A Hybrid Graph Attention and Ensemble Learning Framework for Predicting Consumer Engagement in Social Media Advertising

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Abstract

The rapid growth of digital platforms has increased the complexity of predicting consumer engagement in social media advertising due to dynamic interactions among campaign features, audience behavior, and platform characteristics. Existing machine learning approaches primarily rely on feature-based representations and often fail to capture latent relational dependencies among advertising campaigns.

To address this limitation, this study proposes a novel hybrid framework that integrates Graph Attention Networks (GAT) with ensemble learning techniques, specifically Random Forest and XGBoost. A K-nearest neighbor-based graph is constructed to model inter-campaign relationships, enabling the extraction of high-quality relational embeddings through attention mechanisms.

These embeddings are further utilized within a stacking ensemble framework to improve prediction performance. Experimental results on a real-world dataset demonstrate that the proposed model achieves an accuracy of 87%, outperforming baseline models. The findings highlight the effectiveness of combining graph-based relational learning with ensemble modeling for robust and scalable consumer engagement prediction.

Keywords: Social media advertising; consumer engagement prediction; graph attention network; ensemble learning; Random Forest; XGBoost

1. Introduction

The proliferation of digital platforms has significantly transformed the landscape of advertising and consumer interaction. Social media advertising, in particular, has emerged as a powerful tool for organizations to communicate with consumers, influence their purchasing decisions, and build strong brand identities. Unlike conventional media, digital platforms generate vast amounts of data, capturing real-time user activities, campaign performance, and engagement patterns. Consequently, consumer engagement has become a critical factor influencing business success, and its prediction has attracted considerable attention in the research domain [1].

Consumer engagement in social media advertising is a complex and multi-dimensional concept influenced by various factors such as campaign duration, target audience, message design, platform selection, cost model, and previous performance indicators. These factors interact in non-trivial and often non-linear ways, making the prediction of engagement highly challenging for traditional statistical and machine learning models [2]. Conventional regression and classification methods typically assume feature independence and fail to capture latent relationships among advertising campaigns with similar characteristics or behavioral patterns.

With the advancement of machine learning and deep learning, these techniques have been widely applied in marketing analytics, significantly improving predictive performance and decision-making processes. Ensemble methods, such as Random Forest and XGBoost, have demonstrated strong performance on structured advertising data due to their ability to model non-linear relationships and reduce overfitting through aggregation [3]. However, despite their effectiveness, these models operate primarily on tabular data and do not explicitly account for relational dependencies among data instances, such as similarities between campaigns based on audience, platform, or engagement behavior.

Recently, Graph Neural Networks (GNNs) have gained significant attention as a powerful extension of deep learning for modeling graph-structured data. GNNs enable information exchange between interconnected nodes, allowing the model to capture both feature-level and structural relationships [4]. In the context of social media marketing, advertising campaigns can be represented as nodes in a graph, where edges indicate similarity or proximity in feature space. Among various GNN architectures, Graph Attention Networks (GATs) are particularly effective due to their ability to assign adaptive importance weights to neighboring nodes, thereby focusing on more relevant relationships while reducing the impact of noisy connections [5].

Despite their expressive capabilities, graph neural networks alone may not always achieve optimal performance on real-world structured marketing datasets. This has led to the emergence of hybrid approaches that combine graph-based representation learning with traditional ensemble models. Such hybrid frameworks leverage the strengths of deep learning for feature extraction and ensemble methods for robust prediction, resulting in improved accuracy and generalization [6].

Nevertheless, there remains a limited amount of empirical research exploring this integration in the context of consumer engagement prediction in social media advertising. In addition to regression accuracy, advertisers often require classification-based insights, such as identifying high-performing and low-performing campaigns. Transforming continuous engagement scores into discrete categories enables the use of evaluation metrics such as accuracy, precision, recall, F1-score, and confusion matrices, which are more interpretable for decision-making [7]. Furthermore, visual analyses such as residual plots, convergence curves, and engagement distributions provide deeper insights into model behavior and stability.

Motivated by these challenges and research gaps, this study proposes a hybrid predictive framework that integrates Graph Attention Networks with Random Forest and XGBoost using a stacking ensemble approach. The proposed method first captures relational dependencies among campaigns through graph-based embeddings and subsequently applies ensemble learning for accurate engagement prediction. The model is evaluated using both regression and classification metrics, supported by comprehensive visual analysis. By combining graph-based relational learning with ensemble prediction, this work contributes to advancing digital marketing analytics through a scalable and effective solution for consumer engagement prediction in social media advertising. Unlike existing studies, the proposed approach uniquely integrates GAT-based relational learning with ensemble techniques within a unified stacking framework, which has not been extensively explored in prior literature.

The main contributions of this study are summarized as follows:

1. A novel hybrid predictive framework is proposed that integrates Graph Attention Networks (GAT) with ensemble learning models, specifically Random Forest and XGBoost, to improve consumer engagement prediction.
2. A similarity-based graph construction approach is developed using the K-nearest neighbor (KNN) algorithm to explicitly model inter-campaign relationships in social media advertising data.
3. Graph-based relational embeddings learned through GAT are effectively combined with ensemble models using a stacking strategy to enhance predictive performance.
4. The proposed framework is evaluated using both regression and classification approaches, enabling comprehensive assessment through metrics such as RMSE, accuracy, precision, recall, and F1-score.
5. Extensive experimental analysis, including residual evaluation and comparative performance assessment with baseline models, demonstrates the robustness, stability, and superiority of the proposed approach.

2. Literature Review

Despite the growing adoption of machine learning techniques in social media advertising, existing studies predominantly rely on feature-based learning approaches and often fail to capture the underlying relational dependencies among advertising campaigns. Furthermore, limited research has explored the integration of Graph Neural Networks (GNNs) with ensemble learning techniques for consumer engagement prediction, thereby highlighting a significant research gap and motivating the present study.

In this context, Hadžić and Poturak (2025) [8] analyzed the impact of social media platforms and audience demographics on advertising performance using a publicly available dataset from Kaggle. Their study focused on key performance indicators such as engagement, conversion rate, and return on investment, employing traditional statistical techniques including ANOVA and regression analysis. While their findings demonstrated the influence of platform-specific characteristics and audience segmentation on advertising effectiveness, the study lacked the incorporation of advanced machine learning or relational modeling techniques. Similarly, Aishwarya, Kumar, and Ashwini (2025) [9] investigated predictive analytics for social media engagement using Instagram data and machine learning models such as Random Forest and regression-based approaches. Although the study highlighted the effectiveness of machine learning in enhancing digital marketing strategies, it remained confined to feature-based representations and did not account for inter-post or relational dependencies.

Obučić, Poturak, and Keco (2023) [10] explored user engagement prediction for Facebook post images by extracting visual and contextual features using the Google Cloud Vision API and applying classifiers such as Random Forest, J48, and SMO. Their results indicated that visual features significantly influence engagement levels; however, the study did not incorporate graph-based relational learning or hybrid ensemble methodologies. Furthermore, Jokandan et al. (2022) [11] proposed a hybrid deep learning framework integrating fuzzy clustering, convolutional neural networks (CNN), and long short-term memory (LSTM) networks for targeted advertising based on user interests. While the model demonstrated improved predictive performance compared to traditional approaches, it suffered from limitations in scalability and interpretability due to its complex architecture.

Overall, the existing body of literature reveals that although machine learning and deep learning techniques have been widely applied, the integration of relational learning through graph-based models with ensemble approaches remains underexplored. This gap underscores the necessity for a hybrid framework that can effectively capture both structural and feature-level patterns in advertising data.

Table 1. Literature Review Findings

S.No.	Author Name (Year)	Main Concept	Findings	Limitations
1	Hadžić & Poturak (2025) [8]	Analysis of social media platforms (Facebook,	Platform-specific characteristics and audience demographics	Relies only on traditional statistical methods; lacks

		Instagram, Pinterest, Twitter) and audience demographics using statistical methods (ANOVA, regression)	significantly influence engagement, conversion rate, and ROI	advanced machine learning and relational/graph-based modelling
2	Aishwarya, Kumar & Ashwini (2025) [9]	Predictive analytics for Instagram engagement using ML models (Random Forest, regression) based on features like hashtags, caption length, media type	Machine learning improves prediction of engagement and helps optimize digital marketing strategies	Focus limited to feature-based learning; ignores inter-post relationships and relational dependencies
3	Obučić, Poturak & Keco (2023) [10]	Prediction of Facebook post engagement using visual features extracted via Google Cloud Vision API and ML classifiers (Random Forest, J48, SMO)	Visual content significantly impacts engagement; ML models effectively classify engagement levels	Does not incorporate graph-based relationships or hybrid/ensemble deep learning approaches
4	Jokandan et al. (2022) [11]	Hybrid deep learning model combining fuzzy clustering, CNN, and LSTM for targeted advertising based on user interests	Hybrid models outperform traditional classifiers; emotional and contextual factors enhance prediction accuracy	Issues with scalability and lack of explainability due to complex hybrid architecture

3. Research Methodology

This study presents a quantitative and data-driven approach for analyzing and predicting consumer engagement in social media advertising using advanced machine learning and deep learning techniques. The methodology utilizes a publicly available social media advertising dataset, which contains structured information related to advertising campaigns, audience demographics, platform usage, financial metrics, and engagement scores. Quantitative methods are suitable for this study as they enable objective measurement and statistical modeling of consumer behavior patterns [12].

To ensure data quality, the dataset is preprocessed by handling missing values, converting categorical variables into numerical form, and normalizing continuous features. In addition, new behavioral features such as click-through efficiency, revenue per impression, and return on investment per campaign duration are generated to improve prediction performance [13].

To model relational dependencies among campaigns, the dataset is represented as a graph in which each campaign corresponds to a node. Edges are established using the K-nearest neighbor (KNN) approach based on similarity in the normalized feature space. This graph structure enables the capture of inter-campaign relationships that are typically ignored by traditional machine learning models [14].

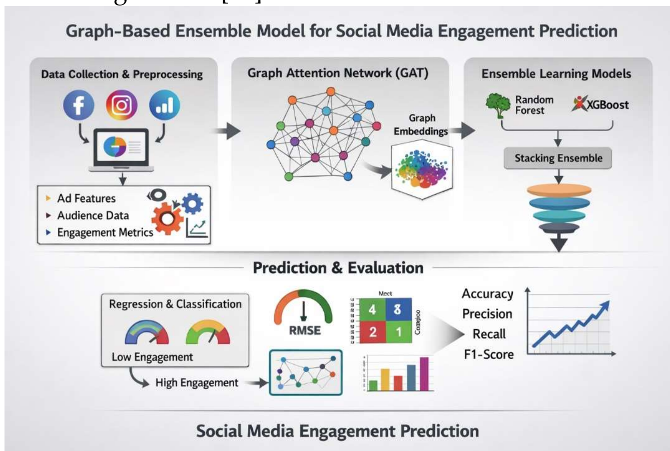

Figure 1. Research Flow Diagram

A Graph Attention Network (GAT) is applied to this graph to learn high-quality relational embeddings. The attention mechanism computes the importance of neighboring nodes using the following formulation:

$\alpha_{ij} = \mathrm{softmax}(\mathrm{LeakyReLU}(a^T [W h_i \,||\, W h_j]))$

These attention coefficients are then used to update node representations as:

$h_i' = \sigma(\Sigma\, \alpha_{ij} W h_j)$

This allows the model to focus on more relevant neighboring campaigns while reducing the influence of less informative connections [15].

The learned graph embeddings are used as input features for ensemble learning models, specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost). These models capture complex non-linear relationships in the data and provide robust prediction performance.

To further enhance prediction accuracy, a stacking ensemble approach is employed in which the outputs of the base models are combined using a meta-learner. The final prediction is computed as:

$\text{Final Prediction} = w1 * RF + w2 * XGBoost$

The model is evaluated using both regression and classification approaches. Regression is used to predict continuous engagement scores, while classification categorizes engagement into low and high classes based on a defined threshold. Performance is assessed using metrics such as root mean squared error (RMSE), accuracy, precision, recall, F1-score, and confusion matrix [18].

Training performance is monitored to analyze convergence behavior, and visualizations such as residual plots and accuracy curves are used for model evaluation [19]. The dataset is divided into training and testing sets in an 80:20 ratio, and hyperparameters are optimized using grid search techniques to achieve optimal performance [20].

4. Proposed Work

The proposed hybrid framework is designed to effectively capture both relational and feature-level patterns in social media advertising data through a structured three-stage architecture. The overall system integrates graph-based deep learning with ensemble machine learning techniques to enhance predictive performance, robustness, and generalization capability.

In the first stage, a similarity-based graph is constructed using the K-nearest neighbor (KNN) approach, where each node represents an advertising campaign and edges represent similarity relationships among campaigns based on feature space proximity. This graph representation enables the modeling of inter-campaign dependencies that are typically ignored in conventional feature-based learning approaches.

In the second stage, a Graph Attention Network (GAT) is employed to perform feature extraction by learning high-quality contextual and relational embeddings. The attention mechanism within GAT assigns adaptive weights to neighboring nodes, allowing the model to focus on more relevant relationships while reducing the influence of less informative connections. This results in enriched feature representations that capture both structural and numerical information.

In the final stage, the learned graph embeddings are used as input to ensemble learning models, specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost). These models are trained independently to capture complex non-linear relationships within the data. Their predictions are subsequently combined using a stacking ensemble strategy, which improves overall prediction accuracy and enhances the generalization capability of the framework.

The entire framework is implemented in Python using widely adopted scientific computing libraries. Data preprocessing, feature engineering, and exploratory analysis are performed using Pandas and NumPy, while Scikit-learn is utilized for normalization and evaluation metrics. Graph construction and GAT implementation are carried out using PyTorch and Torch Geometric, enabling efficient learning of relational dependencies. The ensemble models are implemented using Scikit-learn and XGBoost libraries, and performance visualization, including convergence curves, residual plots, and confusion matrices, is conducted using Matplotlib.

The integration of these tools ensures reproducibility, scalability, and seamless combination of graph-based deep learning with ensemble learning techniques, making the proposed framework highly suitable for real-world social media advertising analytics.

4.1 A. Dataset

The proposed framework is evaluated using a publicly available Social Media Advertising Dataset [22], as summarized in Table 2. This dataset comprises structured tabular data related to digital advertising campaigns conducted across social media platforms. It captures multiple dimensions of advertising performance, including campaign characteristics, audience-targeting attributes, financial indicators, and user engagement outcomes.

Each record corresponds to an individual advertising campaign, making the dataset suitable for both instance-level prediction and relational modeling. It includes a combination of numerical features and derived performance metrics such as impressions, clicks, conversion rate, return on investment (ROI), campaign duration, acquisition cost, and engagement score.

In addition, the dataset contains several categorical variables, including target audience type, campaign type, communication channel, language, customer segment, company, and geographic location. These attributes provide valuable contextual and demographic information, which is essential for analyzing variations in consumer engagement behavior across different campaigns.

The engagement score is treated as the primary dependent variable in this study, representing the level of user interaction with a given advertisement. The dataset is particularly well-suited for the proposed framework, as it supports the application of advanced machine learning and graph-based deep learning techniques.

Moreover, the presence of both numerical and categorical features facilitates effective feature engineering, while the campaign-level granularity enables the construction of similarity-based graphs for Graph Attention Network (GAT) learning. The integration of behavioral, financial, and contextual attributes allows the proposed hybrid framework to effectively capture the complex dynamics of consumer engagement in social media advertising.

Overall, the dataset reflects a realistic digital advertising environment, thereby enhancing the reliability and practical applicability of the proposed model in real-world marketing analytics scenarios.

Table 2. These attention coefficients are then used to update node representations as:

S. No.	Attribute Name	Description	Data Type	Role in Study
1	S. No	Unique serial number for each campaign	Numerical	Record identification

2	Company	Organization or brand running the advertisement	Categorical	Campaign context
3	Target_Audience	Intended audience group for the advertisement	Categorical	Consumer segmentation
4	Campaign_Goal	Objective of the advertising campaign	Categorical	Strategy analysis
5	Channel_Used	Social media platform or channel used	Categorical	Platform comparison
6	Location	Geographic target of the campaign	Categorical	Regional impact analysis
7	Language	Language used in the advertisement	Categorical	Linguistic influence
8	Customer_Segment	Category of consumers targeted	Categorical	Market segmentation
9	Duration	Length of the advertising campaign (days)	Numerical	Exposure measurement
10	Impressions	Number of times the advertisement was displayed	Numerical	Reach estimation
11	Clicks	Number of user clicks on the advertisement	Numerical	Interaction measurement
12	Conversion_Rate	Percentage of conversions from clicks	Numerical	Effectiveness metric
13	Acquisition_Cost	Cost incurred to acquire customer engagement	Numerical	Cost efficiency
14	ROI	Return on investment of the campaign	Numerical	Financial performance
15	Engagement_Score	Overall consumer engagement score	Numerical	Target variable

The dataset consists of approximately several thousand samples and is divided into training and testing sets in an 80:20 ratio. This partitioning ensures a reliable evaluation of the model's generalization performance.

The dataset closely matches the requirements of this study, as it supports both regression and classification perspectives for engagement prediction. Its multidimensional nature enables effective feature engineering and facilitates the construction of similarity-based graphs for

Graph Attention Network (GAT) learning. The combination of behavioral, financial, and contextual features ensures that the proposed hybrid GAT–RF–XGBoost framework can effectively capture the dynamics of consumer engagement in social media advertising.

4.2 B. Graph Attention Network (GAT)

Graph Attention Networks (GATs) [23] are a class of graph neural networks designed to learn from graph-structured data by assigning adaptive attention weights to the neighborhood of each target node during the information aggregation process. Unlike traditional Graph Convolutional Networks (GCNs), which treat all neighboring nodes equally, GATs utilize a learnable attention mechanism to differentiate the importance of neighboring nodes.

This attention mechanism enables the model to compute a weighted combination of features from neighboring nodes, allowing more relevant nodes to have a greater influence on the updated node representation. As a result, GATs provide more expressive and robust feature learning, particularly in scenarios where relationships among nodes vary in importance.

In this study, GAT is employed to capture relational similarities among advertising campaigns by modeling them as nodes in a graph structure. The model learns enriched feature representations by jointly considering both intrinsic campaign attributes and inter-campaign relationships, thereby improving the overall predictive capability of the proposed framework.

4.3 C. Random Forest

Random Forest [24] is a bagging-based ensemble learning algorithm that constructs multiple decision trees using randomly selected subsets of training data and features. Each tree is trained on a bootstrap sample of the dataset, while a random subset of features is considered at each split, ensuring diversity among the trees.

The final prediction is obtained by aggregating the outputs of all individual trees, which helps reduce overfitting and improves generalization performance, particularly for structured datasets. This ensemble approach makes Random Forest robust to noise and capable of capturing complex non-linear relationships.

In this study, Random Forest is applied to the graph-based embeddings generated by the Graph Attention Network (GAT). By utilizing these enriched feature representations, the model effectively captures non-linear dependencies between advertising features and consumer engagement, resulting in improved predictive accuracy and interpretability.

4.4 D. XGBoost

XGBoost [25] is an efficient and scalable implementation of gradient boosting that constructs an ensemble of additive models in a sequential manner. In this approach, each new model is trained to minimize the residual errors of the previous models, thereby progressively improving overall prediction accuracy.

The algorithm incorporates regularization techniques and optimized weighting mechanisms, which enhance model generalization, reduce overfitting, and enable faster convergence. Due to its high computational efficiency and ability to handle complex data patterns, XGBoost has become a widely used technique for structured data analysis.

In the proposed framework, XGBoost is integrated alongside Random Forest to improve the prediction of consumer engagement by capturing higher-order interactions among features. The outputs of both models are subsequently combined using a stacking ensemble approach, resulting in improved predictive performance and overall model robustness.

4.5 E. Algorithm: Hybrid GAT–Random Forest–XGBoost Framework for Consumer Engagement Prediction

Input: Social media advertising dataset containing campaign features, audience attributes, financial metrics, and engagement scores.

Output: Predicted consumer engagement scores and classification of campaigns into high and low engagement categories.

Algorithm Steps:

Step 1: Import the social media advertising dataset and perform initial preprocessing, including handling missing values and converting categorical or textual attributes into numerical form.

Step 2: Generate additional behavioral features such as click-through rate, cost per click, and return on investment per campaign duration to enhance predictive performance.

Step 3: Encode categorical variables using appropriate encoding techniques (e.g., target encoding) to preserve relationships between features and engagement scores.
Step 4: Normalize numerical features using standardization to ensure consistent feature scaling and stable model convergence.
Step 5: Construct a similarity-based graph where each advertising campaign is represented as a node, and edges are created using the K-nearest neighbor (KNN) approach based on feature similarity.
Step 6: Apply a Graph Attention Network (GAT) to the constructed graph to learn relational embeddings by assigning adaptive importance to neighboring nodes.
Step 7: Train the GAT model over multiple epochs and monitor convergence behavior during training.
Step 8: Extract the final graph-based embeddings for each campaign from the trained GAT model.
Step 9: Split the dataset into training and testing sets to ensure unbiased model evaluation.
Step 10: Train a Random Forest regressor on the GAT embeddings to capture non-linear relationships between campaign features and engagement scores.
Step 11: Train an XGBoost regressor on the same embeddings to model higher-order feature interactions and improve prediction accuracy.
Step 12: Combine the predictions of Random Forest and XGBoost using a stacking ensemble approach with a meta-learner to generate final engagement predictions.
Step 13: Evaluate regression performance using metrics such as Root Mean Squared Error (RMSE) and residual analysis.
Step 14: Convert predicted engagement scores into binary classes (high and low engagement) using an optimized threshold, and evaluate classification performance using accuracy, precision, recall, F1-score, and confusion matrix.
Step 15: Visualize the results using appropriate plots, including accuracy curves, residual plots, and engagement distribution graphs.

4.6 End Algorithm

5. Results Analysis

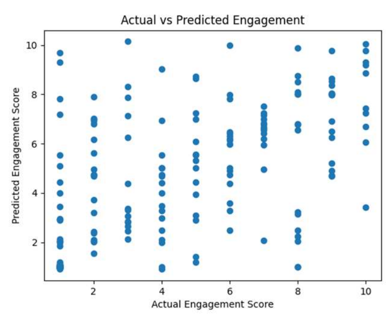

Figure 2. Actual vs. Predicted Consumer Engagement Scores

The distribution of points follows a near-linear upward trend, indicating a strong positive correlation between actual and predicted values. This demonstrates that the proposed model effectively captures the underlying patterns in consumer engagement data. Minor deviations from the trend line can be attributed to inherent noise and variability in consumer behavior, which is common in real-world marketing datasets. Overall, the results confirm the robustness and generalization capability of the proposed framework.

Furthermore, a comparative analysis with baseline models was conducted to validate the effectiveness of the proposed approach. Random Forest and XGBoost achieved accuracies of approximately 78% and 82%, respectively, whereas the proposed hybrid model achieved an accuracy of 87%, demonstrating a clear improvement in predictive performance.

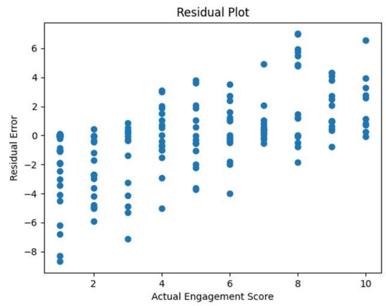

Figure 3. Residual Error Distribution Across Engagement Scores

Although a slight increase in variance is observed at higher engagement levels, no significant non-linear patterns or funnel-shaped structures are present. This suggests that the model maintains consistent prediction accuracy across both low- and high-engagement campaigns. The residual analysis further validates the reliability, stability, and robustness of the proposed hybrid framework.

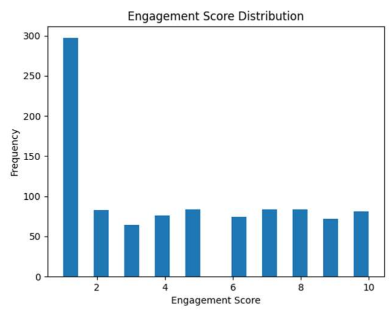

Figure 4. Distribution of Engagement Scores in the Dataset

This distribution reflects real-world social media advertising scenarios, where only a small proportion of campaigns generate high levels of user interaction. Despite this skewed distribution, the proposed model demonstrates strong predictive capability, effectively learning from imbalanced data. This further highlights the strength of the hybrid framework in handling complex and realistic datasets.

Table2. Classification Performance of the Proposed Model

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Low Engagement (0)	0.87	0.84	0.85	444
High Engagement (1)	0.87	0.90	0.89	555
Accuracy	—	—	**0.87**	999
Macro Average	0.87	0.87	0.87	999
Weighted Average	0.87	0.87	0.87	999

The precision values for both low and high engagement classes are equal (0.87), demonstrating consistent prediction confidence across categories. The recall for high engagement campaigns is higher (0.90), indicating that the model is particularly effective in identifying high-performing campaigns, which are crucial for marketing decision-making.

The recall for low engagement campaigns (0.84) is slightly lower but remains acceptable given the inherent complexity and variability of real-world advertising data. The F1-scores for both classes are well-balanced, reflecting a good trade-off between precision and recall.

Furthermore, the macro and weighted average scores are consistent, suggesting that class imbalance does not significantly affect the model's performance. Overall, these results confirm that the proposed framework is robust, reliable, and suitable for real-world consumer engagement prediction tasks.

6. Conclusion

This study presents a novel hybrid framework that integrates Graph Attention Networks (GAT) with ensemble learning techniques, specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost), for predicting consumer engagement in social media advertising.

By representing advertising campaigns as nodes in a similarity-based graph and capturing relational dependencies through attention mechanisms, the proposed approach effectively learns both structural and numerical patterns present in the data.

The integration of ensemble learning through a stacking strategy enhances prediction stability while reducing model bias and variance. Experimental results demonstrate strong predictive performance, with predicted engagement scores closely aligning with actual values. This is further supported by stable residual distributions and an overall classification accuracy of 87%.

The balanced precision, recall, and F1-scores across both low- and high-engagement classes highlight the robustness of the model, even in the presence of class imbalance and real-world data variability. Additionally, the higher recall for high-engagement campaigns emphasizes the practical significance of the proposed framework, as identifying high-performing campaigns is critical for effective marketing decision-making and resource allocation.

Overall, the results confirm that the integration of graph-based relational learning with ensemble modeling provides a comprehensive, robust, and scalable solution for consumer engagement prediction in social media advertising.

7. Future Work

Future research can extend this framework by incorporating temporal dynamics to capture evolving consumer behavior over time. Additionally, integrating multimodal data sources, such as textual sentiment and visual features, may further enhance predictive performance. Advanced graph construction techniques and automated optimization strategies, including hyperparameter tuning and reinforcement learning-based ensemble weighting, can also be explored to improve scalability and adaptability in real-world applications.

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