Smart Phone Addiction Classification

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ABSTRACT

The increasing dependence on smartphones has led to rising concerns about smartphone addiction, particularly among students and working professionals. Excessive usage affects mental health, sleep quality, and productivity, making early detection of addiction essential. This project presents a smartphone addiction classification system using machine learning techniques to identify and categorize user behavior based on usage patterns. Data such as screen time, app usage frequency, notification response time, and call or message duration are collected and analyzed to determine addiction levels. machine learning algorithms, including Random Forest are trained to classify users into normal, moderate, and high addiction categories. The model provides accurate insights into user habits and helps in understanding the correlation between device usage and addiction tendencies. By offering a data-driven approach to behavioral monitoring, the system aims to promote digital well-being and support users in achieving a healthier balance between technology use and daily life.

CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

In the modern digital era, smartphones have become an essential part of everyday life, especially among students and working professionals. While smartphones provide convenience, communication, and access to information, excessive usage has led to growing concerns about smartphone addiction. Continuous engagement with social media, gaming, messaging applications, and online content negatively impacts mental health, academic performance, workplace productivity, and sleep patterns. Therefore, identifying and managing unhealthy smartphone usage has become a significant social and technological challenge.

Smartphone addiction is a behavioral issue characterized by excessive screen time, compulsive checking of notifications, and difficulty in controlling device usage. Traditional methods of detecting addiction mainly rely on self-reported surveys and psychological assessments, which may not always provide accurate or real-time results. To address this limitation, the proposed system introduces a data-driven and automated approach for identifying addiction levels using machine learning techniques. By analyzing real usage patterns instead of subjective responses, the system ensures more reliable and objective classification.

1.2 OBJECTIVE

The main objectives of the project are:

- To develop a machine learning-based system for classifying smartphone addiction levels based on user behavior data.
- To collect and analyze smartphone usage parameters such as screen time, app usage frequency, and notification response time.
- To implement the Random Forest algorithm for accurate classification into normal, moderate, and high addiction categories.
- To provide data-driven insights that help users understand their smartphone usage patterns.
- To promote digital well-being by encouraging balanced and responsible use of smartphones.
- To design a scalable and efficient system capable of handling real-time behavioral data analysis.

CHAPTER 2

LITERATURE SURVEY

1. Parhi, Manoranjan et al., in their paper "Utilizing Digital Data and Soft Computing Techniques for Comprehensive Behavioral Addiction Analysis and Monitoring" presented at IEEE MPSec ICETA 2025, proposed a comprehensive framework that integrates digital behavioral data with soft computing techniques to analyze and monitor addiction patterns. The study emphasizes the importance of collecting real-time digital footprints such as browsing history, application usage statistics, online interaction time, and engagement frequency to identify addictive behaviors. The authors applied soft computing methods including fuzzy logic systems, neural networks, and hybrid optimization algorithms to handle uncertainty and imprecision in behavioral data. Their model focuses on adaptive learning mechanisms that continuously update predictions based on user activity trends. Experimental results demonstrated improved prediction accuracy compared to traditional statistical approaches. The research also highlighted the significance of early detection systems in preventing severe psychological and social consequences associated with digital addiction.
2. Thakur, Jigayasha and Daundey, Rameshwar Prasad in their article "Mobile Phone: A Journey from Necessity to Addiction" published in the International Journal of Computing and Artificial Intelligence (2025), examined the transformation of mobile phones from essential communication tools to sources of behavioral dependency. The study provides a detailed conceptual and psychological analysis of smartphone addiction, discussing factors such as excessive social media engagement, gaming habits, peer pressure, and emotional attachment to digital interactions. The authors explored symptoms including anxiety when separated from devices, sleep disturbances, reduced academic or work performance, and decreased face-to-face communication.
3. Wang, Li in the paper "Smartphone Addiction Analysis Model Based on C5.0 Algorithm" presented at IEEE NMITCON 2024, introduced a structured classification model using the C5.0 decision tree algorithm to analyze smartphone addiction. The study focused on extracting measurable behavioral attributes such as daily screen time, number of app launches, frequency of notifications, and duration of calls or messages. These features were used to train and test the C5.0 algorithm, which generates rule-based decision trees for classification. The research highlighted the interpretability advantage of decision tree models, allowing clear identification of dominant addiction indicators. Performance evaluation metrics such as accuracy, precision, recall, and F1-score were analyzed to validate the effectiveness of the model. The results demonstrated that the C5.0 algorithm achieved reliable classification accuracy while maintaining computational efficiency. The study also compared the model with other traditional classification

techniques, showing competitive performance. This research provides strong evidence that machine learning-based decision tree approaches are effective tools for predicting smartphone addiction levels in data-driven behavioral monitoring systems.

4. Dhanalakshmi, R. et al., in their paper "Breaking the Digital Grip: AI Models for Evaluating the Internet and Mobile Addiction Across All Age Groups" presented at IEEE ICIRCA 2025, investigated the application of multiple artificial intelligence models to evaluate internet and mobile addiction across different age groups. The study analyzed behavioral datasets collected from children, teenagers, adults, and working professionals to identify patterns of digital dependency. Various machine learning algorithms such as Support Vector Machines, Random Forest, and Neural Networks were implemented and compared to determine the most effective predictive model.

5. Pawar, Vivekanand, Patil, Archana Bhaskar, and Santra, Aparna in their paper "Predicting Smartphone Addiction Using Behavioral and Psychological Traits with Machine Learning" presented at IEEE GINOTECH 2025, proposed a multidimensional machine learning framework that integrates both behavioral usage data and psychological traits for addiction prediction. The study collected parameters such as screen time, social media engagement, gaming frequency, and notification interaction along with psychological indicators including stress levels, impulsivity, and emotional stability. Feature selection techniques were applied to identify the most influential predictors. Multiple machine learning algorithms were evaluated, and ensemble-based approaches demonstrated superior performance in classification accuracy. The authors concluded that combining psychological assessments with digital behavioral metrics significantly improves predictive reliability compared to single-dimensional models. The research highlights the importance of holistic data analysis in understanding addiction tendencies and supports the development of advanced classification systems capable of providing accurate and personalized digital well-being insights.

6. Muezzin, Ece Emre, in the paper *"A Review on the Psychological Effects of Smartphone Addiction"* published in *Kıbrıs Türk Psikiyatri ve Psikoloji Dergisi (2023)*, conducted a detailed review focusing on the psychological consequences of excessive smartphone usage. The study systematically analyzes how smartphone addiction influences mental health parameters such as anxiety, depression, stress, and emotional instability. The author highlights that prolonged screen exposure and dependency on mobile devices significantly reduce attention span, disrupt sleep cycles, and increase social isolation. The research emphasizes behavioral symptoms including compulsive checking, withdrawal effects, and reduced real-life social interaction

CHAPTER 3
SYSTEM ANALYSIS

3.1 EXISTING SYSTEM:

In the current scenario, smartphone addiction assessment is primarily conducted through traditional survey-based and self-reporting methods. Psychological questionnaires and manual evaluations are widely used to measure addiction levels among students and working professionals. Although these tools provide general insights into behavioral patterns, they heavily depend on honest responses and self-awareness of users. Many individuals may underestimate or overestimate their smartphone usage, leading to inaccurate results. Furthermore, these assessments are usually conducted periodically rather than continuously, making it difficult to detect early warning signs of addiction in real time.

Another limitation of the existing system is the lack of automated behavioral data analysis. Most monitoring approaches do not utilize real-time smartphone usage statistics such as screen time, application usage frequency, notification interaction rate, or call duration. Without analyzing objective digital footprints, identifying addiction severity becomes subjective and inconsistent. Additionally, manual data collection and evaluation processes require expert supervision, increasing time consumption and operational costs. Institutions and organizations find it challenging to monitor large populations effectively due to the absence of scalable digital solutions.

3.2 PROPOSED SYSTEM:

The proposed Smartphone Addiction Classification System is designed to overcome the limitations of traditional assessment methods by introducing a machine learning-based automated monitoring framework. The system collects real-time smartphone usage data such as daily screen time, frequency of application usage, notification response time, call duration, and messaging activity. These behavioral parameters are processed and transformed into meaningful features that represent user interaction patterns. By analyzing objective digital usage statistics instead of relying solely on self-reported surveys, the system ensures accurate and unbiased addiction detection.

The core of the proposed system is the implementation of the Random Forest machine learning algorithm for classification. The model is trained using labeled datasets to categorize users into normal, moderate, and high addiction levels. Random Forest is chosen due to its high accuracy, robustness, and ability to handle complex behavioral datasets. The system performs data preprocessing, feature extraction, model training, and prediction in a structured workflow. Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model’s effectiveness. The framework is scalable and capable of handling large datasets, making it suitable for deployment in educational institutions and workplaces.

This proposed system promotes digital well-being by providing users with data-driven insights into their smartphone usage habits. It enables early detection of addictive tendencies and encourages behavioral improvements. Unlike traditional systems, it offers continuous monitoring, automated classification, and predictive analytics. The system also ensures secure data handling and structured storage for maintaining privacy. By integrating behavioral analytics with machine learning intelligence, the proposed solution delivers a modern, efficient, and reliable approach to smartphone addiction analysis and monitoring.

3.3 PROPOSED SOLUTION

The Smartphone Addiction Classification System is proposed as a complete data-driven solution to address the growing issue of excessive smartphone usage among students and working professionals. Unlike traditional survey-based assessment methods, the proposed solution focuses on continuous behavioral monitoring using real-time smartphone usage data. The system collects measurable parameters such as daily screen time, application usage frequency, notification response rate, call duration, and messaging patterns. By integrating machine learning techniques, particularly the Random Forest algorithm, the system automates the process of addiction detection and classification. This eliminates reliance on subjective self-reporting and provides a more accurate, objective, and scalable approach to behavioral analysis.

3.4 IDEATION & BRAINSTORMING

The development of the Smartphone Addiction Classification System began with an extensive ideation and brainstorming phase aimed at understanding the real-world impact of excessive smartphone usage. The team analyzed existing addiction assessment methods and identified limitations such as reliance on manual surveys, lack of real-time monitoring, and absence of predictive analytics. Discussions were conducted to explore how machine learning and behavioral data analytics could provide a more objective and automated solution. The brainstorming sessions helped define the scope of the problem, identify relevant behavioral parameters, and determine suitable classification techniques for accurate addiction detection.

During the ideation stage, the team focused on identifying measurable smartphone usage indicators that reflect addictive tendencies. Parameters such as screen time duration, frequency of app switching, social media engagement, notification interaction patterns, and communication activity were shortlisted as key features. The team evaluated different machine learning algorithms including Decision Trees, Support Vector Machines, and Random Forest. After comparative analysis based on accuracy, robustness, and interpretability, Random Forest was selected due to its strong performance with complex behavioral datasets and ability to reduce overfitting. Feature engineering, dataset preparation, and model validation strategies were also finalized during this phase.

The brainstorming process further involved designing the system architecture and workflow. A structured pipeline was proposed including data collection, preprocessing, feature extraction, model training, classification, and result visualization. Security and privacy considerations were emphasized to ensure safe handling of sensitive usage data. The team also discussed user interface requirements to present addiction level results in a simple and understandable format. Future enhancements such as real-time monitoring dashboards, predictive trend analysis, and integration with wellness applications were recorded for further development. This structured ideation phase laid a strong technical and conceptual foundation for implementing an intelligent smartphone addiction detection system.

3.5 PROBLEM–SOLUTION FIT

The concept of Problem–Solution Fit ensures that the developed Smartphone Addiction Classification System effectively addresses real-world challenges related to excessive smartphone usage. Increasing screen time, reduced productivity, sleep disturbances, and mental health concerns highlight the urgent need for early detection mechanisms. Traditional assessment methods lack automation, scalability, and predictive capabilities, making them insufficient for large-scale monitoring. Therefore, the system is designed to bridge this gap through an intelligent and data-driven solution that aligns directly with the identified behavioral problems.

• Identified Problems

The primary problem is the rapid increase in smartphone dependency among individuals, particularly students and professionals. Existing evaluation techniques rely heavily on self-reported surveys and psychological assessments, which may produce biased or inaccurate results. There is no centralized or automated mechanism to continuously analyze real-time smartphone usage behavior. Institutions and organizations find it difficult to monitor large user groups effectively due to manual data collection processes. Additionally, current methods lack predictive analytics to identify early warning signs of addiction. These limitations create the need for a scalable, accurate, and automated behavioral classification system.

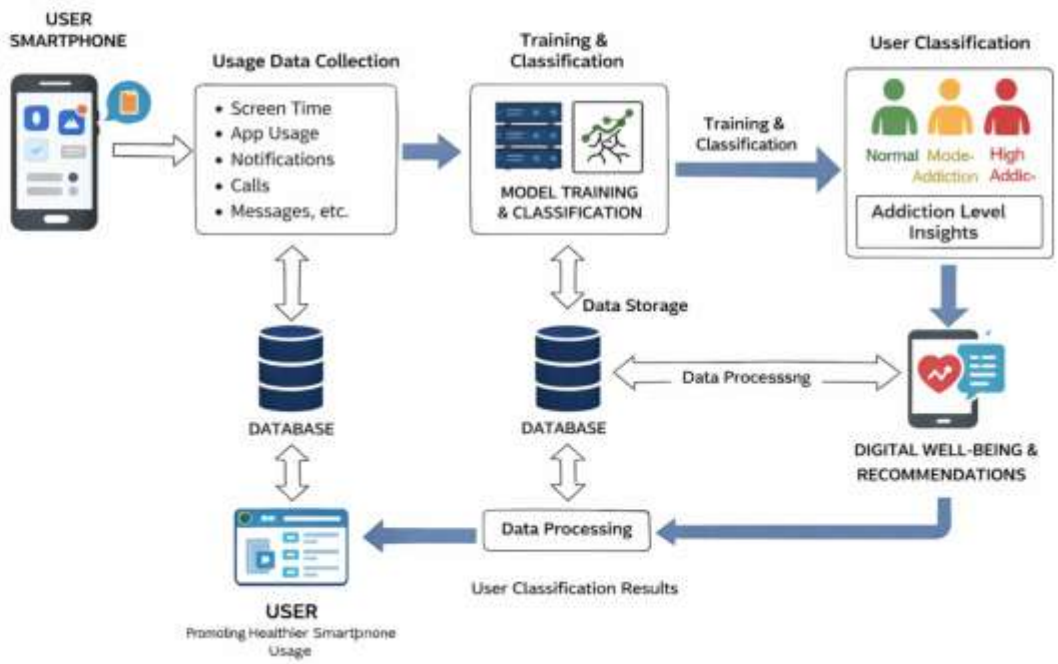
• Proposed Solution

To overcome these challenges, the proposed system implements a machine learning-based framework that automatically analyzes smartphone usage patterns. The system collects digital behavioral data, processes it using preprocessing and feature extraction techniques, and applies the Random Forest classifier to categorize addiction levels. It ensures objective evaluation by relying on measurable usage statistics instead of subjective responses. The architecture supports secure data storage and structured analysis, making it reliable for large-scale implementation in educational institutions and workplaces.

• Fit Analysis

The proposed solution aligns closely with the identified problems by offering automation, objectivity, and scalability. It eliminates manual survey dependency and introduces real-time behavioral analytics. The classification model provides accurate and interpretable results, enabling early intervention and awareness. The system's modular structure allows future expansion with predictive monitoring, personalized recommendations, and integration with digital wellness platforms. Functionally and technically, the solution effectively addresses the growing challenge of smartphone addiction by combining behavioral science principles with advanced machine learning techniques.

3.5. ARCHITECTURE DESIGN:



The presented architecture diagram illustrates a comprehensive Smartphone Addiction Classification System designed to monitor, analyze, and categorize user behavior based on smartphone usage patterns. The process begins with the user's smartphone, where various behavioral data parameters are collected, including screen time, app usage frequency, notification interactions, call duration, and messaging activity. These usage metrics form the foundational input for the system. The collected raw data is transmitted to a centralized database, ensuring structured storage and secure management. This storage layer plays a crucial role in maintaining historical usage records, which are essential for identifying behavioral trends over time. Once stored, the data flows into the training and classification module, where machine learning algorithms are applied. The model training component uses previously labeled datasets to learn behavioral patterns associated with different addiction levels. Through feature extraction and preprocessing techniques, the system converts raw usage statistics into meaningful input variables suitable for classification. The trained model then categorizes users into predefined addiction levels such as Normal, Moderate Addiction, and High Addiction. This structured workflow ensures that the classification process is automated, data-driven, and scalable, enabling efficient analysis of large user populations while minimizing manual intervention.

3.7 DESCRIPTION OF MODULES

3.7.1 USER DATA COLLECTION MODULE

The User Data Collection Module gathers real-time smartphone usage data such as screen time, app usage frequency, notifications, call duration, and messaging activity. It ensures only relevant behavioral data is collected without accessing sensitive personal content. The module follows proper data acquisition methods to maintain accuracy, consistency, and completeness. It also performs basic validation to avoid duplication and ensures secure transmission to the database. User consent and privacy are strictly maintained throughout the process. This module continuously monitors usage patterns over time and provides structured raw data, forming the foundation for further analysis and addiction classification.

3.7.2 DATA PREPROCESSING MODULE

The Data Preprocessing Module refines raw smartphone usage data to make it suitable for machine learning analysis. It handles missing values, removes inconsistencies, and eliminates redundant data entries. The module performs normalization and scaling of numerical features such as screen time and app usage to ensure uniformity. Feature extraction techniques are applied to derive meaningful indicators related to addiction behavior. It also encodes categorical data and detects outliers to reduce noise. Additionally, the processed data is divided into training and testing sets. This module improves data quality, ensuring accurate and efficient model performance.

3.7.3 DATABASE MANAGEMENT MODULE

The Database Management Module stores and manages all system data, including user behavior records, processed features, and classification results. It maintains a centralized database structure to ensure data consistency, scalability, and efficient retrieval. The module supports smooth data flow between different components of the system. Security measures such as authentication and access control are implemented to protect sensitive user information. Regular backups and indexing techniques enhance data integrity and system performance. It also stores historical data for long-term analysis and trend monitoring, acting as the backbone of the system's data handling operations.

3.7.4 MACHINE LEARNING CLASSIFICATION MODULE

The Machine Learning Classification Module uses the Random Forest algorithm to categorize users into Normal, Moderate Addiction, and High Addiction levels. It learns behavioral patterns from labeled datasets during the training phase. The ensemble approach of Random Forest improves accuracy and reduces overfitting by combining multiple decision trees. Once trained, the model predicts addiction levels for new user data. Performance is evaluated using metrics like accuracy, precision, recall, and F1-score. The module continuously updates predictions based on new data, providing reliable and interpretable results that form the core intelligence of the addiction detection system.

3.7.5 RESULT ANALYSIS AND RECOMMENDATION MODULE

The Result Analysis and Recommendation Module interprets classification outputs and provides meaningful insights to users. It identifies key behavioral factors contributing to smartphone addiction, such as excessive screen time or app usage. Based on the addiction level, it generates personalized recommendations like limiting usage, enabling notifications control, and adopting healthier digital habits. The module stores results for progress tracking and future comparisons. It may include visualization tools for better understanding of user behavior trends. By linking detection with actionable guidance, this module promotes digital well-being and encourages users to maintain a balanced smartphone usage lifestyle.

3.8 DATA FLOW DIAGRAM

The Data Flow Diagram of the Smartphone Addiction Classification System illustrates how data moves between modules to ensure efficient and secure processing. The process begins with the User Data Collection Module, where smartphone usage statistics are gathered and transmitted to the centralized database. The Data Preprocessing Module retrieves raw data from the database, cleans and transforms it, and stores the processed dataset back into the system. This structured dataset is then accessed by the Machine Learning Classification Module for training and prediction purposes. The classification results are stored in the database and forwarded to the Result Analysis and Recommendation Module, where insights and personalized suggestions are generated. Finally, these results are presented to the user through an interactive interface. The continuous bidirectional flow between modules and the database ensures data consistency, real-time updates, and reliable addiction monitoring, forming a secure and intelligent behavioral analysis framework.

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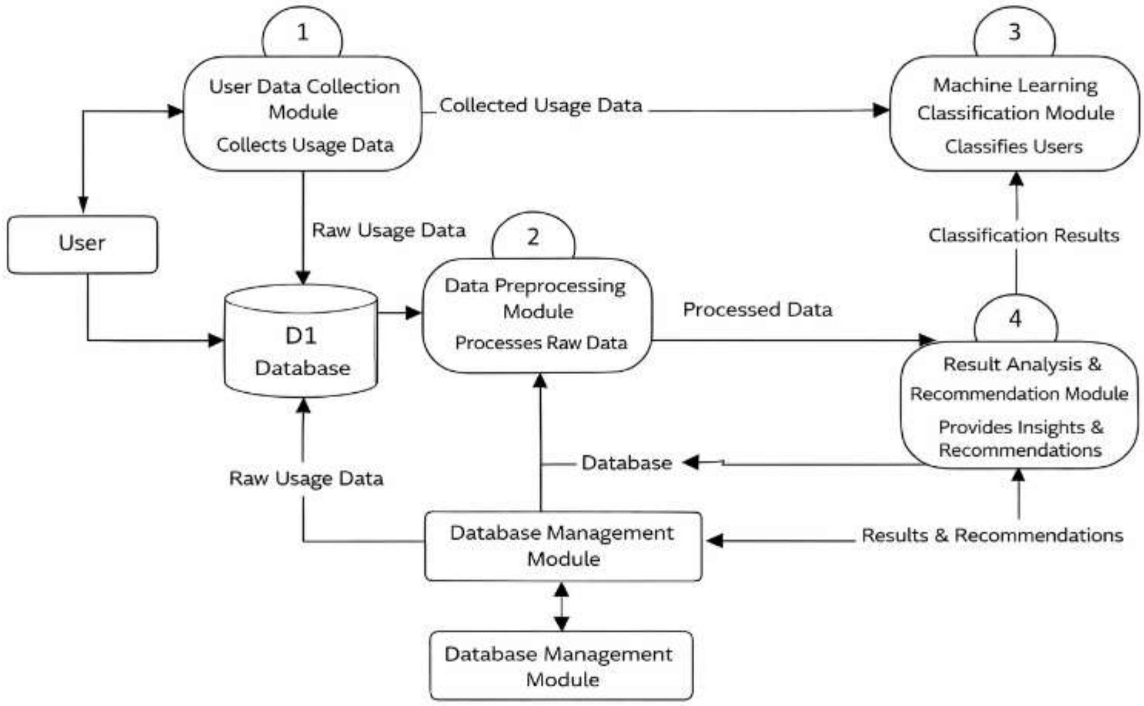


Figure 2: Data Flow Diagram

1. User Data Collection Module

The process begins with the **User**, who interacts with the system through their smartphone. The User Data Collection Module captures various usage-related information such as screen time, app usage frequency, browsing activity, and interaction duration. This collected data is referred to as raw usage data. The module ensures continuous and real-time data acquisition, which is essential for accurate behavioral analysis. The collected data is then stored in the D1 Database for further processing.

2. Data Preprocessing Module

The raw data stored in the database is forwarded to the Data Preprocessing Module. This module is responsible for cleaning and transforming the data into a structured format. It removes noise, handles missing values, and standardizes the data for better analysis. Preprocessing ensures that irrelevant or inconsistent data does not affect the system's performance. The refined data, known as processed data, is then prepared for machine learning analysis.

3. Machine Learning Classification Module

The processed data is passed to the Machine Learning Classification Module, where advanced algorithms are applied to analyze user behavior patterns. This module classifies users into different categories such as normal usage, moderate usage, or addicted users. The classification is based on learned patterns from historical data and predefined behavioral thresholds. The output generated here is referred to as classification results.

4. Result Analysis & Recommendation Module

The classification results are sent to **the** Result Analysis & Recommendation Module. This module interprets the results and provides meaningful insights about the user's smartphone usage behavior. Based on the analysis, it generates personalized recommendations such as reducing screen time, limiting specific app usage, or adopting healthier digital habits. These outputs are termed as results and recommendations.

5. Database Management Module

The Database Management Module plays a central role in maintaining system data. It manages the storage, retrieval, and updating of both raw and processed data, as well as the generated results and recommendations. It ensures data consistency, security, and efficient access across all modules. Additionally, it supports feedback loops where updated data can be reused for continuous system improvement.

CHAPTER 4
SYSTEM REQUIREMENTS

4.1 HARDWARE SPECIFICATION

- Processors: Intel® Core™ i5 processor 4300M at 2.60 GHz or 2.59 GHz (1 socket, 2 cores, 2 threadsper core), 8 GB of DRAM
- Disk space: 320 GB
- Operating systems: Windows® 10, macOS*, and Linux*

4.2 SOFTWARE SPECIFICATION

- Back end : Python 3.7.4(64-bit) or (32-bit)
- Frond End : HTML, CSS, Bootstrap
- IDE : Flask 1.1.1
- Database : MySQL 5.
- Server : WampServer 2i
- OS : Windows 10

4.3 SOFTWARE DESCRIPTION

PYTHON

Python is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. It was created by Guido van Rossum during 1985- 1990. Like Perl, Python source code is also available under the GNU General Public License (GPL). This tutorial gives enough understanding on Python programming language.

Python is a high-level, interpreted, interactive and object-oriented scripting language. Python is designed to be highly readable. It uses English keywords frequently where as other languages usepunctuation, and it has fewer syntactical constructions than other languages. Python is a MUST for students and working professionals to become a great Software Engineer specially when they are working in Web Development Domain.

Python is currently the most widely used multi-purpose, high-level programming language. Pythonallows programming in Object-Oriented and Procedural paradigms. Python programs generally are smaller than other programming languages like Java. Programmers have to type relatively lessand indentation requirement of the language, makes them readable all the time. Python language is being used by almost all tech-giant companies like – Google, Amazon, Facebook, Instagram, Dropbox, Uber… etc. The biggest strength of Python is huge collection of standard libraries whichcan be used for the following:

- Machine Learning
- GUI Applications (like Kivy, Tkinter, PyQt etc.)
- Web frameworks like Django (used by YouTube, Instagram, Dropbox)
- Image processing (like OpenCV, Pillow)
- Web scraping (like Scrapy, BeautifulSoup, Selenium)
- Test frameworks
- Multimedia
- Scientific computing
- Text processing and many more.

Tensor Flow

Tensor Flow is an end-to-end open-source platform for machine learning. It has a comprehensive,flexible ecosystem of tools, libraries, and community resources that lets researchers push the state-of-the-art in ML, and gives developers the ability to easily build and deploy ML-poweredapplications.

Tensor Flow provides a collection of workflows with intuitive, high-level APIs for both beginnersand experts to create machine learning models in numerous languages. Developers have the option to deploy models on a number of platforms such as on servers, in the cloud devices, in browsers, and on many other JavaScript platforms. This enables developers to go frommodel building and training to deployment much more easily.

Keras

Keras is a deep learning API written in Python, running on top of the machine learning platformTensorFlow. It was developed with a focus on enabling fast experimentation.

- Allows the same code to run on CPU or on GPU, seamlessly.
- User-friendly API which makes it easy to quickly prototype deep learning models.
- Built-in support for convolutional networks (for computer vision), recurrent networks (for sequence processing), and any combination of both.
- Supports arbitrary network architectures: multi-input or multi-output models, layer sharing, model sharing,

etc. This means that Keras is appropriate for building essentiallyany deep learning model, from a memory network to a neural Turing machine.

Pandas

pandas is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language. pandas is a Python package that provides fast, flexible, and expressive data structures designed to make working with "relational" or "labeled" data both easy and intuitive. It aims to be the fundamental high-level building block fordoing practical, real world data analysis in Python.

Pandas is mainly used for data analysis and associated manipulation of tabular data in Data frames. Pandas allows importing data from various file formats such as comma-separated values, JSON,Parquet, SQL database tables or queries, and Microsoft Excel. Pandas allows various data manipulation operations such as merging, reshaping, selecting, as well as data cleaning, and data wrangling features. The development of pandas introduced into Python many comparable features of working with Data frames that were established in the R programming language. The panda's library is built upon another library NumPy, which is oriented to efficiently working with arrays instead of the features of working on Data frames

NumPy

NumPy, which stands for Numerical Python, is a library consisting of multidimensional array objects and a collection of routines for processing those arrays. Using NumPy, mathematical andlogical operations on arrays can be performed.

NumPy is a general-purpose array-processing package. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Matplotlib

Matplotlib is a comprehensive library for creating static, animated, and interactive visualizationsin Python. Matplotlib makes easy things easy and hard things possible.

Matplotlib is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK. lay a prominent role in monitoring and controlling external devices.

Python is used for railway track fault detection with image processing and CNN algorithms because it's like a versatile toolbox for solving complex problems. Imagine you have pictures of railway tracks, and you want to teach a computer to find problems like cracks or damage in these pictures.

Python helps us do this by using a smart technique called CNN, which is great at recognizing patterns in images. Python also has many helpful tools that make it easier to teach the computer and analyze the pictures.

So, it's like having a helpful assistant to spot track issues quickly and accurately, making train travel safer and more reliable.

MYSQL

MySQL is a widely used open-source relational database management system (RDBMS) that provides efficient storage, retrieval, and management of structured data. It follows the client-server architecture and supports SQL (Structured Query Language) for performing various operations like querying, updating, and managing databases. MySQL is known for its high performance, scalability, and reliability, making it a preferred choice for web applications, enterprise solutions, and cloud-based services. It is commonly used in combination with programming languages like PHP, Python, and Java to build dynamic and data-driven applications.

One of the key advantages of MySQL is its support for multiple storage engines, such as InnoDB and MyISAM, which allow users to choose the best option based on their requirements. InnoDB provides ACID (Atomicity, Consistency, Isolation, Durability) compliance and transaction support, making it ideal for applications that require high data integrity and reliability. MyISAM, on the other hand, is optimized for read-heavy operations and offers fast query performance. Additionally, MySQL supports replication, sharding, and clustering to enhance data availability and scalability in distributed environments.

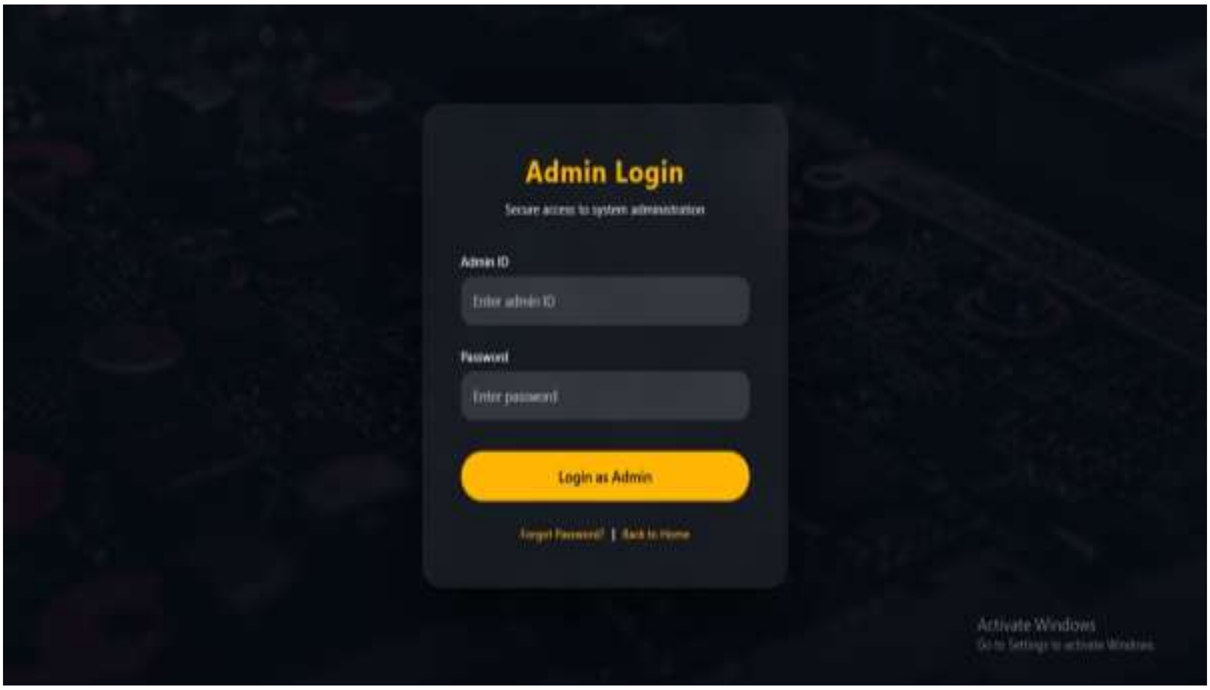
Despite its many advantages, MySQL has some limitations, such as performance bottlenecks in handling extremely large databases and complex queries. It may also face challenges in high-concurrency scenarios where a large number of users access the database simultaneously. Additionally, while MySQL provides strong security features like user authentication, access control, and encryption, improper configuration can lead to vulnerabilities. However, with continuous updates and improvements, MySQL remains a powerful and widely adopted database management system for various applications.

CHAPTER 5

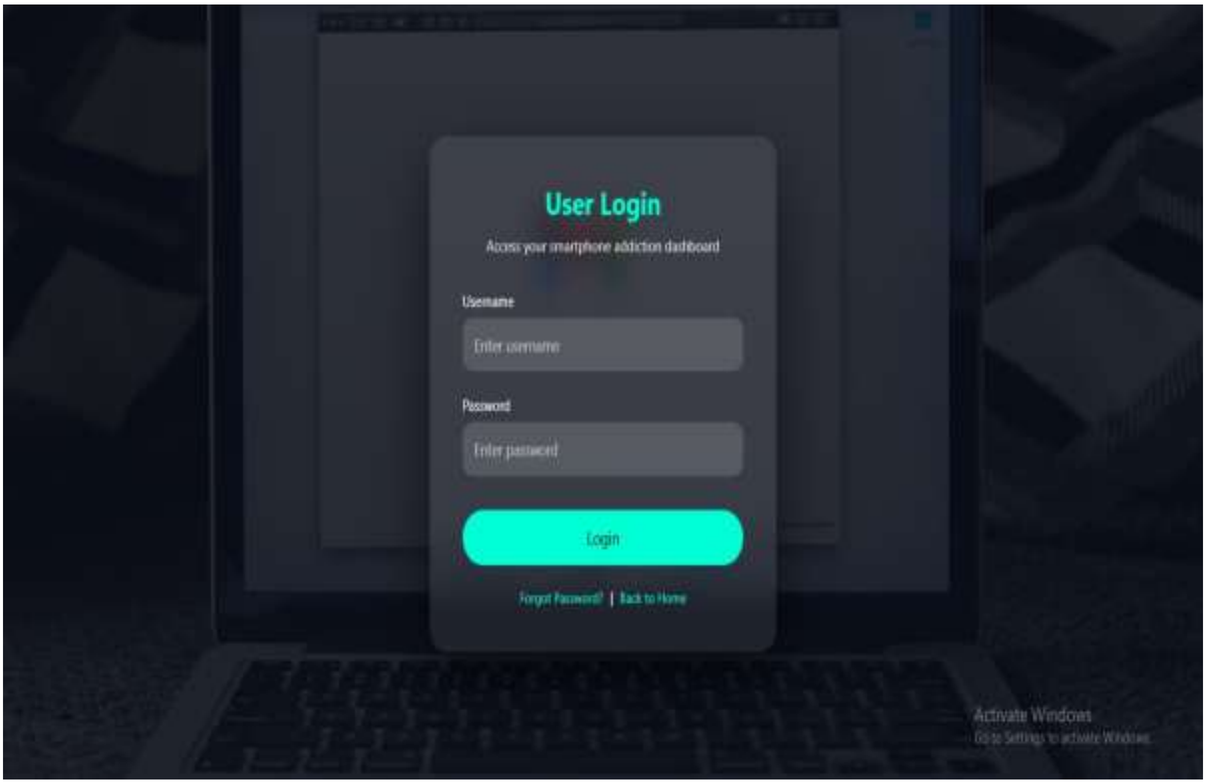
IMPLEMENTATION

5.1 LOGIN PAGE

The Login Page serves as the secure entry point of the Smart Phone Addiction Prediction System. This page allows registered users and administrators to access the system by entering valid credentials such as username/email and password. The frontend of the login page is designed using HTML, CSS, and Bootstrap to provide a clean and responsive interface. Input validation is implemented using JavaScript to ensure that users do not submit empty or invalid fields.



On the backend, Flask 1.1.1 handles authentication by verifying user credentials stored in the MySQL database. Passwords are securely stored using hashing techniques to ensure data security. If the login credentials are valid, the user is redirected to the dashboard page. If invalid credentials are entered, an error message is displayed. This implementation ensures secure access control and prevents unauthorized usage of the addiction prediction system.



5.2 HOME PAGE / DASHBOARD

The Home Page acts as the central dashboard after successful login. It provides an overview of system features such as data submission, addiction prediction, result visualization, and recommendations. The page is developed using HTML, CSS, and Bootstrap to ensure responsiveness and structured layout.

The dashboard contains navigation options to access modules like User Data Entry, Prediction Result, and Analysis Reports. Bootstrap components such as cards and navigation bars are used to maintain a professional appearance. This page improves user interaction by providing easy navigation across the system modules.

5.3 USER DATA COLLECTION PAGE

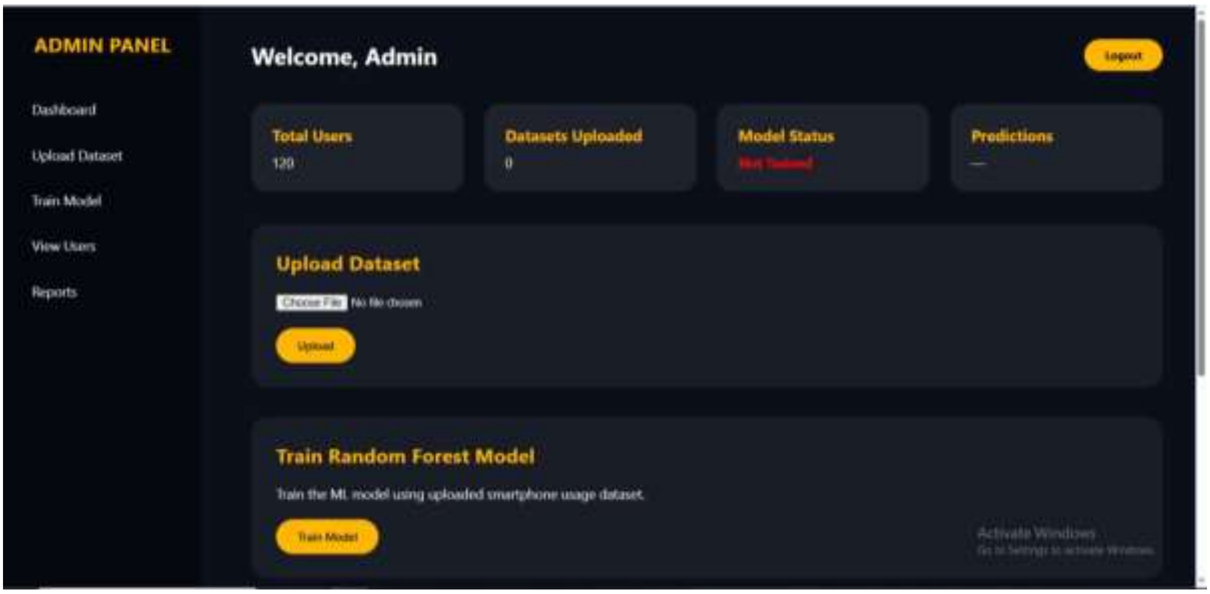
The User Data Collection Page is responsible for gathering smartphone usage details required for addiction prediction. This page includes form fields where users input behavioral information such as daily screen time, social media usage duration, gaming time, number of notifications received, call duration, and messaging frequency. The form is developed using HTML and Bootstrap form components to ensure alignment and readability. JavaScript validation is implemented to verify that numerical values are entered correctly and required fields are not left empty. Clear labels and structured input boxes make the interface intuitive for users of different age groups. This ensures accurate data collection, which is essential for reliable machine learning analysis.

When users submit the form, the data is transmitted securely to the Flask backend via POST requests. The backend performs additional validation and stores the information in the MySQL database. Each submission is associated with the respective user account for tracking and future reference. This module ensures data integrity and prevents incorrect or inconsistent inputs from affecting the classification process. By systematically collecting behavioral indicators, the system builds a structured dataset that forms the foundation for smartphone addiction prediction. This implementation ensures smooth communication between frontend forms and backend storage mechanisms.

The User Data Collection Page allows users to input smartphone usage details such as:

- Daily Screen Time
- Social Media Usage Time
- Gaming Usage Duration
- Number of Notifications
- Call Duration
- Messaging Frequency

The frontend form is built using HTML and Bootstrap form components for better alignment and usability. JavaScript is used for client-side validation to ensure correct numerical input values.



When the form is submitted, Flask receives the data via POST request and stores it in the MySQL database. This collected data forms the input dataset for the machine learning classification process. This page plays a vital role in gathering behavioral indicators necessary for addiction prediction.

5.4 DATA PREPROCESSING IMPLEMENTATION

The Data Preprocessing Module prepares raw smartphone usage data for machine learning classification. After data collection, the stored dataset is retrieved from the database and processed using Python libraries such as Pandas and NumPy. The preprocessing stage involves cleaning inconsistent records, removing duplicates, and handling missing values. Numerical attributes such as screen time and app usage duration are normalized to maintain uniform scaling. Categorical data, if any, is encoded into numerical format to ensure compatibility with the Random Forest algorithm. Feature extraction techniques are also applied to identify key behavioral indicators influencing smartphone addiction. This step ensures that the dataset is structured and optimized for accurate prediction.

5.5 MACHINE LEARNING PREDICTION PAGE

The Machine Learning Prediction Page displays the addiction level determined by the Random Forest algorithm. The Random Forest classifier is implemented using the Scikit-learn library in Python. It builds multiple decision trees using different subsets of the dataset and combines their outputs through majority voting. This method improves accuracy and reduces overfitting compared to single decision tree models. During implementation, the dataset is split into training and testing sets to evaluate performance metrics such as accuracy, precision, and recall. Once the model is trained successfully, it is integrated into the Flask backend to provide real-time predictions for new user inputs.

5.6 RESULT ANALYSIS & RECOMMENDATION PAGE

The Result Analysis and Recommendation Page provides meaningful interpretation of the predicted addiction level. After classification, the system analyzes the results and generates personalized suggestions based on user behavior. The page is designed using Bootstrap components such as alert boxes and information cards to clearly present addiction level, usage summary, and improvement suggestions. Visual elements enhance readability and user engagement. This module ensures that users not only receive a prediction result but also understand its implications and necessary corrective measures.

5.7 DATABASE IMPLEMENTATION

The project uses MySQL 5.x as the database management system. WampServer 2i is used to host Apache and MySQL locally.

The database contains tables such as:

- User Table
- Usage Data Table
- Prediction Result Table

Flask connects to MySQL using database connectors to perform CRUD operations. Each user input and prediction result is securely stored for future analysis. This ensures data consistency and proper record maintenance.

5.8 MODEL TRAINING SCREENSHOT EXPLANATION

The implementation includes model training using Random Forest algorithm. The dataset is loaded, preprocessed, and split into training and testing sets. The model accuracy is calculated to evaluate performance. Majority voting among decision trees ensures better prediction accuracy and reduced overfitting.

This screenshot represents the machine learning workflow integration within the system.

5.9 FINAL RESULT

The Smart Phone Addiction Prediction System has been successfully implemented using Flask, Python, MySQL, and Random Forest machine learning algorithm. The system accurately analyzes smartphone usage patterns and classifies users into different addiction levels. The integration between frontend, backend, database, and ML model ensures smooth functionality.

The implementation screenshots clearly demonstrate:

- Secure Login System
- Data Collection Interface
- ML Prediction Integration
- Result Display with Recommendations
- Database Storage

Overall, the project achieves its objective of detecting smartphone addiction using machine learning and promoting digital well-being through data-driven insights.

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 CONCLUSION

The Smart Phone Addiction Prediction System has been successfully designed and implemented using Machine Learning techniques to analyze user behavior and classify addiction levels. By collecting smartphone usage data such as screen time, app usage frequency, notification count, and communication duration, the system effectively identifies behavioral patterns associated with addiction. The integration of Python, Flask, MySQL, and the Random Forest algorithm ensures accurate classification into Normal, Moderate, and High addiction categories.

The project demonstrates how digital behavioral data can be transformed into meaningful insights through data preprocessing, feature extraction, and model training. The Random Forest algorithm improves prediction accuracy by combining multiple decision trees and reducing overfitting. The system not only detects addiction levels but also provides personalized recommendations to promote healthier digital habits. The user-friendly interface and secure database management ensure smooth operation and data privacy. Overall, the project achieves its objective of supporting early detection of smartphone addiction and encouraging digital well-being through an intelligent, automated, and scalable web-based system.

6.2 FUTURE ENHANCEMENT

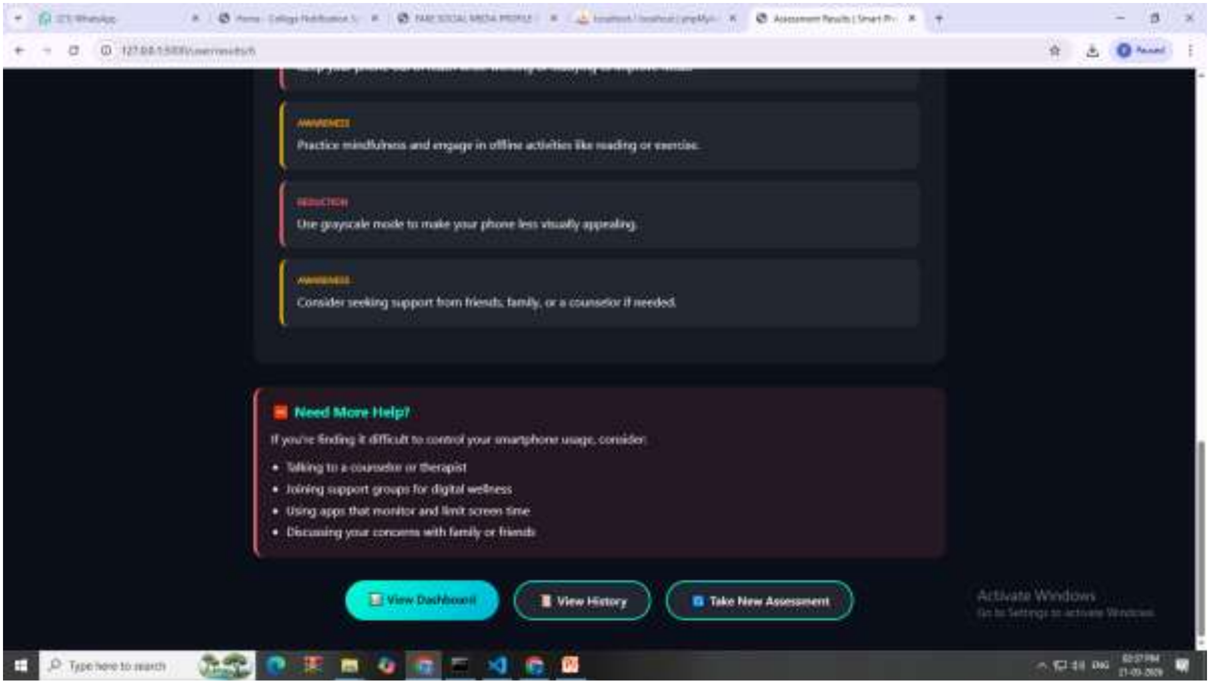
Although the current system performs addiction classification effectively, several enhancements can further improve its functionality and real-world applicability.

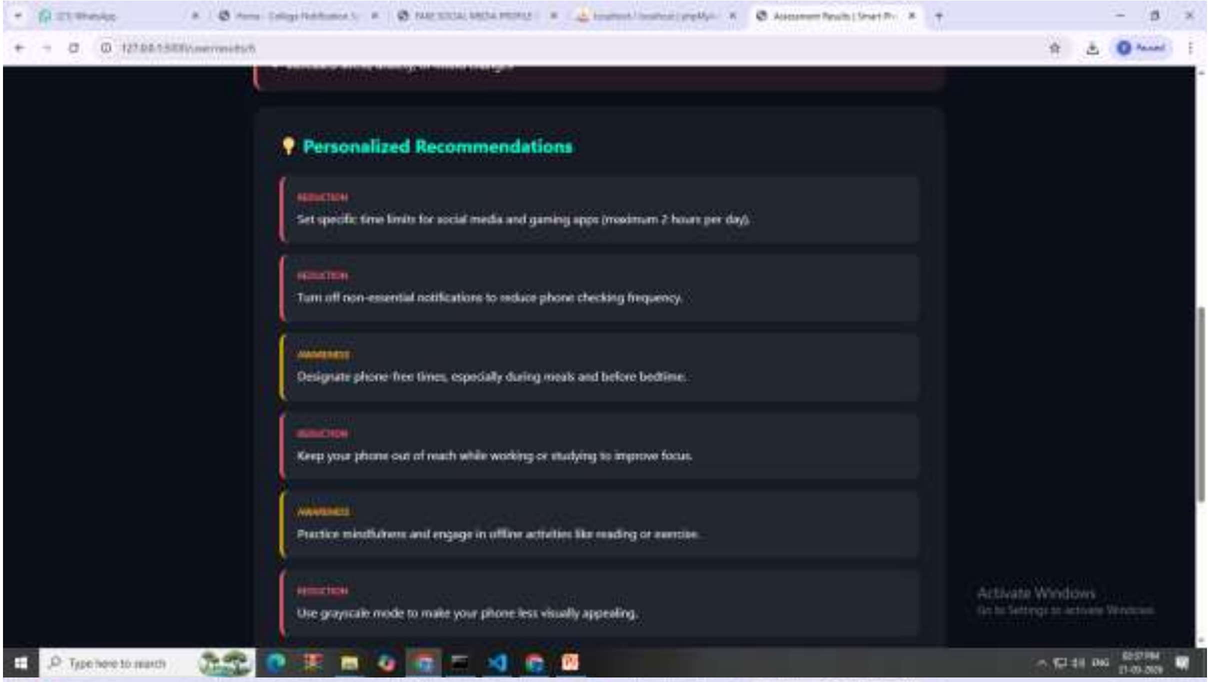
In the future, the system can be integrated with a mobile application to enable real-time data collection directly from smartphone sensors and usage APIs. Cloud integration can be implemented to store and process large-scale user data efficiently, making the system scalable for wider deployment. Advanced machine learning models such as Deep Learning (Neural Networks) or hybrid ensemble models can be explored to improve prediction accuracy further.

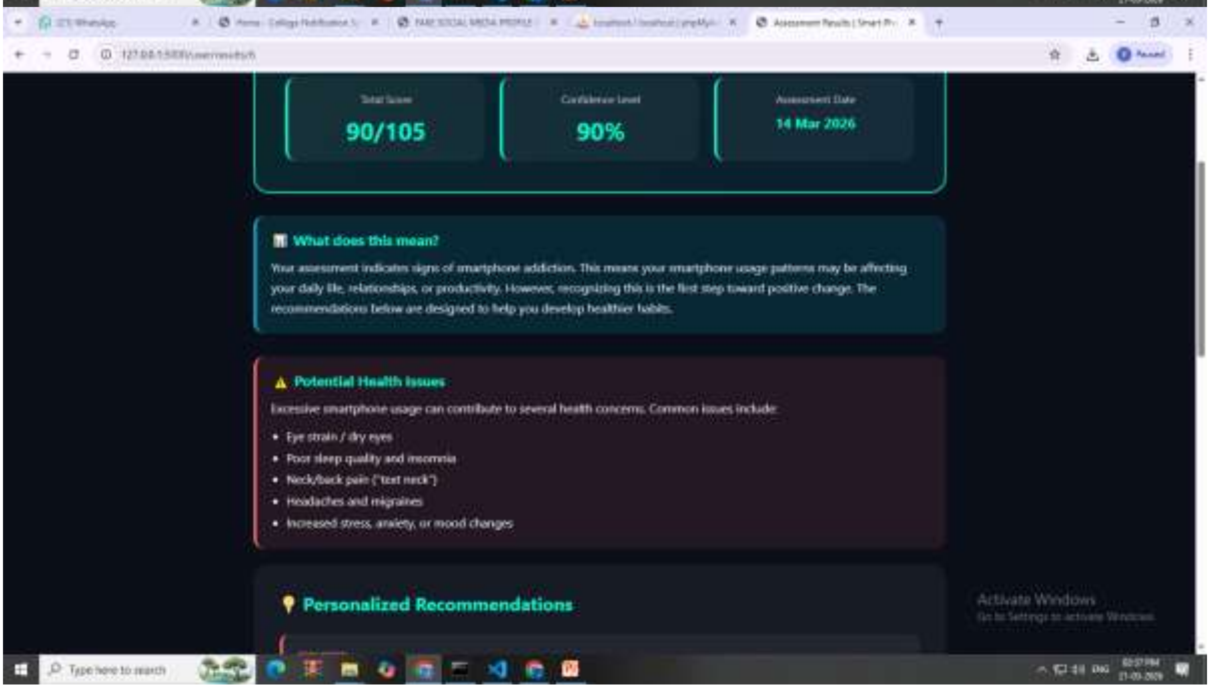
Additionally, the system can incorporate real-time monitoring with alert notifications when excessive usage is detected. Graphical dashboards with advanced data visualization techniques can provide deeper behavioral insights. Integration with wearable devices to analyze sleep and activity patterns could enhance behavioral analysis accuracy. Finally, incorporating psychological assessment questionnaires and mental health support resources would make the system more comprehensive and beneficial for promoting long-term digital wellness.

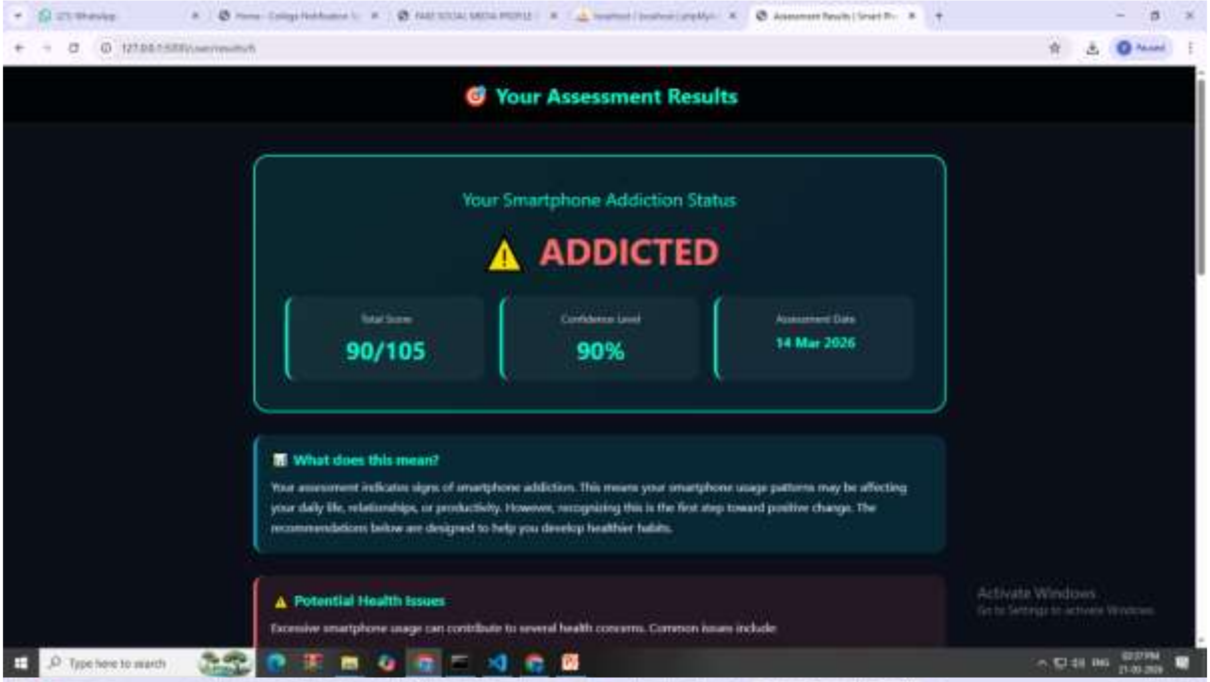
APPENDICES

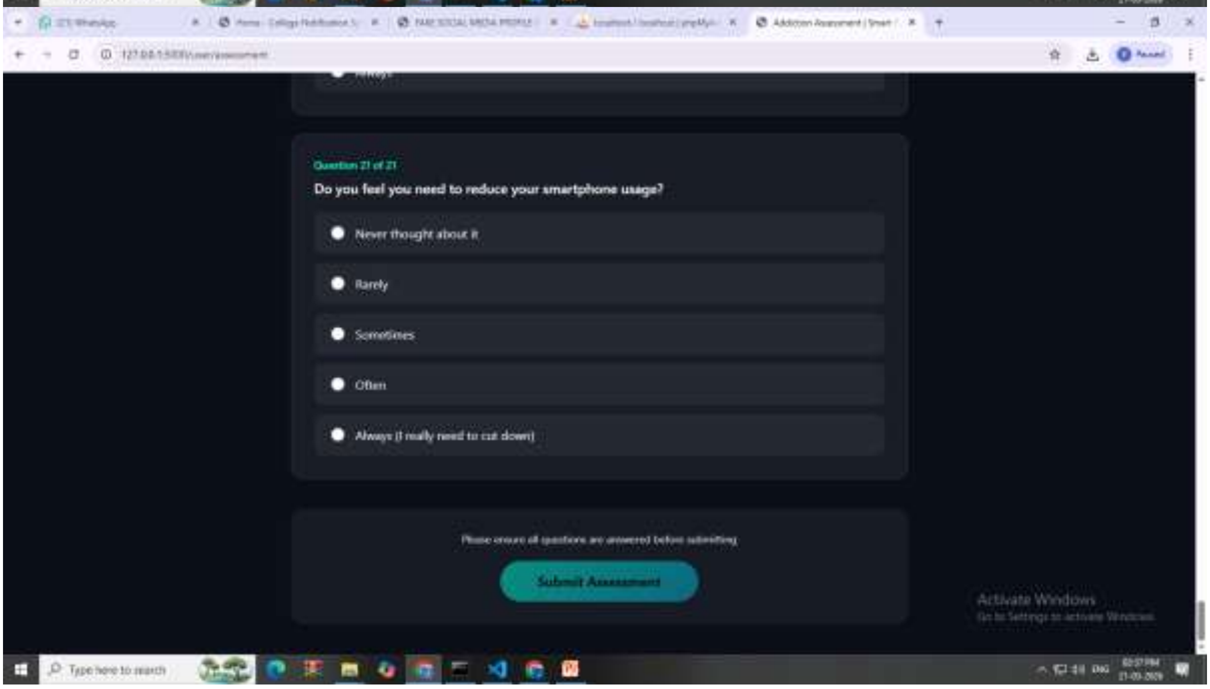
SCREENSHOTS

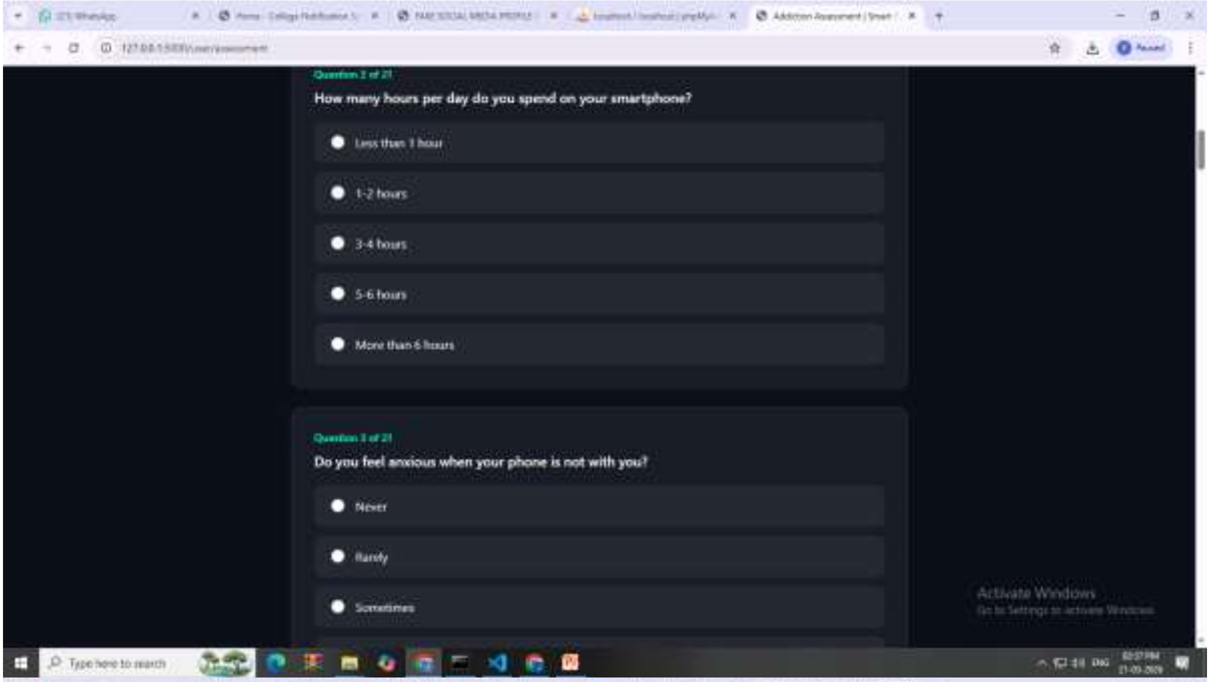


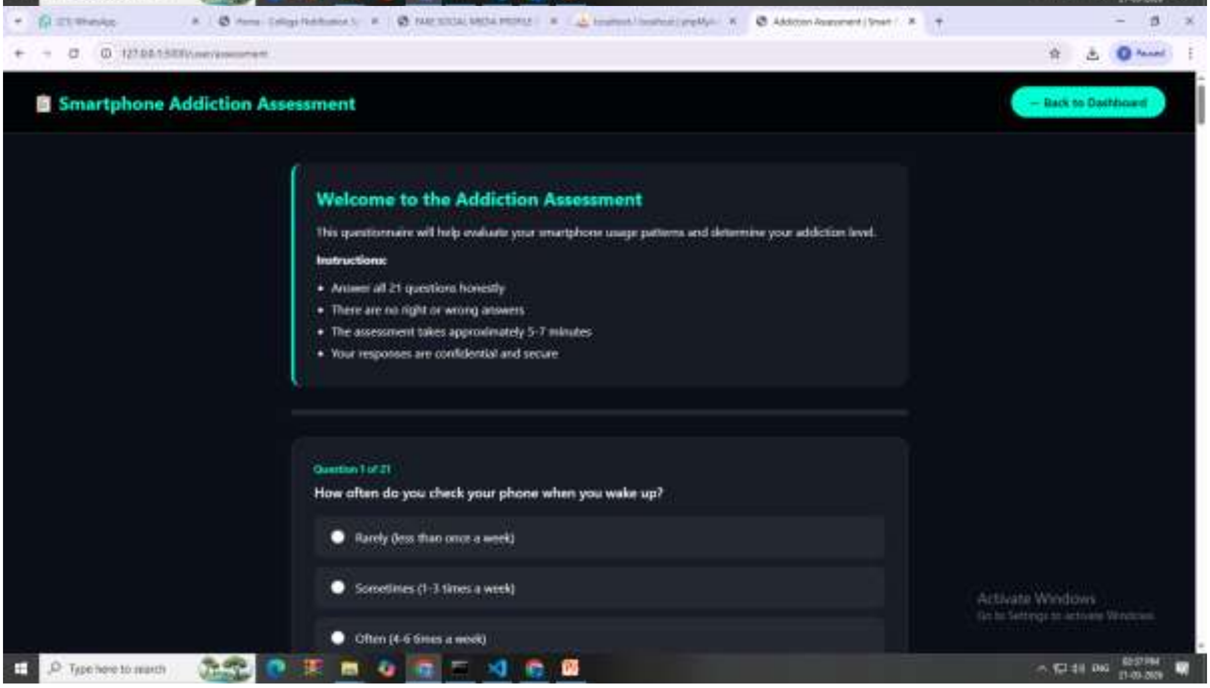

Personalized Recommendations
REDUCTION
Set specific time limits for social media and gaming apps (maximum 2 hours per day).
REDUCTION
Turn off non-essential notifications to reduce phone checking frequency.
AWARENESS
Designate phone-free times, especially during meals and before bedtime.
REDUCTION
Keep your phone out of reach while working or studying to improve focus.
AWARENESS
Practice mindfulness and engage in offline activities like reading or exercise.
REDUCTION
Use grayscale mode to make your phone less visually appealing.
Activate Windows

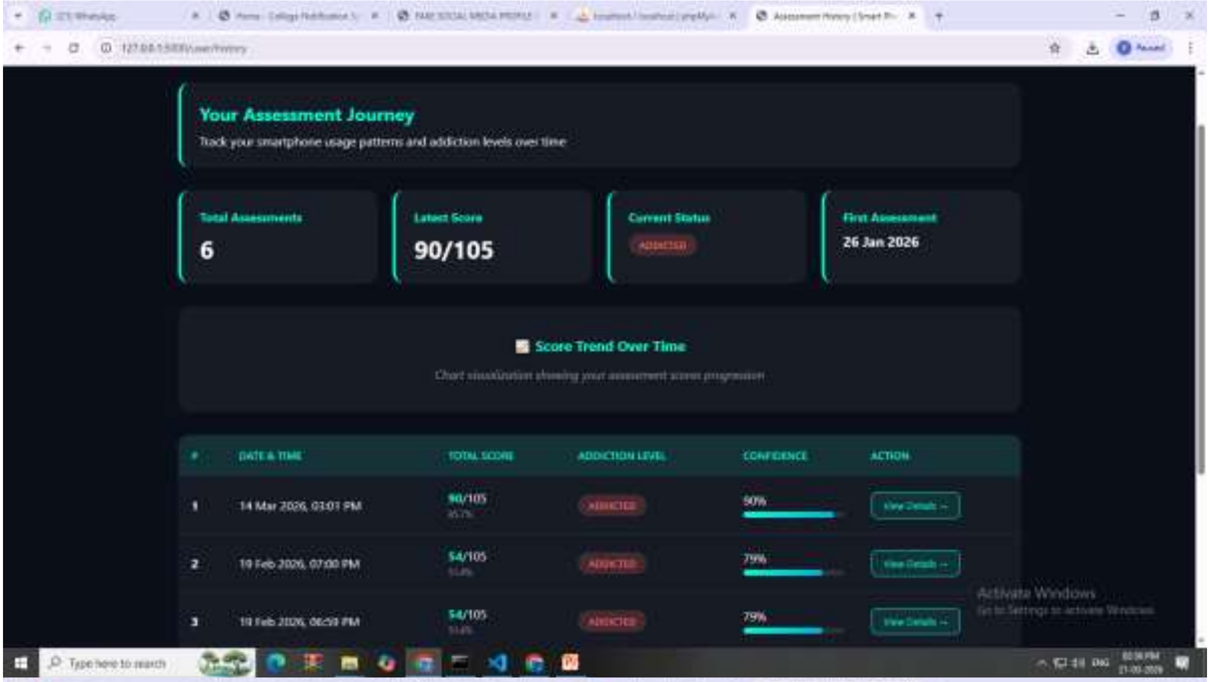

Total Score
90/105
Confidence Level
90%
Assessment Date
14 Mar 2026
What does this mean?
Your assessment indicates signs of smartphone addiction. This means your smartphone usage patterns may be affecting your daily life, relationships, or productivity. However, recognizing this is the first step toward positive change. The recommendations below are designed to help you develop healthier habits.
Potential Health Issues
Excessive smartphone usage can contribute to several health concerns. Common issues include:
Eye strain / dry eyes
Poor sleep quality and insomnia
Neck/back pain ("text neck")
Headaches and migraines
Increased stress, anxiety, or mood changes
Personalized Recommendations
Activate Windows

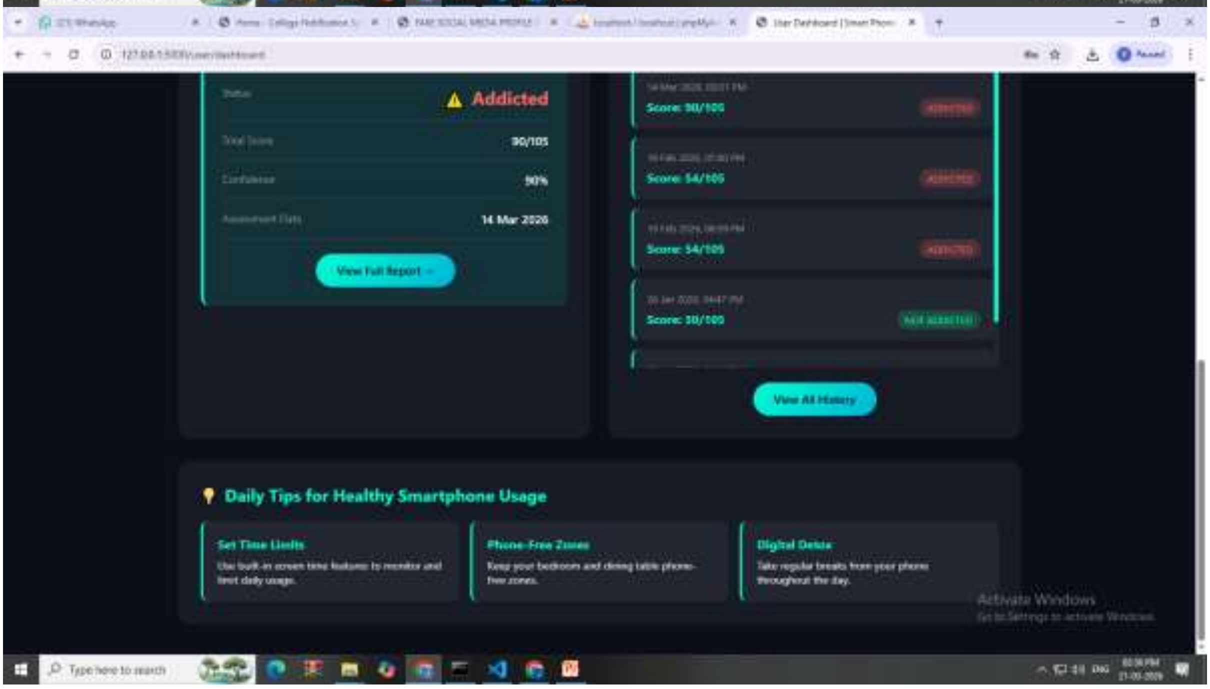

Your Assessment Results
Your Smartphone Addiction Status
ADDICTED
Total Score
90/105
Confidence Level
90%
Assessment Date
14 Mar 2026
What does this mean?
Your assessment indicates signs of smartphone addiction. This means your smartphone usage patterns may be affecting your daily life, relationships, or productivity. However, recognizing this is the first step toward positive change. The recommendations below are designed to help you develop healthier habits.
Potential Health Issues
Excessive smartphone usage can contribute to several health concerns. Common issues include:

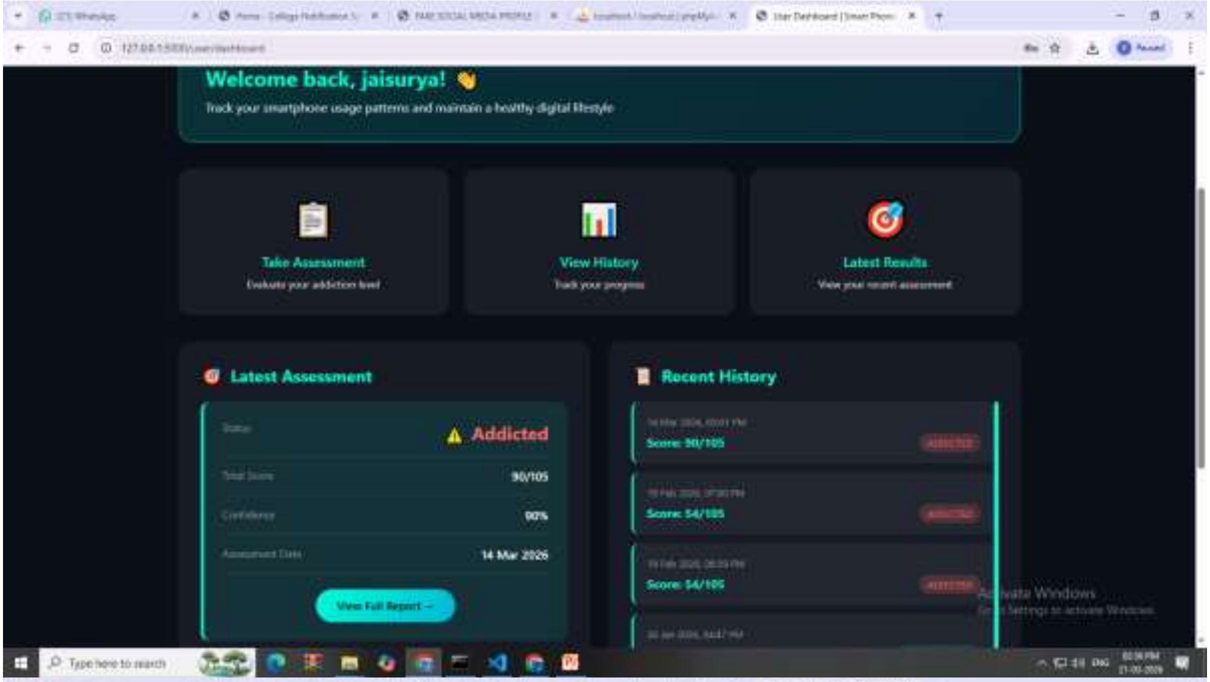

Question 21 of 21
Do you feel you need to reduce your smartphone usage?
Never thought about it
Rarely
Sometimes
Often
Always (I really need to cut down)
Please ensure all questions are answered before submitting
Submit Assessment

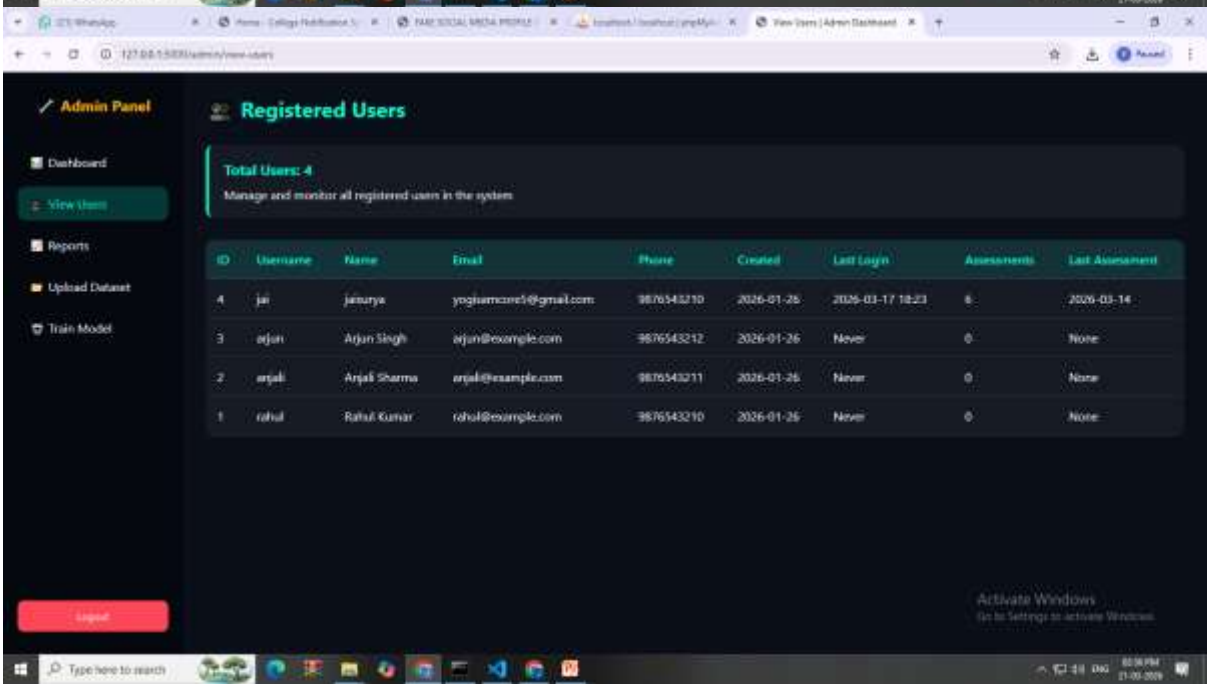

Question 2 of 21
How many hours per day do you spend on your smartphone?
Less than 1 hour
1-2 hours
3-4 hours
5-6 hours
More than 6 hours
Question 3 of 21
Do you feel anxious when your phone is not with you?
Never
Rarely
Sometimes
Activate Windows
Type here to search

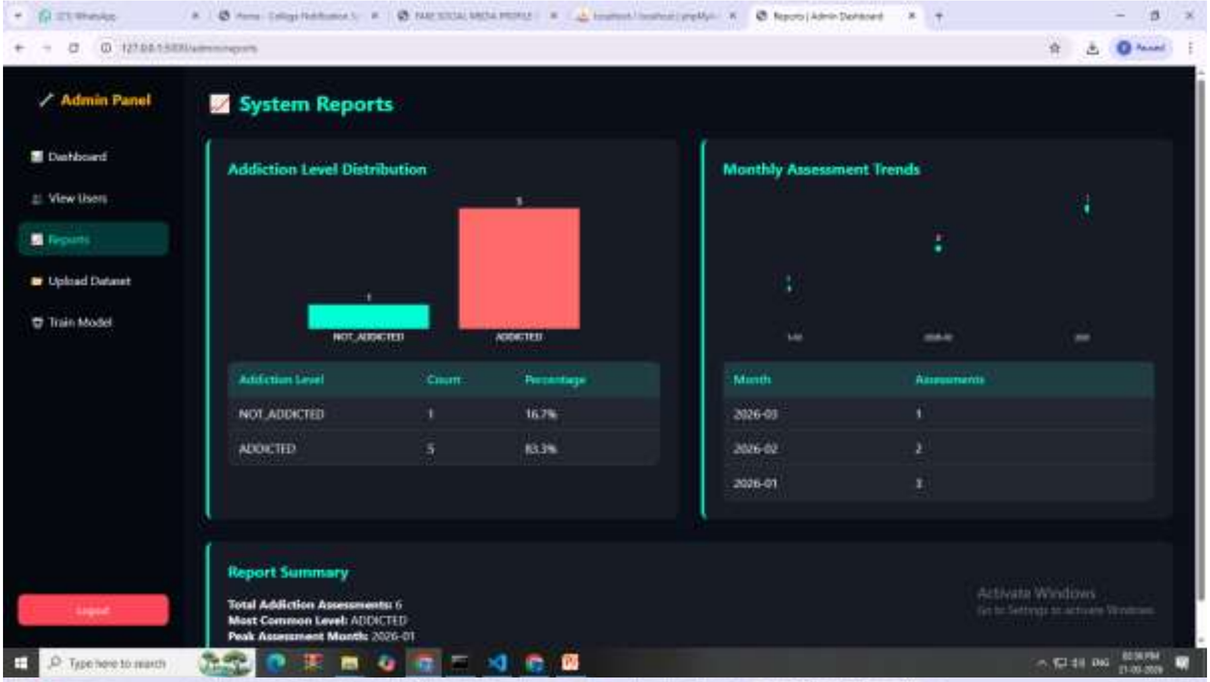

Smartphone Addiction Assessment
← Back to Dashboard
Welcome to the Addiction Assessment
This questionnaire will help evaluate your smartphone usage patterns and determine your addiction level.
Instructions:
Answer all 21 questions honestly
There are no right or wrong answers
The assessment takes approximately 5-7 minutes
Your responses are confidential and secure
Question 1 of 21
How often do you check your phone when you wake up?
Rarely (less than once a week)
Sometimes (1-3 times a week)
Often (4-6 times a week)
Activate Windows
Type here to search

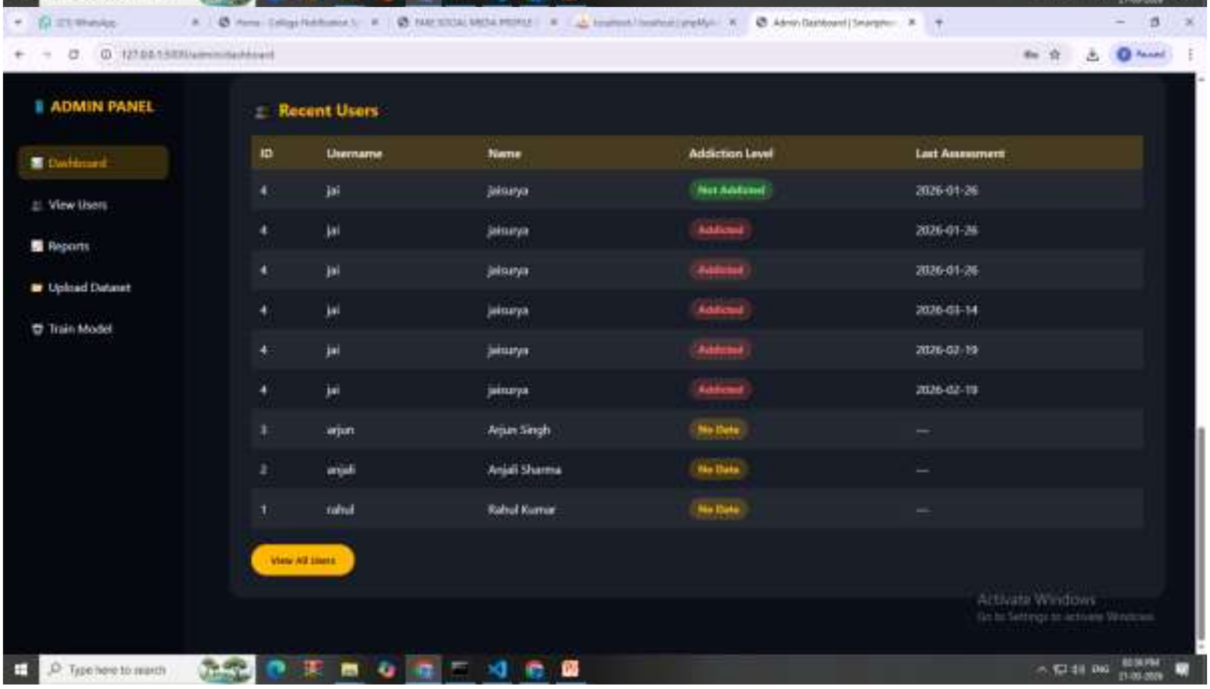

Your Assessment Journey
Track your smartphone usage patterns and addiction levels over time
Total Assessments
6
Latest Score
90/105
Current Status
First Assessment
26 Jan 2026
Score Trend Over Time
#
DATE & TIME
TOTAL SCORE
ADDICTION LEVEL
CONFIDENCE
ACTION
1
14 Mar 2026, 03:01 PM
90/105
90%
2
19 Feb 2026, 07:00 PM
54/105
79%
3
19 Feb 2026, 06:59 PM
54/105
79%
Activate Windows

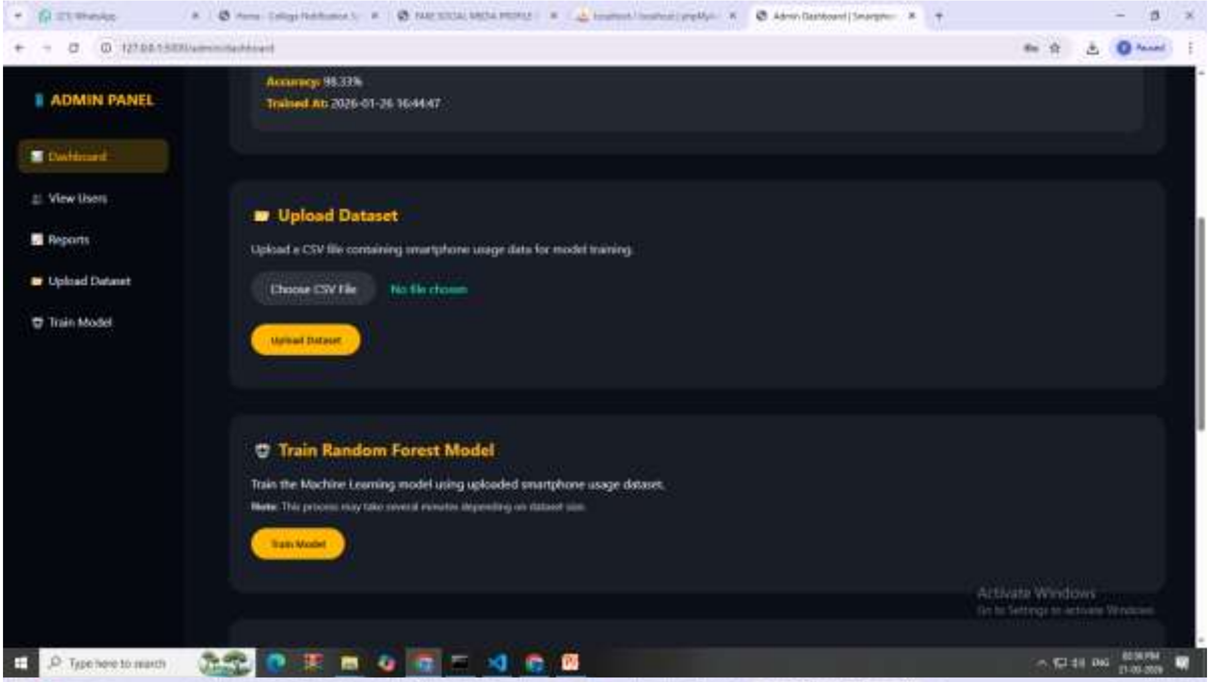

Addicted
90/105
90%
14 Mar 2026
View Full Report →
Score: 90/105
Score: 54/105
Score: 54/105
Score: 30/105
View All History
Daily Tips for Healthy Smartphone Usage
Set Time Limits
Phone-Free Zones
Digital Detox
Activate Windows

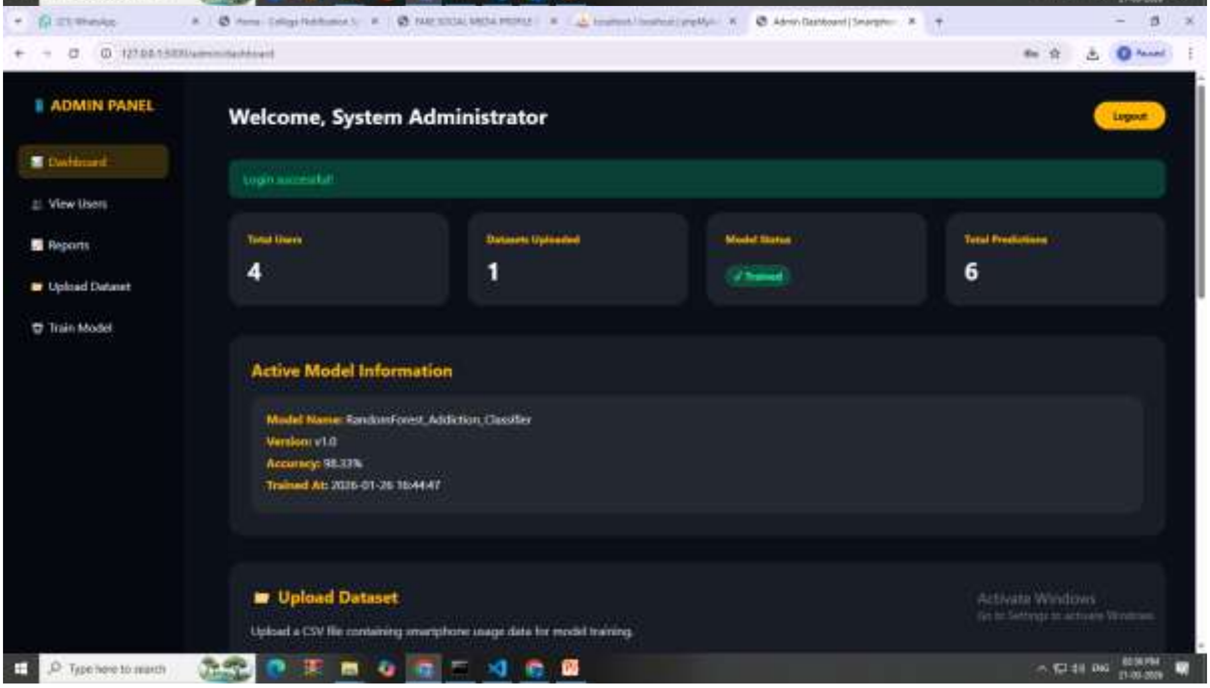

Welcome back, jaisurya!
Track your smartphone usage patterns and maintain a healthy digital lifestyle
Take Assessment
Evaluate your addiction level
View History
Track your progress
Latest Results
View your recent assessment
Latest Assessment
Addicted
90/105
90%
14 Mar 2026
View Full Report →
Recent History
Score: 90/105
Score: 54/105
Score: 54/105
Type here to search

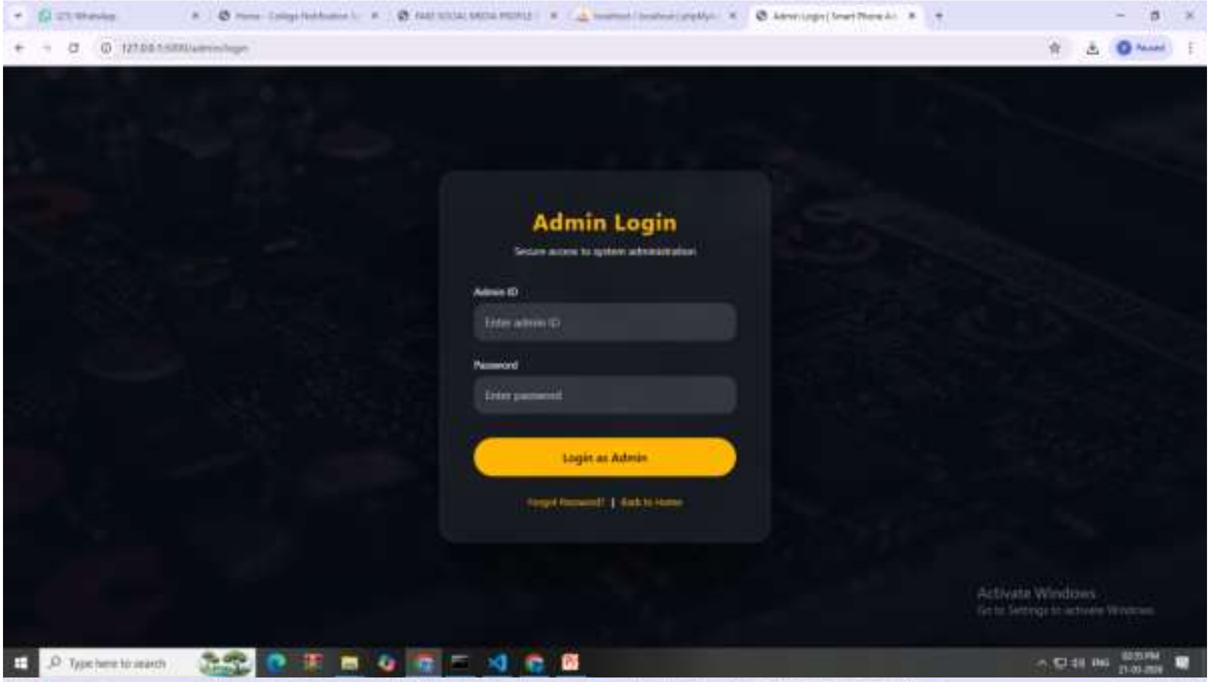

Admin Panel
Dashboard
View Users
Reports
Upload Dataset
Train Model
Logout
Registered Users
Total Users: 4
Manage and monitor all registered users in the system
ID Username Name Email Phone Created Last Login Assessments Last Assessment
4 jai jaisurya yogiamcore5@gmail.com 9876543210 2026-01-26 2026-03-17 18:23 6 2026-03-14
3 arjun Arjun Singh arjun@example.com 9876543212 2026-01-26 Never 0 None
2 anjali Anjali Sharma anjali@example.com 9876543211 2026-01-26 Never 0 None
1 rahul Rahul Kumar rahul@example.com 9876543210 2026-01-26 Never 0 None
Activate Windows
Type here to search

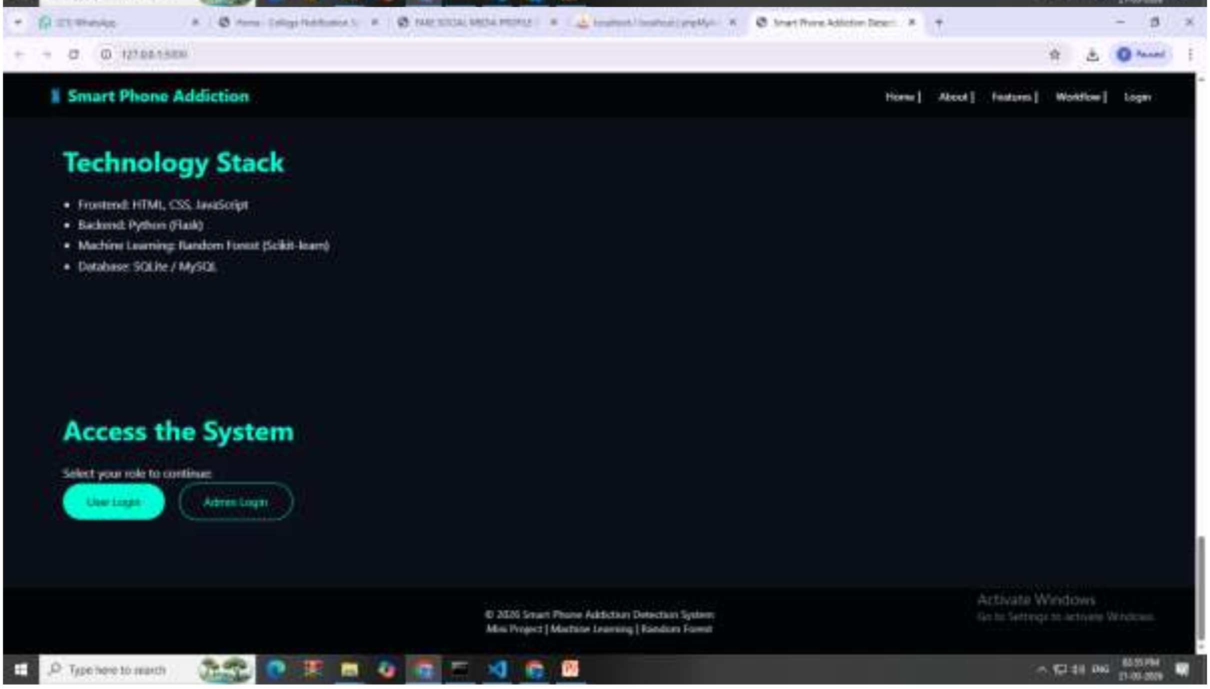

Admin Panel
Dashboard
View Users
Reports
Upload Dataset
Train Model
System Reports
Addiction Level Distribution
NOT_ADDICTED
ADDICTED
Monthly Assessment Trends
Addiction Level Count Percentage
NOT_ADDICTED 1 16.7%
ADDICTED 5 83.3%
Month Assessments
2026-03 1
2026-02 2
2026-01 3
Report Summary
Total Addiction Assessments: 6
Most Common Level: ADDICTED
Peak Assessment Month: 2026-01
Logout

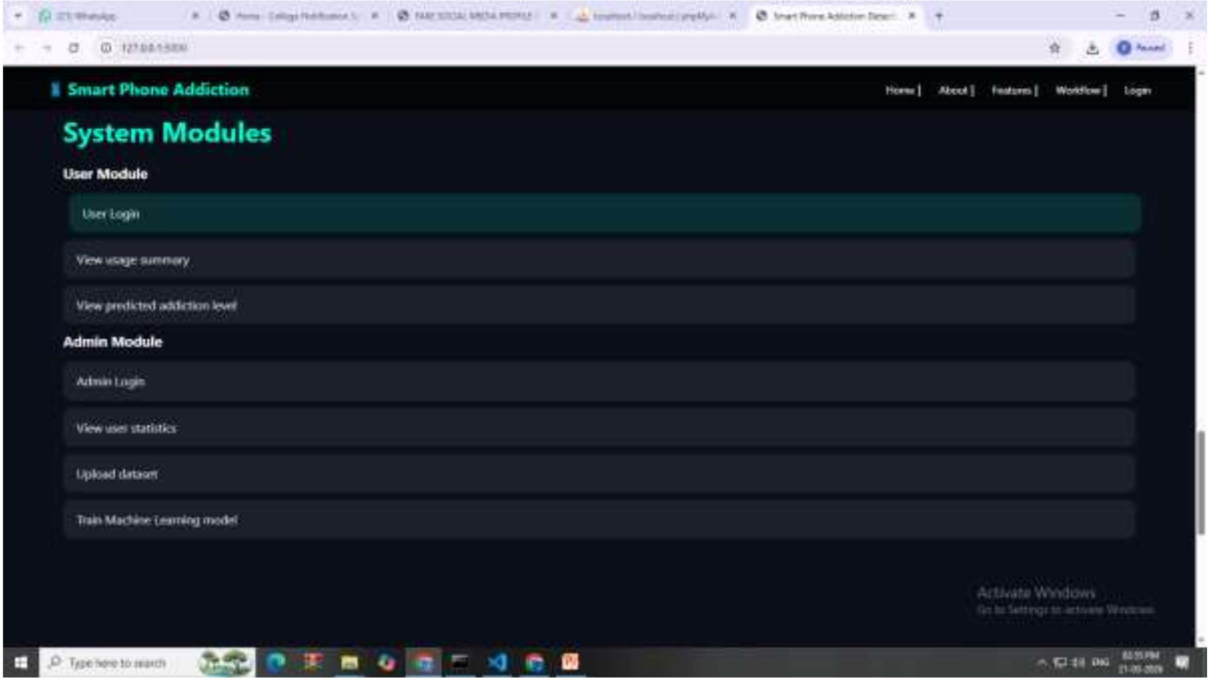

ADMIN PANEL
Dashboard
View Users
Reports
Upload Dataset
Train Model
Recent Users
ID Username Name Addiction Level Last Assessment
4 jai jaisurya Not Addicted 2026-01-26
4 jai jaisurya Addicted 2026-01-26
4 jai jaisurya Addicted 2026-01-26
4 jai jaisurya Addicted 2026-03-14
4 jai jaisurya Addicted 2026-02-19
4 jai jaisurya Addicted 2026-02-19
3 arjun Arjun Singh No Data —
2 anjali Anjali Sharma No Data —
1 rahul Rahul Kumar No Data —
View All Users


ADMIN PANEL
Dashboard
View Users
Reports
Upload Dataset
Train Model
Accuracy: 98.33%
Trained At: 2026-01-26 16:44:47
Upload Dataset
Upload a CSV file containing smartphone usage data for model training.
Choose CSV File
No file chosen
Upload Dataset
Train Random Forest Model
Train the Machine Learning model using uploaded smartphone usage dataset.
Train Model


ADMIN PANEL
Dashboard
View Users
Reports
Upload Dataset
Train Model
Welcome, System Administrator
Logout
Login successful!
Total Users
4
Datasets Uploaded
1
Model Status
Trained
Total Predictions
6
Active Model Information
Model Name: RandomForest_Addiction_Classifier
Version: v1.0
Accuracy: 98.33%
Trained At: 2026-01-26 16:44:47
Upload Dataset
Upload a CSV file containing smartphone usage data for model training.


Admin Login
Secure access to system administration
Admin ID
Enter admin ID
Password
Enter password
Login as Admin
Forgot Password? | Back to Home
Activate Windows


Smart Phone Addiction
Home | About | Features | Workflow | Login
Technology Stack
Frontend: HTML, CSS, JavaScript
Backend: Python (Flask)
Machine Learning: Random Forest (Scikit-learn)
Database: SQLite / MySQL
Access the System
Select your role to continue:
User Login
Admin Login
© 2026 Smart Phone Addiction Detection System
Mini Project | Machine Learning | Random Forest
Activate Windows



SOURCE CODE

```
"""
Smartphone Addiction Detection System - Enhanced Flask Backend
With Complete User Functionalities
"""


from flask import Flask, render_template, request, redirect, url_for, session, flash, jsonify
from werkzeug.security import generate_password_hash, check_password_hash
from werkzeug.utils import secure_filename
import mysql.connector
from datetime import datetime
import os
import pickle
import numpy as np
from functools import wraps


# ============================
# FLASK CONFIGURATION
# ============================
```

```
app = Flask(__name__)
app.secret_key = 'smartphone_addiction_secret_key_2026'
app.config['UPLOAD_FOLDER'] = 'uploads/datasets'
app.config['MODEL_FOLDER'] = 'models'
app.config['MAX_CONTENT_LENGTH'] = 16 * 1024 * 1024

os.makedirs(app.config['UPLOAD_FOLDER'], exist_ok=True)
os.makedirs(app.config['MODEL_FOLDER'], exist_ok=True)

# ============================
# DATABASE CONFIGURATION
# ============================
DB_CONFIG = {
    'host': 'localhost',
    'user': 'root',
    'password': '',
    'database': 'smartphone_addiction_db',
    'charset': 'utf8'
}

def get_db_connection():
    """Create database connection"""
    return mysql.connector.connect(**DB_CONFIG)


# ============================
# DECORATORS
# ============================
def admin_login_required(f):
    """Decorator for admin routes"""
    @wraps(f)
```

```
    def decorated_function(*args, **kwargs):
        if 'admin_logged_in' not in session:
            flash('Please login as admin first', 'danger')
            return redirect(url_for('admin_login'))
        return f(*args, **kwargs)
    return decorated_function


def user_login_required(f):
    """Decorator for user routes"""
    @wraps(f)
    def decorated_function(*args, **kwargs):
        if 'user_logged_in' not in session:
            flash('Please login first', 'danger')
            return redirect(url_for('user_login'))
        return f(*args, **kwargs)
    return decorated_function



# ============================
# ASSESSMENT QUESTIONS
# ============================
ASSESSMENT_QUESTIONS = [
    {
        'id': 1,
        'question': 'How often do you check your phone when you wake up?',
        'options': [
            {'value': 1, 'text': 'Rarely (less than once a week)'},
            {'value': 2, 'text': 'Sometimes (1-3 times a week)'},
            {'value': 3, 'text': 'Often (4-6 times a week)'},
            {'value': 4, 'text': 'Very Often (daily)'},
            {'value': 5, 'text': 'Always (immediately upon waking)'}
```

```
        ]
    },
    {
        'id': 2,
        'question': 'How many hours per day do you spend on your smartphone?',
        'options': [
            {'value': 1, 'text': 'Less than 1 hour'},
            {'value': 2, 'text': '1-2 hours'},
            {'value': 3, 'text': '3-4 hours'},
            {'value': 4, 'text': '5-6 hours'},
            {'value': 5, 'text': 'More than 6 hours'}
        ]
    },
    {
        'id': 3,
        'question': 'Do you feel anxious when your phone is not with you?',
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always'}
        ]
    },
    {
        'id': 4,
        'question': 'How often do you use your phone during social gatherings?',
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
```

```
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always'}
        ]
    },
    {
        'id': 5,
        'question': 'Do you use your phone while eating meals?',
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always'}
        ]
    },
    {
        'id': 6,
        'question': 'How often do you check your phone before going to sleep?',
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always (right before sleeping)'}
        ]
    },
    {
        'id': 7,
        'question': 'Do you feel the need to respond to messages immediately?',
        'options': [
            {'value': 1, 'text': 'Never'},
```

```
        {'value': 2, 'text': 'Rarely'},
        {'value': 3, 'text': 'Sometimes'},
        {'value': 4, 'text': 'Often'},
        {'value': 5, 'text': 'Always'}
    ]
},
{
    'id': 8,
    'question': 'How often do you use your phone while walking or driving?',
    'options': [
        {'value': 1, 'text': 'Never'},
        {'value': 2, 'text': 'Rarely'},
        {'value': 3, 'text': 'Sometimes'},
        {'value': 4, 'text': 'Often'},
        {'value': 5, 'text': 'Always'}
    ]
},
{
    'id': 9,
    'question': 'Do you prefer texting over face-to-face conversations?',
    'options': [
        {'value': 1, 'text': 'Never'},
        {'value': 2, 'text': 'Rarely'},
        {'value': 3, 'text': 'Sometimes'},
        {'value': 4, 'text': 'Often'},
        {'value': 5, 'text': 'Always'}
    ]
},
{
    'id': 10,
    'question': 'How often do you lose track of time when using your phone?',
```

```
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always'}
        ]
    },
    {
        'id': 11,
        'question': 'Do you check your phone during work or study hours?',
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always'}
        ]
    },
    {
        'id': 12,
        'question': 'How often do you feel distracted by your phone?',
        'options': [
            {'value': 1, 'text': 'Never'},
            {'value': 2, 'text': 'Rarely'},
            {'value': 3, 'text': 'Sometimes'},
            {'value': 4, 'text': 'Often'},
            {'value': 5, 'text': 'Always'}
        ]
    },
    {
```

```
    'id': 13,
    'question': 'Do you use social media apps frequently?',
    'options': [
        {'value': 1, 'text': 'Less than 30 minutes/day'},
        {'value': 2, 'text': '30 minutes - 1 hour/day'},
        {'value': 3, 'text': '1-2 hours/day'},
        {'value': 4, 'text': '2-4 hours/day'},
        {'value': 5, 'text': 'More than 4 hours/day'}
    ]
},
{
    'id': 14,
    'question': 'How often do you feel tired or have headaches from phone use?',
    'options': [
        {'value': 1, 'text': 'Never'},
        {'value': 2, 'text': 'Rarely'},
        {'value': 3, 'text': 'Sometimes'},
        {'value': 4, 'text': 'Often'},
        {'value': 5, 'text': 'Always'}
    ]
},
{
    'id': 15,
    'question': 'Do you check notifications immediately when they arrive?',
    'options': [
        {'value': 1, 'text': 'Never'},
        {'value': 2, 'text': 'Rarely'},
        {'value': 3, 'text': 'Sometimes'},
        {'value': 4, 'text': 'Often'},
        {'value': 5, 'text': 'Always'}
    ]
```

```
    },
    {
      'id': 16,
      'question': 'How often do you unlock your phone without a specific purpose?',
      'options': [
        {'value': 1, 'text': 'Never'},
        {'value': 2, 'text': 'Rarely'},
        {'value': 3, 'text': 'Sometimes'},
        {'value': 4, 'text': 'Often'},
        {'value': 5, 'text': 'Always'}
      ]
    },
    {
      'id': 17,
      'question': 'Do you feel uncomfortable when your phone battery is low?',
      'options': [
        {'value': 1, 'text': 'Never'},
```

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2. Thakur, Jigayasha, and Rameshwar Prasad Daundey. "Mobile phone: A journey from necessity to addiction." International Journal of Computing and Artificial Intelligence 6.2 (2025): 23-28.

3. Wang, Li. "Smartphone Addiction Analysis Model Based on C5. 0 Algorithm." 2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON). IEEE, 2024.

4. Dhanalakshmi, R., et al. "Breaking the Digital Grip: AI Models for Evaluating the Internet and Mobile Addiction Across All Age Groups." 2025 6th International Conference on Inventive Research in Computing Applications (ICIRCA). IEEE, 2025.

5. Pawar, Vivekanand, Archana Bhaskar Patil, and Aparna Santra. "Predicting Smartphone Addiction Using Behavioral and Psychological Traits with Machine Learning." 2025 Global Conference in Emerging Technology (GINOTECH). IEEE, 2025.

6. Muezzin, Ece Emre. "A Review on the Psychological Effects of Smartphone Addiction." Kıbrıs Türk Psikiyatri ve Psikoloji Dergisi 5.4 (2023): 361-367.

7. Giansanti, Daniele. "Smartphone addiction in youth: A narrative review of systematic evidence and emerging strategies." Psychiatry International 6.4 (2025): 118.

8. Akhtar, Faijan, et al. "Smartphone addiction among students and its harmful effects on mental health, oxidative stress, and neurodegeneration towards future modulation of anti-addiction therapies: a comprehensive survey based on slr, Research questions, and network visualization techniques." CNS & Neurological Disorders-Drug Targets-CNS & Neurological Disorders) 22.7 (2023): 1070-1089.

9. Gill, Eunsun, and Wankyo Chung. "The effect of smartphone addiction on obesity in children and adolescents." Psychology, Health & Medicine (2025): 1-15.