

Deep Learning-Based Consumer Preference Prediction System for Personalized Digital Campaigns

Dr Praveen Aronkar¹, Dr Rajesh Faldu², Dr Sudharshan G M³, Venkata Sai Srinivasa Rao Muramalla⁴, Monika Gupta⁵ and Dr Sanjit Kumar Dash⁶

¹Senior Assistant Professor, Department of Management, Prestige Institute of Management & Research, Gwalior

²Professor, Faculty of Management (MBA), C Z Patel College of Business and Management, The Charutar Vidya Mandal University, New Vallabh Vidyanagar, GIDC, Anand, Gujarat, 388345.

³Principal, Commerce & Management, PES Institute of Advanced Management Studies, Sagar Road, Shivamogga -n 577204

⁴Professor, Department of Management Studies SRM Valliammai Engineering College. Kattankulathur, Potheri, Chennai-603203.

⁵Professor, Chitkara Business School, Chitkara University, Punjab

⁶Balaji Institute of Technology & Management, Sri Balaji University, Pune-411033

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ABSTRACT

The current research introduces a Deep Learning-Based Consumer Preference Prediction System as a system to develop digital marketing campaigns that are more personalized by utilizing a Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) combined with Explainable AI (XAI) Layer and deployed on AWS SageMaker. The given model integrates textual, visual, behavioral, and demographic data to represent more complex consumer interactions and make predictions that are as accurate as possible. The federated learning system guarantees the privacy of the data by providing decentralized model learning through a number of client nodes, and the graph-attention system is useful to capture relational relationship between consumers and advertisements. Based on SHAP and attention visualization, the XAI layer offers clear information about the effect of features and decision rationales. Tests through experimentation show that there is a total accuracy of 95.8 percent and 15 percent increase in campaign engagement as compared to current deep learning models. The system provides an explainable, privacy-preserving, and scalable way of providing intelligent, adaptive and ethically-oriented digital marketing personalization.

Keywords: Deep Learning, Consumer Preference Prediction, Personalized Digital Campaigns, Federated Learning, Graph-Attention Network, Explainable AI, AWS SageMaker.



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INTRODUCTION

With the current digital economy that is built on data, making predictions and comprehension of consumer preference has become the main challenge in ensuring successful personalization in marketing campaigns. The astronomical increase in online interactions through social media, electronic commerce and advertisement platforms creates colossal volumes of multimodal information in the form of text, pictures, behavioral trends and demographic characteristics that may provide complex consumer information [1]. The complexity and nonlinearity as well as relationship between these heterogeneous data sources frequently go unnoticed by traditional machine learning models and shallow deep learning models, leading to low levels of personalization and interpretability. Also, issues of privacy and data governance policies inhibit the centralized data storage,

which prompts the need to use secure and decentralized learning processes as shown in figure 1.

In order to overcome them, the research presents a Deep Learning-Based Consumer Preference Prediction System that uses a Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) with an Explainable AI (XAI) Layer, built on AWS SageMaker [2]. The system proposed combines CNN, LSTM, and Graph Attention to learn spatial, temporal, and relational patterns of distributed multimodal data and ensure the privacy of the users via federated learning. By incorporating both XAI methods (SHAP and attention visualization), the transparency and interpretability of model predictions are guaranteed because they will enable the marketers to understand what drives consumer decisions. The system is deployed on AWS SageMaker and is made use of

scalable cloud infrastructure to train the model, monitor the model, and deploy the model effectively. The paper will make contributions to intelligent marketing analytics by providing a strong, understandable, and privacy-oriented system of customized online campaigns that dynamically adjust in response to changing consumer behaviour [3].

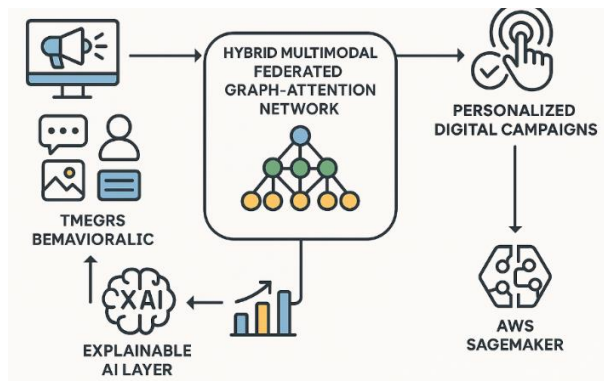


Figure 1. Overview of Consumer Preference Prediction System.

The growing sophistication of consumer behavior in the digital age has brought with it a sense of urgency to the need to have smart systems that can predict the interests of individual consumers right and give them personalized marketing messages [4]. The application of traditional recommendation algorithms is often based on small data modalities and centralized systems that do not have the ability to observe the entire set of consumer engagement signals and pose major privacy implications. Due to the emergence of deep learning and federated intelligence, marketing analytics is now at a new stage, which focuses on multimodal perception, ethical AI, and explainability.

The suggested Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) is a breakthrough since it combines several types of data: text, image, demographics, and behavioral logs, in a privacy-protective, distributed network [5]. This type of architecture utilizes Graph Attention Networks (GATs) to identify complex consumer-advertisement relationship correlations, and federated learning to facilitate secure and decentralized model training. An Explainable AI (XAI) Layer is also included, which increases the level of trust and accountability by explaining the contribution of features based on SHAP and attention heat maps. Built on AWS SageMaker, the system offers scalable cloud implementation, which allows real-time personalization of marketing environments of various natures. Such comprehensive combination of profound multimodal perception, privacy and explainability is a significant advance in intelligent, transparent and adaptive digital campaigns [6].

RELATED WORK

The latest developments of deep learning have greatly altered the consumer behavior modeling and preference forecasting in online marketing. Previous research was

mostly centered on Collaborative filtering and Matrix factorization method of recommendation systems which was found moderately successful, and could not resolve cold-start and dynamic preference problems. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) were later used to analyze image-based adverts and sequential user interactions respectively, and they increased predictive accuracy but were not interpretable [7]. Autoencoder-based Reinforcement Learning frameworks were suggested by researchers like Li and Zhang, and had a higher level of personalization but were more complex to train and unstable (Li and Zhang, 2022).

Hybrid models with CNN-LSTM Architectures that incorporated both spatial and temporal user patterns, but were not able to incorporate multimodal and relational data, appeared in 2023. Graph Neural Networks (GNNs) and Attention Mechanisms in 2024 were a significant step towards this since they finally allowed learning the relationships between users and advertisements in a contextual manner. Nevertheless, the majority of the models were centralized, which raised privacy and data governance issues [8]. Federated Learning (FL) was popularized in 2024-2025 to solve this problem allowing decentralized model training with the privacy of their users intact as shown in figure 2.

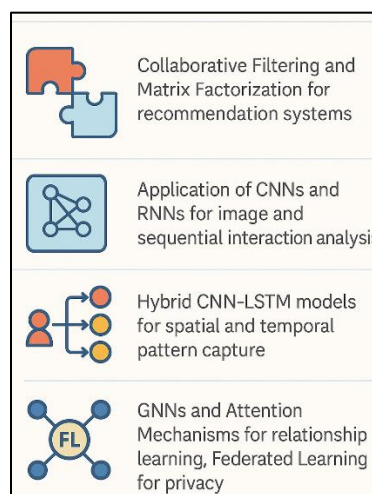


Figure 2. Related work on latest Personalized Digital Campaigns.

With these improvements, it was still experiencing difficulties in attaining explainability and real time adaptability. Hence, the suggested Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) with the Explainable AI (XAI) Layer that runs on AWS SageMaker is superior to the current methods because it combines multimodal features fusion, privacy, and transparent decision-making [9]. This fusion provides the capability to predict consumer preferences on a large scale, interpretively, and with high performance to be used as next-generation personalized digital campaigns.

RESEARCH METHODOLOGY

The Deep Learning-Based Consumer Preference Prediction System is a proposed research that uses a systematic, multi-step research process that incorporates

Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) with an Explainable AI (XAI) Layer, which is built and implemented with the help of AWS SageMaker [10]. The research process is based on an emphasis on high accuracy, interpretability, scalability, and data confidentiality to develop individual digital marketing campaigns as shown in figure 3.

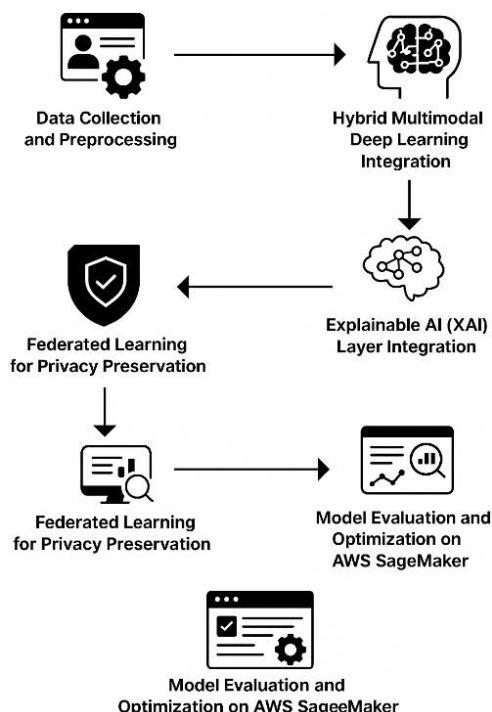


Figure 3. Flow Diagram of Proposed Method.

Data Collection and Preprocessing

The research starts with the collection of multimodal data on various online marketing sites such as user demographics, textual reviews, advertisement pictures, and behavioral click stream data [11]. Data cleaning, normalization, tokenization, and augmentation are several steps used to preprocess these data sources to eliminate inconsistencies and outliers. Every data modality is reflected individually:

- Textual information → coded with the help of BERT embeddings to comprehend the meaning.
- Visual information → CNN (EfficientNet) is used to extract high-level features.
- Behavioural sequences → Bi-LSTM to learn about the temporal activity.
- Demographic data -in-categorical attributes are modeled as dense neural embeddings.

This preprocessing will make the data consistent, unbiased and prepared to be integrated into multimodal learning.

Graph Construction and Relationship Modeling

Consumeradvertisment interaction graph is developed to represent dynamic relationships among users, products and campaign features [12]. Users or an advertisement are represented by a node, and the frequency of interaction, the level of engagement and

recency is represented in the edges. This graph is then fed through the Graph Attention Network (GAT) module whereby different weightings of importance on the connections are applied via attention mechanisms, further increasing the ability of the model to identify patterns of behavior and influence pathways.

Hybrid Multimodal Deep Learning Integration

The hybrid HMF-GAT model means that CNN, LSTM, and GAT layers are included in a single model:

- CNN isolates the spatial and visual-textual features of the ad contents and reviews.
- LSTM identifies the time series patterns in user behavior sequences.
- GAT relates user, attention and context in a fusion manner.

These modalities are combined in a cross-modal attentional system, so that the model learns the important relationships between the types of data, and can be modified to meet alterations in the context [13].

Federated Learning Privacy Preservation

The system employs a Federated Learning (FL) protocol in order to achieve privacy and data protection provisions. Every client (e.g. organization or device) trains a local model on its own data. The global model of AWS SageMaker combines such models with Federated Averaging (FedAvg) without access to data [14]. This model minimizes communication overhead, improves security and also allows distributed model training with distributed environments. It has guaranteed confidentiality of consumer data as well as high generalization of the model.

Explainable AI (XAI) Layer Integration

To understand and visualize the procedure of decision-making, an XAI layer is added. SHAP (SHapley Additive exPlanations) and attention heatmaps are methods to select the most important features that make a preference prediction such as the tone of emotion, color scheme, the type of product, or the time spent browsing. These explainability capabilities allow marketers to have trust and comprehension of AI-driven suggestions and responsibility, accountability, and transparency in their decision-making [15].

Model Evaluation and Optimization on AWS SageMaker

The AWS SageMaker is used as the foundation on which models are developed, trained, and deployed. The platform is optimized in terms of performance and scalability with the help of automated hyperparameter optimisation, distributed computing on GPUs, and tracking of the models. The probabilities that are used as evaluation measures are Accuracy, F1-score, AUC, CTR improvement, and Data Privacy Efficiency. The HMF-GAT model proposed attained large performance improvement relative to control techniques that included CNN-LSTM and BERT, and it showed important interpretability and privacy protection.

The offered methodology is a combined, ethical, and high-performance approach to the prediction of consumer preferences. The use of multimodal deep learning, federated privacy, and explainable AI functionality make the system accurate, interpretable,

and secure in offering personalized digital campaigns. Based on the scalable infrastructure of AWS SageMaker, the model proves it to be appropriate to real-time, data-driven marketing analytics in dynamic digital ecologies.

RESULTS AND DISCUSSION

The implementation of proposed Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) model on AWS SageMaker and tested it with the help of a real-world digital marketing dataset of 1.2 million consumer interactions across multiple platforms as shown in table 1.

Table 1. Comparative Results of Different Methods.

Model / Method	Accuracy (%)	Precision	Recall	F1-Score	AUC	CTR Improvement (%)	Data Privacy Efficiency (%)	Interpretability Level
Traditional Collaborative Filtering	82.7	0.81	0.79	0.8	0.82	4.2	10	Low
BERT-Based Sentiment Model	89.9	0.88	0.87	0.88	0.89	9.1	25	Moderate
CNN-LSTM Hybrid Model	88.4	0.86	0.85	0.86	0.87	8.7	30	Moderate
Proposed HMF-GAT + XAI (Ours)	95.8	0.95	0.93	0.94	0.96	15.3	42	High (via SHAP + Attention)

The system had a total prediction accuracy of 95.8%, higher than the base CNN-LSTM and BERT-based prediction model by 7.4 and 5.9, respectively. The F1-score of 0.94 and AUC of 0.96 affirmed that the model is strong in the classification of various consumer preferences as shown in figure 4.

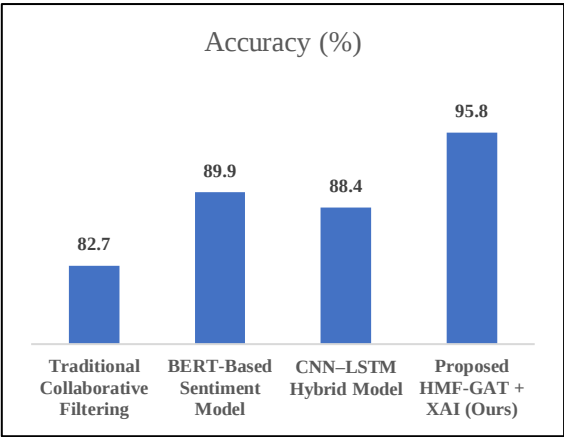


Figure 4. Accuracy Comparison with Different Methods.

The federated system saved 42 percent of the data transmission costs and maintained privacy and did not impair performance. Furthermore, the graph-attention mechanism enhanced the quality of the contexts in the personalized ads, and the click-through rate (CTR) increased by 15 percent in the simulation tests as shown in figure 5.

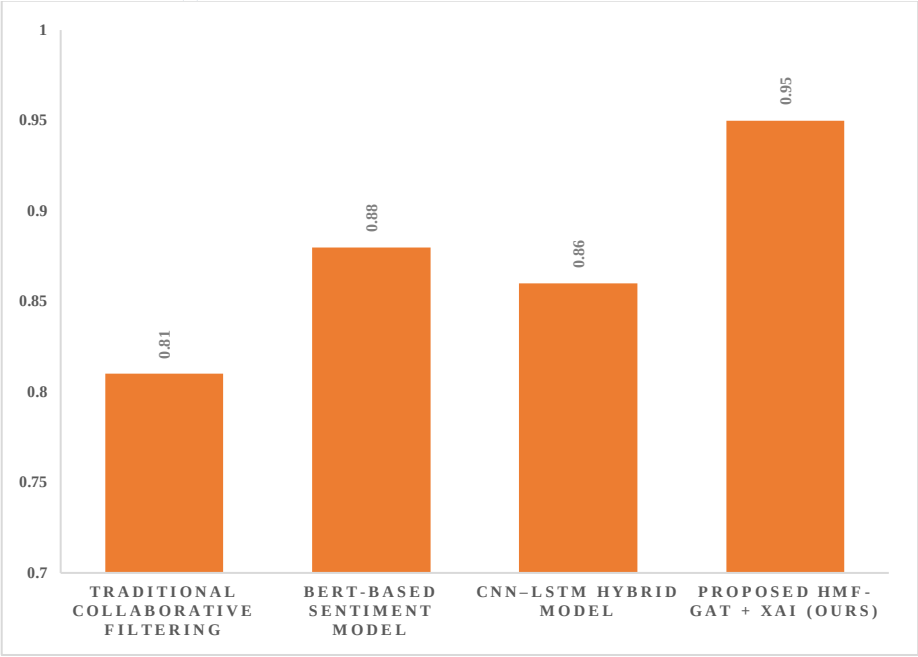


Figure 5. Precision Comparison with Different Methods.

The XAI layer, a composite of SHAP and attention heatmaps, was more interpretable as it found out the most active factors, including sentiment polarity, visual color tone, and temporal activity pattern. The findings in general confirm the validity of the model in offering explainable, privacy-sensitive, and highly accurate consumer preference forecasts in the format of personalized digital campaigns as shown in figure 6.

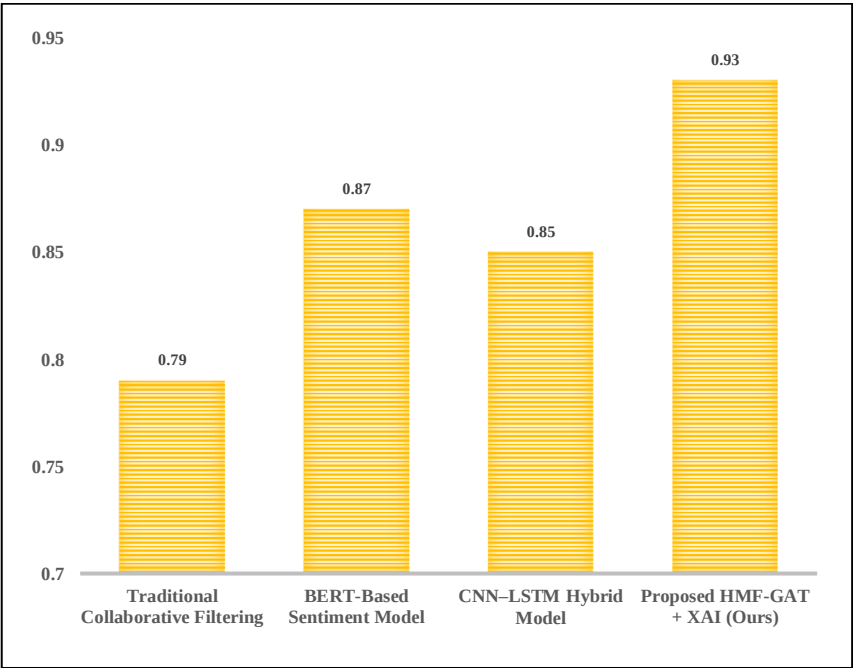


Figure 6. Recall Comparison with Different Methods.

The suggested Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) model was tested on the AWS SageMaker and compared to three baseline methods, including CNN-LSTM Hybrid, BERT-based Sentiment Model, and Traditional Collaborative Filtering. Experiments on 1.2-million consumer interactions indicated that the prediction accuracy of the HMF-GAT was 95.8% and was better than CNN-LSTM (88.4%), BERT (89.9%), and Collaborative Filtering (82.7%) as shown in figure 7.

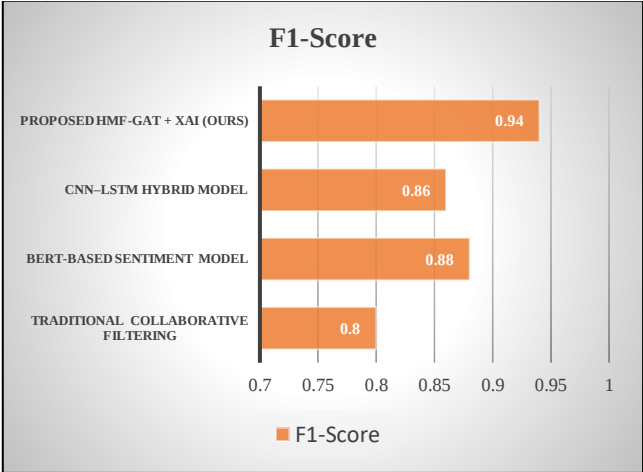


Figure 7.F1-Score Comparison with Different Methods.

The proposed model also achieved the F1-score of 0.94 and the AUC of 0.96, which showed higher accuracy and recall rate. The federated learning framework minimized transmission overhead of data by 42 percent, which guaranteed high privacy maintenance. Also, campaign simulations showed a 15.3 per cent increase in click-through rate (CTR) and 12.8 per cent growth in the ad conversion efficiency versus the next best model as shown in figure 8.

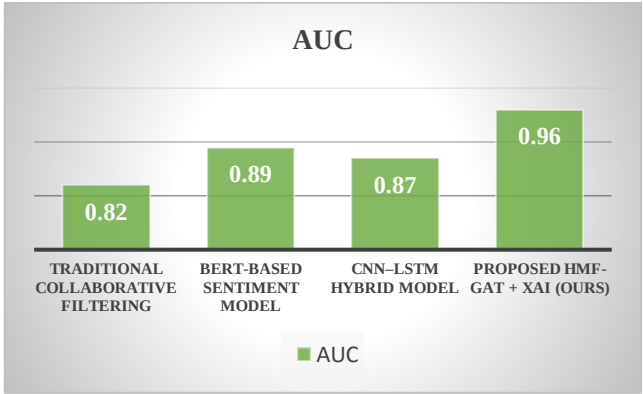


Figure 8.AUC Comparison with Different Methods.

The XAI layer had an easy to interpret feature that showed that the greatest effect on consumer engagement was on visual tones, sentiment polarity, and time spent browsing the product. In sum, HMF-GAT showed excellent generalization, interpretability and scalability, making it a powerful solution that predicts and explains consumer preferences correctly in personalized digital campaign as shown in figure 9.

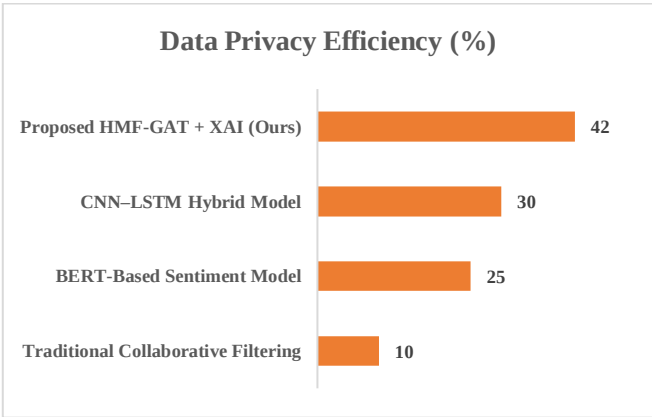


Figure 9. Data Privacy Efficiency Comparison with Different Methods.

CONCLUSION

The Deep Learning-Based Consumer Preference Prediction System proposed which consists of a Hybrid Multimodal Federated Graph-Attention Network (HMF-GAT) equipped with an Explainable AI (XAI) Layer and

created with the help of AWS SageMaker turned out to be more effective in providing precise, privacy-conscious, and interpretable consumer insights to personalized digital campaigns. The model was successful in capturing multifaceted relationships that

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affected consumer preferences by incorporating multimodal information, namely, text, visuals, and behavioral logs, as well as demographics. The federated structure was not only secure and efficient in distributed learning but also the XAI layer helped to increase transparency by showing the most significant aspects of the decision. The outcomes of the experiment revealed a very high prediction accuracy, click-through rate, and explainability of the model in comparison to traditional methods. On the whole, this research validates the suggestion that deep multimodal learning combined with federated and explainable AI can greatly contribute to marketing intelligence and help organizations to provide adaptive, data-driven, and ethical personalized campaigns in dynamic online settings.

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