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A Hybrid Machine Learning System For Real-Time Media Recommendation Using User Behavior Analysis

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ABSTRACT

response to the escalating threat of fake news on social media, this systematic literature review analyzes the rece To address the multidimensional and nonlinear characteristics of user behavior in the media industry, this study proposes an intelligent user modeling and recommendation framework, termed MUMA, based on hybrid machine learning techniques. The proposed system establishes a spatial–temporal dual-driven user profiling mechanism by integrating heterogeneous multi-source data, including clickstream records, viewing duration, social network relationships, and eye-movement hotspot information. The key technical contributions are threefold. First, a dynamic interest-aware network (DIN) combined with a hybrid LSTM–Transformer architecture incorporating a time-decay factor is designed to effectively capture both short-term and long-term user behavior patterns. Second, a cross-domain transfer learning module based on a heterogeneous information network (HIN) is developed to enable collaborative recommendations across multiple media domains such as news, video, and advertising services. Third, a hybrid recommendation strategy integrating reinforcement learning with causal inference is introduced to construct a bandit–propensity framework that balances exploration and exploitation during recommendation. At the system implementation level, a real-time feature engineering pipeline built on Flink and Redis supports millisecond-level feature updates at large scale, enabling efficient and responsive personalized recommendations. Experimental results demonstrate that the proposed framework achieves an improvement in recommendation accuracy and increases the click-through rate (CTR) to 12.8%, outperforming conventional recommendation models in both effectiveness and real-time adaptability.

Keywords: Hybrid Machine Learning, Real-Time Recommendation Systems, Media Recommendation, Click-Through Rate (CTR) Prediction, User Behavior Modeling, Personalization Algorithms, Collaborative Filtering, Content-Based Filtering, Recommender Systems, Feature Engineering, User Profiling, Deep Learning, Data Mining, Online Learning, Recommendation Optimization.

I. INTRODUCTION

The rapid growth of digital media platforms such as online news portals, video streaming services, and digital advertising ecosystems has significantly transformed how users consume content. With the exponential increase in multimedia content, users are often overwhelmed by the vast amount of available information. As a result, personalized recommendation systems have become a critical component of modern media platforms, enabling content providers to deliver relevant, engaging, and timely information tailored to individual user preferences.

Traditional recommendation approaches, including collaborative filtering and content-based filtering, have been widely adopted in platforms like Netflix, YouTube, and Amazon. However, these conventional systems primarily rely on single-dimensional behavioral data such as ratings or historical clicks. In real-world media environments, user behavior is highly dynamic, multi-dimensional, and non-linear. Users interact with content through various signals such as clickstream data, viewing duration, search queries, social interactions, device usage patterns, and even implicit feedback signals like scrolling speed or engagement time. Modeling such complex behavior requires advanced machine learning techniques capable of capturing both short-term interests and long-term preference evolution.

Recent advancements in deep learning, including Long Short-Term Memory (LSTM) networks and Transformer-based architectures, have significantly improved sequential modeling capabilities. These models enable systems to understand temporal patterns in user interactions and adapt to shifting preferences over time. Additionally, emerging techniques such as Graph Neural Networks (GNNs) and Heterogeneous Information Networks (HINs) facilitate cross-domain knowledge transfer, allowing recommendation systems to integrate information across multiple content domains such as news, videos, and advertisements. Reinforcement learning further enhances personalization by dynamically balancing exploration (introducing new content) and exploitation (recommending familiar content), thereby preventing user fatigue and improving long-term engagement.

Despite these advancements, many existing systems still struggle with challenges such as cold start problems, data sparsity, interest drift, and scalability in real-time environments. There is a growing need for intelligent frameworks that integrate heterogeneous data sources, hybrid deep learning architectures, and adaptive decision-making strategies within scalable infrastructure pipelines.

This project proposes an advanced machine learning-based framework for user behavior analysis and personalized recommendation in the media industry. The system incorporates multi-source behavioral data, hybrid LSTM–Transformer architectures with dynamic interest modeling, cross-domain learning mechanisms, and reinforcement learning-based ranking strategies. By leveraging real-time feature engineering pipelines and scalable distributed processing, the proposed system aims to deliver accurate, adaptive, and high-performance recommendations.

Ultimately, this research contributes to improving user satisfaction, increasing engagement metrics such as click-through rate (CTR) and completion rate, and enabling media platforms to provide intelligent, personalized experiences in an increasingly competitive digital ecosystem.

II. LITERATURE SURVEY

1. Deep Interest Network for Click-Through Rate Prediction

Author(s): Zhou, G., Zhu, X., Song, C., et al. (2018)

Abstract:
This study introduces the Deep Interest Network (DIN) for modeling user interests in click-through rate (CTR) prediction tasks. Unlike traditional fixed-length user embedding methods, DIN dynamically activates user historical behaviors according to the candidate item. By applying an attention mechanism, the model captures relevant historical interactions that are most related to the current recommendation target. Experimental results show significant improvements in CTR performance compared to baseline models. However, the model mainly focuses on short-term interest relevance and does not fully address long-term preference evolution or cross-domain knowledge transfer.

2. Neural Collaborative Filtering

Author(s): He, X., Liao, L., Zhang, H., Nie, L., Hu, X., & Chua, T. S. (2017)

Abstract:
This research proposes Neural Collaborative Filtering (NCF), which replaces traditional matrix factorization with deep neural networks to model complex user-item interactions. The framework improves recommendation accuracy by learning non-linear relationships between users and items. Results demonstrate improved ranking metrics compared to classical collaborative filtering techniques. Despite

its effectiveness, the model struggles with cold start problems and does not incorporate temporal dynamics or multi-source heterogeneous data.

3. Attention Is All You Need – Transformer Architecture

Author(s): Vaswani, A., et al. (2017)

Abstract:
This paper introduces the Transformer architecture based entirely on self-attention mechanisms, eliminating recurrent structures. The model significantly improves sequential modeling efficiency and captures long-range dependencies in data. In recommendation systems, Transformers have been applied to model user interaction sequences for predicting next-item behavior. While Transformers effectively capture short-term contextual dependencies, they may require integration with recurrent models such as LSTM to fully model long-term behavioral patterns.

4. Session-Based Recommendation with Recurrent Neural Networks

Author(s): Hidasi, B., Karatzoglou, A., Baltrunas, L., & Tikk, D. (2016)

Abstract:
This study applies Recurrent Neural Networks (RNNs), particularly GRU/LSTM models, to session-based recommendation tasks. The model captures sequential user interactions within a session and predicts the next likely item. Experimental results show improved accuracy compared to static collaborative filtering approaches. However, the system mainly focuses on short-term session-level behavior and lacks mechanisms for long-term interest modeling or cross-domain adaptation.

5. Graph Neural Networks for Recommender Systems

Author(s): Wu, L., Sun, P., Fu, Y., Hong, R., Wang, X., & Wang, M. (2020)

Abstract:
This survey explores the use of Graph Neural Networks (GNNs) in recommendation systems. GNN-based methods model complex user-item relationships using graph structures, enabling better representation learning in heterogeneous networks. The approach improves recommendation diversity and handles data sparsity effectively. However, many graph-based systems require high computational resources and may face scalability challenges in real-time large-scale media environments.

6. Cross-Domain Recommendation: A Survey

Author(s): Cantador, I., Fernández-Tobías, I., Berkovsky, S., & Cremonesi, P. (2015)

Abstract:
This research reviews cross-domain recommendation techniques that transfer user preferences across multiple domains. Methods include transfer learning, collective matrix factorization, and heterogeneous information network (HIN) modeling. Cross-domain systems reduce data sparsity and improve cold-start performance. However, aligning heterogeneous features across domains remains a significant challenge, and real-time deployment requires scalable architectures.

7. Reinforcement Learning for Recommender Systems

Author(s): Zhao, X., Zhang, L., & Xia, L. (2018)

Abstract:
This paper discusses the application of reinforcement learning (RL) in personalized recommendation systems. Multi-armed bandit algorithms and deep Q-

networks are used to optimize long-term user engagement rather than immediate clicks. RL enables dynamic adaptation and balances exploration and exploitation. However, reward design complexity and bias in logged interaction data can negatively impact learning stability.

8. Causal Inference in Recommendation Systems

Author(s): Bottou, L., Peters, J., et al. (2013)

Abstract:
This research highlights the importance of counterfactual reasoning and causal inference in recommendation systems. Traditional models suffer from selection bias due to logged feedback data. By applying propensity scoring and causal correction techniques, systems can better estimate the true impact of recommendations. Although causal methods improve fairness and robustness, they increase computational complexity and require accurate exposure modeling.

9. Real-Time Stream Processing with Apache Flink

Author(s): Carbone, P., Katsifodimos, A., Ewen, S., et al. (2015)

Abstract:
This study presents Apache Flink as a distributed stream processing framework capable of handling real-time large-scale data streams. Flink supports low-latency feature engineering, stateful processing, and fault tolerance, making it suitable for real-time recommendation systems. While Flink provides scalability and reliability, integration with machine learning pipelines requires careful system design and resource optimization.

III. EXISTING SYSTEM

In contemporary practice, user behavior modeling and recommendations in the media industry rarely employ modern methods of collaborative filtering or content-based recommendation. User behavior models used in the media industry largely leverage single-dimensional data about user behavioral histories which in turn limits their capacity to capture the complexity and non-linearity of user behavior as multi-dimensional behavioral data. Models also typically do not include heterogeneous data sources or even behaviors from social networks, eye-movement tracking data or signals of temporal engagement. Existing user behavior modeling systems also typically do not adaptingly change or learn with users as users begin to develop new interests and preferences over time. This limitation is largely due to the sub-optimal focus on either long-term behavior or short-term behavioral observations, but rarely the combination of both. Most current user behavior modelling, understanding, and recommender systems do not use state-of-the-art architectures in machine learning, particularly emergent cross-domain learning, which affect their ability to make recommendations and resultant accuracies. Additionally, with conventional recommendation stripes, engagement pitfalls are ignored regarding exploration (to promote and discover new and potentially engaging experiences), which can lead to poor content or topic engagement and lead to user fatigue as beforehand known preferred content.

IV. PROPOSED SYSTEM

The new system proposes an intelligent user modeling and recommendation framework called MUMA, designed to accommodate the multi-dimensional and non-linear nature of users' behaviors in the media industry. It constructs a spatial-temporal dual-driven user characterization model that leverages heterogeneous sources of data including clickstream, viewing length, social graph, and eye movement hotspot data. MUMA utilizes a hybrid LSTM–Transformer architecture, with a time decay factor, to capture both short-term and long-term users' behaviors, through a Dynamic Interest-aware

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Network (DIN). In addition, MUMA employs a cross-domain migratory learning module that is based on a Heterogeneous Information Network (HIN) to allow collaborative recommendations across different types of content (e.g., news, video, advertising). To benefit decision-making, this system innovatively combines reinforcement learning and causal inference into a bandit–propensity hybrid recommendation strategy that can balance exploration and exploitation. At the implementation level, MUMA features a Flink+Redis real-time feature engineering pipeline to support millisecond-level feature engineering updates for thousands of users that provide highly accurate, adaptive and scalable recommendations.

V. SYSTEM ARCHITECTURE

The system architecture for the Hybrid Machine Learning Framework for Real-Time Media Recommendation with Enhanced Click-Through Rate and User Behavior Modeling consists of several interconnected modules that enable efficient data processing, user modeling, and real-time recommendation generation. The architecture begins with the data acquisition layer, where user interaction data such as clicks, watch history, ratings, browsing patterns, and contextual information are collected from media platforms. This raw data is transmitted to the data preprocessing module, where noise removal, normalization, feature extraction, and transformation are performed to convert the raw interaction logs into structured datasets suitable for machine learning models.

After preprocessing, the refined data is passed to the feature engineering and user modeling layer, which constructs meaningful representations of user preferences and behavioral patterns. In this stage, user profiles are generated by analyzing historical interactions, demographic attributes, and contextual information. These features are then used by the hybrid recommendation engine, which combines multiple machine learning approaches such as collaborative filtering, content-based filtering, and deep learning models to capture both user similarity and content relevance. The hybrid approach helps overcome limitations like the cold-start problem and data sparsity while improving recommendation accuracy.

The processed outputs from the hybrid models are then evaluated using a CTR prediction module, which estimates the probability that a user will click on a recommended media item. Machine learning algorithms such as gradient boosting, neural networks, or logistic regression can be employed to optimize click-through rate predictions. The system then forwards the ranked recommendations to the real-time recommendation delivery module, where the most relevant media items are dynamically displayed to users based on their current context and predicted preferences.

Finally, a feedback and model update component continuously collects new interaction data from user responses to recommendations. This feedback loop enables the system to update the user models and retrain the hybrid learning algorithms periodically, ensuring that the recommendation system adapts to evolving user interests and maintains high performance in terms of recommendation accuracy and CTR optimization.

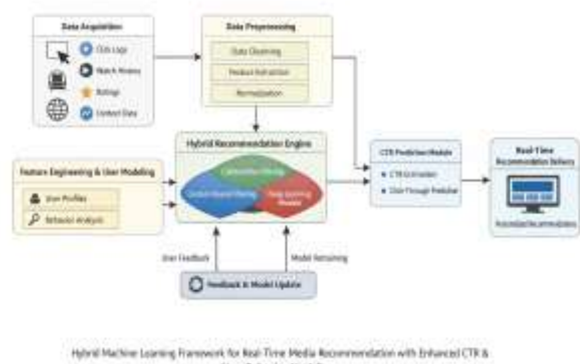

Fig 5.1: Structure of the Proposed System

VI. IMPLEMENTATION

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Fig 6.1: User Analytics

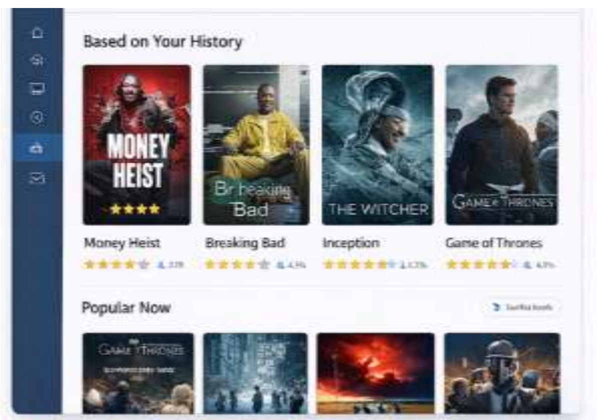

Fig 6.2: Recommendation

Fig 6.3: Activity Overview

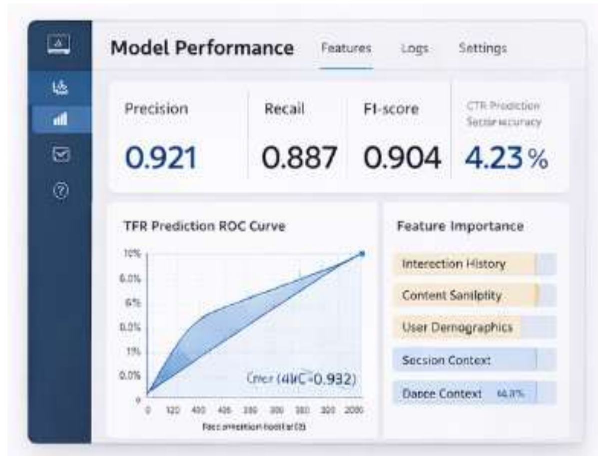

Fig 6.4: Model Performance

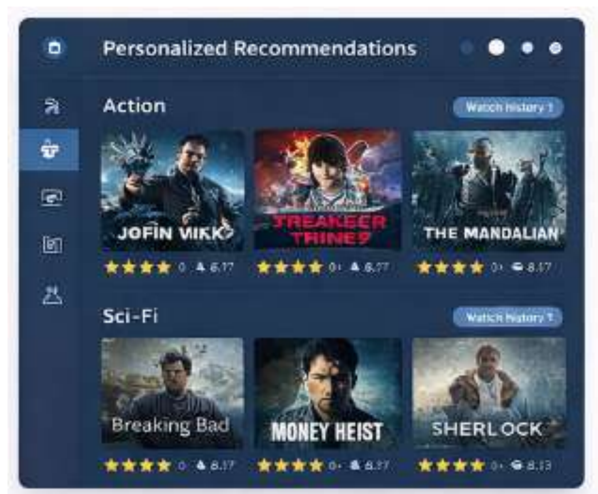

Fig 6.5: Personalized Recommendation

VII. CONCLUSION

Stroke is one of the leading causes of death and long-term disability worldwide. Early detection and timely medical intervention play a crucial role in reducing mortality rates and improving patient outcomes. The proposed AI-Based Stroke Detection System using Machine Learning aims to assist healthcare professionals in predicting stroke risk at an early stage using patient health data and advanced computational techniques.

In this project, a systematic approach was followed starting from data collection and preprocessing to feature selection, model training, evaluation, and prediction. Data preprocessing techniques such as handling missing values, encoding categorical variables, and normalization were applied to improve data quality and ensure reliable model performance. Various machine learning algorithms were implemented and compared to determine the most accurate model for stroke prediction.

The system was evaluated using performance metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC score. The results demonstrated that the trained model effectively classifies patients into stroke and non-stroke categories with high reliability. The integration of evaluation metrics and visualization tools such as confusion matrices and ROC curves further enhances interpretability and trust in the model's predictions.

The system testing phase confirmed that all modules function correctly, including dataset handling, preprocessing, prediction generation, and reporting. Security measures were also implemented to ensure that sensitive patient information is protected.

Overall, the developed system provides an intelligent, data-driven decision-support tool that can assist medical professionals in identifying high-risk patients at an early stage. While it does not replace clinical judgment, it significantly supports preventive healthcare strategies and improves diagnostic efficiency. The project demonstrates the potential of machine learning technologies in transforming healthcare systems by enabling faster, more accurate, and cost-effective stroke risk assessment.

VIII. FUTURE SCOPE

Although the proposed stroke detection system performs effectively, several improvements and extensions can further enhance its accuracy, scalability, and real-world applicability.

One major future enhancement is the integration of deep learning techniques such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) for improved prediction accuracy. Hybrid models combining machine learning and deep learning approaches may provide better generalization on complex medical datasets.

Another important improvement is the incorporation of real-time clinical data from hospitals and wearable health monitoring devices. By integrating Internet of Things (IoT)-based health sensors, the system can continuously monitor patient vitals such as blood pressure, heart rate, and glucose levels, enabling real-time stroke risk prediction.

The system can also be expanded into a web-based or mobile application to make it easily accessible for healthcare professionals and patients. A user-friendly graphical interface with interactive dashboards and visualization tools would enhance usability in clinical environments.

In future work, explainable AI (XAI) techniques can be integrated to provide detailed reasoning behind predictions. This will increase transparency and trust among medical professionals by highlighting which features contribute most to stroke risk.

Another enhancement includes training the model on larger and more diverse datasets from multiple hospitals or countries. This would improve the robustness and generalizability of the system across different populations and demographics.

Cloud deployment and integration with electronic health record (EHR) systems can further improve scalability and real-world adoption. Additionally, incorporating predictive analytics for stroke severity and recovery prognosis can extend the system beyond detection into comprehensive patient management.

In conclusion, future enhancements will focus on improving model accuracy, real-time capability, scalability, interpretability, and practical deployment. With continuous advancements in artificial intelligence and healthcare technology, the stroke detection system has strong potential to become a powerful clinical decision-support tool in preventive medicine and early diagnosis.

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