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Intelligent Prediction of Smartphone Addiction Through Machine Learning Algorithms

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Abstract- — A rising number of individuals are displaying signs such as excessive phone usage, loss of productivity, and even physical and psychological health concerns, making Smartphone addiction a major worry in recent years. The development of reliable instruments for the prediction of Smartphone addiction and the identification of those at risk is, hence, necessary. Using survey data on Smartphone use, we constructed a machine learning model to forecast Smartphone addiction in this research. There was a wide variety of mental health concerns addressed in the survey, including demographics, phone use patterns, and anxiety, despairs, and stress. The model was constructed using a well-liked and efficient machine learning technique. In this work, numerical variables are normalized and categorical variables are encoded as part of the data preprocessing to make sure the model can train properly. Also, we used measures like accuracy to measure the model's performance on the remaining data after training it on a subset of the data. The algorithm has successfully predicted Smartphone addiction with a high degree of accuracy, according to the findings. Use habits of mobile phones, including how often notifications were checked, how many hours spent on the phone daily, and the applications used most often, were the most critical variables for predicting addiction. Age, gender, and stress levels were other important factors. The constructed model has a number of possible uses. Healthcare providers might use it to identify patients at risk of Smartphone addiction and intervene accordingly. Also, app makers may utilize it to make their applications less addicting and more conducive to healthy phone habits. In a nutshell, the results show that machine learning algorithms can effectively predict Smartphone addiction. We need to conduct further studies to confirm our results on bigger and more varied datasets and to investigate other possible uses for this approach.

Keywords: Machine learning methods, decision trees, logistic regression, Convolutional neural networks (CNNs), random forests.

I. INTRODUCTION

Over the past years, there has been a continuous growth in the usage of smart phones, 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 smart phones, demographic data, and psychological aspects maybe created using machine learning.

These models can be used to detect people who may become addicted to smart phones 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.

The use of cell phones, which are now integral to our daily lives, has been steadily increasing over the last few years. There are many positive aspects of mobile phones, but there is also a risk of addiction and negative effects on productivity, social connections, physical and mental health, and relationships when used excessively. Using demographic data, Smartphone use habits, and social media use, and psychological factors, machine learning models may be trained to predict Smartphone addiction.

With these models, we can identify potential Smartphone addicts and provide them the care they need before it's too late. In order to build a machine learning model that can predict Smartphone addiction, it is common practice to collect data from a large population. Their social media and Smartphone use patterns, together with their age, gender, and psychological traits like anxiety, sadness, and stress, would all be part of this data set.

One way to evaluate the model's performance is by looking at its accuracy. The model is fine-tuned by modifying its parameters or using other techniques until it achieves satisfactory performance. After the model is built, it may be used to predict whether someone would get addicted to their

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smart phone based on their input. The programme generates an approvability score that indicates the likelihood of developing an addiction to smart phones. The results may help in determining what kinds of therapies and support are most effective for those who are most vulnerable to addiction. In conclusion, machine learning models have the potential to be an effective weapon in the fight against Smartphone addiction by predicting which individuals are most likely to develop an addiction and which ones are at danger. These models may be useful for healthcare providers and individuals in the fight against addiction and its negative effects. However, it is critical to collect high-quality data and build reliable models that perform well in real-world scenarios.

Fig 1. Block Diagram of Proposed System

One of the metrics used to evaluate the model's efficacy is accuracy. Models are fine-tuned by modifying their parameters or using other techniques until they achieve satisfactory performance. In order to predict if a person would get addicted to their Smartphone, the model may be trained using user input characteristics. The algorithm generates an approval score that indicates the likelihood of developing an addiction to smart phones. Based on their score, those at risk of addiction may get the appropriate treatments and help. In conclusion, machine learning models may help in predicting the probability of Smartphone addiction and in identifying those at risk of developing an addiction. Healthcare providers and individuals alike may benefit from these models as they work to combat addiction and mitigate its negative effects. However, it is critical to collect high-quality data and build reliable models that perform well in real-world scenarios.

II. RELATED WORKS

This chapter provides a concise overview of all the research that has been carried out so far. It also compiles the findings of all the studies that have attempted to forecast Smartphone addiction so far, covering both the successes and failures of earlier technologies and the difficulties that users encounter. The project's issue statement is thus born, detailing the difficulties inherent in bot creation and performance and offering a suggested architectural solution. The effect of mobile learning apps on students' perceptions and academic achievement was examined in a research conducted by Demir and Akpinat (2018).This study examines the academic performance, attitudes, and mobile technologies of undergraduate students.

Mobile learning apps impact levels of learning and animation development.A quasi-experimental design was used for the investigation. The study's participants were undergraduates from Turkey's Buca Faculty of Education at Dokuz Eylul University. In the first semester of the 2013–2014 academic years, the experiment was carried out. In contrast to the control group's 26 students, 15 in the experimental group used a mobile learning approach. Using an attitude scale, we measured students' views on mobile learning, and an accomplishment test, we looked at how students' use of mobile learning apps affected their grades. The students' animations were evaluated using a set of criteria.

They felt that mobile learning was a great strategy that might really inspire them to do better. Scholars and professionals must recognize that mobile learning may motivate students and improve their performance and accomplishments. Abadiyan et al. (2021) conducted a randomized controlled experiment to examine the efficacy of integrating a Smartphone app with global postural re-education in improving outcomes for individuals with nonspecific neck pain. These outcomes included better posture, enhanced quality of life, and endurance. In this study, researchers looked at how individuals with chronic neck pain and forward head posture (FHP) fared after participating in an 8-week global postural reeducation (GPR) programme that included a Smartphone app. The participants' pain levels, endurance levels, quality of life, and FHP were all assessed.

Group 1 consisted of thirty office workers who had recurrent neck pain for an average of 38.5 ± 9.1 years; group 2 consisted of twenty people who received GPR alone; and group 3 consisted of twenty people who received no treatment at all. Twenty of the women in this study and twenty of the men were randomly allocated to these groups. In terms of outcomes, pain was at the top, with disability, quality of life, posture, and endurance following closely after. After 8 weeks of treatment, participants were assessed for pain, disability, endurance, quality of life, and posture using photogrammetric, the progressive is-inertial lifting evaluation (PILE) test, the visual analogue scale (VAS), the quality of life questionnaire (SF-36), and the neck disability index (NDI), respectively. An analysis of covariance (ANCOVA) was used to statistically assess the data.

III. PROPOSED MODEL

The proposed method addresses the increasing issue of Smartphone addiction by using machine learning to predict the likelihood of addiction in Smartphone users. Stress, anxiety, and sadness are just a few of the psychological characteristics that are part of the many datasets that are examined using a multipronged technique that combines categorization algorithms. Other datasets include demographic information and phone use habits. The system acquires pertinent information required for predictive analysis via the exhaustive collection of survey data. Next, the collected data is meticulously preprocessed to make it ready for use by machine learning algorithms. The goal of this preprocessing stage is to fix missing values and encode categorical variables to make the data as good as possible for the following stage of model training. Model training is the meat and potatoes of the proposed method; it teaches ML algorithms to use preprocessed data to predict Smartphone addiction tendencies.

The system is able to construct trustworthy prediction models that can detect patterns indicative of addiction risk by using the Python programming language and popular machine learning frameworks such as Tensor Flow and scikit-learn.These models can efficiently process large datasets, enabling lightning-fast predictions and reactions.Optimising techniques such as parallel processing and model caching further enhance the system's performance and scalability, ensuring accurate and rapid predictions regardless of the increase in user demands. The data gathering processes are made easier with the recommended system because of how easily it integrates and work with existing survey platforms and mobile apps.

The proposed approach has several anticipated benefits. Facilitating the early detection of tendencies towards Smartphone addiction among users allows stakeholders to intervene proactively and give targeted help. It also enhances understanding of the complex relationships between the factors that contribute to addiction, enabling the development of tailored treatments and interventions to kerb the disease. The proposed method's end objective is to improve people's health and happiness in the modern digital age by promoting more responsible Smartphone use.

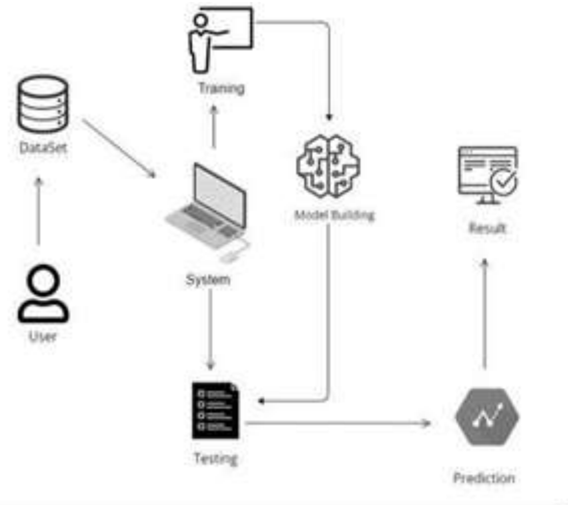

Fig 2. Architecture Diagram

A multi-layer perception (MLP) is a kind of neural network design that uses several levels of coupled nodes. There is an input layer that takes in data, hidden layers that process it, and an output layer that either classifies or makes predictions based on the processed information. Information is transferred from one layer to another by weighted connections between nodes. The network activation functions allow the model to represent complicated data interactions by introducing nonlinearities. The versatility of MLPs makes them well-suited for tasks like classification and regression. Nevertheless, when faced with enormous datasets, they may become computationally costly and are susceptible to over fitting, a phenomenon in which the model memorizes the training data rather than generalizing.

With so many real-world examples, it's clear that trees have had a significant influence on several aspects of machine learning, including regression and classification. Decision trees may be used in decision analysis to formally and visually depict choices and decision making. It employs a decision-tree model, as the name suggests. Regardless, it is a typically used data mining technique for deciding how to accomplish a given task. The root is at the top of an inverted decision tree image. In the image on the left, the tree branches out into edges, as shown by the bold black writing, which represents an interior node or condition. When a branch can no longer divide, it is said to have reached its decision or leaf.

The random forest technique is one machine learning approach to problems with classification and regression. To solve difficult issues, it uses ensemble learning, which involves combining a large number of classifiers. The method known as random forest is really a collection of decision trees. The "forest" that the random forest approach uses to learn is acquired by bagging or bootstrap aggregation. An ensemble met algorithm called bagging helps machine learning algorithms improve their accuracy. The decision trees' predictions are used by the random forest approach to select the result. In order to make predictions, it averages the results from several trees. Results will be more precise as the number of trees utilized increases.

IV. RESULTS AND DISCUSSION

Findings are derived from the dataset that encompasses several behaviors connected to Smartphone use and addiction and has 21 attributes and 500 tuples. Time stamp, full name, and gender are some of the features. Other questions include social behavior, battery dependency, phone use patterns, and gadget reliance in various settings. Questions like "How do you use your phone for schoolwork?" "Do you buy books online?" and "Are you worried about running out of juice?" might provide light on user habits.
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V. CONCLUSION

Created using a variety of machine learning model methods, including decision trees, logistic regression, Adam (Adaptive Moment Estimation), and Multi-Layer-Perception (MLP), we set out to build intuitive software for predicting Smartphone addiction for this project. While some individuals are not hooked, they may be if we used the best tactics we could discover. As part of this research, we were able to create easy-to-use software that can detect Smartphone addiction using Machine Learning Model techniques. The objective was to provide a practical method for determining who was at danger of becoming addicted to their smart phones. Using a large dataset that includes characteristics including screen time, app use, and self-reported behaviors, this research has constructed a robust prediction model by meticulously selecting and adjusting these machine learning algorithms. The goal was to get the most accurate projections possible. The method divides people into three categories: potentially addicted, not addicted, and addicted, which provides valuable information on how people use their smart phones.

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