First 10 rows of this project

pa_df=pd.read_csv("teen_phone_addiction_dataset.csv")
pa_df.head(11)
pa_df.tail(5)

ID	Nar	ne Age	Gender	Location	School_Grade	Daily_Usage_Hours	Sleep_Hours	Academic_Performance	Social_Interactions	 Screen_Time_Before_Bed
0 1	Shann Fran		Female	Hansonfort	9th	4.0	6.1	78	5	 1.4
1 2	So Rodrigu	ott lez 17	Female	Theodorefort	7th	5.5	6.5	70	5	 0.9
2 3	Adri Kn		Other	Lindseystad	11th	5.8	5.5	93	8	 0.5
3 4	Britta Hamilt		Female	West Anthony	12th	3.1	3.9	78	8	 1.4
4 5	Stev Sm		Other	Port Lindsaystad	9th	2.5	6.7	56	4	 1.0
5 6	Ma Ada	ary ms 13	Female	East Angelachester	10th	3.9	6.3	89	3	 1.1
6 7	Hai Mos		Male	North Jeffrey	11th	6.3	6.7	89	3	 0.8
7 8	Veron Marsh		Other	Jenniferport	10th	5.1	6.1	70	2	 1.0
8 9	Edwa Av		Male	Leebury	8th	3.0	9.1	79	0	 0.9
9 10	Jam Car		Other	Prestonview	11th	3.9	5.8	89	8	 0.9

Last 5 rows of this project

pa_df.head(11)
pa_df.tail(5)

	ID	Name	Age	Gender	Location	School_Grade	Daily_Usage_Hours	Sleep_Hours	Academic_Performance	Social_Interactions	Screen_Time_Before_Bed
2995	2996	Jesus Yates	16	Female	New Jennifer	12th	3.9	6.4	53	4	0.3
2996	2997	Bethany Murray	13	Female	Richardport	8th	3.6	7.3	93	5	0.9
2997	2998	Norman Hughes	14	Other	Rebeccaton	7th	3.2	6.5	98	1	0.2
2998	2999	Barbara Hinton	17	Female	Ramirezmouth	9th	6.7	7.5	67	3	1.6
2999	3000	Curtis Johnson	17	Male	Lake Alexander	10th	3.5	6.9	79	4	0.6

5 rows × 25 columns

Checking missing values

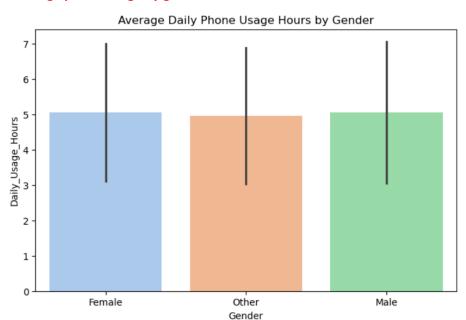
[3]: print("Checking for missing values:")
print(pa_df.isnull().sum())

Checking for missing values: Name 0 Age Gender 0 0 Location 0 School_Grade Daily_Usage_Hours Sleep_Hours Academic_Performance Social_Interactions Exercise_Hours Anxiety_Level Depression_Level Self_Esteem Parental_Control Screen_Time_Before_Bed Phone_Checks_Per_Day Apps_Used_Daily Time_on_Social_Media Time_on_Gaming Time_on_Education
Phone_Usage_Purpose 0 Family_Communication Weekend_Usage_Hours Addiction_Level dtype: int64

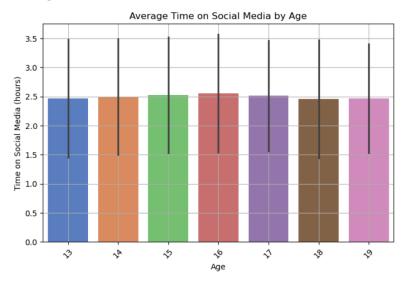
All of the columns

```
pa_df.columns
# pa_df.describe()
```

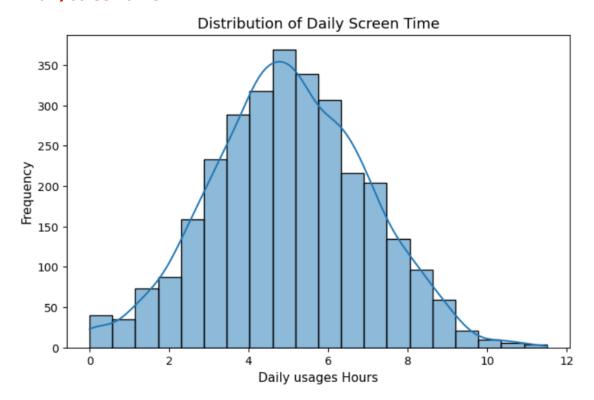
Average phone usage by gender



Average time on social media

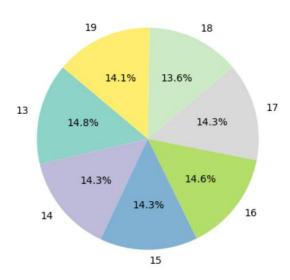


Daily screen time

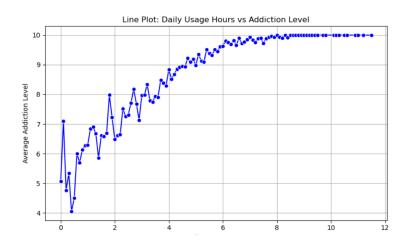


Average self-respect by age





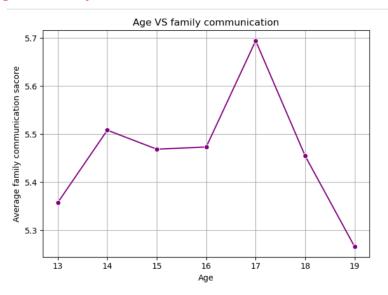
Daily usage hours vs addiction level



Age vs depression level

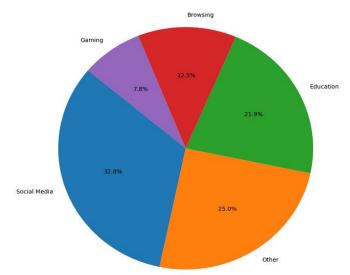


Age vs family communication



Phone usage hours for 5days

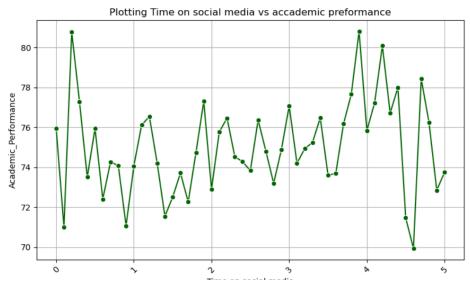




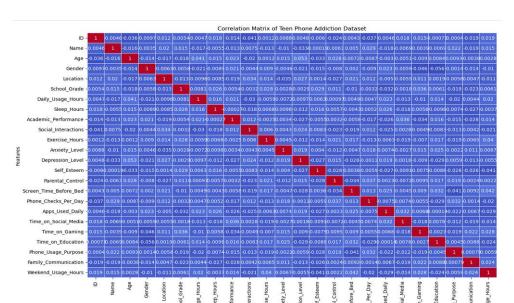
Exercise hours vs addiction level



Social media vs academic performance



Confusion matrix



Some libraries and ml models

```
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler,LabelEncoder
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
import numpy as np
# ML Models
from sklearn.linear model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.svm import SVC
from sklearn.neural_network import MLPClassifier
from xgboost import XGBClassifier
#Train & Evaluate All Models
results = {}
for name, model in models.items():
    print(f"\nTraining {name}...")
    model.fit(X train, y train)
    y pred = model.predict(X test)
    acc = accuracy score(y test, y pred)
    print(f"Accuracy: {acc:.4f}")
    print("Confusion Matrix:")
    print(confusion matrix(y test, y pred))
    print("Classification Report:")
    print(classification report(y test, y pred))
    results[name] = acc
```

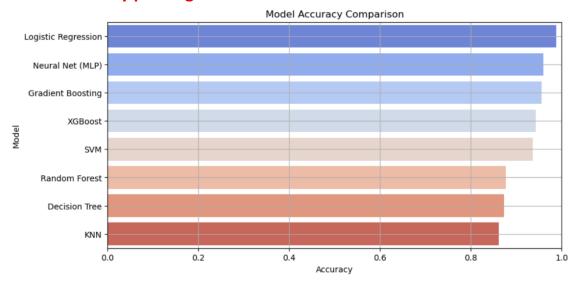
Logistic regressing accuracy score

```
Training Logistic Regression...
Accuracy: 0.9883
Confusion Matrix:
[[ 2 3 0]
[ 0 108 3]
[ 0 1 483]]
Classification Report:
           precision recall f1-score support
         0
              1.00
                      0.40
                               0.57
                                           5
         1
               0.96
                      0.97
                               0.97
                                          111
         2
               0.99
                       1.00
                               1.00
                                          484
                                0.99
                                          600
   accuracy
             0.99
0.99
                        0.79
                               0.85
  macro avg
                                          600
                               0.99
weighted avg
                        0.99
                                          600
```

All models score

```
Model Accuracy Summary:
                 Model
                         Accuracy
   Logistic Regression
0
                         0.988333
      Neural Net (MLP)
7
                         0.960000
     Gradient Boosting
5
                         0.955000
6
               XGBoost
                         0.943333
4
                    SVM
                         0.936667
3
         Random Forest
                         0.876667
         Decision Tree
2
                         0.873333
1
                    KNN
                         0.861667
```

Model accuracy plotting



Build Neural Network

Last few epochs

```
Epoch 35/50
120/120
                           - 1s 7ms/step - accuracy: 0.9591 - loss: 0.1061 - val_accuracy: 0.9708 - val_loss: 0.0762
Epoch 36/50
120/120
                            1s 6ms/step - accuracy: 0.9612 - loss: 0.1126 - val_accuracy: 0.9771 - val_loss: 0.0725
Epoch 37/50
120/120
                            - 1s 6ms/step - accuracy: 0.9646 - loss: 0.1057 - val_accuracy: 0.9604 - val_loss: 0.0809
Epoch 38/50
                            1s 7ms/step - accuracy: 0.9669 - loss: 0.0892 - val_accuracy: 0.9688 - val_loss: 0.0733
120/120
Epoch 39/50
                            - 1s 6ms/step - accuracy: 0.9707 - loss: 0.0890 - val_accuracy: 0.9771 - val_loss: 0.0616
120/120
Epoch 40/50
120/120
                            1s 6ms/step - accuracy: 0.9631 - loss: 0.0897 - val_accuracy: 0.9708 - val_loss: 0.0620
Epoch 41/50
120/120
                            - 1s 6ms/step - accuracy: 0.9676 - loss: 0.0892 - val accuracy: 0.9750 - val loss: 0.0649
Epoch 42/50
120/120
                            1s 7ms/step - accuracy: 0.9741 - loss: 0.0815 - val_accuracy: 0.9688 - val_loss: 0.0782
Epoch 43/50
120/120
                            1s 6ms/step - accuracy: 0.9680 - loss: 0.1033 - val_accuracy: 0.9667 - val_loss: 0.0803
Epoch 44/50
120/120
                            - 1s 6ms/step - accuracy: 0.9666 - loss: 0.0865 - val_accuracy: 0.9708 - val_loss: 0.0706
Epoch 45/50
120/120
                            - 1s 6ms/step - accuracy: 0.9742 - loss: 0.0701 - val_accuracy: 0.9646 - val_loss: 0.0645
Epoch 46/50
120/120
                            - 1s 6ms/step - accuracy: 0.9683 - loss: 0.0865 - val_accuracy: 0.9750 - val_loss: 0.0659
Epoch 47/50
120/120
                            - 1s 6ms/step - accuracy: 0.9646 - loss: 0.0995 - val_accuracy: 0.9688 - val_loss: 0.0728
Epoch 48/50
120/120
                            - 1s 7ms/step - accuracy: 0.9758 - loss: 0.0659 - val_accuracy: 0.9667 - val_loss: 0.0704
Epoch 49/50
120/120
                            1s 7ms/step - accuracy: 0.9690 - loss: 0.0815 - val_accuracy: 0.9729 - val_loss: 0.0677
Epoch 50/50
                            1s 6ms/step - accuracy: 0.9724 - loss: 0.0829 - val accuracy: 0.9750 - val loss: 0.0657
120/120
```

Confusion matrix and classification report

```
[60]: print("Confusion matrics:")
print(confusion_matrix(y_test,y_pred))
print("\nClassification report:")
print(classification_report(y_test,y_pred))
```

Confusion matrics: [[0 5 0]

[0 99 12] [0 6 478]]

Classification report:

2 0.98 0.99 0.98 44 accuracy 0.96 66 macro avg 0.63 0.63 0.63 66		precision	recall	f1-score	support
2 0.98 0.99 0.98 44 accuracy 0.96 66 macro avg 0.63 0.63 0.63 66	0	0.00	0.00	0.00	5
accuracy 0.96 60 macro avg 0.63 0.63 0.63 60	1	0.90	0.89	0.90	111
macro avg 0.63 0.63 0.63 66	2	0.98	0.99	0.98	484
	accuracy			0.96	600
weighted avg 0.95 0.96 0.96 60	macro avg	0.63	0.63	0.63	600
	weighted avg	0.95	0.96	0.96	600

Plotting over Epochs

