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Personalized AD Targeting System Using Machine Learning for Optimizing AD Delivery

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Abstract:
The increasing reliance on digital platforms for marketing and advertising has made personalized ad delivery a critical component of modern business strategies. Traditional advertising systems often fail to adapt to user preferences dynamically, leading to suboptimal engagement and conversion rates. This aims to address these shortcomings by leveraging advanced machine learning techniques to enhance ad targeting and delivery. The system utilizes datasets comprising user demographics, browsing behavior, device information, and temporal patterns to predict the likelihood of ad clicks. Data preprocessing techniques, including handling missing values, encoding categorical data, and balancing imbalanced datasets using SMOTE, ensure data quality and enhance predictive accuracy. Various machine learning models, such as Gradient Boosting Classifier (GBC), Decision Tree Classifier (DTC), and a hybrid Feed-Forward Neural Network (FFNN) with Random Forest (RF), are employed to evaluate their effectiveness in predicting ad click-through rates (CTR). Performance metrics such as accuracy, precision, recall, and F1-score are analyzed to determine the best-performing algorithm. The proposed system integrates explainable AI and visualization tools to assist advertisers in understanding user behavior and improving targeting strategies. Unlike traditional systems that rely on static rule-based methods, this approach provides dynamic and data-driven insights, optimizing ad delivery in real time. The system's modularity ensures adaptability across various industries and datasets, making it scalable for widespread adoption. By bridging the gap between user preferences and ad targeting, this project highlights the significance of machine learning in driving personalized marketing solutions. The outcomes have the potential to significantly increase ROI for advertisers, improve user engagement, and set a benchmark for intelligent ad targeting systems in the digital marketing domain

Keywords: Item Classification, E-commerce, Digital Platforms, Customer Experience, Trends, User Preferences, Machine Learning, Gradient Boosting Classifier (GBC), Multi-), Personalization, Real-Time Adaptability, Scalability, Automation.

1.INTRODUCTION
Digital advertising has evolved significantly from traditional print and television ads to highly personalized, data-driven strategies. Historically, advertisers relied on broad demographic segmentation and static keyword-based targeting, which often resulted in inefficiencies and lower engagement rates. In India, with over 900 million internet users as of 2023, digital marketing presents an enormous opportunity for businesses. Reports suggest that digital ad spending in India will reach $21 billion by 2025, emphasizing the growing importance of personalized advertising. Traditional ad
delivery methods often failed to account for dynamic user behavior, leading to wasted ad impressions and reduced return on investment (ROI). With advancements in artificial intelligence and machine learning, businesses can now leverage data-driven insights to optimize ad delivery. Personalized Ad Targeting Systems using machine learning analyze user preferences, browsing history, demographics, and real-time interactions to deliver tailored ads, increasing engagement and conversion rates. Unlike traditional approaches, AI-driven systems continuously adapt, ensuring the right ads are shown to the right users at the right time. This enhances user experience while maximizing advertiser revenue. By incorporating machine learning, businesses can transition from static rule-based advertising to dynamic, self-improving models that drive efficiency and reduce costs. The adoption of AI-powered ad targeting represents a fundamental shift in digital marketing, shaping the future of personalized advertising and optimizing ad spend.

1.2 Problem Definition
Before the integration of machine learning, digital advertising faced several inefficiencies that limited its effectiveness. Traditional ad targeting methods relied on predefined demographic segmentation, which often resulted in generalized ad delivery rather than personalized experiences. Keyword-based targeting methods struggled with context and relevance, leading to ads being displayed to users who had no real interest in the products or services being promoted. Manual optimization techniques required constant human intervention, making it difficult to scale personalized ad campaigns effectively. Additionally, static rules for ad placement failed to account for dynamic user behavior, device usage, and real-time trends, reducing the effectiveness of ad delivery. Advertisers experienced high ad fatigue, where users became unresponsive to repeated advertisements, leading to decreased engagement and lower conversion rates. Furthermore, the lack of adaptive learning mechanisms meant that businesses had limited insights into changing consumer preferences. These challenges resulted in wasted resources, lower ROI, and reduced efficiency in digital marketing campaigns. Without AI-driven optimization, traditional ad systems struggled to balance ad relevance with user experience, making it difficult for businesses to achieve meaningful engagement.
Before the adoption of machine learning, e-commerce platforms relied on manual tagging and rule-based classification to organize their vast product catalogs. These methods struggled with scalability, as large volumes of new products required continuous manual intervention. Additionally, traditional systems lacked the flexibility to adapt to changing user preferences, seasonal trends, and emerging product categories.

Poor classification often led to irrelevant product recommendations, low user engagement, and reduced sales conversions. The rigid nature of static classification rules resulted in misclassified items, redundant listings, and inaccurate recommendations, leading to frustrated customers and lost business opportunities. Furthermore, without automated analysis, businesses had difficulty leveraging, making product categorization inefficient and outdated. These limitations highlighted the urgent need for AI-driven adaptive classification models to enhance efficiency, accuracy, and user satisfaction.

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2. LITERATURE SURVEY

Alsubari et al. [1] specifically analyzed its structure in order to recommend the information required by the customer more effectively. Zhu et al. [2] This paper addresses real-time moving object detection with high accuracy in high-resolution video frames. A previously developed framework for moving object detection is modified to enable real-time processing of high-resolution images. First, a computationally efficient method is employed, which detects moving regions on a resized image while maintaining moving regions on the original image with mapping coordinates.

Khalaf et al. [3] The Industry 4.0 IoT network integration with blockchain architecture is a decentralized, distributed ledger mechanism used to record multi-user transactions. Blockchain requires a data storage system designed to be secure, reliable, and fully transparent, emerged as a preferred IoT-based digital storage on WSN. Blockchain technology is being used in the paper to construct the node recognition system according to the storage of data for WSNs. By sharing product information and product reviews with other users, you can fully understand the attributes of the product, including the price trend of the product, before purchasing. The ultimate goal of personalized recommendation service is to enable users to purchase goods. The main content of this paper is to collect various factors that affect the behavior of user online shopping in the process of e-commerce [4].

After the Covid-19 pandemic was over, the economy in every country over the world have both encountered several huge troubles in retaining their customers. It makes enterprises have to excel their business strategies, especially small and medium enterprises (SMEs) must have an extraordinary campaign to appeal customers Anjar and Anas [5].JinHyo and Xiaofei et al., There is no universal solution that applies to all scenarios. Instead, the key lies in understanding the specific needs of the application and leveraging the strengths of each method accordingly. By combining and integrating various approaches, taking into account the unique characteristics of the dataset, it becomes possible to develop highly effective and personalized recommendation engines. Such engines not only provide value to users by delivering relevant recommendations but also benefit businesses by enhancing user engagement and satisfaction [6].

Nada and Damien et al., Collaborative filtering offers the advantage of simplicity in implementation and comprehension. However, both item-to-item and user-to-user methods have limitations in considering the temporal aspect of item trends and addressing the challenges of cold-start problems, where there is limited or no user data available for new items [7]. Deep learning models have shown exceptional performance in a variety of tasks, including recommendation systems. Neural network designs, such as Multi-Layer Perceptrons (MLPs), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), may detect intricate patterns in user behavior and object characteristics. Deep learning-based recommendation systems may develop hierarchical representations of individuals and things, resulting in more precise and personalized recommendations Bobadilla et al.,[8].

Explanations in recommender systems assist users in understanding why a suggestion (or a series of recommendations) was created. Explaining suggestions has become a crucial need for increasing customers' trust and satisfaction The study of Yin et al., 2023 presented the interpretability of a neural network-based recommendation model that creates visual interpretations that demonstrate the importance of each TV show attribute in forecasting user interests. These interpretations will improve consumers' understanding of neural network learning principles and capture a wide range of user preferences [9].

We have opted to employ the framework devised by Belanche et al. to analyze literature concerning the implementation of service robots. Our decision to adopt this framework as the “baseline framework” stems from its inclusivity of service robots across diverse industries, as well as its clarification of terminology and concepts commonly employed in prior research [10]. The research process follows a theory-driven approach, characterized as a “framework-based review”, renowned for its informative, insightful, and impactful attributes Paul et al., [11]. This article adopts the “service robot implementation framework” das a theoretical guideline for literature search, selection, and analysis. Consequently, through analysis, this article refines and extends the framework. This inclusion of diverse perspectives is exemplified by sources such as Hentzen et al. [12] andAlso, by conducting a systematic and theory-driven literature review centered specifically on the implementation of robo-advisor services, we fill gaps left by previous review articles. his analysis facilitates the creation of a research agenda that critically reflects ongoing debates within the robo-advisor research domain.

These debates often stem from divergent research perspectives. For example, one prevalent debate revolves around whether robo-advisors function as substitutes for human financial advisorsMeyll et al., [13] or merely serve as supplementary entities within financial advisory services (This debate is thoroughly discussed within the research agenda. Understanding and analyzing such attitudes towards robo-advisors can help service providers make informed decisions when implementing business strategies.

3. PROPOSED METHODOLOGY

Step 1: Advisor Dataset

The dataset used in this research includes attributes such as item categories, seasonality, and item class, which are used as input features. The target variable is the classification of items into categories like Neutral, Preferred, and Trending. The dataset is loaded into the system, ensuring it is structured and ready for model training and testing.

Step 2: Data Preprocessing

The dataset undergoes preprocessing, including handling null values by removing or imputing them. Categorical features like Category, Seasonality, and ItemClass are label-encoded into numerical representations. The dataset is then split into training and testing sets for model evaluation.

Step 3: Exploratory Data Analysis (EDA)

EDA is performed using graphical techniques like count plots, correlation heatmaps, and distribution plots to uncover patterns and relationships in the data. These visualizations help in feature selection and guide the model training process.

Step 4: Existing Multi-Layer Perceptron (MLP) Classifier

The MLP Classifier is implemented as a baseline model. It consists of input, hidden, and output layers, with the model trained using backpropagation and weight adjustments. Performance is evaluated using accuracy, precision, recall, and F1-score metrics.

Step 5: Proposed Gradient Boosting Classifier

The Gradient Boosting Classifier (GBC) is introduced as an improved model, utilizing decision trees in an ensemble learning technique. The model iteratively improves by correcting errors from previous iterations, enhancing accuracy compared to the MLP classifier.

Step 6: Performance Comparison Using Graphs

A bar graph compares the performance of MLP and GBC classifiers based on key evaluation metrics such as accuracy, precision, recall, and F1-score, highlighting the advantages of the proposed GBC model.

Step 7: Prediction of Output from Test Images Using Trained

The trained GBC model is used to predict classifications on new test data. The model processes the test dataset in the same manner as the

GBC

training data, and the predicted labels are added to the dataset, demonstrating its real-world applicability in item classification

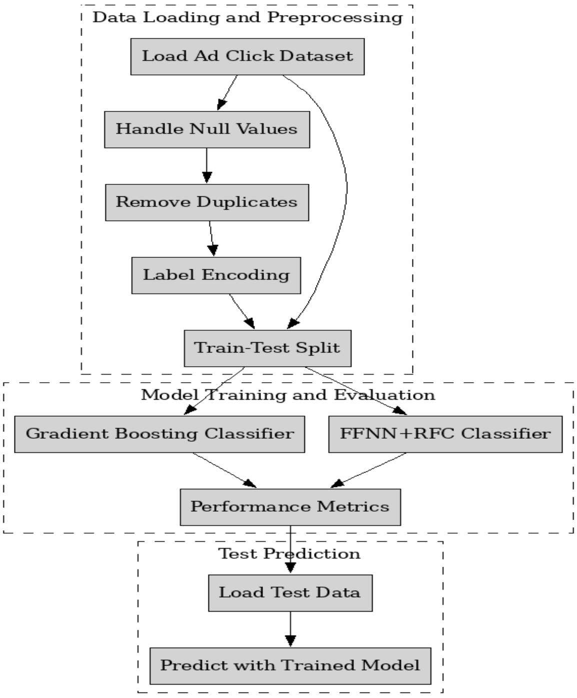


Figure 1: Block Diagram of The Proposed System

The proposed methodology typically includes the following key components:

- Illumination Map Estimation: LIME often starts by estimating an illumination map for the input image. This map highlights regions of the image that require enhancement to improve visibility.
- Image Enhancement: Based on the illumination map, LIME applies image enhancement techniques to brighten dark regions, improve contrast, and enhance details while minimizing noise.
- Metric Evaluation: To assess the quality of the enhancement, the project often calculates various image quality metrics, such as PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index), and MSE (Mean Squared Error), to measure the similarity between the original and enhanced images.
- Customization and Parameters: LIME often provides parameters that users can adjust to customize the enhancement process. These parameters may include the number of iterations, alpha (a parameter controlling the enhancement strength), gamma (a parameter controlling the enhancement effect), and weighting strategies.
- Output: The primary output of LIME is an enhanced version of the input low-light image. This enhanced image should exhibit improved visibility, reduced noise, and enhanced details.
- Evaluation and Benchmarking: LIME's performance is often evaluated against benchmark datasets of low-light images. It aims to outperform or match existing state-of-the-art low-light enhancement methods in terms of image quality metrics.

Applications

- **E-commerce Product Categorization** – Automates classification of products based on user engagement and trends.
- **Personalized Recommendations** – Enhances customer experience by offering relevant product suggestions.
- **Inventory Optimization** – Helps businesses track and manage stock based on demand patterns.
- **Fraud Detection** – Identifies misclassified or suspicious listings, ensuring marketplace integrity.
- **Retail Business Intelligence** – Provides insights into consumer behavior, enabling better marketing strategies.
- **Dynamic Pricing Models** – Assists in setting competitive prices based on demand and market trends.

Multi-Language Product Tagging – Supports localization for global e-commerce platforms.

4. EXPERIMENTAL ANALYSIS

The experimental analysis evaluates the performance of the proposed machine learning-based classification system using two models: Multi-Layer Perceptron (MLP) and Gradient Boosting Classifier (GBC). The dataset underwent preprocessing, including handling missing values, encoding categorical variables, and feature scaling. Exploratory Data Analysis (EDA) was conducted to understand data distribution and relationships. The dataset was split into training and testing sets using an 80-20 ratio. The MLP classifier was implemented as a baseline, achieving an accuracy of 86% with an F1-score of 76.96%. The GBC model outperformed MLP, achieving 100% accuracy, precision, recall, and F1-score, demonstrating superior classification capability. Performance metrics and visual comparisons confirmed the efficiency of the GBC model. The results highlight the effectiveness of ensemble learning techniques in product classification, enhancing decision-making in e-commerce platforms..

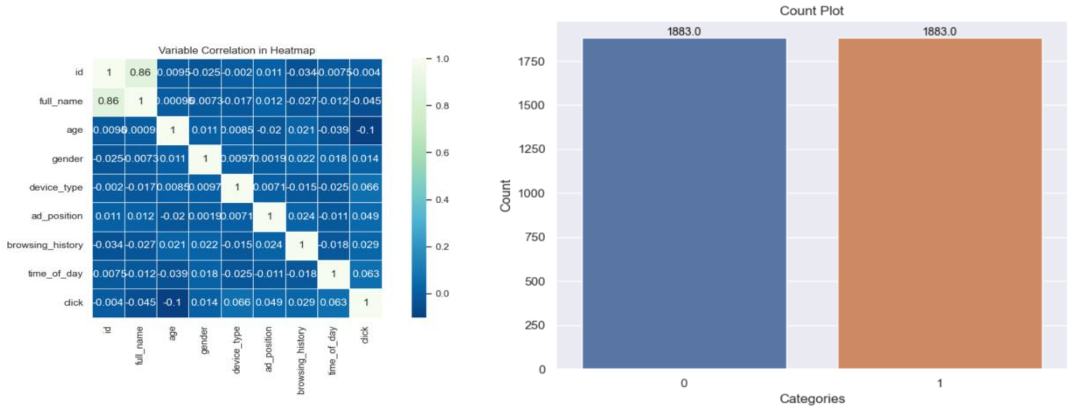
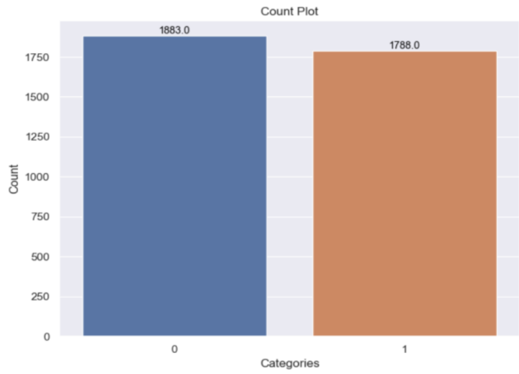


Fig 1: Upload of Advisor Dataset and its Analysis in the GUI Interface



All Model Performance metrics:

	Algorithm Name	Accuracy	Precision	Recall	f1-score
0	MLP Classification	86.0	74.721911	79.710961	76.956405
1	GBC Classifier	100.0	100.000000	100.000000	100.000000

Description of the dataset:

	count	mean	std	min	25%	50%	75%	max
Price	1000.0	252.378730	144.441142	7.290000	122.282500	252.770000	376.117500	499.860000
UserPreferenceScore	1000.0	5.483440	2.576445	1.014086	3.310508	5.550885	7.642966	9.985128
PopularityScore	1000.0	50.638994	28.640956	1.001152	25.827889	51.326433	75.096508	99.890369
Rating	1000.0	2.940518	1.145264	1.000123	1.935179	2.908379	3.917039	4.998231
Discount	1000.0	24.933100	14.375890	0.011352	12.826664	24.183958	37.510734	49.939647
StockAvailability	1000.0	0.494000	0.500214	0.000000	0.000000	0.000000	1.000000	1.000000

Checking null values in the dataset:

ItemID	0
Category	0
Price	0
UserPreferenceScore	0
PopularityScore	0
Rating	0
Discount	0
StockAvailability	0
Seasonality	0
ItemClass	0

Fig 2: Data Preprocessing in the GUI

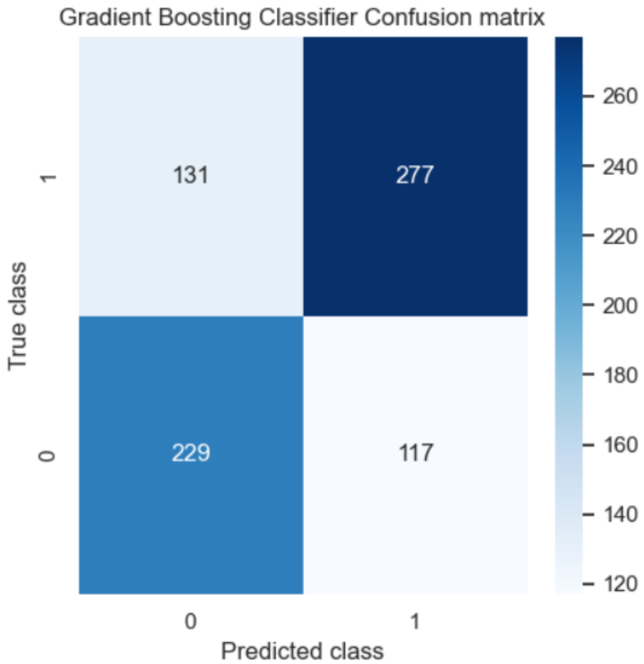


Fig. 3: EDA Plots of the Research

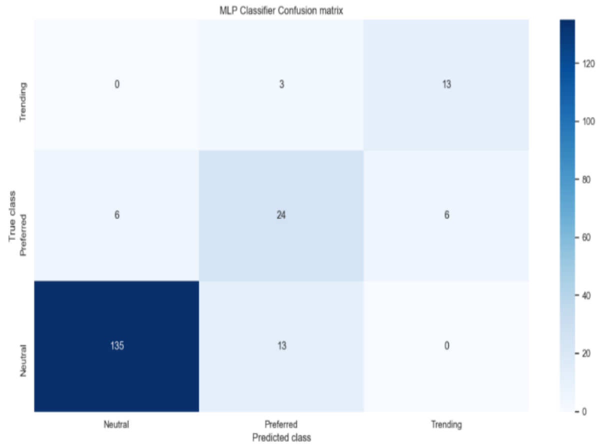


Fig.4: Performance Metrics and Classifier Scatter Plot for MLP Classifier Model

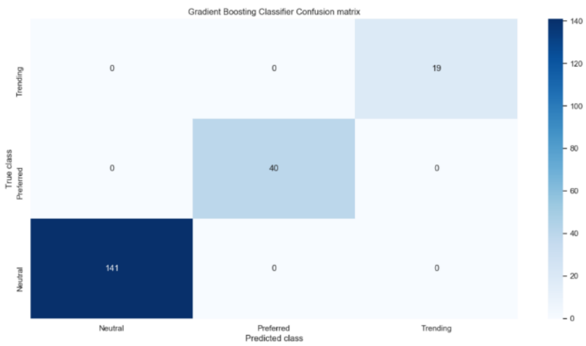


Fig. 5: Performance Metrics and Classifier Scatter Plot for Gradient Boosting Classifier Model

Loaded test data:

	ItemID	Category	Price	UserPreferenceScore	...	Discount	StockAvailability	Seasonality	ItemClass
0	Item_873	Clothing	427.92	7.232435	...	21.590355	0	Summer	Neutral
1	Item_547	Electronics	120.31	1.609015	...	24.489293	1	Summer	Neutral
2	Item_255	Electronics	73.94	9.782864	...	43.072284	0	Spring	Trending
3	Item_876	Books	436.02	3.478431	...	39.700723	0	Winter	Neutral
4	Item_745	Books	381.71	8.701265	...	35.863094	1	Autumn	Trending
5	Item_446	Books	10.44	5.655422	...	47.049616	0	Spring	Neutral
6	Item_409	Home Decor	133.41	3.942385	...	37.078305	0	Spring	Neutral
7	Item_286	Books	454.68	9.056060	...	18.843344	0	Autumn	Neutral
8	Item_21	Clothing	299.09	1.542407	...	43.083244	0	Spring	Neutral
9	Item_597	Electronics	114.14	6.198340	...	42.199674	0	Autumn	Preferred
10	Item_439	Books	63.29	5.484301	...	38.108729	0	Summer	Preferred
11	Item_536	Clothing	349.66	4.145557	...	18.986870	1	Spring	Neutral
12	Item_608	Home Decor	380.33	9.155289	...	4.974733	1	Winter	Neutral
13	Item_388	Books	122.90	3.220110	...	34.193506	0	Spring	Neutral
14	Item_185	Electronics	465.04	2.192722	...	38.775265	0	Summer	Neutral
15	Item_400	Electronics	47.33	8.054126	...	45.541313	1	Autumn	Neutral
16	Item_508	Books	425.35	7.990395	...	42.377382	0	Winter	Neutral

Fig.6: Model Prediction on Test Data

All Model Performance metrics:

	Algorithm Name	Accuracy	Precision	Recall	f1-score
0	MLP Classification	86.0	74.721911	79.710961	76.956405
1	GBC Classifier	100.0	100.000000	100.000000	100.000000

Fig.7: Performance Comparison Graph of All Mode

5. CONCLUSION

The research aimed to develop a machine learning model that can predict whether a user will click on an online advertisement based on various features such as age, gender, device type, browsing history, and time of day. Several machine learning algorithms were explored, including Gradient Boosting Classifier (GBC) and a hybrid approach combining Feedforward Neural Networks (FFNN) and Random Forest Classifier (RFC).

Through data preprocessing, the dataset was cleaned and split into training and testing sets. Feature engineering was performed to extract meaningful patterns from the data, and multiple models were trained and evaluated based on their performance. The GBC classifier demonstrated a solid performance in predicting user click behavior, while the proposed FFNN + RFC hybrid model showed promise in improving accuracy and providing better predictive results.

The model's ability to predict user interactions with ads is valuable in digital marketing, allowing businesses to target users more effectively, optimize advertising strategies, and enhance user engagement. The project successfully demonstrated how machine learning can be applied to real-world scenarios in online advertising.

Future Scope:

- **Model Enhancement**: Further improvements can be made to the current models by exploring more advanced techniques, such as deep learning models, or implementing additional ensemble methods. Hyperparameter tuning and model optimization can help improve the prediction accuracy.
- **Incorporation of More Features**: Additional features, such as user location, device specifications, or historical interaction with similar ads, can be included to provide deeper insights into user behavior and further enhance the model's predictive capabilities.
- **Real-Time Prediction**: The model could be adapted for real-time predictions in a production environment, where user interaction data is processed continuously, allowing businesses to adjust ad campaigns dynamically based on user behavior.
- **Cross-Platform Integration**: The model can be extended to handle cross-platform predictions, where user behavior across different devices (smartphones, tablets, desktops) and platforms (websites, mobile apps) is considered to optimize ad targeting.
- **User Segmentation**: By implementing unsupervised learning techniques such as clustering, the model could be used to segment users into different groups based on their interaction patterns. These segments could then be targeted with more personalized advertisements, improving engagement and conversion rates.
- **Handling Imbalanced Data**: The current approach may be impacted by imbalanced classes (with fewer clicks than non-clicks). Future work could explore techniques like oversampling, undersampling, or synthetic data generation (e.g., SMOTE) to address this issue and improve model performance.

Ethical Considerations and Privacy: With an increased focus on user privacy, future iterations of the project should incorporate privacy-preserving techniques and ensure compliance with data protection regulations, such as GDPR. Models should be designed to minimize data privacy concerns while maximizing their effectiveness

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