Predicting Mobile Screen Time and Addiction Using Regression and Classification Models

By: Abdelrahman Mahdi, Arwa Mostafa, Ethar Mostafa, Kareem Elkenany, Noureen Ibrahim, and Rana Wael

Abstract

This project investigates the relationship between smartphone usage behavior, stress, and mobile phone addiction through machine learning techniques. Using two real-world datasets — one focused on general user behavior and another on mobile addiction — we applied a series of regression models (Linear, Ridge, Lasso, ElasticNet, Decision Tree, Random Forest, and XGBoost) to predict daily screen time. Additionally, classification models (Naïve Bayes, K-Nearest Neighbors, Decision Tree, and Random Forest) were used to predict whether a user is addicted to their phone.

Our results showed that ensemble models like Random Forest and XGBoost performed best in regression tasks, achieving R^2 scores above 0.93. For classification, Naïve Bayes and Random Forest consistently outperformed other models with high accuracy and AUC scores. Feature correlations and model evaluations revealed that behavioral indicators such as app sessions, notifications, and stress levels were strong predictors of screen time and addiction.

This study highlights the effectiveness of machine learning in understanding digital behavior and identifying users at risk of phone addiction, paving the way for targeted interventions and digital wellbeing tools.

Introduction

Background and Context

These days, almost everyone uses a smartphone for communication, entertainment, or staying connected to the world. While phones are useful, using them too much can become a problem, developing something known as mobile phone addiction. This happens when someone feels like they can't stop using their phone, even if it's affecting their daily life, school, or mental health. At the same time, stress has become a big issue, especially for students. School work, exams, social pressure, and other challenges can get overwhelming. Since both stress and phone addiction are common among students, we started wondering, could they be related? That's what our project is about.

Literature Review

Previous research suggests there might be a link between stress and mobile phone addiction. For example, one study conducted by Gao et al. (2022) found that students in a sample of Chinese college students who reported higher stress levels also tended to use their phones more in ways that could be harmful or addictive. Another study conducted by Jeong et al. (2022) showed that stress can lower self-control, which might make people more likely to spend extra time on their

phones to escape or feel better temporarily. These findings made us think that students might use their phones to cope with stress, but that could lead to unhealthy habits.

Project Objectives

In our project, we want to find out if stress levels are connected to mobile phone addiction. Our main goals are:

1. To see if students who feel more stressed are more likely to show signs of mobile phone addiction.
2. To understand whether stress could be used as a predictor of phone addiction in students.

By the end of this project, we hope to better understand how stress and phone use are connected. This could help raise awareness and maybe even lead to ideas for how to manage stress and phone habits in healthier ways.

Materials and Methods

Data Description

In this project we will be using 2 datasets:

1. User behavior dataset
2. Mobile addiction dataset

Dataset 1: user behavior dataset

- **Source of Data:**
  This dataset was sourced from Kaggle and includes behavioral data for 700 smartphone users.
- **Key Variables and Types:**
  The dataset includes both numerical and categorical variables. Some of the key variables are:
  - Numerical: App usage time (minutes), Screen on time (hours), Battery drain (mAh), Data usage (MB), Number of apps installed, Age.
  - Categorical: Device model, Operating system, Gender, User behavior class.
- **Data Size and Structure:**
  The dataset contains 700 rows and multiple columns representing device details, user demographics, and phone usage statistics. It is well-structured with no missing or duplicate values.
- **Data Cleaning and Preprocessing:**
  - No missing or duplicate data was found.
  - Descriptive statistics (mean, standard deviation, quartiles) were calculated for all numerical variables.
  - Outlier detection was performed using the IQR method, but no significant outliers were identified.

- The data showed logical consistency (e.g., screen time > app usage time), and Android users dominated the dataset.

Dataset 2: mobile addiction dataset

- **Source of Data:**
  This dataset was also sourced from Kaggle and includes detailed behavioral data for 13,600 participants (reduced to 13,331 after preprocessing).
- **Key Variables and Types:**
  The dataset consists of mostly numerical variables. Some of the key variables are:
  - Numerical: Daily screen time (hours), App sessions, social media usage (hours), Gaming time (hours), Notifications received, Night usage (hours), Age, Work/study hours, Stress level (on a scale), Apps installed.
  - Categorical: Addicted (Addicted/Not Addicted)
- **Data Size and Structure:**
  The dataset originally had 13,600 records, with each row representing a participant. After removing outliers, the final size was 13,331.
- **Data Cleaning and Preprocessing:**
  - Checked for and confirmed no null or duplicate values.
  - Converted the Addicted column to a categorical variable.
  - Performed statistical analysis (mean, standard deviation, min, max) for all numerical columns.
  - Detected and removed 271 outliers using the Z-test method.
  - Conducted the Anderson-Darling test, which showed the data does not follow a normal distribution.

Methodology

- Data Visualization
- Regression
  We used seven regression models:
  1. **Linear Regression**
     How it works:
     Linear Regression models the relationship between the input features and the target variable by fitting a straight line (or hyperplane) that minimizes the sum of squared residuals (errors between actual and predicted values). It assumes linear relationships between independent variables and the dependent variable.
     Why Chosen:
     - Fast and simple to implement.
     - Provides a clear baseline for performance comparison.
  2. **Ridge Regression**

How it works:

Ridge Regression extends linear regression by adding L2 regularization, which penalizes the sum of the squared coefficients. This discourages large weights and helps prevent overfitting, especially in the presence of multicollinearity (when features are highly correlated).

Why Chosen:

- Addresses multicollinearity effectively.
- Maintains all features while reducing model complexity.
- Useful when interpretability is important, but feature selection is not necessary.

3. **Lasso Regression**

How it works:

Lasso regression uses L1 regularization to minimize the sum of squared errors while penalizing the **absolute** values of coefficients. This encourages sparsity, effectively performing feature selection by shrinking some coefficients to exactly zero.

Why chosen:

- Suitable for datasets with many correlated features.
- Helps reduce overfitting and improves interpretability.
- Acts as a strong baseline linear model.

4. **Elastic Net Regression**

How it works:

Elastic Net combines L1 (Lasso) and L2 (Ridge) regularization in a single model. This allows it to inherit both sparsity (from L1) and coefficient stability (from L2), making it more flexible in handling correlated features.

Why chosen:

- Better suited for correlated features than Lasso alone.
- Provides stable and generalizable predictions.

5. **XGBoost Regression**

How it works:

XGBoost is a gradient boosting algorithm that builds an ensemble of decision trees sequentially. Each tree is trained to correct the errors of its predecessor by minimizing a regularized objective function. It incorporates both L1 and L2 regularization and uses advanced techniques like tree pruning, column subsampling, and parallelization.

Why Chosen:

- Powerful and scalable model.
- Captures complex patterns and interactions.
- Handles missing values and regularizes well.

6. **Random Forest Regression**

How it works:

Random Forest builds multiple decision trees using bootstrapped subsets of the data and averages their predictions to improve generalization. It introduces randomness by

selecting a random subset of features at each split, which reduces variance and overfitting.

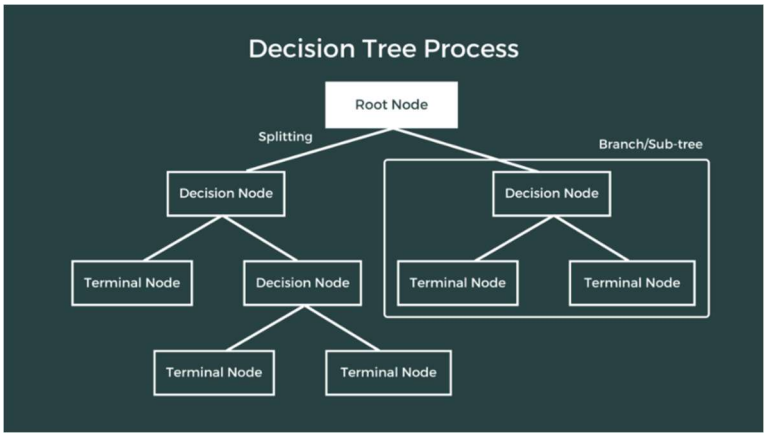
Why Chosen:

- Handles nonlinearity and feature interactions well.
- Robust to multicollinearity and overfitting.
- Effective on moderately sized datasets.

7. **Decision Tree Regression**

How it works:

Decision Tree Regression splits the data into subsets based on feature values that minimize the variance of the target variable within each split. The process continues recursively, creating a tree where each internal node represents a decision rule and each leaf node represents a predicted value. The model makes predictions by traversing the tree from root to leaf based on the input features.



Why Chosen:

- Simple and interpretable model.
- Captures nonlinear relationships and interactions.
- Useful as a baseline for tree-based ensemble methods.

- **Classification**

We used four classification models:

- **Gaussian Naïve Bayes**

  Justification for Choosing Naïve Bayes

  I chose to use the Naïve Bayes classifier because it's a simple and powerful algorithm, especially for binary classification problems like predicting whether a user is addicted or not. The dataset included several numerical features such daily screen time, app sessions, gaming time, which are fit for the Gaussian Naive Bayes variant since it handles continuous data under the assumption of normal distribution.

- **K-Nearest Neighbors**

  Justification for Choosing KNN

I chose KNN because it's a simple algorithm that makes predictions based on how similar (close) the data points are across all selected features by calculating the Euclidean distance. It is non-parametric which means it doesn't assume any specific distribution of the data. Since my dataset (mobile_addiction_cleaned.csv) is made up of clean numerical features (e.g. daily screen time, app sessions, notifications), it fits KNN very well because these types of models work best with numerical, scaled data. Also, KNN is sensitive to the structure of the data, so it was a good candidate for exploring whether natural clusters of "addicted" vs "not addicted" users exist based on mobile usage behavior.

- **Decision Tree**

Justification for Choosing Decision Tree Classifier

I applied a Decision Tree Classifier to the mobile addiction dataset to explore how well it can distinguish between "addicted" and "not addicted" users based on various behavioral features. A decision tree is a supervised machine learning algorithm that splits the dataset into subsets based on feature values, creating a tree-like structure where each parent node represents a feature decision, each branch represents an outcome, and each leaf node represents a class label (in this case, not addicted = 0 or addicted = 1).

Why Decision Tree?

I chose a Decision Tree because:

- It visually represents how decisions are made.
- It is non-parametric meaning it makes no assumptions about data distribution, which is ideal given that many of the features in the dataset are not normally distributed.
- It is effective in modelling complex feature interactions like those observed between social media use, notifications, and stress level.

The core concept behind a decision tree is selecting the best feature or best split to split the data at each node. This is done using impurity measures like Information Gain (Entropy). For example, Entropy is calculated as:

$$Entropy = \sum - \ p_i \ \log(p_i)$$

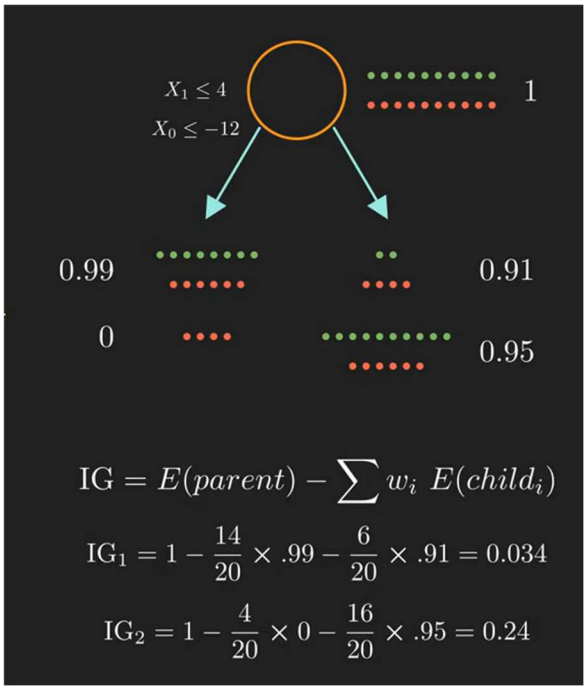
where p_i is the probability of class i. The algorithm calculates the entropy for each node (parent and children) then calculates the information gain using the following equation:

$$\mathrm{IG} = E(parent) - \sum w_i \ E(child_i)$$

where w_i is the weight of the i^{th} child, it is calculated by:

$$\text{weight}(\text{child}_i) = \frac{\text{number of samples in child}_i}{\text{number of samples in parent}}$$

- The algorithm tries every possible split and chooses the split with the highest information gain. NOTE: a "pure" state (all samples belong to one class) has an entropy of 0, while an entropy of 1 indicates equal probabilities of each class (in binary classification, each class would have a probability of 0.5)



- **Random Forest**

  Justification for Choosing Random Forest

  I used the Random Forest classifier because it works well with structured data and is especially effective when the relationship between features and the target variable is non-linear or complex. Unlike single decision trees, which are prone to overfitting, Random Forest builds multiple decision trees and combines their outputs, improving accuracy and reducing variance.

  The dataset contains a mix of numerical features with varying levels of correlation. This makes Random Forest a suitable choice because it can naturally handle feature interactions and is non-parametric meaning it does not assume feature independence or any specific distribution.

  How it Works

The Random Forest Classifier is an optimized version of decision trees that addresses their limitations, such as overfitting and sensitivity to training data. Rather than relying on a single decision tree, a Random Forest constructs a collection (or "forest") of decision trees, each trained on a different subset of the data.
Its steps are:

1. The algorithm generates multiple training datasets by randomly sampling from the original dataset with replacement (bootstrapping). Each of these datasets may contain duplicate samples and will be used to train a separate decision tree.
2. When constructing each tree, the algorithm selects a random subset of features (typically log2 or sqrt of the total number of features) at each split, rather than using all available features. This introduces additional diversity among the trees and reduces correlation between them.
3. Each decision tree is independently trained on its respective bootstrapped dataset using the selected random features.
4. When making a prediction, the input data is passed through all trees in the forest. Each tree produces a classification result, and the final prediction is determined by the majority outcome, the most common class among all trees.

To Evaluate our Classification Models, we used:

- Accuracy score
- F1 score
- Confusion Matrix
- AUC score
- Cross Validation AUC score

Results

- **Key Findings**
  - Data Visualization
  - **Regression**

Our regression models aimed to predict the daily screentime of each user based on their mobile phone usage behavior. Across several regression models, including Linear Regression, Ridge Regression, Lasso Regression, Elastic Net Regression, Random Forest Regression, XGBoost Regression and Decision Tree Regression. Below are the key findings from each model:

1. **Linear Regression:**
   R^2 Score: 0.931
   MSE: 0.61

Observations:

- Strong baseline performance due to highly linear relationships between features and target.

2. **Ridge Regression:**
   R^2 Score: 0.933
   MSE: 0.61 (alpha=1)
   Observations:
   - Very similar to Linear Regression with improved stability.
3. **Lasso Regression:**
   R^2 Score: 0.929
   MSE: 0.637
   Observations:
   - Slightly lower performance.
   - L1 regularization might have removed some mildly important features.
   - Indicates possible slight sparsity in the dataset.
4. **Elastic Net Regression**
   R^2 Score: 0.9253
   MSE: 0.6701
   Observations:
   - Low among the linear models.
   - Suggests that neither strong sparsity nor multicollinearity correction was essential.
5. **XGBoost Regression**
   R^2 Score: 0.939
   MSE: 0.550
   Observations:
   - Very high performance.
   - Slightly below Random Forest, likely due to sensitivity to hyperparameters.
   - Regularization and boosting improved generalization.
6. **Random Forest Regression**
   R^2 Score: 0.944
   MSE: 0.505
   Observations:
   - Best performer overall.
   - Captured non-linear patterns and handled interactions effectively.
   - Robust to noise and overfitting due to ensemble averaging.
7. **Decision Tree Regression**
   R^2 Score: 0.883
   MSE: 1.04
   Observations:
   - Performed the worst among all models.

- Likely overfitted due to lack of ensemble averaging.
- Struggled with capturing strong linear trends in the data.

- **Classification**

Our classification task aimed to predict whether a user is "Addicted" or "Not Addicted" based on mobile phone usage behavior. Across several classification models, including Gaussian Naïve Bayes, K-Nearest Neighbors (KNN), Decision Tree, and Random Forest, we found consistently high accuracy, balanced F1-scores, and strong AUC values. Below are the key findings from each model:

1. **Naïve Bayes:**

- **Training Accuracy:** 98%
- **Testing Accuracy:** 98%
- **F1 Score:**
  - Addicted: 0.97
  - Not Addicted: 0.97
- **AUC Score:** 1.0
- **Observations:**
  - Low misclassification in the confusion matrix (Figure 3.2).
  - Learning curve (Figure 3.3) showed a small and consistent gap between training and validation, indicating a balanced model.
  - Most features followed near-normal distributions and had low to moderate correlations, aligning well with Naive Bayes assumptions.

2. **KNN:**

- **Training Accuracy:** 98%
- **Testing Accuracy:** 97%
- **F1 Score:**
  - Addicted: 0.97
  - Not Addicted: 0.97
- **AUC Score:** 0.99
- **Observations:**
  - The confusion matrix (Figure 3.4) confirmed few misclassifications in either class.
  - ROC curve (Figure 3.3) showed near-perfect separation between classes.
  - Strong feature correlations (e.g., notifications: –0.79, app_sessions: –0.67, stress_level: –0.54) helped the model achieve high precision and recall.
  - StandardScaler was applied to ensure all features contributed equally, as KNN is sensitive to feature scaling.

3. **Decision Tree:**

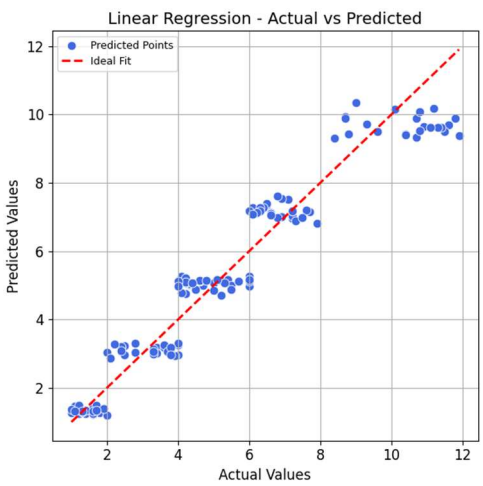
- **Training Accuracy:** 100%

- **Testing Accuracy:** 95%
- **F1 Score:**
    - Addicted: 0.95
    - Not Addicted: 0.95
- **AUC Score:** 0.95
- **Observations:**
    - Maintained consistent performance across 5-fold cross-validation (mean AUC: 0.956), indicating good generalization.
    - Feature correlations supported effective decision splitting.
    - Slightly less accurate than KNN, possibly due to Decision Trees being more prone to overfitting on minor noise.

4. **Random Forest:**

- **Training Accuracy:** 100%
- **Testing Accuracy:** 98%
- **F1 Score:**
    - Addicted: 0.98
    - Not Addicted: 0.98
- **AUC Score:** 1.0
- **Observations:**
    - Very few classification errors in the confusion matrix (Figure 3.8).
    - The ROC curve (Figure 3.7) shows perfect separation.
    - Despite 100% training accuracy, 5-fold cross-validation shows stable validation performance, suggesting only slight overfitting.
    - Strong, structured features with clear boundaries made Random Forest highly effective.

- Visualizations
    - Data Visualization
    - **Regression**


Linear Regression - Actual vs Predicted
Predicted Points
Ideal Fit
Predicted Values
Actual Values
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4
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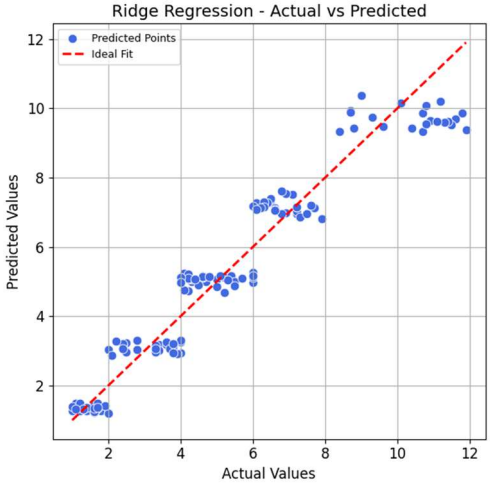
Ridge Regression - Actual vs Predicted
Predicted Points
Ideal Fit
Predicted Values
Actual Values
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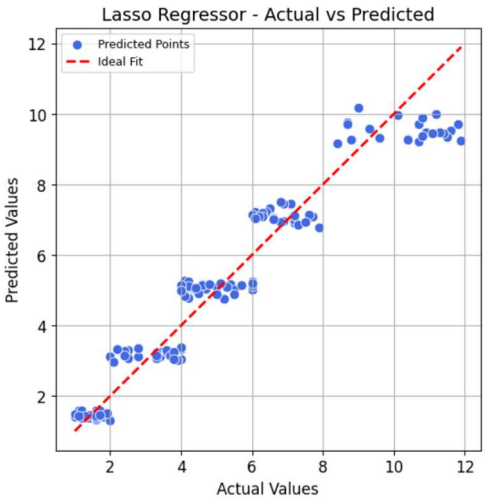
Lasso Regressor - Actual vs Predicted
Predicted Points
Ideal Fit
Predicted Values
Actual Values
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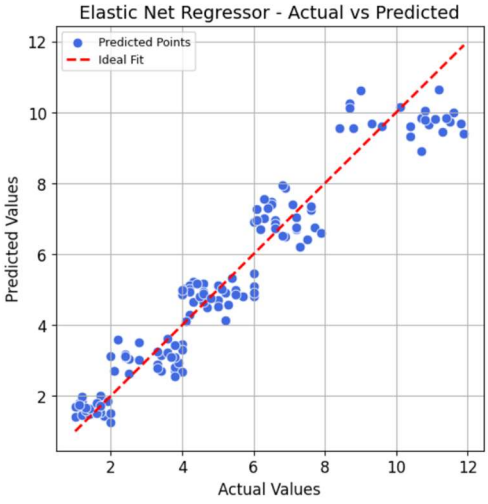
Elastic Net Regressor - Actual vs Predicted
Predicted Points
Ideal Fit
Predicted Values
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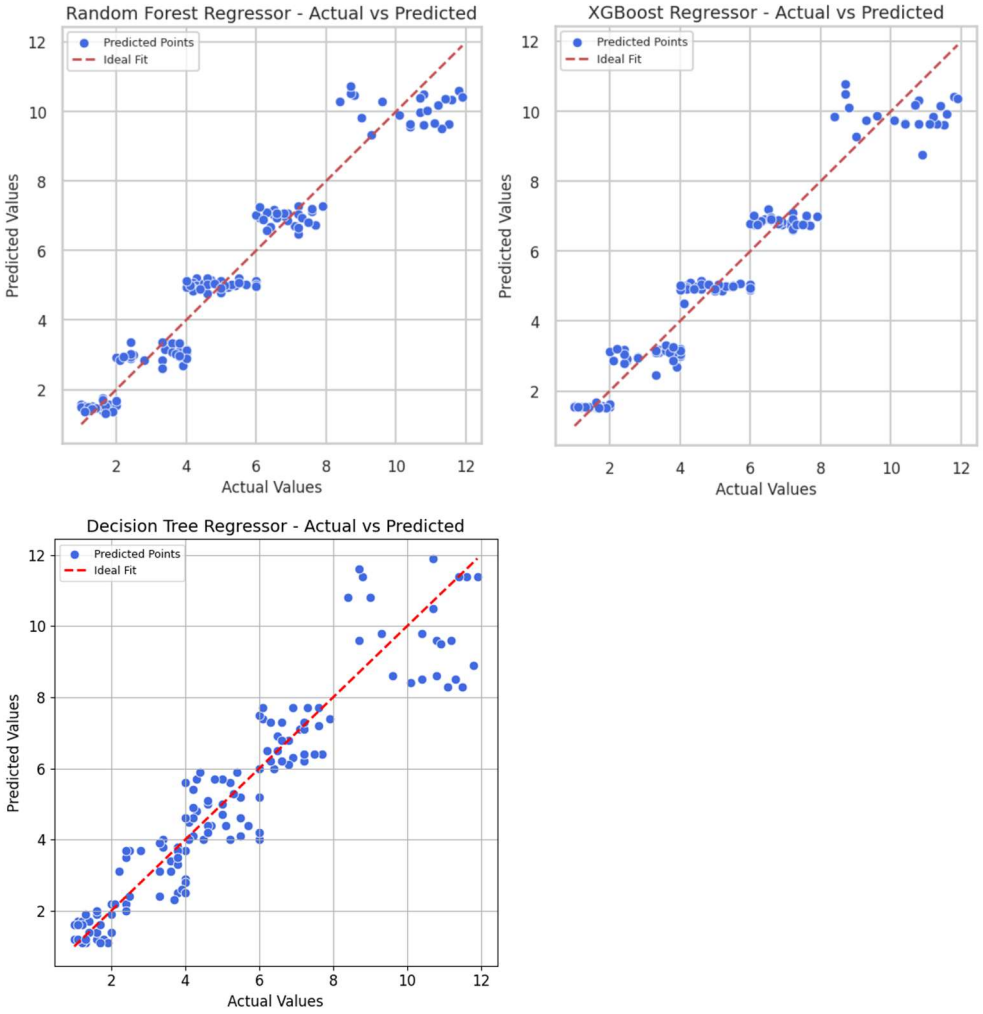


- **Classification**

  1. **Naïve Bays:**

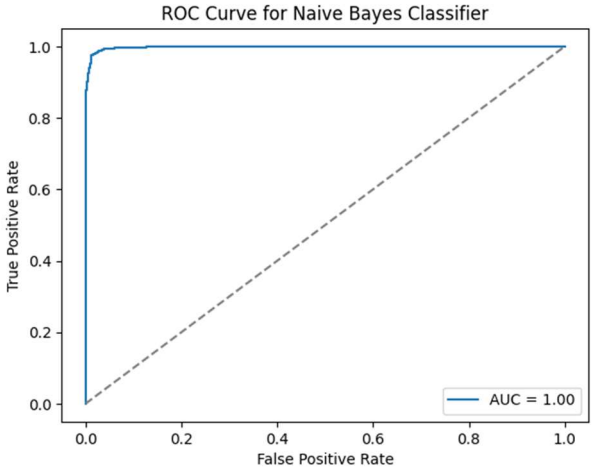


Fig 3.1 ROC Curve of the Naïve Bays Classifier

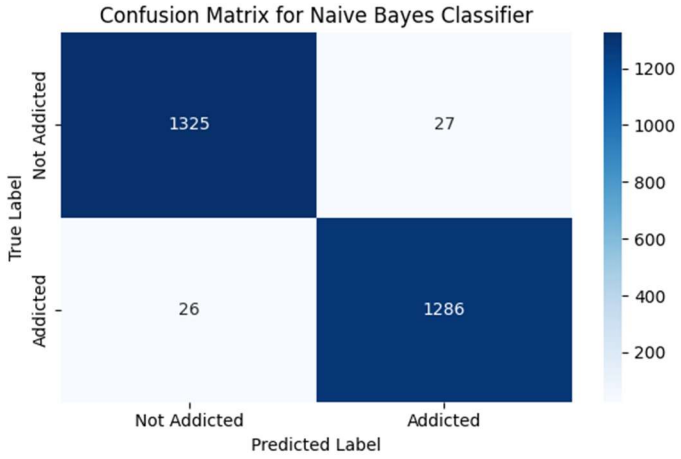
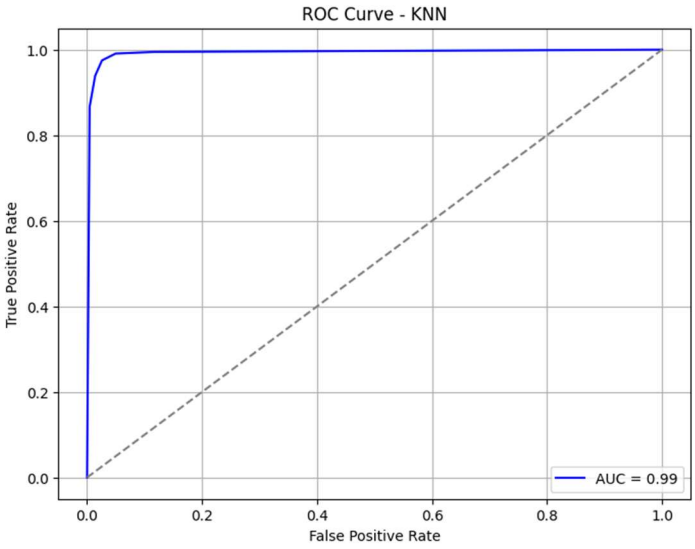


Fig 3.2 Confusion Matrix of the Naïve Bays Classifier

2. K-Nearest Neighbors (KNN):



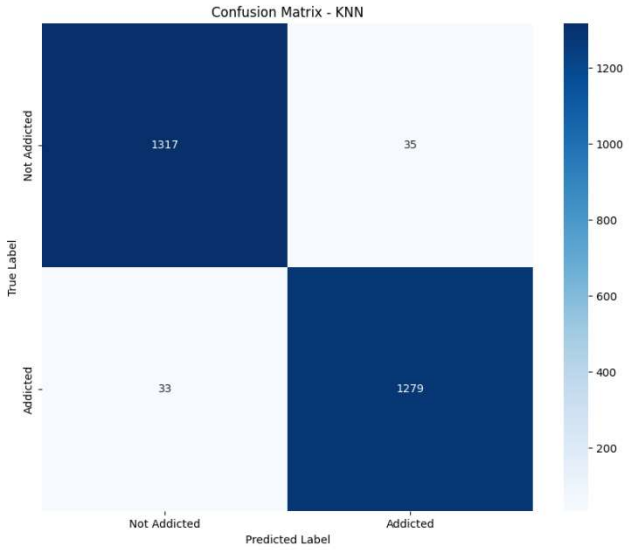
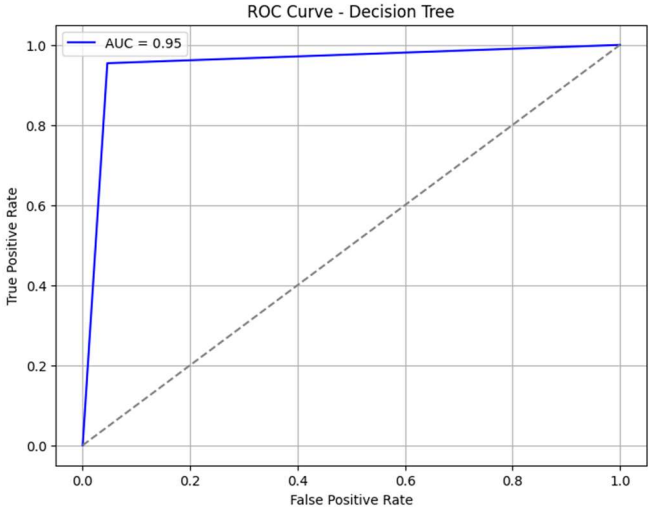
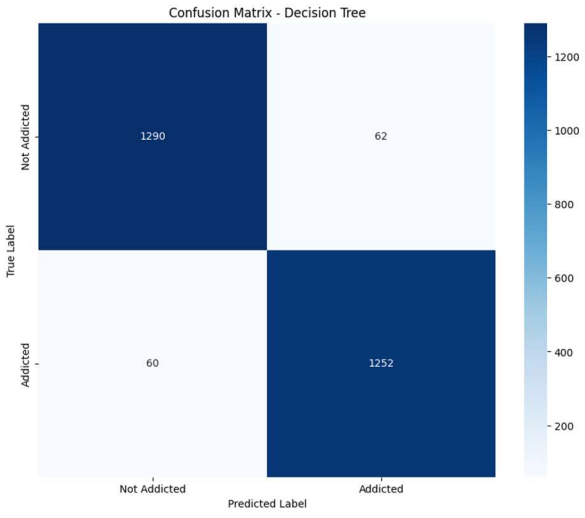


Fig 3.3 RO **Fig 3.4** Confusion Matrix of the KNN Classifier

3. Decision Tree:





4. Random Forest:

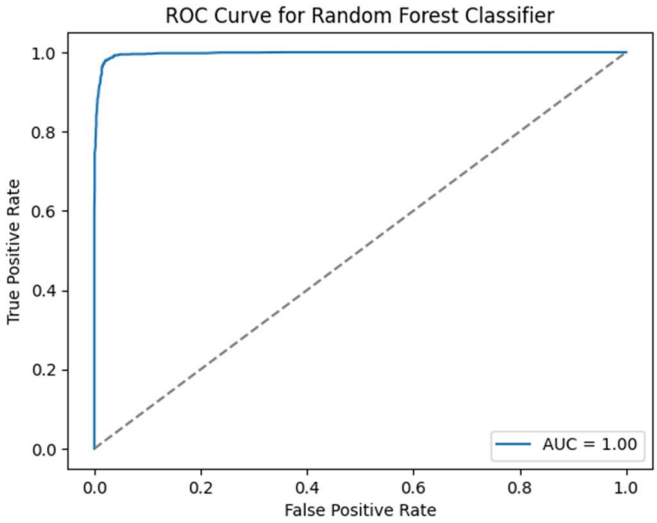


Fig 3.7 ROC Curve of the Random Forest Classifier

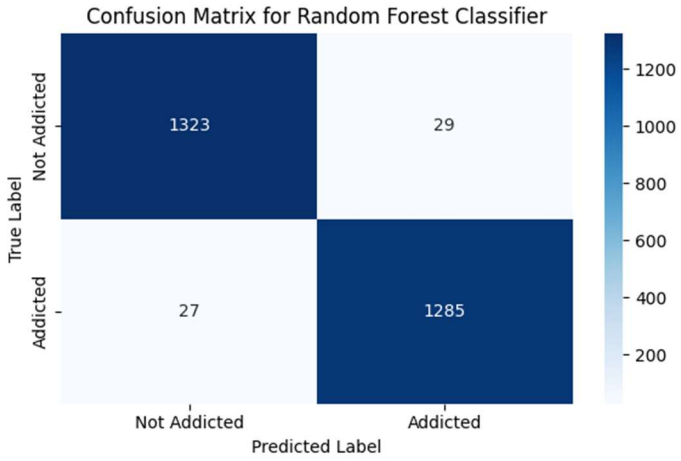


Fig 3.8 Confusion Matrix of the Random Forest Classifier

- Model Performance
  - Regression

Model	R^2 Score	MSE
Linear Regression	93.1%	0.61
Ridge Regression	93.3%	0.61
Lasso Regression	92.9%	0.64
Elastic Net Regression	92.5%	0.67
Random Forest Regression	94.4%	0.51
XGBoost Regression	93.9%	0.55
Decision Tree Regression	88.3%	1.04

Ensemble models, particularly Random Forest and XGBoost, outperformed the others, achieving the highest R^2 scores and the lowest mean squared errors. This is expected as these models combine the predictions of many decision trees, allowing them to better capture non-linear relationships and interactions among features. In contrast, linear models such as Linear Regression, Ridge, Lasso, and Elastic Net performed slightly worse but still demonstrated strong predictive capabilities, indicating that the relationship between features and the target is largely linear with minor complexities. The Decision Tree Regressor, being a single tree, underperformed significantly due to its tendency to overfit, especially in comparison to ensemble methods that average across many trees to reduce variance.

- **Classification**

Model	Accuracy	F1 (Addicted)	F1 (Not Addicted)	AUC
KNN	97.52%	0.98	0.97	0.99
Decision Tree	95.65%	0.96	0.96	0.96
Random Forest	97.7%	0.98	0.98	1.00
Naive Bayes	98.0%	0.98	0.98	1.00

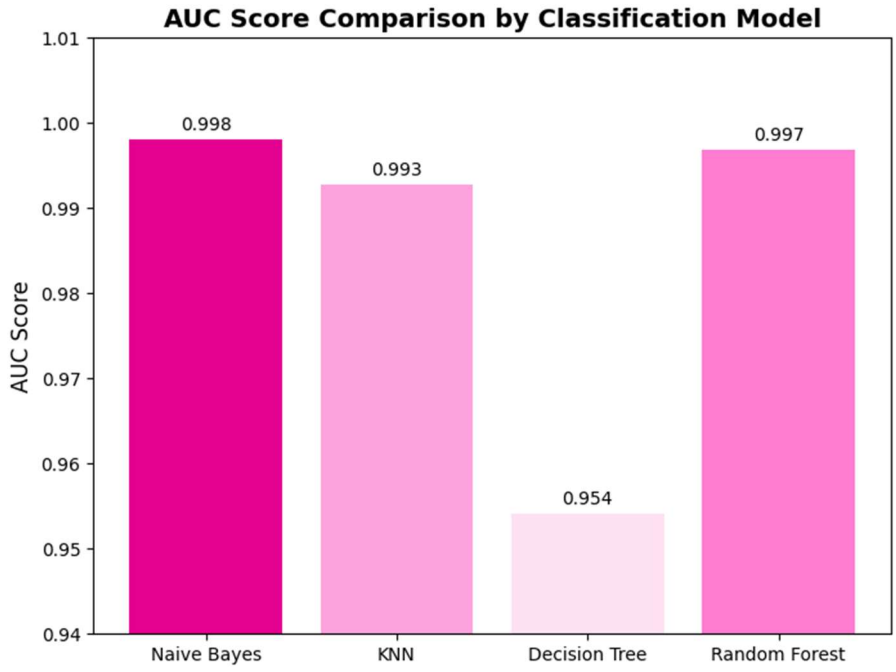


Fig 3.9 Comparison of AUC scores of the classification models

All four models performed extremely well, but Random Forest and Naïve Bayes slightly outperformed others in terms of AUC and F1 balance. Random Forest excelled due to its flexibility with non-linear data and ensemble robustness, while Naive Bayes performed well because of the clean data, near-normal numeric features, and moderate feature independence. Our dataset was well-suited to both, which explains their top-tier performance compared to KNN or Decision Tree alone. These results suggest that mobile phone addiction can be effectively predicted using behavioral and psychological variables such as screen time, app sessions, notifications, and stress level.

Conclusions

This project explored the use of machine learning models to predict daily screen time and detect mobile phone addiction using behavioral and psychological data from two datasets.

Regression Findings

- Random Forest and XGBoost were the highest-performing models for predicting screen time, achieving R^2 scores of 0.944 and 0.939, respectively. These ensemble methods effectively captured non-linear patterns and feature interactions.
- Linear Regression and Ridge Regression also performed strongly ($R^2 \approx 0.93$), suggesting that the relationship between features and screen time is largely linear.
- Lasso and ElasticNet showed slightly lower performance due to aggressive regularization or lack of strong sparsity in the data.
- Decision Tree Regression yielded the lowest performance due to overfitting and the absence of ensemble averaging.

Classification Findings

- Among classification models, Naïve Bayes and Random Forest achieved the highest accuracy and AUC scores.
- Naïve Bayes performed particularly well, likely due to the well-behaved numerical distributions of the features.
- Random Forest, as an ensemble method, demonstrated strong generalization and robustness to noise across both datasets.

Key Insights

Features such as notifications, app sessions, gaming time, and stress level consistently emerged as strong predictors for both screen time and mobile phone addiction. The results support the viability of using behavioral data to model digital habits and inform tools for digital wellbeing and addiction prevention.

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    1. **Data Wrangling:** Abdelrahman Mahdi
    2. **Data Visualization:** Noureen Ibrahim
    3. **Regression Models:** Rana Wael & Kareem Elkenany
    4. **Classification Models:** Ethar Mostafa & Arwa Mostafa
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    1. **Libraries:** numpy, seaborn, matplotlb, plotly, sklearn
    2. **Datasets:** mobile_addiction and user_behavior_dataset from Kaggle
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