Meta-learning contrastive fusion intelligence for domain-adaptive content categorization using adaptive DNN

Janani Sivapriya Venkatakrishnan[1,2], Saravana Moorthy Raja Moorthy[2], Angel Shanmugam[3]
[1]Department of Data Science, Dwaraka Doss Goverdhan Doss Vaishnav College, Chennai, India
[2]Department of Computer Science, Kongunadu Arts and Science College, Coimbatore, India
[3]Department of Cybersecurity with Computer Science, PSGR Krishnammal College for Women, Coimbatore, India

Article Info

Article history:

Received Dec 2, 2025
Revised Jun 3, 2026
Accepted Jun 11, 2026

Keywords:

Categorization
Contrastive learning
Domain-adaptive content
Feature engineering
Meta-learning
Swarm intelligence

ABSTRACT

The rapid growth of heterogeneous digital text sources, including social media, news streams, and scientific literature, poses significant challenges to traditional content categorization models due to domain shift, vocabulary drift, and semantic inconsistencies. Existing deep learning approaches often rely on domain-specific patterns and static representations, resulting in degraded performance when applied to unseen or cross-domain data. Moreover, these methods lack scalability in real-world scenarios characterized by domain drift and limited labeled data. To address these challenges, this study proposes a meta-learning contrastive fusion intelligence (MCFI) framework for domain-adaptive content categorization. The framework integrates domain context-aware normalization (DCAN) for robust preprocessing, binary particle swarm optimization (BPSO) for selecting domain-invariant features, and a hybrid architecture combining contrastive learning-enhanced bidirectional encoder representations from transformers (CL-BERT) with capsule network-enhanced transformer (Caps-Trans). A meta-learning strategy is employed to learn domain-invariant representations and enable rapid adaptation to new domains, while contrastive learning enhances inter-domain separability. A domain-adaptive decision layer further refines feature contributions dynamically. Experimental results on multiple benchmark datasets demonstrate that the proposed MCFI framework consistently outperforms state-of-the-art methods in terms of accuracy, F1-score, and generalization, providing a scalable and effective solution for cross-domain text classification.

Corresponding Author:

Janani Sivapriya Venkatakrishnan
Department of Computer Science, Kongunadu Arts and Science College
Coimbatore, India
Email: janani.sivapriyaphd@gmail.com

1. INTRODUCTION

Social media has transformed modern communication by enabling real-time, dynamic, and large-scale sharing of opinions, experiences, and information across diverse communities. With the rapid advancement of high-speed internet and communication technologies, millions of users actively participate in social networking platforms, generating massive volumes of heterogeneous textual data [1], [2]. These platforms continuously produce opinion-rich content, making automated text classification essential for applications such as content moderation, information retrieval, and sentiment analysis [3]. However, the unstructured, noisy, and domain-variant nature of such data introduces significant challenges for traditional text classification models.

Domain categorization, which involves classifying text based on subject or context, requires models capable of generalizing across diverse linguistic patterns and domains [4], [5]. In real-world scenarios, textual data such as news articles, social media posts, and scientific discussions exhibit domain-specific vocabulary variations and semantic inconsistencies, complicating classification tasks [6], [7].

Although deep learning models, particularly transformer-based architectures such as bidirectional encoder representations from transformers (BERT) [8], have achieved remarkable success, they often suffer from domain shift, where training and testing data distributions differ. Domain adaptation techniques have been proposed to address this issue [9], [10]; however, their effectiveness is limited in large-scale heterogeneous environments with scarce labeled data [11]. Furthermore, recent studies highlight that multi-domain adaptive models struggle to maintain consistent performance under domain skew and semantic drift [12].

Advanced domain adaptation approaches, such as category attention networks [13], aim to reduce inter-domain discrepancies but often overlook feature redundancy, scalability, and adaptive feature weighting. Similarly, recent multimodal and content classification frameworks demonstrate improved performance through deep architectures [14], [15], yet remain heavily dependent on domain-specific labeled datasets and exhibit limited generalization capabilities [16].

Recent developments in contrastive learning and domain generalization, including momentum contrast [17], proxy-based contrastive learning [18], and memory-based supervised contrastive learning [19], have shown promise in improving representation robustness. Additionally, meta-learning approaches enable rapid adaptation to unseen domains [20], while few-shot learning methods enhance classification under limited data conditions [21]–[23]. Techniques such as gradient surgery [24] and cross-domain feature alignment [25] further contribute to improving generalization across domains. However, these approaches are often applied independently and lack integration with feature optimization strategies.

Consequently, several research gaps remain. First, most existing methods rely solely on deep representation learning without incorporating systematic feature engineering or optimization-based feature selection. Second, limited attention has been given to integrating meta-learning with domain adaptation for rapid cross-domain generalization. Third, contrastive learning techniques are not fully leveraged in conjunction with adaptive fusion and feature reweighting mechanisms. Finally, scalability under extreme domain drift and vocabulary variation remains a critical challenge in real-world applications [26].

To address these limitations, this study proposes a meta-learning contrastive fusion intelligence (MCFI) framework that integrates domain-aware preprocessing, swarm intelligence-based feature selection, contrastive representation learning, and adaptive deep neural modeling. The proposed approach enhances cross-domain generalization, reduces feature redundancy, and dynamically adapts to evolving textual distributions through optimized feature selection and contrastive multimodal fusion. By leveraging meta-learned transformer-based encoders and domain-invariant representations, the MCFI framework provides a scalable and robust solution for content categorization in heterogeneous big-data environments with limited labeled data.

2. RELATED WORK

The recent growth of social media and cross-platform communication has stimulated extensive research in real-time text classification, domain adaptation, multimodal fusion, and misinformation detection. Early studies primarily focused on organizing and classifying user-generated content under dynamic conditions. Ijaz *et al.* [1] conducted a comprehensive systematic review on real-time text classification of social media streams, highlighting key challenges such as scalability, streaming latency, and domain variability. Their findings indicate that while deep learning approaches achieve high accuracy, they often struggle to generalize across domains and evolving textual distributions.

In the context of cross-platform dynamics, Xi *et al.* [2] proposed an information diffusion model to analyze the spread of topics across social media platforms. Their work demonstrated that textual content propagates across heterogeneous domains, intensifying domain-shift challenges in classification tasks and emphasizing the need for adaptive learning models.

Foundational work on transferable representation learning was introduced by Rogers *et al.* [3], who proposed a deep learning framework for scalable domain adaptation through transferable feature learning. Similarly, Yin *et al.* [4] developed a weakly supervised domain adaptation approach for aspect extraction using multilevel interaction transfer. Although effective, their method was limited to aspect-level tasks rather than general content categorization.

Zhang *et al.* [5] introduced a GAN-based cross-domain sentiment transfer model capable of generating target-domain content using source-domain annotations. Despite its effectiveness, the model suffers from instability and high computational complexity. Liang *et al.* [6] later proposed a hybrid BiGRU-based framework for cross-domain sentiment classification, combining global semantic and local contextual features. However, the approach lacks integration of contrastive and meta-learning strategies.

With the rise of misinformation detection, multimodal domain-adaptive frameworks have gained attention. Long *et al.* [7] proposed a memory-guided multi-domain fake news detection model, while Kashyap *et al.* [8] introduced a robust cross-modal feature alignment framework for misinformation detection. Zhu *et al.* [9] further proposed a domain-adaptive representation learning model for multimodal deepfake detection. Although these approaches improve cross-modal alignment, they often overlook feature optimization and adaptive feature selection mechanisms.

Recent advancements in transformer-based architectures emphasize efficiency and scalability. Liu *et al.* [10] proposed CLARITY, a lightweight multimodal transformer for harmful content detection, while Lee *et al.* [11] introduced an attention-based framework for misleading content detection. Despite their robustness, these models exhibit limited adaptability under severe domain drift.

Earlier work by Liu [12] explored cross-domain media stream learning using normalization and graph-based ranking techniques. However, their approach lacked deep semantic alignment. More recently, Shanto *et al.* [13] proposed a hierarchical multimodal classification framework for Bengali content, demonstrating improved structured classification, though with limited cross-domain generalization.

Altogether, the current literature shows that domain adaptation, multimodal fusion, sentiment transfer, and misinformation detection have been advanced considerably. However, there are still a few limitations: i) lack of sufficient feature selection based on optimization with deep domain adaptation, ii) less use of meta-learning to quickly generalize to unseen domains, iii) lack of contrastive alignment between heterogeneous domains, and iv) the issue of scalability when applied to large-scale, changing streams of social media. These deficiencies demonstrate that a single framework combining feature engineering, swarm-intelligence optimization, contrastive learning, and adaptive transformer architectures is necessary to offer robust and scale-able domain-adaptive content categorization.

3. METHOD

Figure 1 demonstrates the general structure of the given MCFI framework of domain-adaptive content categorization. It has three steps: preprocessing domain context-aware normalization (DCAN), feature selection based on binary particle swarm optimization (BPSO), and content categorization using the hybrid MCFI model contrastive learning-enhanced (CL-BERT+Caps-Trans). Contextual token refinement, adaptive stop-word removal, morphological normalization, noise filtering and semantic augmentation are performed in the first stage, on the raw multi-domain text. The DCAN mechanism maintains domain invariant linguistic clues as it normalises contextual variation in heterogeneous domains producing clean, semantically consistent textual representations.

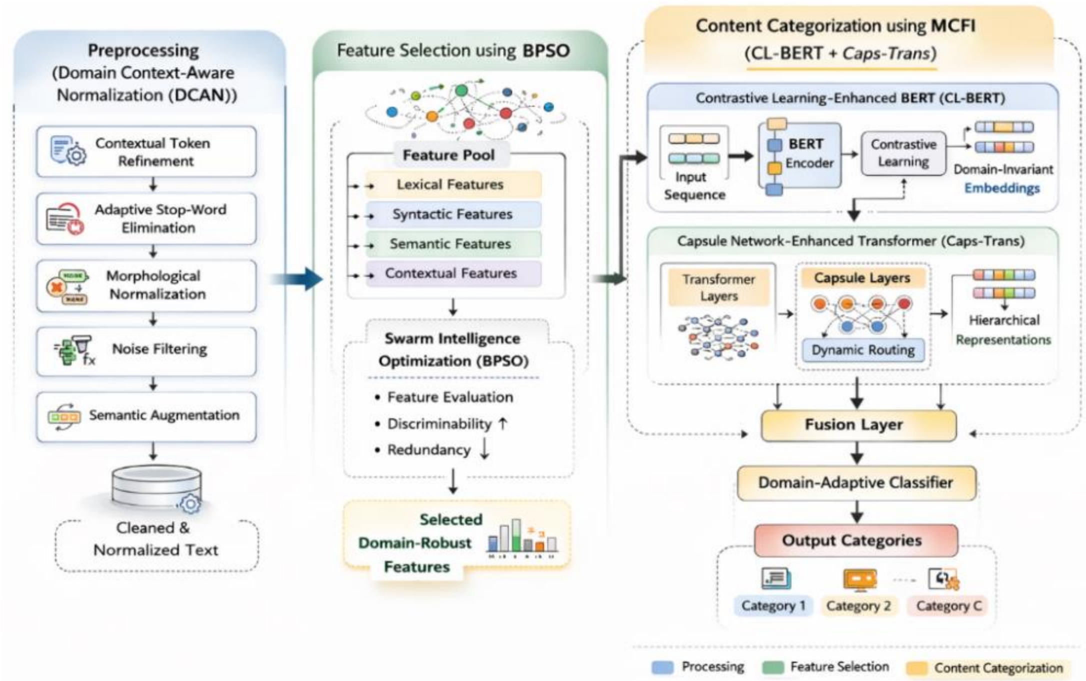

Figure 1. Workflow diagram for domain adaptive content categorization

The second step is known as comprehensive feature engineering that is used to obtain lexical, syntactic, semantic and contextual representations in order to create a high-dimensional feature pool. An efficient subset of domain-robust features is then found using a swarm-intelligence-based BPSO algorithm. The fitness criterion maximizes the cross-domain discriminability and minimizes the redundancy of features, therefore, maximizing the generalization ability and decreasing computational costs.

The selected features are then inputted in the MCFI-based content categorization module in the last phase. An encoder based on meta-learning trained CL-BERT acquires domain-invariant representations by episodic training and contrastive learning, where semantically similar examples across domains are aligned. On a similar note, the Caps-Trans performs hierarchical and multi-scale contextual dependencies through transformer layers, capsule layers, and dynamic routing. The merged representations are then fed to a domain-adaptive classifier in order to produce the end content categories. This combined architecture guarantees high cross domain adaptation, enhanced semantic alignment and higher classification performance.

3.1. Domain context-aware normalization

The suggested DCAN framework is the structured and domain-sensitive preprocessing which enables creating stable semantically consistent textual representations in cross-domain learning. And assume that input corpus is formed by heterogeneous documents representing more than one domain with distributional differences, lexical change and semantic change. DCAN optimizes textual data in systematic refinements that consist of five closely interacting steps namely contextual token refinement, domain-adaptive stop-word removal, morphological normalization, entropy-based noise removal, and embedding-constrained semantic augmentation.

Through joint optimization of semantic alignment, probabilistic relevance and cross-domain stability, DCAN generates a normalized corpus that evokes the least intra-domain variance and the most inter-domain discriminability. Assuming the multi-domain corpus be computed as:

$$\mathcal{D} = \{(d_i, y_i, \kappa_i)\}_{i=1}^{N}$$

where, d_i denotes the i^{th} document, y_i denotes its class label, $\kappa_i \in \{1,2,\dots,K\}$ denotes the domain index, N is the total number of documents, and K is the number of domains.
Each document is represented as a token sequence:

$$d_i = \{w_{i1}, w_{i2}, \dots, w_{iL_i}\}$$

where L_i is the length of document i.
Each token w_{ij} is mapped to a contextual embedding defined as:

$$\mathrm{e}_{ij} = f_\theta(w_{ij}, \mathcal{C}_{ij})$$

herein, $f_\theta(\cdot)$ is a parameterized contextual embedding function, $\mathcal{C}_{ij}$ represents the local context window of token w_{ij}, $\mathrm{e}_{ij} \in \mathbb{R}^d$ is the embedding vector.
After token refinement is performed via similarity-based projection is represented in:

$$w_{ij}^{(r)} = \arg\max_{w\in\mathcal{V}} \cos(\mathrm{e}_{ij}, \mathrm{e}_w)$$

where, $\mathcal{V}$ is the vocabulary space, $\cos(\cdot)$ denotes cosine similarity, and $w_{ij}^{(r)}$ is the refined token.

The DCAN framework thus provides a mathematically based, domain conscious, normalization mechanism which improves semantic stability or domain invariance and the predisposition of discriminative features to follow on adaptive deep neural modeling.
The domain-conditional probability of token w is calculated as:

$$P(w \mid D_k) = \frac{f_{w,k}}{\sum_{w'} f_{w',k}}$$

let us assume that, $f_{w,k}$ denotes frequency of token w in domain D_k.
After that computes the global probability in:

$$P(w) = \sum_{k=1}^{K} \pi_k P(w \mid D_k)$$

where π_k is the prior probability of domain D_k.
Identify the domain relevance score is denoted as:

$$R(w) = \frac{1}{K} \sum_{k=1}^{K} \mid P(w \mid D_k) - P(w) \mid$$

Token elimination criterion as defined as:

$$w \text{ is removed if } R(w) < \delta$$

herein, δ is the domain-discriminability threshold.
Each refined token undergoes canonical transformation:

$$w_{ij}^{(m)} = \phi\left(w_{ij}^{(r)}\right)$$

assuming that, $\phi(\cdot)$ is the morphological normalization operator.
Cross-domain entropy for token w is computed in:

$$H(w) = - \sum_{k=1}^{K} P(w \mid D_k) \log P(w \mid D_k)$$

Normalized entropy defined:

$$\widehat{H}(w) = \frac{H(w)}{\log K}$$

Stability criterion:

$$w \text{ is retained if } \widehat{H}(w) \leq \eta$$

where η is the entropy stability threshold.
For each normalized token $w_{ij}^{(m)}$, an augmented token $w_{ij}^{(a)}$ is selected such that:

$$\cos\left(\mathrm{e}_{ij}^{(m)}, \mathrm{e}_{ij}^{(a)}\right) \geq \tau$$

assuming that, τ is the similarity threshold, and $\mathrm{e}_{ij}^{(m)}$ and $\mathrm{e}_{ij}^{(a)}$ denote embedding vectors. The augmented token set becomes:

$$\widetilde{w}_{ij} = \left\{w_{ij}^{(m)}, w_{ij}^{(a)}\right\}$$

The DCAN-processed document is defined as:

$$d_i^{DCAN} = \left\{\widetilde{w}_{i1}, \widetilde{w}_{i2}, \ldots, \widetilde{w}_{iL_i'}\right\}$$

here, $L_i' \leq L_i$ after refinement and filtering. DCAN aims to minimize intra-domain variance while maximizing inter-domain separability:

$$\min_{\mathcal{N}} \left(\sum_{k=1}^{K} \mathrm{Var}\,(D_k)\right) - \lambda(\mathrm{Disc}_{inter})$$

where, $\mathcal{N}$ denotes normalization operations, $\mathrm{Var}(D_k)$ is intra-domain variance, Disc_{inter} represents inter-domain discriminability, and λ is a balancing coefficient.

3.2. Binary particle swarm intelligence optimization

The suggested framework uses a BPSO mechanism to carry out domain robust feature selection on high-dimensional textual spaces. Allow the DCAN-processed corpus to produce an extensive pool of features consisting of lexical, syntactic, semantic, contextual and statistical features. Lateral selection variability and redundancy of features means that an adaptive selection mechanism is needed to determine the discriminative and domain-invariant attributes.

Each particle is represented as a binary vector as denoted in:

$$\mathrm{p}_i = [p_{i1}, p_{i2}, \dots, p_{iM}]$$

where:

$$p_{ij} = \begin{cases} 1 & \text{if feature } j \text{ is selected} \\ 0 & \text{otherwise} \end{cases}$$

In BPSO, velocity controls the probability of selecting a feature. The velocity of particle i at iteration t is:

$$v_{ij}^{(t+1)} = \omega v_{ij}^{(t)} + c_1 r_1 \left(pbest_{ij} - p_{ij}^{(t)}\right) + c_2 r_2 \left(gbest_j - p_{ij}^{(t)}\right)$$

assuming that, ω refers inertia weight, c_1 lies cognitive coefficient, c_2 presents social coefficient, $r_1, r_2 \sim U(0,1)$, $pbest_{ij}$ lies personal best position and $gbest_j$ depicts global best position.
Velocity is transformed into selection probability using sigmoid function:

$$S\left(v_{ij}\right) = \frac{1}{1+e^{-v_{ij}}}$$

Binary update rule is computed:

$$p_{ij}^{(t+1)} = \begin{cases} 1 & \text{if } rand() < S(v_{ij}^{(t+1)}) \\ 0 & \text{otherwise} \end{cases}$$

The fitness function balances discriminability and redundancy:

$$F(\mathrm{p}_i) = \alpha \cdot D(\mathrm{p}_i) - \beta \cdot R(\mathrm{p}_i)$$

where α, β refers balancing coefficients, $D(\mathrm{p}_i)$ states cross-domain discriminability and $R(\mathrm{p}_i)$ mentions redundancy measure.
Cross-domain discriminability is computed in:

$$D(\mathbf{p}_i) = \frac{1}{K} \sum_{k=1}^{K} \mathrm{Tr}\left(S_B^{(k)} S_W^{(k)^{-1}}\right)$$

herein, K represents number of domains, $S_B^{(k)}$ states between-class scatter matrix in domain k, and $S_W^{(k)}$ presents within-class scatter matrix.
Redundancy measurement is calculated in:

$$R(\mathrm{p}_i) = \frac{1}{|S|} \sum_{f_a, f_b \in S} |\ \mathrm{corr}(f_a, f_b)\ |$$

herein, S denotes the selected feature subset and $\mathrm{corr}(\cdot)$ states correlation coefficient. Optimization objective is estimated as:

$$\max_{\mathbf{p}_i} [\alpha D(\mathrm{p}_i) - \beta R(\mathrm{p}_i)]$$

subject to:

$$\|\ \mathrm{p}_i\ \|_0 \leq M_{max}$$

assuming that, $\|\cdot\|_0$ denotes number of selected features.
Convergence is achieved when:

$$|\ F\left(gbest^{(t+1)}\right) - F\left(gbest^{(t)}\right)\ | < \epsilon$$

The suggested BPSO-based behavioral feature selection mechanism, thus, allows adaptive selection of high-domain insensitive, low-redundancy features by cooperative swarm search and probabilistic binary maximization, which guarantee high discriminative capacity in cross-domain content classifications tasks. Table 1 describes the BPSO approach parameters configuration.

Table 1. BPSO approach parameters configuration

Parameter	Symbol	Description	Value
Swarm size	N_p	Number of particles	30–50
Max iterations	T	Optimization steps	100
Inertia weight	ω	Exploration–exploitation balance	0.7
Cognitive coefficient	c_1	Personal learning weight	1.5
Social coefficient	c_2	Global learning weight	1.5
Discriminability weight	α	Fitness weight	0.7
Redundancy weight	β	Fitness penalty	0.3
Convergence threshold	ϵ	Stopping criterion	$(10^{\{-4\}})$

3.3. Meta-learning contrastive fusion intelligence

The proposed MCFI is a domain-adaptive model that is developed to attain strong content classification when there are cross-domain distribution shifts. MCFI consists of two complementary modules of representation learning: i) a contrastive learning-enhanced BERT (CL-BERT) semantic aligner and domain-invariant embedding generator and ii) a capsule network-enhanced transformer (Caps-Trans) hierarchical semantic aggregation and structural relationship representation. The CL-BERT is a model that cross domain aligns semantically similar samples through contrastive goals, and thus, imposes inter-domain invariance in embedding space. But whereas contrastive alignment facilitates the separation of global representations, hierarchical relations among semantic elements in documents demand institution of structural aggregation. The Caps-Trans module takes this into consideration and identifies part-whole semantic interactions by modeling dynamic routing to allow robust structural feature encoding. The final output of MCFI is a fused domain-adaptive representation vector:

$$\mathrm{z}_{MCFI} = \mathcal{F}(\mathrm{z}_{CL}, \mathrm{z}_{Caps})$$

Let us assume that, z_{CL} denotes contrastively aligned semantic embeddings, z_{Caps} denotes capsule-structured hierarchical embeddings, and $\mathcal{F}(\cdot)$ denotes adaptive fusion.

The resulting representation is cross-domain, increasing in cross-domain discriminability and structural consistency and providing greater stability in categorization.

4. RESULTS AND DISCUSSION

In order to test the efficiency of the suggested MCFI structure, the experiments were carried out with the help of one of the publicly available text categorizing data sets gathered at the Kaggle repository. The data is made up of five content categories namely business, technology, sports, entertainment, and education. All the steps of preprocessing, feature selection, model training, and evaluation were implemented in Python environment with general-purpose deep learning libraries.

The data was divided into 70% and 30% training and testing respectively to have unbiased consideration. Episodic optimization of meta-learning and contrastive embedding alignment was optimized in the training set, and performance validation was only done in the testing set. Figure 2 shows a comparative analysis of the classification performance based on accuracy and F1-score of GAN, BiGRU, DARL, and the proposed MCFI model. It is noted that GAN has 75.4% accuracy and 74.28% F1-score, which means that it has relatively lower classification potential. BiGRU upgrades the accuracy and F1-score to 84.21% and 83.19%, respectively, by being able to capture bidirectional contextual relationships. DARL also provides further results of 89.45% accuracy and 88.04% F1-score because of adaptive representation learning strategy. Nevertheless, the proposed MCFI model is more precise than any of the existing ones with the best accuracy of 92.17 and F1-score of 91.05. The fact that both metrics are steadily increasing proves the strength and balanced classification capability of the suggested framework.

Figure 3 shows a comparative analysis of precision and recall of GAN, BiGRU, DARL, and proposed MCFI model. Based on the outcome, GAN has a precision of 74.2%, which means that it has relatively lower classification than a higher chance of misclassification and missing the relevant cases. BiGRU has a much higher performance which is at 85.14% precision and 84.19% recall, which shows better contextual understanding and less false predictions. DARL also improves the score and the precision and recall are 88.05 and 88.3, respectively.

Figure 4 compares the error rate of GAN, BiGRU, DARL, and the proposed MCFI model. As can be seen, GAN has the largest error rate of 26.5%, with more false classifications between content categories. BiGRU greatly minimizes the error rate at 15.3 showing better context learning on features. DARL also reduces the error rate to 12.17, which shows an improved representation and adaptive learning ability.

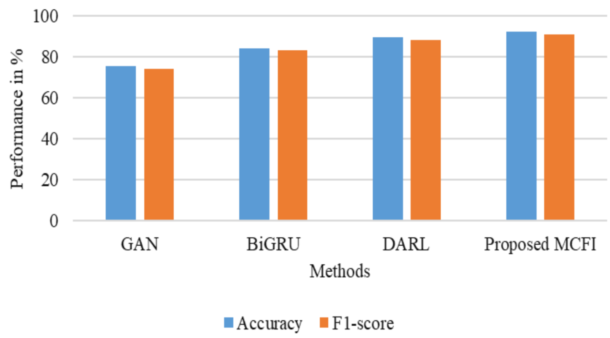

Figure 2. Comparison of accuracy and F1-score performance

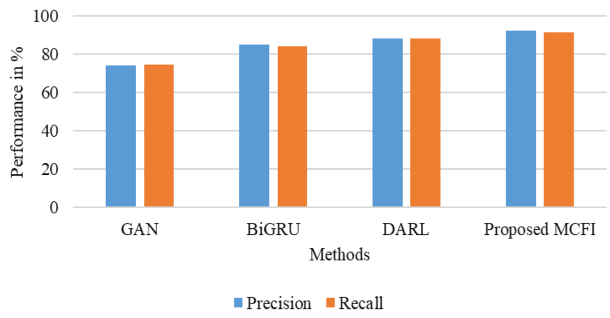

Figure 3. Comparison of precision and recall performance

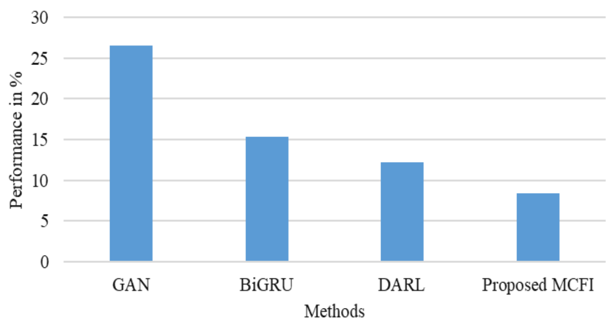

Figure 4. Comparison of error rate

5. CONCLUSION

This study introduced a novel domain-adaptive content categorization framework integrating DCAN, BPSO-based feature selection, and the proposed MCFI model, which combines CL-BERT with a capsule-transformer architecture. The framework was implemented in Python and evaluated on a publicly available Kaggle dataset comprising five categories: business, technology, sports, entertainment, and education. A 70:30 train–test split was adopted to ensure robust performance evaluation. Experimental results clearly demonstrate the superiority of the proposed approach over existing methods such as GAN, BiGRU, and DARL. The MCFI model achieved a classification accuracy of 92.17%, F1-score of 91.05%, precision of 92.27%, recall of 91.15%, and a low error rate of 8.45%. Notably, it outperformed DARL—the strongest baseline—indicating enhanced discriminative capability and balanced precision–recall performance. The consistent improvement across all metrics confirms the model's ability to reduce both false positives and false negatives while preserving contextual and hierarchical semantic relationships. The performance gains are attributed to three key components: i) DCAN-based preprocessing for noise reduction and domain-invariant feature extraction; ii) BPSO-driven feature optimization to eliminate redundancy and mitigate overfitting; and iii) the hybrid CL-BERT with capsule-transformer architecture for capturing both global semantics and hierarchical dependencies.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Janani Sivapriya Venkatakrishnan	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Saravana Moorthy Raja Moorthy		✓	✓	✓	✓	✓		✓	✓	✓			✓	
Angel Shanmugam			✓			✓	✓	✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] M. Ijaz, N. Anwar, M. Safran, S. Alfarhood, T. Sadad, and Imran, "Domain adaptive learning for multi realm sentiment classification on big data," *PLOS ONE*, vol. 19, no. 4, Apr. 2024, doi: 10.1371/journal.pone.0297028.

[2] D. Xi, F. Zhuang, G. Zhou, X. Cheng, F. Lin, and Q. He, "Domain adaptation with category attention network for deep sentiment analysis," in *Proceedings of The Web Conference 2020*, Apr. 2020, pp. 3133–3139, doi: 10.1145/3366423.3380088.

[3] D. Rogers, A. Preece, M. Innes, and I. Spasic, "Real-time text classification of user-generated content on social media: Systematic review," *IEEE Transactions on Computational Social Systems*, vol. 9, no. 4, pp. 1154–1166, Aug. 2022, doi: 10.1109/TCSS.2021.3120138.

[4] J. Yin *et al.*, "Blowing seeds across gardens: Visualizing implicit propagation of cross-platform social media posts," *IEEE Transactions on Visualization and Computer Graphics*, vol. 31, no. 1, pp. 185–195, Jan. 2025, doi: 10.1109/TVCG.2024.3456181.

[5] R. Zhang, Z. Wang, K. Yin, and Z. Huang, "Emotional text generation based on cross-domain sentiment transfer," *IEEE Access*, vol. 7, pp. 100081–100089, 2019, doi: 10.1109/ACCESS.2019.2931036.

[6] T. Liang, W. Wang, and F. Lv, "Weakly supervised domain adaptation for aspect extraction via multilevel interaction transfer," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 10, pp. 5818–5829, Oct. 2022, doi: 10.1109/TNNLS.2021.3071474.

[7] M. Long, J. Wang, Y. Cao, J. Sun, and P. S. Yu, "Deep learning of transferable representation for scalable domain adaptation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 8, pp. 2027–2040, Aug. 2016, doi: 10.1109/TKDE.2016.2554549.

[8] G. S. Kashyap, N. Jain, E. Shabbir, H. Joshi, U. Naseem, and J. Gao, "CLARITY: A lightweight multimodal transformer for harmful content detection," *IEEE Transactions on Artificial Intelligence*, vol. 7, no. 2, pp. 1073–1083, Feb. 2026, doi: 10.1109/TAI.2025.3591585.

[9] Y. Zhu *et al.*, "Memory-guided multi-view multi-domain fake news detection," *IEEE Transactions on Knowledge and Data Engineering*, pp. 1–14, 2022, doi: 10.1109/TKDE.2022.3185151.

[10] H. Liu, W. Wang, H. Sun, A. Rocha, and H. Li, "Robust domain misinformation detection via multi-modal feature alignment," *IEEE Transactions on Information Forensics and Security*, vol. 19, pp. 793–806, 2024, doi: 10.1109/TIFS.2023.3326368.

[11] W.-Y. Lee, W. H. Hsu, and S. Satoh, "Learning from cross-domain media streams for event-of-interest discovery," *IEEE Transactions on Multimedia*, vol. 20, no. 1, pp. 142–154, Jan. 2018, doi: 10.1109/TMM.2017.2726184.

[12] B. Liu, "Research on natural language misleading content detection method based on attention mechanism," *IEEE Access*, vol. 13, pp. 132410–132425, 2025, doi: 10.1109/ACCESS.2025.3591455.
[13] A. M. Shanto, F. S. Tamim, M. S. J. Priya, M. M. Hoque, and E. H. Prince, "TSFC: A hierarchical classification framework for multimodal commercial contents in Bengali," *IEEE Access*, vol. 14, pp. 28411–28434, 2026, doi: 10.1109/ACCESS.2026.3659712.
[14] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of NAACL-HLT 2019*, May 2019, pp. 4171–4186.
[15] K. He, H. Fan, Y. Wu, S. Xie, and R. Girshick, "Momentum contrast for unsupervised visual representation learning," in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2020, pp. 9726–9735 doi: 10.1109/CVPR42600.2020.00975.
[16] X. Chen, H. Fan, R. Girshick, and K. He, "Improved baselines with momentum contrastive learning," *arXiv Preprint*, Mar. 2020, doi: 10.48550/arXiv.2003.04297.
[17] S. Gidaris, P. Singh, and N. Komodakis, "Unsupervised representation learning by predicting image rotations," in *International Conference on Learning Representations (ICLR)*, 2018.
[18] Y. Hu, C. Zhang, M. Yang, X. Liang, C. Li, and X. Hu, "Learning to generalize unseen domains via multi-source meta learning for text classification," in *International Conference on Pattern Recognition*, 2025, pp. 412–428, doi: 10.1007/978-3-031-78495-8_26.
[19] A. Zeng *et al.*, "GLM-130B: An open bilingual pre-trained model," *arXiv Preprint*, Oct. 2023, doi: 10.48550/arXiv.2210.02414.
[20] L. Mansilla, R. Echeveste, D. H. Milone, and E. Ferrante, "Domain generalization via gradient surgery," in *2021 IEEE/CVF International Conference on Computer Vision (ICCV)*, 2021, pp. 6610-6618, doi: 10.1109/ICCV48922.2021.00656.
[21] X. Yao *et al.*, "PCL: Proxy-based contrastive learning for domain generalization," in *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2022, pp. 7087–7097, doi: 10.1109/CVPR52688.2022.00696.
[22] Q. Tan, R. He, L. Bing, and H. T. Ng, "Domain generalization for text classification with memory-based supervised contrastive learning," in *Proceedings of the 29th International Conference on Computational Linguistics*, 2022, pp. 6916–6926.
[23] T. Dopierre, C. Gravier, and W. Logerais, "A neural few-shot text classification reality check," in *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics (EACL)*, 2021, pp. 935–943.
[24] Z.-X. Ye and Z.-H. Ling, "Multi-level matching and aggregation network for few-shot relation classification," in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019, pp. 2872–2881.
[25] H. Zheng, R. Wang, Y. Yang, Y. Li, and M. Xu, "Intelligent fault identification based on multisource domain generalization towards actual diagnosis scenario," *IEEE Transactions on Industrial Electronics*, vol. 67, no. 2, pp. 1293–1304, Feb. 2020, doi: 10.1109/TIE.2019.2898619.
[26] H. Zhang *et al.*, "Effectiveness of pre-training for few-shot intent classification," in *Findings of the Association for Computational Linguistics: EMNLP 2021*, 2021, pp. 1114–1120.

BIOGRAPHIES OF AUTHORS

Janani Sivapriya Venkatakrishnan working as an Assistant Professor in the Department of Data Science at Dwaraka Doss Goverdhan Doss Vaishnav College (Autonomous), Affiliated to University of Madras, Chennai, Tamil Nadu. She has secured her M.Sc. degree in Software Science from JKKN College of Arts and Science, Affiliated to Periyar University, Salem and her M.Phil. in Computer Science from Dhanraj Baid Jain College (Autonomous), Affiliated to University of Madras, Chennai. From December 2023, she has been a Ph.D. scholar in Computer Science at Kongunadu Arts and Science College (Autonomous), Affiliated to Bharathiar University, Coimbatore. Her main research interests include data science and machine learning, text mining, and natural language processing. She can be contacted at email: janani.sivapriyaphd@gmail.com.

Saravana Moorthy Raja Moorthy working as Associate Professor and Head, Department of Computer Science (SF), Kongunadu Arts and Science College, Coimbatore, Tamilnadu. He secured his Docorate in Computer Engineering and post graduate degree in Software Engineering. He is in teaching profession for more than 18 years. He has presented 20 papers in national and international journal, confrence and seminars. He is registered as an author in Google Scholar, Research-Gate and Orcid. His main area of interest includes AI and machine learning. He had setup in ASIAN-Book of Record for conducting non stop 48-hour conclave. He can be contacted at email: drsaravanamoorthy@gmail.com.

Angel Shanmugam working as Assistant Professor, Department of Computer Science with Cyber Security, PSGR Krishnammal College for Women, Coimbatore. She Secured her Doctorate in Computer Science and post graduate degree in M.E. Computer Engineering. She has secured her M.Sc. degree in Software Science from JKKN College of Arts and Science, Affiliated to Periyar University, Salem. She is in teaching profession for more than 14 years. She has presented 20 papers in national and international journal, conference and seminars. She is registered as an author in Google Scholar and Research Gate. Her main area of interest includes AI, machine learning, and cyber security. She can be contacted at email: angelshanmugam@gmail.com.