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Abstract: Social media sentiment analysis faces challenges such as scarce annotated data and complex contextual factors, making it difficult for traditional methods to accurately capture users' genuine emotions. This paper proposes an innovative framework integrating transfer learning and semantic enhancement. By pre-training models on massive unlabeled data and combining them with sophisticated contextual semantic enhancement techniques, it enhances the ability to recognise nuanced emotional expressions in English social media texts. Experiments on public datasets like semantic evaluation-2018 convincingly demonstrate that our method achieves an accuracy of 73.12%, representing a 15.32% improvement over traditional approaches. Statistical tests confirm this enhancement is statistically significant ($p < 0.01$). This research provides more reliable technical support for practical applications such as real-time public opinion monitoring and personalised recommendation systems.

Keywords: transfer learning; semantic augmentation; social media; sentiment analysis.

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Biographical notes: Liping Rao is a Lecturer in the Common Courses Teaching Department at Human Communication Polytechnic, China. She obtained her Bachelor's degree from the Hunan Normal University (2002). She published 13 ISSN index papers. Her research interests include English teaching, higher vocational education, and sentiment analysis.

1 Introduction

Social media platforms have become vital conduits for information dissemination and emotional exchange in modern society, generating billions of text data points daily. These data not only reflect the public's immediate reactions to current events but also encapsulate rich user sentiments and subjective attitudes (Nazir et al., 2022). By conducting sentiment analysis on social media texts, this study can capture real-time fluctuations in public sentiment, gain insights into industry dynamics and market trends, and provide robust support for decision-making (Zou and Wang, 2024). For instance, it

can be instrumental in tracking public perception during major sporting events or product launches. However, social media texts typically exhibit characteristics such as linguistic non-standardisation and high context dependency. For instance, non-standard linguistic elements such as the abbreviation ‘LOL’ or the use of emojis can significantly alter sentiment interpretation. These elements introduce a layer of meaning that is highly context-dependent, thereby adding considerable complexity to the automated analysis of social media texts. Traditional sentiment analysis methods struggle to fully capture their nuanced emotional semantics, a challenge that has spurred ongoing academic exploration of more advanced analytical techniques (Grant, 2024).

In recent years, the field of social media sentiment analysis has undergone a technological evolution from dictionary-based approaches to machine learning and then to deep learning (Persechino et al., 2025). Early research primarily relied on sentiment dictionaries for lexical matching. While simple and efficient, these methods struggled to handle the widespread use of sarcasm, ellipsis, and context-dependent phenomena prevalent in social media. With technological advancements, traditional machine learning methods like support vector machines (SVM) and maximum entropy models were gradually applied to sentiment classification tasks (Andrews et al., 2017). These approaches achieved some success through manually designed features, (e.g., n-grams, part-of-speech tags), but they performed poorly in cross-domain generalisation and incurred high feature engineering costs (Othman and Faiz, 2016). Deep learning approaches, [e.g., long short-term memory (LSTM), convolutional neural network (CNN), bidirectional long short-term memory (BiLSTM)] partially overcome these limitations by automatically learning feature representations, demonstrating significant advantages in text sentiment analysis (Lv and Cai, 2025). However, these models typically require large-scale labelled data for training. High-quality labelled data in social media is relatively scarce and costly to annotate, severely limiting the practical application of deep learning methods (Korot et al., 2021).

To mitigate this reliance on labelled data, transfer learning techniques have been introduced into natural language processing, particularly for social media sentiment analysis tasks (Sarker et al., 2024). Pre-trained language models, [e.g., bidirectional encoder representations from transformers (BERT), generative pre-trained transformer (GPT)] acquire general language knowledge through self-supervised learning on large-scale unlabeled corpora, then adapt to specific downstream tasks via fine-tuning, significantly reducing the need for labelled data (Wang et al., 2023). This capability allows models to achieve robust performance even when the number of annotated samples is limited, a common and practical constraint in social media analysis. By leveraging knowledge from large pre-trained models, the dependency on extensive, manually labelled datasets for each new task or domain is substantially reduced. Transfer learning-based approaches achieved outstanding results on the Semantic Evaluation-2018 (SemEval-2018) ‘Tweet Sentiment Analysis’ task, ranking among the top performers across multiple subtasks, validating the effectiveness of transfer learning in sentiment analysis. Similarly, BERT-based transfer learning models achieved 87% and 79% accuracy on English and urdu hope speech detection tasks respectively, significantly outperforming traditional SVM models (Bagestra et al., 2024). These findings fully demonstrate the potential of transfer learning in cross-lingual sentiment analysis tasks. However, directly applying general-domain pre-trained models to social media sentiment analysis remains limited due to significant domain differences between general corpora and social media texts. Standard pre-trained models struggle to adequately capture the

nuanced emotional semantics and dynamic shifts inherent in social media discourse (Asakura et al., 2020).

New opportunities are offered to enhance the performance of social media sentiment analysis through the development of semantic enhancement methods (Moon et al., 2024). The techniques will help to capture more semantic contents by improving text representation functions (Yamada et al., 2018). The comparison of models that are grounded on attention like attention encoder network (AEN) and local context focus (LCF) show that such models could better handle aspect information and sentiment associated with text (Kusumawardani et al., 2024). AEN and LCF models have demonstrated the best classification on short text social media data such as Twitter. More recent papers have suggested several additional techniques in semantic enhancement, including adversarial training, contrastive learning, and knowledge augmentation, which also further enhance the discriminative power of text representations with the addition of other supervisory information or external knowledge. In the context of multi-label sentiment classification, in particular, the Me-tiek model is the first to incorporate transfer information in the external knowledge (Nema et al., 2024). It improves the SemEval-2018 English dataset by 20.7% in the macro-average score by building a sentiment transfer graph convolutional networks (GCNs) coupled with multi-level attention systems applied and multi-level emotion investment strategies. This development indicates that the dynamic relations between sentiment transfer and composite emotions modelling are relatively very useful in the complex expression of emotions in a model (Gowda, 2025).

Despite significant progress in social media sentiment analysis, several challenges remain (Lin et al., 2018). Non-standard spellings, abbreviations, slang, and emojis prevalent in social media texts complicate sentiment analysis. Simultaneously, sentiment expressions on social media platforms are often ephemeral and topic-dependent, with the same lexical items conveying entirely different emotional orientations across contexts (Zhang et al., 2025). Furthermore, existing approaches predominantly fine-tune pre-trained models without adequately accounting for the unique linguistic characteristics of social media text. Next-generation social media sentiment analysis frameworks require improved modelling of dynamic changes in emotional semantics and integration of multi-source information to enhance analytical performance (Gong et al., 2025).

In order to deal with such challenges, this paper suggests a social media sentiment analysis framework system, which combines transfer learning and semantic augmentation. The framework uses a domain, adaptive pre-training technique to additively train general models on massive social media corpora to minimise discrepancies in domains. It presents a contextual semantic enhancement module, which employs multi-head attention ability to pick overtures in the textual expression of sentiments. There is also a multi-task learning (MTL) architecture which is built in such a way that it optimises as well the sentiment classification as well as sentiment intensity prediction tasks hence enhancing generalisation of the models. Compared to existing research, this study innovatively integrates the domain adaptation capability of transfer learning with the fine-grained sentiment capture ability of semantic enhancement, while optimising the model architecture for social media text characteristics. By systematically combining these strengths, our method achieves more accurate analysis of complex and dynamically changing sentiment semantics in social media texts, offering a novel solution for social media sentiment analysis.

2 Related research

2.1 The technological evolution of social media sentiment analysis

The technological evolution of social media sentiment analysis has progressed from traditional methods to deep learning (Bu et al., 2024). Early research primarily relied on sentiment lexicon approaches, such as the Semantic Orientation CALculator (SO-CAL) method, which determines overall sentiment polarity by calculating the sentiment scores of words within a text. Its fundamental formula can be expressed as: while this approach is effective for analysing standardised text, its reliance on static dictionaries may cause it to struggle with the dynamic and evolving nature of social media content. In such environments, sentiment can shift rapidly based on emerging trends, slang, and contextual cues that are not captured in fixed lexicons.

$$\text{Sentiment}(\text{text}) = \sum_{w \in \text{text}} \text{sentiment}_s \text{core}(w) \quad (1)$$

where w represents a word in the text, and $\text{sentiment}_s \text{core}(w)$ denotes the score of word w in the sentiment lexicon.

With the advancement of machine learning techniques, algorithms such as SVM have been widely applied to sentiment classification tasks (Wathan and Aziz, 2024). The details are as follows:

$$f(x) = \text{sign} \left(\sum_{i=1}^n \alpha_i y_i K(x_i, x) + b \right) \quad (2)$$

where x is the input feature vector, y_i is the class label, α_i is the Lagrange multiplier, $K(x_i, x)$ is the kernel function, and b is the bias term.

2.2 Applications of transfer learning in natural language processing

Transfer learning has achieved significant breakthroughs in natural language processing through pre-training and fine-tuning strategies (Shen et al., 2025). Pre-trained language models such as BERT are trained using tasks like masked language modelling (MLM) and next sentence prediction (NSP). The objective function for masked language modelling can be expressed as:

$$\mathcal{L}_{MLM} = -\mathbb{E}_{x \sim D} \sum_{i \in M} \log P(x_i | x_{\setminus M}) \quad (3)$$

where x is the input sequence, D is the training corpus, M is the set of masked token positions, and $x_{\setminus M}$ is the unmasked context.

Domain adaptation is a crucial branch of transfer learning, whose core idea is to reduce the distributional discrepancy between the source domain D_s and the target domain D_T . Maximum mean discrepancy (MMD) is a commonly used method for measuring distributional differences: MMD is particularly suitable for domain adaptation tasks because it provides a non-parametric method to quantify the discrepancy between two data distributions in a reproducing kernel Hilbert space. This allows for effective alignment of feature distributions without the need for complex, explicit density estimation of the source and target domains.

$$MMD(D_S, D_T) = \left| \frac{1}{n_S} \sum_{i=1}^{n_S} \phi(x_i^S) - \frac{1}{n_T} \sum_{j=1}^{n_T} \phi(x_j^T) \right|_{\mathcal{H}} \quad (4)$$

where $\phi(\cdot)$ denotes the characteristic mapping function, and $\mathcal{H}$ represents the reproducing kernel Hilbert space. Within the MTL framework, the model simultaneously optimises multiple related tasks. The total loss function is typically expressed as a weighted sum of the individual task losses.

$$\mathcal{L}_{total} = \sum_k 1^K \lambda_k \mathcal{L}_k \quad (5)$$

where $\mathcal{L}_k$ denotes the loss function for the k^{th} task, and λ_k represents the corresponding weight coefficient.

2.3 Semantic enhancement technology

Semantic enhancement techniques improve sentiment analysis performance by incorporating external knowledge and refining model architecture. Attention-based models capture the relative importance of different text segments, with their computational process represented as follows: This mechanism enables the model to dynamically weigh the importance of different words in a sequence, allowing it to focus more on key emotional cues. By prioritising salient features such as emphatic adjectives or negation phrases, the model's ability to accurately discern the true sentiment of a text is significantly improved.

$$\alpha_i = \frac{\exp(\text{score}(h_i, q))}{\sum_j \exp(\text{score}(h_j, q))} \quad (6)$$

where h_i is the i hidden representation of the input sequence, q is the query vector, and α_i is the attention weight at position i .

GCNs enhance semantic representations by aggregating information from neighbouring nodes. Their single-layer propagation rule is:

$$H^{(l+1)} = \sigma \left(\tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \quad (7)$$

where $\tilde{A} = A + I$ denotes the adjacency matrix with self-connections added, $\tilde{D}$ is the degree matrix, $H^{(l)}$ represents the node features of layer l , $W^{(l)}$ is the trainable weight matrix, and σ is the activation function.

The sentiment transfer matrix models the transition relationships between different sentiment categories, where state transitions can be expressed as:

$$s_{t+1} = \text{softmax}(T \cdot s_t) \quad (8)$$

where $T \in \mathbb{R}^{K \times K}$ is the sentiment transfer matrix, pointwise mutual information (PMI) is used to quantify the strength of association between words, calculated as follows:

$$PMI(x, y) = \log \frac{P(x, y)}{P(x)P(y)} \quad (9)$$

where $P(x, y)$ is the joint probability of co-occurrence for words x and y , and $P(x)$ and $P(y)$ are the marginal probabilities. The sentiment word strength calculation method based on semantic orientation pointwise mutual information (SO-PMI) can be expressed as:

$$SO-PMI(w) = \sum_{p \in P} PMI(w, p) - \sum_{n \in N} PMI(w, n) \quad (10)$$

where P and N represent the sets of positive and negative sentiment seed words, respectively. Adversarial training enhances model robustness by adding perturbations to the input, with its loss function defined as:

$$\mathcal{L}_{adv} = -\mathbb{E}(x, y) \sim D \log P(y|x + \delta_{adv}) \quad (11)$$

where δ_{adv} is the optimal perturbation computed via gradient ascent, satisfying $|\delta_{adv}| \leq \epsilon$. Adversarial learning aims to learn better representations. Its loss function can be expressed as:

$$\mathcal{L}_{contrastive} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1^N, k \neq i} \exp(\text{sim}(z_i, z_j)/\tau)} \quad (12)$$

where $\text{sim}(\cdot, \cdot)$ denotes the similarity function, τ represents the temperature parameter, and z_i and z_j denote representations of positive sample pairs. Knowledge distillation guides the training of the student model through the teacher model, with its distillation loss defined as:

$$\mathcal{L}_{KD} = \sum_i KL(q_i^T \| q_i^S) \quad (13)$$

where q_i^T and q_i^S denote the predicted distributions for the i^{th} sample from the teacher model and student model, respectively, while KL represents the Kullback-Leibler divergence.

3 A transfer learning and semantic augmentation sentiment analysis framework

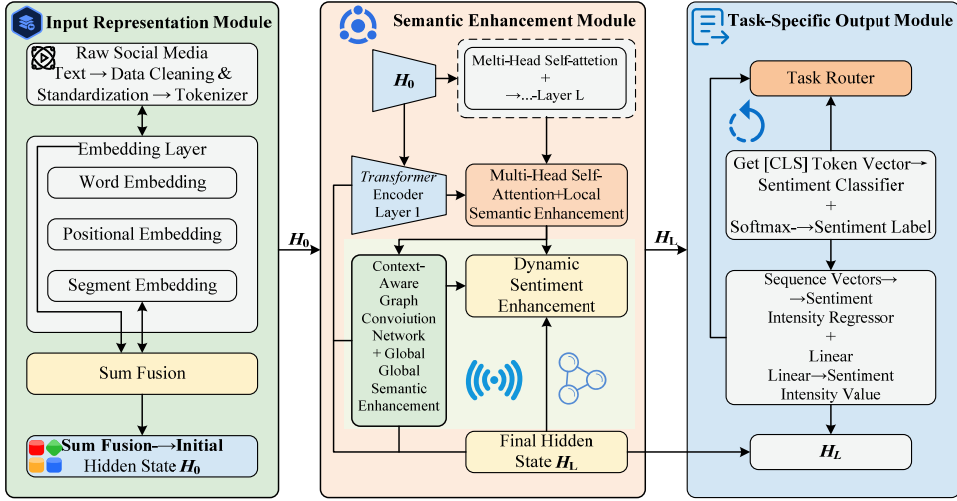
This chapter will provide a detailed exposition of the proposed transfer learning and semantic enhancement sentiment analysis (TL-SE-SA) framework. This framework aims to systematically address core challenges in social media text, including semantic noise, sparse annotated data, and strong context dependency. The following sections will comprehensively describe the methodology across three levels: the overall architecture, the transfer learning framework, and the semantic enhancement module (Liu et al., 2025).

3.1 Overall architecture design

The TL-SE-SA model proposed in this paper is an end-to-end deep learning architecture. Its core idea is to acquire general language knowledge through transfer learning and deepen the understanding of sentiment semantics using semantic enhancement

techniques. The overall workflow of the model is shown in Figure 1, primarily comprising three core stages: input representation, semantic encoding and enhancement, and task-specific output.

Figure 1 Architecture diagram of sentiment analysis system based on transfer learning and semantic enhancement (see online version for colours)



During the input representation stage, raw social media text undergoes data cleaning and standardisation pre-processing before being fed into a pre-trained language model based on the transformer architecture. This model converts each input token into a high-dimensional distributed vector representation. The transformer architecture was selected as the foundational model due to its superior ability to handle long-range dependencies within sequential data. This characteristic is crucial for capturing the full contextual sentiment in social media texts, where the meaning of a word or phrase can be dependent on information located much earlier in the post. Specifically, for an input sequence $X = [x_1, x_2, \dots, x_n]$ of length n , its initial embedding representation H_0 is formed by combining token embedding, position embedding, and segment embedding. The calculation formula is:

$$H_0 = E_{token} + E_{position} + E_{segment} \quad (14)$$

where E_{token} is the token embedding matrix, responsible for converting discrete symbols into continuous vectors; $E_{position}$ is the position embedding matrix, used to encode the positional information of tokens within the sequence; $E_{segment}$ is the segment embedding matrix, employed to distinguish different sentences when processing multi-sentence inputs.

$$H_l = \text{TransformerBlock}(H_{l-1}), l = 1, 2, \dots, L \quad (15)$$

where H_l is the hidden state output of the l^{th} -layer encoder, encapsulating the sequence's semantic information after multi-layer abstraction. Ultimately, the final layer's output H_L serves as the deep semantic representation of the entire input sequence, which will be fed into subsequent semantic enhancement modules for further processing.

3.2 Transfer learning framework

This paper’s transfer learning strategy adopts a two-stage adaptive paradigm: domain-adaptive pre-training followed by task-specific fine-tuning. This approach aims to seamlessly transfer general language knowledge to the specific domain of social media sentiment analysis.

3.2.1 Domain-adaptive pre-training

To bridge the domain gap between general-purpose corpora, (e.g., Wikipedia) and social media text, this paper performs continued pre-training on general-purpose models, (e.g., BERT) using a large-scale, unlabeled social media corpus D_{social} . This stage employs MLM as the self-supervised learning task. Specifically, 15% of tokens in the input sequence are randomly masked, and the model is trained to predict the masked tokens based on context. The loss function $\mathcal{L}_{MLM}$ for this task is defined as:

$$\mathcal{L}_{MLM} = -\mathbb{E}(X) \sim D_{social} \sum_{i \in M} \log P(x_i | X_{\setminus M}) \quad (16)$$

where M denotes the index set of masked tokens, $X_{\setminus M}$ represents the sequence of unmasked contextual tokens, and x_i is the original token masked at position i . By minimising this loss, the model can deeply learn and internalise the linguistic style, lexical usage, and expressive conventions specific to the social media domain.

3.2.2 Multi-task fine-tuning

After obtaining a domain-adapted pre-trained model, this paper fine-tunes it on a labelled sentiment analysis dataset. To enhance the model’s generalisation ability and mitigate overfitting, a MTL strategy is adopted, simultaneously optimising two correlated objectives: sentiment classification (primary task) and sentiment intensity prediction (auxiliary task). Predicting sentiment intensity serves as an auxiliary task that provides a richer, more granular supervisory signal to the model. This process helps the model learn to discern subtle emotional variations between utterances, thereby refining the decision boundaries for the primary task of sentiment classification and leading to more nuanced predictions. The total loss function $\mathcal{L}_{total}$ is composed of a weighted sum of three components:

$$\mathcal{L}_{total} = \alpha \mathcal{L}_{sentiment} + \beta \mathcal{L}_{intensity} + \gamma \mathcal{L}_{reg} \quad (17)$$

where $\mathcal{L}_{sentiment}$ is the cross-entropy loss for the sentiment classification task, used to measure the discrepancy between the model’s predicted sentiment category distribution and the true distribution. For a classification problem with K categories, its calculation formula is:

$$\mathcal{L}_{sentiment} = - \sum_{i=1}^K y_i \log(\hat{p}_i) \quad (18)$$

where y_i is the value of the i^{th} bit in the one-hot encoding of the true label, and $\hat{p}_i$ is the probability predicted by the model for the i^{th} sentiment category. $\mathcal{L}_{intensity}$ is the mean squared error (MSE) loss for the sentiment intensity prediction task, used to regress the continuous intensity value of the predicted sentiment:

$$\mathcal{L}_{intensity} = \frac{1}{N} \sum_{j=1}^N (v_j - \hat{v}_j)^2 \quad (19)$$

where v_j denotes the true sentiment intensity value of the j^{th} sample, $\hat{v}_j$ represents the intensity value predicted by the model, and N is the batch size.

$\mathcal{L}_{reg}$ is the L2 weight regularisation term, which penalises excessively large model parameters to prevent overfitting: $\mathcal{L}_{reg} = \|\theta\|_2^2$, where θ represents all trainable parameters of the model. α, β, γ are hyperparameters used to balance the contribution ratios of different loss terms in the total loss. Furthermore, this paper introduces adversarial training to enhance the model's robustness. By adding a bounded small perturbation δ to the input embedding H_0 and optimising the loss under the worst-case perturbation, the model becomes insensitive to input noise. The adversarial loss $\mathcal{L}_{adv}$ is defined as:

$$\mathcal{L}_{adv} = -\mathbb{E}(X, y) \sim D \log P(y|X; \hat{\theta}, \delta_{adv}) \quad (20)$$

where $\hat{\theta}$ represents the current value of the model parameters, while δ_{adv} denotes the optimal perturbation computed via methods such as fast gradient sign method (FGSM), satisfying $\|\delta_{adv}\| \leq \epsilon$, where ϵ is the hyperparameter controlling the perturbation magnitude.

3.3 Semantic enhancement module

The variable creative heart of TL-SE-SA model is the semantic enhancement module. It tries to extract and combine intricate and subtle emotional semantics of social media texts through multi-level information extraction and fusion. The module consists of three subcomponents, which are local semantic enhancement, global semantic enhancement and dynamic sentiment enhancement.

3.3.1 Local semantic enhancement

Local semantic enhancement primarily relies on the multi-head self-attention mechanism. Given the input H_l at layer l , the computation process for a single attention head $head_i$ is as follows:

$$\begin{aligned} head_i &= \text{Attention}(H_l W_i^Q, H_l W_i^K, H_l W_i^V) \\ &= \text{softmax} \left(\frac{(H_l W_i^Q)(H_l W_i^K)^T}{\sqrt{d_k}} \right) (H_l W_i^V) \end{aligned} \quad (21)$$

where W_i^Q, W_i^K, W_i^V are the linear transformation weights used to generate the query, key, and value matrices, respectively, with dimensions $\mathbb{R}^{d_{model} \times d_k}$. d_k denotes the dimension of the query and key vectors, while $\sqrt{d_k}$ is used to scale the dot product result, preventing gradient vanishing. Then, the outputs from all h attention heads are concatenated and subjected to another linear transformation:

$$\text{MultiHead}(H_l) = \text{Concat}(head_1, head_2, \dots, head_h) W^O \quad (22)$$

where W^O is the output transformation matrix, with dimensions $\mathbb{R}^{h \cdot d_v \times d_{model}}$. In this manner, the model can capture local semantic dependencies in parallel from multiple distinct representation subspaces.

3.3.2 Global semantic enhancement

To capture long-range semantic relationships between words that extend beyond local windows, this paper introduces a context-aware graph convolutional network. First, this article constructs a lexical graph $G = (V, E, A)$ based on co-occurrence statistics and semantic similarity measures, (e.g., cosine similarity) across the entire training corpus. Here, V denotes the node set (lexical items), E represents the edge set, and A is the adjacency matrix, where A_{ij} indicates the connection strength between nodes v_i and v_j .

Then, multiple layers of graph convolutional operations are applied on graph G . Each layer updates the representation of the current node by aggregating information from neighbouring nodes. The l^{th} layer of graph convolutional operation is defined as:

$$H^{(l+1)} = \sigma \left(\hat{D}^{-\frac{1}{2}} \hat{A} \hat{D}^{-\frac{1}{2}} H^{(l)} W^{(l)} \right) \quad (23)$$

where $\hat{D}_{ii} = \sum_j \hat{A}_{ij}$. $H^{(l)}$ represents the feature representations of all nodes in layer l . σ is a nonlinear activation function, such as ReLU. Through graph convolution, the model leverages the global lexical relationship graph to enhance the representation of local context, thereby better understanding the overall sentiment orientation of the text.

3.3.3 Dynamic sentiment enhancement

Dynamic sentiment enhancement aims to model the intrinsic relationships between sentiment labels and the emotional intensity of words. This paper constructs a learnable sentiment transfer matrix $T \in \mathbb{R}^{K \times K}$, where T_{ij} quantifies the transition probability from sentiment i to sentiment j . The concept of a sentiment transfer matrix is inspired by the principles of Markov models, which are used to model state transitions in sequential processes. Here, the states represent different sentiment categories, and the matrix learns the probabilistic transitions between these emotional states within the flow of the text. During inference, the current sentiment state $s_t \in \mathbb{R}^K$ (a probability distribution vector) can predict its dynamic evolution by multiplying it with this matrix:

$$s_{t+1} = \text{softmax}(T \cdot s_t) \quad (24)$$

Additionally, this paper draws inspiration from the SO-PMI approach to compute a word's prior sentiment intensity I_{word} within the model as an additional feature input. For a given word w , its intensity is calculated as follows:

$$I(w) = \sum_{p \in P} \text{PMI}(w, p) - \sum_{n \in N} \text{PMI}(w, n) \quad (25)$$

where P and N represent predefined sets of positive and negative sentiment seed words, respectively. PMI $\text{PMI}(x, y)$ is used to measure the correlation between two words:

$$\text{PMI}(x, y) = \log \frac{P(x, y)}{P(x)P(y)} \quad (26)$$

where $P(x)$ and $P(y)$ represent the marginal probabilities of words x and y , while $P(x, y)$ denotes their joint probability – all derived from statistical analysis of large-scale corpora. A higher $I(w)$ value indicates stronger positive sentiment toward word w , while a lower value signifies stronger negative sentiment. This prior information is integrated into the model's final classification layer to assist the model in making more accurate decisions.

4 Experimental design and results analysis

4.1 Experimental setup

To comprehensively evaluate the proposed TL-SE-SA framework, experiments were conducted using three publicly available social media sentiment analysis datasets: SemEval-2018 Task 1 (Twitter sentiment classification), Micro-Video Induced Emotion (MVIndEmo), and inews (news sentiment). These datasets span diverse social platforms and sentiment expression forms, ensuring broad representativeness of experimental results. The dataset is divided into training, validation, and test sets, with corresponding proportions of 7:1.5:1.5, 8:1:1, and 7:1.5:1.5.

The various assessment indices that were used were accuracy (ACC), precision, recall, F1-score, area under the curve receiver operating characteristic (AUC-ROC), and normalised discounted cumulative gain (NDCG) to measure the performance of the models in a more comprehensive manner. These metrics compare the classification performance, the category balance performance, the quality of rankings and the overall classification performance. Namely, AUC-ROC quantifies the model average to identify positive and negative samples between various thresholds whereas NDCG quantifies the quality of sentiment intensity prediction ranking and is, therefore, specifically applicable to fine-grained sentiment analysis tasks.

4.1.1 Comparison of experiments and algorithms

The experiment will be a comparison between the suggested TL-SE-SA framework and various baseline algorithms, namely: Traditional machine learning methods: Consists of sentiment lexicon-based algorithms that make use of sentiwordnet and SVM algorithms with n-gram features, the latter using bag-of-words models with TF-IDF features. Deep learning methods: Includes LSTM, BiLSTM, and CNN models, architectures that have been extensively validated in text classification tasks. Pre-trained language models: including BERT-base, a robustly optimised Bert pre-training approach, and generalised autoregressive pre-training for language understanding, representing state-of-the-art context-aware text representation techniques. Social media-specific models: including BERTweet and socialBERT, which undergo specialised pre-training on social media text.

4.2 Results and analysis

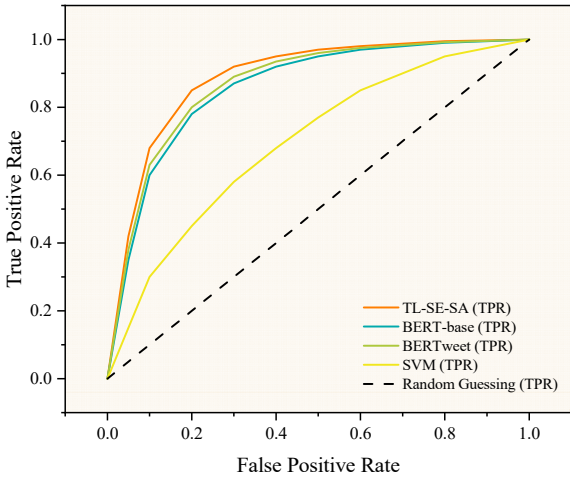
4.2.1 Comparison of experimental results

The comprehensive performance comparison results of the proposed TL-SE-SA model across three datasets are shown in Table 1. It can be observed that TL-SE-SA outperforms baseline methods on most metrics. On the SemEval-2018 dataset, the TL-SE-SA model achieves an accuracy of 73.12% in the sentiment classification task, surpassing BERT-base by 2.45% and traditional SVM methods by 15.32%. On the MVIndEmo dataset, the TL-SE-SA model achieved an F1 score of 71.36%, surpassing the best baseline model by 3.27%. These results validate the effectiveness of combining transfer learning with semantic augmentation.

Table 1 Performance comparison of different models across three datasets

<i>Model</i>	<i>SemEval-2018 Acc</i>	<i>SemEval-2018 F1</i>	<i>MVIndEmo Acc</i>	<i>MVIndEmo F1</i>	<i>iNews Acc</i>	<i>iNews F1</i>
SVM	57.80	56.93	62.17	61.84	65.43	64.87
LSTM	63.45	62.78	65.92	65.13	68.75	67.94
BERT-base	70.67	69.84	68.95	67.83	72.46	71.62
BERTweet	71.28	70.45	69.73	68.67	73.15	72.34
TL-SE-SA	73.12	72.56	71.89	71.36	75.28	74.67

Figure 2 Comparison of ROC curves for different models on the semeval-2018 dataset (see online version for colours)

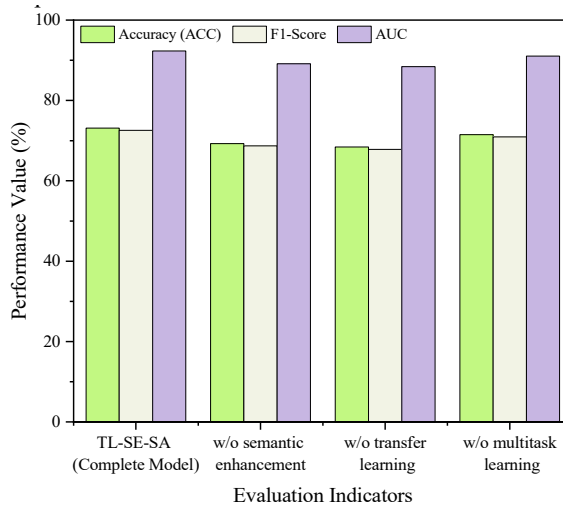


Empirical findings also confirm that models that are optimised specifically on social media, (e.g., BERTweet) yield stable, but limited performance increases over the general BERT, whereas the TL-SE-SA structure introduced in this paper yields bigger returns. It means that domain adaptation pre-training cannot capture complex emotional semantics of social media text completely, and the unnecessary use of specialised semantic enhancement mechanisms is required.

4.2.2 Results of the ablation experiment

This article performed systematic ablation experiments to know the contribution of each of the elements in the TL-SE-SA framework, and results are provided in Figure 3. The experiments contrasted the full model with the following variants: TL-SE-SA w/o semantic enhancement: the semantic enhancement module removal; TL-SE-SA w/o transfer learning: pre-trained weights were not used; TL-SE-SA w/o MTL: only the sentiment classification task was used.

Figure 3 Performance comparison of different model variants on the semeval-2018 dataset (see online version for colours)



Experimental findings indicate that the full model (TL-SE-SA) is better than ablation models on all measures. Transfer learning and semantic augmentation modules have the largest impact on increasing accuracy: the elimination of transfer learning keeps performance accuracy lower by 4.72 and the elimination of semantic augmentation by 3.85. MTL likewise had a favourable effect on performance and the accuracy went down by 1.63% when removed. The findings justify the use and usability of every element of the models.

It is worth noting that the semantic enhancement module has stronger contributions on short text social media databases like SemEval-2018, which can be interpreted as indication of how well it handles those fine emotive clues with minimal setting. MTL, in its turn, produces more significant enhancements in the sentiment intensity prediction tasks, which means that joint learning helps the models get familiar with the differences in the intensity of the emotional expressions.

4.2.3 Statistical significance test

The statistical significance test in the given paper is based on the difference in the performance of TL-SE-SA and the baseline model (BERTweet) on the test set. Paired t-test was used to obtain the comparison of the performances of the two models over 1,000 bootstrap samples, the result of which is presented in Table 2. As it can be observed, the gains in the performance of TL-SE-SA in all the metrics are statistically

significant ($p\text{-value} < 0.01$) which can be taken as evidence that the performance improvement is not referred to random factors.

Table 2 Results of statistical significance tests (TL-SE-SA vs BERTweet)

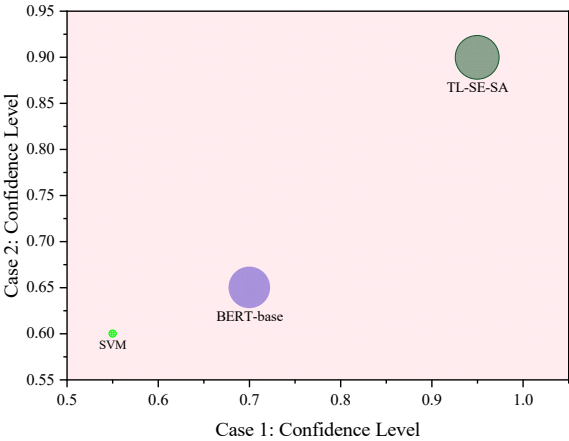
<i>Dataset</i>	<i>Indicator</i>	<i>TL-SE-SA</i>	<i>BERTweet</i>	<i>p-value</i>
SemEval-2018	Accuracy rate	73.12	71.28	0.0032
SemEval-2018	F1 score	72.56	70.45	0.0047
MVIndEmo	Accuracy rate	71.89	69.73	0.0061
MVIndEmo	F1 score	71.36	68.67	0.0053
iNews	Accuracy rate	75.28	73.15	0.0074
iNews	F1 score	74.67	72.34	0.0082

The statistical test involved two tails t-test, the null hypothesis being that there is no difference between the performance of the two methods. The null hypothesis was highly rejected by the test results ($p\text{-value} < 0.01$), which shows that the improvement of performance of the TL-SE-SA model is significant enough. This is a stringent statistical test that helps to verify the validity of the experimental results and gives the sound basis of the approach effectiveness.

4.2.4 The case studies and error analysis

Convenience to illustratively explain the benefits of the model, the paper has picked several representative samples of the SemEval-2018 dataset to be used as a case study as depicted in Figure 4. Tweets with sarcasm, negativity, and complicated linguistic constructions are some of the difficult samples that can be correctly classified by the TL-SE-SA model when misclassified by the base models.

Figure 4 Classification confidence analysis of typical difficult samples across different models (see online version for colours)



As an example, one can speak of the tweet which states the following: an other day, another headache. Just what I needed!’ was misplaced as joy by BERT-base, whereas TL-SE-SA was able to place it properly as anger. It was analysed that the semantic

enhancement module aided the model in identifying the ironic expression, and the domain knowledge through transfer learning aided the model in realising the negative emotional connotation of a headache. The other example is the tweet named ‘The flight was, well, an experience, and it has an implicit negative-sentiment’. Conventional approaches such as SVM recognised it as either neutral or slightly positive, whilst TL-SE-SA, which relied its semantic enhancement mechanism, correctly realised the underlying negative state of interest and determined the underlying response to be sad. This shows that the model can be applied to the nuanced aspects of social media text that reflect emotion on the other end.

4.2.5 Error analysis

We have indicated that the TL-SE-SA model is mostly subject to error in test of samples of overwhelming dependence on external world knowledge, as well as of complex samples with many conflicting emotions. As a case in point, tweets based on a certain cultural territory or current affairs can be wrongly classified because the model lacks the relevant knowledge. This gives useful guidelines in the future research. To mitigate this issue in future work, one promising direction could be the integration of structured external knowledge sources. For instance, incorporating knowledge graphs or domain-specific databases could provide the model with the necessary background information to correctly interpret context-dependent and culturally nuanced references.

4.2.6 Analysis of cross-domain generalisation

In order to test the ability of the model to generalise, further experiments were done in a cross-domain situation. The model was trained using SemEval-2018 (social media domain) and tested using the iNews (news domain) test set. The findings indicate that the performance of the TL-SE-SA model declined by only 5.23% when trying cross-domain, which is way less than the reduction recorded in the other models used (BERT-base: 8.71%, SVM: 12.45%).

This result shows that the TL-SE-SA framework is more ability to learn features domain-invariably and is thus more able to accommodate difficulties of distribution shifts. The most common reasons are the MTL format and the semantic augmentation module of the framework, which first encourages the model to pick up more generalised sentiment features, as opposed to bloat on domain-specific surface indications. The practical usefulness of the TL-SE-SA framework is further confirmed by cross-domain experiments in the context of which the phenomenon of sentiment analysis systems nearly always demand the ability to process textual data that belong to various domains and platforms.

5 Conclusions

The paper posits and confirms a framework of English sentiment analysis of social media using transfer learning with semantic amplification. Using a rigorous experimental assessment, the framework shows the superior and consistent results on three publicly available datasets, SemEval-2018, mvindemo, and iNews as opposed to a variety of baseline models, including classic machine learning, classic deep learning, and recent

state-of-the-art pre-trained models. Precisely, the model has an accuracy of 73.12% in sentiment classification challenges, which is a slight 2.45% higher than the overall BERT-base model and more pronounced 15.32% higher than conventional SVMs. More to the point, the ablation experiments, as well as statistical tests ($p\text{-value} < 0.01$) confirm that the resulting performance improvements are not accidental and are a combined effect of three core modules domain-adaptive pre-training, multi-level semantic enhancement, and MTL. These modules are concerned with some underlying issues in social media sentiment analysis: difference in domains, semantic noise and sparse labelled data.

The implications of the theoretical works of this research are expressed in two important ways. First, it formally verifies that an effective transfer mechanism of general language knowledge into the field of social media can be effectively achieved by means of pre-training domain-adaptive, demonstrating the importance of further pre-training on domain-specific corpora in the acquisition of non-standard linguistic constructions. Second, it plans and executes a semantic enhancement module which incorporates the local and global context. This multi-head attention based and graph convolutional network based module can effectively learn subtle cues of sentiment and long-range semantic dependencies in the text, providing new technical understanding with respect to complex phenomena such as sarcasm and implicit sentiment in discourse in social media.

In practice, this study provides more authoritative technical means to control sentiments, brand management, as well as optimisation of user experience in social networks. As an example, a model of accuracy of 73.12% can allow more accurate real-time monitoring of the trend of popular sentiment about hot topics, which can be used in decision-making. The suggested framework provides strong results working on noisy and abbreviated texts, which is why it can be incredibly helpful in the analysis of actual data in social media. Furthermore, its strong cross-domain generalisation capability (with only a 5.23% performance drop in cross-domain testing, significantly lower than baseline models) indicates its potential for application in diverse scenarios such as ad recommendations and mental health screening.

Declarations

All authors declare that they have no conflicts of interest.

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