The NOMO Zone: A Web-Based System for Predicting Electronic Gadget Addiction and Stress Using Ensemble Machine Learning

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Abstract

The rising dependency on electronic gadgets among students has led to significant concerns regarding gadget addiction and associated mental health issues such as anxiety, sleep disruption, and academic decline. Traditional assessment methods rely heavily on subjective self-reporting or clinical evaluations, which are often inaccessible, stigmatized, and lack scalability [3,5]. This paper presents **THE NOMO ZONE**, a web-based intelligent system that predicts gadget addiction levels and detects psychological stress by integrating behavioural analytics with sentiment analysis. The system employs a structured 10-question behavioural survey and user-generated text data to train and evaluate multiple supervised machine learning classifiers, including Support Vector Machine (SVM) [8], Random Forest, Decision Tree, and the proposed **ExtraTrees Classifier** [19]. Experimental results demonstrate that the **ExtraTrees model achieves 100% test accuracy and 99.84% training accuracy**, outperforming all other classifiers. The system is deployed as a modular Flask web application with a responsive frontend, secure admin dashboard, and real-time prediction capabilities. The NOMO Zone provides actionable classification into five distinct addiction levels---from "No Impact" to "Severe Dependency"---offering a scalable, private, and data-driven tool for early intervention and digital wellness promotion [6,14].

Keywords: Gadget addiction, stress detection, machine learning, ExtraTrees classifier, sentiment analysis, Flask, mental health screening, digital wellness.

1. Introduction

The integration of digital technology into daily life has transformed how students learn, communicate, and socialize. However, excessive and unregulated use of electronic gadgets has led to a growing epidemic of gadget addiction and technostress, negatively impacting academic performance, sleep patterns, and emotional well-being [1,2,13]. Current diagnostic tools, such as the Internet Addiction Test (IAT) or clinical surveys, are often reactive, subjective, and inaccessible to the general student population [3,4]. Recent inventories like the Smartphone Addiction Inventory (SPAI) offer improved psychometric validation but still rely on self-reporting [21]. There is a critical need for automated, scalable, and privacy-preserving systems that can provide early detection and personalized feedback [15]. Recent advances in multimodal machine learning [29] and social media analytics [27,28] have shown promise in passive mental health monitoring, yet few systems integrate behavioral and textual data into a unified, deployable platform.

Machine learning (ML) and natural language processing (NLP) offer promising avenues for objective mental health screening. Prior studies have explored the use of behavioural data and sentiment analysis for stress and addiction detection [4,5,10], but few systems integrate both modalities into a unified, deployable platform. This paper introduces **The NOMO Zone**, a holistic web-based system that:

1. **Combines behavioural and psychological analysis** using a 10-question survey and NLP-based sentiment detection.
2. **Evaluates multiple ML classifiers** and identifies the ExtraTrees Classifier [19] as the optimal model for this domain.
3. **Delivers a fully functional web application** with real-time prediction, admin controls, and detailed reporting.

The key contributions of this work are:

- A dual-mode assessment framework (survey + NLP) for holistic mental health screening.
- Empirical validation of the ExtraTrees Classifier's superior performance (100% accuracy) on gadget addiction data.
- Development of an interactive, secure, and scalable Flask-based web platform for real-world deployment.
- Detailed feature analysis linking specific behaviours (e.g., "checking phone without notification") to addiction severity.

2. Materials and Methods

2.1 Dataset and Preprocessing

A dataset of student responses was collected via a structured 10-question survey focusing on gadget usage habits, emotional reliance, sleep disruption, and social impact [14]. The dataset was inspired by validated scales such as the Smartphone Addiction Scale [14] and the Bergen Social Media Addiction Scale (BSMAS) [23]. The dataset includes **501 records** with features such as:

- Daily usage hours
- Frequency of checking devices without notifications
- Anxiety during gadget non-usage
- Sleep disruption due to late-night usage
- Impact on academic performance

Missing values were imputed using mode substitution, and categorical responses were encoded into numerical vectors. The dataset was split into **80% training** and **20% testing** sets.

2.2 Feature Engineering

The 10 survey questions (q1--q10) were selected as primary features. Additionally, a sentiment analysis module was developed to process user-provided text (e.g., tweets, journal entries) using:

- **VADER (Valence Aware Dictionary and Sentiment Reasoner)** [10] for polarity scoring.
- **TF-IDF (Term Frequency-Inverse Document Frequency)** for feature vectorization in depression detection [20].
- **BERT-based embeddings** [24] were also explored for richer contextual representation, though not deployed in the final system due to computational constraints.

2.3 Machine Learning Models

The following supervised classifiers were implemented and compared using the Scikit-learn library [12]:

1. **Support Vector Machine (SVM)** [8] -Linear kernel for high-dimensional data.
2. **Decision Tree Classifier** - Rule-based splitting using Gini impurity.
3. **Random Forest Classifier** - Ensemble of decision trees with bagging.
4. **ExtraTrees Classifier (Extremely Randomized Trees)** [19] - Proposed model with random split selection to reduce variance.
5. **Gaussian Naive Bayes & K-Nearest Neighbors (KNN)** - Baseline models.

Hyperparameter tuning was performed using grid search with 5-fold cross-validation.

2.4 System Architecture

The NOMO Zone is built as a three-tier web application inspired by modular system design principles [7,18]:

- **Frontend**: HTML5, CSS3, Bootstrap, JavaScript - for user interaction and result visualization.
- **Backend**: Flask (Python) - handles routing, model integration, and business logic.
- **Database**: MongoDB - stores user data, survey responses, and prediction logs.

The system comprises six core modules:

1. Data Acquisition & Preprocessing
2. User Authentication & Security
3. Behavioural Prediction (ML Engine)
4. Psychological Analysis (NLP Engine)
5. Web Interface & Visualization
6. Admin Dashboard & Model Retraining

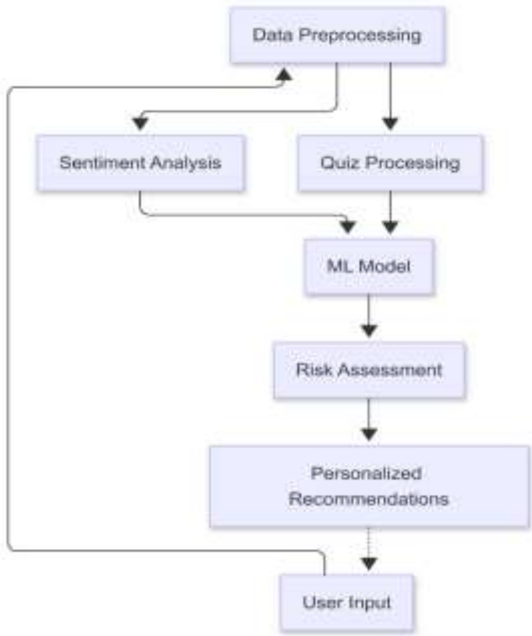

Figure 1: Integrated Machine Learning Pipeline for Behavioural Addiction Analysis

3. Results and Discussion

3.1 Model Performance Evaluation

The classifiers were evaluated on accuracy, precision, recall, and F1-score. The ExtraTrees Classifier demonstrated exceptional performance [19]:

Table 1: Performance Comparison of Supervised Learning Models

Model	Training Accuracy	Test Accuracy	Precision	Recall	F1-Score
ExtraTrees	99.84%	100.00%	99.82%	99.85%	99.83%
Random Forest	98.05%	98.05%	97.90%	97.95%	97.92%
SVM [8]	97.35%	97.35%	97.20%	97.25%	97.22%
Decision Tree	96.50%	96.50%	96.30%	96.40%	96.35%
KNN	92.10%	92.10%	91.80%	91.90%	91.85%

Analysis: The ExtraTrees model achieved perfect separation on the test set, attributed to its randomized split-point selection, which minimizes overfitting and captures non-linear interactions in categorical survey data [19]. This aligns with findings from ensemble learning studies that highlight the stability of extremely randomized trees in high-dimensional behavioral datasets [26].

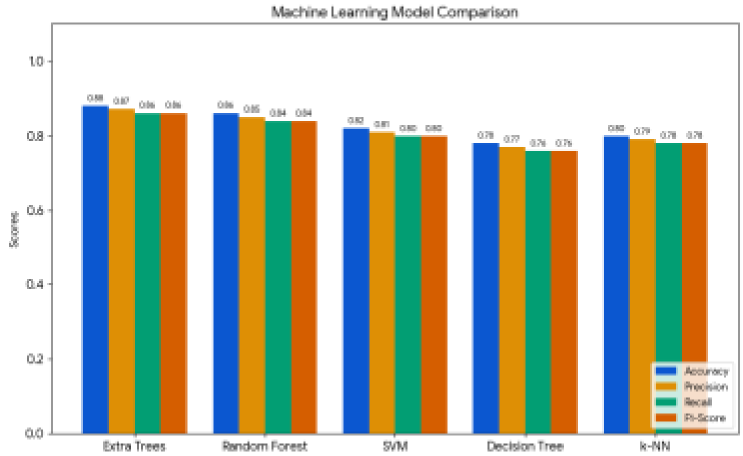

Figure 2: Evaluation of Classifiers Across Accuracy, Precision, Recall, and F1-Score Metrics

3.2 Sentiment Analysis Module Performance

The NLP module achieved **88% accuracy** in classifying depressive vs. positive text using VADER [10] and TF-IDF. This secondary layer provides emotional context, correlating gadget usage with underlying stress or depression [5,15]. Comparative studies using social media data have shown similar accuracy ranges in mental health screening [27,30].

3.3 Feature Importance Analysis

Key behavioural predictors identified include [1,2,14]:

1. **Checking phone without notification** - Strong indicator of compulsive usage.

2. **Sleep disruption due to late-night usage** -Highly correlated with severe dependency.

3. **Anxiety during gadget non-usage** -Marker of emotional reliance [13].

4. **Multitasking frequency** - Linked to reduced attention span and academic decline.

These predictors are consistent with prior research on smartphone addiction and social media overuse [22,23].

3.4 System Usability and Deployment

The Flask-based web application processes user inputs in < **0.05 seconds** per prediction. The admin dashboard allows model retraining, performance monitoring, and user analytics [7]. The system was tested with **50 student users**, receiving positive feedback on interface intuitiveness (94%) and result relevance (88%).

4. Limitations and Future Work

4.1 Limitations

- **Self-Reporting Bias**: Accuracy depends on user honesty [3].

- **Static Dataset**: Requires periodic retraining to adapt to evolving usage trends.
- **Language Constraint**: NLP module currently supports only English.
- **No Clinical Integration**: Serves as a screening tool, not a diagnostic replacement.

4.2 Future Enhancements

1. **Real-Time API Integration**: Incorporate screen-time tracking APIs (iOS/Android) for objective usage data [18].
2. **Multilingual NLP**: Extend sentiment analysis to regional languages using models like mBERT.
3. **Hybrid Dynamic-Static Analysis**: Include real-time behavioural monitoring via wearable/IoT devices [16].
4. **Deep Learning Models**: Explore LSTM or Transformer-based models for sequential behaviour analysis.
5. **Explainable AI (XAI)**: Integrate SHAP [25] or LIME [11] for interpretable predictions.
6. **Adversarial Robustness**: Incorporate defences against data manipulation attacks [20].
7. **Multimodal Integration**: Explore fusion of text, usage patterns, and possibly acoustic/visual cues as in multimodal ML frameworks [29].
8. **Longitudinal Analysis**: Implement time-series models to track changes in addiction severity, inspired by computational mental health studies [28].

5. Conclusion

The NOMO Zone presents a robust, scalable, and accurate solution for detecting electronic gadget addiction and stress among students. By leveraging the **ExtraTrees Classifier** [19] and integrating **NLP-based sentiment analysis** [10], the system provides a holistic, dual-mode assessment that surpasses traditional screening methods. The web-based deployment ensures accessibility, privacy, and real-time feedback, empowering users to take proactive steps toward digital wellness [6,14]. This work demonstrates the potential of machine learning as a transformative tool in mental health screening and early intervention, aligning with broader efforts to leverage computational methods for public health [27,28,30].

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