ISSN 2277-2685
IJESR/April-June. 2026/ Vol-16/Issue-2/1011-1018
A Snithika *et. al.*, / International Journal of Engineering & Science Research

Full Length Article

Digital Detox

Ms V Mrudula[1], A Snithika[2], G Srinidhi[3], B Vaishnavi[4]
[1]Assistant Professor; Department of Computer Science and Engineering Bhoj Reddy Engineering College for Women Hyderabad India.
[2,3,4]B.Tech Student's; Department of Computer Science and Engineering Bhoj Reddy Engineering College for Women Hyderabad India.
Mail Id; srinidhigajarala@gmail.com[3]
Accepted 01-06-2026

Abstract
The project titled "Digital Detox" aims to utilize machine learning algorithms to predict the levels of mobile addiction among individuals. Mobile addiction is a growing concern in modern society, with adverse effects on mental health and productivity. This project focuses on using various predictive models to classify the addiction level into categories such as low, moderate, and high. The proposed method includes a comprehensive data analysis pipeline that begins with data preprocessing, including encoding categorical variables and scaling features. The datasets is then split into training and testing subsets. Multiple machine learning algorithms, including Decision Tree Classifier, Random Forest and Cat boost, are employed to train models on the dataset. The performance of these models is evaluated using key metrics such as accuracy, precision, recall, and F-score. The results are visualized through confusion matrices and classification reports. By leveraging these predictive models, the project aims to provide valuable insights into the factors contributing to mobile addiction, enabling targeted interventions and awareness campaigns.

Keywords: *Machine Learning, Predictive models, Online Learning, Mobile Addiction, Classification, Cat boost, Decision Tree, Random Forest, Accuracy, Precision, Recall, F score, Confusion matrix, Data Preprocessing*

Introduction

Mobile addiction has emerged as a significant global concern, particularly among adolescents and young adults, due to the increasing dependence on smartphones for social networking, gaming, entertainment, and communication. Excessive usage of mobile devices has been associated with several negative consequences, including reduced academic performance, poor mental health, decreased productivity, and weakened interpersonal relationships. To address this growing issue, the present project introduces a "Digital Detox" system that aims to classify individuals based on their level of mobile addiction into three categories: low, medium, and high. The system utilizes behavioral and usage-related data such as screen time, application usage patterns, notification frequency, and user interaction behavior. Machine learning techniques including Decision Tree, Random Forest, and CatBoost are employed to develop predictive models, which are then evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The outcomes are further analyzed through visualization tools like confusion matrices and classification reports to better interpret model effectiveness. Overall, this system is designed to provide an automated and intelligent approach for early detection of mobile addiction risk, thereby supporting timely intervention and promoting improved digital well-being.

Existing System

In traditional approaches, mobile addiction detection is primarily carried out through surveys and questionnaires where users manually report their mobile usage behavior. These methods rely heavily on self-reported information, which may not always be accurate or consistent. Moreover, existing systems typically operate on static datasets and do not incorporate real-time behavioral monitoring, limiting their ability to capture dynamic usage patterns. As a result, the effectiveness of such approaches in accurately identifying addiction levels remains limited, and they often fail to provide timely or preventive insights to users.

Proposed System

The proposed system is designed to overcome the limitations of traditional approaches by incorporating real-time data collection and intelligent analysis. It continuously monitors mobile usage behavior, including screen time, application usage statistics, notification patterns, and interaction activities. This live data collection enables more accurate and dynamic assessment of user behavior.
The system applies machine learning algorithms such as Decision Tree, Random Forest, and CatBoost to analyze collected data and classify users into different addiction levels: low, medium, and high. These models are trained to identify hidden behavioral patterns and improve predictive accuracy. Furthermore, the system is capable of

adapting to evolving user behavior, ensuring more reliable and updated results compared to static systems.

In addition to classification, the proposed model also provides predictive capabilities, allowing it to estimate future addiction risks based on current behavioral trends. This helps in early identification of at-risk individuals and supports timely preventive measures.

Requirements Analysis

The requirements analysis phase defines the functional and non-functional needs of the system along with hardware and software specifications required for implementation.

Computational Resource Requirements

The hardware requirements for the system include a processor equivalent to Intel i5, 8 GB of RAM, and at least 500 GB of hard disk storage. These specifications ensure smooth execution of data processing and machine learning tasks.

The software environment consists of Windows 10 as the operating system, Python 3.12 as the primary programming language, and Django as the backend framework. The frontend is developed using HTML, CSS, and JavaScript. Machine learning and deep learning tasks are supported using libraries and frameworks such as TensorFlow, Keras, NumPy, Pandas, Scikit-learn, Matplotlib, Seaborn, and CatBoost. Development is carried out using IDEs such as Visual Studio Code or PyCharm, and the system uses MySQL or SQLite as the database management system.

Life Cycle Model

The development of the system follows the Agile software development methodology, which is an iterative and incremental approach. In the requirement analysis phase, system needs such as data collection, addiction prediction, and user interaction features were identified. During the system design phase, the overall architecture was planned and appropriate technologies, including Python, Django, and machine learning algorithms, were selected.In the implementation phase, the system was developed in modular form, including components such as user authentication, dataset management, data preprocessing, model training, and prediction generation. Testing was conducted continuously throughout development to identify and resolve errors, ensuring system reliability and performance. Finally, in the deployment phase, the system was released for use, and ongoing maintenance allows for continuous improvements based on feedback and updated data.

Design

System Architecture

The proposed Mobile Addiction Detection System is designed using a layered architecture that integrates data collection, machine learning processing, and user interaction modules. The architecture ensures smooth communication between frontend interfaces, backend services, and the machine learning engine. It is structured in a way that allows efficient handling of user input, data preprocessing, model training, and prediction generation. The system also supports scalability and modular development, making it easier to update or enhance individual components without affecting the overall functionality.

Software Architecture

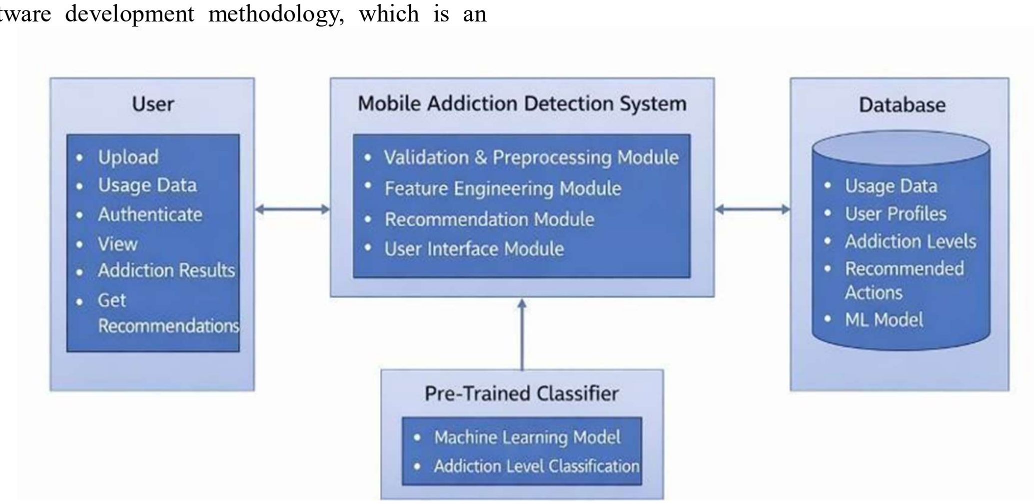

Fig 1; Software Architecture

The software architecture of the system is built on a web-based framework where the frontend interacts with the backend through HTTP requests. The frontend layer is responsible for collecting user inputs such as mobile usage behavior and displaying prediction results. The backend, developed using Django, processes these requests, manages authentication, and communicates with the machine learning model. The ML layer performs data preprocessing, model training, and classification of addiction levels. This separation of concerns ensures better maintainability, security, and performance of the system.

Technical Architecture

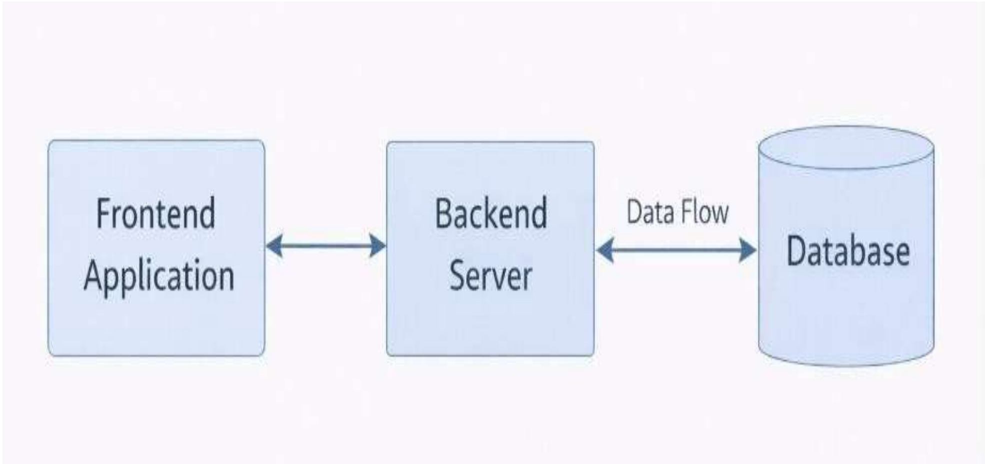

Fig 2 Technical Architecture

The technical architecture consists of multiple components working together to achieve accurate addiction prediction. At the core, Python-based machine learning models analyze behavioral data collected from users. The system uses a database layer (MySQL or SQLite) to store user information, datasets, and prediction outputs. The application layer built using Django manages business logic and API communication, while the presentation layer built using HTML, CSS, and JavaScript provides an interactive user interface. This multi-tier architecture ensures efficient processing, data integrity, and smooth user experience.

Implementation

The Mobile Addiction Detection System is implemented using Python as the primary programming language for building machine learning models and backend logic. The Django framework is used to develop the web-based application, enabling efficient handling of user requests, authentication, and server-side processing. Machine learning libraries such as Scikit-learn, Pandas, NumPy, and CatBoost are utilized for data preprocessing, feature engineering, model training, and prediction tasks. Visualization of data patterns and model performance is achieved using Matplotlib and Seaborn, which help in understanding trends and evaluation results.The frontend of the system is developed using HTML, CSS, and JavaScript to provide a responsive and user-friendly interface for interaction. The system stores user data, datasets, and prediction outputs in MySQL or SQLite databases depending on the scale of deployment. Development and debugging activities are carried out using IDEs such as Visual Studio Code or PyCharm, ensuring efficient coding and testing.

Technologies Used

The implementation of the system relies on several core technologies that contribute to its functionality and performance. MySQL and SQLite are used as database management systems to store structured data such as user credentials, datasets, and prediction results. Django serves as the backend framework, managing application logic, routing, authentication, and integration of machine learning models with the web interface. Scikit-learn provides essential machine learning algorithms including Decision Tree and Random Forest, which are used for classification tasks. Pandas is used for data manipulation and preprocessing, enabling efficient handling of structured datasets, while NumPy supports numerical computations and array-based operations.CatBoost is employed as an advanced gradient boosting algorithm that improves prediction accuracy, especially when handling categorical data. Matplotlib and Seaborn are used for visualizing data distributions, patterns, and model evaluation metrics. HTML, CSS, and JavaScript form the frontend layer, ensuring an interactive and intuitive user experience for end users.

Pseudocode

Pseudocode is a simplified, language-independent representation of the system logic that describes the step-by-step workflow of the Mobile Addiction Detection System. It is used to define the behavior of the system without relying on strict programming syntax, making it easier to understand and design the algorithm.The system begins with initialization, where all required libraries such as Django, Pandas, NumPy, Scikit-learn, CatBoost, and Joblib are imported. Pre-trained machine learning models are loaded, and the web application is initialized for user interaction.In the user registration process, the system collects user credentials including username, email, and password. It verifies whether the username already exists in the database. If it does not exist, the system stores the new user information and confirms successful account creation; otherwise, it returns an error message.

During login, the system validates the entered credentials against stored database records. If the credentials are correct, the user is redirected to the dashboard; otherwise, an invalid login message is displayed.For dataset upload, the system accepts files in formats such as CSV or Excel. The uploaded file is validated, and if it meets the required format, it is loaded using Pandas for further processing. Otherwise, an error message is shown.Model training involves splitting the dataset into training and testing sets, followed by training multiple machine learning models such as Decision Tree, Random Forest, and CatBoost classifiers. The performance of each model is evaluated using accuracy, precision, recall, F1-score, and confusion matrix.In the prediction phase, user inputs such as screen time, app usage behavior, gaming habits, and phone interaction patterns are collected and converted into numerical form. These features are passed to the trained CatBoost model, which predicts the addiction level as low, medium, or high. The result is then displayed to the user.Finally, the logout function securely terminates the user session and redirects the user to the login page, ensuring system security.

Testing

Testing is a critical phase in the development of the Mobile Addiction Detection System, ensuring that all components function correctly and deliver accurate results. It involves evaluating various modules such as authentication, data handling, preprocessing, model training, and prediction generation. Different testing strategies, including functional testing, performance testing, and accuracy testing, are applied to identify and eliminate errors. The system is tested using different datasets to ensure robustness and reliability in predicting mobile addiction levels. Overall, testing enhances system quality, improves accuracy, and ensures user satisfaction.Testing is essential because it improves system performance, ensures reliable predictions, maintains data security, and enhances the overall quality of the application.

Dimensions of Testing

The testing process is carried out across multiple dimensions to ensure complete system validation. These include application layers such as database handling, backend processing, and frontend interface. The system is also evaluated at different scales, including unit testing for individual modules, integration testing for module interaction, and system-level testing for overall functionality.In addition, different types of testing such as functional testing, performance testing, and security testing are applied to ensure system efficiency, responsiveness, and data protection. Both manual testing and basic automated validation techniques are used to verify system accuracy and stability.

Stages of Testing

Testing is conducted in multiple stages to ensure comprehensive validation of the system. In unit testing, individual components such as login, dataset upload, and prediction modules are tested independently to ensure correct functionality. Integration testing focuses on verifying the interaction between different modules, ensuring smooth data flow between frontend, backend, and machine learning components.System testing evaluates the complete application to ensure that all features work together as expected. Acceptance testing is performed to verify that the system meets user requirements and is ready for real-world deployment, ensuring usability, reliability, and overall performance.

Types of Testing

Different types of testing are used to validate the system from multiple perspectives. Black box testing evaluates the system based on input and output behavior without considering internal implementation. It ensures that features such as login, data upload, and prediction generation work correctly from the user's point of view.

White box testing, on the other hand, focuses on internal logic, code structure, and data flow within the system. It is used to verify preprocessing steps, model implementation, and algorithmic correctness, thereby improving code quality and system reliability.

Test Cases

The system is evaluated using multiple test cases designed to validate each functional component under different conditions. These test cases include scenarios for user authentication, dataset upload validation, model training accuracy, and prediction correctness. Each test case is designed to verify expected outputs against actual system responses, ensuring consistency, correctness, and robustness of the application under various input conditions.

Screenshots

ISSN 2277-2685
IJESR/April-June. 2026/ Vol-16/Issue-2/1011-1018
A Snithika *et. al.*, / International Journal of Engineering & Science Research

Fig. 1 Home Page

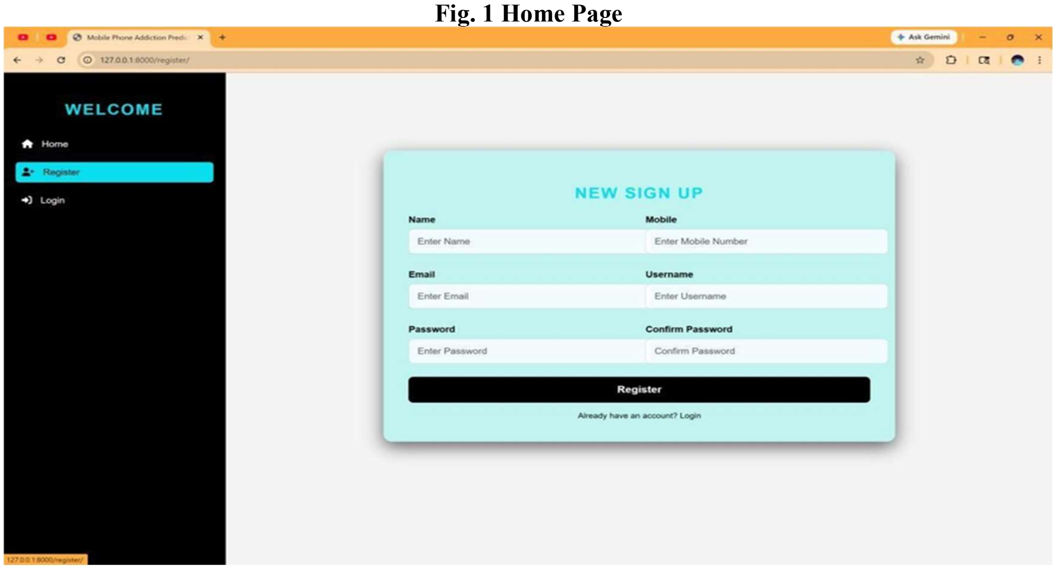

Fig.2 Registration Page

Fig.3 Login Successful

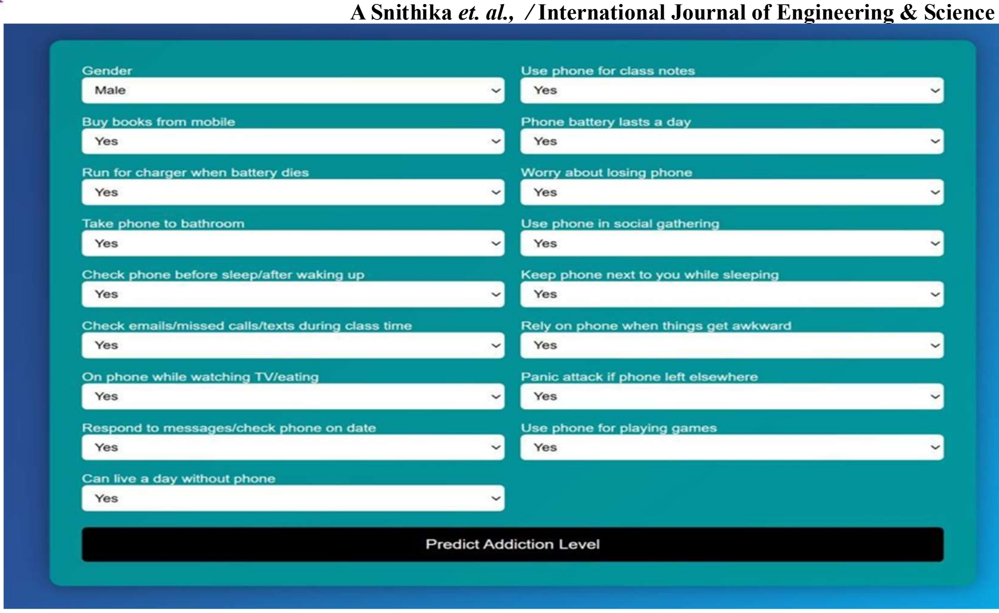

Fig. 4; Prediction Level Questions

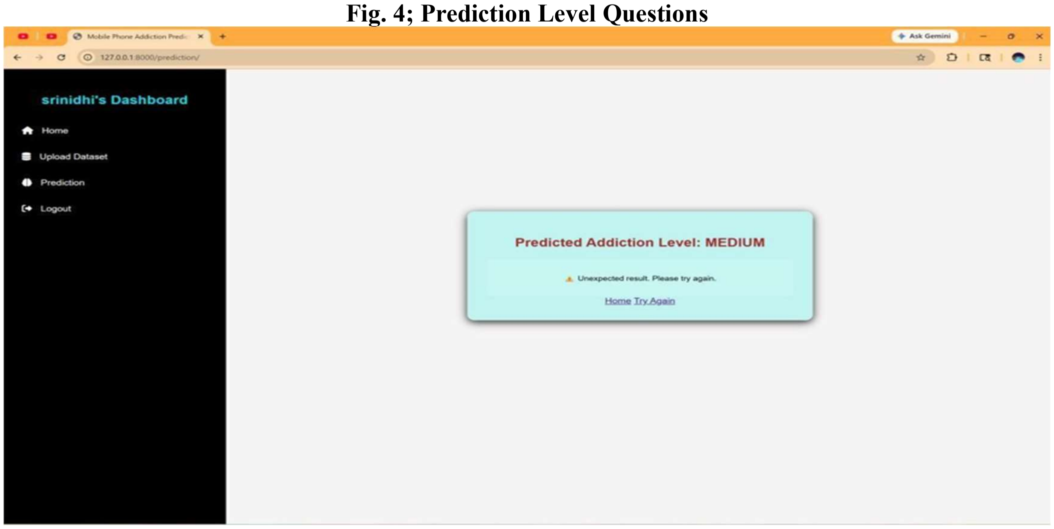

Fig. 5; Medium Level

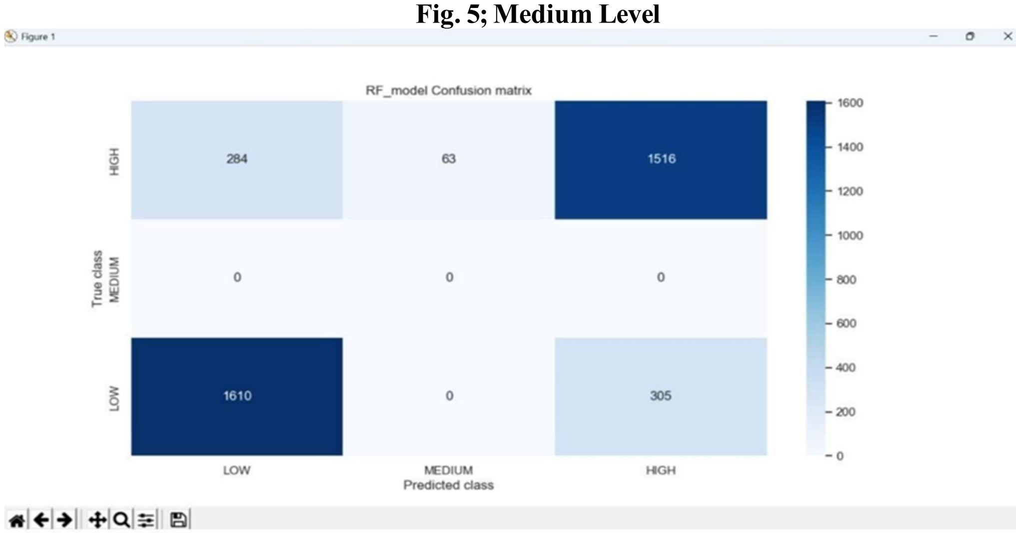

Fig.6; Result of Random Forest Algorithm

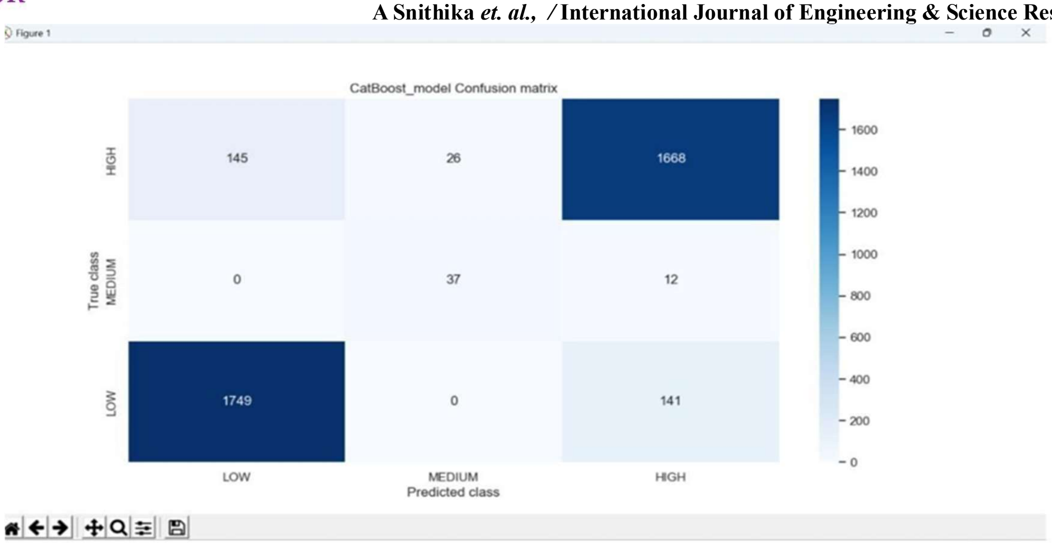

Fig. 7; Result of Cat Boost Algorithm

Conclusion

The increasing adoption of smartphones and mobile applications has significantly transformed daily life, but it has also contributed to rising concerns related to excessive usage and mobile addiction. In response to this issue, the proposed study titled "ML-Based Predictive Models for Mobile Addiction" introduces a data-driven framework that leverages machine learning techniques to identify and classify levels of mobile addiction. Unlike conventional approaches that depend on self-reported surveys, this system utilizes behavioral and usage-based data such as screen time, application usage patterns, and user interaction activities to improve prediction accuracy. The proposed methodology involves several stages, including data preprocessing, feature selection, model training, and performance evaluation. Machine learning algorithms such as Logistic Regression, Decision Trees, and Support Vector Machines are applied to categorize users into different addiction levels, namely low, medium, and high. The effectiveness of the models is assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score. By analyzing individual usage behavior, the system is capable of generating personalized predictions, thereby supporting early identification of potential addiction risks. This makes the proposed approach suitable for deployment in domains such as education, workplaces, and healthcare, where maintaining digital well-being is essential.

Future Scope

The proposed system offers several opportunities for further enhancement and expansion. In the future, prediction performance can be improved by incorporating more advanced machine learning and deep learning techniques, including artificial neural networks and ensemble learning models, which may provide higher accuracy and better generalization. The system can also be extended to support real-time data acquisition directly from mobile devices through dedicated applications and sensor integration, enabling more precise and continuous monitoring of user behavior. Furthermore, the inclusion of intelligent features such as personalized usage recommendations, real-time alerts, and digital well-being guidance can help users actively reduce excessive smartphone usage. Integration with wearable devices and mental health monitoring systems may provide deeper insights into behavioral patterns and psychological well-being. The framework can also be scaled for handling large datasets and deployed as a cloud-based or mobile application to ensure broader accessibility and usability across different sectors such as educational institutions, corporate environments, and healthcare services. Overall, future developments aim to make the system more adaptive, intelligent, and effective in promoting balanced and healthy digital lifestyles.

References

1) Choi, Y., & Park, H. (2019): This research investigates the impact of excessive smartphone usage on adolescent mental health, identifying strong links between mobile addiction, anxiety, stress, and behavioral disturbances, and highlighting the importance of early detection strategies.
2) Chen, L., & Zhao, S. (2018): This study proposes a machine learning-based framework for identifying mobile application addiction patterns using behavioral data, supporting the predictive modeling approach used in this project.
3) Przybylski, A. K., & Weinstein, N. (2017): This work analyzes the influence of mobile communication technologies on social interactions, showing how excessive usage can

reduce face-to-face communication and affect interpersonal relationships.

4) Kim, J., & Lee, M. (2020): This paper examines smartphone usage behavior among young adults and identifies key psychological factors contributing to dependency and overuse.
5) Wang, Y., & Zhang, X. (2021): This study focuses on predictive analytics techniques for behavioral addiction detection using classification algorithms and real-time data analysis.
6) Kumar, R., & Singh, P. (2020): This research explores machine learning applications in behavioral analysis and demonstrates the effectiveness of supervised learning models in classification problems.
7) Liu, H., & Zhao, Q. (2022): This paper presents data-driven approaches for analyzing digital behavior patterns and improving prediction accuracy using ensemble learning techniques.
8) Sharma, A., & Verma, N. (2021): This study highlights the importance of digital well-being and proposes computational models for identifying risky smartphone usage behavior.
9) Brown, T., & Davis, R. (2019): This research investigates technology addiction in youth and emphasizes the role of data analytics in early intervention and prevention strategies.
10) Singh, A., & Patel, K. (2023): This paper discusses advanced machine learning models for behavioral prediction and their applications in health and lifestyle monitoring systems.