IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

SMART PHONE USAGE ANALYTICS USING MACHINE LEARNING

[1]Jayanthi Savitri Harshini, [2]Angirekula Dharshini Renuka, [3]Chimaldinne Naveen Kumar, [4]Dr. S. Sai Kumar

[1,2,3]B.Tech Student, [4]Sr. Assistant Professor

[1,2,3,4]Information Technology,

[1,2,3,4]Prasad V. Potluri Siddhartha Institute of Technology, Vijayawada, India

Abstract: In today's digital era, excessive smartphone usage has become a major factor influencing individual productivity, focus, and overall well-being. While existing applications provide basic screen-time statistics, they fail to deliver meaningful insights or predictive analysis regarding user productivity. This paper presents an **AI-powered Smartphone Usage Analytics and Productivity Prediction System** that leverages real-world usage data combined with behavioral factors such as sleep patterns, stress levels, and focus time. The system utilizes a **deep learning model to classify productivity levels into Low, Medium, and High categories and also generates a quantitative productivity score.** By integrating machine learning with data visualization and database systems, the proposed solution provides personalized insights and actionable recommendations to users. The system is implemented as a web-based application using Streamlit, ensuring accessibility and ease of use. Experimental analysis demonstrates that combining behavioral attributes with usage patterns significantly improves prediction accuracy, enabling users to make informed decisions that enhance productivity.

Keywords: Smartphone Usage Analysis, Productivity Prediction, Deep Learning, Behavioral Analytics, Machine Learning, Streamlit, Data Visualization, User Behavior Modeling, AI-based Recommendation System

I. INTRODUCTION

In recent years, smartphones have become an essential part of daily life, influencing how individuals communicate, learn, and manage their tasks. While these devices provide numerous advantages, excessive and uncontrolled usage has led to reduced productivity, increased distraction, and negative impacts on mental well-being. A significant portion of smartphone usage is often dedicated to social media and entertainment applications, which can divert attention from important activities such as academic work or professional tasks. Existing solutions such as built-in screen time trackers and third-party applications mainly provide statistical summaries, including total usage time, app-wise consumption, and device unlock frequency. However, these systems lack the capability to interpret how such usage patterns affect productivity. They do not incorporate important behavioural factors like sleep duration, stress levels, or focused work hours, which play a crucial role in determining an individual's efficiency. As a result, users are left with raw data without meaningful insights or guidance for improvement.

To address these limitations**, this paper proposes an AI-powered Smartphone Usage Analytics and Productivity Prediction System**. The system integrates real-time smartphone usage data with additional behavioural inputs to perform intelligent analysis. By utilizing a deep learning model, it predicts the user's productivity level and assigns a numerical productivity score. Unlike traditional systems, the proposed solution not only analyses past behaviour but also provides personalized recommendations to help users improve their productivity. Furthermore, the system incorporates interactive data visualization techniques to present insights in a clear and user-friendly manner. It also maintains historical records using a database, enabling users to track their progress over time. **By combining machine learning, behavioural analytics, and visualization**, the proposed system aims to transform raw usage data into actionable intelligence, helping users make better decisions regarding their digital habits.

II. Literature Survey

With the rapid advancement of technology, machine learning and data analytics have been widely applied to analyse human behaviour and improve decision-making processes. Several studies and applications have explored the impact of smartphone usage on productivity and well-being, as well as the use of intelligent systems to monitor and optimize user behaviour.

Many existing works focus on **screen time monitoring systems**, which track metrics such as total usage duration, app-wise consumption, and frequency of device interaction. Built-in tools and third-party applications provide users with basic statistical insights. However, these systems are limited in scope, as they primarily present raw data without offering deeper analysis or interpretation of how usage patterns affect productivity levels.

Research in the field of **behavioural analytics** highlights that productivity is influenced not only by screen time but also by multiple factors such as sleep quality, stress levels, and focused working hours. Studies have shown that combining these behavioural attributes with usage data can provide a more accurate understanding of user efficiency. Despite this, most existing systems fail to integrate these factors into a unified analytical model.

In recent years, **machine learning approaches** have been introduced to predict human behaviour and performance. Algorithms such as regression models, decision trees, and neural networks have been used to identify patterns in large datasets. Deep learning models, in particular, have demonstrated strong performance in capturing complex relationships between multiple input features. However, many implementations are limited to specific domains and do not fully utilize real-time smartphone usage data.

From the analysis of existing literature, it is evident that there is a gap in systems that combine **real-time smartphone usage data, behavioural factors, machine learning prediction, and personalized recommendations** into a single platform. The proposed system addresses this gap by integrating deep learning-based productivity prediction with interactive visualization and user-specific insights, thereby offering a more comprehensive and practical solution.

III. Proposed System

The proposed system introduces an intelligent and data-driven approach to analyse smartphone usage patterns and predict user productivity. Unlike traditional tracking applications that only display raw usage statistics, this system integrates machine learning, behavioural analytics, and real-time data processing to generate meaningful insights and actionable recommendations.

The system is designed as a **web-based application** that allows users to upload their smartphone usage reports and provide additional behavioural inputs such as sleep duration, stress levels, and focus hours. These inputs are combined to form a comprehensive dataset that reflects the user’s daily habits and lifestyle patterns. By analysing both digital behaviour and personal factors, the system ensures a more accurate and holistic assessment of productivity.

A key component of the proposed system is the **deep learning-based prediction model**, which classifies productivity into three categories: Low, Medium, and High. In addition to classification, the system also computes a numerical productivity score on a scale of 0 to 100, making the results more interpretable and user-friendly. This dual output approach helps users clearly understand their productivity status.

The system also includes an **automated application categorization mechanism**, where apps are classified into categories such as drainer (e.g., social media and entertainment) and booster (e.g., productivity tools). This classification plays a crucial role in evaluating how different types of app usage influence overall productivity.

To enhance user experience, the system provides **interactive visualizations** such as charts and graphs that represent usage patterns, productivity trends, and category-wise analysis. These visual elements make it easier for users to interpret their data and identify areas for improvement.

Another important feature is the **recommendation system**, which generates personalized suggestions based on the user's behaviour. For example, the system may recommend reducing social media usage, improving sleep habits, or increasing focused work time to enhance productivity. These recommendations are tailored to each user, making them practical and effective.

The system also incorporates a **database management component**, where user data and daily productivity records are securely stored. This enables users to track their historical performance, compare trends over time, and monitor their improvement.

Overall, the proposed system combines multiple technologies into a unified platform that transforms raw smartphone data into intelligent insights. By integrating deep learning, behavioural analysis, and visualization, it provides a comprehensive solution for improving productivity in the digital age.

IV. METHODOLOGY

The methodology describes the systematic approach followed to design and implement the proposed Smartphone Usage Analytics and Productivity Prediction System. It involves multiple stages including data collection, preprocessing, model development, prediction, and result visualization.

4.1 Dataset Description

The system utilizes a structured dataset designed to represent real-world smartphone usage behaviour and its impact on productivity. The dataset contains a large number of records, where each record represents a user with associated behavioural and usage attributes.

Key features in the dataset includes Age, Gender, Occupation, Device Type, Daily Phone Usage Hours, Social Media Usage Hours, Sleep Duration, Stress Level, Weekend Screen Time, App Usage Count.

The target variable is the **productivity score**, which is further categorized into three classes: Low Productivity, Medium Productivity, High Productivity

Additionally, a derived feature called the **Behavioural Productivity Index (BPI)** is created by combining multiple behavioural factors. This helps in capturing the overall effect of user habits on productivity in a more meaningful way.

4.2 Data Pre-processing

Data pre-processing is a crucial step to ensure the dataset is clean, consistent, and suitable for model training.

The following steps are performed:

- **Data Cleaning:** Removal of unnecessary attributes and handling missing values
- **Feature Engineering:** Creation of Behavioural Productivity Index (BPI)
- **Categorical Encoding:** Conversion of categorical variables (gender, occupation, device type) into numerical format using encoding techniques
- **Feature Scaling:** Normalization of numerical features to ensure uniform contribution
- **Target Transformation:** Conversion of continuous productivity scores into categorical classes using binning techniques

These steps improve the quality of the dataset and enhance model performance.

4.3 Model Description

The proposed system uses a **Deep Learning model (Multi-Layer Perceptron)** for predicting productivity levels.

Model Architecture:

- Input Layer: Accepts all processed features
- Hidden Layer 1: 128 neurons with ReLU activation
- Dropout Layer: Reduces overfitting
- Hidden Layer 2: 64 neurons with ReLU activation
- Hidden Layer 3: 32 neurons with ReLU activation
- Output Layer: 3 neurons with Softmax activation (for classification)

The model is trained using:

- Optimizer: Adam
- Loss Function: Sparse Categorical Cross entropy
- Evaluation Metric: Accuracy

The dataset is split into training and testing sets to evaluate performance effectively.

4.4 Prediction Approach

The prediction process combines both machine learning output and behavioural scoring.
Steps involved:

1. User uploads smartphone usage data
2. Additional inputs such as sleep, stress, and focus hours are collected
3. Data is preprocessed and scaled
4. The trained deep learning model predicts the productivity class
5. A numerical productivity score (0–100) is calculated using a custom scoring algorithm

This hybrid approach ensures both accuracy and interpretability.

4.5 System Flow

The overall workflow of the system is as follows:

User Input → Data Processing → Feature Extraction → Machine Learning Model → Productivity Prediction → Visualization → Recommendation → Data Storage

This flow ensures smooth processing and efficient interaction between different system components.

4.6 System Architecture

The system follows a layered architecture-

Input Layer: Accepts user data and usage reports
Processing Layer: Performs data cleaning and feature extraction
Model Layer: Executes deep learning prediction
Visualization Layer: Displays charts and insights
Database Layer: Stores user data and history

This modular design improves scalability, maintainability, and performance of the system.

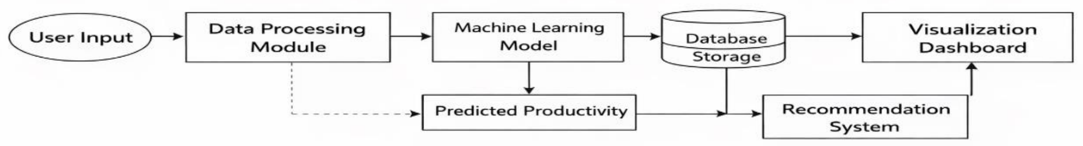

Fig.1: System Architecture of AI-Based Smartphone Usage Analytics and Productivity Prediction System.

4.7 Web Application

The proposed system is implemented as a web-based application to ensure accessibility, ease of use, and real-time interaction. The application is developed using Streamlit, which provides a simple and interactive interface for users to upload their smartphone usage reports and enter behavioral inputs such as sleep hours, stress level, and focus time. Once the data is submitted, the system processes the inputs, performs prediction using the trained deep learning model, and instantly displays the results. The web application presents the productivity score, classification, and detailed insights through interactive visualizations such as charts and graphs. It also provides personalized recommendations based on user behavior to help improve productivity. Additionally, the system includes user authentication and database integration to securely store user data and maintain historical records for future analysis. Overall, the web application ensures a seamless user experience by combining data processing, prediction, and visualization into a single platform.

V. RESULTS AND DISCUSSION

The proposed Smartphone Usage Analytics and Productivity Prediction System successfully demonstrate how machine learning and behavioural analysis can be combined to evaluate and improve user productivity. By utilizing real-time smartphone usage data along with factors such as sleep, stress, and focus hours, the system accurately classifies productivity levels and generates a meaningful numerical score. The integration of an interactive dashboard enhances user understanding, while the recommendation system provides personalized suggestions for improvement. Overall, the system proves to be effective, user-friendly, and practical in helping individuals analyse their digital habits and make informed decisions to enhance their productivity.

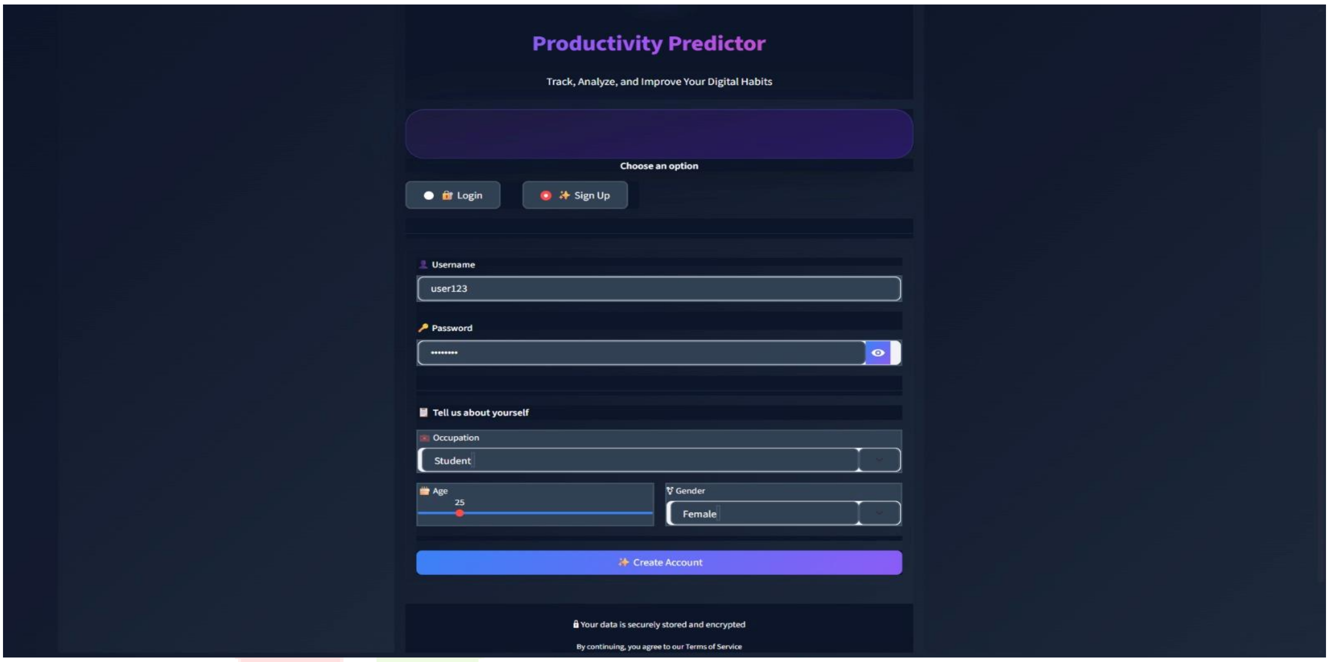

Fig.2: User Login Interface for the AI-Based Smartphone Usage Analytics and Productivity Prediction System

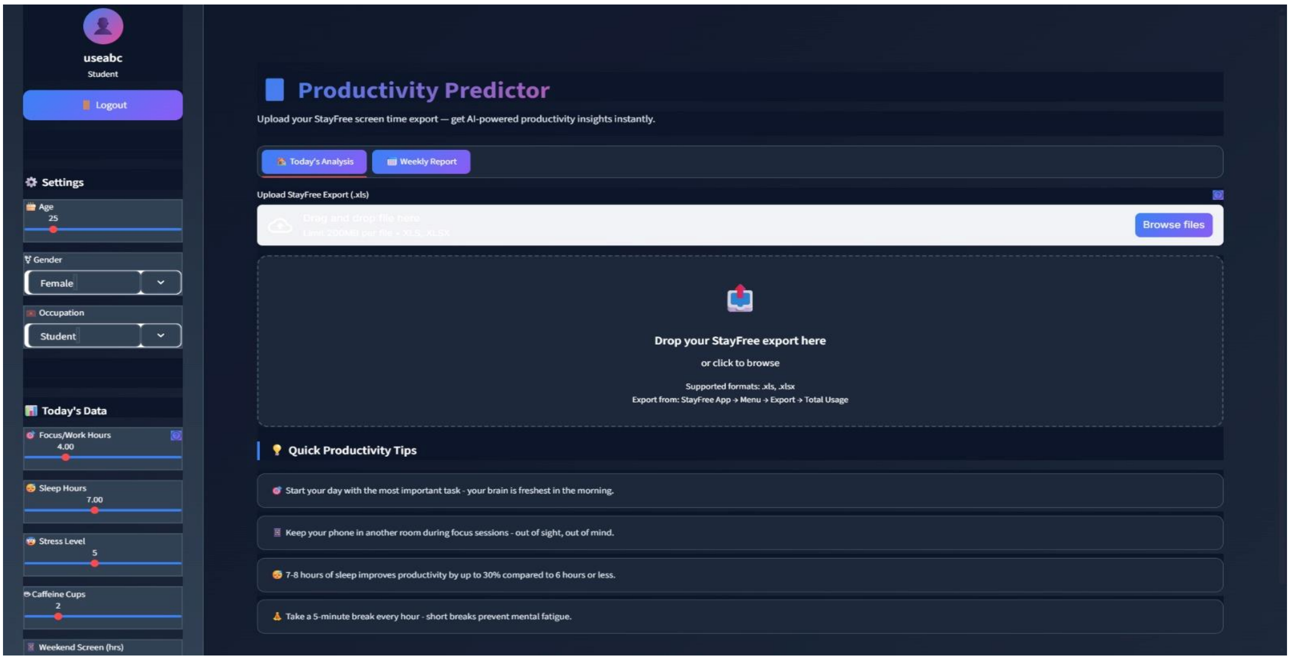

Fig.3: AI-Based Smartphone Usage Analytics and Productivity Prediction System with User Input Interface

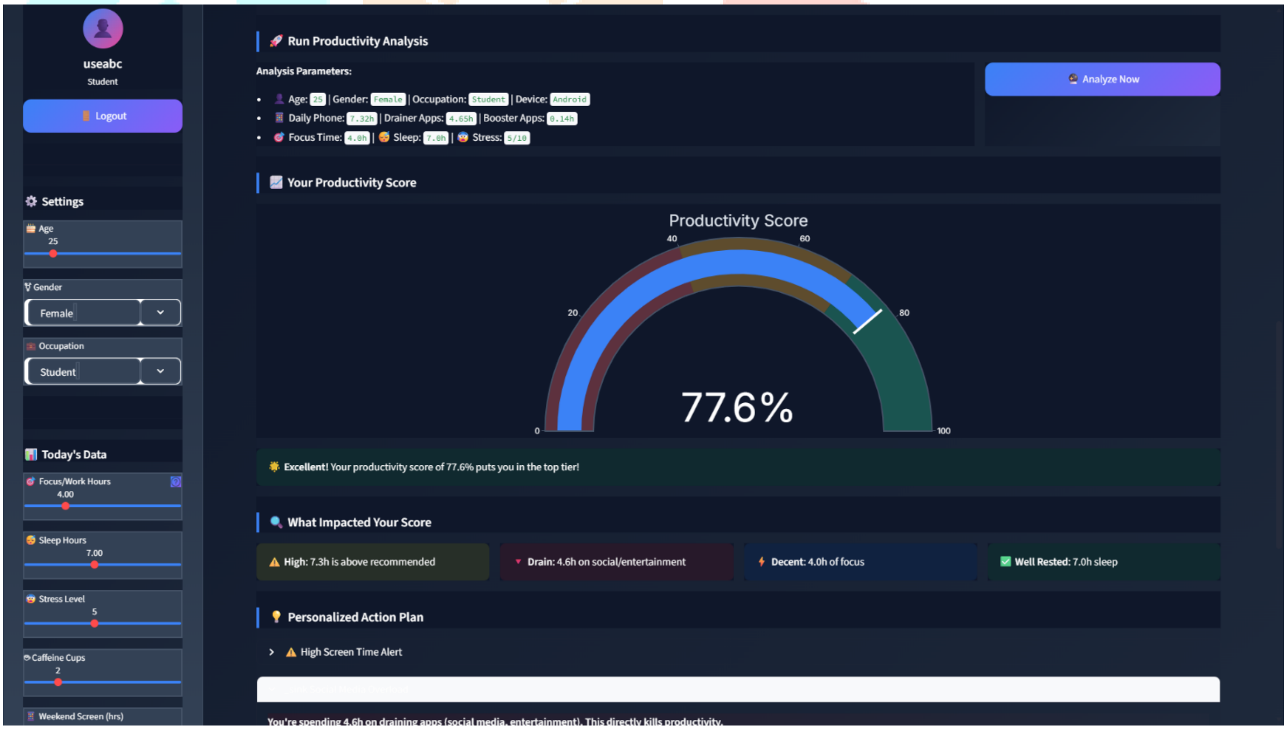

Fig.4: AI-Based Smartphone Usage Analytics and Productivity Prediction System Prediction Results

VI. Conclusion

The proposed Smartphone Usage Analytics and Productivity Prediction System present an effective approach to understanding and improving user productivity by combining machine learning with behavioral analysis. By analyzing smartphone usage patterns along with factors such as sleep, stress, and focus time, the system is able to accurately predict productivity levels and generate a meaningful score. The inclusion of interactive visualizations and personalized recommendations makes the system more practical and user-centric. Overall, the project demonstrates how intelligent data analysis can transform raw usage information into valuable insights, helping users make better decisions and develop healthier digital habits.

VII. ACKNOWLEDGEMENT

The authors would like to express their heartfelt gratitude to **Dr. S. Sai Kumar, Ph.D., Sr. Assistant Professor**, for his invaluable guidance, continuous support, and encouragement throughout the development of this project. His expert advice, constructive feedback, and motivation played a crucial role in shaping this work and bringing it to successful completion.

The authors also sincerely thank the **Department of Information Technology, Prasad V Potluri Siddhartha Institute of Technology**, for providing the necessary resources, facilities, and a supportive academic environment that greatly contributed to the successful execution of this project.

We are equally thankful to the management of **Prasad V Potluri Siddhartha Institute of Technology** for their encouragement and support throughout the project development and presentation.

REFERENCES

[1] J. Lee and W. Kim, "Prediction of Problematic Smartphone Use: A Machine Learning Approach," *Applied Sciences*, vol. 11, no. 12, 2021

[2] Sridhar Rao Muthineni, "Advancements in Mobile AI: A Machine Learning-Driven Approach to Enhance User Experience and Functionality," 2024.

[3] "Explainable Prediction of Problematic Smartphone Use Using Machine Learning," 2024.

[4] Kaggle, "Mobile Device Usage and User Behavior Dataset," 2023. Dataset used for analyzing smartphone usage patterns and behavioral insights. Link: https://www.kaggle.com/datasets/valakhorasani/mobile-device-usage-and-userbehavior-dataset

[5] "Smartphone Addiction Prediction Using Machine Learning Techniques," IEEE, 2022. Referenced for understanding prediction models related to smartphone addiction and behavior. Link: https://ieeexplore.ieee.org/document/9696563

[6] Hammed Jelodar, Yongli Wang, Chi Yuan, Xia Feng, Xia Hui Jiang, Yanchao " LDA and Topic Modelling- Models, Applications, A Survey", Topic Modelling LDA, Tag Recommendations, Semantic Web, Gibbs Samp ling, 2018.

[7] Learning from LDA using Deep Neural Networks, Dongxu Zhang, Tianyi Luo, Dong Wang, The 5th International Workshop on Parallel and Distributed Computing for Large Scale Machine Learning and Big Data Analytics 2018.

[8] Categorizing Research Papers by Topics Using Latent Dirichlet Allocation Model International Journal Of Scientific & Technology Research Volume 8, Issue 12, December 2019.