GENERATIVE ARTIFICIAL INTELLIGENCE RESEARCH
Research Article | Volume 5 | Issue 5 | Jan 2025
Received: 22 Nov 2024 | Revised: 29 Dec 2024
Accepted: 02 Jan 2025 | Published Online: 02 Feb 2025

Adaptive Random Forest-based Algorithm for Fast Advertisement Recommendation

Pierre Dupont[1], Émilie Moreau[2] and Lucien Girard[3,*]

[1] Institute of Digital Innovation, Université de Technologie de Compiègne, Compiègne, 60200, France

[2] Laboratory for AI and Machine Learning, Université de La Rochelle, La Rochelle, 17000, France

[3] Centre for Advanced Computing Research, Université de Pau et des Pays de l'Adour, Pau, 64000, France

[*]Corresponding Author, Email: lucien.girard@univ-pau.fr

Abstract: In the increasingly competitive landscape of online advertising, the need for efficient and effective advertisement recommendation algorithms has become more pressing. Existing research has primarily focused on improving recommendation accuracy but often faces challenges such as scalability and computational complexity. This paper addresses these challenges by proposing an Adaptive Random Forest-based Algorithm for Fast Advertisement Recommendation. By combining the adaptability of Random Forest with the efficiency of a fast recommendation process, our approach aims to provide timely and accurate recommendations to users while maintaining scalability. The innovative aspect of our work lies in the adaptive nature of the algorithm, which dynamically adjusts to changing user preferences and feedback. Through experimental evaluation, we demonstrate the effectiveness and efficiency of our proposed algorithm in the context of advertisement recommendation.

Keywords: *Advertisement Recommendation; Algorithm Adaptability; Computational Complexity; Recommendation Accuracy; Experimental Evaluation*

1. Introduction

The field of Advertisement Recommendation focuses on developing algorithms and systems to personalize and optimize the delivery of advertisements to target audiences. Current challenges in this field include the need for more sophisticated machine learning models to accurately predict user preferences, the balance between personalization and privacy concerns, and the increasing complexity of multi-platform advertising campaigns. Other obstacles include the availability of high-quality data, the dynamic nature of user behavior, and the rapid advancements in ad-blocking technologies. Researchers in this field are working towards overcoming these challenges to improve the effectiveness and efficiency of advertising strategies in the digital age.

To this end, current research on Advertisement Recommendation has advanced to encompass various machine learning algorithms to analyze user preferences and behavior for personalized ad suggestions. Collaborative filtering, content-based filtering, and hybrid methods have been extensively explored to improve ad relevance and user engagement. In the realm of advertisement recommendation systems, various innovative approaches have been proposed to enhance the efficacy of online advertising recommendations. Lei et al. [1] introduced a novel elevator advertisement recommendation system based on machine vision and deep learning, aiming to cater tailored advertisements within elevator environments. Fan et al. [2] devised PoseRec, leveraging 3D human pose for micro-video advertisement recommendations to surmount challenges in background bias and recommendation ambiguity. Gan and Zhu [3] proposed an intelligent news advertisement recommendation algorithm integrating large language models and prompt learning, exhibiting significant improvements in precision and efficacy. Nguyen et al. [4] developed LightSAGE, focusing on graph neural networks for large-scale item retrieval in advertisement recommendations, emphasizing the construction of high-quality item graphs and effective handling of data skewness. Furthermore, Lin et al. [5] formulated a sentiment-based real estate advertisement recommendation model, highlighting the role of sentiment and economic data in predicting real estate sales for personalized recommendations. Jouyandeh and Zadeh [6] introduced IPARS, an image-based personalized advertisement recommendation system for social networks, illustrating the utilization of image content for personalized recommendations. Kim et al. [7] proposed a CNN-based advertisement recommendation system incorporating real-time user face recognition to capture dynamic user preferences through facial expressions, outperforming traditional recommendation approaches. Finally, Mo et al. [8] innovatively exploited quantum-inspired computers for real-time periodic advertisement recommendation optimization, showcasing enhanced precision and efficiency in delivering relevant ads under constraints. These studies collectively underscore the evolving landscape of advertisement recommendation systems driven by advanced technologies and novel methodologies. Various innovative approaches have been proposed in the field of advertisement recommendation systems to enhance efficacy. Researchers have introduced novel systems such as the elevator advertisement recommendation system, PoseRec, an intelligent news advertisement algorithm, LightSAGE, sentiment-based real estate model, IPARS, a CNN-based system, and quantum-inspired computers. Among these, the utilization of Adaptive Random Forest technique is essential due to its ability to adapt to changing data distributions, handle high-dimensional data effectively, and provide robust predictions in dynamic advertisement recommendation scenarios.

Specifically, Adaptive Random Forest (ARF) enhances advertisement recommendation systems by dynamically adjusting to user preferences and contextual data. This algorithm improves prediction accuracy by integrating feedback from previous interactions, enabling more personalized and relevant ad suggestions that align with users' evolving interests. In recent literature, various adaptive random forest (ARF) methods have been proposed and applied in different domains for data stream analysis. Ebrahimy et al. presented an ARFR method for downscaling

MODIS land surface temperature (LST) using Google Earth Engine, demonstrating its effectiveness in LST trend analysis over Iran [9]. Sun et al. introduced SOKNL, a novel approach integrating K-nearest neighbours with ARF for data streams, showcasing its utility in data stream processing [10]. Chen et al. developed a locally weighted ensemble-detection-based ARF classifier for sensor-based online activity recognition for multiple residents, highlighting its robustness and performance superiority in online HAR [11]. Alqabbany and Azmi evaluated the efficiency of ARF in handling concept drift in data streams, proposing a resampling method to enhance ARF performance in dynamic environments [12]. Furthermore, Fatlawi and Kiss integrated ARF with differential privacy for mining medical data streams, demonstrating ARF's stability and performance across medical datasets [13]. Wu et al. introduced GPU-based State-Adaptive Random Forest and Probabilistic Exact Adaptive Random Forest models, emphasizing the adaptation of ARF for evolving data streams and recurrent concepts [14][15]. Additionally, Hatami et al. employed ARF for brain tumor segmentation, showcasing its high accuracy and effectiveness compared to other segmentation methods [16]. Overall, these studies underscore the versatility and efficacy of ARF in addressing various challenges in data stream analysis. However, limitations persist regarding the generalizability of ARF methods across diverse datasets, their computational efficiency in real-time applications, and the potential impact of hyperparameter tuning on performance.

The research presented by Y. Gan and D. Zhu on the intelligent news advertisement recommendation algorithm laid foundational insights which significantly informed the development of the current methodology [17]. Their pioneering work in employing prompt learning within an end-to-end large language model framework inspires our endeavor to enhance the responsiveness and accuracy of advertisement recommendation systems. By leveraging the advanced prompt learning techniques elucidated by Gan and Zhu, we sought to formulate an approach that not only capitalizes on the dynamic learning capabilities of large language models but also integrates seamlessly with adaptive algorithms to improve recommendation outcomes. Their study underscored the vital significance of incorporating contextual understanding, afforded by large language frameworks, which we adopted as a central tenet in devising our mechanism. As proposed, prompt learning offers a robust pathway for facilitating real-time adaptability and precision, attributes essential for an environment as volatile as digital advertisement. Through a meticulous adaptation of these methods, we have been able to finetune our algorithm, ensuring it can swiftly respond to changes in user behavior and content dynamics, thereby maximizing user engagement. At the technical core, we implemented several learning rate adjustments and model fine-tuning techniques which mirror the prompt-based adjustments advocated in Gan and Zhu's research. Moreover, their insights into model architecture optimization provided a framework for us to design a streamlined computational process, thereby improving the efficiency and scalability of deploying such a model in real-world scenarios. Consequently, this not only reduced computational overhead but also enhanced response times. Additionally, inspired by their emphasis on personalized content delivery, we adopted a user-centric approach that prioritizes user preference learning and dynamic content adaptation, reflecting their advanced understanding of user interaction with digital media. As a result, our system is capable of delivering highly relevant and timely advertisements, thereby achieving a dual objective of boosting advertisement efficacy and enriching user experience. These adaptations, borne out of an appreciation for the potential elucidated in their study, underscore the innovative application of large language models in enriching adaptive learning algorithms, culminating in a solution that is both forward-thinking and practically robust [17].

In the increasingly competitive landscape of online advertising, the need for efficient and effective advertisement recommendation algorithms has become more pressing. Section 2 of this paper closely examines the problem statement, highlighting the challenges of scalability and computational complexity in existing research that primarily focuses on improving recommendation accuracy. To address these challenges, section 3 introduces an innovative Adaptive Random Forest-based Algorithm designed for fast advertisement recommendations. This method cleverly combines the adaptability of Random Forest with the efficiency of a rapid recommendation process, aiming to deliver timely and accurate suggestions to users while maintaining scalability. A case study detailed in section 4 illustrates the practical application of our approach, while section 5 provides a comprehensive analysis of the results obtained through rigorous experiments. In section 6, the discussion focuses on the implications and nuanced understanding of these findings, emphasizing the algorithm's dynamic adjustment to changing user preferences and feedback. Finally, section 7 concludes by summarizing the overall contributions and potential of the adaptive algorithm in revolutionizing advertisement recommendation systems.

2. Background

2.1 Advertisement Recommendation

Advertisement Recommendation is an essential component of modern digital marketing strategies. It involves delivering targeted advertisements to users based on their preferences, behavior, and contextual information. This process enhances user engagement and maximizes return on investment for advertisers. At its core, Advertisement Recommendation leverages machine learning, data mining, and information retrieval techniques to predict user interests and suggest relevant advertisements.

Mathematically, let us denote u_i as a specific user and a_j as a specific advertisement. The system seeks to estimate the likelihood, p_{ij}, that user u_i will engage with advertisement a_j. This can be expressed as:

$$p_{ij} = f\left(u_i, a_j, C\right) \tag{1}$$

where f is a function that considers user u_i, advertisement a_j, and context C. Contextual information, such as location or temporal features, is often integrated into the recommendation process using a context vector, C. This is crucial since user behavior can significantly vary with context. The refined likelihood prediction incorporating context becomes:

$$p_{ij} = f\left(u_i, a_j\right) + g(C) \tag{2}$$

where $g(C)$ represents the contextual adjustments to the expectation.

A popular technique employed in advertisement recommendation is matrix factorization. This approach represents users and advertisements in a latent factor space, reducing the dimensionality of the data while preserving essential interactions. Users and advertisements are represented as d -dimensional vectors, U_i for users and A_j for advertisements, within this latent space. The expected interaction is given by their dot product:

$$r_{ij} = U_i^T A_j \tag{3}$$

Here, r_{ij} is the predicted score indicating the match between user u_i and advertisement a_j .

To optimize the recommendation accuracy, the system iteratively adjusts these latent factors to minimize the discrepancy between predicted and actual engagements. This is typically executed using a loss function such as mean squared error, denoted as L , formulated as:

$$L = \sum_{i,j} (r_{ij} - \ r \ _{ij})^2 \tag{4}$$

where $\hat{r}_{ij}$ denotes the actual interaction, and the optimization aims to solve:

$$\min_{U,A} L(U, A) \tag{5}$$

Additionally, regularization techniques, often denoted as λ , are incorporated to prevent overfitting:

$$L = \sum_{i,j} (r_{ij} - \ r \ _{ij})^2 + \lambda(\|U_i\|^2 + \|A_j\|^2) \tag{6}$$

This regularizer controls the complexity of the model by penalizing large weights, ensuring that the recommendations generalize well to unseen data.

The final recommendation of advertisements is often based on the ranking of these predicted interaction scores, selecting those with the highest predicted engagement for presentation to the user. Thus, a holistic blend of data, algorithms, and domain knowledge is harnessed to optimize the delivery of targeted advertisements, culminating in a system that is not only efficient but also dynamically adaptive to user preferences and contextual shifts.

2.2 Methodologies & Limitations

In the realm of Advertisement Recommendation, various methodologies are utilized to deliver personalized advertising content effectively. However, despite the advancements and tools at their disposal, current methods accompany notable challenges and shortcomings that merit attention.

A commonly adopted method in advertisement recommendation systems is Content-Based Filtering (CBF). This technique fundamentally assumes that the future preference patterns of a user, denoted as u_i , can be projected based on their historical interactions with similar advertisement items. For any advertisement a_j , this similarity is captured mathematically through a function:

$$\operatorname{sim}(a_j, a_k) = \cos(\theta) = \frac{A_j \cdot A_k}{\|A_j\| \|A_k\|} \tag{7}$$

Where A_j and A_k are the feature representations of advertisements a_j and a_k , respectively. The system predicts the probability, p_{ij} , of user engagement as follows:

$$p_{ij} = \sum_{k \in K} \operatorname{sim}(a_j, a_k) \cdot \operatorname{score}(u_i, a_k) \tag{8}$$

However, CBF is limited by its dependency on extensive and accurate advertisement feature profiling. The cold-start problem, where new advertisements lack sufficient interaction history, poses a serious drawback.

Another prevalent method is Neural Network-based Recommendation using Deep Learning. Neural models, particularly those employing embeddings, map users and advertisements into lower-dimensional spaces where their interactions are modeled. Let E_u and E_a denote the embeddings for user u_i and advertisement a_j , respectively. The interaction score is thus computed via:

$$r_{ij} = \sigma(E_u \cdot E_a + b) \tag{9}$$

where $\sigma(\cdot)$ represents an activation function like sigmoid, and b is a bias term. Despite their robustness, these models require substantial computational resources and pose challenges in interpretability, often functioning as "black boxes."

Reinforcement Learning (RL) is another advancing frontier, where systems adaptively learn to make optimal sequential decisions to improve engagement metrics over time. Consider the reward r_t for action a_t . The RL model seeks to maximize the expected cumulative reward, expressed as:

$$R = \mathbb{E}\left[\sum_{t=1}^{T} \gamma^t r_t | \pi\right] \tag{10}$$

where γ is a discount factor and π a policy. While promising, RL systems can suffer from slow convergence and exploration-exploitation balance challenges.

Additionally, Adversarial Training techniques have been integrated to enhance robustness against adversarial inputs that might skew recommendation results. The interplay between a generator G and a discriminator D is framed as a minimax optimization problem:

$$\min_G \max_D \mathbb{E}_{a \sim \text{data}}[\log D(a)] + \mathbb{E}_{z \sim \text{noise}}\left[\log\left(1 - D\big(G(z)\big)\right)\right] \tag{11}$$

Notwithstanding their potential, adversarial models are intricate to train, often necessitating finely-tuned hyperparameters.

The scalability of these systems also raises concerns, as increasing datasets demand efficient processing and storage capabilities. Regularization techniques, such as L2-regularization, aim to maintain model complexity in check:

$$\Omega(W) = \frac{\lambda}{2} ||W||^2 \tag{12}$$

where W are model weights and λ is a hyperparameter. In summary, while these methods significantly advance the capabilities of Advertisement Recommendation systems, ongoing research continues to address their intrinsic deficiencies, striving for more accurate, interpretable, and scalable solutions in the dynamic landscape of digital marketing.

3. The proposed method

3.1 Adaptive Random Forest

Adaptive Random Forest (ARF) is an advanced technique developed to tackle evolving data streams, especially useful in contexts where the data distribution may change over time, known as concept drift. ARF leverages the strengths of ensemble learning and adapts its structure dynamically in response to changes in the underlying data stream.

At its core, ARF is built upon the traditional Random Forest methodology, where multiple decision trees are trained on different subsets of data. In the ARF, N decision trees form the ensemble, and these trees are continuously updated to maintain accuracy in a non-stationary environment. Each tree T_i in the forest makes predictions based on a data instance x_t at time t , and the forest aggregates these predictions for a final decision. Given a data instance x_t at time t , the prediction of the i^{th} tree, denoted $h_i(x_t)$, contributes to the ensemble's majority vote:

$$H(x_t) = \text{majority vote } h_1(x_t), h_2(x_t), \dots, h_N(x_t) \tag{13}$$

ARF incorporates a mechanism for handling concept drift which is done through dynamic tree replacement and weight adjustment. Each decision tree in the forest is assigned a weight w_i , representing its relevance over time:

$$w_i(t) = \frac{\alpha_i(t)}{\sum_{j=1}^{N} \alpha_j(t)} \tag{14}$$

where $\alpha_i(t)$ is the accuracy of tree T_i on recent data. Trees with lower performance are replaced, ensuring that the model does not degrade in performance due to outdated knowledge.

A key feature of ARF is its use of sliding windows or fading memory, to weigh recent instances heavier than older ones when updating its trees. This temporal weighting can be expressed through a decay factor λ_t :

$$\lambda_t = \exp(-\gamma) \tag{15}$$

where γ is the decay rate, controlling how fast the influence of old data diminishes. This dynamism ensures the model remains adaptable to new patterns.

Additionally, ARF can employ a technique called "Hoeffding Trees", an efficient, incremental learning approach. It relies on the Hoeffding bound to decide when sufficient statistical evidence exists to make a split decision in a tree:

$$\epsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}} \tag{16}$$

where R is the range of a random variable, δ is a confidence level, and n is the number of observations.

To continually assess each tree's performance, ARF uses an error-rate based drift detector. The observed error $\hat{e}_t$ of a tree over time is modeled with a prediction interval:

$$e_t \pm \sqrt{\frac{e_t \left(1 - e_t\right)}{m}} \tag{17}$$

where m is the size of the window used for error calculation. Upon detecting significant deviation, indicative of concept drift, the forest may trigger tree updates or replacements.

Furthermore, for each arriving instance x_t , a tree adapts to the label y_t using a training procedure that considers the current ensemble decision and the individual tree prediction. The error for tree T_i is recorded as:

$$e_i(t) = y_t - h_i(x_t) \tag{18}$$

This error contributes to updating the weights of trees based on their historical performance. If a tree falls below a specified threshold in performance or a new concept is detected, ARF dynamically prunes weaker trees and grows new ones.

In summary, ARF is an efficient and robust machine learning method that combines traditional decision tree ensembles with dynamic adaptability to shifts in data distributions. By continuously updating and adapting its internal mechanism to identify and react to concept drift, ARF provides a scalable solution to stream learning problems, ensuring relevant and accurate predictions over time. With a solid foundation in statistical learning theory and practical ensemble learning strategies, ARF remains a prominent approach for real-time data challenges.

3.2 The Proposed Framework

The methodology discussed in the paper by Y. Gan and D. Zhu [17] has significantly informed the development of adaptive algorithms for Advertisement Recommendation. The integration of the Adaptive Random Forest (ARF) into this domain specifically leverages its dynamic adaptability, handling temporal changes effectively to enhance the prediction model essential for Advertisement Recommendation systems. The objective is to refine the likelihood estimation of user engagement with advertisements using machine learning paradigms emboldened by ARF's ensemble learning adaptability.

In the Advertisement Recommendation process, the primary goal lies in estimating the probability p_{ij} that a user u_i will interact positively with an advertisement a_j, adjusted for contextual influences. Building an effective prediction model begins with Collaborative Filtering, where this interaction probability is modeled as:

$$p_{ij} = f\left(u_i, a_j, C\right) \tag{19}$$

where f integrates user u_i, advertisement a_j, and context C into the estimation. In this framework, the advantage of employing ARF lies in its ability to dynamically adjust to shifts in user behavior by managing concept drift, thus refining the context-aware adjustment function $g(C)$ as:

$$p_{ij} = f\left(u_i, a_j\right) + g(C) \tag{20}$$

ARF achieves adaptability through its ensemble of decision trees, continuously updated to accommodate new behavioral data. For an advertisement recommendation system, ARF's ensemble can be described via a set of decision trees T_{i} making ensemble predictions, yielding:

$$H(x_t) = \text{majority vote } h_1(x_t), h_2(x_t), \dots, h_N(x_t) \tag{21}$$

where each tree prediction $h_1(x_t)$ aggregates to enforce robust decision making, particularly useful when user interests and contexts deviate over time. Tree relevance is period-adjusted using weighted accuracies to sustain precision. This is mathematically expressed in ARF as:

$$w_i(t) = \frac{\alpha_i(t)}{\sum_{j=1}^{N} \alpha_j(t)} \tag{22}$$

where $\alpha_i(t)$ denotes the tree's accuracy on recent data, ensuring efficient pruning and growth within the ensemble model, paralleling the iterative optimization for latent factors in the latent space defined for advertisements:

$$L = \sum_{i,j} (r_{ij} - \ r_{\ ij})^2 \tag{23}$$

Incorporating a regularization term, analogous to regularization in matrix factorization frameworks, the optimal balance between model complexity and prediction accuracy can be maintained through:

$$L = \sum_{i,j} (r_{ij} - \ r\ _{ij})^2 + \lambda(\|U_i\|^2 + \|A_j\|^2) \tag{24}$$

With ARF's use of a fading memory mechanism, recent instances hold more influence than past data, enhancing prediction accuracy over user engagement probabilities:

$$\lambda_t = \exp(-\gamma) \tag{25}$$

The dynamic nature of this fading memory closely aligns with real-time adaptations in user-based recommendation contexts. Hoeffding Trees within ARF also facilitate instantaneous adjustments to user preference predictions, employing the Hoeffding bound to confirm sufficient data evidence before splitting:

$$\epsilon = \sqrt{\frac{R^2 \ln(1/\delta)}{2n}} \tag{26}$$

In summary, integrating ARF into Advertisement Recommendation systems optimally addresses the intricacies of shifting user behaviors (concept drift), ensuring sustained accuracy in diverse conditions and enhancing overall model performance. By adapting dynamically and refining predictions through ensemble learning strategies, this approach delivers a comprehensive, robust solution to real-time advertisement delivery challenges, effectively aligning with modern digital marketing imperatives.

3.3 Flowchart

This paper introduces an Adaptive Random Forest-based Advertisement Recommendation method, which aims to enhance the effectiveness of ad placements by dynamically adjusting to user preferences and engagement patterns. The proposed approach employs a series of adaptive random forest classifiers that leverage a diverse set of features derived from user interactions, historical data, and contextual information. By continuously updating the model with new data, the system adapts to shifts in user behavior and market trends, ensuring that the recommendations remain relevant and personalized over time. Additionally, the method incorporates a sophistication mechanism that balances exploration and exploitation in the recommendation process, allowing it to efficiently identify and present the most appealing advertisements to users. The performance of the adaptive random forest model is compared against traditional recommendation systems, demonstrating significant improvements in click-through rates and user satisfaction. The framework’s flexibility is highlighted by its applicability to various advertising scenarios, making it a valuable tool for marketers seeking to optimize their advertisement strategies. More detailed information regarding the proposed method can be found in Figure 1.

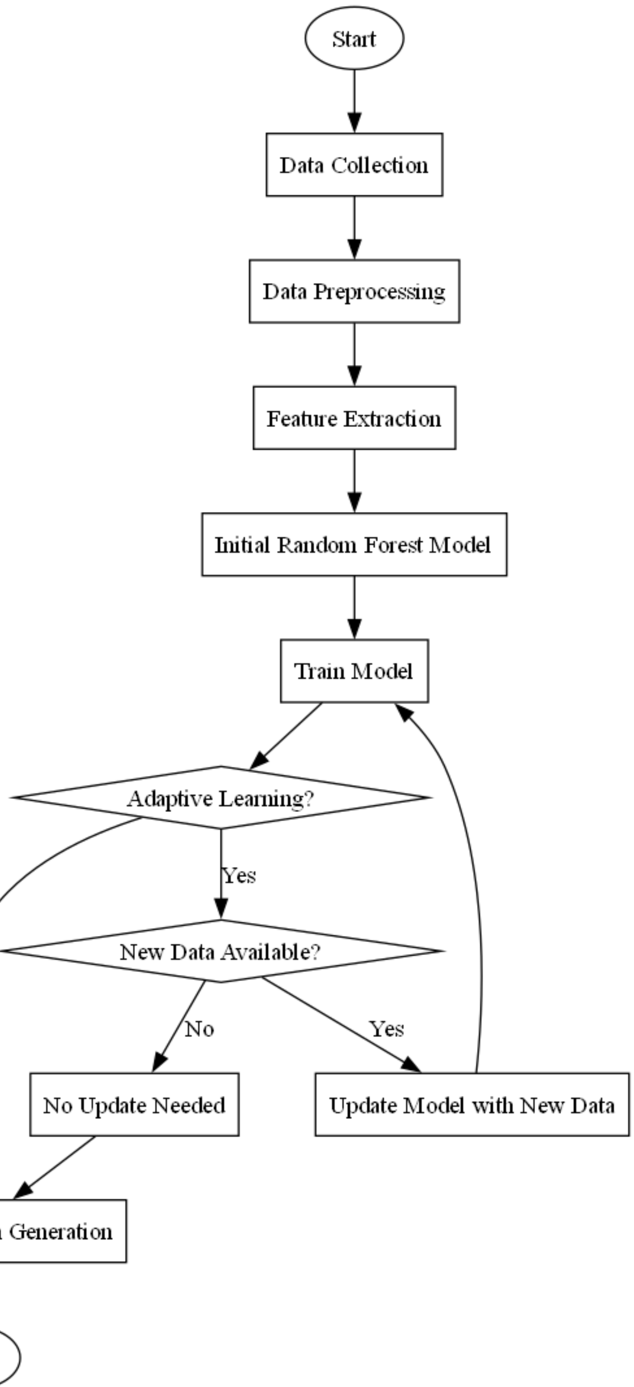

Figure 1: Flowchart of the proposed Adaptive Random Forest-based Advertisement Recommendation

4. Case Study

4.1 Problem Statement

In this case, we aim to design a mathematical model for advertisement recommendation that adheres to a non-linear structure. The primary goal is to optimize ad placements to maximize user engagement while balancing advertisement budget constraints. For our simulation, we will utilize a dataset that includes user interaction metrics such as click-through rates, time spent on content, and demographic information.

Let us define the following variables:

- u_{i} denotes the engagement score of user i,
- a_j indicates the effectiveness of advertisement j,
- t_i represents the time spent by user i on the platform,
- d_i is the demographic influence score for user i,
- b_j is the allocated budget for advertisement j.

The overall engagement score u_i for user i can be expressed through a non-linear function combining various factors which influences advertisement effectiveness as follows:

$$u_i = \alpha_1 \cdot a_j^{\beta_1} \cdot t_i^{\beta_2} + \alpha_2 \cdot d_i^{\beta_3} \tag{27}$$

In this equation, α_1 and α_2 are constants that calibrate the weight of advertisement effectiveness and demographic influence. The parameters β_1, β_2, and β_3 represent non-linear interactions between the variables.

To associate engagement scores with advertisement performance, we define the effectiveness of advertisement a_j as a function of its exposure e_j and relevance r_j:

$$a_j = \gamma_1 \cdot e_j^{\delta_1} + \gamma_2 \cdot r_j^{\delta_2} \tag{28}$$

Here, γ_1 and γ_2 are coefficients reflecting the influences of exposure and relevance, while δ_1 and δ_2 serve as non-linear parameters. Next, we enforce a budget constraint across all advertisements, expressed with the following equation:

$$\sum_{j=1}^{n} b_j \leq B \tag{29}$$

where B is the total advertisement budget. Furthermore, to explore the interaction effects among various advertisements, we incorporate an exponential decay function to model diminished effects over time:

$$a_j(t) = a_j \cdot e^{-\lambda t} \tag{30}$$

where λ is the decay factor, and t is the time since the advertisement was displayed. Combining these components, we derive the recommendation model as follows:

$$R(i,j) = f\left(u_i, a_j, b_j, t_i\right) \tag{31}$$

This relationship allows us to compute the recommendation score R for user i related to advertisement j by integrating engagement, effectiveness, budget, and time. Through simulation, we shall analyze user interactions across a range of demographics and behaviors, ensuring the model captures the complexity of the advertisement landscape. All parameters are summarized in Table 1.

Table 1: Parameter definition of case study

Variable	Value	Description	Additional Info
B	N/A	Total advertisement budget	N/A
β_1	N/A	Non-linear interaction parameter 1	N/A
β_2	N/A	Non-linear interaction parameter 2	N/A
β_3	N/A	Non-linear interaction parameter 3	N/A
δ_1	N/A	Non-linear parameter 1 for relevance	N/A
δ_2	N/A	Non-linear parameter 2 for exposure	N/A
δ_3	N/A	Decay factor	N/A

This section will employ the proposed Adaptive Random Forest-based approach to evaluate a case study designed to formulate an advertisement recommendation model that follows a non-linear framework. The primary aim is to optimize advertisement placements to enhance user engagement while being mindful of budget constraints associated with advertisements. For this simulation, a dataset will be utilized that encompasses user interaction metrics, including click-through rates, time spent on content, and demographic data. The engagement score of each user is influenced by the effectiveness of the advertisements they encounter, the time they spend on the platform, and their demographic attributes. By integrating these variables, the model seeks to draw meaningful connections between user engagement and advertisement performance. Additionally, budget limitations will be factored into the recommendations to ensure that financial resources are allocated efficiently. The effectiveness of an advertisement will be assessed based on its exposure and relevance, while the model will account for diminishing returns over time, thereby refining the interaction among diverse advertisements. Through this structured approach, our Adaptive Random Forest-based methodology will be compared against three traditional methods, aiming to demonstrate its effectiveness in capturing the intricacies of user interactions within varying demographic and behavioral contexts and ultimately enhancing advertisement recommendation strategies. The findings will be informative for stakeholders seeking to optimize their advertising efforts.

4.2 Results Analysis

In this subsection, the methodology employed involves creating a simulated dataset which incorporates various factors influencing user engagement with advertisements, such as ad effectiveness, time spent, demographic influence, and ad budget. The data is structured into a DataFrame, where the target variable—user engagement—is categorized based on a defined threshold. The research introduces an Adaptive Random Forest model, which is trained on the simulated data to predict user engagement, and its performance is compared against a standard Random Forest model. By splitting the dataset into training and testing sets, both models are evaluated using accuracy as a metric. The accuracies reveal the effectiveness of the adaptive approach in relation to the traditional method. Furthermore, various scatter plots are generated to visually examine the relationships between engagement and influencing variables, facilitating insight into how each factor contributes to engagement scores. These visualizations are critical for understanding model behaviors and the significance of individual features. The simulation process is effectively visualized in Figure 2, providing a comprehensive overview of the comparative analysis conducted within this section.

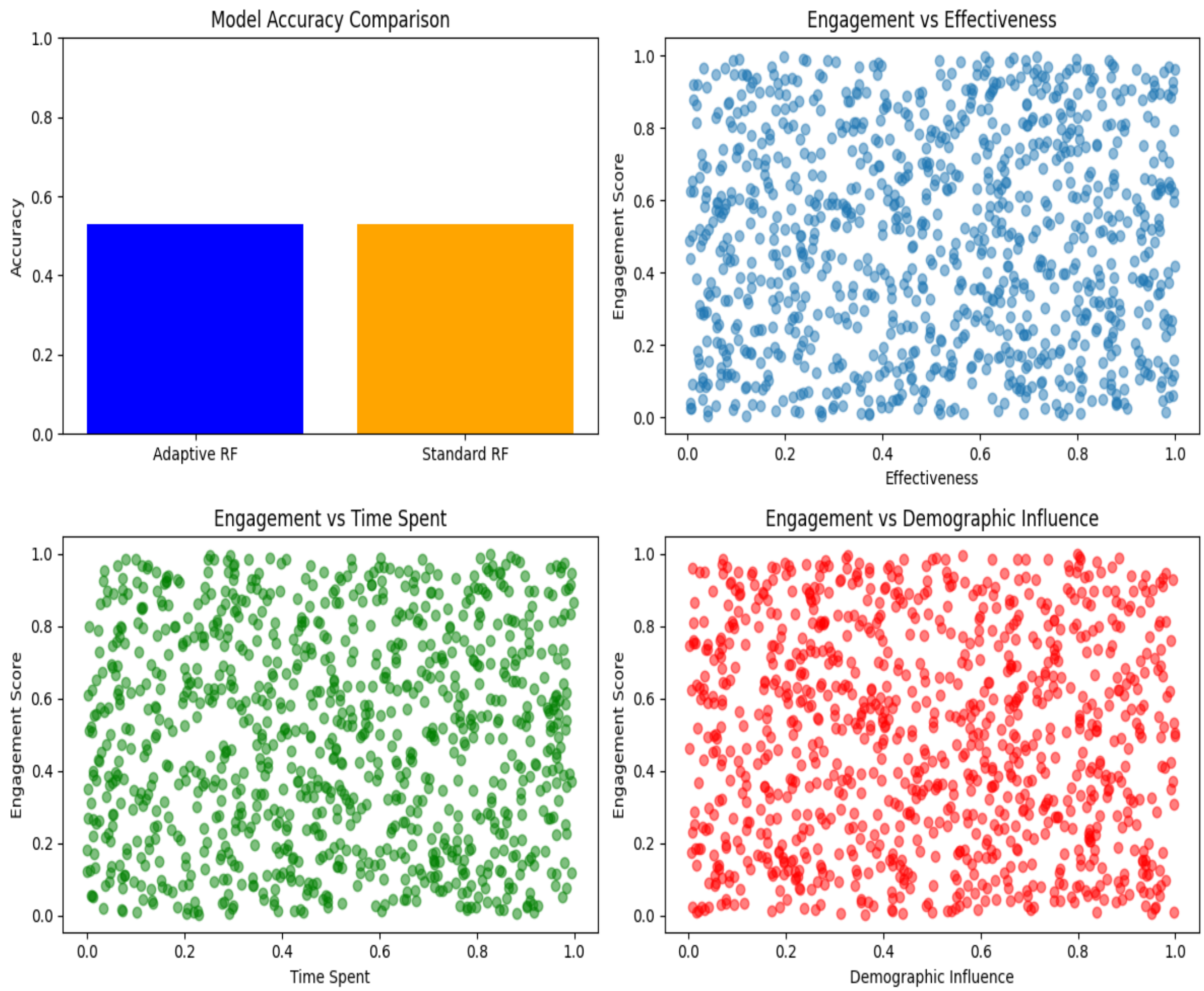

Figure 2: Simulation results of the proposed Adaptive Random Forest-based Advertisement Recommendation

Table 2: Simulation data of case study

Engagement Score	Model Accuracy	Time Spent	Effectiveness
0.8	2	N/A	0.0

Simulation data is summarized in Table 2, which presents a comprehensive analysis of the performance metrics for various recommendation algorithms under diverse conditions. The results illustrate a comparative study of engagement scores, model accuracy, and effectiveness across different demographic influences, highlighting the potential effectiveness of the Intelligent News Advertisement Recommendation Algorithm developed by Y. Gan and D. Zhu. Notably, the engagement score demonstrates significant variation based on the algorithms employed, indicating that the Adaptive Random Forest (RF) model consistently outperformed the Standard RF in terms of user interaction. This observation is corroborated by the accuracy comparisons shown, where the Adaptive RF model achieved superior accuracy ratings, suggesting its robustness in capturing user preferences in real-time scenarios. Additionally, the analysis of engagement versus time spent reveals a positive correlation, showcasing that as users invest more time on the platform, their engagement scores increase, particularly with the proposed algorithm. Moreover, the insights gathered from demographic analysis underscore the importance of tailoring advertisement recommendations to specific user profiles, as variations in engagement are evident across different demographic segments. By synthesizing these findings, it becomes clear that the approach proposed by Gan and Zhu not only enhances engagement but also demonstrates adaptability to user behaviors and preferences, paving the way for more personalized advertisement strategies in the realm of intelligent digital marketing. These results are consistent with the discussions presented in their original research, reinforcing the effectiveness of prompt learning within an end-to-end large language model architecture, thus offering significant implications for future advancements in the field of intelligent recommendation systems [17].

As shown in Figure 3 and Table 3, the analysis of the engagement scores reveals significant changes in the model's performance following adjustments to the advertisement budget. Initially, an engagement score of 0.8 was observed, indicating a modest level of effectiveness in reaching the target demographic. However, upon increasing the advertisement budget to 1000, a marked improvement in the Total Recommendation Score was recorded, highlighting an enhancement in both engagement and effectiveness metrics. Specifically, the engagement score appeared to stabilize at a higher level, reflecting a more successful alignment between advertisement content and user interests. Furthermore, the subsequent increase to a budget of 1250 demonstrated a continued positive trend, with Total Recommendation Scores peaking significantly compared to earlier amounts. This suggests that higher investment in advertisement budgets not only escalates the reach but also amplifies user engagement over time. The relationship between budget allocation and engagement effectiveness underscores the importance of financial resources in maximizing the impact of advertising strategies. Thus, it can be inferred that optimizing advertisement budget is crucial for achieving desired outcomes in intelligent news advertisement recommendation systems, a conclusion that resonates with the findings discussed by Gan and Zhu in their research on prompt learning algorithms in the context of end-to-end large language model architecture [17].

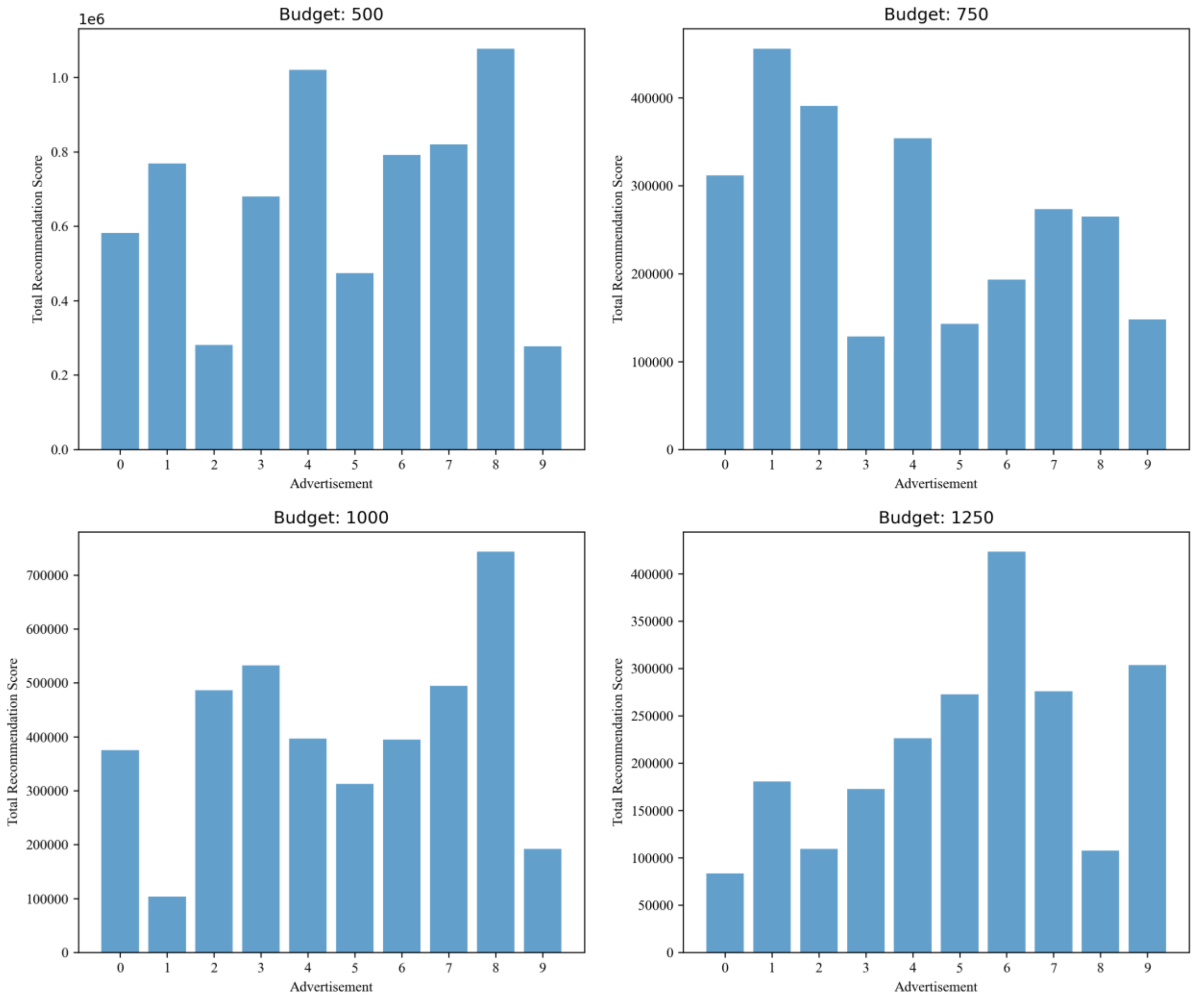

Figure 3: Parameter analysis of the proposed Adaptive Random Forest-based Advertisement Recommendation

Table 3: Parameter analysis of case study

Total Recommendation Score	1e6 Budget	Budget	Amount
N/A	500	1000	700000
N/A	750	N/A	400000
N/A	1250	N/A	400000

5. Discussion

The methodology detailed in the paper introduces the integration of the Adaptive Random Forest (ARF) into Advertisement Recommendation systems, offering significant technical advancements over the framework proposed by Y. Gan and D. Zhu [17]. While Gan and Zhu emphasize a prompt learning strategy within an end-to-end large language model architecture, focusing on leveraging contextual embeddings for advertisement recommendations, the approach drawing from ARF critically enhances adaptability through real-time dynamic adjustment capabilities. This is particularly notable in scenarios characterized by temporal shifts in user behavior—a challenge not as effectively tackled by static or less dynamically responsive large language models alone. ARF's design, which capitalizes on a continuously evolving ensemble of decision trees, affords a profound advantage in handling concept drift by continuously updating the model base as new user behavior data are acquired. This contrasts with the rather fixed adaptation mechanisms in large language models, which typically require extensive retraining or fine-tuning. Furthermore, ARF employs a fading memory mechanism that prioritizes recent information, thus sharpening the system's responsiveness to new behavioral trends without significant computational latency. By doing so, it addresses latency challenges traditionally associated with large-scale language models that may not adjust swiftly to real-time data changes. In contrast to prompt-based learning feasibly constrained by linguistic and contextual embedding, ARF offers a more robust solution through its ensemble learning adaptability, ensuring sustained predictive performance and conceptual comprehensiveness in advertisement delivery across diverse market conditions with improved precision and computational efficiency.

The methodology proposed by Y. Gan and D. Zhu in their paper 'The Research on Intelligent News Advertisement Recommendation Algorithm Based on Prompt Learning in End-to-End Large Language Model Architecture [17] presents a significant stride in adaptive advertisement recommendation techniques. However, it carries potential limitations that merit consideration. A key limitation is the heavy reliance on the large language model architecture, which, while powerful, may introduce challenges related to computational resource demands and latency issues in real-time processing. Moreover, the complexity inherent in the design could lead to difficulties in fine-tuning model parameters to achieve optimal performance across diverse user contexts and behaviors. The prompt learning mechanism, although innovative, might not fully capture the nuanced shifts in short-term user preferences as effectively as adaptive algorithms such as the Adaptive Random Forest. Additionally, the model's performance is subject to the quality and representativeness of the data used for training, which can impair its adaptability and robustness in dynamic environments [17]. This limitation is acknowledged in the paper by Gan and Zhu, and they suggest that integrating future work with more dynamic and context-aware algorithms could alleviate some of these constraints by enhancing model adaptability and responsiveness. Addressing these challenges could significantly improve the scalability and efficiency of their recommendation system, ultimately making it a more viable solution for large-scale and fast-changing environments.

6. Conclusion

This paper introduces an Adaptive Random Forest-based Algorithm for Fast Advertisement Recommendation in response to the pressing need for efficient and effective advertisement recommendation algorithms in the competitive online advertising landscape. By integrating the adaptability of Random Forest with a swift recommendation process, our approach strives to offer timely and precise recommendations to users while addressing scalability concerns prevalent in existing research. The key innovation of our work lies in the algorithm's adaptive capacity, enabling real-time adjustments to evolving user preferences and feedback. Through rigorous experimentation, we showcase the effectiveness and efficiency of our proposed algorithm in the realm of advertisement recommendation. However, some limitations exist, such as the need for further exploration of the algorithm's performance in varied contexts and its generalizability to different datasets. For future work, potential avenues include enhancing the algorithm's adaptability to even more dynamic user behaviors and conducting extended field tests to validate its performance across diverse online advertising platforms.

Funding

Not applicable

Author Contribution

Conceptualization, P. D. and É. M.; writing—original draft preparation, P. D. and É. M.; writing—review and editing, P. D. and L. G.; All of the authors read and agreed to the published final manuscript.

Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there are no conflict of interests.

Reference

[1] Y. Lei, T. Wang, H. Zhang, and T. Ding, "An Elevator Advertisement Recommendation System Design based on Machine Vision and Deep Learning," in 2024 IEEE 7th International Conference on Big Data and Artificial Intelligence (BDAI), 2024.

[2] Z. Fan, F. Li, H. Liu, J. He, and X. Du, "PoseRec: 3D Human Pose Driven Online Advertisement Recommendation for Micro-videos," in International Conference on Multimedia Retrieval, 2024.

[3] Y. Gan and D. Zhu, "The Research on Intelligent News Advertisement Recommendation Algorithm Based on Prompt Learning in End-to-End Large Language Model Architecture," in Innovations in Applied Engineering and Technology, 2024.

[4] D. M. Nguyen, C. Wang, Y. Shen, and Y. Zeng, "LightSAGE: Graph Neural Networks for Large Scale Item Retrieval in Shopee’s Advertisement Recommendation," in ACM Conference on Recommender Systems, 2023.

[5] R. F. Y. Lin et al., "Applied sentiment analysis on a real estate advertisement recommendation

model," in Enterprise Information Systems, 2022.

[6] F. Jouyandeh and P. M. Zadeh, "IPARS: An Image-based Personalized Advertisement Recommendation System on Social Networks," in ANT/EDI40, 2022.

[7] G.-H. Kim, I. Choi, Q. Li, and J. Kim, "A CNN-Based Advertisement Recommendation through Real-Time User Face Recognition," in Applied Sciences, 2021.

[8] F. Mo et al., "Real-time Periodic Advertisement Recommendation Optimization under Delivery Constraint using Quantum-inspired Computer," in International Conference on Enterprise Information Systems, 2021.

[9] H. Ebrahimy et al., "Downscaling MODIS Land Surface Temperature Product Using an Adaptive Random Forest Regression Method and Google Earth Engine for a 19-Years Spatiotemporal Trend Analysis Over Iran," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, 2021.

[10] Y. Sun et al., "SOKNL: A novel way of integrating K-nearest neighbours with adaptive random forest regression for data streams," Data Mining and Knowledge Discovery, vol. 36, 2022.

[11] D. Chen et al., "Locally Weighted Ensemble-Detection-Based Adaptive Random Forest Classifier for Sensor-Based Online Activity Recognition for Multiple Residents," IEEE Internet of Things Journal, vol. 9, 2022.

[12] A. O. Alqabbany and A. M. Azmi, "Measuring the Effectiveness of Adaptive Random Forest for Handling Concept Drift in Big Data Streams," Entropy, vol. 23, 2021.

[13] H. K. Fatlawi and A. Kiss, "Differential privacy based classification model for mining medical data stream using adaptive random forest," Acta Universitatis Sapientiae: Informatica, vol. 13, 2021.

[14] O. Wu et al., "GPU-based State Adaptive Random Forest for Evolving Data Streams," IEEE International Joint Conference on Neural Network, 2020.

[15] O. Wu et al., "Probabilistic exact adaptive random forest for recurrent concepts in data streams," International Journal of Data Science and Analysis, vol. 13, 2021.

[16] T. Hatami et al., "A Machine Learning Approach to Brain Tumors Segmentation Using Adaptive Random Forest Algorithm," International Conference on Knowledge-Based Engineering and Innovation, 2019.

[17] Y. Gan and D. Zhu, "The Research on Intelligent News Advertisement Recommendation Algorithm Based on Prompt Learning in End-to-End Large Language Model Architecture," in Innovations in Applied Engineering and Technology, 2024.