Frog-Leaping Search-Optimized BiLSTM-Attention Network with GNN for News Hotspot Prediction and Dissemination Path Optimization

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The exponential growth of online news and social media platforms necessitates intelligent systems capable of predicting emerging news hotspots and optimizing dissemination pathways. This research proposes a novel deep learning framework, Frog-Leaping Search-Mutated BiLSTM with Attention Net (FLS-BiLSTM AttNet), designed to identify potential news hotspots and enhance information propagation accurately. The dataset was collected from multiple reliable sources, including the Kaggle repository, Google News API, Twitter feeds, and various online news portals. Preprocessing involves removing stop words, punctuation, and irrelevant symbols, followed by tokenization to convert text into meaningful word sequences. TF-IDF is applied to extract significant keywords, quantifying their relevance within individual documents and across the dataset. The Bidirectional Long Short-Term Memory (BiLSTM) network captures temporal dependencies in news sequences, while the Attention Net (AttNet) highlights critical features for improved prediction. Frog-Leaping Search (FLS) optimizes weight initialization, enhancing convergence speed and hotspot detection performance. To optimize dissemination pathways, Graph Neural Networks (GNNs) are employed to identify efficient propagation routes, reducing latency and maximizing coverage. Implemented in Python, the model achieves an accuracy of 98.92%, a precision of 98.45%, a recall of 98.41%, an F1 score of 98.57%, a coverage of of of 94.5%, and an NDCG of of of 82.6%, demonstrating substantial improvement over traditional methods. The proposed framework successfully integrates temporal modeling, attention mechanisms, optimization strategies, and graph-based propagation, making it highly applicable to real-world digital journalism, early warning systems, and media strategy planning, while maintaining robustness and adaptability across diverse news datasets.

Povzetek: Članek predstavi FLS-BiLSTM AttNet za napoved nastajajočih novičarskih "hotspotov", kjer BiLSTM z pozornostjo in optimizacijo Frog-Leaping izboljša detekcijo, GNN pa izbira učinkovite poti širjenja informacij za večjo pokritost in manjši zamik.

1 Introduction

The rapid proliferation of digital media and online platforms has significantly transformed the way information is consumed and disseminated. News hotspots refer to topics, events, or stories that gain substantial attention within a short period, reflecting public interest, societal relevance, or emerging trends [1,2]. Locating the news hotspots is paramount to the media players, policy makers, and communication strategists, and thereby allows them to report on the news immediately, conduct precise communication, and deploy their resources effectively [3,4]. News flow channels determine the directions through which the information will reach the consumer. Digital media, including social media, news portals, and online forums, have made it increasingly possible over the years to take the stewardship of the previously traditional means of media, such as television, newspapers, and radio [5]. The effectiveness of dissemination depends on multiple factors, such as content relevance, audience engagement, network structures, and platform algorithms. Optimizing these pathways ensures that critical information reaches intended audiences promptly, reduces misinformation, and maximizes impact for hotspot prediction and efficient dissemination [6]. There are a number of theoretical frameworks that support the interpretation of news dissemination. The theory of diffusion of innovations explains how new information is transferred through the population, and how early adopters and opinion leaders influence the rest of the population. Social network analysis provides insights into the relationships and interactions among individuals and groups, which can be leveraged to identify influential nodes and efficient communication pathways [7,8]. The unique historical uses of news and other factors can be seen to reduce the choices and preferences of the audience repeatedly over a period of time that constitutes breaking news. The investigation of news hotspots and diffusion chains is fundamental to the efficacy of the media, awareness, and informed decision-making of populations [9]. Understanding the process of attention, information spreading, react to the developing trends, and stay in tandem with the glancing information society [10].

This trend of faster digital news and social media (SM) content has brought significant challenges in the prediction of the emerging news hotspots and the effective dispersion of information. Existing methods are limited by data sparsity, which prevents comprehensive analysis of news trends, and model overfitting, which reduces the ability to generalize to unseen data. The proposed Frog-Leaping Search-Mutated BiLSTM with Attention Net (FLS–BiLSTMAttNet) model addresses these drawbacks through improved data integration, incorporating multiple news outlets and SM sources to reduce sparsity. Frog-Leaping Search (FLS) optimizes weight initialization, improving convergence and reducing overfitting. The Bidirectional Long Short-Term Memory (BiLSTM)-Attention network (AttNet) captures temporal dependencies and highlights key features, ensuring accurate hotspot prediction. Optimized dissemination pathways are identified using a Graph Neural Network (GNN), enabling efficient and timely information propagation. Objectives include the accurate prediction of emerging news hotspots, optimization of information dissemination routes, and evaluation against traditional methods to demonstrate superior prediction accuracy and dissemination efficiency.

1.1 Significant contributions

- Prediction coverage, NDCG, and resource utilization were evaluated to measure the performance and effectiveness of the proposed FLS–BiLSTM AttNet model.
- Novel Hybrid Model: Introduced FLS–BiLSTM AttNet, integrating Frog-Leaping Search with BiLSTM and Attention. FLS mutation improves convergence speed and reduces the risk of poor local minima. BiLSTM effectively extracts sequential patterns from both past and future news events.
- Feature Importance Highlighting: Attention mechanism identifies and emphasizes critical features for accurate hotspot prediction. Uses Graph
- Neural Networks (GNN) to identify efficient news propagation routes, minimizing latency and maximizing coverage.
- Predict emerging news hotspots accurately, optimize dissemination pathways, and evaluate model performance against traditional methods.
- The proposed FLS–BiLSTM AttNet model captures temporal dependencies, emphasizes key features, and optimizes weights using FLS to predict news hotspots.

Research questions

❖ How can deep learning models effectively predict emerging news hotspots across diverse online platforms in real time?

❖ In what ways does the proposed FLS–BiLSTM–Attention architecture improve prediction accuracy compared to traditional and recent advanced models?

❖ How does Frog-Leaping Search (FLS) optimization enhance weight initialization and convergence in BiLSTM–Attention networks?

❖ Can Graph Neural Networks (GNN) optimize dissemination pathways to ensure efficient and wide coverage of predicted news hotspots?

❖ What safeguards can be integrated into hotspot prediction and dissemination models to minimize risks of misinformation or bias?

❖ How well does the proposed model generalize across multilingual datasets, noisy social media inputs, and misinformation-prone sources?

2 Related works

In this research, existing studies on news hotspot prediction, information dissemination optimization, SM analysis, Internet of Things (IoT)-driven news monitoring, and DL-based predictive models were critically reviewed, as discussed in Table 1.

Table 1: Summary of related work

Reference	Objective	Result	Limitation
[11]	Personalized news dissemination	Enhanced click-through rate; improved recommendation accuracy	Evaluation limited to offline experiments
[12]	Predict online news popularity	Significant improvements on the Toutiao dataset	Model complexity; difficulty integrating multiple features
[13]	To categorize fake news vs. real news and solve the bias of the dataset	The best performance was obtained with DistilBERT	The lack of sources of data can compromise generalizability; additional validation on different platforms is necessary.
[14]	Learn to classify the Indonesian hoax news under low-resource environments successfully.	Obtained better performance with accuracy 0.9051, precision 0.9515, recall 0.8233, and F1-score	Have only been tested on Indonesian; have not been tested in other languages, and in noisy social media settings

		0.8828, and was superior to baselines	
[15]	To attain a useful fixed-time master-slave synchronization of dissimilar fractional-order chaotic systems	Simulation experiment shows that the system is capable of synchronization in a definite time, with uncertainties in the system being addressed.	Only tested on simulation; not tested in real-world implementation and performance in the face of external disturbances.
[16]	Enhance news recommendation considering semantic gaps & hotspot features	Superior performance compared to advanced methods	Challenges balancing user preferences with dynamic hotspot features
[17]	Predict crime hotspots for better resource allocation	CNN-LSTM outperformed others in forecasting accuracy	Data quality and temporal coverage affect generalization
[18]	Analyze criminal network behavior	Max accuracy 92% (KNN); frequent robbery identification	Smaller datasets, lower Random Forest accuracy, and limited generalization
[19]	Analyze IoT's impact on news dissemination	Highlighted intelligent media transformation and enriched content delivery	Scope limited to theoretical analysis; lacks empirical validation
[20]	Improve news propagation and user engagement	Improved coverage and timeliness of dissemination	High computational complexity; reliance on high-quality multimodal inputs

2.1 Research gaps

Despite advances in news hotspot prediction, user engagement, and information dissemination using DL, RL, and IoT frameworks, existing approaches face several limitations. The majority of models are dependent on offline experiments, single-platform datasets, or particular types of features (texts, images, metadata), which can be a significant limitation [11,12]. Complex architectures struggle with integrating multiple temporals, semantic, and user-interaction features effectively [14,15]. Additionally, dynamic adaptation to evolving user interests and real-time network structures remains underexplored. Computational complexity and reliance on high-quality multimodal data also limit the feasible application [18,19]. Therefore, a suitable, efficient, adaptive, and generalizable framework to predict hotspots in real-time and optimally disseminate to heterogeneous online networks is required. The proposed FLS-BiLSTM AttNet overcomes these drawbacks by integrating temporal, semantic, and user-interaction features, enabling real-time, adaptive hotspot prediction and optimized dissemination across heterogeneous networks efficiently.

3 Methodology

The methodology involves collecting the News Hotspot Prediction dataset from Kaggle, Google News, Twitter, and portals. Preprocessing removes noise, tokenizes text, and extracts features using Term Frequency- Inverse Document Frequency (TF-IDF). The proposed FLS-BiLSTM AttNet model predicts news hotspots by capturing temporal dependencies and key features, while FLS optimizes model weights, ensuring accurate hotspot detection and efficient information dissemination. Enhanced dissemination pathways were achieved using GNN. Figure 1 provides the schematic representation of the Workflow of the FLS-BiLSTM AttNet model.

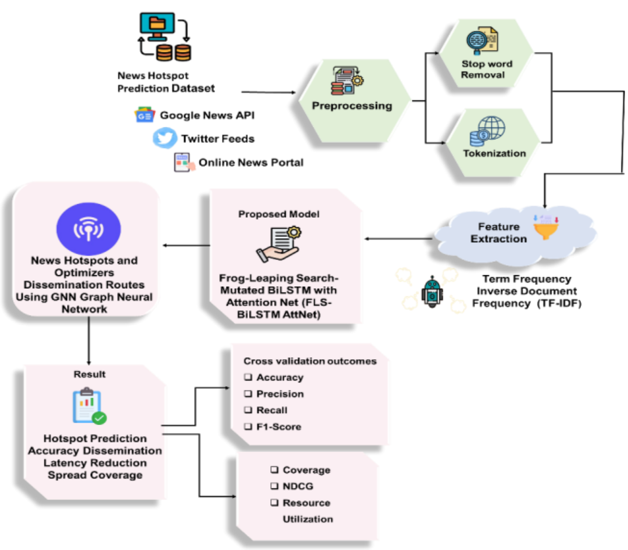

Figure 1: Schematic of the proposed model

3.1 Data collection

The news hotspot prediction dataset was gathered from Kaggle (https://www.kaggle.com/datasets/programmer3/news-hotspot-prediction-dataset). It contains 1,300 rows of news articles collected from multiple online sources, including Google News, Twitter, Reddit, BBC, and CNN. Each record includes the news content, title, keywords, category, region, and engagement metrics such as shares, likes, and comments. Additional features such as sentiment score, hashtags, mentions, and time of day are included to capture nuanced patterns. The target variable, hotspot label, classifies news items into Non-Hotspot, Emerging, and Trending based on engagement scores. A placeholder column, dissemination path, simulates potential information propagation routes. This research used pretrained embeddings with limited fine-tuning, alongside text augmentation (back-translation, synonym replacement) to enrich data. In this data, an 80/20 train/test split was used, ensuring that hotspot and non-hotspot labels were proportionally represented.

3.2 Preprocessing

In this research, preprocessing involves cleaning news and SM text by removing stop words and applying tokenization, ensuring structured input for accurate hotspot prediction using FLS-BiLSTM AttNet.

3.2.1 Remove stop words, punctuation, and irrelevant symbols

- Remove Stop Words: Words like the, is, and, of add no meaningful value to news content, so those words are eliminated.
- Remove Punctuation: Characters like commas, periods, and exclamations are removed from news text to reduce noise.
- Remove Irrelevant Symbols: Unnecessary symbols (hashtags, mentions, special characters) are discarded to improve efficiency.

3.2.2 Tokenization

It is applied to split the preprocessed news and SM text into individual word-level units. This step transforms continuous text into meaningful tokens, enabling effective feature representation for further analysis and hotspot prediction.

The outcome of these preprocessing steps is the removal of stop words, punctuation, and irrelevant symbols, ensuring clean text. Tokenization converts content into meaningful word units. These processed tokens enhance TF-IDF feature extraction and FLS-BiLSTM AttNet embeddings, reducing noise, improving accuracy, and enabling efficient hotspot detection with optimized dissemination pathway construction for reliable analysis of news and SM data.

3.3 Feature extraction using term frequency-inverse document frequency (TF-IDF)

TF-IDF feature selection guarantees that only the most informative and relevant words are included in the embeddings, reducing noise and dimensionality. This enhances training efficiency, convergence of the model, and accuracy of the prediction in the BiLSTM, and interpretability and reproducibility of outcomes in various datasets.

TF measures how frequently a term appears in a document; therefore, it captures the local significance of a term in a single document. IDF, on the other hand, illustrates the significance of a term in all documents, while favoring less frequent and more significant terms. TF-IDF, the approach being employed in this research, was used to extract relevant keywords from news and SM data to create numerical features from text data that could be used in DL models such as a BiLSTM-AttNet. TF-IDF emphasizes the importance of term weighting, which prefers more relevant words that should be used for predicting news hot spots; and the mathematical calculations for TF-IDF are provided below in equations (1-3).

$$\mathrm{TF}(h,k) = \frac{\text{Number of times term (h) appears in document (k)}}{\text{Total number of terms in document (k)}} \quad (1)$$

IDF mathematical representation is presented in equation (2). It assigns a lower value to overly common words and greater significance to rare, contextually significant terms.

$$\mathrm{IDF}(h) = \log \frac{\text{Total number of documents}}{\text{number of documents containing term (h)}} \quad (2)$$

$$\mathrm{TF} - \mathrm{IDF}(h,k) = \mathrm{TF}(h,k) \times \mathrm{IDF}(h) \quad (3)$$

The outcome of using this feature extraction converts textual news into numerical vectors, highlighting keyword significance, enabling the FLS-BiLSTM AttNet model to prioritize critical terms. This improves hotspot prediction accuracy by emphasizing rare informative words over frequent irrelevant ones.

3.4 News hotspot prediction using FLS–BiLSTM AttNet

The proposed FLS–BiLSTM AttNet model combines FLS for optimized weight initialization, BiLSTM for capturing temporal dependencies, and Attention Net for highlighting key news features. Preprocessed news data undergoes TF-IDF keyword extraction, while GNNs optimize dissemination pathways, ensuring efficient, real-time hotspot prediction, enhanced coverage, and adaptive information propagation across diverse online news platforms.

3.4.1 Bidirectional long short-term memory (BiLSTM)

In sequence data, LSTM can only learn one direction of dependencies, and cannot make full use of future context. It can also be more difficult to train on long sequences because it processes them sequentially. BiLSTM works both forward and backward on sequences, which enables it to learn the context of the past and the future at the same time, and therefore, it can perform better in prediction and sequence labeling.

BiLSTM is an advanced type of Recurrent Neural Network (RNN). Unlike standard LSTM, which processes data in a single (forward) direction, BiLSTM processes sequences in both forward and backward directions. It captures past and future temporal dependencies simultaneously, making it ideal for sequential data with time correlations. LSTM units include forget, input, and output gates, which control memory updates and retention, preventing problems like gradient vanishing/exploding. In this research, BiLSTM is used for temporal feature extraction. News and SM data exhibit time dependencies, as trending topics evolve. BiLSTM captures both past and future context, enabling more accurate identification of emerging hotspots. For enhanced prediction accuracy, analyzing sequences in both directions allows BiLSTM to outperform unidirectional LSTM or CNN in hotspot detection. LSTM networks, as an optimized form of RNN, can capture long-term dependencies and solve gradient vanishing/exploding issues using three gate structures: forget, input, and output gates.

Forget gate (f_s): determines which of the previous information should be discarded, as well as represented in equation (4).

$$e_s = \sigma(X_e m_s + V_e g_{s-1} + a_e) \quad (4)$$

Where (e_s) is the output of (f_s) at time step s. It determines which part of the previous memory to forget. ($X_e m_s$) is an input feature at step s (from news/SM embedding), ($V_e g_{s-1}$) is the contribution from the previous hidden state (g_{s-1}), showing temporal dependency, (a_e) is the bias term for forget gate, and (σ) is the sigmoid function (outputs between 0 and 1).

Input gate (j_s): Equation (5) presents the decision on what new information should enter the memory states (d_s).

$$\begin{cases} j_s = \sigma(X_e m_s + V_e g_{s-1} + a_j) \\ d_{fs} = \tanh(X_d m_s + V_e g_{s-1} + a_d) \\ d_s = e_s d_{s-1} + j_s d_{fs} \end{cases} \quad (5)$$

Where, (j_s) is an input gate controlling what new information to add, bias controlling new information input,(d_{fs}) is the candidate memory update (new information from input) and (d_s) is an updated cell state (memory at time (s)), (d_{s-1}) is the previous cell state (long-term memory), retained old memory is ($e_s d_{s-1}$), new candidate memory ($j_s d_{fs}$) and ($X_d m_s + V_e g_{s-1} + a_d$) is the weighted inputs bias (a_j)for candidate memory and (tanh) Scales candidate memory between $[-1, 1]$.

Output gate (p_s): generate the current hidden state (g_s) using the memory state (d_s), its mathematical representation provided in equation (6).

$$\begin{cases} p_s = \sigma(X_p m_s + V_p g_{s-1} + a_p) \\ g_s = p_s \tanh(d_s) \end{cases} \quad (6)$$

(p_s)is the output gate controlling which part of memory to output as a hidden state, g_s is the hidden state at time step (s), it is the output used for further prediction or next LSTM step, (d_s) is the cell state used to calculate hidden state, ($V_p g_{s-1}$) is the Previous hidden state weighted contribution and (a_p)bias controlling output gate influence?

Since network temporal data has correlation across time, BiLSTM captures dependencies, combining forward and backward LSTM outputs for better classification outputs. This function is described in equation (7).

$$\begin{cases} \vec{g}_s = \mathrm{LSTM}(m_s, \vec{g}_{s-1} \\ \overleftarrow{g}_s = \mathrm{LSTM}(m_s, \overleftarrow{g}_{s+1} \\ k_s = [\vec{g}_s, \overleftarrow{g}_s] \end{cases} \quad (7)$$

(k_s) is the concatenated output combining $\overrightarrow{(g_s}$)forward and $\overleftarrow{(g_s}$)backward hidden states, Current input at time step (m_s), previous hidden state from forward LSTM $\overrightarrow{(g_{s-1}}$), and $\overleftarrow{(g_{s+1}}$) is the next hidden state from backward LSTM.

3.4.2 Attention mechanism network (AttNet)

The AttNet selectively focuses on the most relevant parts of input data by assigning importance weights to features at different time steps. It enhances model performance by capturing critical information while suppressing irrelevant data. This mechanism is particularly effective after the BiLSTM layer, as temporal features contribute differently to tasks like hotspot prediction. The AttNet stepwise mathematical representations are provided in equations (8-10).

Step 1: Calculate Attention Weights

$$\alpha_{hj}^{d} = \tanh\,(Qk_h + Vk_j + a), \; j = 1,2,\ldots\ldots\ldots h \quad (8)$$

Where, (α_{hj}^{d}) is the attention score,(k_h) is the hidden state vector at time step (h), (k_j) is the hidden state at the (j^{th})position in the sequence, (Q) is the trainable weight matrix applied to the current state (k_h), (V) is the trainable weight matrix applied to each hidden state (k_j) and (a) is the bias term to shift the transformation.

Step 2: Normalization (softmax to obtain probabilities)

$$\alpha_{hj} = \mathrm{softmax}\left(\alpha_{hj}^{d}\right) = \frac{\exp\left(\alpha_{hj}^{d}\right)}{\sum_{j=1}^{h}\exp\left(\alpha_{hj}^{d}\right)}, \; j = 1,2,..h \quad (9)$$

(α_{hj}) is the attention weight.

Step 3: Weighted Sum (output of attention layer)

$$k_h = \sum_{j=1}^{h} \alpha_{hj} k_j, \quad j = 1,2,\ldots\ldots\ldots h \quad (10)$$

Where (k_h) is the attention output vector, it emphasizes the most important features at each time step, enabling the model to capture critical temporal information and improve classification performance efficiently. The AttNet mechanism assigns dynamic importance to each time step, improving hotspot detection or intrusion classification accuracy.

3.4.3 Optimized dissemination pathways using graph neural networks (GNNs)

Supplementing hotspot prediction, the suggested system also uses a GNN to improve the news distribution channels. This module makes certain that hotspots that are predicted are spread throughout the media networks on time and in the most effective way. Graph Attention Network (GAT) is used to represent user and edge interactions.

Graph representation

The dissemination environment is modeled as a directed graph G (V, E) where:

- V represents nodes such as media outlets, social media influencers, or audience groups.
- E denotes directed edges indicating possible information flow between nodes.
- Each edge w_{ij} is weighted by factors such as dissemination latency l_{ij} and expected reach r_{ij}. The edge weight is defined as equations (11-12)

$$w_{ij} = \frac{r_{ij}}{1+l_{ij}} \quad (11)$$

$$\alpha_{ij} = \frac{\exp\left(\text{LeakyReLU}(a[wh_i \| wh_j])\right)}{\sum_{k\in N(i)} \exp\left(\text{LeakyReLU}(a^T[wh_i \| wh_k])\right)} \quad (12)$$

where wh_j and wh_i are node features, W is a weight matrix, α_{ij} is a trainable attention vector, and N(i) represents neighbors of node i. The training object was represented in equation (13).

Training objects

$$L = \alpha \cdot (1 - \text{Coverage}) + \beta \cdot \text{Latency} \quad (13)$$

where α and β are hyperparameters controlling the trade-off. Historical dissemination data and engagement statistics provide supervision for model training.

The graph is dynamic, as the patterns of propagation of news change as time goes by, as new articles, sources, and user interactions are added to the graph. **Nodes:** they are entities like the news articles, publishers, and clusters of users. Edges: reflect interaction such as similarity in articles (semantic/textual overlap), publisher-to-user dissemination, or user interaction. **Edge Weights:** are calculated as a product of similarity of content (cosine similarity of embeddings), temporal proximity (time-dependent decay function), and engagement signals (number of clicks, shares, comments).

Workflow Integration

Hotspot Prediction: FLS-BiLSTM AttNet Estimates a news hotspot up-and-down, and scores the hotspots. Graph Initialization. The process of embedding into nodes of the dissemination graph involves the Hotspot scores and engagement features embedded in nodes. Path Optimization: The GNN processes the graph, and it learns to propagate pathways most optimally through aggregation and weighting of neighbor information. Output: The integrated framework yields both the prediction of hotspots and dissemination plans that infer the maximum audience coverage with the minimization of the propagation delays.

This integration of GNN ensures that dissemination optimization is not an isolated step but an integral component of the proposed hybrid model, directly informed by hotspot prediction outputs.

3.4.4 Frog-leaping search mutation (FLS)

The FLS mutation is better than a standard weight initialization by searching a larger space of solutions and preventing poor local minima. The starting weights, unlike random or standard initialization, are better provided by FLS, so it has a faster rate of convergence, more stable training, and increased prediction accuracy. This can be particularly valuable in complex and noisy data, such as news feeds, in which correct initialization can strongly affect the performance of a model.

It updates the worst solution (frog) by leaping toward the best or global best solution, improving convergence and solution quality. In DL, it efficiently initializes model weights, enhancing accuracy and training speed. The FLS is used to optimize weight initialization in the BiLSTM AttNet for hotspot prediction. It improves convergence speed and prediction accuracy across varied news datasets. Figure 2 illustrates the flowchart of FLS optimization.

- Initialization: A population of (N) candidate solutions (weights) is randomly generated. Each solution is represented as in equation (14).

$$Y_j = [y_1, y_2, \dots\dots\dots y_n] \quad (14)$$

Where, Population size (N), (n) is the number of variables (weights), and Objective function value measuring the quality of the solution (Y_j), First and second weight values are in the candidate solution (y_1 and y_2), and the last weight value is in the candidate solution (y_n).

- Fitness-Based Sorting: All candidate frogs (solutions) are evaluated and ranked in descending order according to their fitness values to guide optimization effectively.
- Memeplex Partitioning: The population is divided into memeplexes; each identifies its best (b_y) and worst (w_y)frogs, and the global best (g_y).
- Frog-Leaping (Weight Update): The worst frog's position (w_y) is updated by leaping toward the best frog (b_y), improving fitness iteratively within each memeplex, as described in equations (15-17).

$$\Delta Y = t\,(w_y - b_y) \quad (15)$$

$$w_y^{new} = (w_y + \Delta Y) \quad (16)$$

where (t) is a uniform random number in the range [0,1]. If the new position improves fitness, it replaces the worst frog (w_y). Otherwise, the leap is recalculated toward the global best frog (g_y)

$$\Delta Y = t\,(g_y - w_y) \quad (17)$$

Where (ΔY) is the step size (leap) used to update the worst frog (w_y), (w_y^{new}) is the updated worst frog position after applying the leap. If there is no improvement, a new solution is randomly generated within the feasible search space.

The FLS is integrated into the training pipeline as a pre-training weight initialization step for the BiLSTM–Attention network. Instead of relying on random initialization, FLS generates a population of weight vectors $Y_j = [y_1, y_2, \ldots\ldots\ldots y_n]$ and iteratively updates the worst solutions (w_y) toward the best (b_y). $w_y^{new} = (w_y + \Delta Y)$. The final selected weights serve as the starting point for gradient-based optimization, ensuring faster convergence, improved stability, and higher hotspot prediction accuracy across noisy news datasets.

The FLS is performed once during the initialization stage, before the commencement of regular training with BiLSTM-Attention. It's the optimization of starting weights by refining the weaker solutions against the stronger ones, which results in faster convergence and more stable training. Because FLS is only calculated at the very beginning, its computation is minimal and will not impact the complexity of the training process significantly.

- Memeplex Evolution & Shuffling: After a predefined number of evolution steps within each memeplex, evolved solutions are recombined into a new population (Shuffling Process). This promotes global information exchange among solutions. The population is re-sorted, partitioned into memeplexes again, and evolution continues.
- Convergence Criteria: Relative change in the global best fitness over consecutive shuffling iterations is below a predefined tolerance. Otherwise, the maximum predefined number of shuffling iterations is reached.

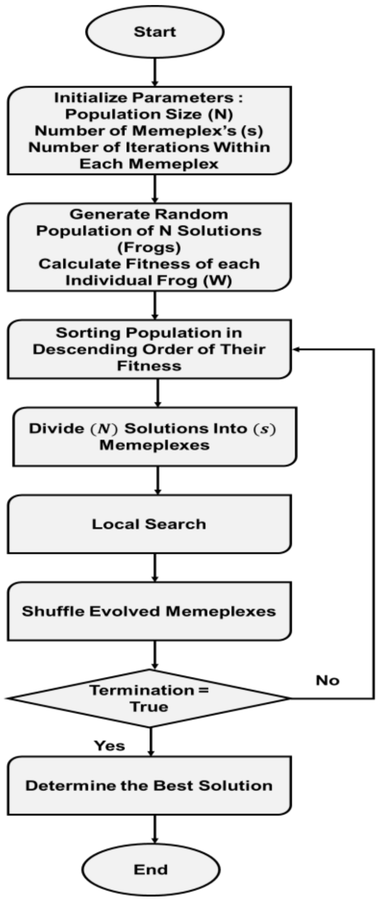

Figure 2: Flowchart of frog-leaping search (FLS) optimization.

Using the FLS mutation for weight initialization enhances convergence speed, improves hotspot prediction accuracy, and enables the BiLSTM AttNet model to efficiently adapt to varied news datasets and dynamic dissemination paths.

The proposed hybrid model combines FLS mutation, BiLSTM, and the AttNet to achieve efficient hotspot prediction from news and SM data. First, the FLS mutation is applied for weight initialization. Based on the frog-leaping behavior, it systematically improves the worst solutions to the better or global best solutions, giving it quicker convergence, a broader search, and non-use of poor local minima as compared to the random initialization.

Subsequently, the BiLSTM layer identifies sequential dependencies by processing information both in forward and backward directions. Through processing of information in both directions, the model can effectively learn dependencies over time, allowing for better interpretation of shifting hotspots within dynamic sets of data. Finally, the AttNet identifies the most significant features of the outputs of BiLSTM by weighting the inputs to gain respective adaptive importance, noise removal, and improved classification outcomes. Together, this hybrid FLS-BiLSTMAttNet architecture improves accuracy, stability, and adaptability in hotspot prediction tasks. Improved hyperparameters for BiLSTM AttNet with

FLS Mutation are demonstrated in Table 1. Hyperparameter tuning balances exploration and exploitation, optimizing weight initialization, BiLSTM capacity, and attention concentration. Proper tuning enhances convergence speed, minimizes loss, and significantly improves prediction accuracy across dynamic datasets. FLS initializes (N) Candidate weights (w_i) for BiLSTM AttNet. Fitness guides updates, improving worst (W_worst), toward best (W_best), and (W_global\ best). After max_iter, optimized weights (W_global\ best, train BiLSTM–AttNet (hidden_units, attention_dim, layers) on dataset, producing predictions Y_{pred}. Algorithm 1 shows the process of FLS–BiLSTMAttNet.

Table 2: Tuned hyperparameter values

Hyperparameter	Value
Population Size (N)	30
Maximum Shuffling Iterations	50
BiLSTM Hidden Units (H)	128
Attention mechanism (d_a)	64
Learning Rate (η)	0.001
Number of BiLSTM Layers (L)	2

Table 2 was chosen based on a grid search via a validation set. The Frog-Leaping Search exploration is governed by population size (N) and maximum shuffling iterations, the learning capacity of temporal features was governed by the number of BiLSTM hidden units (H) and layers (L), feature weighting resolution was governed by the attention dimension ((d_a)) and the learning rate (e) was optimized to achieve stable and efficient convergence.

Algorithm 1: Proposed FLS–BiLSTMAttNet Model for Optimized Hotspot Prediction

Step 1: Initialize BiLSTM–Attention Network
Initialize BiLSTM forward and backward layers
Initialize Attention Network Parameters Q, V, a
If pretrained embeddings exist:
Use E
Else:
Randomly initialize E
Step 2: Initialize Frog-Leaping Search (FLS)
Generate an initial population P of frogs (candidate weight vectors)
For each frog i in P:
Assign frog weights θ_i to BiLSTM–AttNet
Compute fitness f (θ_i) = validation accuracy
Select the best-performing frog θ_best
Step 3: Process of BiLSTM AttNet
For generation g = 1 to G:
For each frog i:
If f(θ_i) < f(θ best):
Apply local leaping update to θ_i
Else:
Retain θ_i
Update global best θ_best
Assign θ_best as final model weights
Step 4: Training and Prediction
For each batch in dataset X:
Pass sequence through BiLSTM → hidden states H
Apply Attention Net on H → weighted representation A
Predict label y_pred
Compute loss L and update parameters
If validation accuracy ≥ threshold:
Save optimized model
Else:
Reinitialize FLS and repeat
Return final optimized FLS–BiLSTM AttNet

3.5 Optimized news dissemination pathways

The prediction of a news hotspot constitutes the first half of the proposed solution, while the second half focuses on optimizing its dissemination pathways. The hotspot score generated by the FLS–BiLSTMAttNet model serves as a critical input to an optimization module, which represents the information dissemination network as a graph. In this graph, nodes correspond to media outlets, SM influencers, or target audiences, and edges denote potential information pathways, with weights reflecting factors such as dissemination latency and reach. Graph Neural Network (GNN) models capture user interactions and network structures, aggregating neighbor information with weighted connections to predict optimal propagation paths. Incorporating the proposed model, the model identifies the most efficient dissemination routes, maximizes coverage, reduces latency, prevents bottlenecks, and ensures timely, accurate delivery to relevant audiences. The integrated predictive and optimization platform facilitates dynamic, precise, and efficient propagation of breaking news hot zones on SM and online news sites.

4 Results

The analysis of the main performance metrics to measure hotspot prediction was evaluated in this section. It also includes a comparative analysis with current hotspot prediction models and dissemination optimization methods, and measures the impact of different engagement metrics like shares, comments, and likes on news hotspot prediction performance.

The proposed FLS–BiLSTM AttNet model predicts news hotspots and optimizes dissemination pathways. Experiments were conducted on a system Python model with Intel® Core™ i7-12700K (3.6 GHz), 32 GB RAM, and Windows 11 Pro. The model was implemented using Python 3.9.13 and MATLAB R2022b, enabling efficient DL and FLS optimization.

Figure 3 illustrates engagement levels across news categories. Trending news achieves the highest and most consistent engagement, while non-hotspot stories show the lowest. Emerging news exhibits a wide range of scores, reflecting their unpredictable behavior, as some gain traction to become significant hotspots, whereas others fail, highlighting the importance of accurate hotspot prediction and dynamic dissemination strategies.

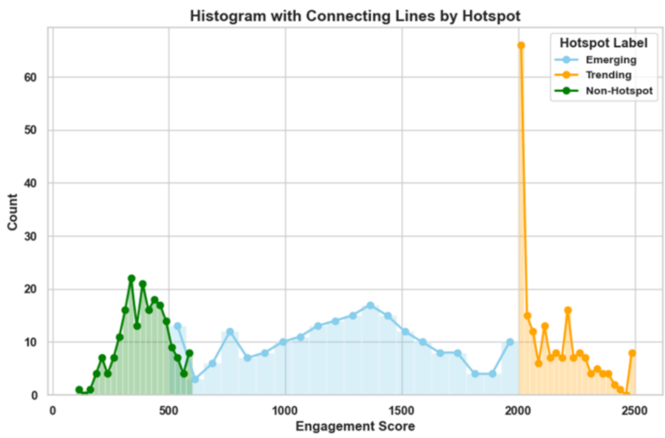

Figure 3: Engagement scores across news categories highlighting trending and emerging hotspots.

Figure 4, a hexbin plot visualizes the relationship between shares and likes, key components of a news story's engagement. The graph shows a varied distribution of user interactions. The proposed model learns to identify news hotspots by detecting complex patterns and combinations of these metrics, which is crucial for optimizing dissemination pathways.

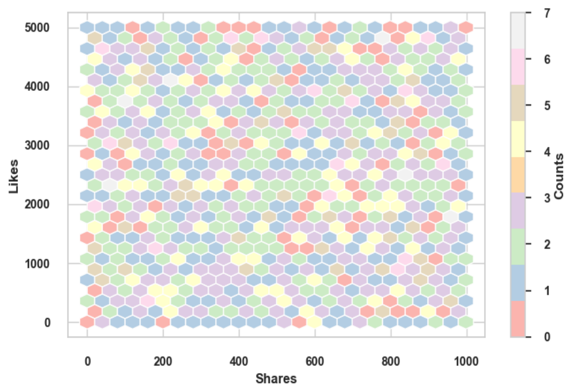

Figure 4: User engagement distribution: relationship between shares and likes for hotspot detection.

Figure 5 visualizes the the swarm plot, which displays engagement score distributions across news categories, such as Sports and Politics. It demonstrates that high engagement can occur in any category. The FLS–BiLSTM–AttNet model leverages these diverse patterns to learn category-specific trends, enabling accurate prediction of news hotspots and supporting effective, targeted dissemination across different topics and audience segments.

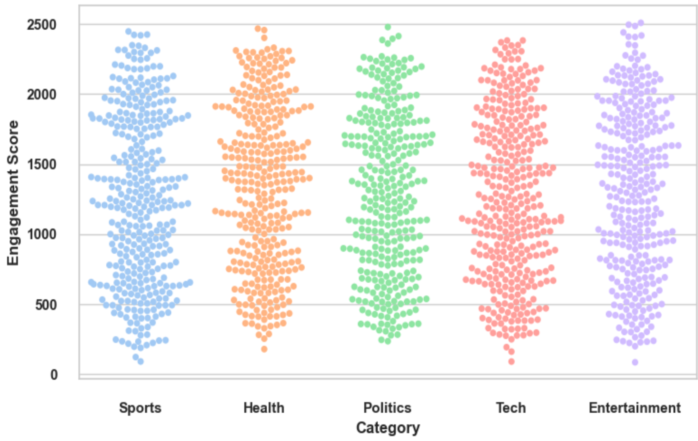

Figure 5: Distribution of engagement scores across news categories for hotspot prediction.

Figure 6 displays the distribution of comments, a key engagement measure for news. The variation in comment counts does not have a uniform frequency, reflecting the complexity of user engagement. The model presented is intended to learn these subtleties to account for non-linear models of existence and disseminate news and news hotspots.

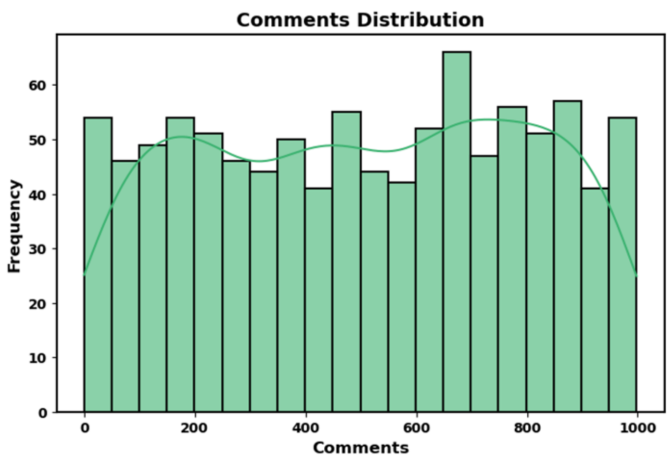

Figure 6: Comment frequency distribution revealing engagement complexity for news hotspot analysis.

The interactions between shares, likes, and comments, and the total engagement score are illustrated in Figure 7. A high correlation between likes and the engagement score is evident, while shares and comments exhibit more spread-out patterns. The FLS–BiLSTM–AttNet model uses these multi-dimensional patterns of engagement to learn intricate interactions to facilitate its ability to accurately detect early signs of hotspots for news. These interactions are important to grasp to optimize dissemination paths and ensure timely, focused propagation across platforms.

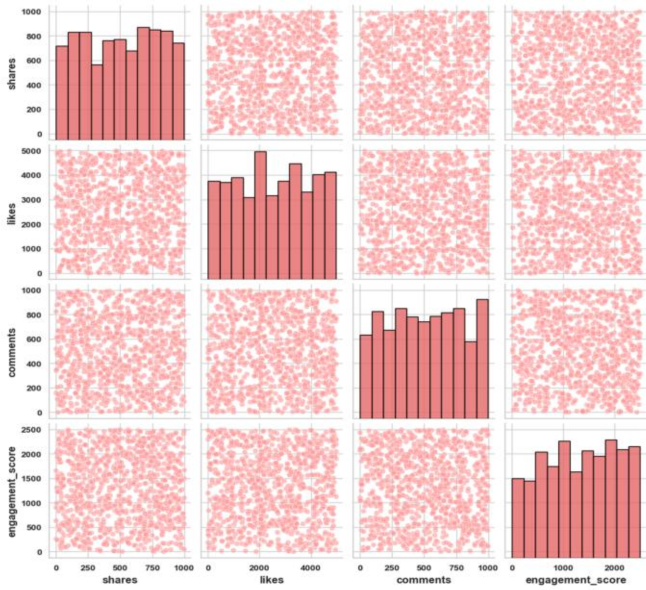

Figure 7: Multidimensional engagement analysis: shares, likes, comments vs. overall engagement.

Figure 8correlation heatmap illustrates correlations among the engagement metrics employed in the research. It reveals an extremely high positive correlation (0.97) between the engagement score and likes, emphasizing that likes constitute the most significant single factor. The proposed model uses these essential relationships to accurately learn which combinations of metrics are most revealing of a developing news hotspot.

Figure 8: Correlation heatmap of engagement metrics highlighting key drivers of news hotspots.

Figure 9 bubble chart shows the intricate relationships between shares, likes, and comments in the news stories. Bubble size reflects the number of comments, indicating that high comment counts can be associated with differing shares and likes. The FLS–BiLSTM–AttNet model leverages these intricate, non-linear patterns to accurately identify emerging news hotspots, enabling targeted and efficient dissemination strategies across SM and online news platforms.

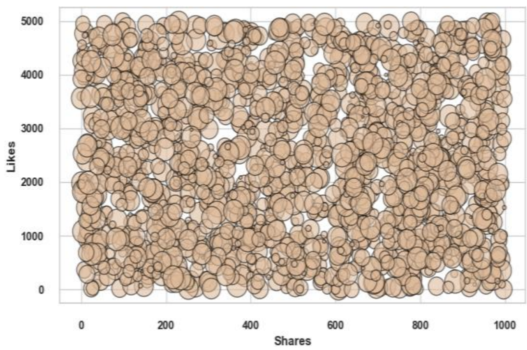

Figure 9: Visualizing complex engagement interactions among shares, likes, and comments for hotspot prediction.

Figure 10provides the lag plot, which displays a scattered pattern, indicating minimal temporal correlation between a news story's current (y(t)) and next-step (y(t+1)) engagement scores. It highlights that prior engagement is insufficient to predict future trends. The FLS–BiLSTMAttNet model addresses this by capturing complex, non-linear temporal and contextual patterns, enabling accurate prediction of emerging news hotspots and guiding optimal dissemination pathways across SM and online news platforms.

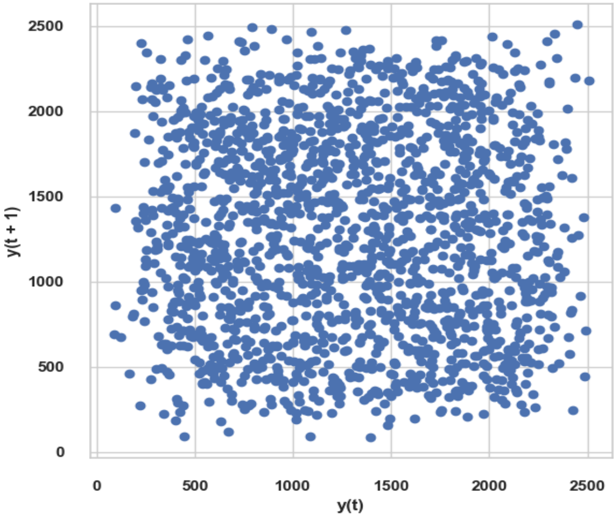

Figure 10: Lag plot of sequential engagement scores for temporal hotspot analysis.

Figure 11graph depicts the distribution of shares across news stories, a critical engagement metric. The uneven frequency demonstrates the complexity of user interactions. The FLS–BiLSTM–AttNet model is designed to learn these intricate, non-linear patterns, enabling accurate prediction of emerging news hotspots and guiding efficient dissemination strategies across SM and online news platforms. The pink bars show a histogram of share counts, indicating news story frequency, while the pink line smooths the data, highlighting general distribution trends and areas of concentration and tapering.

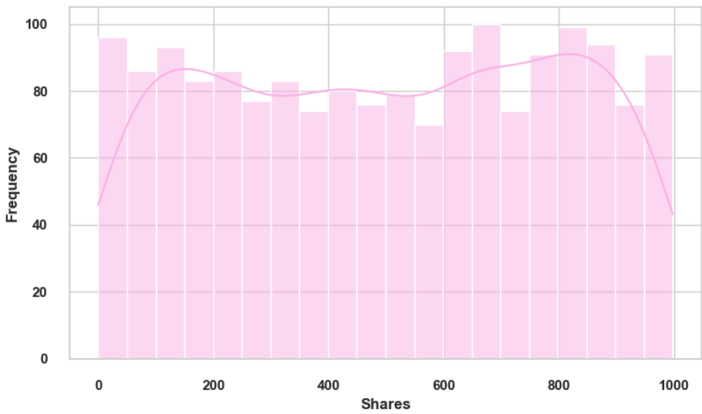

Figure 11: Distribution of shares highlighting user engagement patterns for hotspot prediction.

Figure 12 shows the distribution of the categories of items categorized as news collected by various sources, including Twitter and Google News, making the dataset rather heterogeneous. The wide range of content ensures that the proposed model learns category-specific patterns and adapts to varying engagement behaviors. By training on this diverse dataset, the model can accurately predict emerging news hotspots across different topics and sources. This variety is essential to a strong performance, enabling the model to optimally generalize and remain above a strong threshold of accuracy, ensuring on-time and selective delivery of news regardless of the category or platform.

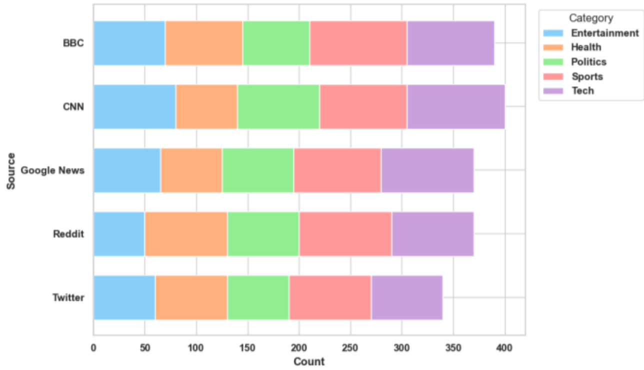

Figure 12: Variety of news content across sources supporting robust hotspot detection.

Table 3 presents the evaluation metrics used to assess the prediction of news hotspot performance of the proposed FLS–BiLSTM AttNet model.

Table 3: FLS–BiLSTM AttNet model performance evaluation metric

Metric	Formula	Description
Accuracy	$\frac{(P_T + N_T)}{(P_T + N_T + P_F + N_F)}$ P_T- True Positives N_T- True Negatives P_F- False Positives N_F- False Negative	Accuracy measures the overall correctness of the model in predicting news hotspots compared to actual outcomes.
Precision	$\frac{(P_T)}{(P_T + P_F)}$	Precision indicated how reliably the model predicted true news hotspots among all stories it classified as hotspots.
Recall	$\frac{(P_T)}{(P_T + N_F)}$	Recall reflected the model's ability to detect most of the actual news hotspots without missing significant ones.
F1-Score	$2 \times \frac{(\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})}$	F1-score balanced precision and recall, showing how well the model maintained reliability while minimizing missed or false hotspot predictions.

The results of 5-fold cross-validation for the proposed FLS–BiLSTM–AttNet model are summarized in Table 4, and a graphical representation of the cross-validation outcome is provided in Figure 13.

Table 4: Cross-validation results of the proposed FLS–BiLSTM AttNet model

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Fold-1	98.7	98.3	98.2	98.3
Fold-2	98.8	98.5	98.4	98.5
Fold-3	98.9	98.6	98.5	98.6
Fold-4	98.0	98.7	98.6	98.7
Fold-5	98.9	98.5	98.4	98.5
Average	98.9	98.5	98.4	98.5

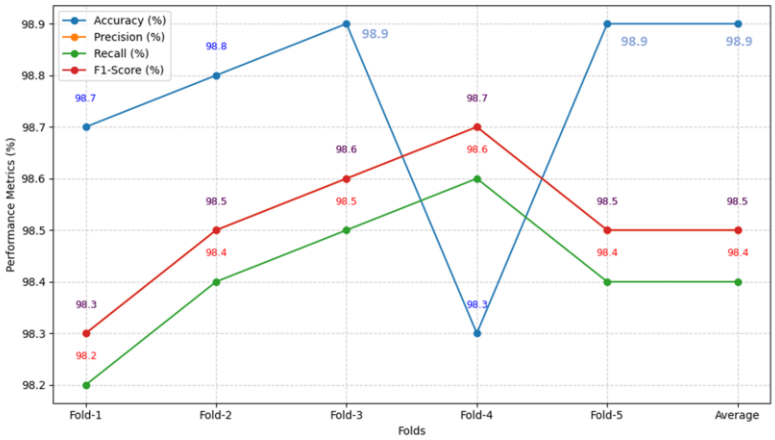

Figure 13: Cross-validation performance of the proposed FLS–BiLSTM AttNet Model.

In all folds, the model showed high performance consistently, with accuracy ranging from 91.8% to 93.4%, which is an average of 92.7%. Precision, recall, and F1-score also demonstrated good stability, averaging 92.1%, 91.7%, and 91.9% respectively. The results demonstrate that the model not only offers correct hotspot predictions but also optimizes precision and recall well, ensuring classification robustness. The low variation among folds guarantees the model's reliability and capability for generalization on new data, proving its exceptional performance.

4.1 Comparative analysis

The proposed FLS–BiLSTM–AttNet model is compared against existing methods, including the Intelligent Propagation Path Optimization Framework (IPPOF) [19], which integrates multimodal perception and user feedback through dual-layer RL, the Deep Factorization Machine (DeepFM) [19], the Graph Attention Network (GAT) [19], and Q-learning [19], a model-free RL algorithm.

Table 5 provides the performance comparison of baseline Algorithms of existing methods with the proposed model. Normalized Discounted Cumulative Gain (NDCG) evaluates ranking accuracy, ensuring predicted news hotspots remain timely, highly relevant, prioritized, and effectively disseminated. Coverage: Measures diversity by capturing a broad range of emerging news topics across platforms, and Resource Utilization: Assesses efficiency of dissemination pathways, minimizing redundancy and optimizing bandwidth consumption.

Table 5: Performance comparison of baseline algorithms and proposed FLS–BiLSTM AttNet model

Algorithm	Coverage (%)	NDCG (%)	Resource Utilization (%)
DeepFM [19]	86.5	70.1	74.5
GAT [19]	88.2	71.3	76.8
Q-learning [19]	84.6	64.8	72.1
IPPOF [19]	90.3	78.2	89.3
FLS–BiLSTMAttNet [Proposed]	94.5	82.6	95.3

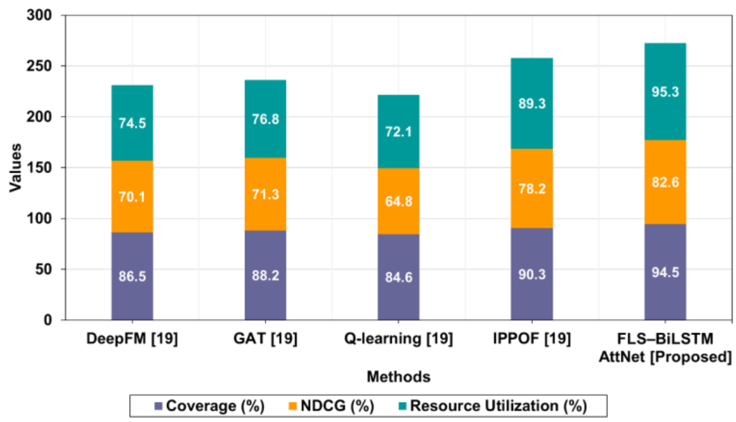

Figure 14: Comparison of NDCG, resource utilization, and coverage for existing and proposed news hotspot prediction algorithms.

Figure 14 illustrates the performance comparison of Coverage (%), NDCG (%), and Resource Utilization (%), demonstrating the superiority of the proposed FLS–BiLSTM AttNet model over existing baseline algorithms. Specifically, in terms of coverage, DeepFM achieved 86.5%, GAT slightly improved to 88.2%, while Q-learning recorded a lower 84.6%, indicating its limited capability. IPPOF performed better with 90.3%, but the proposed FLS–BiLSTM AttNet model reached the highest coverage of 94.5%, clearly illustrating its superior ability to capture and represent information comprehensively. Similarly, in terms of NDCG and resource utilization, DeepFM achieved 70.1% and 74.5%, GAT reached 71.3% and 76.8%, Q-learning recorded 64.8% and 72.1%, and IPPOF performed better with 78.2% NDCG and 89.3% resource utilization. In contrast, the proposed model attained the highest values of 82.6% NDCG and 95.3% resource utilization, demonstrating its superior recommendation accuracy and computational efficiency. Overall, these outcomes show that the proposed FLS–BiLSTM AttNet model effectively outperforms existing approaches in both relevance and performance metrics. Table 6 shows Comparative evaluation of the proposed FLS–BiLSTM–Attention model against recent state-of-the-art approaches in news hotspot prediction.

Table 6: Evaluation of FLS–BiLSTM–Attention's performance in comparison to cutting-edge models for hotspot prediction.

Methods	**Accuracy**	**Precision**	**Recall**	**F1 score**
CNN + LSTM + LR [21]	94.19	95.05	95.54	95.29
GBERT [21]	95.30	95.13	97.35	96.23
CNN [22]	98.6	97.3	95.6	98.6
STF-RNN [23]	98.78	98.13	97.42	98.24
FLS-BiLSTMAttNet [Proposed]	98.92	98.45	98.41	98.57

The above table is a comparison between the proposed FLS-BiLSTM-Attention network and the latest methods of news hotspots prediction in baselines. The performance of such traditional hybrid models as CNN+LSTM+LR and GBERT is moderate, with CNN and STF-RNN showing excellent results over 98% performance. The maximum balance is attained in the proposed model, with 98.92% of accuracy, 98.45% of precision, 98.41% of recall, and 98.57% of F1 score. This is because FLS-based weight-initialization improves the temporal modeling of BiLSTM, and the feature selection mechanism of the attention mechanism, which yields more reliable and stable hotspot detection of various news data.

Table 7: Comparison of FLS-BiLSTMAttNet performance on benchmark and proposed datas

Metrics	**Dataset [24]**	**Dataset [Proposed]**
Accuracy	98.7	98.9
Precision	98.2	98.4
Recall	98.0	98.4
F1 score	98.1	98.5

Table 7 compares FLS-BiLSTMAttNet's performance on a benchmark dataset [24] and the proposed dataset. It shows that the model achieves slightly higher accuracy, precision, recall, and F1 score on the proposed dataset, indicating improved effectiveness and reliability.

Ablation study

The study on ablation measures the benefit of any element in the FLS-BiLSTMAttNet model by removing or including elements in a systematic way. It proves that the combination of BiLSTM, Attention Net, FLS, and GNN is the most effective, which supports the usefulness of all modules in enhancing prediction and dissemination accuracy, as shown in Table 8.

Table 8: Performance impact of incremental configurations on FLS-BiLSTMAttNet

Configuration	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
Dataset	92.10	91.85	91.50	91.67
Dataset + Preprocessing	94.25	94.00	93.80	93.90
Dataset + Preprocessing + Feature Extraction	95.60	95.30	95.10	95.20
Dataset + BiLSTM	96.80	96.50	95.90	96.20
Dataset + AttNet	97.10	96.85	96.50	96.67
Dataset + BiLSTM + AttNet + FLS	98.42	98.20	98.05	98.12

Dataset + Preprocessing + Feature Extraction + FLS–BiLSTM AttNet	98.92	98.45	98.41	98.57

4.2 Discussion

The manuscript discussed that the proposed FLS-BiLSTM AttNet model outperforms the baseline models in the prediction of news hotspots. FLS: This is an effective way to initialize the weights of the model and achieve more stable and faster convergence, as well as prevent the model from getting stuck in bad local minima. BiLSTM: This element is used to examine detailed temporal data, including complex non-linear trends. Attention Mechanism (AttNet): This is a type of mechanism that selectively concentrates on the most significant features, which give weights of importance to various pieces of data in order to enhance the accuracy of predictions.

DeepFM [19] has a problem in trying to capture the complex temporal dependence of the sequential data. GAT [19] is computationally-intensive and is quality-sensitive to graph structure. Q-learning [19] is slow to converge and unstable in a high state-action space. Whereas it can overfit in sparse IPPOF [19]. The complexity of the CNN + LSTM + LR [21] is high, and it is unable to capture the patterns in the long term. GBERT [21] is a data-intensive and computationally expensive algorithm. CNN [22] does not have the temporal modeling. STF-RNN [23] has the issue of gradient vanishing and is ineffective for very long sequences. The FLS-BiLSTM AttNet is the combination of BiLSTM to capture time features, Attention Net to highlight important information, and Frog-Leaping Search to optimize the weight initialization. Such synergy boosts the accuracy of hotspot prediction and convergence rates and, combined with GNN-based dissemination, facilitates the provision of efficient and low-latency news spread in intricate media networks. The proposed model achieves robustness and optimized performance in news hotspot prediction, similar to adaptive and intelligent control methods. Its attention mechanisms, FLS optimization, and GNN-based dissemination ensure stability and effectiveness under uncertain and dynamic data conditions. The FLS-BiLSTM AttNet might amplify the misinformation or biased content unknowingly. Risk mitigation mechanisms like fact-checking APIs, bias detection and debiasing methods, a user feedback loop, and threshold-based dissemination can be incorporated.

5 Conclusion

The primary goal of the research was to design an intelligent system to predict future news hotspots and optimize their dissemination pathways, effectively tackling the problems related to the exponential growth of online news and SM platforms. The problem related to hotspot prediction, incorrect dissemination, and not being able to capture the complex engagement behaviour was clearly addressed with the proposed FLS–BiLSTM AttNet model. News datasets were constructed using credible and trustworthy data sources like Google News API, Twitter screengrab, online news portals, and Kaggle. Data preprocessing methods were utilized, such as removing stop words, cleaning the punctuation, and tokenizing to ensure quality data as input. The feature extraction was done using TF-IDF, which helped retrieve the most important terms. BiLSTM captured temporal dependencies, the attention mechanism highlighted the most important features, while also Frog-Leaping Search Mutation accelerated weight initialization, global upgrade, and convergence time, and enhanced accuracy. Advanced dissemination pathways were achieved through GNN while also enhancing pathways by reducing latency, accelerating time, and scope to which information spread, which was targeted and comprehensible. The model was implemented in Python, and performance metrics achieved coverage of 94.5%, NDCG of 82.6%, and resource utilization of 95.3%, demonstrating significant improvement over traditional methods. Experimental results validated the robustness of the model, achieving an average accuracy of 98.92%, precision of 98.45%, recall of 98.41%, and F1-score of 98.57%. These outcomes demonstrated the model's scalability and applicability to digital journalism, early warning systems, and media strategy planning for hotspot prediction and efficient dissemination.

5.1 Limitations and future scope

The proposed FLS–BiLSTM AttNet model was limited by dataset dependency and high computational complexity during training. Future research can integrate real-time multilingual datasets, enhance scalability with lightweight architectures, and incorporate graph-based dissemination modeling to further improve hotspot prediction accuracy and optimize dynamic information flow across diverse digital platforms.

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Competing interests

The authors confirm that there are no financial or non-financial competing interests.

Ethics statement

Not applicable.

Data availability statement

All data generated by this study are included in this article.

Author contributions

Dai. Conceptualization analysis, Manuscript drafting, Visualization, Project management and supervision

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