Predicted risk level

Visualization was implemented with color-coded bars representing risk levels:

- **Green** - (≤30%) - Low Risk
- **Orange** - (31–70%) - Moderate Risk
- **Red** - (>70%) - Critical Risk.

3.5 Module 5: Data Storage and Management

This module describes how prediction results and test histories are securely stored and maintained.

3.5.1 Data Storage Design

A CSV file format was used for recording user test results. Each row stored a username, timestamp, addiction score, and the corresponding risk category. This structure allowed efficient loading and analysis using data tools like pandas.

3.5.2 Secure Data Access

User authentication was implemented using Flask sessions, ensuring that test histories are visible only to the respective users. Sensitive data collection was avoided, thereby reducing privacy risks. All session transitions were secured to prevent unauthorized access.

3.5.3. Backup and Recovery

Backups were maintained by periodically saving user_history.csv in a secure location. Recovery strategies included:

- Manual restoration from backup copies
- Exporting backup files to USB or cloud platforms like Google Drive

3.6 Module 6: Results

This module presents how the prediction results were served to users and how the model's performance was evaluated and visualized.

3.6.1 Running the Flask Application

After completing the model training and integrating it with the Flask backend, the application was executed locally using Flask's development server.

By default, Flask runs on the following address:

URL: http://127.0.0.1:5000 or http://localhost:5000

This address allows the developer to test and interact with the application locally using any web browser. Once the server is running, users can access the homepage, navigate through the quiz pages, submit responses, and view addiction risk predictions and their history.

3.6.2 Prediction Output Format

After completing the quiz, the user receives a prediction categorized into one of the following risk levels:

- Low Risk
- Moderate Risk
- Critical Risk

• The output is shown immediately along with personalized suggestions to help manage gadget use.

3.6.3 Sample Result Output for Users

Example: "Your addiction score is 72%, which falls under the Critical Risk category. It is recommended that you reduce screen time and avoid gadget use before sleep."

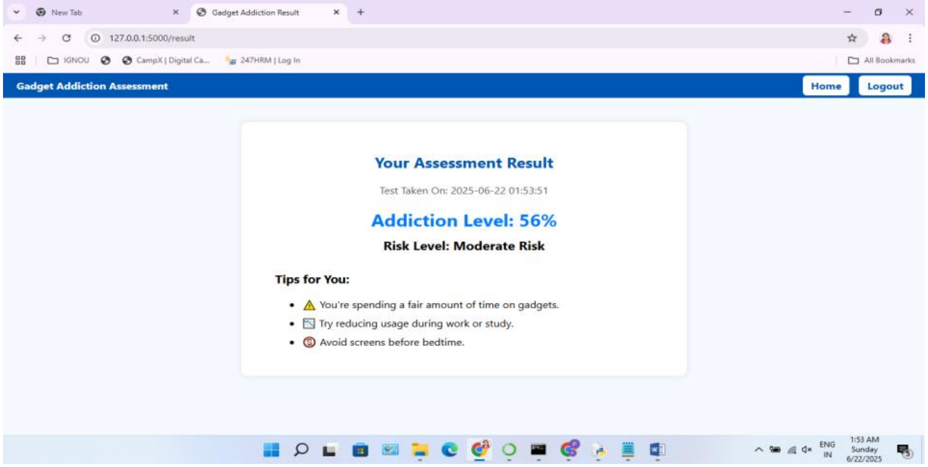

Fig 3. 5 Sample User Result Output

IV. RESULTS AND DISCUSSIONS

This chapter presents the results obtained from the implementation of the gadget addiction prediction system. Various modules of the system such as registration, login, quiz interface, prediction result generation, and result visualization are shown using screenshots captured during system execution. These results demonstrate the working and effectiveness of the complete system.

4.1 Home, Registration and Login Module

The system begins with a well-structured home page that introduces the primary objective of the project—assessing and predicting electronic gadget addiction among students using machine learning techniques. This page creates awareness about the importance of the issue and encourages users to proceed with the self-assessment.

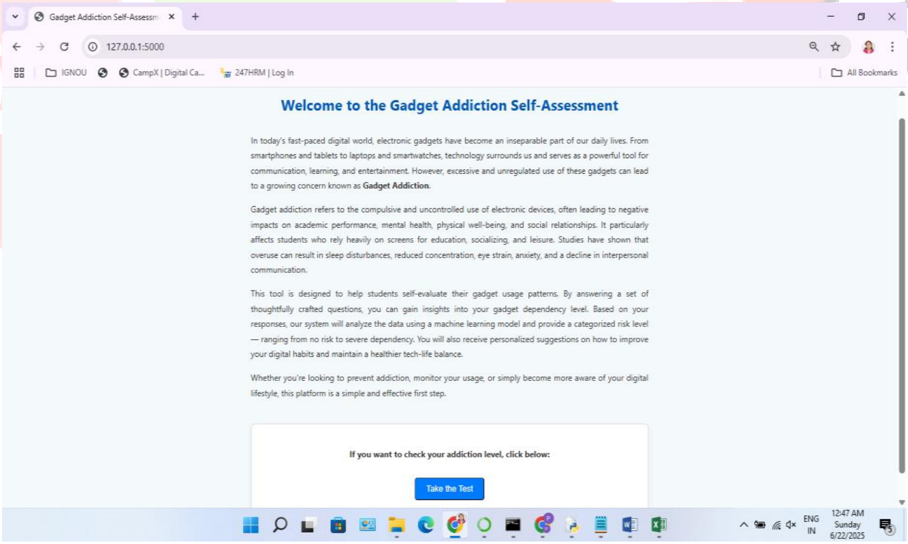

Fig 4. 1 Home Page

The home page includes navigation link to a motivational message like: "If you want to check your addiction level, click below." Shown in Fig 4.1. After visiting the home page, users can either register or log in to take the assessment quiz by login with user authentications.

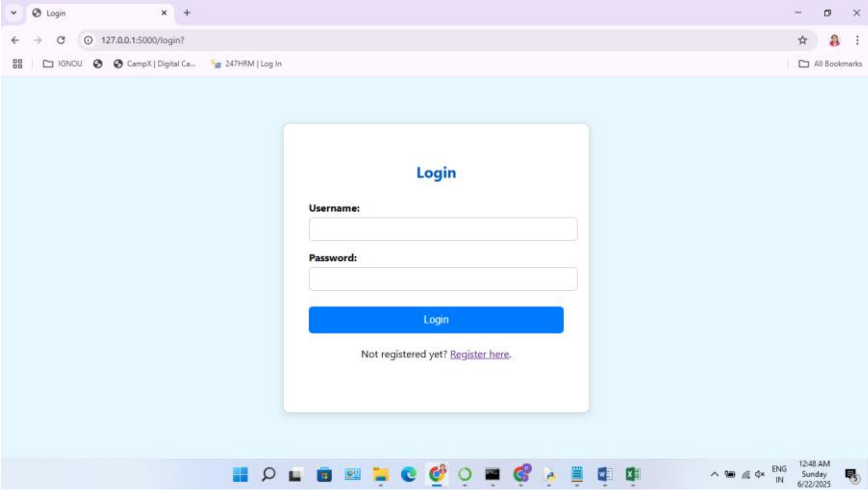

Fig 4. 2 Login Page

The login page (Fig 4.2) is the entry point for users into the system in secure mode. The user is required to provide his/her registered email and password to authenticate himself/herself. Validations are properly done to verify login credentials as correct, preserving user data privacy and security.

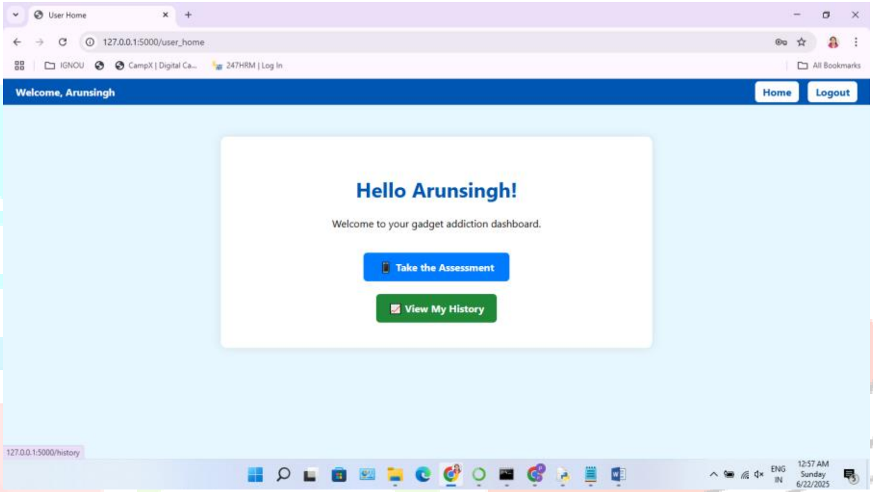

Fig 4. 3 User home page

Upon successful login, the user is directed to the main dashboard in Fig 4.3. The home page presents navigation choices like beginning the quiz, looking at previous test scores, or logging out. The design is made to be simple, clear, and easy to use, with quick access to all major functionalities.

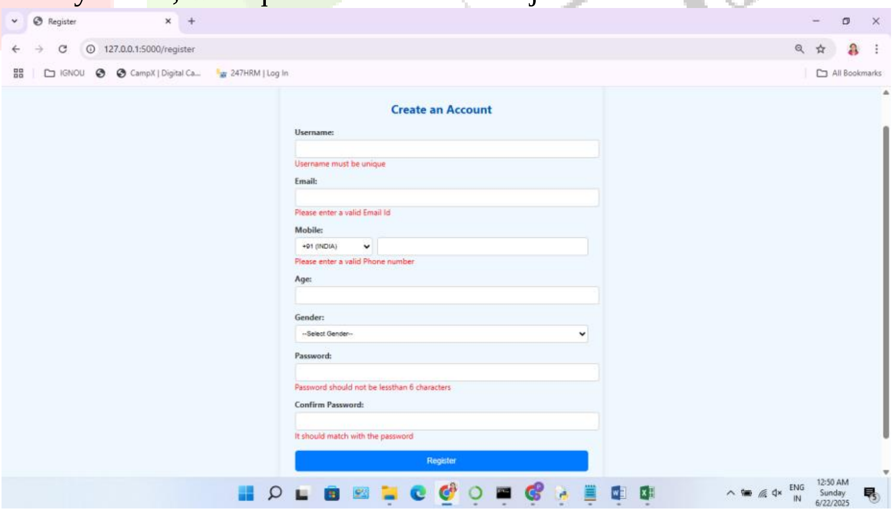

Fig 4. 4 Fig Registration Page

Fig 4.4 shows the registration page on which new users can register themselves by filling in their name, email, and password. Input validation ensures the use of matching and correctly spelt information. This is important to enable personalized access to the addiction assessment system.

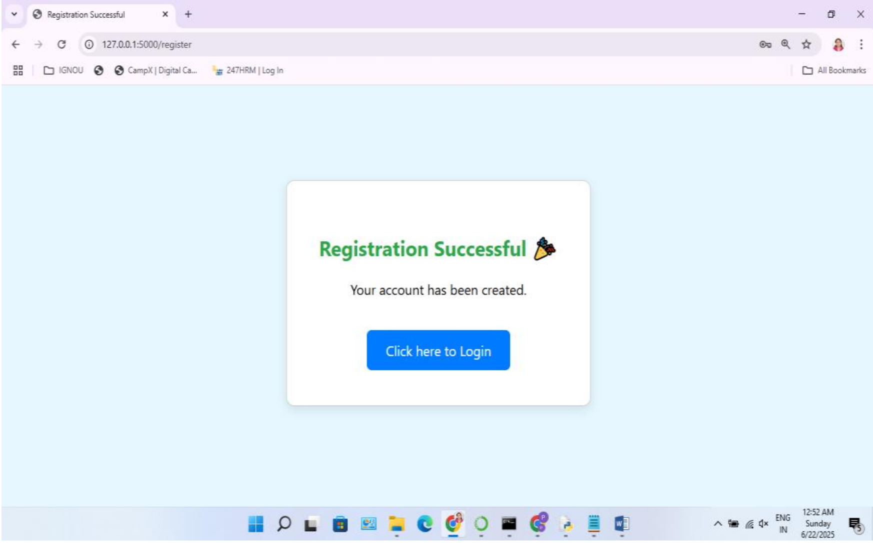

Fig 4. 5 Registration success Page

After finalizing the registration process, the system navigates the user to a confirmation page as depicted in Fig 4.5. The page shows a success message and also includes an immediate link to the login page. The page ensures that the user's account has been created and leads them to start utilizing the system.

4.2 Quiz Module

After a login successfully, the user is directed to the quiz module. The quiz comprises a total of 16 questions, distributed across multiple HTML pages. Each page contains two questions designed to evaluate the user’s gadget usage patterns, including screen time, emotional dependence, academic impact, and physical well-being.

To enhance user engagement and reduce the chances of quiz drop-off, motivational messages or virtual reward prompts are displayed after each quiz page starting from page 2 to page 8. These short, encouraging messages are meant to reward the user’s progress and inspire them to complete the full assessment.

Examples of such messages include:

🎉 Great job! You've completed another step. Keep going — you're doing amazing!
🌟 You're on a roll! Your awareness matters — keep moving forward!
💡 Awesome! Every answer you give makes the result more accurate.
🌈 You're doing really well! Every step is helping you understand yourself better.
🚀 You’re doing great! Stay focused — you’re almost there!
🛸 You’re nearly there! Just one last page to go — you’ve got this!
🎉 You've made it to the end! Get ready to see your personalized results!

The test pages constitute the main evaluation module of the system, where users respond to a structured set of questions aimed at analyzing their gadget usage behavior. The quiz is divided into multiple pages, each containing two questions with predefined multiple-choice options to ensure clarity and ease of completion. To keep users motivated throughout the assessment, encouraging messages or reward prompts are displayed after each page, except the first. The questions are carefully designed based on behavioral indicators relevant to electronic gadget addiction. This step-by-step approach ensures focused participation and helps the model gather meaningful input for accurate prediction. The sequence and design of these quiz pages are illustrated in Figures 4.6 to 4.13.

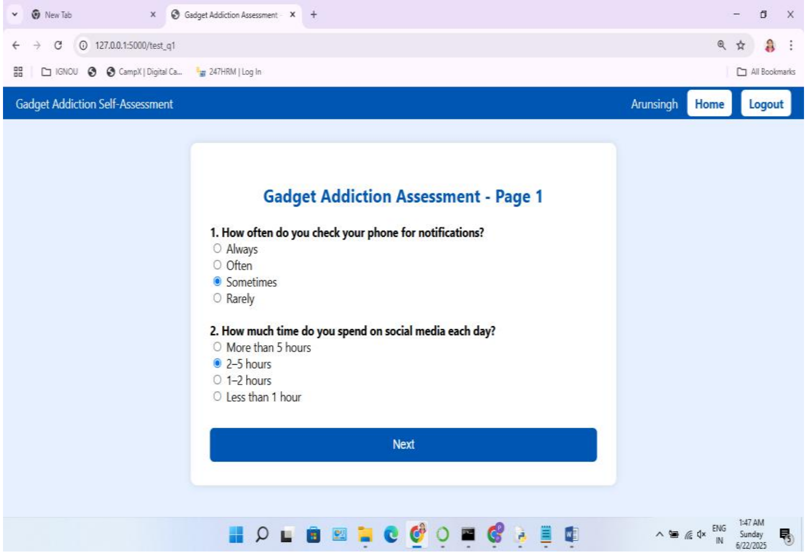

Fig 4. 6 Test page-1

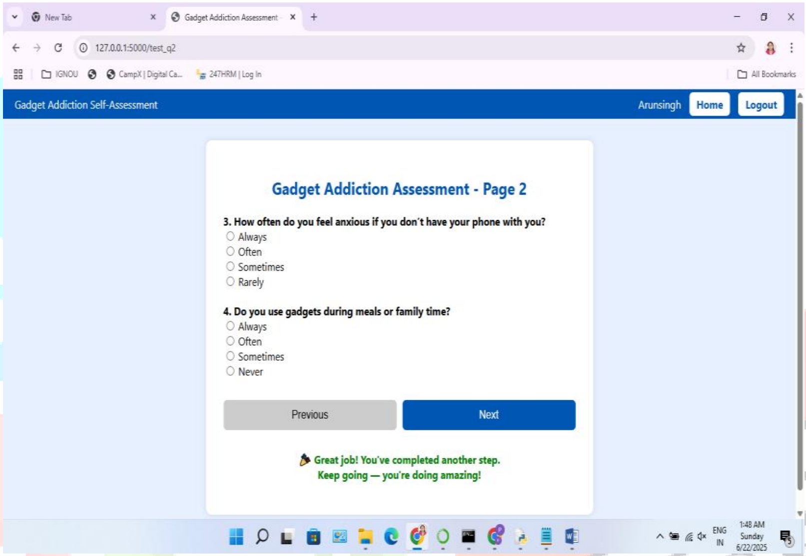

Fig 4. 7 Test page-2

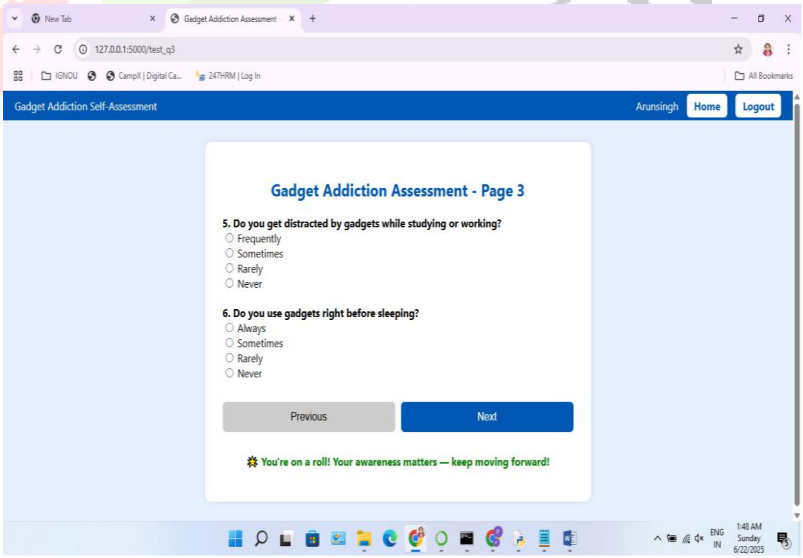

Fig 4. 8 Test page-3

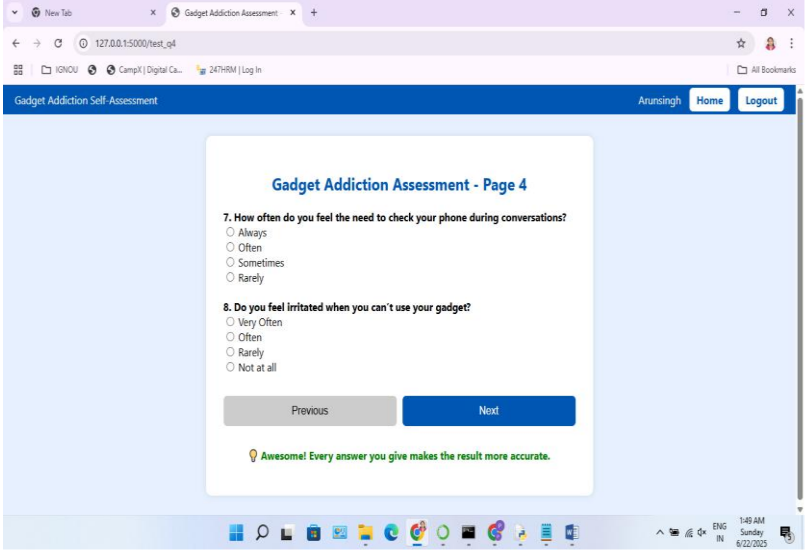

Fig 4. 9 Test page-4

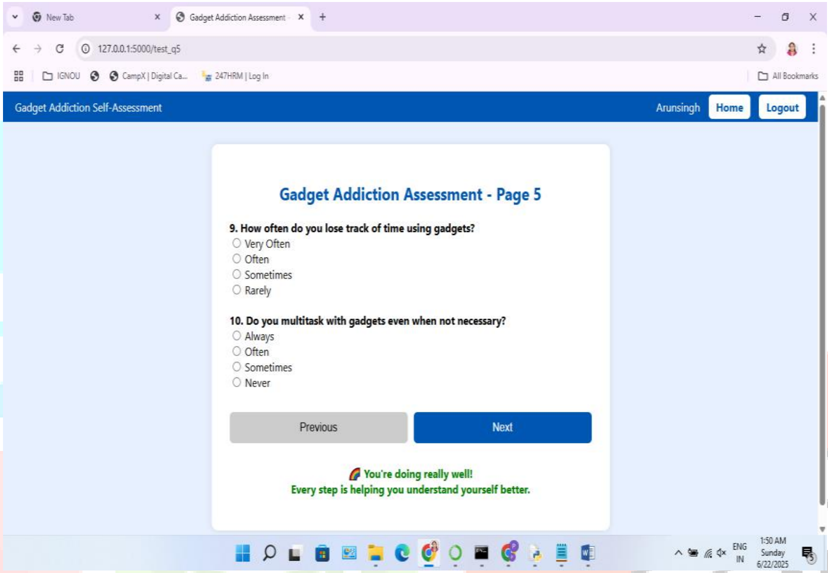

Fig 4. 10 Test page-5

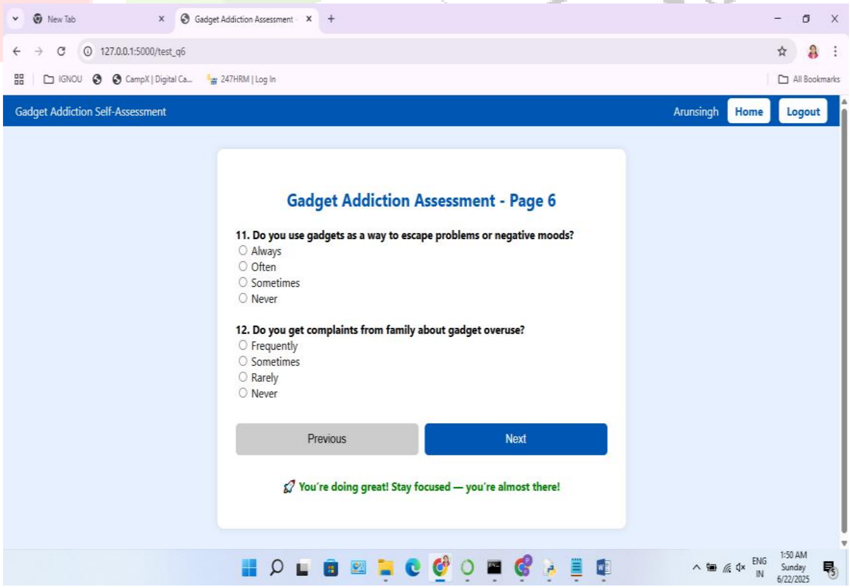

Fig 4. 11 Test page-6

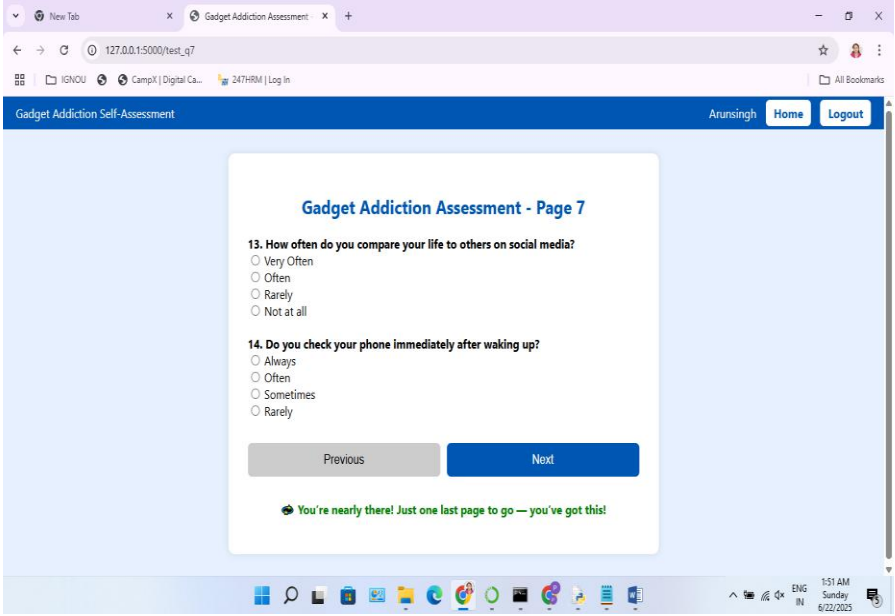

Fig 4. 12 Test page-7

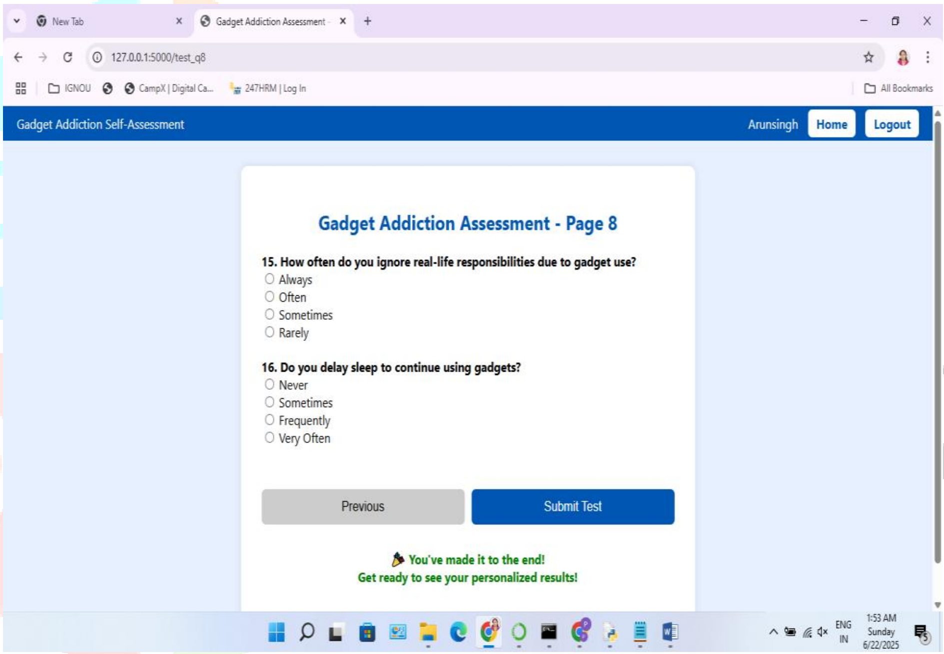

Fig 4. 13 Test page-8

4.3 Prediction Results

Once the user submits the final quiz page, the system automatically processes all the responses collected across the eight quiz pages and a prediction about the user's gadget addiction level will display.

The prediction is generated almost instantly, and this page not only shows the user's addiction category but also provides personalized feedback and recommendations based on their risk level. The model classifies each user into one of the following three risk categories:

- **Low Risk**: Indicates normal and healthy gadget usage. The user is likely managing screen time well. A positive message is displayed encouraging them to continue maintaining balance. From Fig 4.14
- **Moderate Risk**: Suggests that the user may be developing unhealthy gadget habits. A warning is given, along with advice to reduce screen time, set usage limits, and take regular breaks. From Fig 4.15
- **Critical Risk**: Reflects a high possibility of gadget addiction. The user is urged to take corrective action immediately. The system provides strong recommendations such as seeking guidance from mentors, engaging in offline activities, and possibly consulting professionals if the behavior continues. From Fig 4.16

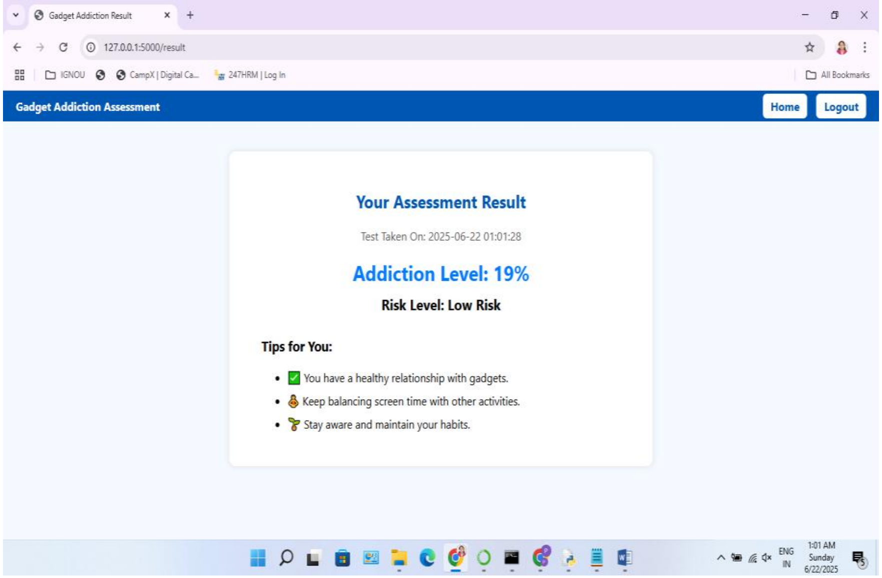

Fig 4. 14 Result page with Low risk level

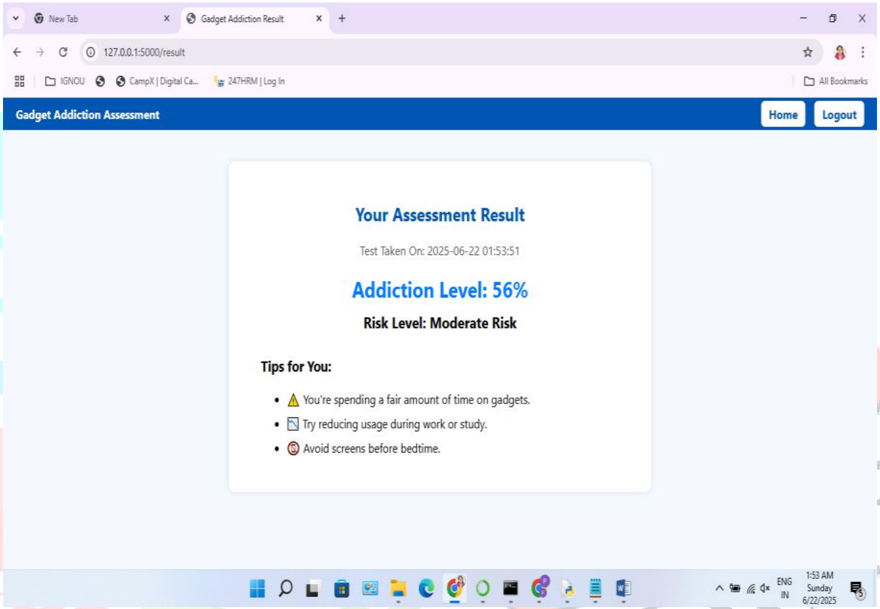

Fig 4. 15 Result page with Moderate risk level

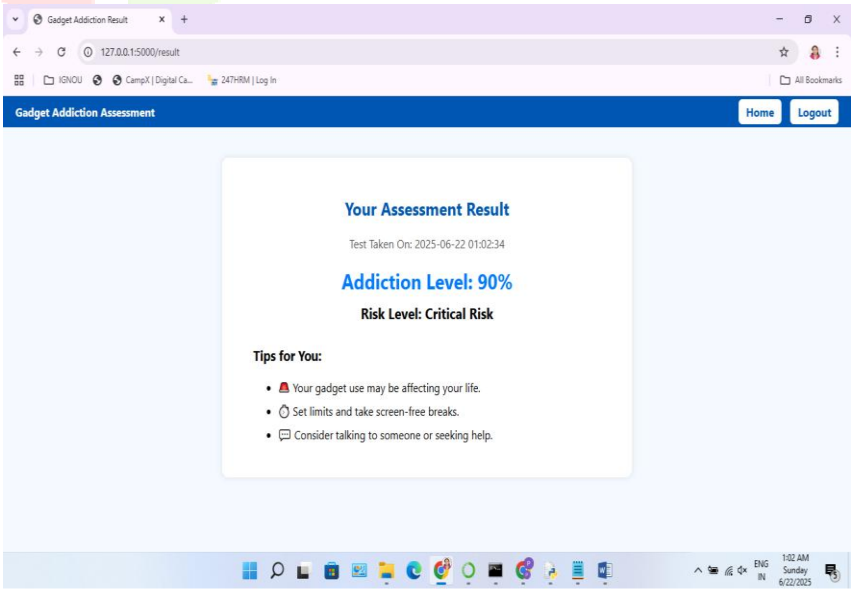

Fig 4. 16 Result page with High risk level

The result page is kept visually clear and concise, using colored indicators and meaningful text to make the output understandable even for non-technical users. Additionally, users are shown motivational messages that acknowledge their participation and encourage them to reflect on their gadget usage habits, regardless of the outcome.

4.4 Test History and Visualization

Each user's previous test outcomes are stored in a database and can be retrieved to display a history of their addiction levels over time. This is helpful for self-monitoring and behavioral tracking. The history module includes a tabular view of test dates and predicted outcomes. Visualizations such as line charts or bar graphs are used to show progress over time.

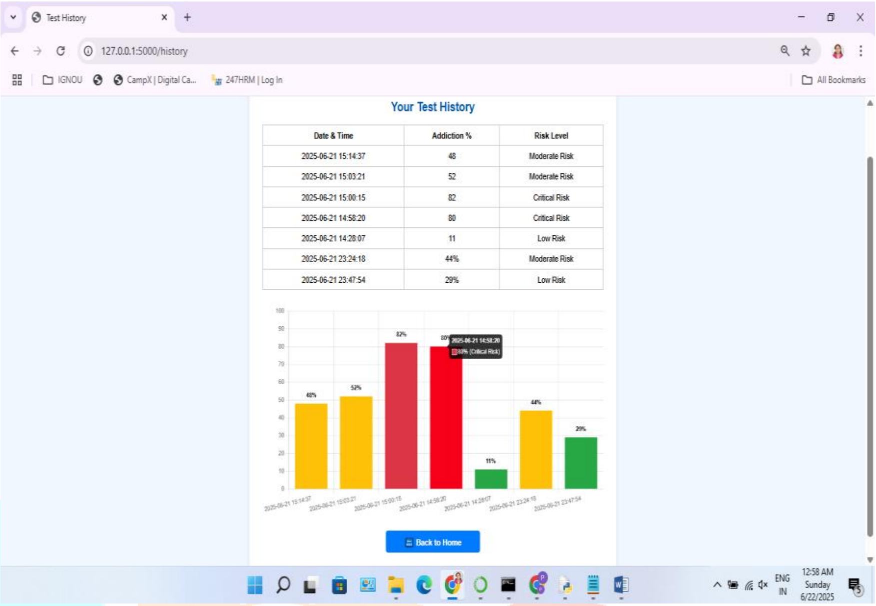

Fig 4. 17 User’s Test History with Corresponding Risk Levels and Visual Trends

As illustrated in Fig 4.17, the test history module records each user’s addiction assessment results over time, showing the date and time, the predicted addiction percentage, and the corresponding risk level (Low, Moderate, or Critical). This historical log is presented both in tabular format and as a bar chart for visual interpretation. The bar chart highlights addiction trends across multiple test attempts, allowing users to reflect on their digital behavior patterns and observe improvements or declines. This visualization supports personalized feedback and encourages students to monitor and reduce their gadget use proactively.

4.5 Discussion

The simulation and testing of the proposed system demonstrate that it performs efficiently and effectively across all its functional components. The integrated modules work together seamlessly to offer a smooth and meaningful user experience. Each aspect of the system—from data input to prediction and result visualization—has been carefully designed and tested to ensure usability and accuracy.

Users are able to interact with the quiz interface intuitively. The question-wise distribution across multiple pages along with motivational messages after each section, keeps users engaged throughout the quiz. The structure ensures that even non-technical users can comfortably complete the assessment without confusion or delay.

Upon completion of the quiz, the system immediately processes the responses. It successfully categorizes users into Low Risk, Moderate Risk, or Critical Risk categories, each accompanied by appropriate guidance.

Another key strength of the system lies in its ability to track and visualize user progress over time. By storing each prediction result, the system allows users to revisit their past assessments and analyze trends in their gadget usage behavior. The integration of Chart.js for generating dynamic bar graphs enhances user understanding through clear and colorful visual feedback.

The selection of technologies has contributed significantly to the system’s success. Flask, a lightweight web framework, serves as the backbone of the application, handling routing, user authentication, and quiz logic. Random Forest, known for its robustness and high classification accuracy, ensures dependable prediction outcomes. Chart.js adds an interactive visual layer, making the historical analysis both informative and user-friendly.

Overall, the system delivers a comprehensive and interactive solution for predicting electronic gadget addiction. It is user-centric, educational, and adaptable for continuous self-assessment, making it a valuable tool for students and educational institutions alike.

V . CONCLUSION AND FUTURE SCOPE

This chapter summarizes the key outcomes of the project and reflects on how the objectives were achieved. It highlights the effectiveness of using machine learning, especially the Random Forest model, for predicting gadget addiction based on behavioural data. The study's contributions, practical implications, and limitations are also discussed. Finally, potential areas for future research are suggested, such as integrating real-time usage tracking, improving prediction accuracy with larger datasets, and developing mobile-based interventions for high-risk users.

5.1 Conclusion

This research effectively created a machine learning model to forecast electronic device addiction in students between 18–25 years of age. With responses to quizzes, the Random Forest algorithm identified users as Low, Moderate, and High risk. Major behavioral attributes such as screen time, anxiety, and device reliance were found to be effective for precise prediction. Web-based implementation guarantees accessibility and scalability, with planned future improvements such as personalized suggestions and feedback likely to increase its relevance for education and mental health purposes.

5.2 Future Scope

- Feedback Loop Integration: One of the key future improvements is the addition of a feedback mechanism, allowing students to rate the accuracy of their predicted addiction level. These responses can be collected by system administrators or academic guides to fine-tune or retrain the model with real-world feedback over time.
- Personalized Recommendations: Based on prediction results and feedback, students can be provided with tailored suggestions, such as attending awareness programs, reducing screen time, or seeking counseling.
- Awareness Material Integration: The system can be extended to offer follow-up content — such as articles, videos, or helpline information — based on the student's addiction risk level, enabling holistic digital well-being support.
- Dataset Expansion: Including more diverse student data from various institutions can improve generalization and enhance model performance.
- Multimodal Data Integration: Combining quiz data with screen time logs or app usage statistics can further refine predictions in future iterations.

REFERENCES

[1]Ahuja, R., & Banga, A. (2019). Mental Stress Detection in University Students using Machine Learning Algorithms. Procedia Computer Science, 152, 349–353. https://doi.org/10.1016/j.procs.2019.05.007

[2] Anosike, C., Ogbu, M. A., Ugochukwu, E. J., Osefo, R. C., & Nwaji, J. C. (2024). Effect of smartphone addiction on mental health and sleep quality among undergraduate pharmacy students in a Nigerian public university. The Journal of Mental Health Training Education and Practice, 19(4), 201–212. https://doi.org/10.1108/jmhtep-12-2023-0106

[3] Aruna, A., Sri, K., Dharsha, M., Shadrak, Ch., Kareem, A., Kumar, A., & Department of Computer Science and Engineering, Dhanekula Institute of Engineering and Technology, Vijayawada, India. (2025). AI-Driven Gadget Addiction Predictor. International Journal of Creative Research Thoughts (IJCRT), 13(3), e96–e98. https://ijcrt.org/papers/IJCRT2503464. pdf

[4] Balasubramanian, N., & Parayitam, S. (2022). Antecedents and consequences of internet addiction among school and college students: evidence from India. Global Knowledge Memory and Communication, 72(8/9), 813–834. https://doi.org/10.1108/gkmc-12-2021-0211

[5] Balhara, Y. P. S., Doric, A., Stevanovic, D., Knez, R., Singh, S., Chowdhury, M. R. R., Kafali, H. Y., Sharma, P., Vally, Z., Vu, T. V., Arya, S., Mahendru, A., Ransing, R., Erzin, G., & Le, H. L. T. C. H. (2019). Correlates of Problematic Internet Use among college and university students in eight countries: An international cross-sectional study. Asian Journal of Psychiatry, 45, 113–120. https://doi.org/10.1016/j.ajp.2019.09.004

[6] Cha, S., & Seo, B. (2018). Smartphone use and smartphone addiction in middle school students in Korea: Prevalence, social networking service, and game use. Health Psychology Open, 5(1). https://doi.org/10.1177/2055102918755046

[7] Daniyal, M., Javaid, S. F., Hassan, A., & Khan, M. a. B. (2022). The Relationship between Cellphone Usage on the Physical and Mental Wellbeing of University Students: A Cross-Sectional Study. International Journal of Environmental Research and Public Health, 19(15), 9352. https://doi.org/10.3390/ijerph19159352

[8] Demir, K., & Akpinar, E. (n.d.). (2018). The Effect of Mobile Learning Applications on Students' Academic Achievement and Attitudes toward Mobile Learning. https://eric.ed.gov/?id=EJ1174817

[9] Dharmadhikari, S. P., Harshe, S. D., & Bhide, P. P. (2019). Prevalence and Correlates of Excessive Smartphone Use among Medical Students: A Cross-sectional Study. Indian Journal of Psychological Medicine, 41(6), 549–555. https://doi.org/10.4103/ijpsym.ijpsym_75_19

[10] García-Santillán, A., & Espinosa-Ramos, E. (2021). Addiction to the smartphone in high school students: how it's in daily life? Contemporary Educational Technology, 13(2), ep296. https://doi.org/10.30935/cedtech/9609