International Journal of Research Publications in Engineering, Technology and Management (IJRPETM)

|www.ijrpetm.com | ISSN: 2454-7875 | editor@ijrpetm.com |A Bimonthly, Peer Reviewed & Scholarly Journal|

||Volume 9, Issue 2, March - April 2026||

DOI:10.15662/IJRPETM.2026.0902003

Electronic Gadget Addiction Prediction using Machine Learning

Rupika.M[1], Nandini.G[2], Mythri.M[3], Vasu.K[4], Abhiram.M[5], Shivalingam.N[5],

Dr. Prasad Dharnasi[7]

Student, B.Tech CSE 4 year, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[1]

Student, B.Tech CSE 4 year, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[2]

Student, B.Tech CSE 4 year, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[3]

Student, B.Tech CSE 4 year, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[4]

Student, B.Tech CSE 4 year, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[5]

Assistant Professor, Dept. of CSE, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[6]

Professor, Dept. of CSE, Holy Mary Inst. of Tech. and Science, Hyderabad, TG, India[7]

Publication History: Received: 10.02.2026; Revised: 01.03.2026; Accepted: 05.03. 2026; Published: 08.03.2026.

ABSTRACT: The widespread use of electronic devices has really changed how we live day to day. This brings up worries about using them too much and how that affects our mental health, how well we work, and how we talk to each other. So, being able to guess who might get addicted to these gadgets is super important so we can step in early and make smarter choices. In this study, we've put together a machine-learning system to guess gadget addiction using info about how people act.

The process includes grabbing data, cleaning it up by getting rid of empty spaces and repeats, sorting it into categories, fixing any uneven data using SMOTE, and picking the best features with Recursive Feature Elimination (RFE).

We also did some exploring with plots and charts to understand how different features relate to each other. We tried out a bunch of classification models, like Random Forest, Support Vector Machine, XGBoost, Multi-Layer Perceptron, and a Voting Classifier that mixes Gradient Boosting, LightGBM, XGBoost, and CatBoost. Plus, we used deep learning models like LSTM and CNN-LSTM. The results showed that the Voting Classifier did the best, hitting around 98.6% for accuracy, precision, recall, and F1-score, which is better than the other models. To get clearer explanations, we used Explainable AI methods like LIME and SHAP to see how each feature played a role. Then, we put the top model into a web app using Flask, so people can get real-time predictions through an easy-to-use setup.

KEYWORDS: Gadget Addiction, Machine Learning Model, Prediction Model, Random Forest, Logistic Regression, Support Vector Machine (SVM), Data Preprocessing.

I. INTRODUCTION

Today's electronic devices like smartphones, tablets, and computers are a big part of how we live. They shape how we talk, work, learn, and have fun. They're handy and keep us connected, but too much use can lead to what people call device addiction. This means long hours staring at screens, constantly checking apps, and ignoring what's important in the real world. This can mess with how well we work, our mental state, and how we relate to others.

Since these devices have quickly become part of our daily lives, it's tough to keep track of how much we're using them. That's why we need smart systems that can spot risky habits and give us advice when we need it. The rise of digital habits has created tons of data on how we use devices, like how often we use them, which apps we like, and how long we spend on them. Looking at this data can show patterns that point to addictive behavior, helping us find people who might be at risk early on. Machine learning and deep learning are good at finding tricky patterns in this kind of data, giving us info about what users do and like.

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These systems can back efforts to make people aware, come up with plans to help, and give custom advice to cut down on device use. Putting smart prediction systems together with easy-to-use interfaces lets people check if they're at risk of device addiction.

This not only helps them understand their own device habits but also supports bigger programs for digital well-being, mental health, and using tech the right way. By using behavior analysis and prediction models, we can keep an eye on, manage, and lessen device addiction in our routine lives.

II. LITERATURE REVIEW

Experimental Design to Predict Students' Electronic Gadget Addiction.
This study came up with a Neural Network model (ONC-M) to spot gadget addiction in students. They used questionnaires from parents about device usage, gaming, reactions when devices are taken away, and social stuff. They trained and tested it on 512 responses. The model sorts addiction into two levels and was pretty accurate (98.40%). The goal is to catch it early so teachers and parents can step in but there are privacy issues since they're using personal data.

Application of Machine Learning in Predicting Adolescent Internet Behavioral Addiction
This research looks at internet addiction in 4,461 high schoolers, using info about their background, family, and mental state. They split the students into addicted and not addicted groups, and stats helped them find the main risk factors. They put six machine learning methods head-to-head, like neural networks, SVM, random forest, and XGBoost. Extreme Gradient Boosting came out on top. The study shows that addiction risk is tied to personality (being moody, hostile, or depressed), family life, and gender, which is helpful for prevention programs.

AI-Driven Digital Well-being Model for Internet Addiction
This one uses public datasets (like smartphone data and mental health info) to create AI models that guess internet addiction and encourage digital well-being. They used a bunch of methods: Random Forest, XGBoost, Neural Networks, clustering, anomaly detection, and Natural Language Processing to check out emotional patterns in user data. Neural networks were the most accurate (around 91%). The study focuses on solutions that can keep an eye on behavior and suggest help but also brings up ethics stuff like data privacy and using AI responsibly.

Predictive Modeling of Smartphone Addiction and Academic Impact
This study zooms in on smartphone addiction and how it affects schoolwork. They got info from 500 people about their phone habits, addiction scores, sleep, and personality. They found the most predictors, like screen time, app use, sleep problems, impulsiveness, and worry.
They tested several machine learning models, and Gradient Boosting did best (91.2% accuracy). The research wants educators to get why the predictions are made, not just the results.

Ensemble Learning for Gaming Addiction Prediction
This paper is about gaming addiction in teens, using data from universities in Thailand. They tested a few data mining methods and used ensemble techniques to do better. Bagging with neural networks was the most accurate (99.35%), which is super accurate. They turned the model into a web app, showing it can be used to check for gaming addiction and help with programs.

III. PROBLEM STATEMENT

The fact that everyone has smartphones, tablets, and devices to get on the internet, along with everyone spending too much time staring at screens, being on social media, playing games online, and not controlling themselves, has caused people to get hooked on gadgets. People not knowing enough, being dependent on how they act, and not having ways to spot this early makes gadget addiction even worse. • Going digital so fast means that electronic gadgets are now a part of how we learn, work, talk to each other, and have fun. While this is good, being exposed to gadgets all the time has changed what we do every day and how we act. How we check for addiction now depends a lot on people telling on themselves and looking at things by hand, which is based on opinion, takes too much time, and doesn't work well when trying to find addiction on a big scale or right away.

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• Kids, teens, students, people who work, and people who depend on digital stuff a lot are the ones that are hit the hardest. Using gadgets too much messes with how well you do in school, how much you get done at work, how you sleep, and how you feel, so it's super important for people, families, teachers, and doctors to spot this early.
• Gadget addiction leads to feeling stressed, worried, not being able to pay attention, feeling alone, and health problems later on. To fix this, we're going to make computer programs that can learn to look at how people act, guess who's at risk of addiction, give good advice, and help people become aware and stop it in time through a smart guessing system.

IV. RESEARCH AND METHODOLOGY

To predict addiction to electronic gadgets, we used a step-by-step machine learning plan. This involved getting data, cleaning it up, training a model, testing how well it works, and then putting it to use. Our goal was to create a system that can correctly spot addiction and figure out patterns from how people act.

1. Data Collection
To figure out who might be hooked on electronic devices, we used a step-by-step machine-learning plan. It goes like this: grab data, clean it up, train a model, test it out, and then put it to work. We're trying to create a system that's both spot-on and easy to figure out, so it can sniff out addiction habits from how people act.

2. Data Preprocessing
Okay, so raw data from behavior studies? It's messy. It's got errors, missing bits, just junk. We have to clean it before we can train our model.
Here's how we fix the data:
* Fill in any blanks using stats.
* Get rid of any rows that are repeats or just broken.
* Turn categories into numbers that the model can read.
* Scale features with normalization.
* Balance the classes, using SMOTE.

This makes the data better and lowers bias when training.

3. Feature Selection
We used Recursive Feature Elimination (RFE) to pick out the most important things that point to tech obsession. This cuts down on data size and makes things run faster.
The features we picked really help nail down correct predictions by ditching stuff that doesn't matter. Getting the best features means the model can learn real behavior patterns.

4. Exploratory Data Analysis
We explored the data to figure out how things were related. We looked at a few things using charts:
* How many users were addicted versus not addicted
* How behaviors connect to each other
* How usage and addiction seem to go together

This helped us see patterns in behavior and pick the right model.

5. Model Development
We tried out a bunch of machine learning and deep learning methods to see which one worked best. Here's what we used:
* Random Forest Classifier
* Support Vector Machine
* Gradient Boosting (XG Boost)
* Multi-Layer Perceptron
* Voting Classifier (a mix-and-match model)
* Long Short-Term Memory network
* CNN–LSTM combo

Each model looks at addiction patterns in its own way. By mixing the predictions from different models, we get better, more dependable results.

6. Model Evaluation
We checked how well the model did using these common measures:
* Accuracy
* Precision
* Recall
* F1-score
* Confusion matrix

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Cross-validation makes sure the model works on different datasets. The ensemble Voting Classifier did the best in guessing and staying consistent.

7. Explainable AI Integration

To keep things clear, we use explainable AI methods:

* LIME tells you why the system made a specific prediction.
* SHAP shows which features matter most overall.

These tools make the system easier to understand and build confidence in it.

8. Deployment

We've put the model into a Flask web app. Now, people can enter their info and see their addiction risk right away.

Here's what the app does:

* Lets users log in and put in info.
* Classifies data ASAP.
* Shows results visually.
* Keeps data safe.

This makes the research a helpful, real-world tool for digital well-being.

V. CONCLUSION

This study shows that using machine learning to look at behavior can really predict if someone's addicted to electronic devices. It's reliable and can be used easily. We cleaned up the data, used a method called SMOTE to balance the learning, and picked the best features with Recursive Feature Elimination. This makes sure our model learns well and isn't unfair.

The Voting Classifier, which combines a couple of models, worked best. It got about 98.6% on accuracy, precision, remember, and F1-score. So it works for datasets that're real and complex, where one model might not be good enough.

We didn't just want good guesses; we wanted to know why. So, we used Explainable Artificial Intelligence techniques. LIME tells us why each guess was made, and SHAP tells us which features matter most. This helps us understand what behaviors lead to device addiction. Knowing why makes people trust the results and helps them make good choices, especially when it involves users.

To make it usable, we put the model into a simple web framework using Flask. People can easily use it through a website and get addiction risk scores right away. Putting it online proves that the system can grow and change for use in checking systems.

Basically, we see that combining ensemble learning with explainable AI and a simple web setup is really effective. This makes a great start for smart, clear, and easy-to-get digital well-being tools.

We built a machine learning model that guesses how at risk college students are for gadget addiction. It looks at quiz answers and uses the Random Forest algorithm to sort people into Low, Medium, and High risk categories. Screen time, anxiety, and how much someone depends on their device seem to be the best clues for guessing right. It's on the web, so anyone can get to it, and we can easily make it bigger if we need to. Eventually, we want to add personalized tips and advice to make it even more helpful for schools and mental health.

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