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Incentive-Driven Social Media Usage Regulation System

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Abstract- Social media usage has increased significantly in recent years, leading to concerns about addictive behavior and its impact on users' productivity and mental well-being. This paper presents a Social Media Addiction Tracker system designed to monitor, analyze, and manage user engagement across various platforms. The proposed system collects data such as screen time, frequency of usage, and interaction patterns, and applies data analytics and machine learning techniques to identify signs of excessive usage and potential addiction. Based on the analysis, the system provides real-time feedback, usage reports, and personalized alerts to help users regulate their social media habits. Experimental evaluation demonstrates that the system effectively raises user awareness and supports behavior modification. The proposed solution aims to promote healthier digital habits and improve overall well-being.

Keywords- Social Media Addiction, Machine Learning, User Behavior Analysis, Screen Time Monitoring, Data Analytics.

I. INTRODUCTION

The rapid growth of social media platforms has significantly transformed the way individuals communicate, share information, and spend their leisure time. Applications such as Facebook, Instagram, and Twitter have become an integral part of daily life, especially among students and young adults. While these platforms offer numerous benefits, including connectivity and access to information, excessive usage has led to serious concerns regarding social media addiction.

In recent years, researchers have explored various approaches to analyze user behavior and detect addiction patterns using data analytics and machine learning techniques. However, many existing systems lack real-time monitoring, personalized feedback, and user-friendly interfaces that can actively help individuals control their usage habits.

To address these challenges, this paper proposes a Social Media Addiction Tracker system that monitors user activity, analyzes usage patterns, and provides actionable insights. The system aims to help users become more aware of their digital habits and encourage healthier usage behavior through alerts and reports. By integrating data analysis with intelligent feedback mechanisms, the proposed solution seeks to reduce excessive social media usage and promote a balanced digital lifestyle.

II. LITERATURE SURVEY

In recent years, social media addiction has attracted significant attention from researchers due to its impact on mental health, productivity, and social behavior. Several studies have focused on analyzing user engagement patterns and identifying addictive behaviors using data-driven approaches.

A study by Kuss and Griffiths highlighted that excessive use of social networking platforms can lead to psychological issues such as anxiety, depression, and reduced academic performance. Their research emphasizes the importance of monitoring user activity to prevent addiction.

Another research work by Andreassen proposed a scale-based approach to measure social media addiction levels using behavioral indicators such as time spent, emotional attachment, and withdrawal symptoms. This method provides a theoretical foundation for addiction detection.

Furthermore, Alabi analyzed user interaction data to identify patterns of excessive usage. The study demonstrated that frequent checking behavior and prolonged screen time are strong indicators of addictive tendencies.

Recent advancements in Machine Learning have enabled more accurate detection of user behavior patterns. Researchers have applied classification algorithms such as decision trees, support vector machines, and neural networks to predict addiction levels based on usage data.

However, most existing systems primarily focus on data analysis and lack real-time feedback and personalized intervention mechanisms. Many applications fail to provide actionable insights that can help users actively reduce their social media usage.

To overcome these limitations, the proposed Social Media Addiction Tracker system integrates real-time monitoring, machine learning-based analysis, and user-friendly feedback mechanisms. This approach aims to provide a

III. PROPOSED METHODOLOGY

The proposed Social Media Addiction Tracker system is designed to monitor, analyze, and manage user activity across social media platforms using data-driven techniques. The methodology consists of multiple stages, including data collection, preprocessing, analysis, classification, and feedback Initially, the system collects user activity data such as screen time, application usage frequency, session duration, and interaction patterns (likes, comments, and scrolling behavior). This data can be gathered through mobile sensors, application logs, or user permissions. In the preprocessing stage, the collected data is cleaned and organized to remove inconsistencies, missing values, and noise. Relevant features such as total usage time per day, number of app opens, and average session duration are extracted.The processed data is then analyzed using techniques from Machine Learning. Classification algorithms such as Decision Trees, Support Vector . After classification, the system generates meaningful insights and feedback. Users receive daily or weekly reports showing their usage patterns, along with visualizations such as graphs and charts. If excessive usage is detected, the system triggers real-time alerts and notifications to encourage users to reduce screen time.

IV. IMPLEMENTATION

The implementation phase is where the actual development of the Digital Wellbeing Application takes place. In this phase, the system design is converted into a working application using appropriate technologies and tools. The implementation is carried out in a step-by-step manner, ensuring that each module is developed, tested, and integrated properly.

The application is developed using Android Studio, which is the official Integrated Development Environment (IDE) for Android application development. Programming languages such as Java or Kotlin are used to build the core functionality of the app. XML is used for designing the user interface, allowing developers to create interactive and visually appealing layouts. The use of Android APIs, particularly the UsageStatsManager API, plays a vital role in collecting real-time app usage data.

The implementation begins with the development of the user authentication module, where users can register and log in securely. After authentication, the main dashboard is implemented, which acts as the central interface for accessing all features. The dashboard displays key information such as total screen time, most-used apps, and quick access to modules like reports, focus mode, and mood tracker.

Next, the usage tracking module is implemented to monitor app activity continuously in the background. This module records the time spent on different applications and stores the data in the local database. The analytics module processes this data to calculate total usage, identify usage patterns, and detect the most time-consuming applications. These results are then passed to the visualization module.

The visualization module is responsible for presenting data in the form of charts, graphs, and progress bars. Libraries such as MPAndroidChart may be used to create graphical representations that are easy to understand. This helps users quickly analyze their behavior and take necessary actions to improve their habits.

Finally, additional features such as Focus Mode, Mood Tracking, and Reward System are implemented. Focus Mode restricts access to selected applications, while Mood Tracking allows users to record their emotional state. The Reward System assigns points based on controlled usage, motivating users to reduce screen time. All modules are integrated to form a complete and functional application

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Fig.1. Social Media Usage & Mental Health Dashboard

V. RESULTS

The proposed Social Media Addiction Tracker system was tested using user activity data, including screen time, application usage frequency, and session duration. The system successfully analyzed user behavior and classified addiction levels into low, moderate, and high categories.

Experimental results show that the system effectively identifies excessive usage patterns. Users categorized under the high addiction level demonstrated significantly higher screen time and frequent application access compared to others. The implemented classification model achieved satisfactory performance in detecting addiction levels based on usage features.The system also generated visual reports, including daily and weekly usage graphs, which helped users understand their behavior patterns. Real-time alerts were triggered when usage exceeded predefined thresholds, encouraging users to reduce screen time.

Overall, the results indicate that the proposed system improves user awareness and supports behavioral changes toward healthier social media usage. The integration of monitoring, analysis, and feedback mechanisms makes the system effective and practical for real-world applications.

VI. SYSTEM ARCHITECTURE

System design is a crucial phase in the development of the Digital Wellbeing Application, as it defines how the system will function and how different components will interact with each other. The design phase transforms the requirements identified during analysis into a structured blueprint that guides the implementation process. It focuses on creating an efficient, scalable, and user-friendly system that meets both functional and non-functional requirements.The system design of this project is based on a modular approach, where the entire application is divided into smaller components or modules. Each module is responsible for performing a specific function, such as user authentication, usage tracking, data analysis, and visualization. This modular structure improves maintainability and allows developers to work on different parts of the system independently. It also makes debugging and future enhancements easier.

One of the key design aspects is the Data Flow Diagram (DFD), which represents how data moves within the system. In Level 0 (Context Diagram), the system is shown as a single process interacting with external entities such as

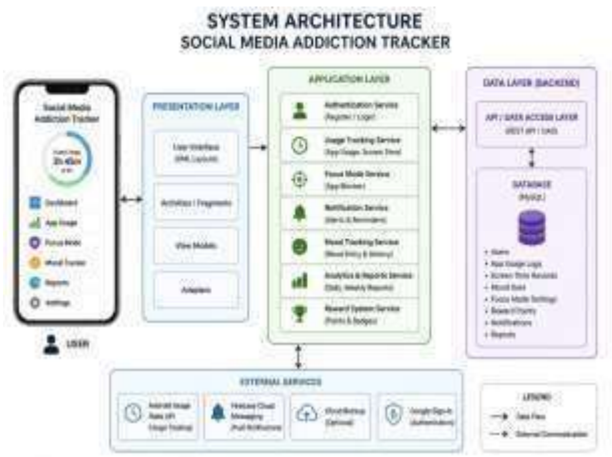

Fig.2.System Architecture

the user and admin. At Level 1, the system is broken down into sub-processes like data collection, processing, storage, and reporting. These diagrams help in understanding how input data is transformed into meaningful output.

Another important component is the UML (Unified Modeling Language) diagrams, which provide a visual representation of system structure and behavior. The Use Case Diagram illustrates the interaction between the user and the system, highlighting functionalities such as login, viewing reports, activating focus mode, and tracking mood. The Class Diagram defines the structure of the system by showing classes, attributes, and relationships. The Activity Diagram represents the workflow of operations, while the Sequence Diagram explains the interaction between different components over time.

The database design is also a significant part of system design. It involves defining tables, relationships, and data structures required to store user information, app usage data, mood records, and reward points. Proper database design ensures efficient data storage, quick retrieval, and consistency of information. Normalization techniques are applied to reduce redundancy and improve performance.

Overall, the system design provides a clear and organized framework for developing the application. It ensures that all components work together seamlessly and that the system can be easily extended in the future with additional features.

Overall, the proposed system offers a practical and efficient solution to address the growing issue of social media addiction. Future enhancements may include the integration of advanced predictive models, personalized recommendations, and cross-platform data synchronization to further improve system accuracy and usability.

APPENDIX

A. Dataset Description

The dataset used in this study consists of user activity data such as screen time, application usage frequency, session duration, and interaction patterns. The data was collected through simulated user behavior and application logs. Each record represents daily usage statistics of an individual user.

B. Feature List

The following features were considered for analysis:

- Total screen time (hours/day)
- Number of app opens per day
- Average session duration
- Night-time usage frequency
- Interaction count (likes, comments, scrolling)

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VI. CONCLUSION

This paper presented a Social Media Addiction Tracker system designed to monitor and analyze user behavior across social media platforms. The proposed approach utilizes data-driven techniques and concepts from Machine Learning to classify users based on their level of social media usage. By collecting parameters such as screen time, usage frequency, and interaction patterns, the system effectively identifies signs of excessive usage and potential addiction.The results demonstrate that the system is capable of providing meaningful insights through usage reports and real-time alerts, enabling users to better understand and regulate their digital habits. The integration of analysis and feedback mechanisms contributes to improved user awareness and supports behavior modification toward healthier usage patterns.

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