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PREDICTING SMART PHONE ADDICTION USING A MACHINE LEARNING APPROACH

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***Abstract*—** The iss.ue of Smart.phone addic.tion has bec.ome one of the top.ics of conc.ern over the last few yea.rs, as more peo.ple find thems.elves with exces.sive use of the dev.ice, loss of produc.tivity, and are physi.cally and psycholo.gically affected. There.fore, the need to deter.mine accurate meas.ures of predi.cting smart.phone addic.tion and find.ing out who is at risk is incre.asing. This stu.dy applies mach.ine lear.ning to come up with a mod.el that can pred.ict smart.phone addiction usi.ng the data, whi.ch was colle.cted in the sur.vey condu.cted on smart.phone use.rs. Demogr.aphic (incl.uding age, gen.der), behav.ioral (incl.uding the usa.ge of smartphones, the.ir usa.ge frequ.ency, time spe.nt on them), and psychol.ogical (incl.uding str.ess, anxi.ety, depre.ssion, etc.) inform.ation is also encl.osed in the data.set. The mod.el is trai.ned usi.ng a sub.set of the data and it is tes.ted on the rest of the data usi.ng perfor.mance measures like accu.racy. Accor.ding to experi.mental find.ings, the proposed mod.el is of high predi.ctive perfor.mance. Smart.phone usa.ge hab.its, like the frequ.ency of checking notific.ations, the time spe.nt at the phone eve.ry day, and the most frequ.ently used typ.es of applic.ations, are some of the key aspe.cts of addic.tion predi.ction. On the who.le, this pap.er sho.ws that mach.ine lear.ning meth.ods can be effec.tive and appli.cable in predi.cting smart.phone addic.tion.

Keywords— Deci.sion Tree, Ran.dom Forest, Logi.stic Regression, Convolu.tional Neu.ral Netw.ork (CNN), Mach.ine Lear.ning techn.iques.

INTRODUCTION

Smart.phone usa.ge has bec.ome a huge tre.nd in rec.ent yea.rs, and the.ir use is now rega.rded as the insepa.rable compo.nent of everyday life. Even tho.ugh sma.rt pho.nes have a host of advantages, when used too much and out of cont.rol, peo.ple bec.ome addi.cted to them, which negat.ively impa.cts on the.ir productivity, soc.ial life, as well as the.ir phys.ical and men.tal hea.lth.

Machine lear.ning (ML) can be a valuable appr.oach to predicting smart.phone addic.tion, it is poss.ible to use its too.ls thro.ugh the anal.ysis of smart.phone usa.ge behav.iors, demogr.aphics, and psychol.ogical aspe.cts, i.e. str.ess, anxi.ety, and depre.ssion. The.se predictive mod.els can be used to identify peo.ple who are at risk and take ear.ly acti.ons to ens.ure that tho.se peo.ple ado.pt better usa.ge hab.its.

The crea.tion of an ML-based predi.ction mod.el sta.rts with gathe.ring the data on the large-po.pulation by usi.ng the sur.vey met.hod. The varia.bles consi.dered in the data.set are the usage behav.iour in smartp.hones and soc.ial med.ia, demographic varia.bles like age and gen.der, psychological indic.ators.

A suit.able ML algor.ithm is then cho.sen and is trained with the proce.ssed data.set in ord.er to get a relati.onship between input feat.ures and addic.tion outc.omes. The perfor.mance on the mod.el is deter.mined bas.ed on the test.ing data and accu.racy is a prim.ary meas.ure of evalu.ation. The trai.ned mod.el com.es up with a probab.ility score whi.ch is the prope.nsity of an indiv.idual to be addi.cted to a smart.phone

Other behavior characteristics including screen time daily, the number of times one uses the apps, sleep interruption and late-night patterns also help in increasing the prediction accuracy. Data balancing and cross-validation techniques enhance the robustness and reliability of the models, which can be appropriate to use the suggested approach in the actual situation regarding smartphone addiction prediction.

LITERATURE REVIEW

Chapter gives a brief literature review on the previous studies concerning smartphone use, mobile technology, and challenges related to it. It outlines the research on smartphone addiction prediction, mentions technological progress, and explains challenges users experience. According to the given review, the gaps in the research are recognized, and the problem statement is formulated covering the issues of the system development and performance and stating the relevant architectural framework.

Demir and Akpinary researched the contribution of mobile learning applications to the academic performance of student as well as their attitude towards mobile learning [1]. The authors checked the influence of mobile scale methods of instruction in terms of academic performance, attitudes to mobile learning and skills in development of animation among the undergraduate students. In a quasi- experience based design, the experimental group (n = 15) used mobile learning strategies, whereas the control group (n = 26) relied on traditional lecture based teaching of the students in Dokuz Eylul University, Turkey. It was assessed with regards to attitudes, academic performance, and animation productions and it was found out that mobile learning highly boosted motivation and academic success [1].

Abadiyan et al. used a randomized controlled trial to measure the efficacy of global postural re- education (GPR) along with a smartphone application in patient care with nonspecific neck pain [4]. The standardized instruments that were used to measure pain level, level of disability, endurance, posture and quality of life included Visual Analog Scale (VAS), Neck Disability Index (NDI), and SF-36 questionnaire. The outcomes of ANCOVA have shown that the use of smartphones applications with postural re-education to achieve better clinical outcomes is significant when compared to traditional methods [4].

A systematic review conducted by Osorio-Molina et al. indicated an issue of smartphone addiction among nursing students and its adverse consequences in terms of academic achievements and wellbeing [3]. Equally, a study by Sohn et al. assessed the connection between smartphone and sleeping behavior in young adults with the results revealing high correlation between high usage of smartphones and sleep disturbances [2]. Wilkerson et al. delved into musculoskeletal and cognitive consequences of smartphone use by finding out that the result of the prolonged use of smartphones was detrimental to hand- or pinch-grip strength along with other health outcomes [5]. The findings are correlated with the investigations that highlight physical and psychological dangers of overuse of the smartphone [4], [5].

A number of studies have examined predictive modeling of smartphone addiction using machine learning models. Behavioral and demographic data have been analyzed with the help of the Random Forest, Decision Trees, and logistic regression to discover risk factors of addiction [7], [8], [9]. Wayahdi and Ruziq have employed K-Nearest Neighbors to forecast the level of addiction to smartphones with reference to user behavioral patterns [10] whereas vimala and sheela have utilized machine learning models to assess the contribution of addiction to academic performance [11]. Kalpana and Susheela verified the effectiveness of various machine learning and algorithms in addiction tendencies prediction [12], whereas Sangeetha and Noortaj applied the logistic regression model in risk forecasting [13]. There have also been advanced methods of classifying users based on the severity of addictions like latent class analysis [14]. The systematic reviews further emphasize related health outcomes and risk factors in adult population and recent studies included the use of the app application data in conjunction with the predictive model on mental health and wellbeing [17], [18].

All in all, these researches show the variability of these applications of smartphones in education, clinical, and behavioral spheres [1], [2], [3], [4], [5]. The results demonstrate the need to create smart and data-driven models to track smartphone usage and make predictions about developing addiction tendencies, thus enabling timely treatment and effective decision-making [2], [3], [7], [10],[12].

PROPOSED MODEL

The proposed approach addresses the growing concern of smartphone addiction by leveraging machine learning techniques to predict addictive tendencies among smartphone users. The system follows a multidimensional framework that integrates classification-based models to analyze heterogeneous data, including smartphone usage behavior, demographic characteristics, and psychological factors such as stress, anxiety, and depression. Data required for prediction is collected through structured surveys, ensuring comprehensive coverage of user behavior and mental health indicators.

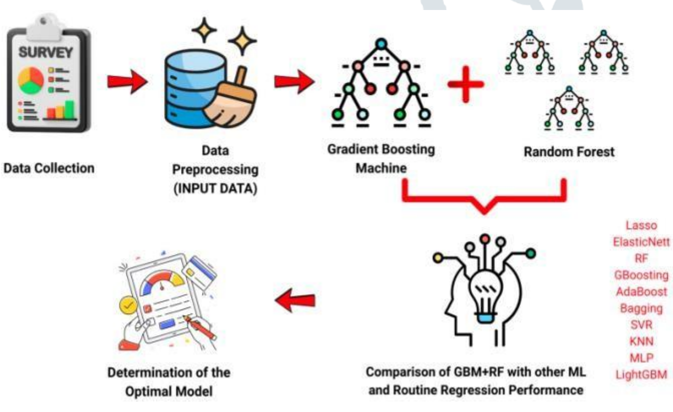
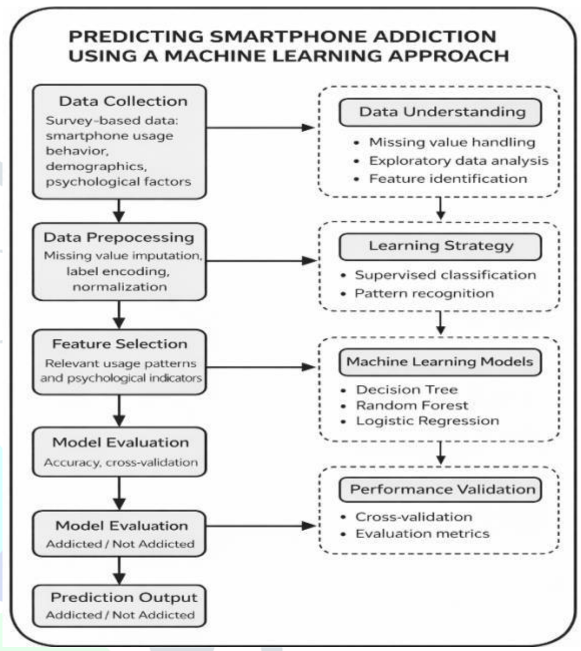


Fig: System architecture

After data acquisition, a systematic preprocessing phase is carried out to enhance data quality. This includes handling missing values through imputation, encoding categorical variables into numerical form, and structuring the dataset to make it suitable for machine learning analysis. These steps ensure reliable feature representation and improved model performance.To support scalability and real-time applicability, the system

The core component of the system is the model training phase, where selected machine learning algorithms are trained on the preprocessed dataset to estimate smartphone addiction risk. The implementation is carried out using Python and established machine learning libraries such as **scikit-learn** and **TensorFlow**, enabling efficient model development and evaluation. The trained models learn behavioral patterns associated with excessive smartphone usage and generate accurate predictions.



is designed to handle large datasets efficiently. Optimization strategies such as parallel processing and model caching are incorporated to enhance computational performance while maintaining prediction accuracy. The proposed framework facilitates early identification of individuals at risk of smartphone addiction, enabling timely intervention strategies. Ultimately, the system aims to promote healthier smartphone usage habits and improve overall user well-being in the modern digital environment by employing reliable and effective machine learning models.

ALGORITHMS USED

1. Decision Tree

A tree-based model used for classification and regression. Internal nodes represent conditions, while leaf nodes indicate decisions.

Gini Impurity :

$$Gii(t) = 1 - \sum_{i=1}^{C} p^2{}_i$$

2. Random Forest

An ensemble of decision trees using bagging to improve prediction accuracy by averaging outputs from multiple trees.

Final Prediction :

$$\hat{y} = \mathrm{mode}\{h_1(x), h_2(x), \dots, h_n(x)\}$$

3. Logistic Regression

Logistic Regression is a statistical model used for binary classification by estimating the probability of an outcome using a sigmoid function.

Sigmoid Probability Function:

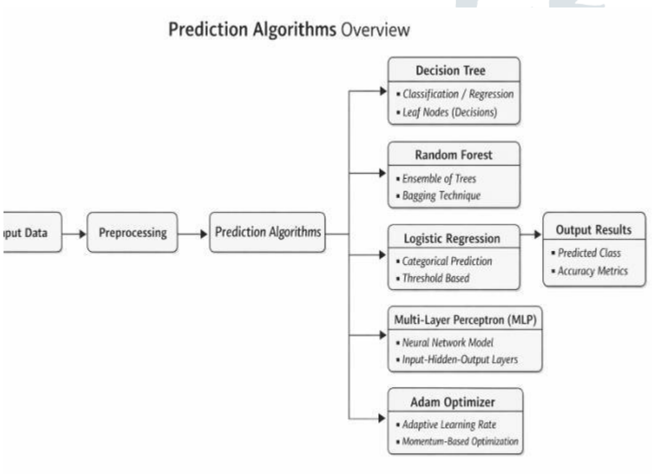
$$P(y = 1 \mid x) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}}$$

4. Multi-Layer Perceptron (MLP)

MLP is a feedforward neural network capable of learning complex nonlinear patterns through weighted connections and activation functions.

Neuron Activation:

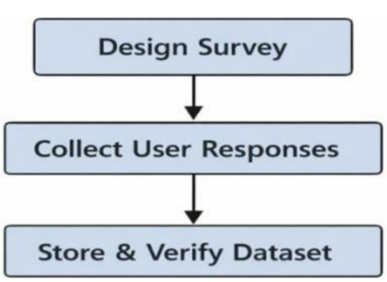
$$z = \sum_{i=1}^{n} w_i x_i + b$$



METHODOLOGY

1. Data Collection

The dataset was collected through a structured survey of **500 smartphone users**, capturing demographics (age, gender), smartphone usage behavior (daily screen time, phone-check frequency, app categories), and psychological factors (stress, anxiety, dependency).

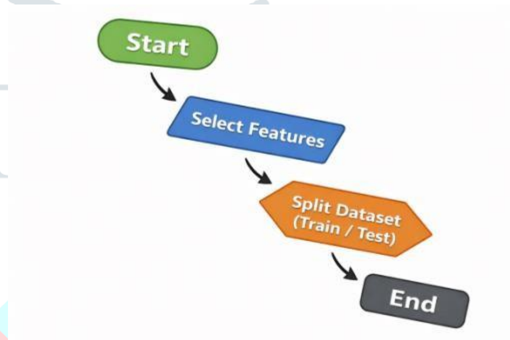


2. Data Preprocessing

The dataset was cleaned to handle missing values, inconsistencies, and redundancies. Categorical variables were converted to numerical form using label encoding, and numerical features were normalized to a common scale for fair contribution during model training.

3. Feature Selection and Dataset Splitting

Key features influencing smartphone addiction such as screen time, notification frequency, app usage patterns, and anxiety indicators were selected based on exploratory analysis. The preprocessed dataset was then split into **training and testing sets** to enable model development and evaluation.

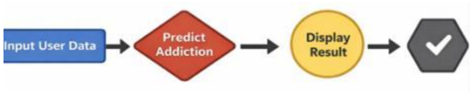


4. Model Development and Evaluation

Various machine learning and deep learning models such as Decision Tree, Random Forest, Logistic Regression and Multi-layer Perceptron (MLP) were applied in predicting smart phone addiction. The training dataset was used to train models in order to learn the relationships between the selected features and addiction labels. The Adam algorithm was used to optimize neural networks faster and stabilize the results because of the high convergence rate, and also enhanced accuracy characterization of the ensemble models such as Random Forest was used by utilizing more than one tree. The class imbalance management and hyperparameter optimization were used to improve the performance and minimize overfitting. The models were tested on the testing data by using the accuracy as the main metric. Comparative analysis was used to find the most effective approach and the importance of features analysis was used to show how much it was contributed by particular attributes to the prediction.

5. This is predicted and explained.

After training and validation, the final model creates a prediction on whether a user is addicted or not addicted to the smart phones. The outcome of prediction can be used to detect people at high risk who can be subjected to early intervention. The findings prove that behavioral and psychological data could be analyzed using machine learning techniques and predict smartphone addiction with a high level of reliability.



RESULTS AND ANALYSIS

The proposed smartphone addiction prediction system was evaluated on a dataset of 500 records with 21 features covering usage behavior, demographics, and psychological factors.

Model Performance Comparison

Model	Accuracy (%)	Precision (%)	Recall	F1-Score (%)
Decision Tree	78.6	76.2	74.8	75.5
Random Forest	88.4	89.1	86.7	87.9
Logistic Regression	81.2	80.4	79.5	79.9
MLP	87.1	85.6	84.2	84.9
Adam Neural Network	85.7	86.3	83.9	85.1

1. Accuracy

Measures the overall correctness of the model:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. Precision

Measures the proportion of predicted positives that are actually positive:

$$\text{Precision} = \frac{TP}{TP + FP}$$

3. Recall (Sensitivity / True Positive Rate)

Measures the proportion of actual positives correctly identified:

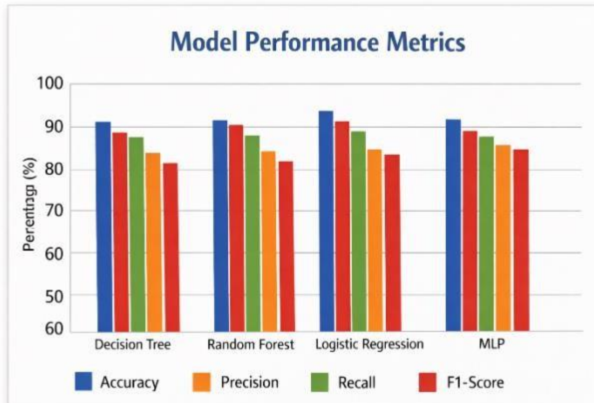
$$\text{Recall} = \frac{TP}{TP + FN}$$

4. F1-Score

Harmonic mean of Precision and Recall, balancing both metrics:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Data preprocessing included label encoding and normalization. Several machine learning and deep learning models Decision Tree, Random Forest, Logistic Regression, Multi-Layer Perceptron (MLP), and Adam-optimized neural networks were trained and tested. Random Forest and MLP achieved the highest accuracy by capturing complex patterns, while Logistic Regression provided stable baseline results and Decision Tree offered interpretability but was sensitive to data variations. Feature importance analysis identified screen time, phone-check frequency, application usage, and anxiety related to smartphone dependence as key indicators, with age and gender showing moderate influence. The system effectively classified users into addiction categories, demonstrating the potential of machine learning for behavioral prediction.



CONCLUSION

The given paper presented a machine learning-driven solution to predicting smartphone addiction, basing on survey-based behavioral and psychological data. Several classification and deep learning algorithms were used and the system was successful in detecting addiction tendencies of users. The evidence of the experiment reveals that machine learning models have the capability of studying the smartphone usage behavior with a high degree of accuracy and arriving at meaningful predictions, which may serve as a useful solution to detecting individuals at an earlier stage; later, which can take appropriate protective actions to mitigate the problem.

Future research will aim at increasing the number of samples to generalize better, including real-time usage of smartphones, and considering other sophisticated deep learning architecture like CNNs or hybrid architecture to learn the more complicated behavioral patterns. The introduction of explainable AI methods can improve the level of transparency and user trust, and a system can be further expanded into a mobile application to conduct constant monitoring and provide individual advice on interventions, which will encourage responsible smartphone use and digital wellbeing.

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