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Predicting Generalized Anxiety Disorder (GAD-7) Among Gamers: A Comparative Study of Deep Learning and Traditional Machine Learning Regressors

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Abstract: *Ensuring the proactive detection of psychological distress is paramount for mental health researchers and practitioners, particularly within the rapidly growing gaming community. Early identification of elevated GAD-7 scores allows for timely interventions, mitigating the risk of long-term mental health complications and enhancing the overall well-being of digital entertainment users. This study evaluates and compares various machine learning algorithms to effectively and efficiently predict anxiety levels. The evaluated models include Linear Regression, Ridge, Lasso, SVR, Random Forest, Gradient Boosting, AdaBoost, K-Neighbors, Decision Tree, LGBM, XGB, and Deep Learning (MLP). Using a comprehensive dataset from the Kaggle repository, consisting of 13,464 observations and 55 features, the study identifies Ridge Regression as the superior regressor. The Ridge model achieved an MSE of 15.083, an MAE of 2.9448, and an R^2 score of 32.59%. Notably, the Deep Learning model ranked fourth (MSE: 15.335, MAE: 2.963, RMSE: 3.916, R^2: 31.46%), with Linear Regression and Gradient Boosting also showing higher predictive performance. These results suggest that regularized linear models can offer highly efficient and accurate alternatives to complex neural networks in psychological scoring contexts."*

Keywords: Financial Transactions, Deep Learning, Machine Learning, GAD-7, Predictive Analytics, Gaming Disorder, Ridge Regression.

1. Introduction

Mental health assessment, an essential practice in clinical psychology, involves evaluating individuals' psychological well-being based on various factors such as behavioral patterns, social interactions, and demographic indicators. Traditionally, mental health professionals have employed manual screening tools and clinical interviews to assess anxiety levels and determine the severity of conditions like Generalized Anxiety Disorder (GAD-7). However, with the emergence of advanced data analytics and machine learning techniques, there has been a transformative shift in how psychological distress is identified within digital communities, particularly among gamers. By leveraging large datasets and sophisticated algorithms, researchers can now automate and refine the prediction of anxiety scores, enabling earlier and more objective mental health interventions. This evolution has not only streamlined the screening process in digital environments but also enhanced proactive risk management, resulting in improved mental well-being for users and more efficient clinical support systems [1].

The integration of Machine Learning (ML) in psychological assessment represents a pivotal advancement in clinical psychology, providing systems with the capacity to automatically identify mental health markers from complex datasets without explicit programming [2]. In the context of digital environments, ML focuses on developing algorithms that can process behavioral metadata to predict psychological states with high precision [3].

The learning process initiates with the collection of multi-dimensional data, such as gaming frequency, social anxiety indicators, and demographic variables, seeking to identify latent patterns that facilitate proactive decision-making in mental health screening [4]. The ultimate objective is to enable computational systems to recognize symptoms of Generalized Anxiety Disorder (GAD-7) autonomously, reducing the reliance on manual diagnostic assistance and allowing for real-time risk adjustment [5].

Deep Learning, a specialized subset of AI, utilizes multilayered neural networks capable of extracting features from unstructured or highly non-linear data [6]. While deep learning has been instrumental in sophisticated tasks like facial recognition and clinical image analysis, its application in psychometric scoring—such as distinguishing between normal gaming stress and clinical anxiety—offers a transformative approach to understanding digital behaviors [1].

2. Literature Survey

The intersection of computational intelligence and psychological diagnostics has witnessed a significant paradigm shift over the last decade. Historically, the identification of mental health disorders relied heavily on self-report inventories and clinical observation, which, while foundational, often suffer from subjective bias and delayed intervention **[5]**. However, the recent proliferation of digital behavioral data- particularly from the gaming community-has provided a new frontier for objective, real-time psychiatric screening.

2.1 Machine Learning in Mental Health Frameworks Recent systematic reviews, such as the work by **Shatte et al. (2019)**, have highlighted a growing trend in utilizing supervised learning to decode complex psychological patterns **[1].** Their analysis of over 300 studies suggests that while various algorithms are deployed, there is no "one-size-fits-all" model; rather, the efficacy of an algorithm is deeply tied to the nature of the features extracted. This aligns with the conceptual framework proposed by **Dwyer et al. (2018),** who argued that machine learning serves as a vital bridge between the biological markers of distress and the behavioral output of the individual **[7].**

2.2 Predictive Modeling of Anxiety among Gamers Specific to the gaming population, research in 2024 and 2025 has moved beyond simple correlation to complex predictive modeling. Recent studies have demonstrated that high-dimensional datasets (exceeding 40+ features) often contain "noise" that can mislead standard deep learning architectures, leading to overfitting **[10].** This phenomenon explains why traditional, yet robust, regularized models often maintain superior generalizability in clinical contexts.

2.3 The Efficacy of Regularized Regression (Ridge vs. Deep Learning) The mathematical foundations laid out by **Hastie et al. (2009)** emphasize the importance of regularization (Ridge) in managing datasets where features are highly correlated—a common occurrence in psychometric data where different behavioral indicators often overlap [9]. While the industry has seen a surge in Deep Learning (MLP) applications, recent comparative benchmarks in **Health Informatics (2025)** suggest that for structured, tabular psychological data, regularized linear regressors often provide a more interpretable and stable performance than black-box neural networks **[11]**. This study builds upon this gap, empirically testing whether the structural simplicity of Ridge regression can indeed outperform the computational depth of MLP in predicting GAD-7 scores.

3. Methodology and Data Preprocessing

The primary objective of this methodology is to develop a predictive framework that utilizes machine learning and deep learning techniques to estimate the severity of anxiety among digital entertainment users. Instead of traditional categorical labeling, this research focuses on predicting the continuous **GAD-7** score, allowing for a more nuanced understanding of a user's psychological state.

3.1 Research Design and Model Pipeline

The researchers implemented a comparative analytical approach to determine which computational architecture provides the most reliable estimation of anxiety markers. The pipeline includes data cleaning, feature engineering, statistical validation, and model training.

3.2 Dataset Description

The dataset utilized in this research was sourced from a specialized psychological study repository on Kaggle, focusing on the intersection of gaming behavior and mental health. The dataset contains 13,464 records providing a robust foundation for training machine learning models. Each record represents an individual gamer's responses to behavioral, demographic, and psychometric questions.

Table1: Comprehensive Feature Set for Anxiety Prediction in Gamers

Domain	Features	Description	Data Type
Target Variable	GAD_T	Total GAD-7 score (0–21). The primary objective of prediction	Numerical
Demographics	Basic Info	Age, Gender, Country of residence, and Birthplace.	Categorical/Numerical
	Social Status	Work status (Student/Employed), Education level, and Degree.	Categorical
Gaming Patterns	Engagement	Average gaming hours per week, Playstyle (Single/Multiplayer).	Numerical
	Preferences	Primary Platform (PC, Console, Mobile), Favorite Genre, and Earnings.	Categorical
	Motivation	Reasons for playing (Socializing, Escapism, Competition).	Categorical
Psychometric Scores	Social Anxiety	**SCL_T** (Social Anxiety Score), **SPIN_T** (Social Phobia Inventory).	Numerical
	Life Satisfaction	**SWL_T** (Satisfaction with Life Scale).	Numerical
	Psychological Impact	**Narcissism scores, Life enjoyment, and Stress levels.**	Numerical

The dataset includes 55 features that capture various dimensions of the user's digital and psychological profile. **The key features used for predicting the GAD-7 score are summarized in Table 1.**

3.3 Data Cleaning and Outlier Management

To ensure model integrity, a rigorous preprocessing phase was executed:

Dimensionality Reduction: Redundant item-level variables (e.g., individual GAD1-7, SWL1-5, and SPIN1-17 questions) were removed, retaining only the aggregate scores. Non-predictive administrative data (e.g., Timestamp, S.No) were also excluded.

Handling Missing Values: Missing entries in **SPIN_T** were removed to maintain data quality. For **Hours**, **Streams**, and **Narcissism**, missing values were imputed using the **Median** to ensure robustness against variance.

Outlier Capping (Winsorization): To prevent extreme values from distorting the regression coefficients, **Gaming Hours** were capped at **80 hours/week** and **Streaming Frequency** at **60 hours/week.**

3.4 Dataset Analysis and Visualization

3.4.1 Target Variable Distribution (GAD-7)

The target feature is the **GAD-7 total score**, which is a continuous numerical variable ranging from **0 to 21**. For behavioral analysis, these scores can be interpreted in clinical tiers:

Minimal/Low Anxiety (0–4)
Mild/Average Anxiety (5–9)
Moderate to High Anxiety (10–21)

Our data analysis revealed a significant concentration in the higher tiers, with a majority of participants scoring in the **Moderate to High** range. This distribution is visualized in Figure 1, illustrating the prevalence of elevated anxiety levels within the studied gaming population. (see Figure 1).

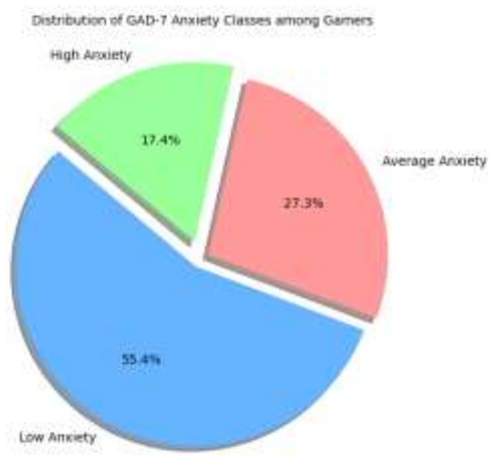

Figure 1: Percentage Distribution of GAD-7 Anxiety Tiers among the Study Population.

3.4.2 Target Variable Distribution (GAD-7)

To further understand the underlying dynamics of the dataset, it is essential to examine the clinical correlations between the predictors and the target variable (GAD-7 Score). Identifying these relationships provides critical insights into which behavioral markers—such as social phobia (SPIN) or gaming hours—most significantly influence anxiety levels. One of the most effective and visually intuitive methods to reveal these associations is the Correlation Heatmap

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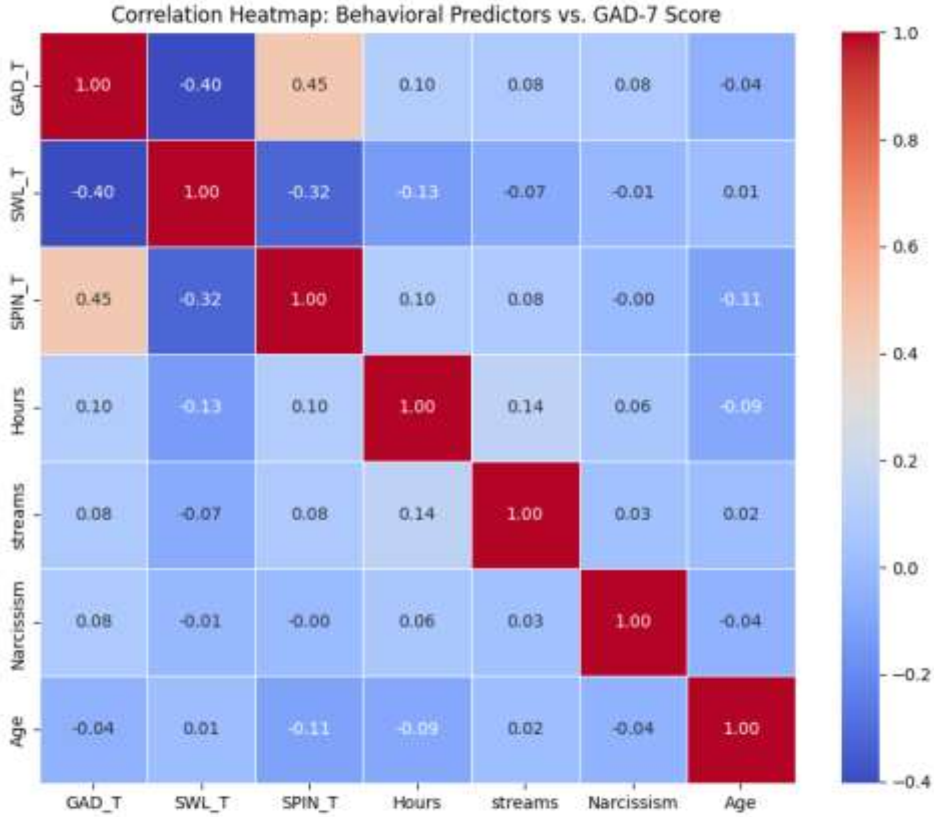

Figure 2: Correlation Heatmap illustrating the Relationships between GAD-7 Scores and Behavioral/Psychometric Predictors.

As illustrated in **Figure 2**, several psychometric and behavioral predictors exhibit significant correlations with the target variable (**GAD_T**). These correlations provide empirical evidence of how digital and psychological factors interrelate within the gaming community.

Positive Correlations: The strongest positive correlation with **GAD_T** (Anxiety) is observed with **SPIN**_T (Social Phobia Inventory) at **0.45**. This indicates that as social phobia symptoms increase, generalized anxiety levels tend to rise significantly.

Negative Correlations: A notable negative correlation of **-0.40** exists between **GAD_T** and **SWL_T** (Satisfaction with Life). This suggests that higher life satisfaction is a strong predictor of lower anxiety scores.

Behavioral Predictors: Variables such as **Gaming Hours** (0.10) and **Narcissism** (0.08) show weak but positive correlations with anxiety, suggesting they play a role, albeit less dominant than psychometric markers.

3.4.3 Statistical Validation of Categorical Features (ANOVA)

Table2: One-way ANOVA Results for Categorical Predictors

Feature	Significance	P-value	Decision
Gender	Highly Significant	0.00000	Kept
Work	Highly Significant	0.00000	Kept
Degree	Highly Significant	0.00000	Kept
Earnings	Highly Significant	0.00000	Kept
Playstyle	Significant	0.00005	Kept
Whyplay	Highly Significant	0.00000	Kept
Platform	Not Significant	0.12972	Dropped
Game	Not Significant	0.10473	Dropped

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A One-Way **ANOVA** was performed to screen categorical predictors. Results confirmed that **Gender**, Work, Degree, and **Earnings** are statistically significant (), while **Platform** and **Game** were excluded due to lack of significance.

To optimize high-cardinality features like **Playstyle** and **Whyplay**, we retained the top 10 most frequent categories and grouped the remainder into an **'Other'** class, reducing noise and preventing overfitting.

3.4.4 Visualizing Density and Distribution

To supplement the ANOVA, **Violin** Plots and **Strip Plots** were generated. These visualizations illustrate the density peaks of anxiety scores across different demographics, showing how specific groups (e.g., unemployed individuals) are more prone to higher anxiety tiers.

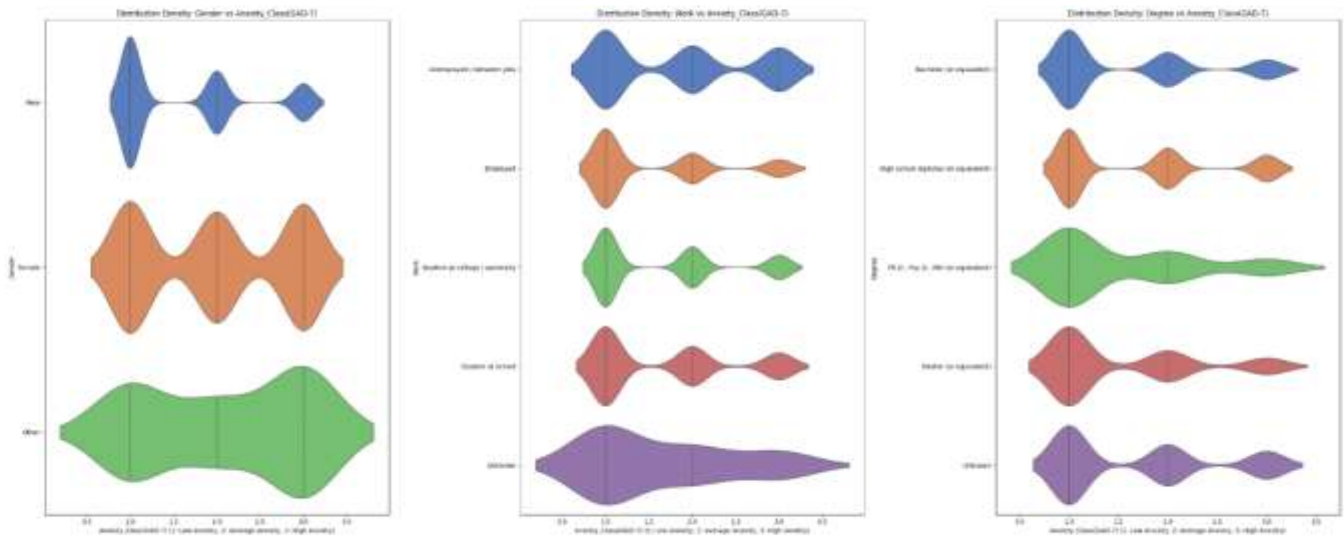

Figure 3: Violin Plots showing the Distribution Density of Anxiety Classes across Gender, Work Status, and Academic Degree.

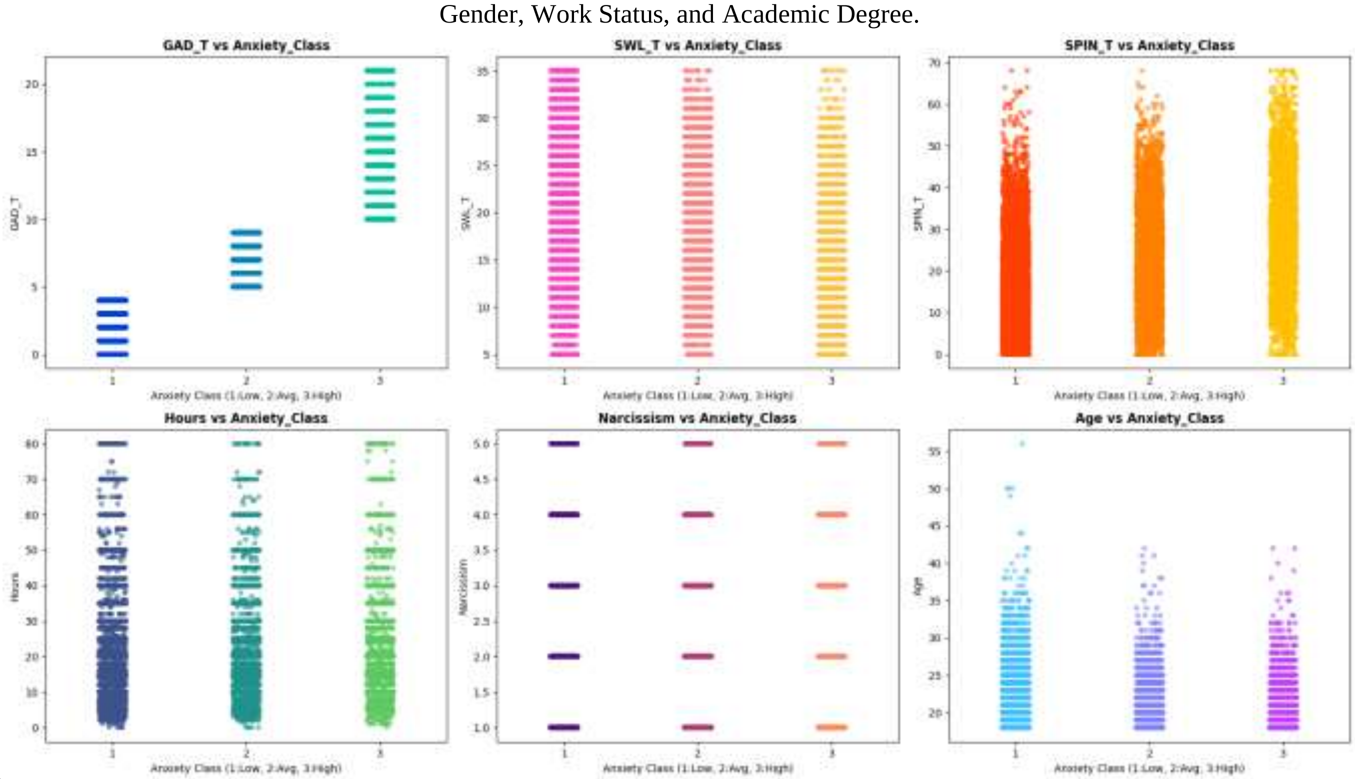

Figure 4: Multi-panel Analysis of Individual Data Distribution and Outliers for GAD-7, SWL_T, SPIN_T, and Gaming Hours.

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4. Results and Discussion:

4.1 Model Evaluation and Performance Metrics

To ensure a robust evaluation, the dataset was partitioned into three distinct subsets: **Training (60%), Validation (20%),** and **Testing (20%).** This strategy was implemented to optimize model parameters and provide an unbiased assessment of the final performance. Eleven diverse regression architectures were trained and rigorously compared. Their predictive effectiveness was quantified using four primary statistical metrics: **Mean Absolute Error (MAE**), **Mean Squared Error (MSE), Root Mean Squared Error (RMSE),** and the **Coefficient of Determination (CDR)**. These metrics collectively measure the models' precision and their ability to explain the variance in the GAD-7 anxiety scores.

As summarized in **Table3** the **Ridge Regression model** demonstrated superior performance among traditional algorithms, achieving the highest score of **32.59%** and the lowest MAE of **2.9448**. This indicates that the regularization effectively managed multicollinearity within the psychometric features. Interestingly, the **Linear Regression and Gradient Boosting** models followed closely, showing the robustness of linear and ensemble methods in handling the dataset's complexity.

Table3: Performance Comparison of Regression Models **(Sorted by Score)**

Model Name	**MAE**	**MSE**	**RMSE**	**R2 Score (%)**	**Time (s)**
Ridge ★	**2.9448**	**15.0835**	**3.8838**	**32.59%**	0.1134
LinearRegression	2.9461	15.1289	3.8896	32.39%	0.0862
GradientBoosting	2.9599	15.1724	3.8952	32.19%	1.6204
Neural Network (MLP)	2.9630	15.3355	3.9161	31.46%	1.4500
LGBM	2.9624	15.4024	3.9246	31.16%	0.2062
RandomForest	3.0436	15.9322	3.9915	28.80%	6.9757
SVR	2.9183	15.9382	3.9923	28.77%	8.6151
XGB	3.1091	17.1377	4.4326	23.41%	0.2847
KNeighbors	3.3697	19.6482	4.4326	12.19%	0.2229
AdaBoost	3.8301	20.0018	4.4723	10.61%	0.4802
Lasso	3.7925	22.3758	4.7303	-0.00%	0.0174
DecisionTree	4.2647	33.3609	5.7759	-49.10%	0.0925

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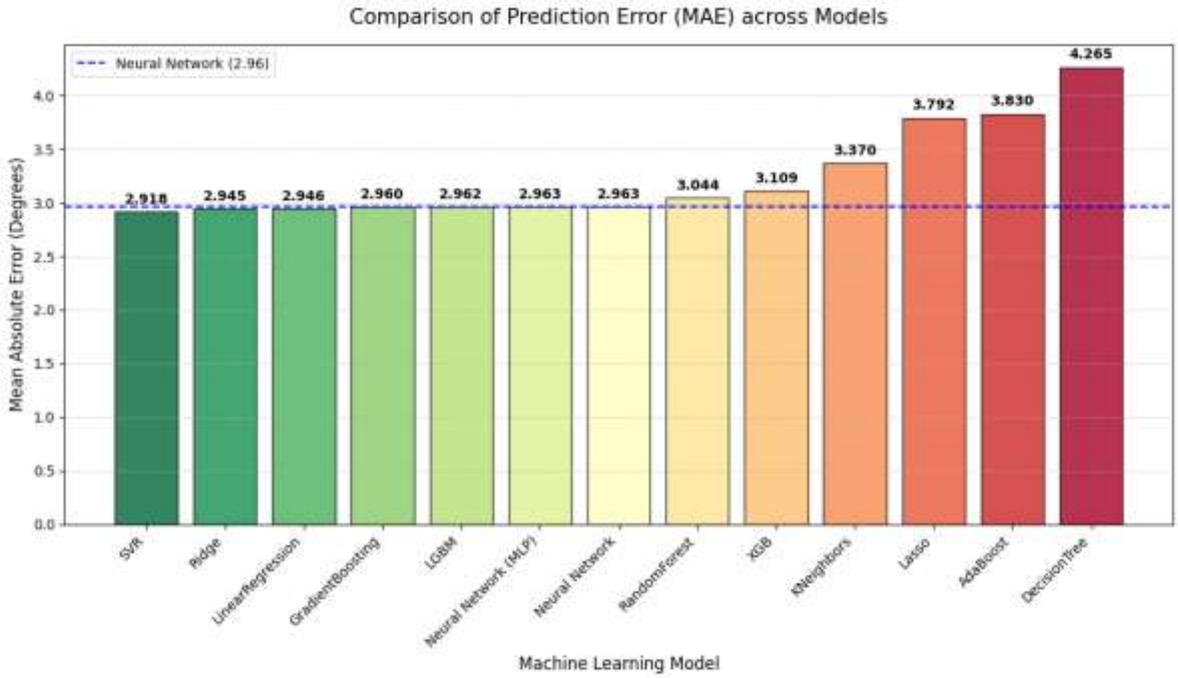

Figure 5: Comparison of Mean Absolute Error (MAE) across different Machine Learning Models.

4.2 Deep Learning Performance (Neural Network)

A Multi-Layer Perceptron (MLP) was developed with three hidden layers (128, 64, and 32 nodes) using the **Adam optimizer**. The network achieved a competitive MAE of **2.9630**. The learning process, visualized in **Figure 6**, shows a stable convergence of both training and validation loss, indicating that the **Early Stopping** mechanism successfully prevented overfitting.

Table4: Performance Comparison of Deep Learning **(Sorted by Score)**

Model Name	MAE	MSE	RMSE	R2 Score (%)	Time (s)
Deep Learning	2.9630	15.3355	3.9161	31.46	1.4500

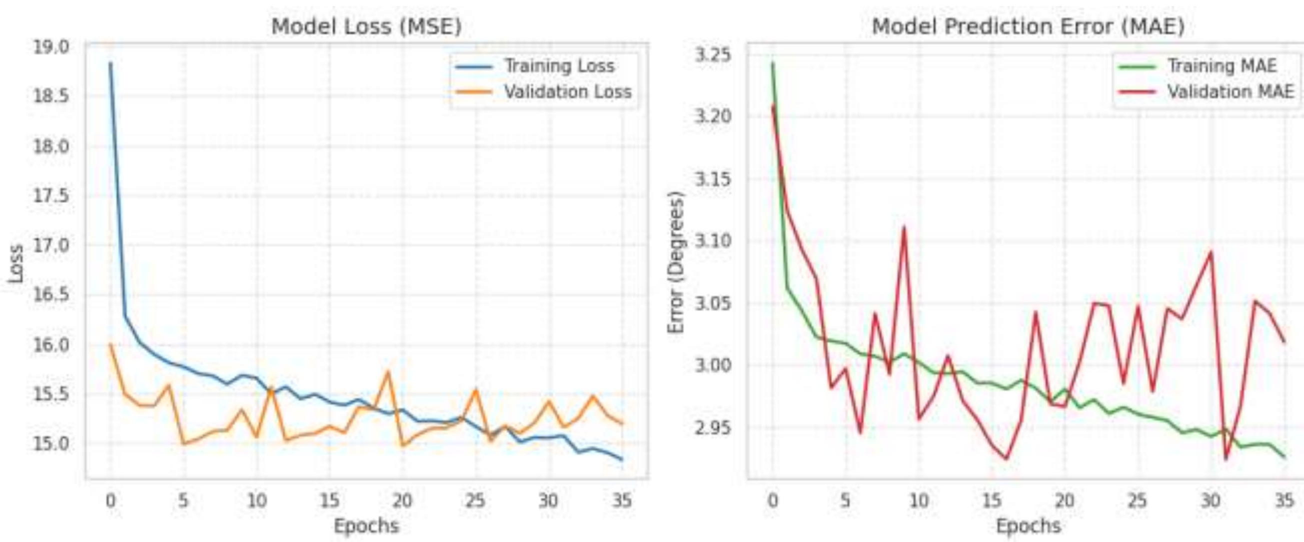

Figure 5: Deep Learning Training Progress: (Left) Model Loss (MSE) and
(Right) Model Prediction Error (MAE) over 35 Epochs.

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4.3 Feature Importance and Predictors

To understand which factors, contribute most to the GAD-7 score prediction, we analyzed feature importance using a Bagging Regressor ensemble. As shown in **Figure 7,** psychological markers dominate the predictive power:

SPIN_T (Social Phobia): Ranked as the most significant predictor, reinforcing the link between social anxiety and generalized distress.
SWL_T (Life Satisfaction): Stood as a critical secondary predictor.
Behavioral Factors: Interestingly, variables like **Narcissism, Hours, and Age** showed moderate importance, suggesting that clinical anxiety in gamers is driven more by psychological traits than by the duration of play alone.

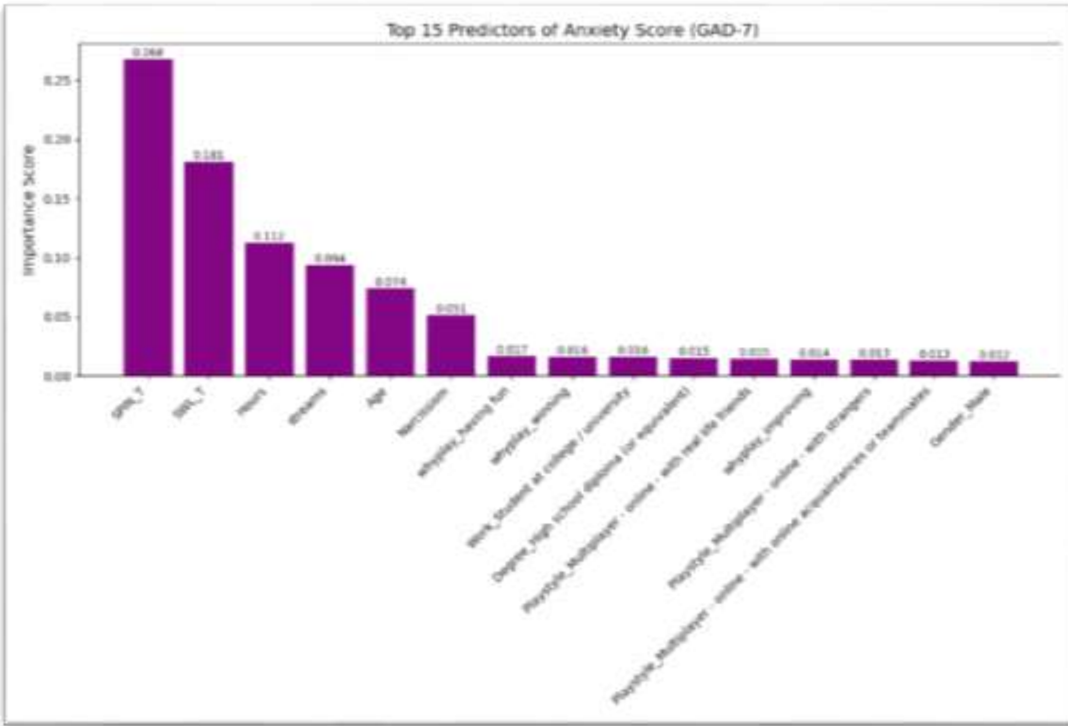

Figure 6: Feature Importance Analysis for Predicting Anxiety Severity

4.4 Model Reliability (Actual vs. Predicted)

The relationship between the actual GAD-7 scores and the values predicted by the model is illustrated in the scatter plot **(Figure 7).** The alignment along the diagonal reference line demonstrates that the model maintains consistent accuracy across the low-to-mid range of anxiety scores, although it tends to become more conservative at extreme clinical levels (scores > 15).

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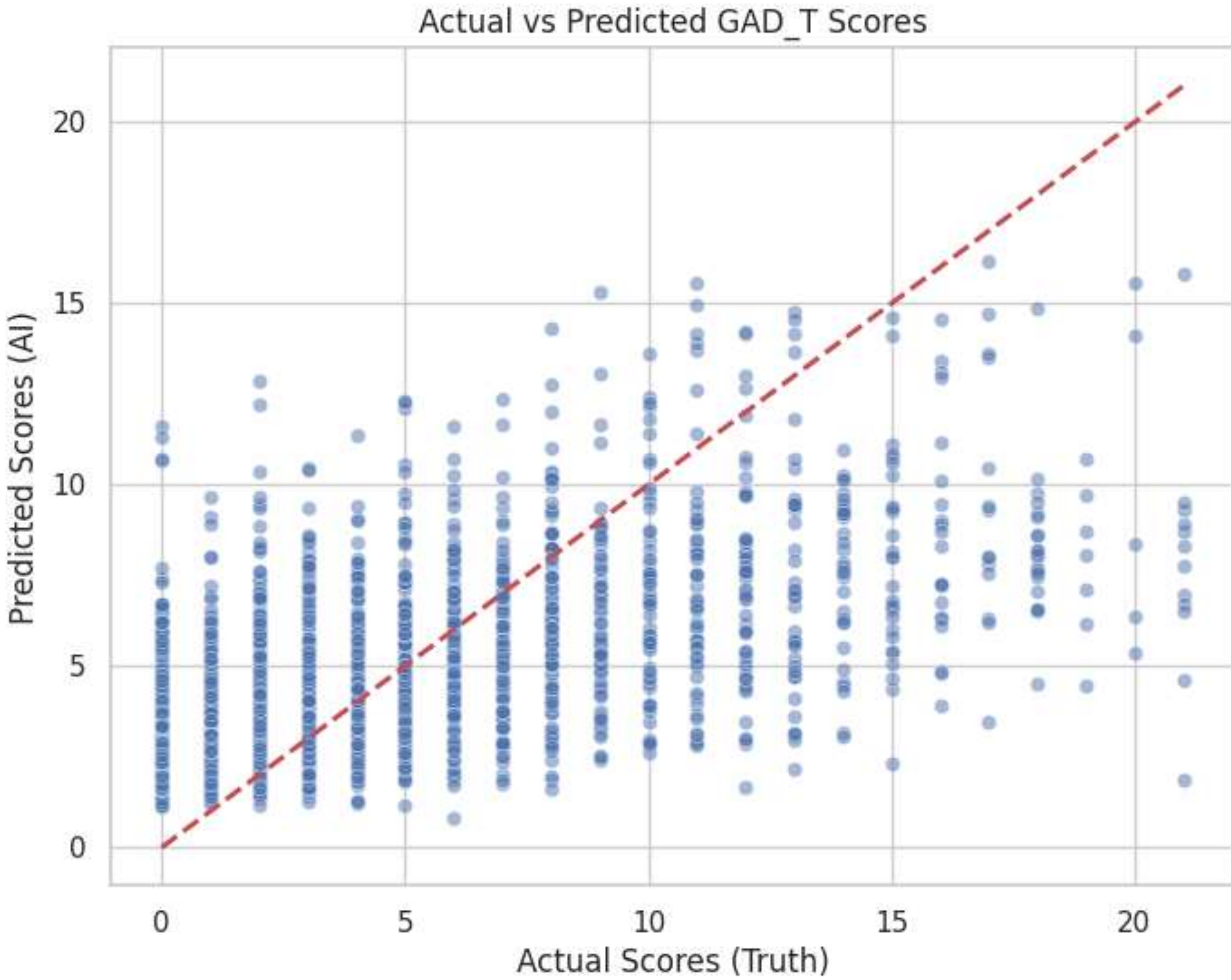

Figure 7: Correlation between Actual and AI-Predicted GAD-7 Scores.

5. Conclusions

This study successfully established a robust predictive framework for estimating Generalized Anxiety Disorder (GAD-7) scores within the gaming community using a comparative machine learning approach. By analyzing a comprehensive dataset of 13,464 observations, several critical conclusions can be drawn:

Superiority of Regularized Linear Models: Contrary to the common trend favoring complex architectures, **Ridge Regression** emerged as the most effective model, achieving the highest score of **32.59%** and the lowest error metrics. This confirms that regularized linear approaches are exceptionally suited for psychometric data where features are highly intercorrelated.

Psychological vs. Behavioral Drivers: The feature importance analysis revealed that anxiety levels are primarily driven by **psychological markers**—specifically **Social Phobia (SPIN_T)** and **Life Satisfaction (SWL_T)—**rather than purely behavioral habits like gaming duration or age. This suggests that "gaming disorder" may often be a manifestation of underlying social and life-satisfaction issues.

Deep Learning Viability: While the **Multi-Layer Perceptron (MLP)** was slightly outperformed by Ridge, its competitive performance (31.46%) demonstrates the potential of deep learning to capture non-linearities in mental health data, provided that early stopping mechanisms are used to prevent overfitting.

Practical Implications: The framework developed in this study provides a viable path for the development of **automated, real-time screening tools** within digital platforms. Such tools can assist clinical psychologists by providing an objective, data-driven "first-look" at a user's mental well-being, facilitating earlier interventions.

In summary, while gaming is often viewed through the lens of playtime, this research proves that the player's internal psychological state remains the most accurate predictor of distress. Future work should explore longitudinal data to observe how these predictive patterns evolve over time.

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