MACHINE LEARNING MODEL FOR PREDICTION OF SMARTPHONE ADDICTION

[1]K.SRUJANA, [2]CH. SURYA PRAKASH
[1]Student, [2]Assistant Professor
[12]DEPARTMENT OF COMPUTER APPLICATIONS
[12]RAJAHMAHENDRI INSTITUTE OF ENGINEERING AND TECHNOLOGY, Rajahmahendry

***Abstract*—Smartphone addiction is an increasing concern due to its negative impact on productivity, physical health, and mental well-being. This study developed a machine learning model to predict smartphone addiction using survey data that included demographic information, smartphone usage patterns, and psychological factors such as stress, anxiety, and depression. The data was pre-processed through categorical variable encoding and numerical data normalization to improve model performance. The model was trained on a portion of the dataset and evaluated using accuracy metrics on the remaining data. Results demonstrated high predictive accuracy, with key factors influencing addiction risk including daily phone usage duration, notification-checking frequency, and frequently used app categories. Demographic variables and stress levels also contributed significantly to prediction outcomes. The developed model can assist healthcare professionals in identifying individuals at risk of smartphone addiction and enable early intervention. Additionally, it can help app developers create fewer addictive applications and encourage healthier smartphone usage habits. Overall, the study highlights the effectiveness of machine learning techniques in predicting smartphone addiction, while emphasizing the need for further research using larger and more diverse datasets to improve generalizability and explore broader applications.**

***Index Terms*—MACHINE,PREDICTION OF SMARTPHONE**

I. Introduction

Over the past years, there has been a continuous growth in the usage of smartphones, which have become an essential part of our lives. Even while mobile phones have many advantages, using them excessively can cause addiction and have a detrimental effect on a person's productivity, social connections, physical and mental health, and relationships. Models that predict smartphone addiction based on a variety of parameters, including social media usage, usage patterns of smartphones, demographic data, and psychological aspects, may be created using machine learning. These models can be used to detect people who may become addicted to smartphones and to help them receive the right assistance and therapies. Usually, the first step in creating a machine learning model to forecast smartphone addiction is gathering data from a sizable sample of people. Information on their social media and smartphone usage habits, as well as demographic details like age and gender and psychological characteristics like stress, anxiety, and depression, would all be included in this data. After the data is gathered, it is cleaned and preprocessed to eliminate any unnecessary or missing data points. During the preprocessing of the data, it is required to replace imputations and label encoding. Replacing imputations means it can handle all the null values and replace them as 0 or 1 by considering the particular value as an outlier. Label Encoding modifies the categorical data into numerical values. Then the data will be preprocessed and it will be split into training data and testing data.

Next, based on the type of data and the problem at hand, an appropriate machine learning method is chosen. After that, the data is divided into two sets: a testing set and a training set. By providing the machine learning model with input characteristics and matching output labels, the training set is utilized to train the model. By identifying patterns in the data, the model is able to determine a correlation between the input characteristics and the output labels. The model is tested on the testing set once it has been trained in order to assess its performance. Accuracy is one of the measures used to gauge the model's performance. Until the model performs well enough, it is further improved by adjusting its parameters or using other methods. Once the model is created, user input features may be fed into it to forecast a person's likelihood of developing a smartphone addiction. A probability score showing the chance of developing a smartphone addiction is produced by the model. People who are at risk of addiction can receive the proper interventions and assistance based on their score. To sum up, machine learning models can be a useful tool for identifying those who are at risk of smartphone addiction and forecasting the likelihood of addiction. These models can assist people in preventing addiction and lessening its harmful impacts, as well as healthcare professionals. Nonetheless, gathering high-quality data and creating precise, trustworthy models that work well in practical situations are crucial.

II. SYSTEM ANALYSIS

2.1 Existing System:

Currently, smartphone addiction is predominantly identified through subjective methods, including self-reported surveys and psychological evaluations conducted by healthcare professionals. These assessments often rely on individuals to accurately report their behaviours and emotions, which can lead to inconsistencies due to factors like mood, self-perception, or misunderstanding of survey questions. These methods may include standard questionnaires such as the Smartphone Addiction Scale (SAS), which evaluates addiction levels based on self-reported data on phone usage and associated feelings. However, this reliance on subjective responses introduces a substantial margin for error, as people may underreport or inaccurately gauge their usage habits. Additionally, there is no universally adopted scale to measure smartphone addiction, meaning that different studies or healthcare providers might use varying benchmarks, which affects the comparability and reliability of results. Existing smartphone monitoring applications, though helpful in tracking metrics like screen time or specific app usage, fall short in offering a holistic view of addiction risk. They often overlook crucial psychological and demographic factors that influence addiction and lack predictive power, providing only descriptive summaries of behaviour without insight into future risk. Consequently, the current system is limited in its capacity to proactively identify individuals at risk of developing smartphone addiction, and intervention often occurs after negative impacts on productivity, social interactions, and mental well-being have already materialized.

Disadvantages:

- **Dependence on self-reported data** can lead to inaccurate or biased responses.
- **Users may not recognize or honestly report** their actual smartphone usage habits.
- **Difficult to accurately assess addiction severity** based on subjective information.
- **Psychological assessments are time-consuming** and require significant effort.
- **Need for expert interpretation** makes assessments costly and less accessible.
- **Lack of standardized measurement methods** reduces consistency across studies and populations.
- **Limited applicability across different demographics** and usage contexts.
- **Monitoring apps mainly track screen time and app usage**, providing limited insights.
- **Psychological factors** such as stress, anxiety, and depression are often ignored.

- **Insufficient data analysis capabilities** prevent comprehensive addiction evaluation.
- **Reactive approach** identifies problems only after symptoms become noticeable.
- **Delayed intervention** may lead to negative effects on mental health, productivity, and social relationships.
- **Lack of early prediction mechanisms** makes prevention difficult.

2.2 Proposed System:

The proposed system aims to address the limitations of traditional approaches by employing machine learning to predict smartphone addiction risk based on a range of data inputs, including demographic information, smartphone usage patterns, and psychological factors. Data collected from a survey of smartphone users, covering variables like age, gender, phone usage habits, and mental health indicators such as stress and anxiety, are pre-processed to ensure accuracy and consistency. This preprocessing includes encoding categorical variables and normalizing numerical data, which enhances model performance and enables meaningful comparisons across diverse data points. After preprocessing, the data is split into training and testing sets, allowing the model to learn correlations between input features and addiction risk. The machine learning model is then trained using methods such as decision trees, random forests, and logistic regression, chosen for their ability to capture complex patterns in the data. After training, the model evaluates its predictive performance using metrics like accuracy and recall, providing an objective assessment of addiction risk. With this model, healthcare providers can identify individuals at high risk for addiction based on real-time data inputs and recommend timely interventions.

Advantages:

- **Provides objective results** by using data instead of relying only on user opinions.
- **Reduces errors and bias** caused by inaccurate self-reporting.
- **Analyses multiple factors**, such as screen time, notification checks, stress, and anxiety.
- **Gives a complete picture** of a person's smartphone usage and addiction risk.
- **Detects addiction risk early**, before serious problems develop.
- **Supports timely intervention** to prevent negative effects on mental health and daily life.
- **Offers accurate predictions** using machine learning techniques.
- **Helps app developers** create apps that encourage healthier smartphone habits.
- **Automates data collection and analysis**, saving time and effort.
- **Can be used for large populations** without requiring extensive manual work.
- **Works across different age groups and demographics**, making it widely applicable.
- **Promotes healthier smartphone use** and better digital well-being.
- **Supports healthcare professionals** in identifying and helping at-risk individuals.

2.3 FEASIBILITY STUDY

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are,

- ECONOMICAL FEASIBILITY
- TECHNICAL FEASIBILITY
- SOCIAL FEASIBILITY

2.3.1 ECONOMICAL FEASIBILITY

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

2.3.2 TECHNICAL FEASIBILITY

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

2.3.3 SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

2.4 HARDWARE AND SOFTWARE REQUIREMENTS

SYSTEM SPECIFICATION:

HARDWARE REQUIREMENTS:

- System : Intel i7
- Hard Disk : 1 TB.
- Monitor : 14’ Colour Monitor.
- Mouse : Optical Mouse.
- Ram : 8GB.

SOFTWARE REQUIREMENTS:

- ❖ Operating system : Windows 10.
- ❖ Coding Language : Python.
- ❖ Front-End : Html. CSS
- ❖ Designing : Html,css,javascript.
- ❖ Data Base : SQLite.

REQUIREMENT ANALYSIS

The project involved analyzing the design of few applications so as to make the application more users friendly. To do so, it was really important to keep the navigations from one screen to the other well-ordered and at the same time reducing the amount of typing the user needs to do. In order to make the application more accessible, the browser version had to be chosen so that it is compatible with most of the Browsers.

REQUIREMENT SPECIFICATION

Functional Requirements

- Graphical User interface with the User.

Software Requirements

For developing the application, the following are the Software Requirements:

- Python
- Django

Operating Systems supported

- Windows 10 64-bit OS

Technologies and Languages used to Develop

- Python

Debugger and Emulator

- Any Browser (Particularly Chrome)

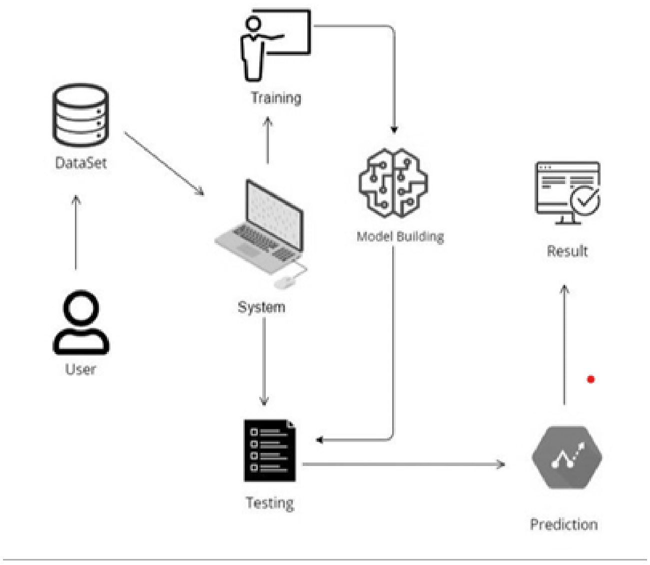
Hardware Requirements

For developing the application, the following are the Hardware Requirements:

- Processor: Intel i9
- RAM: 32 GB
- Space on Hard Disk: minimum 1 TB

III. SYSTEM DESIGN

3.1 SYSTEM ARCHITECTURE:



3.2 DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.

IV. CONCLUSIONS

For this project, we used machine learning model approaches such decision trees, random forests, logistic regression, Multi-Layer-Perceptron (MLP) and Adam (Adaptive Moment Estimation) to create a user-friendly application named prediction of smartphone addiction. Using the finest methods we could find, we were able to demonstrate that while some people are not addicted, they may be. We have successfully developed a user-friendly application in this project that uses Machine Learning Model approaches to predict smartphone addiction. The goal was to provide a workable way to identify those who could be at risk of developing a smartphone addiction. For the most accurate forecasts, this study has carefully selected and adjusted these machine learning algorithms and developed a strong prediction model by utilizing a broad dataset that included several variables including screen time, app usage, and self-reported behaviours. This approach offers important insights into consumers' smartphone usage behaviours by classifying them into three groups: possibly addicted, not addicted, and addicted.

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