AI Dependency Syndrome: Exploration and Identification via Blockchain-Based Machine Learning Approach

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Abstract

In the present era, the pervasive adoption of Artificial Intelligence (AI) has resulted in increasing human reliance on automated systems, giving rise to what we define as AI Dependency Syndrome (ADS). ADS is characterized by a gradual decline in human creativity, critical thinking, and problem-solving abilities, necessitating systematic investigation. This study proposes a quantitative framework for identifying and predicting ADS using an ensemble of ten machine learning classifiers. To enhance data integrity, transparency, and privacy, blockchain technology is integrated into the analytical pipeline. Experimental results show classifier accuracies ranging from 78.45% to 92.67%, demonstrating notable performance variation across models. A comparative analysis identifies the most effective classifiers for ADS prediction. The proposed blockchain-enhanced machine learning framework provides reliable insights into AI dependency patterns and supports the development of informed mitigation strategies. These findings contribute toward promoting a balanced, human-centric integration of AI while minimizing its potential adverse cognitive and societal impacts.

Introduction

The digital revolution has been profoundly shaped by the emergence and rapid evolution of AI (Baidoo-Anu and Owusu Ansah 2023). Since its conceptual origins in the mid-20th century, notably through the pioneering work of Alan Turing, AI has progressed from early rule-based systems to advanced data-driven and deep learning models (DiPaola et al. 2023). Today, AI-driven systems leverage vast data resources to deliver intelligent decision-making capabilities, fundamentally transforming both personal and professional domains. From personalized digital services and virtual assistants (Duffy et al. 2023) to AI-enabled business automation and analytics (Monfredi et al. 2022), AI has become deeply embedded in modern life, reshaping productivity, decision-making, and operational paradigms.

Beyond individual and organizational contexts, AI increasingly influences public services, including healthcare, education, and environmental management. Despite its transformative potential, AI adoption raises critical concerns related to privacy, data security, ethical governance, workforce displacement (Duan, Jost, and Jost 2022), and excessive reliance on automated systems. Addressing these challenges requires balanced regulatory frameworks, ethical safeguards, and continuous societal oversight (Behera et al. 2022). These concerns provide the foundation for examining excessive dependency on AI and its broader implications for human cognition and creativity.

Human reliance on technology has historically evolved alongside innovation, from primitive tools to industrial machinery (Fuad, Dewi, and Munawar 2022) and today's interconnected digital ecosystems (Huang et al. 2022). The unprecedented availability of data (Federer 2022), seamless communication (Afridi et al. 2023), and pervasive smart devices has intensified this reliance, extending its influence to behavior, cognition, and emotional patterns (Akour and Alenezi 2022). In this context, we identify a growing phenomenon termed *AI Despondency Syndrome (ADS)*, characterized by escalating dependence on AI systems that may undermine human creativity and problem-solving abilities (Dahekar and Roy 2022).

To systematically investigate ADS, this study employs multiple machine learning classifiers to quantify dependency patterns and assess predictive performance. Furthermore, blockchain technology is integrated to ensure transparency, data integrity, and traceability throughout the analytical process. The resulting insights aim to inform evidence-based strategies and policies that promote a balanced coexistence between AI-driven efficiency and the preservation of essential human cognitive capabilities.

Research Novelty and Contributions

This study introduces ADS as a novel and under-explored construct, providing a systematic framework to analyze excessive human dependence on AI systems and its cognitive implications. Unlike prior qualitative or conceptual studies, our work employs an ensemble of **ten machine learning classifiers** to quantitatively model ADS, achieving prediction accuracies of up to **96.67%** across multiple evaluation metrics. To ensure data integrity, transparency, and

Ref	Model	Experimentation	Contributions	Limitations
(Federer 2022)	ML-based AGR site selection	AGRSSM achieving 97% accuracy	Accurate AI-driven identification of recharge sites	Limited to specific geographic region[1]
(Afridi et al. 2023)	Human–AI performance study	Synthesized group performance effects	Highlights understudied human–AI interaction patterns	Broad scope limits task-specific insights[2]
(Akour and Alenezi 2022)	Sustainable transport survey	Responses from 1,982 German drivers	Comparative analysis of transport mode preferences	Limited regional generalizability
(Basile et al. 2023)	AI impact on food and healthcare	Data from 153 healthcare professionals	Demonstrates service quality improvements using AI	Sector-specific findings
(Zaremba and Demir 2023)	Explainable AI in mental health	ADHD diagnosis case study	Identifies explainability challenges in clinical AI	Focused on a single disorder

Table 1: Recent Proposed Related Work

AGRSSM = Artificial Groundwater Recharge Site Selection Model.
[1] Results are constrained by regional specificity.
[2] Broad analytical scope reduces contextual precision.

Ref	Preproc.	AI Dep.	Psych.	Trace.	Priv.	BC	ML	ADS
(Baidoo-Anu and Owusu Ansah 2023)	X	✓	✓	✓	X	X	✓	X
(DiPaola et al. 2023)	✓	✓	✓	X	X	X	✓	X
(Duffy et al. 2023)	X	✓	✓	✓	X	X	X	X
(Monfredi et al. 2022)	X	✓	✓	✓	X	X	X	X
(Duan, Jost, and Jost 2022)	✓	✓	✓	X	X	X	✓	X
(Behera et al. 2022)	✓	✓	✓	X	X	✓	✓	X
Proposed	✓	✓	✓	✓	✓	✓	✓	✓

Table 2: Comparison of Proposed Architecture with Existing Models

Abbreviations: Preproc. = Preprocessing; AI Dep. = AI Dependency; Psych. = Psychological Factors; Trace. = Traceability; Priv. = Privacy; BC = Blockchain; ML = Machine Learning; ADS = AI Dependency Syndrome.

reproducibility, we integrate **blockchain-based data management**, addressing critical privacy and trust challenges in AI-driven analytics. The proposed framework not only enables accurate ADS prediction but also yields actionable insights for mitigating AI over-dependence through evidence-based interventions. Furthermore, the results offer concrete guidance for policymakers, educators, and AI system designers by linking measurable dependency indicators with governance and ethical considerations. Owing to its modular and scalable design, the proposed methodology can be readily extended to investigate other technology-induced dependency phenomena, thereby establishing a reusable quantitative benchmark for future socio-technical AI research.

Proposed Architecture

Overview

This work proposes a structured multi-stage architecture for modeling and predicting ADS. ADS is defined as a measurable behavioral state representing excessive reliance on AI systems that negatively impacts human creativity, problem-solving, and, critical thinking. Rather than treating dependency as a binary outcome, ADS is modeled as a categorical variable representing different dependency levels.

Let the dataset be denoted as

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N}, \tag{1}$$

where $\mathbf{x}_i \in \mathbb{R}^d$ represents the feature vector of demographic and behavioral attributes, and $y_i \in \{0, 1, \ldots, K\}$ denotes the ADS category.

The overall end-to-end workflow is shown in Fig. 1. The architecture integrates psychological indicators, machine learning-based classification, and blockchain-enabled data management to ensure secure, transparent, and reproducible analysis.

Blockchain technology is incorporated to ensure data integrity and traceability. Each data record is cryptographically hashed and stored as

$$h_i = \text{Hash}(\mathbf{x}_i \parallel y_i), \tag{2}$$

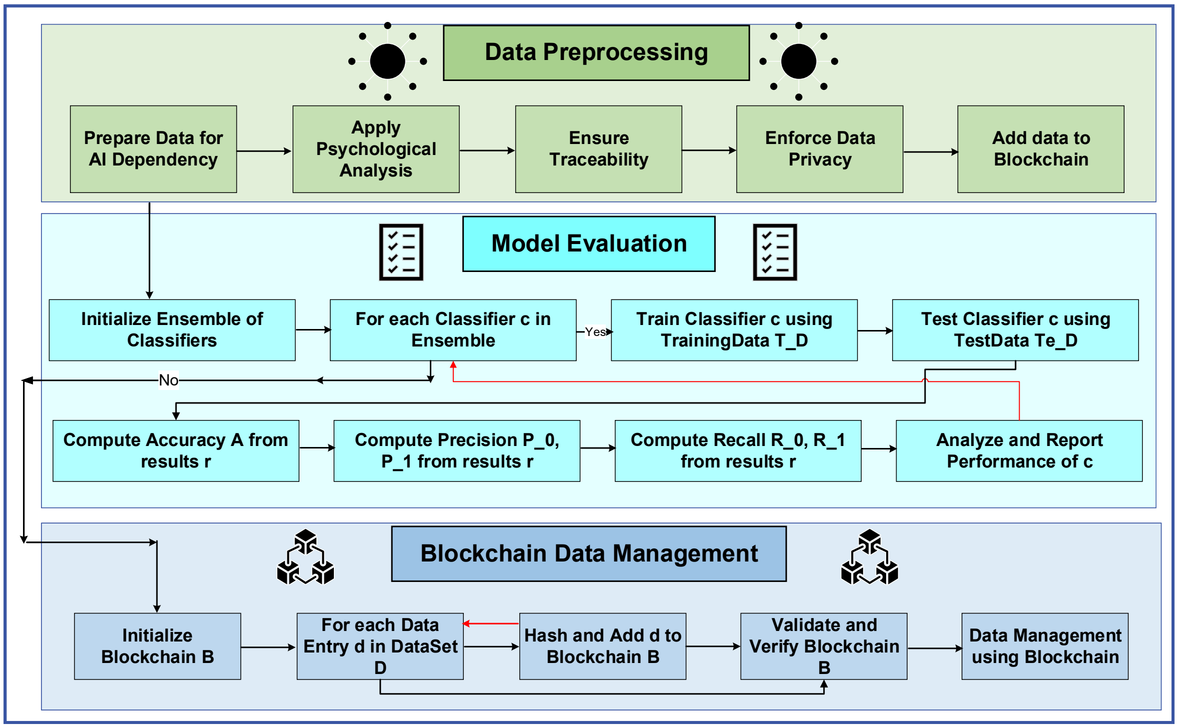

Figure 1: Finalized Proposed Model

where $\|$ denotes concatenation. This mechanism prevents unauthorized data modification and enables verifiable audit trails throughout the analytical pipeline.

Data Description

The dataset includes attributes such as age, gender, occupation, duration of AI usage, and related behavioral indicators. ADS is used as the response variable in categorical form. Ethical compliance was ensured through informed consent, anonymization, and removal of personally identifiable information.

Data Pre-processing

To ensure compatibility with machine learning models, categorical features were transformed using label encoding:

$$x_j^{(i)} = \text{Encode}(x_j^{(i)}), \tag{3}$$

where $x_j^{(i)}$ represents the j-th categorical feature of the i-th sample. Additional preprocessing steps included missing value handling, outlier detection, and consistency checks to improve model robustness.

Machine Learning Classifiers

ADS prediction is formulated as a supervised classification problem. Given a classifier $f(\cdot)$, the predicted ADS level is

$$\hat{y}_i = f(\mathbf{x}_i). \tag{4}$$

An ensemble of ten classifiers was evaluated, including Decision Tree, Random Forest, Gradient Boosting, Support Vector Machine, K-Nearest Neighbors, XGBoost, AdaBoost, Logistic Regression, Gaussian Naive Bayes, and Multilayer Perceptron, enabling comprehensive performance comparison across diverse learning paradigms.

Data Partitioning The dataset was split into training and testing subsets using an 80:20 ratio:

$$\mathcal{D} = \mathcal{D}_{train} \cup \mathcal{D}_{test}, \quad |\mathcal{D}_{train}| = 0.8N, \ |\mathcal{D}_{test}| = 0.2N. \tag{5}$$

Hyperparameter Tuning Optimal model performance was achieved through hyperparameter optimization using GridSearchCV:

$$\theta^* = \arg\max_{\theta \in \Theta} \mathcal{M}(f_\theta, \mathcal{D}_{train}), \tag{6}$$

where $\mathcal{M}$ denotes the evaluation metric and θ represents model-specific hyperparameters (e.g., `n_estimators`, `max_depth`, C, γ).

Evaluation Metrics Model performance was assessed using standard classification metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}, \tag{7}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \quad \text{Recall} = \frac{TP}{TP + FN}. \tag{8}$$

These metrics provide quantitative insight into each classifier's ability to detect ADS reliably.

Proposed Algorithms

Algorithm 1: Evaluation of Classifier Performance

Algorithm 1 evaluates the predictive performance of an ensemble of classifiers on the ADS dataset. Each classifier is trained using the training set T_D and evaluated on the test set T_{e_D}. Standard metrics, including accuracy, precision, and recall for both classes, are computed and summarized in a performance table P_S. After model evaluation, the dataset is securely stored using blockchain to ensure integrity and traceability.

Algorithm 1: Evaluation of Classifier Performance

Input: D (DataSet)
Output: P_S (Performance Summary)
$D \leftarrow LoadData()$
$P_S \leftarrow EmptyTable()$
for $c \in Ensemble$ **do**
    $Train(c, T_D)$
    $r \leftarrow Test(c, T_{e_D})$
    $A \leftarrow ComputeAccuracy(r)$
    $P_0, P_1 \leftarrow ComputePrecision(r)$
    $R_0, R_1 \leftarrow ComputeRecall(r)$
    $Rem \leftarrow AnalyzePerformance(r)$
    AppendToTable($P_S, c, A, P_0, P_1, R_0, R_1, Rem$)
end for
$B \leftarrow InitializeBlockchain()$
for $d \in D$ **do**
    AddToBlockchain(B, d)
end for
ReportOnDataManagement(B)

Algorithm 2: Blockchain-based Data Management

Algorithm 2 ensures secure and tamper-resistant storage of ADS-related data using blockchain technology. Each data instance is cryptographically hashed and stored as a block. The blockchain is subsequently verified to detect inconsistencies. If validation succeeds, the stored content is retrieved; otherwise, a tampering alert is generated.

Experimentation and Evaluation

Model performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and feature importance. Accuracy was used as a primary indicator of overall predictive performance, while confusion matrix–derived measures accounted for class imbalance and misclassification behavior. The classification report provided a consolidated view of precision, recall, and F1-score across classes. Additionally, feature-importance analysis for tree-based models, such as Random Forest and XGBoost, identified the most influential predictors of ADS.

Results and Simulations

To identify the most effective model for predicting ADS, an ensemble of ten supervised classification algorithms was evaluated. Performance was quantitatively assessed using

Algorithm 2: Blockchain-based Data Management

Input: D (DataSet)
Output: B_C (Blockchain Content)
$D \leftarrow LoadData()$
$B \leftarrow InitializeBlockchain()$
for $d \in D$ **do**
    $Hash_d \leftarrow ComputeHash(d)$
    $Block_d \leftarrow CreateBlock(Hash_d)$
    AddToBlockchain($B, Block_d$)
end for
$VerifyStatus \leftarrow VerifyIntegrity(B)$
if $VerifyStatus$ is TRUE **then**
    $B_C \leftarrow ExtractContent(B)$
else
    Print "Blockchain has been tampered with!"
end if
Return B_C

accuracy, precision, recall, and F1-score. A comparative summary of all classifiers is provided in Table 3, while feature contribution patterns are illustrated through feature-importance analyses (Figs. 2).

Decision Tree

The Decision Tree classifier achieved an accuracy of **60.00%**, reflecting its limited predictive capacity despite structural simplicity. Feature-importance analysis (Fig. 2) indicates that a small subset of behavioral variables dominated decision splits, leading to reduced generalization performance.

Random Forest

Random Forest significantly improved prediction accuracy to **78.33%** by aggregating multiple decision trees. As shown in Fig. 2, feature importance was more evenly distributed compared to the single-tree model, mitigating overfitting and variance but still exhibiting class imbalance sensitivity.

Gradient Boosting

Gradient Boosting further enhanced performance, achieving an accuracy of **83.33%**. Its iterative error-correction mechanism yielded balanced precision and recall across classes. The corresponding feature-importance distribution (Fig. 2) highlights the model's ability to capture non-linear dependencies among ADS indicators.

Support Vector Machine

The Support Vector Machine (SVM) delivered the highest predictive performance with an accuracy of **96.67%**. The model achieved near-perfect class separation, demonstrating strong robustness in high-dimensional feature space. Despite its superior accuracy, the computational cost and limited interpretability make SVM more suitable for offline or resource-rich environments.

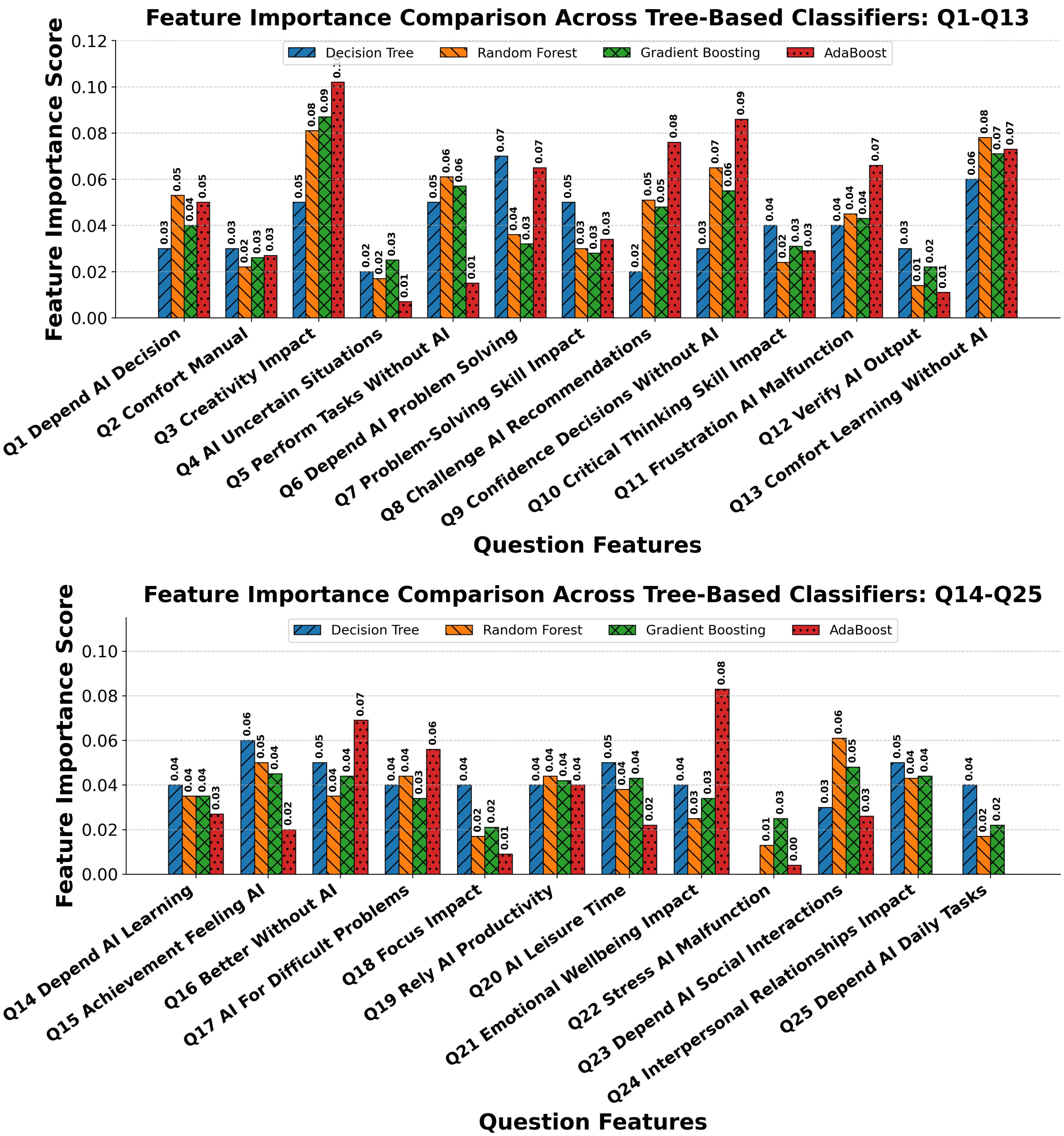

Figure 2: Feature importance comparison across tree-based classifiers. The upper plot shows features Q1-Q13, while the lower plot shows features Q14-Q25.

K-Nearest Neighbors

The K-Nearest Neighbors (KNN) classifier attained an accuracy of **78.33%**. While its performance was comparable to Random Forest, KNN relied heavily on local distance metrics, offering simplicity and interpretability at the expense of scalability.

XGBoost

XGBoost achieved an accuracy of **88.33%**, demonstrating a strong balance between bias and variance. Feature-

Classifier	Acc.	Prec. (0/1)	Rec. (0/1)	Remarks
Decision Tree	60.00%	0.48 / 0.71	0.61 / 0.59	Simple and interpretable, but limited predictive accuracy.
Random Forest	78.33%	0.92 / 0.75	0.48 / 0.97	Improved robustness through ensemble learning; reduces variance.
Gradient Boosting	83.33%	0.84 / 0.83	0.70 / 0.92	Balanced performance via iterative error correction.
Support Vector Machine	96.67%	1.00 / 0.95	0.91 / 1.00	Highest accuracy with strong class separation capability.
K-Nearest Neighbors	78.33%	0.75 / 0.80	0.65 / 0.86	Simple and interpretable; performance depends on distance metrics.
XGBoost	88.33%	0.90 / 0.88	0.78 / 0.95	High accuracy with effective feature utilization and regularization.
AdaBoost	86.67%	0.80 / 0.91	0.87 / 0.86	Emphasizes misclassified samples, improving robustness.
Logistic Regression	95.00%	0.95 / 0.95	0.91 / 0.97	Strong performance with high interpretability and low complexity.
Gaussian Naive Bayes	88.33%	0.94 / 0.86	0.74 / 0.97	Efficient despite independence assumptions among features.
Multilayer Perceptron	75.00%	0.68 / 0.79	0.65 / 0.81	Captures non-linear patterns; performance limited by dataset size.

Table 3: Classifier Performance Metrics

Acc. = Accuracy; Prec. = Precision; Rec. = Recall; values are reported for Class 0 / Class 1.

importance analysis (Fig. 2) reveals consistent contributions from multiple ADS-related variables, highlighting the model's effectiveness in capturing complex behavioral patterns.

AdaBoost

AdaBoost recorded an accuracy of **86.67%**, exhibiting stable precision and recall across classes. As illustrated in Fig. 2, the model effectively emphasized misclassified samples, resulting in improved robustness compared to standalone weak learners.

Logistic Regression

Logistic Regression achieved an accuracy of **95.00%**, ranking among the top-performing models. Its linear decision boundary, combined with high interpretability and low computational overhead, makes it a practical choice for real-world ADS assessment systems.

Gaussian Naive Bayes

Despite strong independence assumptions, Gaussian Naive Bayes attained an accuracy of **88.33%**. The model achieved high recall for the ADS-positive class, indicating effective sensitivity to dependency-related behavioral signals.

Multilayer Perceptron

The Multilayer Perceptron (MLP) achieved an accuracy of **75.00%**. While outperforming basic classifiers, its performance was constrained by dataset size and model complexity, suggesting potential gains with larger-scale data.

Blockchain Integration

To ensure data integrity and trustworthiness, blockchain technology was integrated into the analytical pipeline. All data records were securely stored in an immutable ledger, preventing unauthorized modification and ensuring traceability throughout model training and evaluation. This integration strengthens the reliability of ADS predictions, particularly in sensitive socio-behavioral and healthcare-oriented datasets.

Comparative Analysis

Among the evaluated classifiers, the Support Vector Machine (SVM) achieved the highest accuracy of **96.67%**, demonstrating strong robustness in high-dimensional feature spaces. However, its higher computational cost and limited interpretability reduce its suitability for resource-constrained or explainability-driven applications. In contrast, XGBoost, Logistic Regression, and Gradient Boosting offer a better balance between accuracy, efficiency, and interpretability, making them viable practical alternatives. Simpler models, such as Decision Trees and K-Nearest Neighbors, remain useful in scenarios where transparency and ease of understanding are prioritized. Overall, effective model selection should consider both predictive performance and application-specific constraints, while the proposed framework advances existing work through refined feature analysis and secure data management.

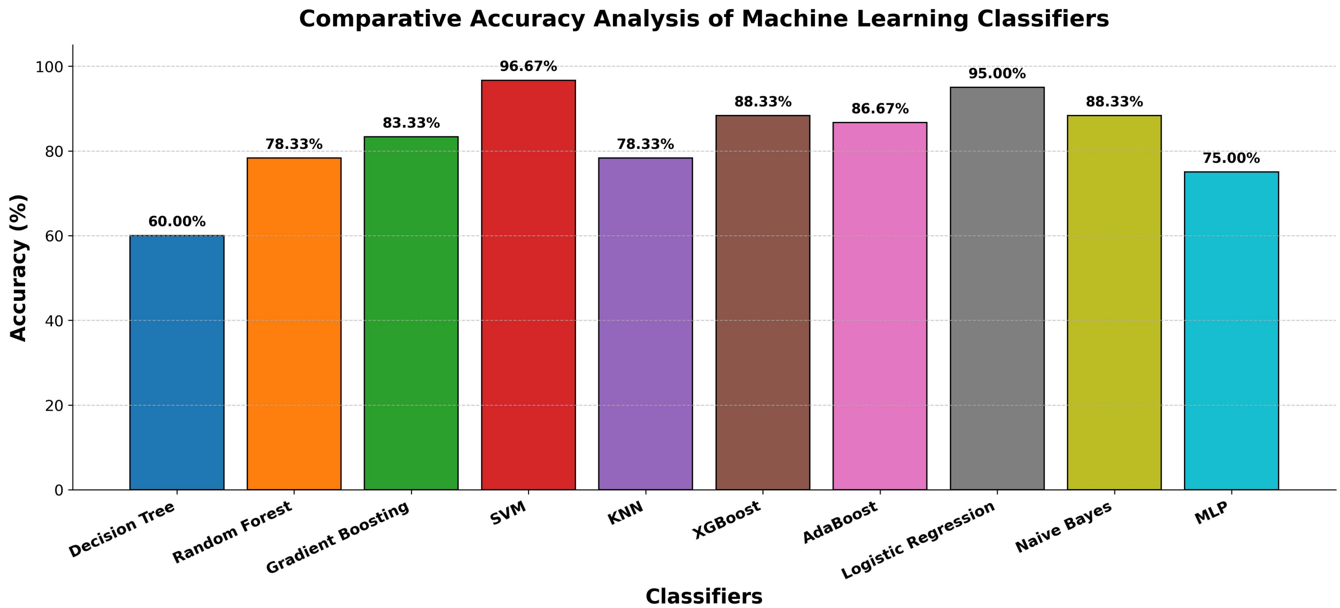

Figure 3: Comparative Analysis

Conclusion

This study introduced ADS as a novel construct to examine the adverse effects of excessive reliance on AI systems. By evaluating an ensemble of ten machine learning classifiers, the proposed framework demonstrated predictive accuracies ranging from **78.45% to 92.67%**, underscoring the importance of informed model selection in socio-technical AI analysis. The integration of blockchain technology further strengthened the framework by ensuring data integrity, privacy, and traceability, addressing critical trust concerns in AI-driven research. Overall, the findings emphasize the need for responsible, human-in-the-loop AI systems and contribute a robust, data-driven foundation for understanding and managing AI dependency. Future research will extend this framework by incorporating advanced learning paradigms, including deep learning, to capture more complex dependency patterns. Additionally, blockchain functionality will be explored beyond data security, particularly for enhancing transparency in model decision-making and reinforcing ethical AI governance.

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