IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 26 September 2024, accepted 9 October 2024, date of publication 16 October 2024, date of current version 1 November 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3481658

RESEARCH ARTICLE

Real-Time Emotional Topic Recommendation in Social Media News Using MDT and Hypergraph-Based Neural Networks

CHANGCHUN TAO[1] **AND BILAL ALATAS**[2]
[1]School of Media and Communication, Wuhan Textile University, Wuhan, Hubei 430073, China
[2]Department of Software Engineering, Firat University, 23119 Elâzığ, Türkiye

Corresponding author: Changchun Tao (whfztcl@163.com)

ABSTRACT In the intelligent recommendation of user emotional topics within social media news dissemination, the system must adapt to the dynamic changes in user interests and enhance the real-time accuracy of recommended content. To address this, a multiple decision tree (MDT) recommendation model is first proposed, which combines with a neural network structure optimization model based on hypergraphs (NNSO-hy) to construct a user interest topic recommendation model. Additionally, to cope with the rapid change of news topics, dynamic window technology is used to capture the dynamic changes of news topics and to adjust the recommended content, where the short text clustering model is designed to optimize the objective function, utilizing an improved Non-negative Matrix Factorization (NMF) model to cluster the window news. The experimental results show that the proposed model effectively captures news topics in real-time across different datasets. Moreover, our precision rates for dynamic burst topic detection are 0.72, 0.85, and 0.83, respectively. When conducting intelligent user sentiment topic push notifications on the three datasets, the precision rates are 0.74, 0.85, and 0.84, respectively. After 30 iterations, the loss function of MDT-NNSO-hy stabilizes, achieving an accuracy (P), recall (R), and F1 score of 0.82, 0.81, and 0.87, respectively, on average across three datasets. In summary, this study realizes the intelligent push of users' emotional topics in social media news dissemination by integrating MDT, NNSO-hy, and dynamic topic detection technology. This not only improves the accuracy and real-time performance of recommendations but also provides new ideas and methods for the development of personalized recommendation technology.

INDEX TERMS Social media news, MDT, NNSO-hy, dynamic topic detection, sentiment analysis, deep learning.

I. INTRODUCTION

With the rapid development of social media, information dissemination has become an indispensable part of modern society. In this era of information explosion, users are inundated with vast amounts of news and various types of information daily. Efficiently filtering and delivering content that aligns with users' interests and emotional states has become an urgent challenge. In the realm of news dissemination, users' emotional responses can significantly impact the speed, breadth, and depth of information spread [1]. This is because social media provides users with a platform for emotional expression and interaction. Users can express their emotions and attitudes towards news content through likes, comments, shares, and other means. At the same time, they can also receive emotional support, recognition, or rebuttal and criticism from the feedback of different users. This interaction further deepens users' understanding of the news content and their sense of engagement.

Moreover, when reading news, users tend to interpret the content based on their own experiences, values, and emotional states. When news content triggers a certain emotional resonance in users, such as joy, sadness, anger, or surprise, they are more likely to be attracted and deeply engaged.

The associate editor coordinating the review of this manuscript and approving it for publication was Muhammad Asif.

This resonance prompts users to share their opinions and feelings on social media, further expanding the scope of news dissemination. However, traditional news dissemination often overlooks users' individualized needs and emotional states, leading to a lack of targeted and effective information delivery [2]. Consequently, intelligently pushing news topics that align with users' emotional changes and interest preferences has become a hot topic in current research.

In recent years, the rapid advancement of technology, particularly innovations in deep learning, has brought unprecedented opportunities to the field of social media news dissemination. Complex network models such as Recurrent Neural Networks (RNN) [3], Long Short-Term Memory (LSTM) networks [4], and Graph Neural Networks (GNN) [5] have revolutionized the landscape. These adaptive deep learning models can deeply mine users' historical behavioral data, accurately capture their interest preferences and emotional fluctuations, and automatically extract critical features from massive news texts. This capability enables an in-depth understanding and efficient processing of information. By integrating attention mechanisms and other optimization techniques, the predictive ability and robustness of these models have been significantly enhanced, providing solid technical support for personalized content delivery.

Although current decision tree models and deep learning models can address these issues to a certain extent, there are still limitations. Decision tree models, primarily trained and predicted based on historical data, lack adaptability and flexibility when confronted with rapidly evolving dynamic topics on social media. Moreover, when handling high-dimensional and complex social media data, decision trees may struggle to capture the intricate relationships and hidden patterns among the data, resulting in suboptimal performance in dynamic topic detection. Meanwhile, deep learning models generally require extensive training data to optimize their performance. However, in some cases, labeled data specific to certain dynamic topics may be scarce, affecting the model's generalization capability. While deep learning models excel at processing complex data, their speed of updating and adjustment may not align with the real-time requirements when dealing with rapidly changing dynamic topics.

At the same time, the rapidly changing nature of news topics demands that push systems be highly sensitive and flexible. Self-media platforms, such as blogs, microblogs, and WeChat, generate vast amounts of data and accelerate information dissemination, particularly concerning emergencies and major events, which have a significant impact [6]. Understanding the network communication patterns of emergencies and major events, as well as the behaviors of netizens can help positively guide public opinion and maintain social stability. However, because most of this data is presented as large-scale, uncertain information, conducting in-depth data mining and analysis is challenging. A system capable of dynamically capturing news hotspots in real-time ensures the relevance and timeliness of the content pushed. By integrating user emotional data, this intelligent push strategy, based on both topic and emotion dimensions, not only meets users' desires for fresh information but also enhances the personalization and emotional resonance of their experience, further improving the precision and efficiency of social media news dissemination.

Existing social media news recommendation systems, while achieving a degree of personalization, still face significant shortcomings in the intelligent pushing of user emotional topics. Traditional recommendation systems often rely on static user interest models, which struggle to adapt to dynamic changes in user interests, leading to poor real-time accuracy and relevance of recommended content. Additionally, current methods face considerable challenges in real-time detection and response to breaking news topics, often failing to adjust recommendations promptly to meet users' immediate needs. These issues limit the practical effectiveness of recommendation systems. Therefore, this study proposes a novel user-emotional topic recommendation model that integrates Multiple Decision Trees (MDT), a Neural Network Structure Optimization model based on Hypergraphs (NNSO-hy), and dynamic topic detection technology to address these issues. This approach aims to enhance the accuracy and real-time performance of personalized recommendations and provide new ideas and methods for the advancement of customized recommendation technology.

The specific contributions of this paper are as follows:

1. We not only consider the single dimension of users' historical click-through rates but also introduce an emotional tag weighting mechanism. It fine-tunes the click-through rate weights based on users' historical feedback on different emotional topics, enabling the recommendation model to capture subtle changes in users' emotional preferences more precisely. Moreover, the model possesses self-learning capabilities, dynamically adjusting the branching logic of the decision tree based on user feedback, continuously optimizing the personalization of the recommendation list, and further enhancing user experience.

2. By mapping the neural network architecture into a hypergraph form, the NNSO-hy model not only achieves a visual representation of the network structure but also introduces differentiable operations, enabling the search process of the network architecture to be conducted within a continuous space. This transformation significantly accelerates the training speed of neural networks. It allows the model to automatically explore the optimal architecture configuration during training, thereby considerably improving the accuracy and response speed of user emotional topic recommendations.

3. We propose a dynamic breaking news topic inspection model. This model employs dynamic sliding window technology to capture the trends of topic changes in real-time news streams, ensuring that the recommendation system can quickly respond to sudden news hotspots. Additionally, the model integrates a topic strength evaluation module that quantifies the popularity and influence of news topics, providing more precise criteria for the recommendation system to filter topics. In this paper, we present an overview of

adaptive learning and examine the current state of research on adaptive deep learning within the context of the broader development of deep learning, as detailed in Section II. Section III introduces the MDT-NNSO-hy adaptive deep learning model and the dynamic breaking news topic-checking model. In Section IV, we describe the experimental results and analyze the performance of both the dynamic breaking news topic-checking model and the MDT-NNSO-hy model. Section V provides a summary, reflecting on the MDT-NNSO-hy model and outlining potential directions for future research.

II. RELATED WORKS

Adaptive learning refers to the use of computer technology and artificial intelligence algorithms to provide personalized learning support and resource recommendations by assessing individual learners' needs and learning behaviors, with the goal of enhancing learning outcomes and experiences [7]. This approach leverages learners' prior experiences, learning habits, cognitive characteristics, and other factors to offer tailored resource recommendations and adjust the learning process to meet personalized needs, thereby improving learning efficiency and quality. The effectiveness of adaptive learning depends on a comprehensive and accurate analysis of learners and the provision of personalized, intelligent learning resources. Learning resource recommendation builds upon the advancements of recommender systems [8] in various fields. By analyzing users' historical behavior, interests, hobbies, and subject knowledge, these systems can automatically identify and recommend the most relevant resources, facilitating better access to resources and services and enhancing the effectiveness and satisfaction of online learning experiences.

Knowledge representation plays a crucial role in the implementation of adaptive learning. Literature [9] introduces an ontology-based knowledge representation method designed to improve computer understanding and processing of knowledge, as well as to enhance knowledge sharing and communication across different domains. Literature [10] presents the Conversational Intelligent Tutoring System (CITS), which automatically predicts users' learning styles and provides intelligent support and suggestions to boost learning efficiency and quality. Literature [11] investigates the relationship between user motivation and performance in gamified intelligent tutoring systems. When integrated with emotional analysis technology, the system is capable of real-time identification of users' emotional states (such as joy, frustration, confusion, etc.) during learning games or tasks. By analyzing the emotional shifts in the learning process, the system can discern which factors best stimulate users' learning motivation. Based on these findings, the system can design more engaging game elements or reward mechanisms to maintain users' learning momentum and participation. Literature [12] presents an E-Learning course recommendation system grounded on historical data, which employs association rules and clustering algorithms for course recommendation. The integration of emotional analysis technology enables the system to delve deeper into users' emotional attitudes towards courses, such as satisfaction and interest levels. These emotional insights serve as crucial inputs for the recommendation algorithm, assisting the system in more accurately predicting users' potential interests in upcoming courses, thereby enhancing the accuracy and credibility of recommendations.

With the advancement of deep learning and neural network technologies, adaptive deep learning algorithms have evolved to minimize human intervention and utilize limited computational resources more efficiently [13]. As described in the literature [14], the Net2Net method is a network transformation technique that increases the size of the convolutional kernel in the training network while maintaining the original network functions. Although this approach does not alter initial performance, it allows for further performance enhancement through additional training on the expanded network capacity. Conversely, literature [15] introduces NAS-RL. This method uses a recurrent network to generate a coded sequence derived from layer connections, kernel sizes, step sizes of the convolution, and activation functions. Each generated sub-architecture is trained 50 times, with its final validation accuracy used to refine the recurrent network through reinforcement learning. Although the best architecture found surpasses the performance of the popular ResNet variant [16], the training of the recurrent network required the Google Brain team to run for 28 days using 800 GPUs, amounting to a total of 22,400 GPU hours.

These methods face significant challenges related to long evaluation training times when applied to social media news dissemination, due to the vast variability in search space, hyperparameters, and techniques across different neural network methods. Therefore, exploring more efficient adaptive deep learning algorithms is crucial for achieving intelligent topic recommendations in the context of social media news dissemination.

III. METHODOLOGY

Considering that users in social media news dissemination have diverse objectives, including knowledge and skill acquisition, learning motivation, different user types, a sense of

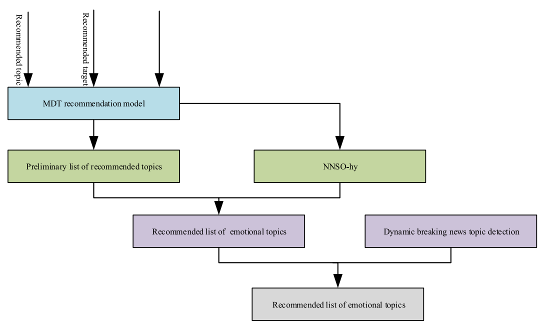

FIGURE 1. Model framework.

achievement, and learning coherence, a model based on multiple decision trees is employed to optimize the varying needs of different user types, knowledge goals, and learning motivation [17]. As illustrated in Fig. 1, this paper proposes the MDT-NNSO-hy adaptive deep learning algorithm, which is integrated with a dynamic breaking news topic-checking model to enable intelligent topic recommendations for users.

A. MDT-NNSO-HY ADAPTIVE DEEP LEARNING

The MDT-NNSO-hy algorithm aims to address the issues of information overload and insufficient personalization prevalent in traditional recommendation systems. Integrating the decision-making capabilities of a Multi-Decision Tree (MDT) model with the optimization potential of deep learning models achieves a significant enhancement in recommendation accuracy. This algorithm not only considers users' historical behavioral data but also incorporates their prior information (such as age, gender, interest preferences, etc.) and specific recommendation target requirements to generate recommendation schemes that are more aligned with users' actual needs.

$$T = \{x_1, x_2, \ldots, x_n\} \tag{1}$$

The top Top-k selected topics in the scheme T are used as the recommended subset:

$$Q = \{z_1, z_2, \ldots, z_k\}, \quad k < n \tag{2}$$

Subset Q is also the final recommendation scheme component. It will be input into NNSO-hy for optimization and screening. The recommendation decision strategy is decided by the historical behavioral features and the recommendation subset is output:

$$L = \{z_1, z_2, \ldots, z_{k'}\}, \quad k' < k \tag{3}$$

where L is the optimized recommended solution.

1) RECOMMENDATION MODEL BASED ON MDT

In the initial stage of the multi-decision tree model recommendation, a recommendation degree parameter is defined for each topic. Depending on the user type, the corresponding strategy is selected, and the topic recommendation degree is adjusted based on factors such as the user's historical topic click rate to complete the screening and rearranging of topics. We construct the MDT model by recursively partitioning the dataset into smaller subsets. Each internal node represents a test on an attribute, each branch signifies an output of the test, and each leaf node stores a decision outcome. By performing cross-validation on trees of varying depths, we can observe the trend in model performance as the tree depth changes. Once the tree depth increases to a certain extent, the model performance may reach saturation or even start to decline, typically due to overfitting. Therefore, the optimal depth is chosen as the point where performance begins to plateau or slightly decline, which is why a tree depth of 13 is selected in this paper. This choice maintains model performance while reducing computational complexity and the risk of overfitting. The number of leaf nodes directly impacts the complexity and performance of the model. Too many leaf nodes can lead to an overly complex model, increasing the risk of overfitting, while too few may limit the model's expressive power. By adjusting the number of leaf nodes and observing changes in model performance, we can find the optimal balance. Ultimately, through testing, our decision to choose a tree depth of 13 and a leaf node count of 90 is based on careful consideration of model performance, computational efficiency, complexity, generalization ability, and data characteristics. These choices aim to ensure that the MDT model maintains high performance while also demonstrating robust generalization and practicality. The decision tree utilizes an optimization strategy informed by the user's historical topic click rate. The parameter is set as 0.1 and the parameter = 0.05. Firstly, the historical click rate of all topics for each user is input. A low click rate indicates that the user is not interested in the topic, suggesting that the recommendation degree should be decreased accordingly. Conversely, a high click rate signals user interest in the topic, warranting an increase in the recommendation degree. For observed topics with a click-through rate of less than 0.5, the recommendation degree is adjusted as follows:

$$\varpi = \varpi - \gamma \tag{4}$$

When the topic has a value of 0.5 < click-through rate < 0.8, make.

$$\varpi = \varpi + \theta \tag{5}$$

When the click-through value of the topic is > 0.8, make.

$$\varpi = \varpi + \gamma \tag{6}$$

Finally, iterate through all the topics and sort the output of each topic's recommendation ϖ.

2) NETWORK TRAINING

We address the structural search problem in neural networks by transforming it into an optimization problem through the introduction of a hypergraph. A hypergraph is an advanced concept in graph theory and represents an extension of traditional graphs. In traditional graphs, an edge can only connect two vertices, forming a binary relationship. However, in a hypergraph, a "hyperedge" can connect any number of vertices, creating a multi-way relationship. This characteristic allows hypergraphs to represent complex connections and relationships in the real world more flexibly, such as groups in social networks and multi-table joins in databases. Specifically, the neural network architecture design is represented as a directed acyclic graph (hypergraph), where nodes denote neurons or feature maps, and hyperedges represent connections between these elements, encompassing possible operations such as convolution, pooling, or constant mapping. Unlike traditional methods for neural network structure search that operate within a discrete search space, NNSO-hy leverages differentiable operations to create a continuous search space. NNSO-hy obtains gradient information for the hypergraph structure by first unfolding the entire network based on the current hypergraph configuration to form a complete network with weight parameters, followed by end-to-end training of this network.

The feature graph or neuron corresponding to each node in the hypergraph is denoted as x_i, and each hyperedge connection is denoted as $\varepsilon_{i,j}$, thus the hyperedge structure consists of n possible operations and n structural parameters $a_i (i = 1, 2, \ldots, n)$, and for each hyperedge, $\varepsilon_{i,j} = 1$ if it has a connection, otherwise $\varepsilon_{i,j} = 0$.

Since the objective is to find the optimal combination of hyperedge structures, it is essential to optimize the hypergraph structure during the search process. This optimization aims to determine the connection probabilities of the structure and ensure that the resulting network architecture is tractable, thereby controlling the sparsity of the network. To achieve this, NNSO-hy employs a softmax function to transform the discrete choice of edges into a continuous space, ensuring the differentiability of the network structure. Let c_i be the probability of connection on this hyperedge; the continuous relaxation operation is denoted as:

$$c_i = \frac{\exp(a_i)}{\sum_{j=1}^{n} \exp(a_i)}, \sum\nolimits_{i=1}^{n} c_i = 1 \tag{7}$$

Ultimately, the objective function is expressed as shown in Equation (8):

$$L_{train}(w, a) = \frac{1}{|D_{train}|} \sum\nolimits_{(x,y) \in D_{train}} L(f(x), y) \tag{8}$$

where D_{train} is the training set, $f_{w,a}(x)$ denotes the neural network with hypergraph structure a, and w is the weight parameter. l denotes the loss function, which can be changed according to different tasks.

During the training process, NNSO-hy optimizes both the structural parameters and the weight parameters w using gradient descent. This approach allows NNSO-hy to adapt to different training tasks without the need to re-search the structure. Through continuous iterative search and optimization, NNSO-hy can automatically identify the optimal neural network structure. Compared to traditional methods that rely on manual network design, NNSO-hy offers greater efficiency and accuracy. It significantly reduces the workload associated with manual design while maintaining network performance and effectively enhancing the training performance of emotional topic recommendation models.

B. DYNAMIC NEWS THEME DETECTION MODEL

To detect breaking topics in real-time social media news dissemination, this section proposes a breaking topic detection framework based on dynamic topic detection, as illustrated in Fig. 2. The breaking topic detection process comprises three main stages: breaking feature identification, dynamic window determination, and breaking topic window clustering.

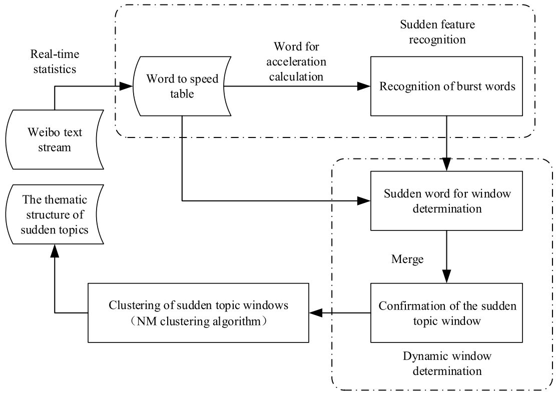

FIGURE 2. Framework of dynamic topic detection model.

Burst feature recognition distinguishes burst topic detection from other topic detection methods. In this paper, word pair acceleration is utilized as a burst feature. Upon the arrival of a new topic, burst feature identification is conducted by counting the frequency of all word pairs in social media news, updating the word pair velocity table, and calculating the acceleration of each word pair. If the acceleration of a word pair exceeds a predefined threshold, it is labeled as a burst word pair. By analyzing the burst duration of historical breaking news data, which refers to the time required for a news event to reach its peak from its inception, we can estimate the optimal window size. If the average burst duration of a specific type of news event is known or can be reasonably estimated, the window size can be set to a value close to this average. However, given the unpredictable and variable nature of burst durations in emergencies, this approach may have certain limitations. Therefore, in this paper, upon detecting a burst term pair, we determine the time interval during which the burst term pair appears relatively frequently based on its emergence rate, effectively defining the burst term pair window. When multiple intersecting, overlapping, or adjacent burst term pair windows are detected, we consolidate the tweets within these windows to form a burst topic window.

To derive the thematic structure of the news within the breaking topic window, this paper employs an improved Non-Negative Matrix Factorization (NMF) clustering method. This method incorporates robust norms to design an optimized objective function for the short text clustering model, thereby minimizing the impact of noise data from short texts on the clustering results. Additionally, a word pair velocity table T, which is an $N \times N$ array, is utilized to store the velocities of all word pairs within the news text stream, i.e., the two velocity values and of the word pair, as shown in Fig 3.

When new news arrives, the word pair velocity table T is updated, and the acceleration of word pairs is computed. The magnitude of the acceleration is used to determine whether there is a burst of word pairs, enabling dynamic topic checking.

In the dynamic topic detection model, output news text stream D, time slices ΔT_1 and ΔT_2, word pair acceleration

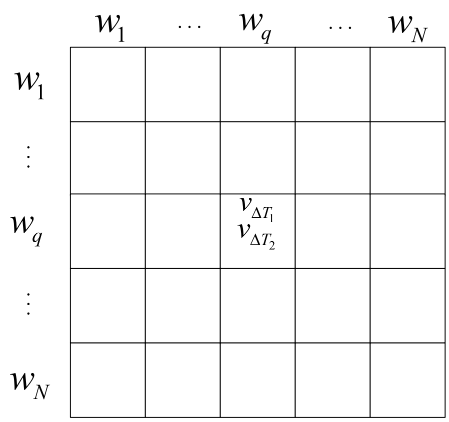

FIGURE 3. Word pair speed update process.

threshold α, bursting word pair velocity threshold β, merge window number threshold ϕ, and number of clusters k. Firstly, compute $v_{\Delta T_1}$, $v_{\Delta T_2}$ and velocity *speed* of for each word pair (w_p, w_q) at the time of t, and update the word pair velocity table T. If $speed > \alpha$, the bursting word pair $W_{p,q}$ are obtained. For each $W_{p,q}$, determine the window of burst word pairs and judge whether the windows of burst word pairs are crossed, overlapped, or adjacent to each other. If the number of intersecting, overlapping, or neighboring burst word pair windows is C, and $C > \phi$, then the burst topic window can be calculated as shown in Equation (9):

$$DW = \bigcup_{j=1}^{C} W_j \tag{9}$$

The news within the DW is clustered using NMF [18] to obtain the class center matrix P and the text affiliation matrix Q. The final output is the class center matrix P and the text affiliation matrix Q.

IV. EXPERIMENTAL ANALYSIS

In this section, we evaluate the performance of the proposed MDT-NNSO-hy and assess the performance improvements of the designed user sentiment topic recommendation model through experimental comparisons and ablation studies.

A. EXPERIMENTAL ENVIRONMENT AND DATASETS

All experiments in this paper were conducted on a PC equipped with an Intel Core 3.60GHz processor, 8GB RAM, and running the Windows 7 operating system. The dataset was constructed using social media data from Weibo, specifically Sina Weibo. The experimental data were extracted from microblogs, including text information and release times, to create a data stream of microblog text. The preprocessing involved several steps: emoticons, URLs, and "@users" were removed; the Chinese lexical module Jieba in Python was used for lexical analysis and removal of stop words; and tweets with fewer than three words were deleted. After preprocessing, over 350,000 data samples were obtained, encompassing 57 emergent topics, each with a duration ranging from 0.5 to 10 hours. Each topic was labeled with corresponding user click rates and other relevant metrics. Finally, the labeled microblog data were divided into three datasets—Date1, Date2, and Date3—based on the time of data collection for experimentation. The data features are summarized in Table 1.

TABLE 1. Units for magnetic properties.

Date set	Number of microblogs	topic duration	Number of topics
Date1	140 thousand	2-8 hour	25
Date2	110 thousand	0.5-7 hour	18
Date3	100 thousand	3.5-10 hours	21

B. EVALUATION INDEX

To validate the effectiveness of the model, this paper employs three metrics—accuracy (P), recall (R), and F1 score—for comparative analysis of both dynamic breaking topic detection and sentiment topic recommendation performance. The computational formulas for these metrics are expressed as follows:

$$P = \frac{s}{c} \tag{10}$$

$$R = \frac{s}{r} \tag{11}$$

$$F1 = \frac{2 \times P \times R}{P + R} \tag{12}$$

where s represents the number of topics correctly detected or recommended by the algorithm, c denotes the number of emergent topics detected or recommended by the algorithm, and r indicates the number of dynamic emergent or recommended topics that have been labeled.

C. PERFORMANCE ANALYSIS OF DYNAMIC TOPIC DETECTION

The word pair acceleration threshold is set to 0.15; the burst word pair velocity value is 5.0; the burst word pair window merge number threshold is 4; the number of clusters is 8, and $\Delta T_1 = 15$ minutes and $\Delta T_2 = 30$ minutes. Two comparison algorithms are parameterized and compared with the proposed method under the same experimental conditions. The first comparison is with the algorithm from the literature [19], which introduces a fixed-length sliding window for emergent topic detection and is referred to as the BIC algorithm in this paper. For the experiments, the emergent word weight is set to 30, the incremental clustering threshold is set to 200, and the size of the fixed-length sliding window is 3 hours. The second comparison is with the algorithm from the literature [20], which improves upon the method in [19] but also utilizes a fixed-length sliding window detection algorithm, denoted as INF in this paper. In this experiment, the breaking word weight threshold is set to 3.0, the inter-cluster distance threshold is set to 600, and the fixed-length sliding window size is maintained at 3 hours.

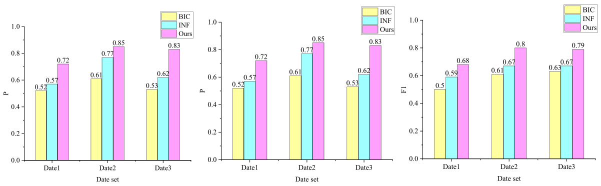

FIGURE 4. Dynamic topic detection performance comparison.

As shown in Fig. 4, the precision (P), recall (R), and F1 scores of the dynamic breaking topic detection algorithm proposed in this paper are significantly higher than those of the BIC and INF algorithms across all three datasets. Analysis of the experimental data reveals that the duration of dynamic breaking topics is unpredictable. In contrast, the BIC and INF algorithms rely on fixed-length sliding windows, which often fail to align with the timing of breaking topics. Consequently, selecting an appropriate "sliding window size" is a major challenge for these algorithms. The fixed 3-hour sliding window size used by both BIC and INF algorithms limits their ability to detect emergent topics that occur over shorter time periods. In contrast, the dynamic window technique employed in this paper enables accurate detection of all types of topics in social media.

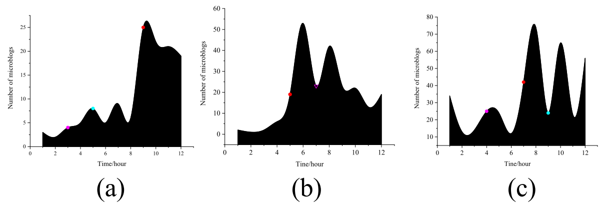

FIGURE 5. Detection real-time comparison.

To evaluate the real-time performance of the dynamic breaking topic-checking algorithm, we compared its detection time with that of the BIC and INF algorithms for the same breaking topics. Figure 5 illustrates the variation in the number of relevant tweets per unit of time for six breaking topics over time and the detection times of the three algorithms. In Fig. 5, the red, pink, and blue dots represent the time points at which topic changes are detected by the proposed algorithm, BIC, and INF algorithms, respectively. It is evident from Fig. 5 that the algorithm proposed in this paper detects emergent topics at an earlier stage and identifies the time of topic changes within a shorter period, demonstrating its superior dynamic detection capability. This improvement is attributed to the BIC and INF algorithms' reliance on detecting changes in word frequency within the current and historical sliding windows, which limits their ability to detect breaking topics until the end of the sliding window.

In contrast, the proposed algorithm detects word pair acceleration in microblogs in real-time, allowing it to identify breaking topics as soon as the acceleration exceeds a predefined threshold. In sub-figure (b) of Fig. 5, the pink triangles mark the detection times of topic changes by the BIC and INF algorithms. The detection time of the proposed algorithm is approximately 2 hours earlier than that of the BIC and INF algorithms. This discrepancy occurs because the sliding window of the BIC and INF algorithms spans from 6:00 to 8:00 pm, resulting in the detection of breaking topics only at 7:00 pm.

D. PERFORMANCE ANALYSIS OF TOPIC RECOMMENDATION

Fig. 6 clearly demonstrates the variation of the Loss parameter in the MDT-NNSO-hy model during the training process as the number of iterations of the NNSO-hy network increases. Specifically, as the training iterations progress, the Loss parameter exhibits a pronounced downward trend, which intuitively reflects the model's gradual optimization of its internal parameters to fit the training data better. Notably, when the number of iterations reaches approximately 30, the rate of decline in the Loss parameter significantly slows down and gradually plateaus, indicating that the model has essentially completed its learning process on the training data, achieving a relatively stable performance state. This phenomenon not only validates the effectiveness of the MDT-NNSO-hy model in complex emotional topic recommendation tasks but also further underscores its robust learning capability and adaptability. The steady decline and eventual convergence of the Loss parameter serve as a direct manifestation of the model's continuously enhanced performance, portending MDT-NNSO-hy's capability to more effectively capture the intricate features of emotional topics when integrated with dynamic image topic detection, thereby enabling precise recommendations of user emotional topics. This finding provides robust data support for the performance advantages of the proposed model in practical applications.

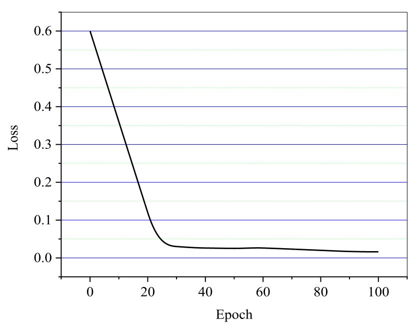

FIGURE 6. Loss function change curve.

This study provides a comprehensive analysis of the intelligent recommendation performance of user sentiment topics, focusing on 30 iterations. Subfigures (a), (b), and (c) in Fig. 7 present the experimental results on three datasets: Date1, Date2, and Date3. Compared to traditional decision tree algorithms, the adaptive deep learning and dynamic topic detection fusion model MDT-NNSO-hy demonstrates significant advantages in precision, recall, and F1 score.

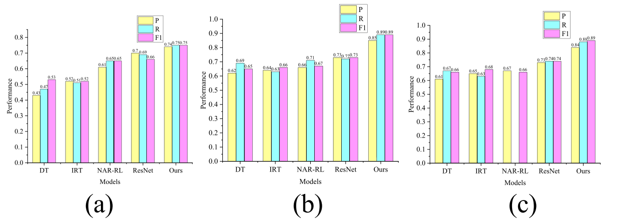

FIGURE 7. User emotion topic recommendation performance comparison.

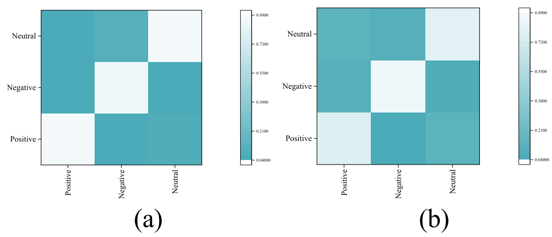

FIGURE 9. Confusion matrix.

These metrics are notably higher than those of NAS-RL [15], [24], ResNet [16], the decision tree DT model [21], and the IRT model [22], [23]. Specifically, after fine-tuning the model's optimization sub-modules and enhancing the prediction network's performance, the MDT-NNSO-hy model shows a modest yet consistent improvement, further validating its superior effectiveness in social media news dissemination scenarios. Furthermore, Each experiment should be conducted under the same or similar conditions to ensure the stability and reliability of the results. The consistent outcomes from multiple experiments can also indicate that the performance stabilizes after 30 iterations. Therefore, this paper concludes that 30 iterations are sufficient for achieving stability.

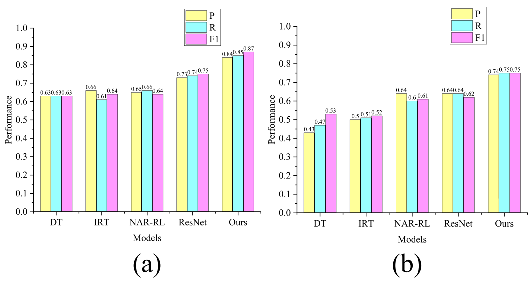

FIGURE 8. Comparison of performance of topic recommendation among different users' emotions.

Further analysis of different user groups, such as those in categories A and B, reveals important insights. Users in category A are highly engaged with news topics, while users in category B are less sensitive or involved. The results, illustrated in Fig. 8, show the mean performance metrics for each index across three datasets under different models for categories A and B. Sub-figures (a) and (b) highlight that while MDT-NNSO-hy generally improves recommendation effectiveness, there is notable room for enhancement, particularly for category B users. Specifically, the precision, recall, and F1 scores for category B users are significantly lower compared to category A. Despite MDT-NNSO-hy outperforming comparison models overall, this disparity indicates a need for further refinement. The model should better address the personalized needs and emotional characteristics of category B users to improve the relevance and effectiveness of recommendations for this group.

To further evaluate the performance of intelligent, emotional topic recommendations, we conducted a confusion matrix analysis for users in categories A and B. Microblog topics were categorized into positive, negative, and neutral sentiments. The results are displayed in Fig. 9, where sub-figures (a) and (b) show the confusion matrix analysis for categories A and B, respectively. In the confusion matrix, values along the diagonal represent the probability of correct model recommendations, with higher diagonal values indicating more accurate predictions. Conversely, off-diagonal values reflect misclassifications by the model. The results indicate that the recommendation algorithm performs less effectively for category B users, particularly in recommending positive and negative topics. This suggests a need for targeted improvements in recommending these emotionally charged topics to enhance the algorithm's performance for category B users. In the future, we will utilize sentiment dictionaries to conduct preliminary sentiment polarity judgments on texts and perform fine-grained sentiment classification. This will facilitate more accurate identification of positive and negative emotions in Weibo, enabling deep learning models to capture the complex semantics and emotional tendencies within texts, thereby improving the accuracy of sentiment analysis.

When applying hypergraph-optimized neural network architectures to process large-scale datasets, trade-offs exist between the expansion of computational costs, accuracy, and computational time, as well as other potential limitations. To overcome these limitations, it is imperative to adopt suitable optimization strategies such as model pruning, sampling techniques, and parallel computing. Simultaneously, there is a need to continually explore novel algorithms and technologies to enhance the efficiency and performance of hypergraph neural networks in dealing with large-scale datasets.

V. CONCLUSION

To address the demands for emotion perception and real-time performance in intelligent recommendation systems for user emotional topics in social media, this paper integrates adaptive deep learning and dynamic topic detection techniques. The MDT-NNSO-hy user emotion topic recommendation model combines the MDT recommendation model with the NNSO-hy model to enhance the accuracy and timeliness of personalized recommendations. The model refines candidate topic selection based on the MDT recommendation framework and incorporates users' historical behavioral patterns, thereby improving recommendation precision. Additionally, it employs dynamic window technology to monitor and adapt to the evolving nature of news topics in real-time, ensuring rapid adjustment of recommended content. Experimental results demonstrate that the proposed dynamic breaking news topic detection model and the MDT-NNSO-hy user sentiment topic recommendation model achieve high performance across multiple datasets. However, challenges remain in accurately capturing the needs of user groups with lower sensitivity or engagement with news topics, as their subtle emotional expressions are complex to detect. Future research can use deep reinforcement learning for adaptive personalization, multimodal data fusion to capture nuanced emotional cues, and advanced neural architectures like transformers for improved contextual understanding to better mine and extract personalized needs and subtle emotional traits.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers whose comments and suggestions helped improve this manuscript.

REFERENCES

[1] L. Zhang, L. Xu, and W. Zhang, "Social media as amplification station: Factors that influence the speed of online public response to health emergencies," *Asian J. Commun.*, vol. 27, no. 3, pp. 322–338, 2017.
[2] J. Ding, X. Chen, P. Lu, Z. Yang, X. Li, and Y. Du, "DialogueINAB: An interaction neural network based on attitudes and behaviors of interlocutors for dialogue emotion recognition," *J. Supercomput.*, vol. 79, no. 18, pp. 20481–20514, Dec. 2023.
[3] Z. Qin, S. Yang, and Y. Zhong, "Hierarchically gated recurrent neural network for sequence modeling," in *Proc. Adv. Neural Inf. Process. Syst.*, 2024, pp. 1–15.
[4] Y. Wang, Y. Huang, M. Xiao, S. Zhou, B. Xiong, and Z. Jin, "Medium-long-term prediction of water level based on an improved spatio-temporal attention mechanism for long short-term memory networks," *J. Hydrol.*, vol. 618, Mar. 2023, Art. no. 129163.
[5] T. Li, S. Hui, S. Zhang, H. Wang, Y. Zhang, P. Hui, D. Jin, and Y. Li, "Mobile user traffic generation via multi-scale hierarchical GAN," *ACM Trans. Knowl. Discovery Data*, vol. 18, no. 8, pp. 1–19, Sep. 2024.
[6] L. Li, H. Wen, and Q. Zhang, "Characterizing the role of Weibo and WeChat in sharing original information in a crisis," *J. Contingencies Crisis Manage.*, vol. 31, no. 2, pp. 236–248, Jun. 2023.
[7] S. Wang, C. Christensen, W. Cui, R. Tong, L. Yarnall, L. Shear, and M. Feng, "When adaptive learning is effective learning: Comparison of an adaptive learning system to teacher-led instruction," *Interact. Learn. Environments*, vol. 31, no. 2, pp. 793–803, Feb. 2023.
[8] F. Huang, Z. Wang, X. Huang, Y. Qian, Z. Li, and H. Chen, "Aligning distillation for cold-start item recommendation," presented at the *Proc. 46th Int. ACM SIGIR Conf. Res.*, 2023.
[9] M. A. Osman, S. A. Mohd Noah, and S. Saad, "Ontology-based knowledge management tools for knowledge sharing in organization—A review," *IEEE Access*, vol. 10, pp. 43267–43283, 2022.
[10] W. Kaiss, K. Mansouri, and F. Poirier, "Effectiveness of an adaptive learning chatbot on Students' learning outcomes based on learning styles," *Int. J. Emerg. Technol. Learn. (iJET)*, vol. 18, no. 13, pp. 250–261, Jul. 2023.
[11] A. Ramadhan, H. L. H. S. Warnars, and F. H. A. Razak, "Combining intelligent tutoring systems and gamification: A systematic literature review," *Educ. Inf. Technol.*, vol. 29, no. 6, pp. 6753–6789, 2024.
[12] L. E. Y. E. Idrissi, I. Akharraz, and A. Ahaitouf, "Personalized E-learning recommender system based on autoencoders," *Appl. Syst. Innov.*, vol. 6, no. 6, p. 102, Oct. 2023.
[13] H. Abdel-Jaber, D. Devassy, A. A. Salam, L. Hidaytallah, and M. EL-Amir, "A review of deep learning algorithms and their applications in healthcare," *Algorithms*, vol. 15, no. 2, p. 71, Feb. 2022.
[14] J. Luo, W. Si, and Z. Deng, "New classes inference, few-shot learning and continual learning for radar signal recognition," *IET Radar, Sonar Navig.*, vol. 16, no. 10, pp. 1641–1655, 2022.
[15] Y. Lin, Y. Endo, J. Lee, and S. Kamijo, "Bandit-NAS: Bandit sampling and training method for neural architecture search," *Neurocomputing*, vol. 597, Sep. 2024, Art. no. 127684.
[16] W. Xu, Y. L. Fu, and D. Zhu, "ResNet and its application to medical image processing: Research progress and challenges," *Comput. Methods Programs Biomed.*, vol. 240, Jun. 2023, Art. no. 107660.
[17] Z. Sun, G. Wang, P. Li, H. Wang, M. Zhang, and X. Liang, "An improved random forest based on the classification accuracy and correlation measurement of decision trees," *Expert Syst. Appl.*, vol. 237, Mar. 2024, Art. no. 121549.
[18] J. Wang, L.-P. Wang, S.-S. Yuan, F. Li, J.-X. Liu, and J.-L. Shang, "NLRRC: A novel clustering method of jointing non-negative LRR and random walk graph regularized NMF for single-cell type identification," *IEEE J. Biomed. Health Informat.*, vol. 27, no. 10, pp. 5199–5209, Oct. 2023.
[19] Z. Zhang, J. Wan, M. Zhou, Z. Lai, and C. J. Tessone, "Temporal burstiness and collaborative camouflage aware fraud detection," *Inf. Process. Manage.*, vol. 60, no. 2, 2023, Art. no. 103170.
[20] Z. Zeng, L. Cui, M. Qian, Z. Zhang, and K. Wei, "A survey on sliding window sketch for network measurement," *Comput. Netw.*, vol. 226, May 2023, Art. no. 109696.
[21] A. J. Myles, R. N. Feudale, Y. Liu, N. A. Woody, and S. D. Brown, "An introduction to decision tree modeling," *J. Chemometrics*, vol. 18, no. 6, pp. 275–285, Jun. 2004.
[22] D. Chakraborty, H. Babu Singu, A. Kumar Kar, and W. Biswas, "From fear to faith in the adoption of medicine delivery application: An integration of SOR framework and IRT theory," *J. Bus. Res.*, vol. 166, Nov. 2023, Art. no. 114140.
[23] S. Pan, G. J. W. Xu, K. Guo, S. H. Park, and H. Ding, "Video-based engagement estimation of game streamers: An interpretable multimodal neural network approach," *IEEE Trans. Games*, vol. 1, no. 2, pp. 1–12, Dec. 2023.
[24] W. Zheng, L. Lin, X. Wu, and X. Chen, "An empirical study on correlations between deep neural network fairness and neuron coverage criteria," *IEEE Trans. Softw. Eng.*, vol. 50, no. 3, pp. 391–412, 2024.

CHANGCHUN TAO received the B.A. degree in Chinese language and literature from Hubei University of Arts and Sciences, Hubei, China, in 1996, and the M.S. degree in journalism and communication and the Ph.D. degree from Wuhan University, Hubei, in 2006 and 2014, respectively. Before he became an Associate Professor at Wuhan Textile University, in 2006, he worked as a journalist for ten years and won several national and provincial awards. He is chairing a provincial sociological research program and has chaired two other provincial sociological philosophy programs. He is currently an Assistant Director of *Sports Vision* magazine.

BILAL ALATAS received the B.S., M.S., and Ph.D. degrees from Firat University. He is currently a Professor in software engineering at Firat University, where he is also the Head of the Software Engineering Department. He is the Founder Head of the Computer Engineering Department, Munzur University, and Software Engineering Department, Firat University. He has published over 250 papers in many well-known international journals and proceedings of the refereed conference since 2001. He has been an editor of 12 journals five of which are indexed in SCI and reviewer of seventy SCI-indexed journals. His research interests include artificial intelligence, data mining, social network analysis, metaheuristic optimization, and machine learning.