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Enhancing Adolescent Smartphone Addiction Screening Using a Weighted Radial Basis Function Neural Network

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Abstract

Smartphone addiction among adolescents threatens mental health, sleep, academic performance, and social functioning, creating an urgent need for objective, scalable screening tools. This study evaluates whether a weighted RBFNN (Radial Basis Function Neural Network) with learnable per-feature weights can improve early identification of smartphone addiction in adolescents. Using a questionnaire-derived dataset of 394 participants, features were standardized, hidden-unit centers were initialized with k-means clustering, and both conventional and weighted RBFNN architectures were trained and compared under stratified ten-fold cross-validation while sweeping the number of hidden units. Models were assessed by accuracy, precision, recall, F-measure, area under the receiver operating characteristic curve, and computation time. The weighted RBFNN consistently outperformed the conventional variant and previously reported baselines, achieving a mean cross-validation accuracy 97.99% across all cluster settings, with best performance of 98.48% (at cluster 6) and an area under the curve near 0.989, with very low false positive and false negative rates and reduced computation time at larger cluster settings. Learnable feature weighting mitigated noisy predictors and improved generalization, while results underscored sensitivity to cluster-count selection and preprocessing choices. These findings indicate that a weighted RBFNN is a promising, efficient approach for automated adolescent smartphone addiction screening.

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INTRODUCTION

Smartphone use has become nearly ubiquitous among young people, and a growing body of evidence indicates that problematic or excessive use can produce harm analogous to other behavioral addictions. Empirical studies document associations between high smartphone exposure and a range of adverse outcomes—psychological distress, disrupted sleep, diminished academic performance, and impaired social functioning—thereby elevating smartphone addiction to a pressing public-health concern, especially for adolescents who remain developmentally vulnerable. Early adolescence is a formative period for self-regulation and social development, and longitudinal and cross-sectional reviews have reported links between excessive smartphone engagement and later mood disturbances, attentional difficulties, and social withdrawal (Okfalisa et al., 2020; Przybylski & Weinstein, 2019; Zhu et al., 2025). Meta-analytic and field studies have further connected problematic use to depressive and anxiety symptoms and poorer life satisfaction (Afshan et al., 2022; Alfitri & Widiatrilupi, 2020; Anshori et al., 2023; Nikolić & Šipetić-Grujičić, 2023; Sarhan, 2024; Widhigdo, 2020). These converging findings underscore the need for reliable, scalable methods to identify at-risk individuals before adverse trajectories consolidate.

Conventional assessment of problematic smartphone use relies primarily on self-report instruments and clinician judgment. Although questionnaires and screening scales provide useful descriptive information, they are limited by subjectivity, recall bias, and logistical constraints that reduce their utility for early, population-level screening (Busch & McCarthy, 2021). Interventions such as cognitive–behavioral therapy, psychoeducation, and structured digital-detox programs can mitigate harms when applied early, but their effectiveness depends on timely identification of those in need (Ding et al., 2022; Mayerhofer et al., 2024). Accordingly, there is a demonstrable demand for objective, automated screening tools that can augment existing assessment pipelines and enable proactive, data-driven triage within school and primary-care settings.

Machine learning (ML) methods have emerged as powerful tools for extracting predictive structure from behavioral, usage, and psychometric datasets, providing an opportunity to transform screening from retrospective description to prospective risk detection (Habehh & Gohel, 2021). Recent ML work in mental health and behavioral domains demonstrates that supervised algorithms can learn complex, nonlinear relationships between multi-modal predictors and clinically relevant outcomes (Garriga et al., 2022; Likhith et al., 2024; Maharana & Acharya, 2024; Sari et al., 2023). In the specific context of smartphone addiction, prior studies have applied diverse classifiers---support vector machines, discriminant analyses, ensemble learners, and neural networks---reporting high accuracy in constrained datasets (Anshori & Pangestu, 2024; Musthofa & Anshori, 2025a). For instance, SVM with a linear kernel achieved 96.45% accuracy and LDA reached 94.16% on similar adolescent datasets. Nevertheless, performance differences across algorithms and sensitivity to model configuration remain important considerations for practical adoption.

Radial Basis Function Neural Networks (RBFNNs) represent a class of supervised models that balance expressive nonlinear approximation with computational tractability. RBFNNs approximate continuous functions through localized basis units and a linear output layer, enabling universal approximation while often exhibiting rapid convergence and interpretability of hidden units (Sun et al., 2023), ("A Review of Radial Basis Function (RBF) Neural Networks," 1999). Their architecture---centroid-based hidden units with Gaussian activation---permits parameter initialization via clustering (e.g., k-means) rather than full nonlinear optimization, simplifying training and reducing susceptibility to local minima (Dash et al., 2016a; Julita et al., 2023; Luján et al., 2022; Wang et al., 2020). Prior applications of RBF-style architectures in adjacent mental health tasks (e.g., Internet addiction prediction, mood disorder classification) suggest that RBFNNs can model multifactorial behavioral phenomena effectively (Luján et al., 2022). However, critical choices such as the number of hidden units (clusters), the spread parameter, and potential input feature weighting substantially influence performance and generalizability.

Existing solutions in the literature illustrate two salient pathways for improving predictive screening: (1) selecting or engineering richer features and psychometrics to capture the latent constructs of addiction, and (2) refining model architectures and training procedures to increase discrimination while moderating computational cost (Dash et al., 2016b; Garriga et al., 2022; Habehh & Gohel, 2021; Likhith et al., 2024; Maharana & Acharya, 2024; Sari et al., 2023). Studies employing discriminant analysis and support vector machines have reported high accuracies (e.g., LDA ≈94.16%, SVM linear

≈96.45%) on similar adolescent datasets, demonstrating the feasibility of algorithmic prediction but also indicating room for further gains (Anshori & Pangestu, 2024), (Musthofa & Anshori, 2025b). On the model-engineering front, enhancements such as input-feature weighting and supervised estimation of radial-basis parameters have been proposed to allow networks to learn the relative importance of heterogeneous predictors, thereby improving robustness to noisy or redundant dimensions (Dash et al., 2016a; Frank, 2014; Jena et al., 2022a; Marfo & Przybyla-Kasperek, 2022; Ningrum et al., 2025; Oti et al., 2021).

A review of the literature reveals an important gap: while many prior works compare off-the-shelf classifiers or tune global hyperparameters, fewer studies systematically investigate RBF network variants that incorporate learnable input-feature weights together with a principled analysis of hidden-unit (cluster) selection in adolescent smartphone datasets. This gap is consequential because behavioral datasets often contain mixed demographic and psychometric variables with uneven predictive value, and because RBF performance is notably sensitive to centroid initialization and spread selection. Consequently, existing benchmarks may understate the attainable performance of appropriately adapted RBFNNs for this task. The novelty of this study lies in three specific contributions: (1) architectural innovation—unlike conventional weighted RBF approaches that apply a single global feature-weight vector, we introduce per-hidden-unit feature weights (α_{ji}), allowing each basis function to selectively emphasize different input dimensions; (2) systematic optimization—we provide a principled grid-based exploration of cluster counts (1-10) combined with stratified 10-fold cross-validation to identify optimal configurations; and (3) application context—to our knowledge, this is the first study to systematically evaluate per-unit weighted RBFNN for adolescent smartphone addiction screening with rigorous leakage prevention and comprehensive benchmarking.

Motivated by these considerations, the present study aims to develop and validate a weighted RBFNN model for the early prediction of smartphone addiction in adolescents, to examine the influence of cluster-level parameterization on classifier performance, and to compare the proposed model against published baselines. The novelty of this work lies in combining input-feature weighting (learnable α parameters) with systematic exploration of hidden-unit counts and k-means-based center initialization to produce a model that is both highly discriminative and computationally efficient. We hypothesize that a weighted RBFNN, trained and evaluated with rigorous k-fold cross-validation on a comprehensive adolescent questionnaire dataset, will outperform traditional RBFNN implementations and several prior classifiers (e.g., LDA, QDA, SVM variants) in accuracy and AUC, while maintaining acceptable runtime for potential deployment in screening contexts. The scope of the study encompasses model design decisions, validation on the provided Mendeley dataset (demographic and Likert-scale items), and comparative evaluation using standard metrics (accuracy, precision, recall, F1, AUC, computational time), thereby delivering both methodological insight and practical guidance for scalable adolescent screening.

RESEARCH METHODS

The steps in the proposed workflow generally involve data collection, preprocessing, RBFNNs modeling, experiments, and evaluation, as shown in Figure 1.

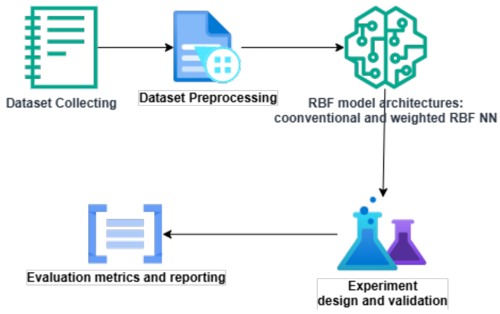

Figure 1. Overview of the research methodology workflow

Table 1. Dataset Details

Variable	Type
No	Numeric
Smartphone-usage Duration	Numeric
Social Media Usage	Numeric
The Most Frequent Usage	Numeric
Age	Numeric
Gender	Categorical
Question 1	Numeric
Question 2	Numeric
Question 3	Numeric
Question 4	Numeric
Question 5	Numeric
Question 6	Numeric
Question 7	Numeric
Question 8	Numeric
Question 9	Numeric
Question 10	Numeric
Class	Binary

The first step was to gather the dataset. The study uses a secondary, questionnaire-derived dataset published on the Mendeley Data repository and is publicly accessible at https://doi.org/10.17632/m6s3d8kvsm.3 (Jena et al., 2022b). The details of the dataset are shown in Table 1.

The second step is data preprocessing, which follows a deterministic pipeline. First, non-informative or unused variables were removed, and categorical variables were encoded numerically according to the questionnaire scheme. Missing-value checks were performed, and any incomplete records were handled according to the dataset owner's guidance. Because k-means and Euclidean-distance-based RBF hidden units are sensitive to scale, all numeric features were standardized using z-score scaling. The aim is to ensure balanced contribution across heterogeneous features and to prevent distance-based algorithms from being dominated by features with larger scales. For each feature, standardization was performed using:

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

Equation (1) is the formula to calculate standardization, where x is a feature value, μ its sample mean, and σ its standard deviation (mean = 0, std = 1) (Dimas Pratama & Salam, 2025; Shapcott, 2024). Standardization ensured balanced contribution across heterogeneous features.

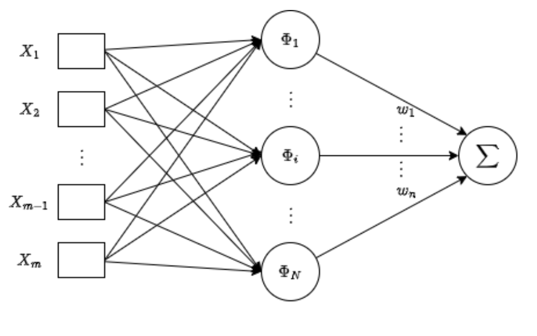

Figure 2. Architecture of the radial basis function neural network (RBFNN)

The third step is to build the RBFNN classifier. The architecture of the RBFNN is shown in Figure 2 and consists of 3 layers: input, hidden, and output. Where x input vector, M is the number of input neurons, N is the number of hidden neurons, ϕ rbf activation function, and w weight (Wahyuningrum, 2020). The workflow is as follows: the input layer takes in data and propagates it to the hidden layer. The hidden layer, which is the core of the RBF neural network, consists of hidden neurons that use a radial basis function as their activation function. The results from the hidden neuron calculations are then passed to the output layer to generate the final prediction.

Two RBF neural network variants were implemented and compared: (i) a conventional RBFNN (α fixed = 1 for all input dimensions) and (ii) a weighted RBFNN that introduces learnable input-feature weights α_{ji}, allowing the network to adaptively scale each input dimension for each basis unit. The hidden layer comprises N radial-basis units with Gaussian activation; for an input vector, x, the j-th basis response is defined as equation (2):

$$\phi_j(x) = \exp\left(-\sum_{i=1}^{m} \frac{\alpha_{ji}\|x_i - c_{ji}\|^2}{2\sigma_j^2}\right) \tag{2}$$

where m is the input dimensionality, c_j the center (centroid) of the unit j, σ_j the spread (width) of the Gaussian, and α_{ji} the per-feature weight (traditional RBF uses $\alpha = 1$). Hidden-unit centers c_j were initialized using k-means clustering applied to the standardized inputs; each centroid equals the mean of points assigned to its cluster as usual: $c = \frac{1}{|S_k|}\sum_{x_i \epsilon S_k} x_i$. The Gaussian spread σ_j was initialized via the heuristic of using the maximum squared Euclidean distance between any pair of cluster centers to ensure adequate coverage and empirically robust training (Frank, 2014; Ningrum et al., 2025). The number of hidden units (clusters) was treated as an explicit hyperparameter and varied systematically. The network output is a linear combination of hidden activations defined in equation (3) below:

$$y(x) = \sum_{j=1}^{N} w_j \phi_j(x) + b \tag{3}$$

where w_j the output weights and b a bias term. Weight initialization used small random values drawn from a uniform heuristic range, and bias was initialized as in common practice (Sivaraman & Sumitha, 2023).

For the traditional RBFNN, after center and spread initialization, the output-layer weights w_j were learned via closed-form or gradient-based least-squares fitting on the hidden activations. For the weighted RBFNN, per-feature weights α_{ji} were optimized using gradient-based methods (backpropagation on the learnable α parameters) so the model could learn relative input importance; this follows the common supervised weighting approach reported in the literature (Jena et al., 2022a). Training used standard regularization heuristics to avoid overfitting where appropriate

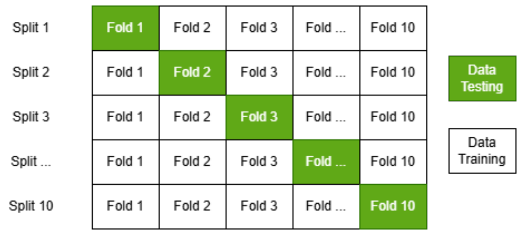

Figure 3. Illustration of k=10-fold cross-validation

The fourth stage is to conduct experiments by creating an RBF NN model based on k-fold cross-validation. Model validation employed stratified k-fold cross-validation with k = 10 to estimate generalization performance and mitigate overfitting (Anshori et al., 2019). According to Figure 3, the dataset is divided into ten folds. In each iteration, nine folds are used as training data, and the remaining one fold serves as testing data. This process is repeated ten times so that each fold is used once as the test set. (Choirunnisa et al., 2025). Iteratively, this process is carried out until the 10-fold criterion is satisfied. For each fold, the pipeline (preprocessing, k-means centroids, RBF construction, and weight estimation) was executed exclusively on the training folds and evaluated on the held-out fold. Experiments systematically swept the number of clusters (hidden units) from 1 to 10 and compared the traditional RBFNN and the weighted variant across all cluster settings; each configuration was repeated, and mean metrics were recorded. Computational time per experiment was measured and averaged across repeats to compare efficiency.

Evaluating each model acquired in the preceding step is the last step. Performance was assessed with standard classification metrics computed from confusion matrices: accuracy, true positive rate (TPR), false positive rate (FPR), precision, recall, F-measure (F1), and area under the ROC curve (AUC). The equations used are those established in the source (accuracy, TPR, FPR, precision, recall, F-measure). Computational time (seconds) was reported to assess practical deployability. Results were compared against prior baselines (LDA, QDA, and SVM variants) reported in the literature to contextualize gains.

$$accuracy = \frac{TN+TP}{total\ row\ data} \times 100\% \quad (4)$$

$$TPR = \frac{TP}{TP+FN} \times 100\% \quad (5)$$

$$FPR = \frac{FP}{FP+FN} \times 100\% \quad (6)$$

$$precision = \frac{TP}{TP+FP} \times 100\% \quad (7)$$

$$recall = \frac{TP}{TP+FN} \times 100\% \quad (8)$$

$$F - measure = 2 \times \frac{recall \times precision}{recall + precision} \times 100\% \quad (9)$$

The accuracy of the model was determined using equation (4). TPR is used to determine the correct rate of the classifier, and the equation is shown in equation (5). Equation (6) is used to calculate the FPR to determine the incorrect rate of the model predictor. TN = true negative, TP = true positive, FN = false negative, FP = false positive. This variable was obtained from the confusion matrix. FPR and TPR are used to draw the receiver operating characteristic (ROC) graph to model errors and determine the reliability of the algorithm in carrying out predictions (Anshori & Haris, 2022). Precision is the degree of accuracy of the model in predicting and recalling all the positive rates. Each formula is shown in equations (7) and (8). Equation (9) presents the formulation for the application of the F-measure evaluation.

RESULT AND DISCUSSION

The reported performance metrics represent the mean across 10 folds of stratified cross-validation. The final reported performance is the mean 10-fold cross-validation accuracy for the optimal cluster configuration, which is the primary result of this study.

According to Figure 4, the dataset used for all experiments comprised N = 394 adolescent records drawn from the Mendeley questionnaire (17 variables including demographic fields and 10 Likert-type behavioral items). The sample was imbalanced toward the positive class: 242 cases (61%) labeled “Yes” versus 152 cases (39%) labeled “No.” Preliminary inferential checks reported that nearly all predictor variables achieved very small p-values ($p < 0.005$), indicating that observed relationships are unlikely to be due to chance and that the dataset contains a meaningful signal for predictive modeling.

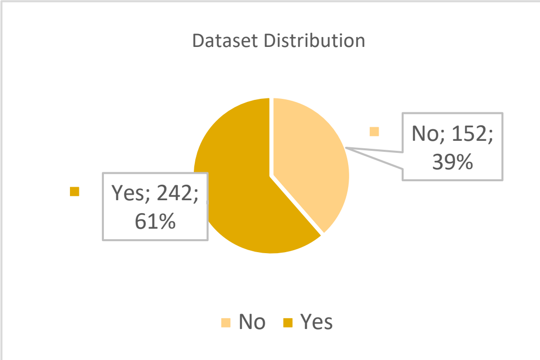

Figure 4. Distribution of dataset classes (Yes/No) for the 394 adolescent participants.

Model comparison focused on two radial basis function neural network variants: a conventional (unweighted) RBFNN and a weighted RBFNN that permits learnable per-feature scaling. Experiments followed a stratified 10-fold cross-validation procedure and systematically varied the number of hidden units (k-means clusters) from 1 to 10.

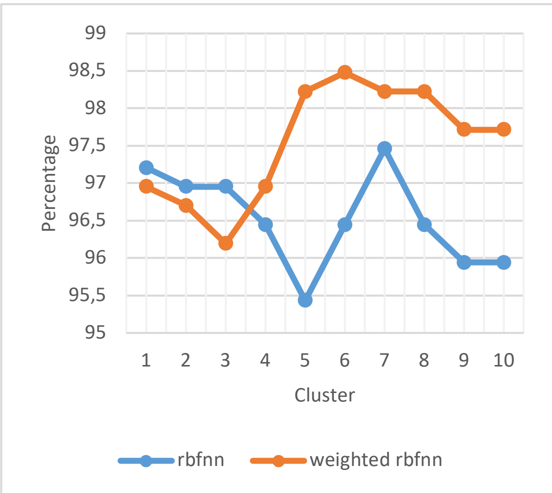

Figure 5. Accuracy comparison based on the experiment

The performance of two models, conventional RBFNN and weighted RBFNN, across different cluster sizes (1 to 10) is contrasted in this visualization, which is based on Figure 5. When compared to the conventional RBFNN model, the weighted RBFNN model regularly shows superior accuracy. This is seen by the orange line (weighted RBFNN), which is continuously higher than the blue line (RBFNN). In cluster 3, the weighted RBFNN achieves its peak accuracy of 98.48% at cluster 6, while the conventional RBFNN peaks at 97.46% at cluster 7. The weighted RBFNN maintained accuracy above 96% across all cluster settings, with the best performance (98.48%) achieved at cluster 6. This finding is crucial as it demonstrates that the weighted RBFNN algorithm is a superior option for classification, particularly when the number of clusters varies.

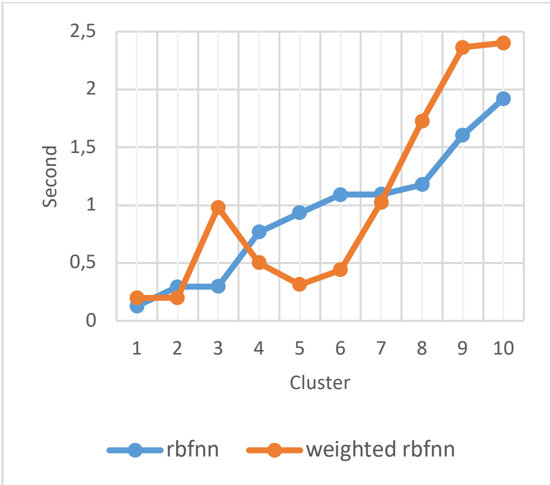

Figure 6. Computational time comparison

This visualization, which is based on Figure 6, shows that computation-time measurements indicate that the weighted RBFNN is not only more accurate but also more efficient in practice. Averaged timing across three repeated runs shows that both models' runtimes increase with the number of clusters. The weighted RBFNN exhibited comparable or slightly lower computation time for smaller cluster counts (1-6), while for larger clusters (8-10), the traditional per-feature weight optimization incurred modest overhead. At cluster 10, runtimes were 1.92 s (conventional) and 2.4 s (weighted). This trade-off of improved accuracy accompanied by lower or comparable runtime supports the weighted RBFNN as a feasible candidate for scalable screening applications.

According to Figure 7, the confusion-matrix analysis of the best weighted-RBFNN fold quantifies the practical error profile: True Positives = 240, True Negatives = 148, False Positives = 4, and False Negatives = 2, yielding a total misclassification rate of (4+2)/394 ≈ 1.5%. This low error rate is reflected in discrimination metrics: the weighted model's ROC curve is strongly bowed toward the upper-left corner, and the Area Under the Curve (AUC) equals 0.9890 as shown at Figure 8. This graph indicates excellent separability between the two classes across thresholds.

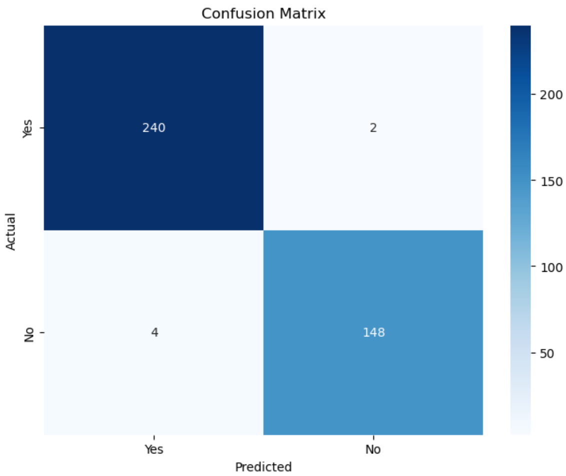

Figure 7. Confusion matrix of weighted RBFNN

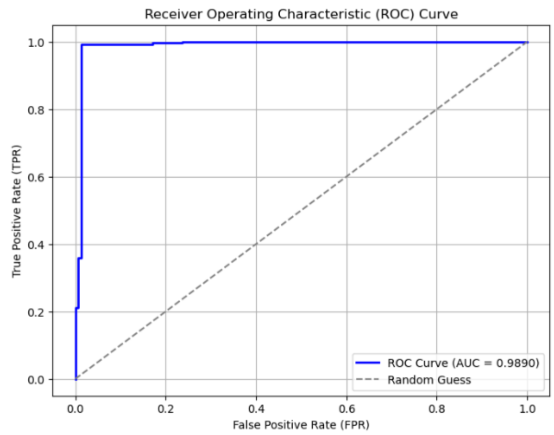

Figure 8. AUC of weighted RBFNN

Table 2. Comparison of accuracy between RBFNN and prior research

Method	Accuracy
LDA (Musthofa & Anshori, 2025b)	94.16%
QDA (Musthofa & Anshori, 2025b)	90.86%
SVM (Linear) (Anshori & Pangestu, 2024)	96.447%
SVM (Poly) (Anshori & Pangestu, 2024)	93.401%
SVM (rbf) (Anshori & Pangestu, 2024)	95.4315%
SVM (sigm) (Anshori & Pangestu, 2024)	93.401%
RBFNN	97.4619%
RBFNN (weighted)	**98.4772%**

Comparative benchmarking against previously published classifiers on the same problem emphasizes the magnitude of improvement. Table 2 reports prior accuracies: LDA ≈ 94.16%, QDA ≈ 90.86%, SVM (linear) ≈ 96.447%, and several other SVM kernels between ≈93.40–95.43%. The weighted RBFNN (98.4772%) surpasses these baselines and the conventional RBFNN, indicating that the combination of input-feature weighting and careful cluster selection yields measurable gains over standard discriminant and SVM approaches documented in the literature.

The interpretation of these results is consistent with known RBFNN behavior: radial-basis architectures approximate nonlinear decision surfaces by localized basis functions whose centers and spreads govern representational granularity. Introducing learnable per-feature weights allows the model to attenuate noisy or redundant dimensions and accentuate features with higher predictive value; in heterogeneous psychometric/demographic data, this capacity reduces variance and improves generalization. Moreover, centroid initialization via k-means and an explicit sweep of hidden-unit counts revealed that model performance is sensitive to clustering choices; hence, the empirical recommendation is to include cluster-count tuning in any practical deployment. In summary, the results show that a weighted RBFNN, when combined with disciplined preprocessing, k-means center initialization, and explicit cluster-count tuning, achieves superior accuracy (98.4772%) and discrimination (AUC = 0.9890) for adolescent smartphone addiction screening compared with both a traditional RBFNN and several established classifiers. The weighted variant also offers practical computational advantages.

CONCLUSION

This study developed and validated a weighted Radial Basis Function Neural Network (RBFNN) to screen for smartphone addiction among adolescents, using a questionnaire dataset (N = 394). The weighted RBFNN achieved superior predictive performance (98.4772% accuracy, AUC = 0.989) and reduced computation time compared with a conventional RBFNN and previously reported baselines (LDA, QDA, SVM). Introducing learnable per-feature weights improved discrimination by attenuating noisy predictors and emphasizing informative dimensions; systematic tuning of hidden-unit (cluster) counts further enhanced stability. These outcomes indicate that judicious architectural adaptation of RBF models yields highly accurate and efficient classifiers. With further validation on diverse, independent datasets and prospective testing in real-world settings, the weighted RBFNN has the potential to support large-scale screening efforts in educational and primary-care contexts. However, the model should be viewed as a screening aid rather than a standalone diagnostic tool, and any deployment would require rigorous prospective evaluation and integration with existing clinical workflows. Methodologically, the work contributes by integrating input-feature weighting with k-means centroid initialization and by presenting a reproducible protocol for selecting the cluster count under stratified cross-validation. Nonetheless, reliance on a single self-reported dataset and class imbalance limits immediate generalizability; performance may be sensitive to preprocessing choices and initialization seeds. To create a fairer model, future research will focus on balancing the dataset using oversampling (e.g., SMOTE) or undersampling techniques. Additionally, it will compare RBFNN with architecturally related models such as Extreme Learning Machines (ELM).

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