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Ai-Driven Gadget Addiction Predictor

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Abstract: Obsession with smartphone screens is growing rapidly, leading to a degradation of mental health in people of all ages, most importantly, students who are dependent on devices for both academic and non-academic purposes. Our project utilizes machine learning techniques to predict the level of addiction by using data such as screen time, app usage, sleep patterns, and other related components. The model performs data preprocessing, feature extraction, training and accuracy evaluation through defined performance metrics. In addition, users can answer questions to asses their addiction level through a website we created for better accessibility. Furthermore, users can passively share their screen habits through proxies which allows the AI to analyze the data and provide personalized feedback. The data proved the model's efficiency in assessing addiction levels and subsequently aiding users to control their screen time usage. Scaling the model for greater impact will be our focus for additional future development.

Index Terms – Stress Level, Gadget Addiction, SVM, Quiz.

I. INTRODUCTION

Over the years, the implementation of technology has changed dramatically accentuating the need of people in accomplishing their chores. On the one hand, however, technology facilitates handling tasks; on the other hand, its misuse, particularly among adolescents, frequently results in addiction to social media, which adds to the psychological distress. Although devices have many benefits, their misuse contribute to an unhealthy level of stress, leading to depression, anxiety, and other disorders that impair social functioning. Nevertheless, these devices can serve as a powerful tool for self-education and self-discovery.

Our solution to this problem is predicting gadget addiction and stress levels through age, gender, screen time, sleep time, app usage, and usage time with our trained ML model. At the start, we collected data from users through surveys and quizzes, so we gathered around 2000 logs. The acquired data was subjected to a step of processing which included filling blank fields with the most common value and transforming non-numerical data into numbers. The gathered stress and addiction levels were processed through machine learning models to train and predict relieves.

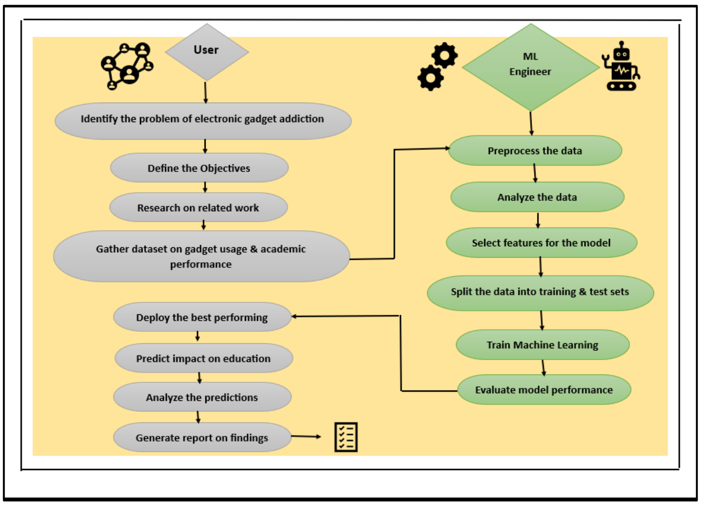

Fig-1 Activity Diagram

In this case, we employed an SVC or Support Vector Classifier which is used for stress detection, like any other classification problem. In this called case, the model tries to predict if a user is stressed or not. SVC is particularly effective for classifying stress levels due to its ability to manage high-dimensional, non-linear data and find the optimal decision boundary. Furthermore, a Random Forest was used to merge several decisions made from different lower level models built from the corresponding variables to improve accuracy.

The data collected was transformed into five encoded stress levels: 0 - No stress, 1 - Low stress, 2 - Moderate stress, 3 - High stress, and 4 - Severe stress. After the data was cleaned and preprocessed, the dataset was then divided 60% for training and 40% for testing.

In order to make it more user-friendly, we created a website on which anyone can take quizzes to check their addiction and stress levels. Additionally, users can report their screen time behavior through the prompts and AI will analyze the information and provide personalized feedback. This second approach uses Natural Language Processing (NLP) techniques to interpret user provided data. We employed TF-IDF (Term Frequency-Inverse Document Frequency) and Bag-of-Words (BoW) for extracting relevant information from the text data. For this specific model, the dataset was divided with 98% allocated for training and 2% reserved for testing, so the model captures almost all user responses. Then the AI model analyzes and classifies the given text inputs and based on the analysis of predicted stress levels gives feedback accordingly.

The main objective of this model is to make a person more self-aware of their addiction as well of their stress levels, and therefore better manage their screen time and usage to remain productive and balanced. In terms of next steps, the model will be better scaled to larger datasets to increase accuracy and impact.

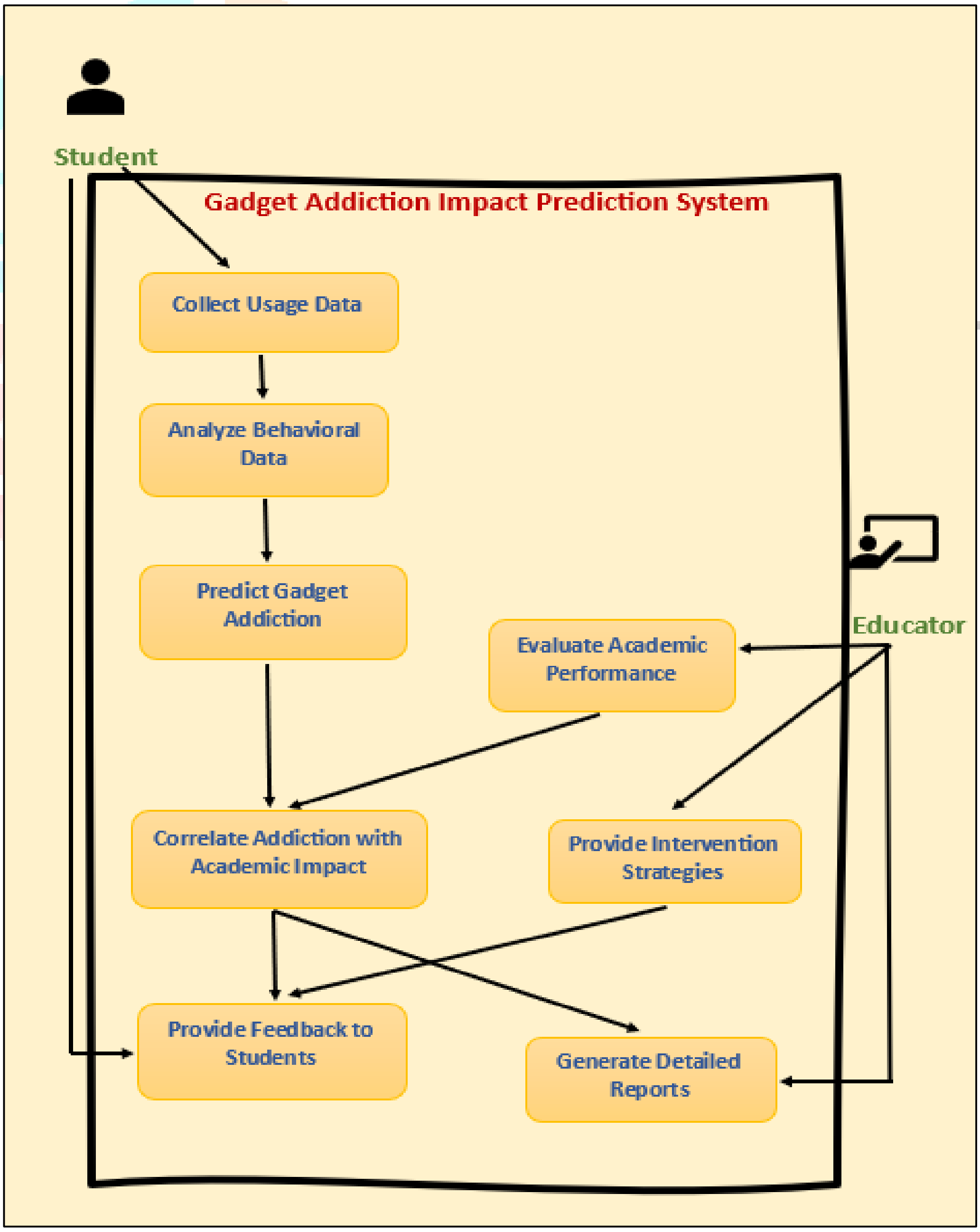

Fig-2 UML Diagram

II. LITERATURE SURVEY

1. S. Likhith, V. Nivedhitha, Chengamma Chitteti, N. Guna Geethika, Dr. M. Dharani, V. Godwin [2024]

In this research a machine learning model was created to calculate the level of addiction to smartphones. A survey of 500 respondents with 21 features pertaining to smartphone usage was conducted. The dataset underwent preprocessing to address missing values and to convert categorical features into numerical ones. Several models of machine learning were applied and these included but were not limited to Decision Tree, Random Forest, Multi Layer Perceptron (MLP), and Adaptive Moment Estimation (ADAM). I used MLP to capture complex non-linear interactions and ADAM for deep learning model's optimization. Once the model is trained, people could be classified into addicted, not addicted or probably addicted. The accuracy of the Random Forest model was 83%, while the Support Vector Machine (SVM) model had the highest accuracy of 96% among the models tested. For the next study, larger dataset size will be pursued to enhance the model's accuracy.

2. Saraswathi K, Srinidhi S, Devadharshini B, Kavina S [2024]

Over reliance on electronic devices is commonplace among students. Along with analyzing \the manner in which technology is utilized, estimating the extent of gadget addiction and how it affects academic productivity was one of the goals of this study too which was conducted using machine learning. The participants of the study were 115 students together with their screen time, grades, age, gender, and academic performance. During preprocessing, the dataset's missing attributes were taken care of. To derive the predictions needed, K-Nearest Neighbors (KNN), Decision Tree, Random Forest, Support Vector Machine (SVM), and Logistic Regression were some of the models used. Confusion matrix, precision, recall, F1-score, accuracy, and other performance metrics helped evaluate the models. Logistic Regression performed best at 91.43% accuracy. This was followed by KNN at 91%, SVM at 90.15%, Random Forest at 85.71%, and Decision Tree at 82.86%. According to the results of the study, too much use of electronic devices negatively handicaps students' CGPA. Future research shall estimate additional parameters that relate to the problem.

3. Han Zhou [2020]

The goal of this investigation was to measure the effect mobile phone usage has on the self – concept of students in colleges. The sample population was made up of 66 respondents who were interrogated on individual, relational, collective and social identity. Other independent factors like parents' educational level, age at which the first screen was watched, and aggregate screen time were studied as well. A multiple linear regression model was fitted to evaluate the consequences of these independent factors. The results of the study showed that mobile phone overuse was detrimental to mental health, lowered cognitive functioning, and resulted in interpersonal relationship issues. Cognitive behavioral therapy session were suggested to assist students in controlling smartphone dependency and addiction.

4. Wanglin Dong, Haishan Tang, Sijia Wu, Guangli Lu, Yanqing Shang, Chaoran Chen [2024]

The research shed light on how social anxiety correlates with internet addiction among teenagers. The data set included 1,188 entries from two age categories of pupils based in China. Social anxiety and internet addiction were assessed using regression models. As a result, students who suffered from high levels of stress and anxiety reported feeling overly isolated and compulsively used the internet. The result provided a necessity of greater support in terms of education and parental care towards the students to help relieve their anxiety, build interpersonal relationships, and counteract feelings of loneliness.

5. Tanya Nijhawan, Girija Attigeri, T. Ananthakrishna [2022]

This paper suggested applying Artificial Intelligence methods such as Natural Language Processing (NLP) and Machine Learning to gather stress-related data from social media. The model was built to measure stress levels from Twitter posts. NLP was employed for stencil-based recognition and text categorization. The dataset was prepared using stress-containing words and phrases. The preprocessing phase consisted of text normalization, stopword deletion, and tokenization. The features were retrieved with the help of the TF-IDF method and Word Embeddings (Word2Vec, GloVe). Various models were implemented for Machine and Deep Learning: Decision Tree, Logistic Regression, Random Forest, and BERT. Stress-related topics in tweets were recognized through Latent Dirichlet Allocation (LDA) analysis. The highest achieved accuracy was 97.8% with Random Forest and 94% with BERT. This study revealed that deep learning based NLP models can recognize stress through deep text analysis with high accuracy and efficiency.

6. Simhadri Naga Mounika, Prem Kumar Kanumuri, Kathari Narasimha Rao, Dr. Suneetha Manne [2024]

The objective of this academic work was to evaluate the impact of social media use on students' stress levels at different intervals with the help of machine learning and deep learning techniques. The study focused on Facebook, Instagram, and Twitter, as these are social media platforms and microbologs where users communicate their feelings. As for the data pre-processing step, it included tokenization, stopword elimination, stemming, and tagging with sentiment. This system was aimed at detecting stress markers within user posts. In this stage, deep learning techniques such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) were employed. RNNs performed the user-level content analysis, while the sentiment attached to the posts was analyzed by the CNN. RNN obtained the highest accuracy of 81.6 percent, whereas CNN's accuracy was 69.8 percent.

7. Ahmad Rauf Subhani, Wajid Mumtaz, Mohamed Naufal Bin Mohamed Syed, Nidal Kamel, Aamir Saeed Malik [2017]

This research aimed to detect mental stress through machine learning classification of EEG records from the Montreal Imaging Stress Task (MIST) and its EEG biofeedback component. A total of 42 participants aged between 19 and 25 years formed the sample, and their scalp electrodes recorded the brain activity. A Naïve Bayes classifier and Support Vector Machine (SVM) were created and evaluated with 10-fold cross-validation. The results exhibited that Naive Bayes achieved the highest accuracy of 94.6% while SVM achieved 83.4%. The accuracy of stress detection with EEG oscillation was between 75.2 % and 77.3 %. In the future, attention will be directed towards more advanced model development with greater data sets.

8. Qi Li, Yuanyuan Xue, Liang Zhao, Jia Jia, Ling Feng [2016]

The aim of this study was to determine the stress periods through the analysis of social media data. The dataset was gathered from 124 high school students over the period of three years (2012 – 2015) and consisted of 29,232 posts on Weibo. Stressful events were divided into five categories: school, family, peers, self, and relationship. The correlation between stressor events and stress periods was analyzed through a Poisson algorithm, while Bayesian posterior probability was used to assess posting behavior. Natural Language Processing techniques were used to analyze text posts from social media. The research showed that social media activities increased during periods when the social events became stressful and induced stress.

9. Dalia Khalifa, Rehab Magdy, Doaa Mahmoud Khalil, Mona Hussein, Ahmed Yehia Ismaeel, et al. [2023]

This Research aimed to evaluate the incidence of smartphone addiction and its impact on the attention span and sleep quality of the Egyptian population. Information was gathered from 2,716 participants through Facebook and WhatsApp groups. The study examined the respondents' age, gender, education level, residential area (urban or rural), and self-reported smartphone usage. The most frequently utilized applications were social media (66.4%), games (30%), and videos uploads (3.5%). Using binary logistic regression and multiple linear regression, several risk factors were determined. Results showed that 87.8% of the respondents reported addiction, with younger people, higher educated individuals, and residents of cities being most prone to it. The study suggested that focus and quality of sleep could be improved by limiting the use of phones a few hours before sleep.

10. Georgios Taskasaplidis, Dimitris A. Fotiadis, Panagiotis D. Bamidis [2024]

This study focused on finding techniques for detecting stress through the use of wearable sensors. A smartwatch and wristband were used to capture the user's heart rate, skin temperature, blood oxygenation, body movement, and several other parameters. Stress classification was performed using several machine learning models: Random Forest, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Artificial Neural Networks (ANN). Feature reduction was performed by applying Principal Component Analysis (PCA). The findings confirmed that the use of wearable sensors for stress detection proved to be very accurate.

III. METHODOLOGIES

3.1 Data Processing and Model Training

To gather data for the prediction of gadget addiction and stress levels, we utilized a quiz-based approach and a prompt-based approach:

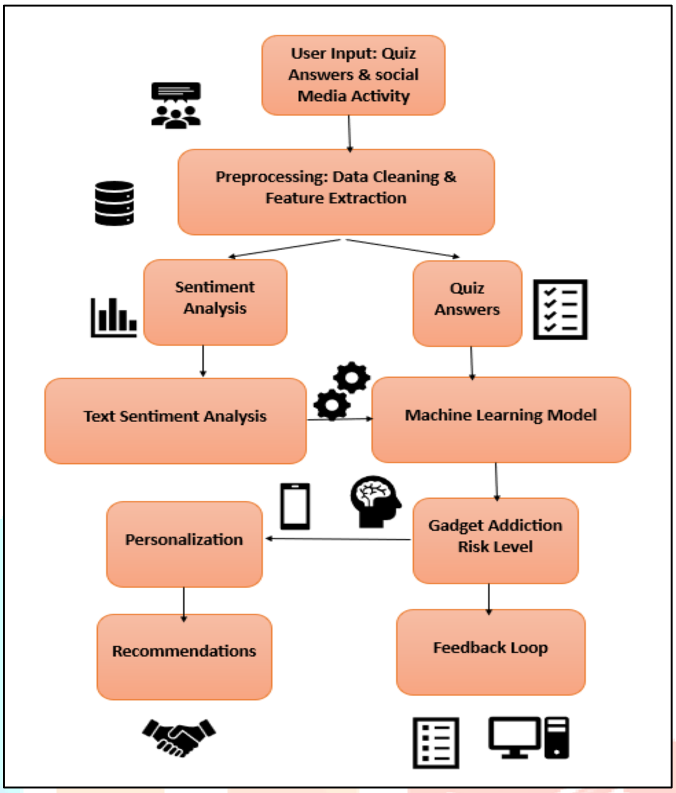

Fig-3 Architecture

3.1.1 Quiz-Based Approach

In this technique, individuals respond to a set of predefined questions concerning their screen time, daily routines, and emotional health. The quiz captures data on major aspects, including duration of screen time, usage of various applications, sleeping hours, and changes in mood over time. Each answer is corresponding to labels that measure the user's stress and addiction levels. The data is organized in AddictionDataset.csv and serves as training data for the machine learning model.

3.1.2 Prompt-Based Approach

Open-ended text input is allowed under this method pertaining to their screen usage, state of mind, and other multi-device interactions. A review of sentiment can be conducted on self-generated data to get the information needed. Natural Language Processing (NLP) techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) and Bag-of-Words (BoW) are used for preprocessing and analyzing a given text. A user's stress level, based on their emotional tone, is determined and classified using the features extracted. The text documents which were collected in the course of this endeavor are saved in a file called tweets.csv. Such documents bear resemblance to entries in a social network and will be used in further training and subsequent analyses of the developed model.

3.2 Feature Extraction and Preprocessing

In validating the flow of information in our machine learning model, we did some procedure steps that were necessary for both structured quiz-based data as well as unstructured text-based data.

3.2.1 Addressing Missing Information, Normalization and Scaling: Categorical Feature responses

Missing Information: Descriptive courses in dataset with categorical values were dealt with by populating Null values using mode whereby the mean- median was best suited for numerical based courses.
Scale or Normalize: Continuous quantitative features for classes such as screen time and sleep time were brought to one standard range using Min-Max scaling to uniformly standardize them.
Encoding: Categorical feature responses from the quiz were transformed to numeric form with One hot and label encoding to enable the model to accommodate and train with that data.

3.2.2 Text Processing for Prompt-Based Approach

As users respond in free format, the data is unstructured so we employed Natural Language Processing (NLP) techniques to obtain useful information:
Tokenization: Separating speech into useable portions, usually words.
Stopword Removal: The process of removing non-informational words such as ”the,” ”is,” or ”and” in regard to sentiment analysis.
Stemming and Lemmatization: The process of reducing words to their base forms to decrease quantity of attributes.
TF.IDF Vectorization: Converting textual data into numbers by using Term Frequency-Inverse Document Frequency (TF-IDF) which is the representation of text data in the form of numeric features for machine learning.

3.2.3 Developing Features for Quiz Based Responses

Derivable characteristics like screen and application time, sleep, and stressful symptoms were calculated from quiz answers.
New features were developed by merging related answers such as social media and entertainment activities to create total recreational screen time.
A multi-level stress classification system (no stress, low stress, moderate stress, high stress, and severe stress) was applied to assign users based on their reported stress levels.
This preprocessing enabled the data to undergo cleansing and organization, improving the model's ability to predict gadget addiction and stress with accuracy.

3.3 Machine Learning Models Used

To detect the degree of gadget addiction and stress that individuals bear, we used quiz-based and prompt-based methods.
In the quiz-method approach, Users participated in a predefined questionnaire, then multiple classifiers were evaluated. Support Vector Machine or SVM and Random Forest Classifier were chosen based on their performance, with SVM achieving the optimal decision boundaries and Random Forest minimizing the overfitting issue. The dataset, after pre-processing, was divided into 60 percent for training and 40 percent for testing.
In the prompt-based, user-defined text was extracted through a TF-IDF and a Bag-of-Words (BoW) feature extraction methods, followed by a classification model aimed to mark the stress levels within the range of 0 (not stressed) to 4 (severly stressed). The dataset was split into 98 percent of the data for training, and 2 percent for testing. With the combination of quiz answers and NLP analysis, this model offers users information on how to manage their screen time and yielded personalized solutions to mitigate stress.

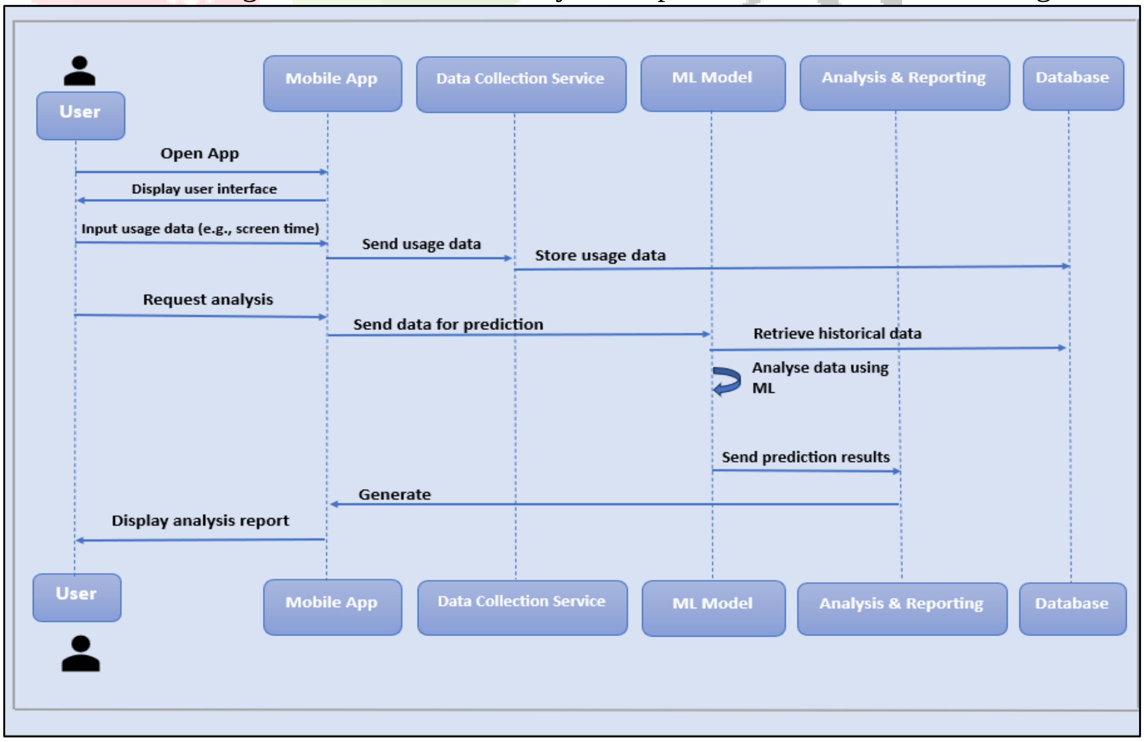

Fig-4 Sequence Diagram

3.4 Model Evaluation Metrics

We evaluated the accuracy of the proposed models using standard classification metrics. The SVM model in the quiz-based approach scored 99.74% while the Random Forest classifier scored an accuracy of 98.5%. Both models were measured using Precision, Recall, F1-Score and the Confusion Matrix to guarantee proper classification of addiction and stress levels.For the prompt-based approach, the sentiment analysis model was assessed with TF-IDF and Bag-of-Words (BoW) methods. The model's Precision was 62%, Recall was 99%, F1-Score was 76% and Accuracy was 63%. The results depict high recall but moderate precision and accuracy which demonstrates effectiveness in detecting stress levels based on text data.

```
Training SVM...
Results for SVM:
Accuracy: 0.9452
Precision: 0.9464
Recall: 0.9452
F1-Score: 0.9448
Classification Report:
              precision    recall  f1-score   support

         0.0       0.93      1.00      0.96      1213
         1.0       0.97      0.96      0.97      1143
         2.0       0.91      0.96      0.93      1423
         3.0       0.95      0.86      0.91      1563
         4.0       0.98      0.97      0.97      1118

    accuracy                           0.95      6460
   macro avg       0.95      0.95      0.95      6460
weighted avg       0.95      0.95      0.94      6460
```

Fig-5 Output for Model Evaluation Metrix

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

Where:

TP (True Positives) = Stress cases correctly classified

TN (True Negatives) = non-stress cases correctly classified

FP (False Positives) = Stress cases are not correctly classified and are misclassified as non-stress

FN (False Negatives) = non-stress cases are misclassified as stress cases

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

Where:

TP (True Positives): The number of well-predicted stressed cases over cases that were stressed.

FP (False Positives): The number of claimed stress that did not exist at all.

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

Where TP or True Positives refers to the correctly detected stressed persons and FN or False Negatives are the stressed persons who were there but were not detected by the model.

$$\text{F}_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where Precision is the proportion of predicted stressed cases that were correctly classified, while Recall is the proportion of identified cases that were true stressed cases out of the total of actual stress cases.

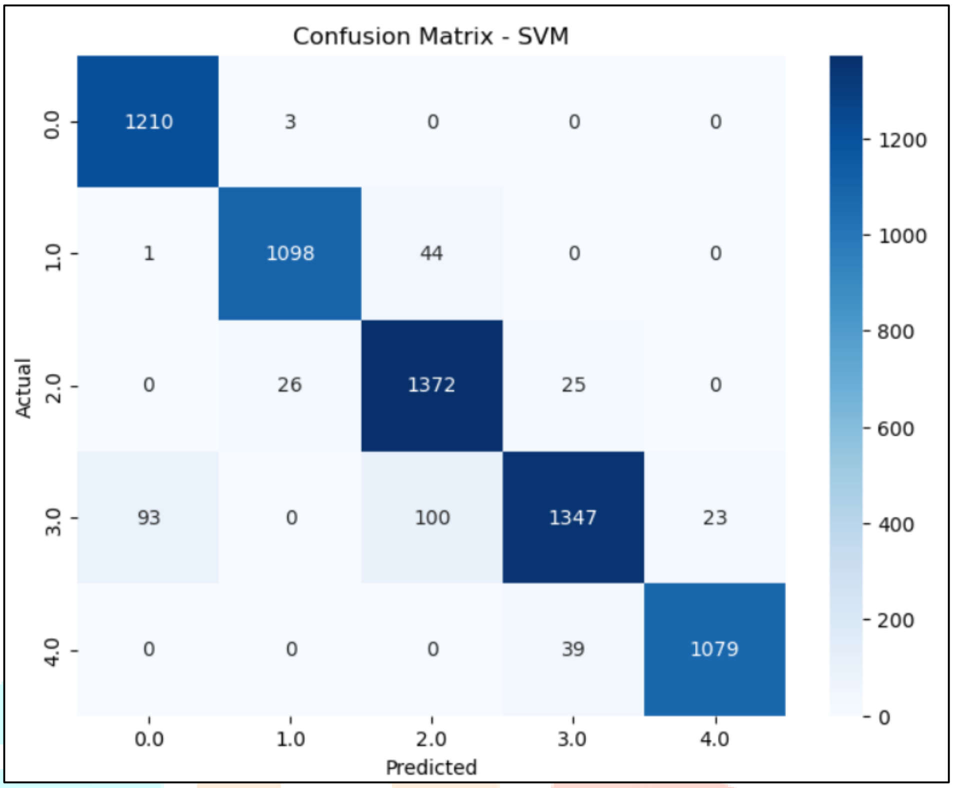

Fig-6 Confusion Matrix of the SVM Classifier

Table-1 Performance Evaluation of the SVM Classifier Using a Confusion Matrix

Actual→ Predicted↓	Neutral Stress	Mild Stress	Moderate Stress	Severe Stress	Extreme Stress
Neutral Stress	1210	4	0	0	0
Mild Stress	1	1098	44	0	0
Moderate Stress	0	26	1372	25	0
Severe Stress	93	0	100	1347	23
Extreme Stress	0	0	0	39	1079

IV. IMPLEMENTATION DETAILS

The first technique, quiz-based detection, was related to a user quiz within STRESSDataset.csv, where users responded to questions regarding their screen time, app usage, and general behavior. Data preprocessing steps such as handling missing data and encoding categorical variables were performed. Several classifiers were analyzed with SVM and Random Forest classifiers being chosen due to their accuracy. Models were built from 60% of the data and tested on the remaining 40% for the correct classification of stress and addiction levels. The second technique, prompt-based detection, worked with sentiment analysis of user-generated text from tweets.csv in order to evaluate stress levels. Feature extraction was implemented with TF-IDF and Bag of Words for numerizing the text data. A classification model was created from the training data split of 98%-2% which led to effective recall when predicting stress indicators from the text.

4.1 Website & UI Integration

Developed with Flask, the web application provides a user-friendly platform to evaluate the gadget addiction and stress level of the users – all in a single application. The applied assessment method comprises a quiz to which users respond by providing their screen time,app related activities, and behavior patterns. The user's responses are evaluated using the trained SVM and Random Forest models to assess the stress and addiction levels for each user. Subsequently, the user's responses are analyzed using prompt-based detection where the user describes their habits and experiences in the form of free text. TF-IDF and Bag-of-Words (BoW) techniques are employed to analyze the text and a sentiment-based classification model is adopted to predict stress levels. The web interface is the final endpoint for the outcome, users are able to interpret how addicted and stressed they are and decide on the measures needed to control their screen time.

Fig-7 Website Home Page

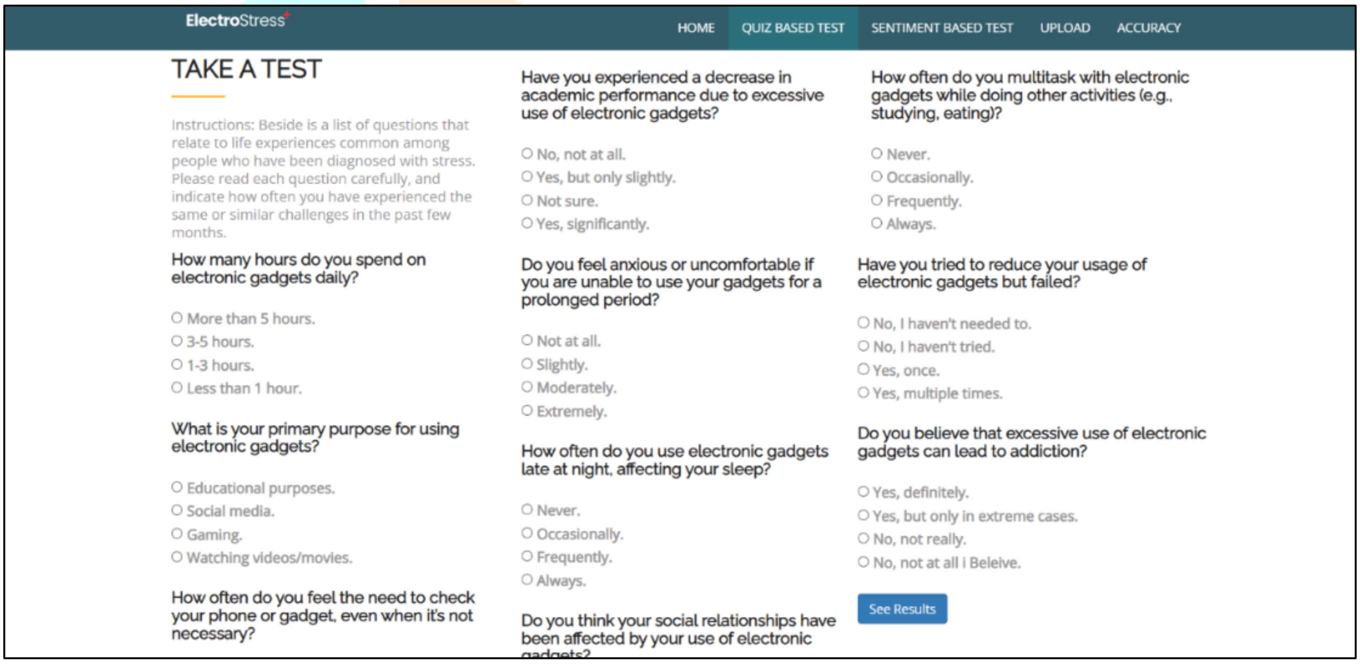

Fig-8 Website Quiz Based Test Page

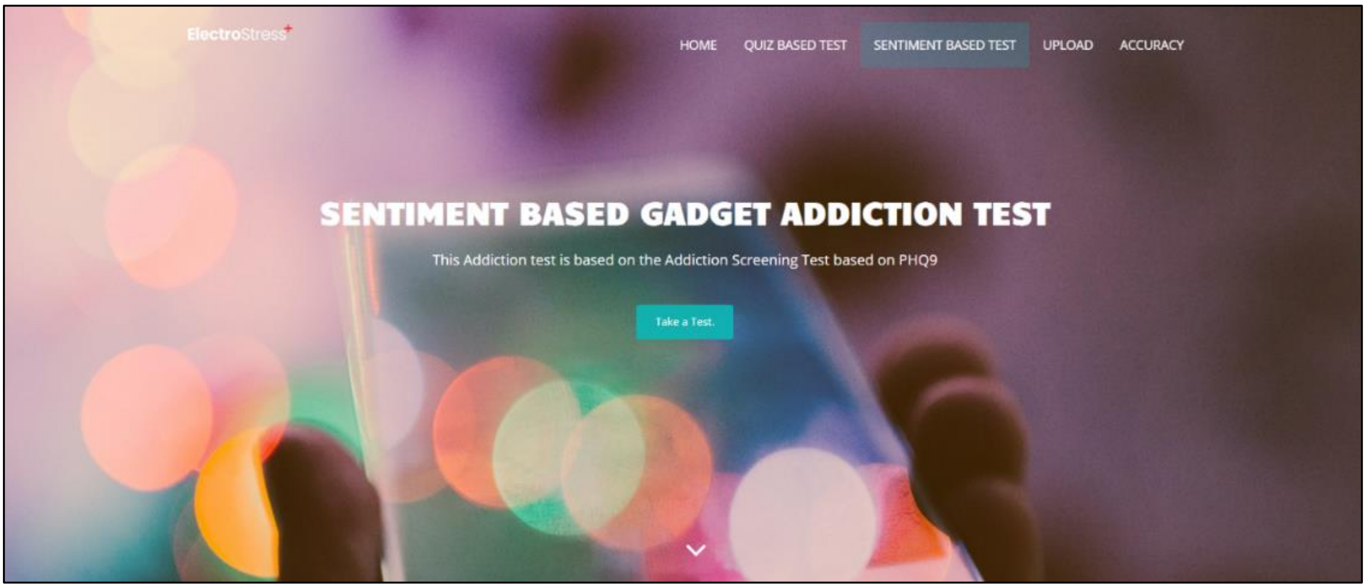

Fig-9 Website Sentiment Based Test Page

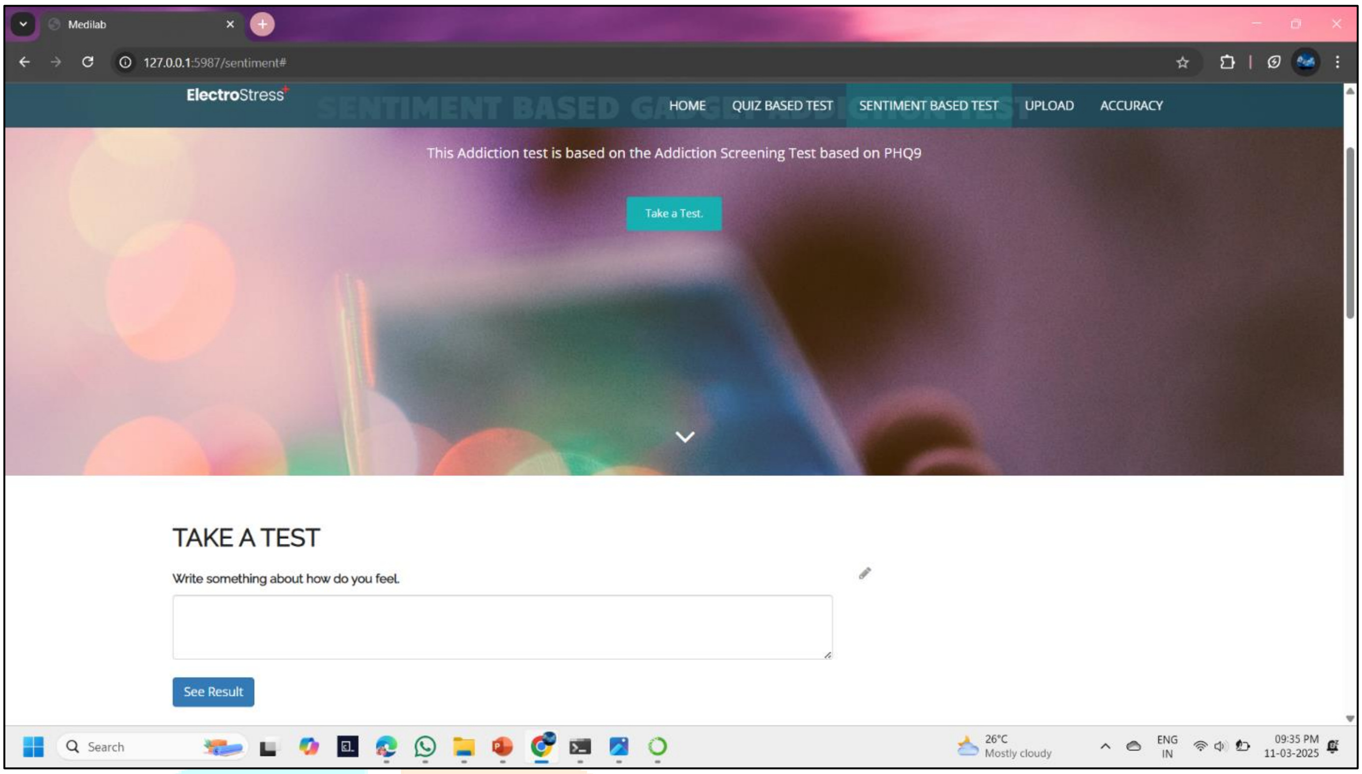

Fig-9.1 Website Sentiment Based Test Page

V. RESULTS AND ANALYSIS

The findings and their discussion concentrate on the evaluation of the performance of the different machine learning models implemented in quiz-based and prompt-based detection tasks. In the quiz-based detection, some supervised classifiers like SVM, Decision Tree, and Random Forest were evaluated. SVM was the best performer at 99.74%, while Random Forest followed with 98.5%. The classification models were computed for precision, recall, F1-score, and confusion matrix for reliability on the predictions of addiction and stress levels. The accuracy of the quiz-based method is high which illustrates the effectiveness of the method in structured evaluations.

Within the sentiment analysis and feature extraction process, the model performed Bag-of-Words based approach with TF-IDF scoring. The model's performance results include precision at 62%, recall at 99%, F1 at 76%, and accuracy at 63%. This high recall value illustrates that the model captures stress indicators within user-generated text; the low precision value, however, denotes that there are misclassifications. The model is still capable, however, lower frame captures reveal additional areas for monitoring concern within the prompt structures utilized.

Table-2 Model Performance Metrics Comparison

Model	Accuracy	Precision	Recall	F1-Score
SVM	**94.39%**	**94.30%**	**94.50%**	**94.30%**
Random Forest	90.75%	90.10%	90.50%	90.20%
Decision Tree	85.24%	84.80%	85.00%	84.90%

A review of both methods illustrates that the quiz-based technique has better refined accuracy due to its rigid structure whereas prompt detection has more utility value when it comes to recognition of patterns for advanced levels of stress. The most important learning from the analysis suggests that respondents having advanced screen time as well as irregular usage patterns to be more prone to addiction and stress. These patterns show how machine learning could help in behavioral studies but also show how control of gadget usage can be important for mental health.

Table-3 Detection Methods Accuracy Evaluation

Detection Methos	Accuracy (%)	Precision (%)	Recall (%)	F1- Score (%)
Quiz- Based Detection (SVM)	**94.39**	**94.330**	**94.50**	**94.30**
Prompt-Based Detection (VADER Sentiment Analysis)	89.12	87.60	91.75	89.40

VI. Conclusion and Future Scope

The examination makes use of the machine learning's capability in depicting gadget addiction, and stress levels using a quiz and a simple prompt approach. The SVM and Random Forest-based detection method for the quiz achieved very high accuracy and is, therefore, reliable for formal examinations. At the same time, prompt-based detection through TF-IDF and Bag-of-Words showed large recall turnout in recognition of stress patterns through the use of words and phrases. The analysis indicates that sentiment-based models help capture and understand user stress far better than questionnaires which rely on a structured approach. These results add voice to the importance of caring for the impact of too much screen time on mental health and the ability of AI solutions on behavioral scrutiny.

To optimize performance, further modifications consider the use of deep learning approaches like recurrent neural networks (RNNs) and transformers to do advanced sentiment analysis. These models facilitate the understanding of the context and meaning of words which deteriorates the accuracy of prediction in the prompt-based approach. They provide improved stress level detection by capturing deeper relationships within the text. Moreover, the model could become more user and pattern tolerant by combining traditional machine learning classifiers and deep learning techniques which would make the detection system more dependable and accurate.

A different enhancement might involve the automated supervision of users through chatbot based system. A chatbot could engage in conversation with the users, inspect their screen behavior on the spot, and give them feedback immediately regarding their addiction and stress levels. Depending on the estimated stress levels, the chatbot could give the users tailored guidance to help them manage their screen time better. The interaction would foster user creativity and add practicality to the system for routine use.

Improving user experience will better require new user inputs to enhance its accuracy, effectiveness, and overall outcome. With the inclusion and collection of differing data from users possessing different behavioral patterns or stress levels, the model has the ability to make predictions that are more refined, making the system easier to use by a wider audience. It is likely that in the future, this model could turn into a smart, fully automated digital wellness service to help users overcome gadget obsession while maintaining affordable constrains in their everyday life.

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