An Enhanced LSTM Model Based on Feature Attention Mechanism and Emotional Intelligence for Advanced Sentiment Analysis

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***Abstract*—Sentiment analysis, a crucial yet complex task in natural language processing (NLP), is extensively employed to identify sentiment polarity within user-generated content. Traditional deep learning methods for textual sentiment analysis often overlook the influence of emotional modulation on extracting sentiment features. At the same time, their attention mechanisms primarily operate at the word or sentence levels. Such oversight of higher-level abstractions may hinder the learning of nuanced sentiment patterns, ultimately damaging the accuracy of sentiment analysis. Addressing these gaps, this study proposed a novel framework, the Two-State Enhanced LSTM (TS-ELSTM), which integrated Emotional Intelligence (EI) and a Feature Attention Mechanism (FAM) to enhance the identification of relevant features during selection. Furthermore, this study employed a dual-phase training strategy of LSTM to accelerate learning and minimize information loss. A dynamic topic-level attention mechanism is also introduced to optimize hidden text representation weights. By integrating EI with a topic-level attention mechanism, the proposed framework efficiently extracts valuable features and enhances the feature learning ability of the conventional LSTM model. This novelty attains emotion-aware learning through two key components: an emotion modulator and an emotion estimator, which successfully normalize the system's learning dynamics by combining emotional context. The experimental outcomes demonstrated that the proposed approach achieved an accuracy of 84.20%, 94.12% using MR and IMDB, respectively. The proposed approach significantly improves sentiment analysis accuracy, outperforming traditional deep learning models by a notable margin.**

***Keywords*—Sentiment analysis; emotional intelligence; attention mechanism; two-state LSTM; long-term dependencies**

I. Introduction

The exponential growth of social media platforms has raised sentiment analysis and opinion mining, and become critical areas in Natural Language Processing (NLP) applications [1-3]. Traditional sentiment analysis algorithms often produce a single polarity score for a complete text, which is insufficient when analyzing complicated content. For sentiment analysis illustration, a user review might praise the robustness of a product, whereas criticize the customer support, a scenario where existing approaches collapse such nuanced sentiments into a remarkable polarity score, failing to extract context-specific disparities. This generalization can result in misunderstandings and misinterpretations of user experiences in real-world applications [4]. Based on the recent literature review, deep learning (DL) approaches, mainly recurrent neural networks (RNNs), has dominated advance developments in various NLP tasks such as spam filtering, and topic classification [5, 6], question answering [7] keywords extraction [8] and anomaly detection [9], however, these conventional methods face challenges such as vanishing gradient decay and difficulty to retain long-range dependencies in sequences [10]. To address these issues, two advanced variants of the RNNs were introduced [11], known as LSTM and GRU, which retain the long-term dependencies. Modern implementations integrated attention mechanisms with hybrid architectures that deal with sequence information like CNNs [12] and RNNs [13], improving both predictive accuracy and interpretability. In sentiment analysis (SA), attention allows models to assign higher weights to sentiment-laden terms while suppressing irrelevant content [14], overcoming the inefficiencies of processing entire sentences sequentially [15]. Conversely, attention mechanism enables targeted concentration on specific parts of the input text during sequential analysis, allowing adaptive weighting of contextually critical components in real-time.

Cognitive research [16, 17] demonstrates the link between emotion-associated and human decision-making: positive emotions (e.g., enthusiasm) foster creative problem-solving, while negative emotions (e.g., anxiety) impair cognitive performance. Despite this, traditional LSTM-based approaches neglect the influence of emotion on sentiment feature extraction, potentially undermining their analytical efficacy. While sentiment and emotion are intertwined yet distinct psychological constructs, existing text sentiment analysis frameworks often conflate these terms. Sentiment refers to a persistent cognitive stance, such as opinions reflected in social media posts or brief videos, whereas emotions are transient psychological reactions that influence behavior and modulate neural activity (e.g., enhancing or suppressing neural responses to positive or negative stimuli). These dynamics can refine the adaptability of neural networks such as LSTM by imitating feedback-driven learning processes. This study focuses on detecting latent sentiments in social media content, though the proposed TS-ELSTM framework is designed for broader applicability in machine learning tasks, a direction reserved for future exploration. Crucially, this work rigorously differentiates between sentiment (as a sustained attitude) and emotion (as an ephemeral state) to ensure conceptual clarity.

In conclusion, the developed TS-ELSTM model offers unique advantages compared to traditional approaches in two key ways: firstly, unlike most traditional neural network models that overlook the role of emotional modulation, TS-ELSTM integrates emotion-based modulation to enhance the learning capacity of neural units by mimicking human emotional processes. Secondly, the existing attention mechanisms usually operate at lower abstraction levels, such as words or phrases. The topic-level attention mechanism in TS-ELSTM extracts higher-level cognitive concentration similar to that of the human brain, resulting in more refined sentiment representations of textual data. The primary contributions of this study are outlined as follows.

1) ELSTM Architecture. We present ELSTM, a novel LSTM variant inspired by emotional intelligence theory. By leveraging the synergistic interplay between emotion and cognition, ELSTM enhances the model's inference capabilities. To our knowledge, this is the first time a human-inspired emotional mechanism has been embedded to strengthen LSTM learning abilities.

2) Dynamic topic-level attention. This study introduces an innovative topic-level attention mechanism that dynamically adjusts the weights of hidden representations for text subsequences, enabling more focused feature extraction.

3) TS-LSTM framework. We design Two-State LSTM (TS-LSTM), a deep network for sentiment analysis that incorporates the ELSTM units with the developed topic-level attention, enhancing text sentiment detection.

4) Empirical validation. Through comprehensive experiments on standard sentiment analysis benchmarks, experimental findings demonstrate that our developed approach performs better than traditional approaches.

This study is organized as follows: Section II describes the details of related work employing deep learning approaches for sentiment analysis. The proposed methodology and its flow diagrams, as well as various sentiment analysis phases, are briefly illustrated in Section III. Section IV refers experimental setup, along with dataset description and evaluation metrics, while Section V presents the results and discussion. Finally, Section VI provides a conclusion and future direction.

II. RELATED WORK

This section investigates the traditional research work on sentiment analysis that influences LSTM architectures and attention mechanisms. Recent developments in RNNs illustrate that integrating LSTMs with their efficient gating for sequence modeling and attention layers are particularly effective for NLP tasks, while attention mechanisms dynamically prioritize salient features in sequences, making their integration a powerful approach for sentiment analysis [18]. Deep learning has already been adopted across NLP tasks such as topic modeling, text categorization, question answering, speech recognition, spam filtering, keyword extraction, machine translation, and information retrieval [19]. The implementation of deep learning in sentiment classification has grown exponentially, with attention-based methods driving innovation. For instance, one research study exhibited that embedding sentiment lexicon features alongside an attention mechanism boosts word representations for overall sentiment classification tasks without specific targets.

Furthermore, Toma and Choi [20] introduced two-directional LSTMs that capture bidirectional context more effectively than a vanilla LSTM. Zulqarnain et al. [21] introduced a bistatic GRU-encoder framework for sentiment analysis, outperforming standalone GRU and LSTM models in accuracy. Jang et al. [22] further advanced the field by combining bidirectional GRU, Word2vec embeddings, and attention mechanisms, achieving state-of-the-art results in sentiment analysis. Building on these ideas, BiLSTM+Attention architectures emphasize their capacity for sentiment-bearing features, further improving classification accuracy. Aspect-level sentiment analysis has progressively relied on attention-based neural networks to model relationships between context and specific terms. Wang et al. [23] referred ATAE-LSTM architecture, integrating LSTM with attention to evaluate contextual relevance for aspect terms. Zhao et al. [24] and Zulqarnain et al. [25] employed a hierarchical attention mechanism to pinpoint sentiment-critical information and achieve a good result, while Yang et al. [26] accomplished a multi-grained fusion network and multigranularity attention to capture word-level interactions and obtained superior performance against state-of-the-art methods. Moreover, Tan et al. [27] designed a dual attention network to detect conflicting opinions, while Ouyang et al. [28] presented Interactive Attention Networks (IAN) for bidirectional context-aspect learning. Graph Convolutional Networks (GCNs) have also emerged as pivotal tools in modern sentiment analysis frameworks.

Emotional intelligence (EI) research highlights emotions' influence on decision-making. Khashman [29] pioneered DuoNeural, an architecture unifying emotion and cognition in intelligent systems. Lotfi and Akbarzadeh [30] developed LiAENN, a neural network modeling emotional states like anxiety during learning. Hassan et al. [31] highlighted an emotional multi-agent reinforcement learning framework to foster cooperative behaviors, while Oyedotun and Khashman [32] unified adaptive and prototype learning theories in emotional neural networks. Markadeh et al. [33] utilized brain-emotional learning to control induction motors. Building on these insights, the proposed TS-ELSTM integrates emotional reasoning into intelligent systems, reinforcing the view that affective dynamics are essential to intelligent reasoning.

Conclusion remarks in terms of limitations of the existing literature review are as follows: traditional deep learning approaches excel in either contextual modeling (BiLSTM+Attention [20, 22-28]) *or* emotional reasoning (DuoNeural/LiAENN [29-33]), but they fail to synergize these capabilities. Aspect-level deep learning architectures (ATAE-LSTM [23], hierarchical attention [24-25]) capture contextual nuances but ignore affective dynamics critical for sentiment interpretation. Conversely, emotional neural networks [29-33] lack linguistic grounding for NLP tasks. Furthermore, existing models neglect the sentiment-emotion discrepancy and treat sentiment and emotion as isomorphic (e.g., lexicon-enhanced attention [18]).

III. Proposed Methodology

This study outlines the methodology of the proposed framework, which integrates emotional intelligence and a two-state LSTM strategy with an adaptive attention mechanism. The key contributions lie in its structured workflow, comprising in several phases: 1) systematic data acquisition and preprocessing, 2) feature embedding via pre-trained technique (GloVe), 3) sequential modeling using recurrent architectures (V-RNN, LSTM, and GRU), 4) integration of an attention layer and 5) performance assessment. Each component is comprehensively explored in depth in the following sections.

A. Embedding Layer

In the sentiment classification process, the embedding layer serves an important function by transforming raw text into structured numerical inputs. During sentence analysis, the initial preprocessing phase involves sanitizing textual data to remove noise. Neural networks, constructed on linear algebra operations and nonlinear activation functions, necessitate textual inputs to be translated into dense numerical vectors within a low-dimensional space [34]. To attain this, we utilize a pre-trained 300-dimensional Global Vectors (GloVe) technique [35] in the word embedding layer, which maps each word in a sentence to a continuous vector representation. GloVe influences global statistical patterns during the embedding stage and efficiently captures semantic and syntactic co-occurrence relationships across corpora, combining the benefits of matrix factorization and context window methods. This method improves its competence in managing lexical ambiguities, such as synonyms and polysemous terms. In contrast, network-dependent embeddings, the GloVe method arises word vectors directly from corpus statistics, bypassing iterative training procedures and allowing effective parallelization for scalable implementation.

B. Vanilla Recurrent Neural Network (V-RNN)

The Vanilla RNN is the most basic variant of the RNN model. The V-RNN includes a single recurrent layer that manages both current input information and the previous hidden state to produce an output while simultaneously updating its hidden state for subsequent steps. The term "vanilla" replicates its simplicity, as its deficiencies are advanced structural elements like gating mechanisms, which are frequently used to handle long-term dependencies or gradient issues [35, 36].

C. LSTM

The LSTM model is an advanced variant of standard RNNs, initially introduced by Sepp Hochreiter and Jürgen Schmidhuber in 1997 [37]. LSTMs are well-known for addressing long-term dependencies in sequential data. LSTMs are frequently integrated with architectural designs like inception modules to expand their ability and examine temporal patterns in time-series datasets. Unlike Vanilla RNNs, LSTM uses particular internal memory cells and gated mechanisms to moderate information loss during sequential data processing.

These networks manage the information flow across sequences utilizing gate mechanisms including input, forget, output, and a special internal memory cell, which cooperatively stimulate the hidden layer's output at each timestep [38]. By dynamically regulating data holding and propagation, LSTMs demonstrate better performance in the NLP tasks requiring nuanced temporal understanding.

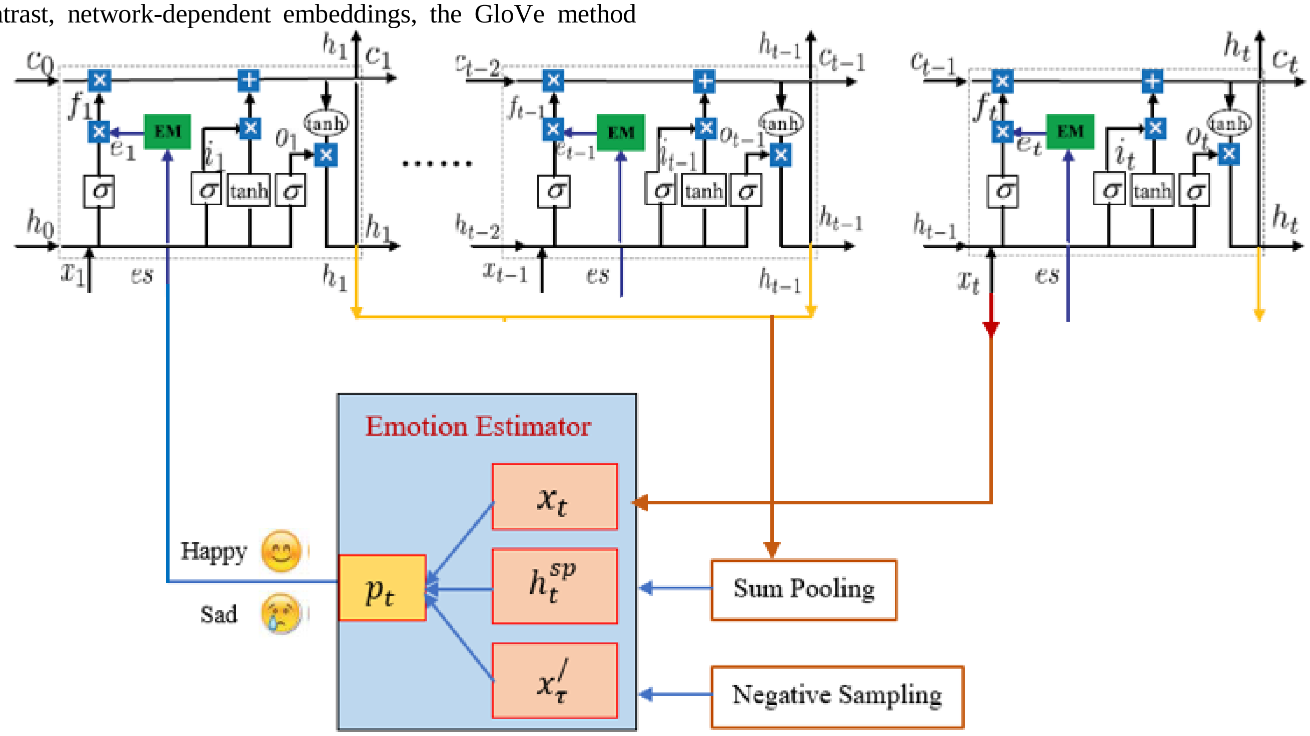


Fig. 1. Developed emotional LSTM.

D. Emotion-Enhanced LSTM

Conventional RNNs offer an effective approach for modeling sequential text data by leveraging contextual relationships between adjacent words. However, conventional RNNs suffer from gradient instability (vanishing or exploding gradients) and struggle to extract long-range semantic or sentiment dependencies. To address these drawbacks, Hochreiter and Schmidhuber [39], proposed the LSTM network, which incorporates gated memory cells and has demonstrated superior sequence-representation capabilities, significantly improving performance in tasks requiring temporal understanding. LSTM block mirrors certain features of the brain's memory and language-processing systems. Cognitive neuroscience research [40] highlights emotion's role in memory processes, enhancing information encoding, consolidation, and retrieval. For instance, a person's emotional state during perception can improve the encoding of information into both short-and long-term memory. As observed in previous work, it confirms that embedding emotional cues can lead to higher-quality decision-making in intelligent systems. Yet, traditional LSTMs update their memory cells solely based on input and past hidden states, ignoring any emotional modulation.

To bridge this gap, we propose Emotion-enhanced LSTM (ELSTM), a novel architecture inspired by EI principles. As illustrated in Fig. 1, ELSTM introduces three gates (input, forget, output), three states (hidden, cell, emotion), an emotion-based modulator (EM), and an emotion estimator. The network's output at each timestep feeds back into both the gate inputs and the emotion estimator. Formally, ELSTM core equations are as follows [Eq. (1) to Eq. (7)]:

$$i_t = \sigma(W_{xi}x_t + U_{hi}h_{t-1} + b_i) \tag{1}$$

$$e_t = EM(es) \tag{2}$$

$$f_t = e_t * \sigma(W_{xf}x_t + U_{hf}h_{t-1} + b_f) \tag{3}$$

$$o_t = \sigma(W_{xo}x_t + U_{ho}h_{t-1} + b_o) \tag{4}$$

$$\hat{a}_t = tanh(W_{x\hat{a}}x_t + U_{h\hat{a}}h_{t-1} + b_{\hat{a}}) \tag{5}$$

$$c_t = f_t * x_{t-1} + (i_t * \hat{a}_t) \tag{6}$$

$$h_t = O_t * tanh\,(c_t) \tag{7}$$

where, σ is the sigmoid activation, * denotes element-wise multiplication, and W, U, and b are trainable parameters. The emotion modulator produces a signal e_t from the emotional state e_s (as discussed in Section III-G), which is integrated into the forget gate f_t, balancing the retention of past cell state c_{t-1} against new input x_t.

ELSTM operates in four sequential phases:

1) Forgetting. The forget gate uses both the previous hidden state h_{t-1}, the current input x_t, and the emotion signal t_e to determine what to retain in c_{t-1}.

2) Emotion-estimation. An internal estimator infers the new emotional state e_s based on past outputs (see Section III.H).

3) Updating. During the updating process, the input gate i_t and the candidate state $\hat{a}_t$ manage which new information arrives in the cell, completing the update in Eq. (6).

4) Output. Finally, the output gate o_t filters the updated cell state over a *tanh* function to generate the new hidden state h_t, as in Eq. (7).

In this study, the ELSTM architecture illustrates three important novelties to enhance sequence modeling. First, its Emotion-Aware Forgetting mechanism reinterprets the forget gate of the traditional LSTM by incorporating emotion-derived signals, consenting to dynamic modifications to the retention of preceding context h_{t-1}, and the modification of new inputs x_t. This mechanism confirms a contextually balanced trade-off between memory preservation and adaptability. Second, its Brain-Inspired-Design extends standard LSTM by embedding emotion modulation, adjusting with neuroscientific insights on emotion's role in memory. Finally, this study describes the Dynamic Adaptation of emotional intelligence (EI) to prioritize contextually salient information during gating operations, improving decision-making over real-time relevance weighting.

By retaining the main memory-and-gating mechanisms of the conventional LSTM and expanding them with emotion-driven modulation, ELSTM efficiently balances information retention and forgetting, yielding a richer, more brain-inspired sequence model.

E. Two-State LSTM (TS-LSTM)

LSTM is an enhanced variant of conventional RNNs used for sequential modeling. At each time step t, they compute a hidden state $h_t \in \mathbb{R}^n$ illustrated in Eq. (8):

$$h_t = f(W_{xt} + Uh_{t-1} + b) \tag{8}$$

where, $W \in R^{m\times n}$, $b \in R^{m\times m}$, $b \in R^{m}$, refers to weight matrices and biases, respectively, and f represents a nonlinear activation [30]. Although LSTMs struggle with gradient instability (vanishing or exploding gradients) and inherently prioritize forward linguistic context, they neglect backward dependencies critical for tasks like sentiment analysis. Yet natural language understanding often benefits from both preceding and succeeding context.

To address this, we introduce the Two-State LSTM (TS-LSTM), which processes inputs in two passes: one from left to right (forward or positive) and one from right to left (backward or negative) inspired by bidirectional RNNs, as illustrated in Fig. 2. During training, these pathways independently analyze temporal sequences and merge their outputs to capture comprehensive contextual relationships.

1) Forward Pass. The forward LSTM computes hidden states $\overrightarrow{C_t}$ using the input gate $\overrightarrow{\iota_t}$, forget gate $\overrightarrow{f_t}$, and candidate state $\overrightarrow{\hat{a}_t}$ gates are defined as [Eq. (9) to Eq. (15)]:

$$\overrightarrow{\iota_t} = \sigma(\overrightarrow{W_{x\iota}} \times [\,\overrightarrow{C_{t-1}}, \overrightarrow{h_{t-1}}, \overrightarrow{x_t} + \overrightarrow{b_\iota}) \tag{9}$$

$$\overrightarrow{e_t} = \overrightarrow{EM(es)} \tag{10}$$

$$\overrightarrow{f_t} = e_t * \sigma(\overrightarrow{W_{xf}} \times [\,\overrightarrow{C_{t-1}}, \overrightarrow{h_{t-1}}, \overrightarrow{x_t} + \overrightarrow{b_f} \tag{11}$$

$$\overrightarrow{o_t} = \sigma(\overrightarrow{W_{xo}} \times [\,\overrightarrow{C_{t-1}}, \overrightarrow{h_{t-1}}, \overrightarrow{x_t} + \overrightarrow{b_o}) \tag{12}$$

$$\overrightarrow{\hat{a}_t} = tanh(\overrightarrow{W_{x\hat{a}}} * [\overrightarrow{h_{t-1}}, \overrightarrow{x_t} + \overrightarrow{b_{\hat{a}}}) \tag{13}$$

$$\overrightarrow{C_t} = \overrightarrow{f_t} * (\,\overrightarrow{C_{t-1}} + \overrightarrow{\iota_t} * \overrightarrow{\hat{a}_t}) \tag{14}$$

$$\overrightarrow{h_t} = \overrightarrow{o_t} * \overrightarrow{tanh}(\overrightarrow{C_t}) \tag{15}$$

2) Backward pass. Proportionally, the backward LSTM processes sequences in reverse, with analogous [Eq. (16) to Eq. (22)] for $\overleftarrow{\iota_t}$, $\overleftarrow{f_t}$, $\overleftarrow{C_t}$,$\overleftarrow{o_t}$ and $\overleftarrow{\hat{a}_t}$

$$\overleftarrow{\iota_t} = \sigma(\overleftarrow{W_{x\iota}} \times [\overleftarrow{C_{t-1}}, \overleftarrow{h_{t-1}}, \overleftarrow{x_t} + \overleftarrow{b_\iota}) \tag{16}$$

$$\overleftarrow{e_t} = \overleftarrow{EM(es)} \tag{17}$$

$$\overleftarrow{f_t} = e_t * \sigma(\overleftarrow{W_{xf}} \times [\overleftarrow{C_{t-1}}, \overleftarrow{h_{t-1}}, \overleftarrow{x_t} + \overleftarrow{b_f}) \tag{18}$$

$$\overleftarrow{o_t} = \sigma(\overleftarrow{W_{xo}} \times [\overleftarrow{C_{t-1}}, \overleftarrow{h_{t-1}}, \overleftarrow{x_t} + \overleftarrow{b_o}) \tag{19}$$

$$\overleftarrow{\hat{a}_t} = tanh(\overleftarrow{W_{x\hat{a}}} * [\overleftarrow{h_{t-1}}, \overleftarrow{x_t} + \overleftarrow{b_{\hat{a}}}) \tag{20}$$

$$\overleftarrow{C_t} = \overleftarrow{f_t} * [\overleftarrow{C_{t-1}}, \overleftarrow{\iota_t} * \overleftarrow{\hat{a}_t}) \tag{21}$$

$$\overleftarrow{h_t} = \overleftarrow{o_t} * \overleftarrow{tanh}(\overleftarrow{C_t}) \tag{22}$$

For an input sequence $(x_1, x_2, \dots, x_n)$, each token at position t is first encoded by the forward LSTM into $\overrightarrow{C_t}$ (left-to-right context) and by the backward LSTM into $\overleftarrow{C_t}$ (right-to-left context). These two vectors are then concatenated as referred to in Eq. (23):

$$C_t = \overrightarrow{C_t}, \overleftarrow{C_t} \tag{23}$$

This dual-direction formulation allows TS-LSTM to capture comprehensive contextual information from both surrounding directions.

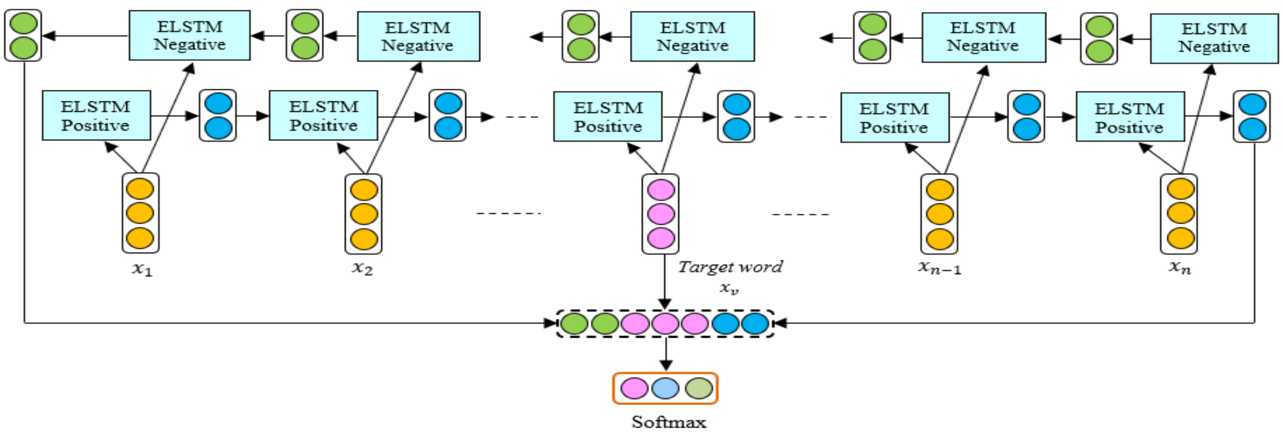


Fig. 2. Two-state strategy.

F. Attention Layer

The attention mechanism assists in highlighting the most relevant parts of the input data while minimizing the influence of less important information. By assigning differentiated weight values to features based on their emotional relevance, this mechanism permits the model to efficiently filter out non-essential textual content. This targeted concentration facilitates more accurate learning of emotionally substantial textual features, thereby improving the efficacy of implicit sentiment analysis tasks.

In most textual data, words that convey emotional tone are particularly impactful in determining the complete sentiment. In this research, we incorporate an attention mechanism that emphasizes emotionally charged features within sentences expressing implicit sentiment. Specifically, this study applies attention to both local and global feature matrices represented as $R = [r_1, r_2, r_3 \dots r_n,]$ and $H = [h_1, h_2, h_3 \dots h_n,]$ respectively, to enhance sentiment polarity.

The attention scores are calculated over the following transformations as Eq. (26) and (27):

$$Local\ features = u_{ri} = \tanh(W_r r_i + b_r) \tag{26}$$

$$Blobal\ features = u_{hj} = \tanh(W_r r_j + b_h) \tag{27}$$

where, W_r and W_h are the learnable weight matrices, b_r and h_r are biased terms, and $tanh$ is the activation function.

The attention weights a_i and a_j for local and global features are calculated using the softmax function [Eq. (28) and (29)]:

$$a_i = \frac{\exp(u_{ri})}{\sum_{i=1}^{m} \exp(u_{ri})} \tag{28}$$

$$a_j = \frac{\exp(u_{rj})}{\sum_{j=1}^{m} \exp(u_{rj})} \tag{29}$$

Using these attention weights, the local and global feature representations are computed as weighted sums [Eq. (24) and (25)]:

$$s_i = \sum_{i=1}^{m} a_i r_i \tag{24}$$

$$s_h = \sum_{j=1}^{m} a_j r_j \tag{25}$$

This dual-channel attention mechanism dynamically assigns importance to emotionally relevant word vectors, significantly improving the effectiveness of the developed TS-ELSTM approach. As a result, the network demonstrates better precision in emotion detection and analysis within the human-computer interactive dialogue environment. The overall architecture of the proposed model is demonstrated in Fig. 3.

The output layer of the TS-ELSTM model combines both local and global feature vectors by concatenation [Eq. (30)]:

$$s = [s_r, s_h] \tag{30}$$

To reduce the risk of overfitting, dropout is applied before passing the concatenated vector through a fully connected neural network. The final output is computed using the softmax function as in Eq. (31) and (32):

$$o = f[W_s s + b] \tag{31}$$

$$g = softmax(0) \tag{32}$$

where, o refers to the output from the fully connected layer, W is the weight matrix, b is the bias term, and g is the resulting output vector utilized for classification.

G. Emotion-Based Estimator

Emotional responses arise from fast neural signaling activated by external stimuli, mirroring the brain's capability to process information quickly. Inspired by this fast and efficient emotional reaction, we developed a novel emotion estimator integrated with negative sampling that influences similarity-based cognition. From a linguistic perspective, within a given text sequence $(x_1, x_2, \dots, x_{t-1}, x_t, \dots.)$, a subsequence $(x_{t-\tau}, x_{t-\tau+1}, \dots, x_{t-1})$ often holds strong semantic relevance to the current word x_t.

To capture this association, we compute the semantic similarity over the inner product between the vector representation of the current word x_t and the sum-pooled representation of the preceding subsequence $h_t^{sp} = SumPooling(x_{t-\tau}, x_{t-\tau+1}, \dots, h_{t-1})$. This system permits us to estimate the likelihood that x_t follows the subsequence using the softmax function as in Eq. (33):

$$P_t = \frac{\exp(h_t^T h_t^{sp})}{\sum_{i=1}^{V} \exp(h_i^T h_t^{sp})} \tag{33}$$

where, V represents the total vocabulary size. However, computing this across all vocabulary items is computationally expensive and contradicts the efficiency expected from emotion-driven systems. To overcome this, negative sampling is employed [41], significantly minimizing computation cost by selecting a limited number of negative examples from a background distribution. With this technique, the equation becomes [Eq. (34)]:

$$P_t = \frac{\exp(h_t^T h_t^{sp})}{\exp(h_i^T h_t^{sp}) + \sum_{i=1}^{NS} \exp(h_i^T h_t^{sp})} \tag{34}$$

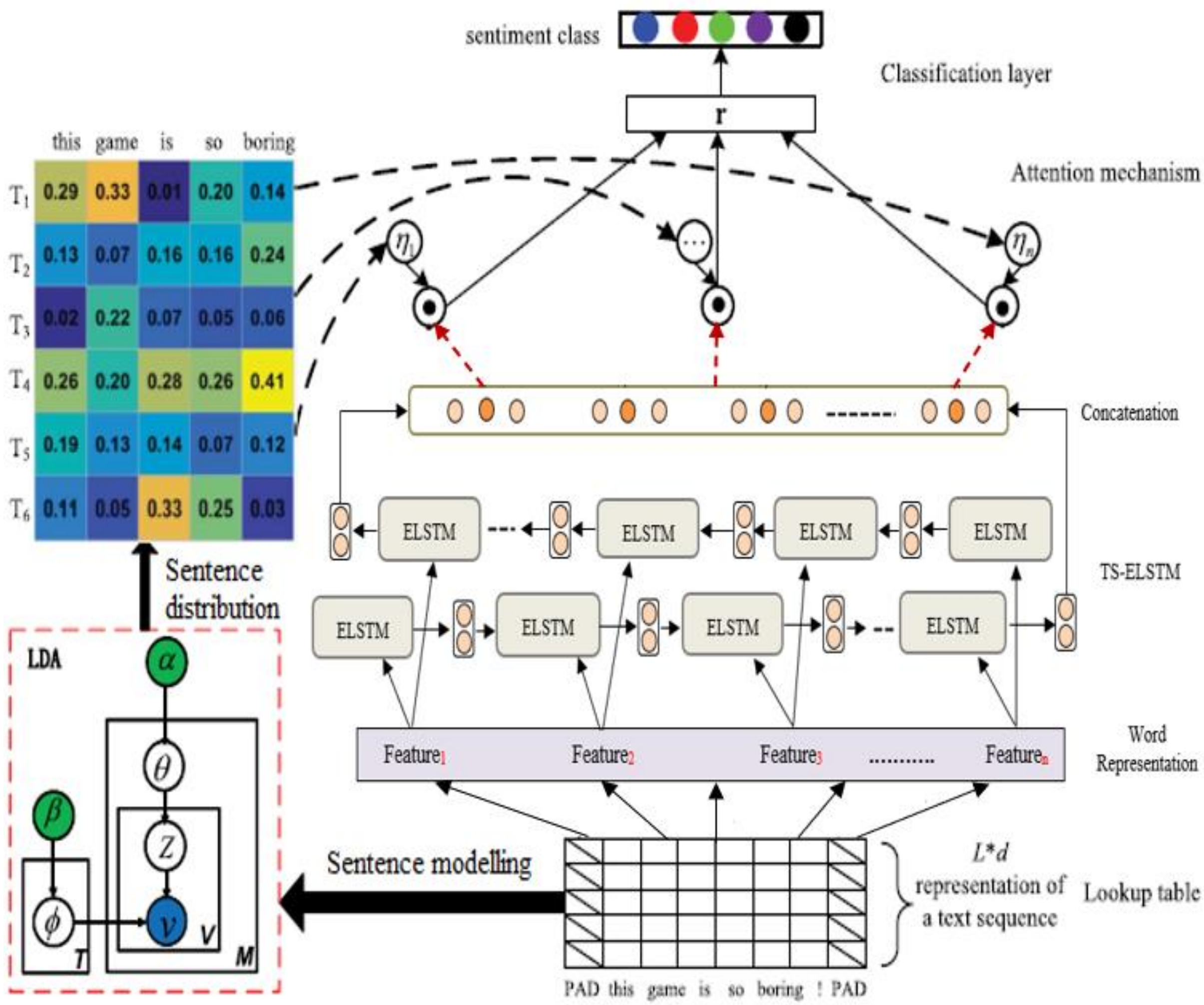


Fig. 3. Overall proposed TS-ELSTM architecture.

where, NS denotes the number of sampled negative instances, which is considerably smaller than V.

Rule 1: (Emotion Classification Rule): If $P_t > ET$ (a predefined threshold), the emotion estimator classifies the state as "Happy"; otherwise, it outputs "Sad".

H. Emotion-Based Modulation

The key role of the emotion-based modulator is to convert the emotional state es detected by the system into the corresponding modulation behavior. This conversion follows a set of predefined mappings, detailed in Rule 2 and Rule 3.

Rule 2: (Enhance Emotion Modulation): This rule is activated when the ELSTM (Emotion-augmented LSTM) experiences a "Happy" emotional state, typically triggered by successfully learning the semantic relationship between a subsequence $(x_{t-\tau}, x_{t-\tau+1}, \ldots, x_{t-1})$, and its next token x_t. Success indicates effective semantic comprehension, which reinforces TS-ELSTM's tendency to retain learned information by increasing its modulation factor, favoring memory over forgetting.

Rule 3 (Reduce Emotion Modulation): Conversely, failure to accurately learn the sequence embedding implies a poor understanding, causing a "Sad" state. In response to the current state, the proposed TS-ELSTM decreases its modulation factor to promote forgetting of low-quality or misleading information.

In this mechanism, the emotional coefficient p plays a key role. The modulation factor is calculated based on Eq. (35):

$$e_{t+1} = \begin{cases} e_t + \rho * \left|h'_t - h_t^{sp}\right| if\ es = H \\ e_t - \rho * \left|h'_t - h_t^{sp}\right| if\ es = S \end{cases} \tag{35}$$

where, $|.|$is the absolute value operator, $\acute{h}_t$ is the output vector for the current input x_t, while h_t^{sp} sum-pooled depiction of preceding outputs, and $H\ and\ S$ illustrate the emotional states "Happy" and "Sad", respectively.

To dynamically adjust p during training, a self-adaptive strategy is utilized as in Eq. (36):

$$p_{ep} = (p_{max} - p_{min}) * \frac{EPOCH - ep}{EPOCH} + p_{min} \tag{36}$$

where, p_{min} and p_{max} define the constraints of the inertia coefficient, while $EPOCH$ is the total number of training epochs, and ep is the current epoch.

This method confirms that p_{ep} starts its maximum value when training begins $(sp = 0)$ and progressively reduces toward p_{min} as training developments. The rationale aligns with deep learning algorithms: initially, a high inertia coefficient accelerates learning, while in later stages, a reduced value ensures constancy of the system converges.

IV. Experimental Setup

Several experiments were carried out to assess the effectiveness of the developed TS-ELSTM model in comparison to existing approaches. The simulations of the proposed study were performed on a system powered by an Intel Core i7-3770 CPU (3.40 GHz) and 32 GB RAM, running Windows 10. Python 3.13 and Anaconda utilized the computational environment for data preprocessing and analysis, supported by TensorFlow 2.4.1 and Keras 2.3 as deep learning frameworks. The Natural Language Toolkit (NLTK) was employed for word embedding tasks. Exploiting Keras's compatibility with CPU architectures, the setup optimized hardware resources to accelerate network training and inference. The detailed optimal hyperparameter settings utilized to train the developed model are illustrated in Table I.

TABLE I. Optimal Hyperparameter of the Developed Model

Parameter Name	**Parameter Value**
Optimizer	Adam
Word vector dimension	300
Batch size	64
Learning Rate	0.001
Attention Mechanism	350 units
Dropout	0.5
Activation function	ReLU/tanh
Loss Function	Cross-entropy
Learning rate decay	0.01
Network epochs	30

A. Dataset Description

The experiments were carried out using three publicly available datasets, all centered around sentiment analysis of movie-related opinions. The selected datasets are: Stanford Internet Movie Database (IMDB), and Movie Review (MR). These datasets are designed for binary sentiment classification to predict whether a review expresses a positive or negative sentiment. Key statistical details of the datasets, including size and class distribution, are summarized in Table II.

TABLE II. Statistical Details of the Dataset

Detail	**MR**	**IMDB**
Train	8654	37,500
Validation	CV	CV
Test	1062	12,500
Max.length	52	1825
Ave.length	18.6	180.4
V-size	18,990	88,712
D-size	10,660	50,000
No. Of Classes	2	2

B. Evaluation Metrics

To assess the effectiveness of the proposed method in sentiment analysis tasks, various evaluation metrics were employed. Commonly used metrics include accuracy, precision, recall (also known as sensitivity), and the F1-score. Each metric provides insights into different aspects of the model's performance as in Eq. (37) to (40):

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \tag{37}$$

$$Precision = \frac{TP}{(TP + FP)} \quad (38)$$

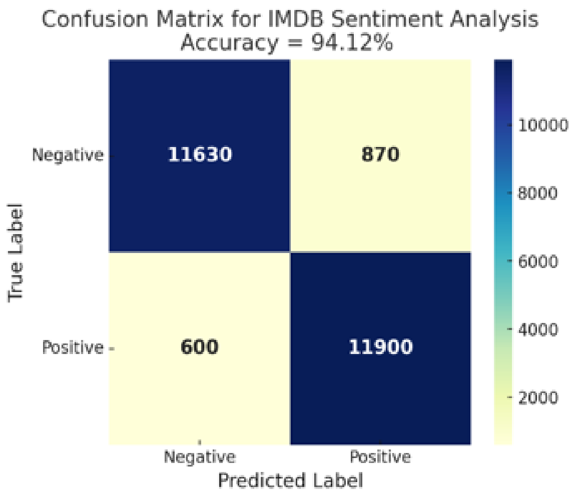
$$Sensitivity = Recall = \frac{TP}{(TP + FN)} \quad (39)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (40)$$

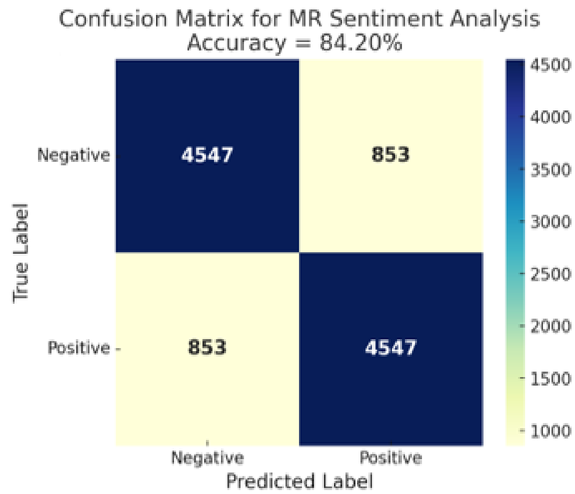
In these equations, TP, TN, FP, and FN stand for True Positive, True Negative, False Positive, and False Negative, respectively.

V. Results and Discussion

Our experimental analysis summarizes the performance outcomes of the TS-ELSTM approach, benchmarked against existing deep learning methods using two text classification datasets. The assessment, employing multiple evaluation criteria, demonstrates consistently superior accuracy across all benchmarked datasets. Fig. 4 shows the confusion matric performance of the proposed model using both datasets, while Table III describes the overall performance of the proposed model.



(a)



(b)

Fig. 4. Confusion matrix of the proposed model (a) IMDB, (b) MR.

TABLE III. Proposed Model Performance

	Evaluation Parameters			**Average Values**		
Datasets	Precision (%)	Recall (%)	F1 Score (%)	Test size	Accuracy (%)	F1 score (%)
MR	83.56	84.14	83.85	CV	**84.20**	**83.970**
	84.73	83.47	84.09	CV		
IMDB	94.38	93.69	94.07	CV	**94.12**	**93.965**
	93.90	94.04	93.86	CV		

A. *First Dataset (MR) Results*

The performance of the developed TS-ELSTM model on the MR dataset is illustrated in Table IV. The developed model obtained precision scores of 83.56% for positive instances and 84.73% for negative instances, with corresponding recall rates of 84.14% and 83.47%. These metrics culminated in an F1-score of 83.970% and an overall accuracy of 84.20%. Comparative analysis against existing studies underscores the model's superiority. For instance, Chen et al. [42] accomplished a BiLSTM with conditional random fields, attaining 82.30% accuracy, while Fu et al. [43] developed ALE-LSTM, a lexicon-enhanced LSTM with attention strategy, which achieved 79.90% accuracy on the MR dataset. The developed TS-ELSTM outperformed both these approaches, as well as Zhang et al.'s [44] proposed hybrid BiGRU+CNN, and reported 78.30% accuracy, our model highlighted 6.08% improvement over the existing approaches. Similarly, Qian et al. [45] introduced deep learning integrated models with sentence-level classification, and achieved an accuracy of 82.30%. Moreover, Usama et al. [46] reported accuracies of 79.80% and 80.20% using a multi-level feature extraction model combining GRU, LSTM, and CNN, results surpassed by the proposed framework. Furthermore, Mohammed et al. [47] proposed a recurrent attention GRU with a self-attention mechanism using the MR dataset, and reported an accuracy of 82.38%.

The proposed TS-ELSTM also excelled on the MR dataset, exceeding the performance of prior studies [42–49] despite their more complex architectures, detailed comparison is represented in Table IV.

TABLE IV. COMPLEXITY AND ACCURACY-BASED ANALYSIS WITH TRADITIONAL STUDIES ON THE MR DATASET

Methods	Model Complexity	Accuracy (%)
BiGRU+CNN [44]	Sequential combination of BiGRU and CNN framework	78.30
MV+RNN [48]	The joint strategy of analyzing trees and the RNN model	79.00
WALE+LSTM [43]	Implementation of WALE and attention mechanism jointly with LSTM	79.90
Self-Att-LSTM+word2vec [49]	Implemented Self-attention mechanism with LSTM based on word2vector	79.93
Hierarchical-Att-GRU+Dropout [49]	Investigated Hierarchical-attention mechanism with GRU based on word2vector	79.97
CNN-GRU-multilevel and multitype fusion [46]	Proposed combined methodology in terms of multilevel and multi-type features based on CNN and GRU models	80.20
SA-RA+GRU [47]	Proposed self-attention with recurrent attention GRU (SA+RA-GRU)	82.38
BiLSTM-CRF [42]	Fusion of bidirectional LSTM with CRT combined with CNN	82.30
LR+BiLSTM [45]	Illustrated sentence-level representation based on LR, and combined with BiLSTM	82.10
TS-ELSTM (Proposed)	**Two-State Enhanced LSTM (TS-ELSTM) + Emotional Intelligence (EI)**	**84.20**

B. *Second Dataset (IMDB) Results*

The proposed framework showed remarkable enhancements in sentiment analysis performance on the IMDB dataset, and compared results with state-of-the-art approaches, as demonstrated in Table III. The model achieved precision rates of 93.90% for positive reviews and 94.38% for negative critiques, with corresponding recall values of 94.04% and 93.69%, respectively. These metrics yielded an F1-score of 93.965% and an overall accuracy of 94.12%, outperforming conventional methods. For instance, Long et al. [50] introduced a cognition-based attention (CBA) method, which integrated dual attention frameworks with LSTM, achieved 90.10% accuracy, falling short despite its architectural complexity. Similarly, Collados and Pilehvar's [51] proposed a hybrid CNN-LSTM approach, incorporated preprocessing techniques and multi-modal fusion, attained 88.9% accuracy, underscoring the efficacy of our streamlined design.

Further comparisons reveal the framework's superiority over Ouyang et al. [52] CNN-based approach, and achieved an accuracy of 88.22% based on attention strategy, while Fu et al. [43] reported two various kinds of deep learning models, such as ALE-LSTM and WALE-LSTM approaches, which described an accuracy of 89.30% and 89.50%, respectively. Moreover, Kardakis et al. [49] explored the hybrid attention-based models and incorporated with LSTM/GRU, reporting an accuracy of 89.71% and 87.92%, respectively. Similarly, on the MR dataset, Mohammed et al. [47] proposed an attention-based recurrent neural network, such as GRU with a self-attention and recurrent attention mechanism, and reported an accuracy of 92.17%. While Zulqarnain et al. [21] reported 91.32% accuracy using a normalized auto-encoder with improved GRU. Furthermore, Islam et al. [53] explored the various hybrid deep learning models such as RoBERTa+DNN and BERT+DNN on the IMDB dataset, reported an accuracy of 92.05%, and 91.35%, respectively. Additionally, Lio Bing [54] proposed a CBOW-CNN method for sentence classification, attained an accuracy of 87.20%, and Yohong et al. [55] accomplished FARNN-Att mechanism, and highlighted an accuracy of 89.22% were outperformed by significant margins. In contrast, Danyal et al. [56] introduced a sentiment analysis model, such as XLNet (Extra-Long NN), using imdb dataset, achieving an accuracy of 93.74%, while Boewen Zhang [57] proposed a hybrid BERT-CNN model for sentiment analysis, reporting an accuracy of 92.90%.

By leveraging two-state layers alongside emotional intelligence, our proposed architecture highlighted excellent performance than existing studies based on architecture and accuracy comparison, detailed comparisons illustrated in Table V. The overall accuracy of two sentiment analysis datasets, showing IMDB at 94.12% and MR at 84.20%, graphical illustration is represented in Fig. 5.

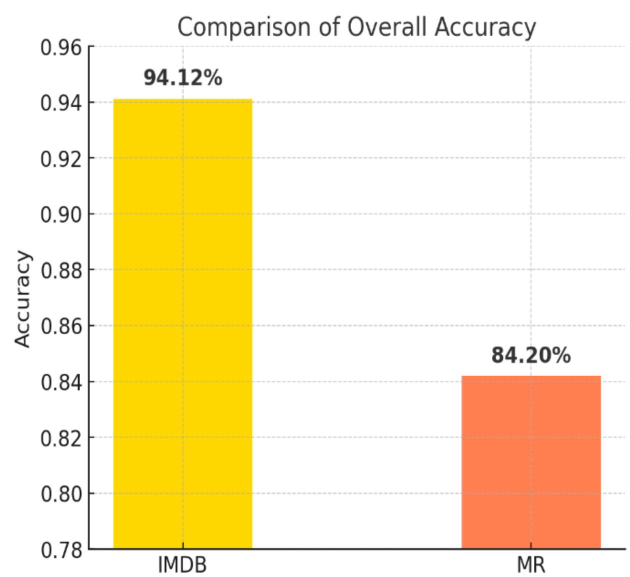


Fig. 5. Overall accuracy of the proposed model on both datasets.

Additionally, training dynamics were analyzed by tracking loss rates and epochs. Fig. 6 visualizes the epochs and loss rate of the proposed method alongside five conventional models (e.g., LSTM, Bi-GRU, BERT, BERT-CNN, and BERT-BiGRU) on a validation set. Over 25 epochs, the TS-ELSTM exhibited faster convergence, improved stability, and higher training efficiency, attributed to its emotional intelligence and topic-attention layers. These components optimize the representation of textual structure, enabling the model to capture contextual dependencies more effectively than traditional architectures.

TABLE V. COMPLEXITY AND ACCURACY-BASED ANALYSIS WITH TRADITIONAL STUDIES ON THE IMDB DATASET

Methods	Model Complexity	Accuracy (%)
CNN [52]	number of layers, filter sizes, strides, and input dimensions, leading to a computational cost-proportional	88.22
FARNN-Att [55]	Attention mechanism and adversarial training with BiLSTM	89.22
WALE-LSTM [43]	The combination of lexicon and attention layers with LSTM	89.50
CNN+LSTM [51]	Combination of CNN and LSTM with different cleaning processes	88.90
Self-Att-LSTM+word2vec [49]	Implemented Self-attention mechanism with LSTM based on word2vector	89.71
Hierarchical-Att-GRU+Dropout [49]	Investigated Hierarchical-attention mechanism with GRU based on word2vector	87.92
CBOW+D-CNN [54]	Combined the CBOW method with the CNN algorithm	87.20
LSTM+CBA+LA [50]	Integrated of two different feature attention frameworks with LSTM	90.11
BERT [58]	Bidirectional Encoder Representations from Transformers	85.83
XLNeT [58]	Transformer-XL with a two-stream attention mechanism	91.10
NAE-GRU [21]	Combined Auto-encoder with GRU through batch normalization	91.32
BERT+DNN [53]	Bidirectional encoder representations from transformers combined with deep neural network	91.35
RoBERTa+DNN [53]	R0bustly optimized BERT combined with deep neural network	92.05
SA-RA+GRU [47]	Proposed self-attention with recurrent attention unit GRU (SA+RA-GRU)	92.17
XLNet [56]	Extra-Long neural network	93.74
BERT-CNN [58]	Bidirectional encoder representations from transformers combined with CNN	92.90
TS-ELSTM (Proposed)	**Two-State Enhanced LSTM (TS-ELSTM) + Emotional Intelligence (EI)**	**94.12**

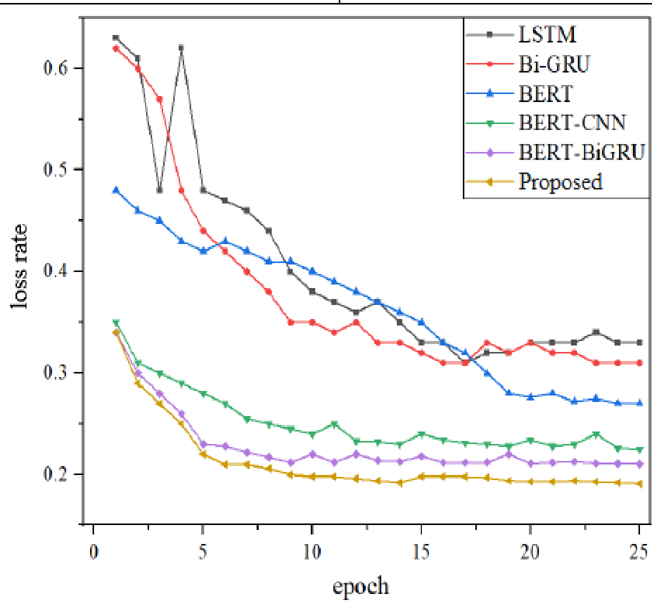


Fig. 6. Loss-based comparison of the proposed and traditional approaches.

VI. CONCLUSION AND FUTURE DIRECTION

Recurrent Neural Networks (RNNs) have become prominent in Natural Language Processing (NLP) for their effectiveness in modeling sequential data, yet they often struggle with vanishing gradient decay over long sequences and difficulty retaining distant contextual dependencies. To alleviate these drawbacks, attention mechanisms have been successfully combined as a transformative solution with deep learning algorithms, enhancing performance across NLP tasks. This study proposed TS-ELSTM, a novel deep learning architecture designed for sentiment analysis in textual sequences. The proposed framework integrates intelligence from emotional psychology and cognitive science, featuring an enhanced LSTM variant (ELSTM) that embeds emotional intelligence to dynamically balance information retention and forgetting. Additionally, a topic-aware attention mechanism dynamically adjusts the weighting of hidden representations in text subsequences, while an ELSTM layer synergizes with Latent Dirichlet Allocation (LDA) for topic modeling. Experimental outcomes show that the proposed TS-ELSTM accomplished excellent performance in sentiment analysis tasks compared to state-of-the-art models.

In the proposed study, we describe two limitations regarding our developed model: 1) The TS-ELSTM model was exclusively trained and tested on general-domain datasets (e.g., IMDB, Yelp, Amazon reviews). Its reliance on domain-specific linguistic patterns and emotional lexicons limits applicability to specialized contexts (e.g., clinical, financial, or low-resource languages). 2) The TS-ELSTM emotional gating mechanism and dual-polarity kernels increase computational cost and interpretation latency by ~35% compared to traditional LSTMs. This challenges scalability for real-time applications (e.g., live chat sentiment monitoring or high-frequency social media analysis), particularly on edge devices.

In future work, we plan two extensions. First, we extend to adapt TS-ELSTM model for aspect-level sentiment classification by incorporating fine-grained sentiment priors from lexical resources. Second, we will explore multi-objective optimization to tune TS-ELSTM parameters, striking an optimal trade-off between fitting accuracy and network sparsity, thereby enhancing both its robustness and generalization.

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