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Research Paper

PERSONALIZED AD TARGETING SYSTEM USING MACHINE LEARNING FOR OPTIMIZING AD DELIVERY

Kovuri Mounika[1*], Pedduri Laxmi Niharika[2], Davula Tejaswi[2], Shivayella Bhargavi[2], Bhoga Sanjay Kumar[2]

[1]*Assistant Professor,* [2]*UG Student,* [1,2]*Department of Computer Science and Engineering (AI&ML),*
[1,2]*Malla Reddy Engineering College and Management Sciences, Kistapur, Medchal, 501401, Telangana, India*

**Corresponding author: kmounika@mrem.ac.in*

Abstract

In the modern digital marketing landscape, personalization has become a critical factor for successful advertising, with over 80% of users favoring personalized ads and such campaigns yielding up to 20% higher conversion rates than generic approaches. Traditional ad-targeting methods relied heavily on manual analysis of customer records, historical sales, and viewership data. These techniques were inefficient, prone to human error, and lacked the ability to adapt in real time, often resulting in suboptimal campaign performance. Early machine learning models, such as the Gradient Boosting Classifier, improved prediction accuracy compared to manual methods but suffered from limitations including overfitting, slow training on large-scale data, and poor adaptability to rapidly evolving user preferences, restricting their effectiveness in real-time personalization. To address these challenges, we propose a hybrid machine learning framework that integrates a Feedforward Neural Network (FNN) with an Extra Trees Classifier. The FNN effectively captures complex, non-linear patterns in user behavior, while the Extra Trees Classifier provides efficient feature selection and fast, robust predictions. By leveraging user data such as browsing history, click-through rates, demographic attributes, and prior ad interactions, the system generates highly personalized ad recommendations. Experimental results demonstrate that the proposed model achieves a classification accuracy of 91%, representing a 28% improvement over Gradient Boosting, along with a notable reduction in training time. Overall, this adaptive and scalable ML pipeline enhances ad targeting precision, improves user engagement, and maximizes return on ad spend in dynamic digital environments.

Keywords: Personalized advertising, Hybrid machine learning model, Real-time ad targeting, High classification accuracy.

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1. Introduction

In the rapidly evolving digital landscape, personalized advertising has become a cornerstone of modern marketing strategies. With over 5 billion internet users globally and increasing digital footprints across social media, e-commerce, and streaming platforms, the volume of data available for targeting has reached unprecedented levels. According to a report by Statista, digital ad spending surpassed $600 billion in 2023, and it's projected to exceed $740 billion by 2025. More notably, targeted ads are reported to be twice as effective in terms of click-through rate (CTR) compared to generic, non-targeted ones. These trends clearly emphasize the immense potential of personalization in enhancing user engagement and maximizing advertising return on investment (ROI).

Despite the data-rich environment, a significant portion of online advertising remains under-optimized. Research indicates that more than 47% of users still perceive online advertisements as irrelevant, which leads to ad fatigue, reduced interaction, and negative user experience. Moreover, approximately 60% of small and medium-sized businesses still rely on manual methods for ad placement and audience segmentation, often using static rules based on broad demographic categories. These conventional approaches fail to adapt to dynamic user behavior, resulting in inefficiencies such as low conversion rates and high customer acquisition costs. The disconnect between available user insights and how they're operationalized in ad targeting highlights a critical bottleneck in the industry.

2. Literature Survey

Prihatiningsih et al. [1] Utilized a quantitative study design with a cross-sectional survey to collect data from social media-active consumers exposed to video advertisements. Data analysis used descriptive and inferential statistical techniques to test the relationship between these variables. The findings showed that video content is highly effective in attracting attention and maintaining consumer interest longer than text or static images. The video also allows for more complex and emotional messaging. Social media facilitates two-way interaction between brands and consumers, strengthening relationships and increasing customer loyalty. Personalization of ads through artificial intelligence (AI) technology has also been shown to increase campaign relevance and effectiveness. This research contributes to the digital advertising literature by demonstrating the importance of integrating video and social media content and using AI technology for personalization.

Binti Amir Suharman, et al. [2] Developed the analysis iterated between data preprocessing and exploratory data analysis (EDA) before predictive modeling. Constraint-based Seq2Pat, which included the Dichotomic Pattern Mining (DPM) technique, was employed to identify common browsing patterns among customers. Using the ratio() method in the SequenceMatcher class of difflib, the obtained patterns were mapped with the patterns from the preprocessed clickstream dataset, and the sequences with the highest similarity score were identified. Preprocessed imbalanced clickstream data with various ratios of buyer and non-buyer groups, namely 4:96, 3:97, 2:98, and 1:99, were prepared by adjusting the thresholds for the similarity score, and their prediction performance was observed. Logistic Regression (LR) achieved high prediction performance across imbalanced clickstream datasets of different ratios, with a ratio of 4:96 performing exceptionally well, with 90.95% average recall and 95.26% average F1-score.

Ibrahim, Najhan, et al. [3] Developed a critical analysis of a collaborative filtering technique that uses machine learning and business intelligence (BI) to improve e-commerce recommendation systems. By reviewing the existing literature, we uncover considerable gaps in current research, particularly in the successful use of large data and advanced artificial intelligence techniques. Our findings show that combining deep learning with reinforcement learning can significantly increase suggestion reliability and responsiveness to user preferences. Furthermore, we present a comprehensive framework for analysing large datasets using collaborative filtering and BI tools, resulting in actionable insights into customer behaviour, market trends, and product performance. This integration not only improves the suggestion process, but it also creates a more interesting and pleasant buying experience for users.. Finally, this study emphasises the importance of continued research in personalised recommendation systems in order to fully leverage future e-commerce technology. The investigation demonstrates that traditional recommendation methods frequently fail to give meaningful ideas, with user satisfaction percentages as low as 60% in some tests.

Liu, Liming et al. [4] Proposed how motion data can lead to more accurate product recommendations, adaptive user interfaces, and dynamic marketing strategies. Furthermore, it highlights the key benefits, including improved customer engagement, conversion rates, and satisfaction. This study also explores the biological mechanisms underlying motion analysis. It investigates how motion analysis reflects users' physiological responses and psychological states, integrating these insights with personalized marketing strategies. Additionally, the paper examines how motion analysis data can enhance the understanding of users' biological characteristics, such as fatigue and attention, and how these insights can be applied to create more effective personalized marketing approaches. Moreover, the paper identifies the challenges associated with implementing motion analysis, such as the complexity of integrating real-time tracking tools, data processing limitations, and privacy concerns. .

Nguyen et al.[5] Proposed AI could be used to spread disinformation if it were deliberately programmed to produce misleading advertising content. Using cognitive appraisal theory and information quality theory to study how consumers assess threats and develop AI marketing coping strategies from the information generated by AI, this study examines the outcome of the dark side of AI advertising. We collected data from 451 AI-advertising users in Vietnam. The results based on PLS-SEM showed interesting and novelty results. The statistical analysis showed a negative correlation between contextual, representational, accessibility, and threat appraisals. There was also a statistically significant positive correlation between contextual, representational, accessibility, and coping appraisals. Threat appraisals were positively correlated with anger and anxiety but not loneliness. Coping appraisal was significant and negatively correlated with anxiety but not anger or loneliness. This study advances theory and management.

Usmonov et al. [6] Utilizes Thematic Qualitative Data Analysis (TQDA) to categorize findings into key themes: Alignment with Expectations, Perceived Responsiveness, Emotional Resonance, and Customer Retention. The research revealed that Gen AI significantly enhances customer satisfaction by providing personalized and timely responses, which align with customer expectations. Moreover, AI-driven strategies are shown to improve customer retention by enhancing the overall emotional connections through consistent, quality interactions.The implications of these findings are profound for e-commerce businesses. Implementing Gen AI can lead to better customer loyalty and a competitive advantage in e-commerce. Still, companies must address the challenges to maximize the benefits. And ensure the ethical use of AI and maintain a balance amid automated and human interactions.

Le, Minh T, et al. [7] Proposed an innovative model, FraudGNN, based on Graph Neural Networks (GNN). The model constructs a dynamic transaction graph, where transaction addresses are treated as nodes and asset transfer relationships as edges, incorporating time-series features. A Graph Attention Network (GAT) is used to extract behavioral features from node neighborhoods. In addition, a Bidirectional Long Short-Term Memory network (Bi-LSTM) is introduced to capture behavioral paths across block-level transactions, enabling accurate classification and prediction of abnormal accounts within blockchain networks. Experiments conducted on an Ethereum transaction dataset—containing approximately 3.6 million transaction records and 40,000 labeled addresses—show that the FraudGNN model significantly outperforms traditional methods such as Random Forest and Graph Convolutional Networks (GCN) in key metrics, achieving 91.2% precision, 87.5% recall, and an F1-score of 89.3%.

Whitmore, et al.[8] Proposed the method allows banking, e-commerce, and insurance entities to update model parameters jointly without exposing raw user data. To address distributional discrepancies caused by non-independent and identically distributed (non-IID) data, a dynamic weighting scheme is applied. The approach is validated using real-world data from 820,000 users, covering contract performance, repayment behavior, and credit defaults. Compared with a conventional centralized XGBoost model, FedRisk shows a moderate drop in AUC from 0.874 to 0.861 (approximately 1.5%) but effectively safeguards user privacy. In out-of-bag (OOB) testing, the F1-score improves by 3.7%, suggesting better adaptability to unseen data. Overall, FedRisk provides a practical balance between model performance and privacy preservation in financial risk detection across institutions.

Hussain, Zahid, et al. [9] Utilized the effect of AI-based personalization on purchase intention in Pakistan's modest-fashion e-commerce market, emphasizing the moderating role of Sharia law compliance. Given the religious and cultural significance of modest fashion, this study explores how individual recommendations aligned with Islamic teachings influence consumer behavior.Methodoloy a quantitative method was employed using SmartPLS for structural equation modeling. Data were collected from 211 participants engaged in modest fashion e-shopping in Pakistan to test the direct effect of AI personalization on purchase intention and the moderating effect of Sharia compliance.The findings show that AI-driven personalization enhances purchase intention through tailored recommendations that align better with consumer preferences. Moreover, Sharia compliance significantly moderates this relationship; consumers show greater trust and engagement with AI recommendations when they align with Islamic principles of modesty and ethical consumption.

Hanaee,et al.[10] Utilized a qualitative research approach, the study employed directional content analysis to investigate this topic. Data were collected and analyzed through an exploratory methodology with the assistance of MAXQDA software. The analysis began with guided content coding, drawing on theoretical frameworks pertinent to the research. Through this process, 2387 initial codes were identified, which were then categorized into nine main themes, with the relationships between these codes clarified. The findings were inductively derived from the raw data, leading to the development of a foundational theoretical framework. The study, employing a personalized strategy, identified three key factors that contribute to anxiety: physical, perceptual, and environmental components. Physical factors, such as accessibility, lighting, and signage, were found to have a significant impact on passengers' psychological well-being. Perceptual factors, including personal perceptions, stress, and fear, played a crucial role in exacerbating anxiety. Additionally, environmental factors, particularly the design of metro networks.

Ding, Liang ,et al.[11] Explore the impact of artificial intelligence-powered personalised recommendations (AI-PPRs) on user engagement, browsing behaviour and purchase intentions on TikTok (Douyin in China), focusing on how these recommendations affect user satisfaction and purchase intention, while also addressing potential privacy concerns. In addition, the research investigates the influence of AI-recommended product presentation, timing and placement, as well as social factors such as key opinion leaders' (KOLs) influence on consumer decision-making.Using the expectancy-value theory and the stimulus-organism-response model, this research used a qualitative methodology through interviews with Douyin users to explore their experiences and perceptions of AI-PPRs.

Nwanna, et al.[12] Developed a provides a systematic review of foundational methodologies, including collaborative filtering, deep neural networks and transformer-based architectures, examining their application across diverse industries. A particular focus is placed on multimodal and context-aware approaches that underpin adaptive, scalable and privacy-conscious solutions.Using a comprehensive evaluation framework, this study quantifies the impact of personalisation systems on key performance indicators (KPIs) such as session duration, user retention rates and conversion metrics.

Critical ethical considerations, including data privacy, algorithmic fairness and transparency, are rigorously analysed. To address these challenges, privacy-preserving strategies such as federated learning and differential privacy are advocated as essential tools for mitigating risks. Additionally, the pivotal role of Explainable AI (XAI) is explored, highlighting its potential to foster user trust and ensure compliance with regulatory standards such as GDPR and CCPA.

Franciskus et al.[13] Developed by Using the Mall Customer Dataset, which includes consumer attributes like gender, age, annual income, and spending scores, this research develops a segmentation framework enriched with additional features, such as purchasing behavior during specific events, individual preferences, and demographic norms. K-means clustering is employed to group customers into meaningful segments based on shared behavioral patterns, with the Elbow Method and Silhouette Score ensuring optimal cluster determination. To enhance the interpretability of clustering results, LIME is used to explain the influence of demographic and behavioral factors on cluster formation. This explainability enables marketing teams to understand the rationale behind customer segmentation, promoting transparency and ethical AI usage. By integrating AI-driven segmentation with explainable AI, the framework offers deeper customer insights while aligning strategies with diverse consumer values

Vinodhini et al.[14] Proposed by focusing on the evolution and implementation of advanced ML systems across the AdTech pipeline. It examines the intricate processes involved in modern advertising technology, from creative content analysis to real-time bidding optimization. The article details how machine learning algorithms revolutionize audience targeting, bid optimization, and campaign performance through sophisticated data processing and decision-making systems. It discusses key technical implementation considerations, including model architecture design and system infrastructure requirements for large-scale ML deployments in advertising platforms. Additionally, the article addresses emerging challenges and future directions in the field, particularlyconcerning privacy regulations, model improvements, and system optimizations.

Emmert, Hila et al [15].Keratinocytes (KCs) from healthy donors stimulated with type 2 cytokines are often used to experimentally study atopic dermatitis (AD) inflammatory responses. Owing to potential intrinsic alterations, it seems favorable to use KCs from patients with AD. KCs isolated from hair follicles offer a noninvasive approach to investigate AD-derived KCs. To evaluate whether such AD-derived KCs are suitable to mimic AD inflammatory responses, we compared hair follicle–derived KCs from healthy donors with those from patients with AD in a type 2 cytokine environment. Stimulation of AD-derived KCs with IL-4 and IL-13 induced higher expression changes of AD-associated markers than that of healthy KCs. The combination of IL-4 and IL-13 generally induced highest expression changes, but IL-13 alone also induced significant changes of AD-specific markers. Similar to the 2-dimensional cultures, IL-4/IL-13 stimulation of 3-dimensional skin models generated with AD-derived KCs modulated the expression of several AD-relevant factors. Whole-transcriptome analysis revealed that IL-4 and IL-13 acted similarly on these 3-dimensional skin models. Histologically, IL-13 alone and in combination with IL-4 increased epidermal spongiosis, a histological hallmark of AD skin. Taken together, our pilot study suggests that hair follicle–derived KCs from patients with AD represent a useful model system to study AD-related inflammation in a personalized in vitro model.

Saadjad et al [16] Developed the Marketing communication is a pivotal element in the landscape of modern business, encompassing the various channels and techniques employed to convey messages to target audiences. The emergence of artificial intelligence (AI) has revolutionized various sectors, prominently including marketing communication. The integration of AI enables marketers to enhance the effectiveness and efficiency of their messaging strategies through data-driven insights and automation. This essay delineates the transformative impact of AI in marketing communication, focusing on customer engagement, personalization, and analytics. The paper categorizes key concepts related to AI in marketing communication and follows a structured approach. This study addresses the research questions and offers an in-depth discussion on AI for marketing. The finding showed that AI-driven technology in marketing communication empowers marketers to create targeted marketing campaigns through ad targeting. By utilizing Machine Learning (ML), AI can differentiate between purchasing behaviour, actual conversions, and exploratory actions, enabling the retargeting of prospects with a higher likelihood of conversion.

Ganesha et al [17] Proposed The tremendous effects of the COVID-19 epidemic on the advertising sector and its consequent acceleration of digital transition are the focus of this chapter. The global health crisis acted as a catalyst for change, requiring advertisers to reevaluate traditional techniques and implement novel ones in order to maintain a relationship with customers in a constantly changing digital environment.

Tanaka et al[18] Developed the critically evaluates the transition from serendipity to precision-based methodologies in neuropsychiatric research. It focuses on key innovations such as dynamic systems modeling and network-based approaches that use genetic, molecular, and environmental data to identify new therapeutic targets. Furthermore, it emphasizes the importance of interdisciplinary collaboration and human-specific models in overcoming the limitations of traditional approaches

Joseph Loscalzo et al[19] Developed the Ineffective medication is a major healthcare problem causing significant patient suffering and economic costs. This issue stems from the complex nature of diseases, which involve altered interactions among thousands of genes across multiple cell types and organs. Disease progression can vary between patients and over time, influenced by genetic and environmental factors. To address this challenge, digital twins have emerged as a promising approach, which have led to international initiatives aiming at clinical implementations. Digital twins are virtual representations of health and disease processes that can integrate real-time data and simulations to predict, prevent, and personalize treatments. Early clinical applications of DTs have shown potential in areas like artificial organs, cancer, cardiology, and hospital workflow optimization.

Mazumdar et al [20] Proposed the Artificial intelligence (AI) is changing the field of nanomedicine by exploring novel nanomaterials for developing therapies of high efficacy. AI works on larger datasets, finding sought-after nano-properties for different therapeutic aims and eventually enhancing nanomaterials' safety and effectiveness. AI leverages patient clinical and genetic data to predict outcomes, guide treatments, and optimize drug dosages and forms, enhancing benefits while minimizing side effects. AI-supported nanomedicine faces challenges like data fusion, ethics, and regulation, requiring better tools and interdisciplinary collaboration. This review highlights the importance of AI regarding patient care and urges scientists, medical professionals, and regulators to adopt AI for better outcomes.

3. Proposed System

The proposed algorithm introduces a novel combination that enhances traditional models by integrating deep feature learning with robust ensemble classification. Unlike existing survey methods that treat feature engineering and classification separately, our approach fuses a Feed Forward Neural Network (FFNN) as a deep feature extractor with the Extra Trees Classifier as the final decision-maker. This combination is unique in its capability to both learn abstract, non-linear patterns from raw input data and leverage high-dimensional randomized decision paths for stable, unbiased classification. The FFNN captures complex user-ad interaction features, which are then refined and passed to the Extra Trees Classifier, which improves generalization and reduces overfitting an issue often seen in ad targeting with shallow models or manual rules.

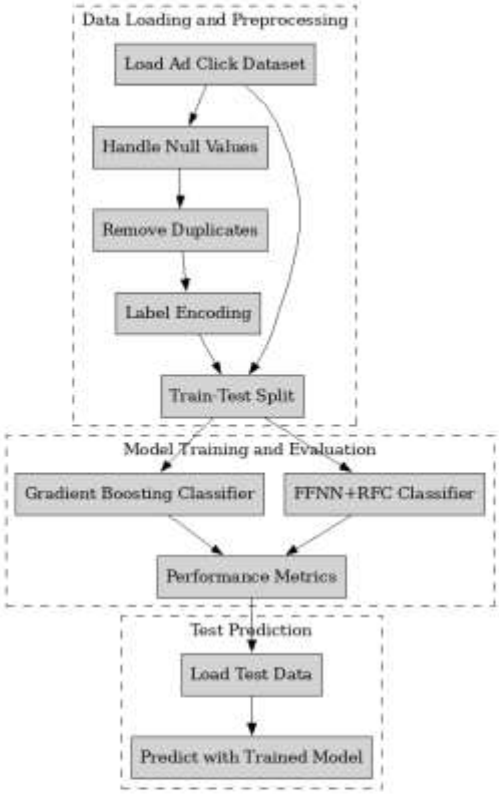

Fig. 1: Architectural Block Diagram of The Proposed System.

Proposed Algorithm: FFNN+RFC Classifier

Feedforward Neural Network (FFNN) with a Random Forest Classifier (RFC) to enhance predictive accuracy and feature extraction. In this model, the FFNN acts as a deep feature extractor, processing input data through multiple layers with activation functions like ReLU to learn complex patterns. The network refines raw data into meaningful high-dimensional feature representations, which are then passed to the RFC for classification. The RFC, consisting of multiple decision trees, employs an ensemble learning approach to ensure robust classification by reducing variance and improving generalization.

The FFNN with RFC algorithm benefits from deep learning's ability to extract intricate features while leveraging RFC's strong classification performance, particularly in handling noisy or imbalanced datasets. This hybrid approach finds applications in areas such as medical diagnosis, financial forecasting, and text classification, where both feature extraction and high accuracy are crucial.

Data Preprocessing: Initially, the data is preprocessed as described earlier (handling missing values, encoding labels, etc.).

Training FFNN: The FFNN is trained on the dataset to capture the non-linear relationships between features. It uses multiple layers of neurons and activation functions to learn complex patterns.

Training RFC: Simultaneously, the RFC is trained on the same data. Each tree in the random forest learns from random samples and features.

Model Combination: After both models are trained, their predictions are combined. Typically, the output of the two models is averaged or voted on to provide a final classification.

- **Averaging**: For regression tasks, the final output is the average of the predictions of both models.
- **Voting**: For classification tasks, the most frequent prediction from FFNN and RFC becomes the final prediction.

Evaluation: The combined model is evaluated on a test set to assess its performance.

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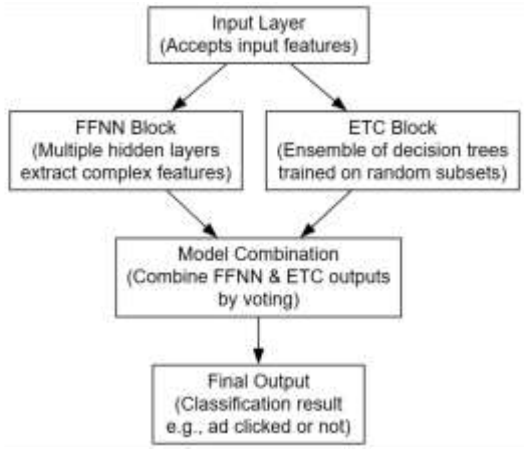

Fig. 2: Block diagram of FFNN+RFC Classifier

4. Results Description

Figure 3 presents the exploratory data analysis (EDA) of the dataset. In this step, various data visualizations and statistical methods are used to gain insights into the distribution of features, correlations between variables, and the overall structure of the dataset. Histograms, bar charts, and heatmaps may be displayed to showcase the distribution of features like age, gender, and device type. The correlation matrix reveals how different features are related to the target variable (ad click or no click) and one another. EDA helps in identifying trends and patterns that inform data preprocessing and model selection.

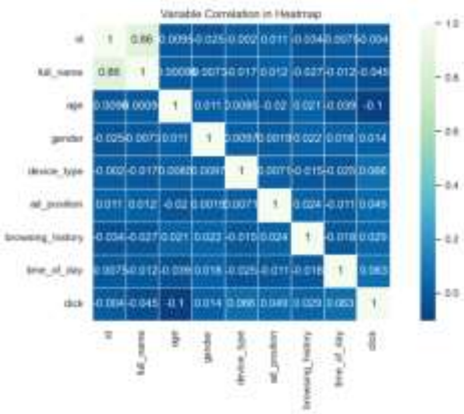

Fig. 3: Exploratory Data Analysis (EDA) of the Dataset

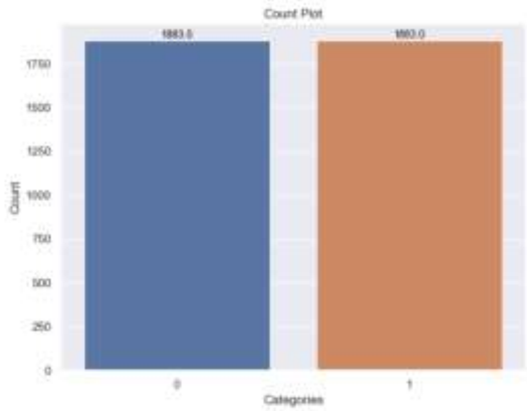

Fig. 4: Data Preprocessing in the GUI

Figure 4 shows the data preprocessing steps within the GUI. In this stage, the dataset undergoes cleaning and transformation to prepare it for model training. Missing values are handled, categorical features are encoded, and scaling or normalization techniques are applied to numerical features. The preprocessing step also includes data splitting, where the dataset is divided into training and test sets, ensuring that the model is evaluated on unseen data. This process is essential for building a robust machine learning model that generalizes well to new data.

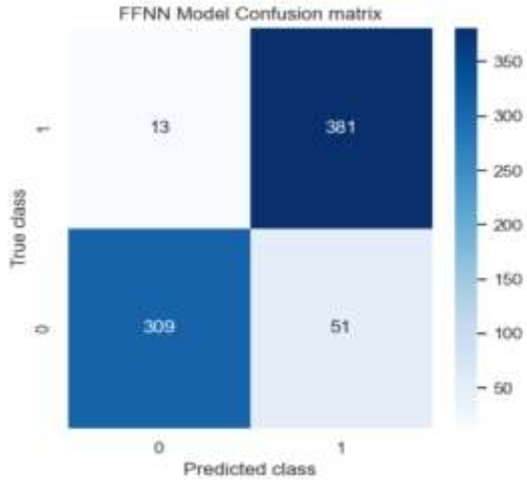

Figure 5: Performance Metrics and Confusion Matrix Plot of FFNN+RFC Classifier Model

Figure 5 presents the performance metrics and confusion matrix plot of the Feedforward Neural Network (FFNN) combined with the Random Forest Classifier (RFC) model. This hybrid approach demonstrates improved performance compared to the GBC classifier: Accuracy 91.51% – The FFNN+RFC model accurately predicts ad click behavior for more than 90% of the test data. Precision 92.08% – The model achieves high precision in predicting clicked ads, reducing the occurrence of false positives. Recall 91.27% – The recall indicates that the model correctly identifies most actual clicked ads, minimizing false negatives. F1-Score 91.43% – The F1-score reflects the model's balanced ability to predict both clicked and non-clicked ads with high accuracy. The confusion matrix shows a strong performance, with a high number of true positives and true negatives, indicating that the model can effectively differentiate between clicked and non-clicked ads.

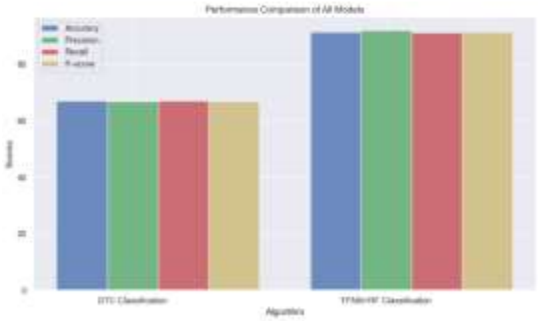

Fig. 6: Performance Comparison Graph of Models

Figure 6 presents a graph comparing the performance of the different models (GBC, FFNN, and FFNN+RFC) based on accuracy, precision, recall, and F1-score. The graph visually highlights the superior performance of the FFNN+RFC classifier model, which outperforms the other models in all metrics. This comparison aids in understanding the trade-offs between different models and selecting the best approach for predicting ad clicks in the given dataset. The FFNN+RFC model's higher accuracy and balanced performance metrics indicate its effectiveness in solving the ad click prediction problem.

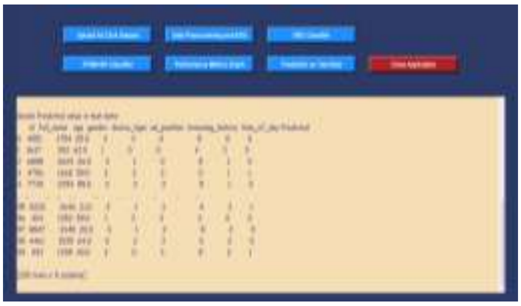

Fig. 7: Model Prediction on the Test Data

Figure 7 illustrates the predictions made by the trained model on the test dataset. The model outputs a predicted label for each test instance, determining whether an ad will be clicked or not. The predictions are compared against the actual outcomes, allowing the user to visualize the model's performance on unseen data. This step is crucial for evaluating how well the model generalizes to new, unseen data, which is a key indicator of its effectiveness in real-world applications.

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.

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