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Aspect-based Sentiment Analysis in Microblogs through Fuzzy Logic Techniques

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Abstract

The advent of social networks has elevated user-generated microblog text to a valuable asset for sentiment analysis, particularly among university students. Their microblogs serve as a portal to their psychological states and emotional inclinations. Traditional sentiment analysis methods, however, encounter limitations when grappling with the intricacies and nuanced variations in emotional expression. This study introduces and implements an innovative framework for aspect-based sentiment analysis (ABSA) of university students' microblogs, integrating fuzzy logic techniques. A methodology is presented for the identification of emotional tendencies in microblog content, amalgamating sentiment analysis with intuitionistic fuzzy set (IFS) theory. This approach effectively addresses the inherent multidimensionality and ambiguity in emotional expressions. Further, an aspect-based sentiment classification model, rooted in the fuzzy neural network (FNN), has been developed. This model enhances both the precision and sensitivity of sentiment classification. Results from this study signify a marked enhancement in ABSA over conventional methods. This advancement offers substantial support for data-driven decision-making in areas such as higher education management and psychological health services, underscoring the practical applications of the research.

Keywords: aspect-based sentiment analysis, microblog, fuzzy logic, intuitionistic fuzzy set, fuzzy neural network, university students.

1 Introduction

With the emergence of social media platforms, notably microblogs, online text has emerged as a pivotal channel for emotional expression, particularly among young adults [1, 2]. The realm of university students, recognized as active social media users, contributes extensively to this digital landscape, sharing aspects of their daily lives, emotional experiences, and personal viewpoints. This activity generates a substantial corpus of textual data [3]. Embedded within this data is a wealth of aspect-based emotional information, offering significant insights into the emotional states and mental health of university students [4, 5]. The challenge arises in the multidimensional and subjective nature of emotional expression, which complicates sentiment analysis. Traditional sentiment analysis methodologies often falter in capturing the nuanced shifts and complexities of emotions within microblog texts [6, 7, 8, 9].

The rapid development of social media in recent years has positioned sentiment analysis as a prominent area of research. Microblogging platforms, particularly within university student communities, have become significant venues for emotional expression. Existing sentiment analysis methodologies predominantly focus on traditional sentiment analysis and ABSA. However, these approaches often fail to adequately address the ambiguity and multidimensional nature of emotions. By critically examining these methodologies, limitations in handling complex emotional expressions have been identified. This study proposes a novel fine-grained sentiment classification model by integrating fuzzy logic, aiming to overcome these challenges. The literature review is structured into three subsections: the first outlines the progress in traditional sentiment analysis, the second explores recent advancements in ABSA, and the third examines applications of fuzzy logic in sentiment analysis. Sentiment analysis stands as a critical area within natural language processing, its relevance being indisputable. The sentiment analysis of university students' social media, in particular, not only fosters the advancement of emotion computation theory but also finds pragmatic application in fields such as educational guidance and mental health monitoring [10, 11]. An in-depth analysis of emotional expressions within these platforms can yield a deeper understanding of their psychological needs, thereby offering vital data support for the domains of higher education management and psychological health services [12, 13, 14].

Despite advancements in sentiment analysis research, the field still faces challenges in accurately recognizing aspect-based emotions [15, 16, 17]. Predominantly, methodologies rely on traditional sentiment dictionaries or machine learning algorithms, which encounter limitations when dealing with ambiguous emotional expressions and often struggle to distinguish subtle emotional nuances [18, 19]. Moreover, the prevailing research tends to overlook the inherent uncertainty and fuzziness in emotional expression, leading to a deficit in the flexibility and adaptability of the analytical outcomes [20, 21, 22].

This study aims to explore and refine methods for fine-grained sentiment analysis of microblog texts posted by university students. The primary contribution lies in integrating sentiment analysis with IFS theory to propose a novel framework for sentiment tendency identification. The proposed framework effectively captures the inherent ambiguity and multidimensional characteristics of emotions, thereby improving the precision and granularity of sentiment classification. By designing a fine-grained sentiment classification model based on FNN, this study addresses existing gaps in the literature and offers a new perspective on sentiment analysis in social media contexts. The structure of this study is as follows: Section 2 provides a comprehensive literature review; Section 3 details the research methodology; Section 4 presents the experimental results; and the final section offers a summary and discussion of future prospects.

2 Identification of sentiment tendencies in university students' microblogs

In addressing the multifaceted issues pertinent to mental health, public opinion monitoring, campus management, and personalized services, a model for ABSA of university students' microblogs has been developed. The IFS theory possesses unique advantages in addressing ambiguity and uncertainty, making it particularly suitable for analyzing the multidimensional and fuzzy nature of emotions in sentiment analysis. Conventional sentiment analysis approaches frequently overlook the multi-layered and ambiguous characteristics inherent in emotional expression. In contrast, IFS effectively handles such fuzziness, providing a more precise framework for identifying sentiment tendencies. FNN combines the strengths of fuzzy logic and the neural network, enabling adaptive adjustments and optimization of classification rules in complex data environments. This integration significantly enhances the accuracy and granularity of sentiment classification. The selection of this combined approach was motivated by its capability to effectively capture emotional nuances and ambiguities in microblog texts, thereby improving the precision of sentiment tendency identification. This model, grounded in Bidirectional Encoder Representations from Transformers (BERT) pre-training and attention mechanisms, is designed to surmount several practical challenges in ABSA. It provides mental health professionals with tools for the timely identification of potential psychological health issues, such as depressive tendencies or anxiety symptoms, by tracking shifts in emotional tendencies. This capability forms the foundation for early intervention and psychological counseling. Furthermore, the model is utilized by university administrators for monitoring campus public opinion, enabling swift comprehension of student emotional fluctuations and thereby facilitating the effective organization of student activities and policy revisions.

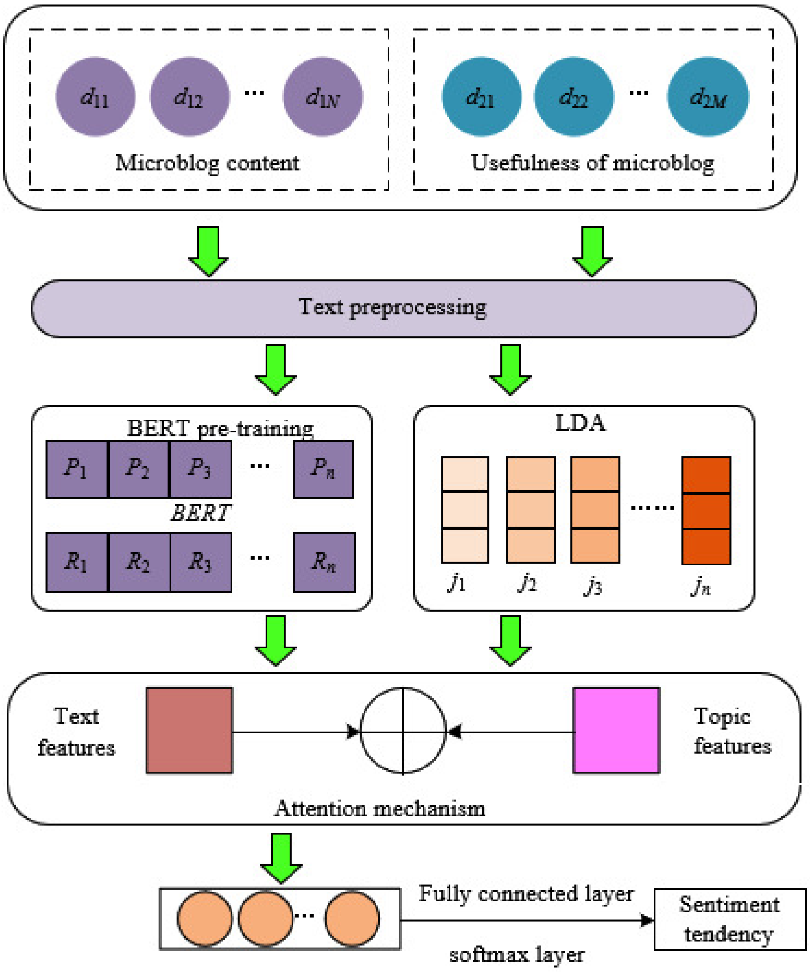

Figure 1: Structure of the microblog sentiment tendency identification model for university students

The model encompasses an input layer, a preprocessing layer, Latent Dirichlet Allocation (LDA) for extracting topic features, a BERT pre-training layer, an attention layer, and an output layer. Figure 1 illustrates the structural composition of the microblog sentiment tendency identification model for university students. The input layer, crucial in the initial processing of microblog texts, is adept at effectively receiving and transforming texts authored by university students. These texts are characterized by a proliferation of internet-specific language, emojis, abbreviations, and misspellings, representative of non-standard language forms. The model's ability to comprehend these informal text contents hinges on the input layer's capacity to convert these unique characters and expressions into a standardized format, encompassing both basic character encoding conversions and specific algorithms to interpret and process elements such as emojis or internet slang.

In the domain of sentiment analysis for university students' microblogs, the preprocessing layer of the model is tasked with addressing not only general textual noise, such as irrelevant characters and formatting issues, but also the distinctive features of student language. The prevalence of slang, colloquialisms, and emergent internet jargon in these microblogs poses a challenge to the accuracy of sentiment analysis. Consequently, it is imperative for the preprocessing layer to be equipped with the capacity to update and expand its tokenization and vocabulary recognition capabilities, encompassing the latest internet language and expressions unique to the youth. Additionally, the process of stopword removal must be attuned to the specificity of microblog text, targeting the elimination of not only standard stopwords but also microblog-specific elements that do not contribute to sentiment analysis, such as excessive repetitions or interjections. This refinement enhances the overall quality and efficiency of subsequent analyses.

Preprocessing microblog texts is a critical step in sentiment analysis, particularly due to the prevalence of non-standard expressions in social media content. The following steps were employed to preprocess the microblog texts:

(a) Noise removal: Irrelevant punctuation marks, advertising phrases, and other meaningless symbols were eliminated.

(b) Handling slang and abbreviations: Normalization of frequently used internet slang in microblogs was performed using a pre-constructed slang dictionary.

(c) Processing emojis: Emojis, as a significant means of emotional expression in microblogs, were mapped to their corresponding sentiment-related lexical representations.

(d) Tokenization and part-of-speech tagging: Tokenization was conducted on the microblog texts, and part-of-speech tagging was utilized to further identify the positions of sentiment-related words.

The application of the LDA topic model is instrumental in revealing the implicit content within texts, a task of particular importance when analyzing university students' microblog texts. These students often express specific interests and preferences in their posts. The LDA model facilitates the identification of these underlying themes from an extensive collection of microblog texts. These themes, potentially associated with students' emotional states, societal events, or aspects of campus life, are vital for accurate sentiment analysis. For example, themes such as "exams," "stress," or "study" might gain prominence during exam periods, strongly correlating with the emotional tendencies of students. The integration of topic information with sentiment analysis enables a more precise capture of students' emotional states, thereby providing valuable data for institutions in areas like mental health monitoring and counseling services.

University students' microblogs are often rich in contextual information. The model's BERT pretraining layer, leveraging a self-attention mechanism, is adept at discerning the relationships among words within a sentence. This ability is particularly crucial for interpreting microblog content that may contain irony, puns, or ambiguous emotional expressions. The BERT layer, a bidirectional pretrained language model based on the Transformer architecture, processes the vector representation of individual words (Ru) and the hidden layer outputs (Su). After undergoing weighting through the bidirectional Transformer's attention module, Ru encompasses comprehensive information about all words in the current sentence. Extensive pre-training on a broad corpus endows the BERT layer with a wealth of prior knowledge, facilitating its fine-tuning to the specific linguistic and emotional expression patterns prevalent in university student microblogs. During this fine-tuning process, BERT adapts to the unique internet language and expressive habits of university students, thereby enhancing the model's accuracy and sensitivity in sentiment analysis.

In the sentiment analysis of university students' microblogs, the employment of the attention layer is integral for pinpointing the most emotionally resonant words or phrases within the text. This layer employs a multi-head attention design, facilitating simultaneous focus on various segments of a sentence, a critical aspect for interpreting complex emotional expressions. For example, a microblog might simultaneously express positive sentiments about one event and negative emotions towards another aspect. The multi-head attention mechanism enables distinct capture of these nuanced details. The query vector matrix, denoted by W, and the key vector matrix, indicated by J, are crucial components in this process. The normalized weight vector, represented as β, and the attention representation vector, denoted as N^*, are computed through a series of steps s [21, 22]. The scoring function $SC(W, J)$ first measures the similarity between W and J. The vector β, is derived using the formula $\beta = softmax(SC(W, J))$. Subsequently, the vector N is determined by processing βN, culminating in the representation N^*.

The model's output layer is composed of one or several densely connected network layers, tasked with translating the sophisticated features from the attention layer into definitive sentiment labels. In the context of ABSA for university students' microblogs, this layer's scope transcends basic positive or negative sentiment classifications, encompassing a spectrum of nuanced emotional categories, such as anxiety, excitement, or anger. The softmax function plays a pivotal role in the output layer, transforming the neural network's outputs into a probability distribution indicative of the likelihood of microblog texts aligning with diverse emotional categories. The parameters of the softmax function are represented by Qt and yt, as expressed in the formula:

$$b = \mathrm{softmax}\left(Q_t N^* + y_t\right) \tag{1}$$

For the sentiment analysis of university students' microblogs, the output layer can be further refined into discrete emotional subcategories, like varying intensities of anxiety. The set of university students' microblog texts is denoted by u, and the set of emotional tendencies classified is indicated by k. The $L2$ regularization parameter is symbolized by η, and all parameters involved in the model's computational process are represented by ϕ. The model's loss function is articulated as a regularized cross-entropy function, formulated as follows:

$$LOSS = -\sum_u \sum_k b_u^k \log_{b_u^*} k + \eta \|\phi\|^2 \tag{2}$$

In the analysis of university students' microblogs, the complexity of emotional expressions, such as sarcasm, humor, or ambiguous descriptions, challenges the assignment of a single sentiment label to fully encapsulate the text's emotional nuances. To address this, IFS is employed, providing a nuanced portrayal of diverse emotional dimensions. IFS, incorporating degrees of non-membership and hesitation, enriches each emotional category with measures reflecting affirmation, negation, and the uncertainty of emotions. This study utilizes IFS to transform sentiment tendency identification outcomes from university students' microblogs, enhancing the analysis and handling of aspect-based emotional variances in the texts. Consequently, this approach yields more precise emotional metrics, benefiting applications such as psychological analysis and public opinion monitoring.

The following enumerates the symbols and specific meanings of the sets and variables involved:

(a) The collection of alternative microblog topics is denoted by $X = X1, X2, ..., Xv$, with each alternative topic, such as X_u, representing the u-th topic.

(b) The set of l attributes for alternative topics, symbolized by $D = d_1, d_2, ..., d_l$, includes attributes such as d_k representing the k-th attribute.

(c) The attribute weight vector for these topics is represented by $q = [q_1, q_2, ..., q_l]$, where the weight corresponding to the attribute d_k is denoted by q_k, adhering to the condition $q_k >= 0$, and the sum $\sum_{k=1}^{l} = m$ with $k = 1, 2, ...l$.

(d) The vector signifying the count of university students' microblogs on alternative topics is expressed as $W = [w_1, w_2, ..., w_v]$, where w_u signifies the number of microblogs for the topic X_u.

(e) For a given topic X_u, the set of university students' microblogs is represented by $E = E_{u1}, E_{u2}, ..., E_{wu}$, with Euj indicating the j-th comment on topic Xu.

(f) The quantity of comments on topic X_u manifesting positive, neutral, and negative sentiments for attribute d_k is represented by V_{uk}^1, V_{uk}^0, V_{uk}^{-1}, respectively.

In sentiment classification tasks, FNN addresses the uncertainty and ambiguity inherent in emotional expressions by incorporating fuzzy logic. Compared to traditional neural network methods, FNN demonstrates superior capability in handling ambiguous sentiment data. For instance, sentiments in microblog texts often exhibit nuanced ambiguity, such as "happy but somewhat regretful" or "a bit disappointed but overall fine." Traditional neural networks tend to categorize such expressions into a single emotional class, whereas FNN can manage these ambiguous sentiment boundaries, enabling more fine-grained sentiment analysis. The selection of this fuzzy membership function was motivated by its adaptability, allowing the membership degree to be flexibly adjusted according to the distribution of input data. Traditional approaches typically employ fixed-shaped membership functions, which are less suited to capturing the complexity of emotional expressions. By dynamically adjusting the shape and parameters of the membership function, the proposed model effectively captures the diversity and ambiguity of sentiments. This adaptability can significantly improve sentiment classification accuracy compared to traditional methods.

In this study, the constructed IFS encapsulates the dimensions of positive, negative, and neutral emotional tendencies in university students' microblogs, translating these into the respective membership degree $\omega_x(a)$, non-membership degree $n_x(a)$, and hesitation degree $1 - \omega_X(a) - n_X(a)$. The membership degree is directly defined by the model's output of emotional probability, whereas the non-membership degree is determined by the complement of this emotional probability. The hesitation degree, indicative of the uncertainty between membership and non-membership degrees, is calculated based on their differential. An optimization algorithm may be necessitated to ensure adherence to the IFS constraints. The classification of microblog texts into emotional tendency categories, based on the highest membership degree or optimal IFS score, is executed through decision rules. This categorization process treats the positive, negative, and neutral emotional tendencies in university students' microblogs as indicative votes of support, opposition, or abstention, respectively. The emotional tendencies represented in university students' microblogs toward various attributes of alternative topics are denoted by $a = (\omega, n)$, with the IFS for topic Xu on attribute dk being $a_{uk} = (\omega_{uk}, n_{uk})$. The subsequent formulas articulate the conversion of emotional tendencies from university students' microblogs into the IFS membership degree, non-membership degree, and hesitation degree for each attribute of alternative topics:

$$\omega_{uk} = \frac{V_{uk}^{1}}{V_{uk}^{1} + V_{uk}^{0} + V_{uk}^{-1}} \tag{3}$$

$$n_{uk} = \frac{V_{uk}^{-1}}{V_{uk}^{1} + V_{uk}^{0} + V_{uk}^{-1}} \tag{4}$$

$$\tau_{uk} = \omega_{uk} - n_{uk} \tag{5}$$

The above equations describe the relationship between sentiment-laden texts and different sentiment categories, facilitating the mapping of emotional information in the texts to the membership values of each sentiment category. The sentiment analysis model was utilized to calculate the degree of alignment between the text and each sentiment category. The membership value indicates the intensity of emotional tendencies of the text within a particular category. For instance, if a microblog text has a membership value of 0.9 in the "positive" category, it signifies a strong tendency towards positive sentiment. In contrast to membership, non-membership measures the degree of misalignment between the text and a given sentiment category. A higher non-membership value indicates a weaker association between the text and the sentiment category. When the association of a text with multiple categories cannot be clearly determined, a degree of hesitancy can be computed. A higher hesitancy value reflects greater uncertainty in sentiment classification.

3 Aspect-based sentiment classification in university students' microblogs using FNN

Figure 2 illustrates the research methodology of this study. The study thoroughly addresses the emotional nuances present in university students' microblog texts. It encompasses aspects such as the interrelation among various microblog texts from university students, the interconnectedness within the same text across different topics, and the inherent fuzziness and temporal continuity of these texts. A seven-layer model for aspect-based sentiment classification of university students' microblogs has been methodically devised. This comprehensive model incorporates a vectorization convolution layer, an input layer, a fuzzification layer, a spatial activation layer, a recurrent layer, a result layer, and a defuzzification (output) layer. It is engineered to capture the evolution of emotions over time within microblog texts, discern the emotional links across different microblogs, and maintain emotional coherence throughout various topics. This enhances both the precision and sensitivity of emotion classification. Furthermore, the model adeptly addresses the ambiguous boundaries and multiple meanings within texts, facilitating a thorough analysis of uncertainties and subtle variances in emotional categories. Consequently, it offers enhanced emotional cognition services in areas such as public opinion surveillance, mental health assessment, and personalized recommendation systems. An in-depth examination of the model's seven layers is presented.

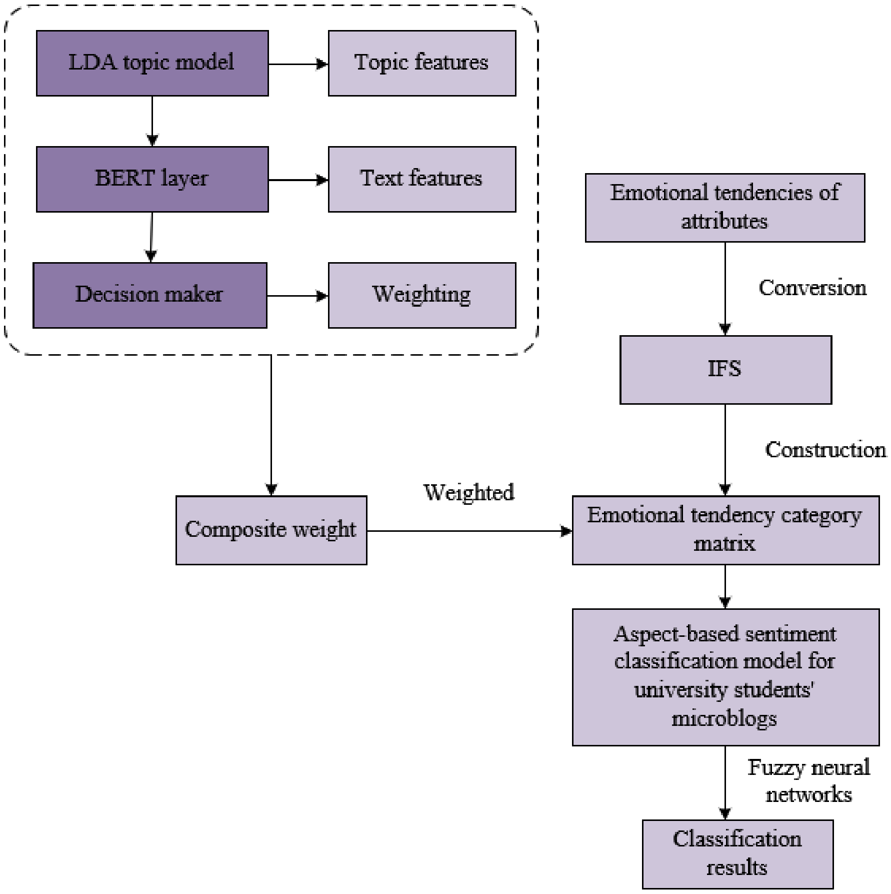

Figure 2: Research approach employed in this study

(a) The first layer (vectorization convolution layer)

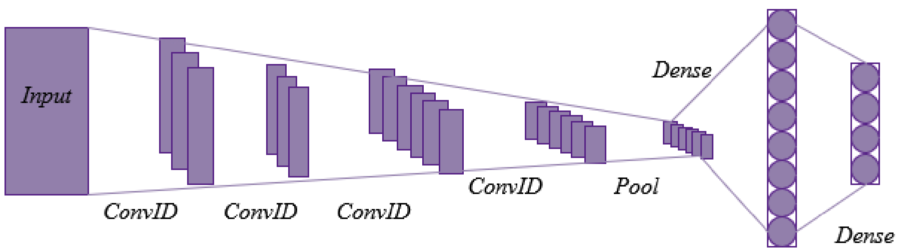

Figure 3: Architecture of the vectorization convolution layer

Comprising the foundational segment of the model is the vectorization convolution Layer, constituted by four one-dimensional convolutional layers, a pooling layer, and two fully connected layers, as depicted in Figure 3. Within this layer, microblog texts from university students undergo an initial transformation into vectors within a high-dimensional space, utilizing tokenization and word embedding techniques. The input feature matrix, designated as A_D, is transposed into a series of corresponding vectors, labeled as $i^{(1)} = [i^{(1)}1, i^{(1)}2, ..., i^{(1)}m]$. Subsequent to this vectorization, convolution operations are executed on these vectors across the various layers. Each convolution layer is equipped with v convolutional kernels, thus facilitating v distinct convolution operations. This structure enables the capture of local features at diverse scales, where each filter's window size is designed to encapsulate combinations of words or phrases within a specified range. Ultimately, v vectors, each of dimension 3*1, are amalgamated to form an augmented matrix of dimension $3{*}v$. The methodology of the one-dimensional convolution operations is elucidated in Figure 4.

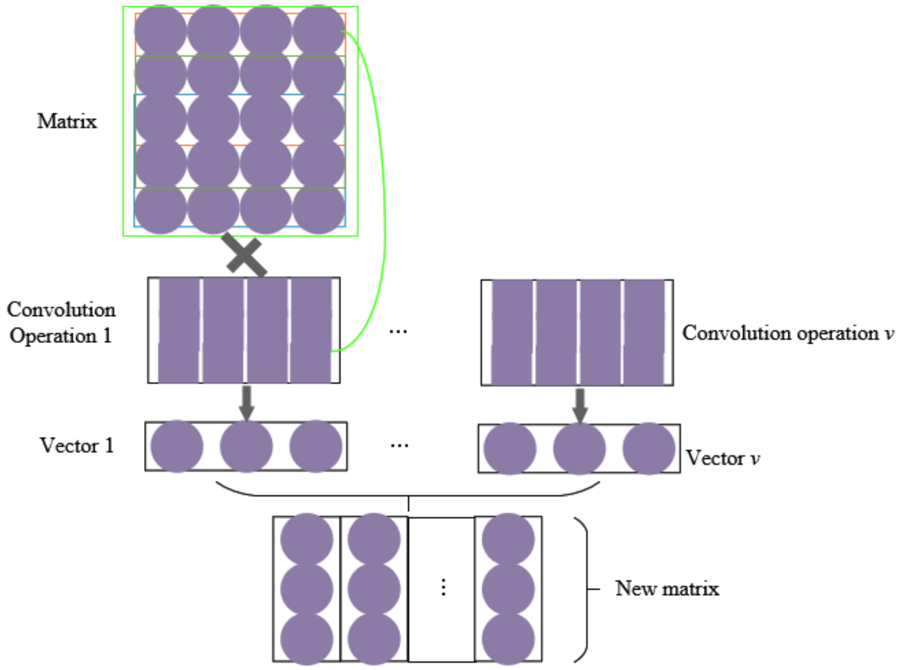

Figure 4: One-dimensional convolution operation process

(b) The second layer (input layer)

Functioning as the model's portal, the input layer is designated for receiving preprocessed text data. This data encompasses more than just word vectors; it also includes additional features vital for emotional expression, such as punctuation marks, special characters, and emojis. The specific operational expression of this layer is denoted as follows:

$$i_u^{(2)} = i_u^{(1)} u \in [1, m] \tag{6}$$

(c) The third layer (fuzzification layer)

Given the inherent vagueness and multidimensionality of emotions in microblog texts, straightforward binary or multi-classification may fall short in capturing the authors' true emotional states. In the fuzzification layer, vectors representing each word or phrase undergo a transformation into fuzzy sets. This process involves assigning to each element a degree of membership and non-membership, accompanied by a hesitation degree that signifies indecisiveness, thereby reflecting the uncertainty of elements' association with various emotional categories. The Gaussian membership function's mean and variance between the u-th node of the second layer and the k-th node of the third layer are expressed by l_{uk} and $\delta^2 uk$, respectively. The value for the k-th node in the third layer, corresponding to the input from the u-th node $i_u^{(2)}$ of the second layer, is symbolized by $i_{uk}^{(3)}$. The operation of the fuzzification layer is encapsulated in the following formula:

$$i_{uk}^{(3)} = \exp\left(-\frac{\left[i_{ul}^{(2)} - l_{uk}\right]}{\delta_{ukk}^2}\right) k \in [1, \eta], u \in [1, m] \tag{7}$$

(d) The fourth layer (spatial activation layer)

The spatial activation layer plays a crucial role in the context of microblog texts, characterized by length constraints and high information density. Users often express emotions using a limited number of keywords within the concise text format of microblogs. Hence, the model is designed to identify and concentrate on these essential elements. Known as spatial rule nodes, each node within this layer represents a specific fuzzy rule. The layer consists of a total of η such nodes. The spatial activation strength, denoted by D^k, and the specific activation strength of the k-th spatial rule node, indicated as $i_k^{(4)}$, are calculated as per the following formula:

$$i_k^{(4)} = D^k = \prod_k i_{uk}^{(3)} k \in [1, \eta], u \in [1, m] \tag{8}$$

(e) The fifth layer (recurrent layer)

University students' microblogs are often imbued with rich emotional content and metaphorical language, necessitating the analysis of entire sentences or a sequence of sentences for accurate interpretation. The recurrent layer, employing recurrent neural networks, is tasked with processing this textual data. It plays a pivotal role in recognizing and memorizing the sequential information unfolding over time within the text, which is integral for understanding contextual nuances and long-distance dependencies. In the case of microblogs by university students, this layer enables the model to grasp emotional details that are succinctly expressed due to the brevity of the text. The time step is represented by s, with the weight of $\theta_w^k(s-1)$ symbolized by q_k. The outputs of the recurrent structure at times s-1 and s are represented by $\theta_w^k(s-1)$ and $\theta_w^k(s)$, respectively, signifying the temporal activation strength of the k-th neuron at different time intervals. The output of the recurrent layer, denoted as $\theta_w^k(s)$, is influenced by both the spatial activation strength from the previous layer, $i_k^{(4)}$, and its preceding temporal state, $\theta_w^k(s-1)$. The computational process within the k-th node of this layer is articulated in the subsequent formula:

$$i_k^{(5)} = \theta_w^k(s) = \frac{1}{\frac{1}{i_k^{(4)}} - \log\left(sigmoid\left(q_k \theta_w^k(s-1)\right)\right)} k, w \in [1, \eta] \tag{9}$$

(f) The sixth layer (result layer)

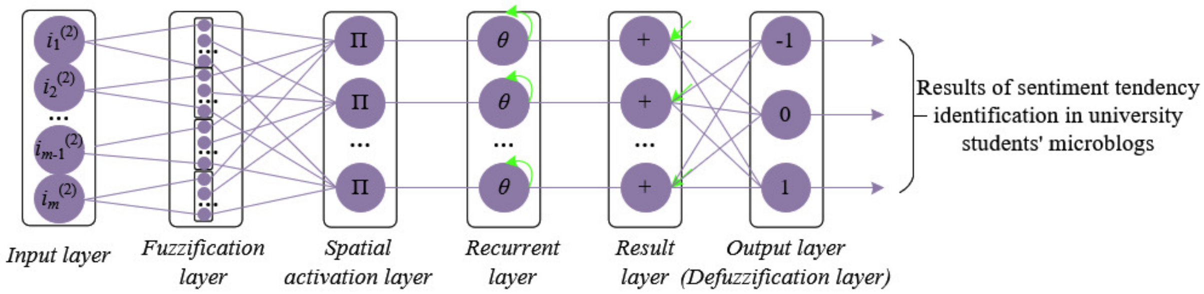

Figure 5: Architecture of the other six layers

In the domain of ABSA of university students' microblog data, the model is required to discern subtle emotional nuances. The result layer, bearing significant complexity, is entrusted with processing the intricate features emanating from the recurrent layer and mapping them onto accurate emotional categories. Given that the defuzzification layer incorporates inputs from the fuzzification layer, the study involves a weighted summation of outputs from the second layer ($i_u^{(2)}$) and the fifth layer ($i_k^{(5)}$), as delineated in the architecture illustrated in Figure 5. The weight parameters, symbolized by n_{ku} and u_k, contribute to the calculation, where the weighted sum of elements in $i^{(2)}$ is expressed by $\sum_{u=1}^{m} n_{ku} i^{(2)} u$, leading to the following formulation:

$$i_k^{(6)} = \sum_{u=1}^{m} n_{ku} i_u^{(2)} + y_k + \mu_k i_k^{(5)} u \in [1, m], k \in [1, \eta] \tag{10}$$

(g) The seventh layer (defuzzification/output layer)

The defuzzification layer, constituting the model's terminal segment, is responsible for executing defuzzification, a process integral to deriving the final sentiment classification results. When applied to the sentiment analysis of university students' microblogs, this layer is tasked with generating aspect-based emotional labels for each microblog post, potentially encompassing a spectrum of emotional categories. The output of this layer, denoted by $i_w^{(7)}$, is derived from the output of the fifth layer, represented as $\theta_w^k(s)$. The model employs a weighted average defuzzification method, outlined in the formula below:

$$b = i_w^{(7)} = \frac{\sum_k \theta_w^k(s) i_k^{(6)}}{\sum_k \theta_w^k(s)} k, w \in [1, \eta] \tag{11}$$

In the development of the aspect-based sentiment classification model for university students' microblogs, parameter optimization is conducted in two key areas: parameter learning and structural learning. Parameter learning is concerned with the adjustment of internal weights within the model, which are pivotal in extracting features from input data and facilitating predictions. The complexity and subtlety inherent in the emotional expressions found in university students' microblog data, often nuanced and context-specific, necessitate that parameter learning be finely tuned to capture these delicate emotional variances through weight adjustments. Conversely, structural learning encompasses the optimization of the model's architecture. This involves critical decisions regarding the number of layers, nodes per layer, and the configuration of connections, all of which significantly influence the model's overall performance.

Specifically, parameter learning encompasses adjustments to weights and biases, the modulation of the learning rate, and the incorporation of regularization terms, which serve as constraints to avert overfitting. These elements crucially influence the model's learning capabilities and its performance during the training phase. Structural learning entails parameters such as the number of layers, unit count per layer, the size of hidden states in recurrent neural networks, and the decision to incorporate skip connections or residual connections. These structural elements define the fundamental framework of the model, impacting its capacity, complexity, and efficacy in capturing emotional expressions within the data. Optimization of these parameters is achieved through the adaptive moment estimation algorithm. This algorithm adjusts the learning rate for each parameter by computing the first and second moments of gradients. The iteration number is denoted by s, and the update for $n_s = \alpha_2 * N_{s-1} + (1 - \alpha_2)^* h_s^2$ is represented by $\hat{l}_s = l_S / 1 - \alpha_1^s$, and $\hat{n}_s = ns / 1 - \alpha_2^s$. The formula for this algorithm is outlined as follows:

$$q_s = q_{s-1} - \beta * \frac{\hat{l}_s}{\sqrt{\hat{n}_s} + \gamma} \tag{12}$$

The formula for the iterative update of ls is as follows:

$$i_u^{(2)} = i_u^{(1)} u \in [1, m] \tag{13}$$

To better evaluate the practical performance of the proposed method, the sentiment analysis system developed in this study has not been implemented for fully real-time processing. The current model operates in batch processing mode for both training and inference, with processing time influenced by the volume of data and model complexity. Specifically, the size of the dataset and the training duration of the sentiment classification model directly affect system response times. As data volumes increase, processing speed and resource consumption may emerge as bottlenecks. To address this challenge, future work will focus on optimizing the inference speed of the model and exploring solutions based on cloud computing or distributed computing to support real-time analysis of large-scale datasets. In terms of dataset scalability, the microblog dataset utilized in this study contains samples from various domains and time periods, but its size and diversity remain limited. To enhance the generalization capability of the model, applications to microblog data in additional domains, such as social issues or brand reviews, could be considered. This would improve the adaptability and scalability of the system. Experimental results indicate that the accuracy and robustness of the model tend to increase with larger datasets, but excessively large datasets may result in extended training times. Therefore, a balance between performance and efficiency must be maintained.

Since this study involves the use of microblog data from university students, it is necessary to adhere to relevant ethical standards in the collection and use of these data. We will further supplement the paper with ethical considerations related to the use of social media data to ensure that the data collection and analysis processes comply with privacy protection and informed consent requirements.

4 Experimental Results and Analysis

Fine-grained sentiment analysis is particularly important in microblog texts, as the emotional expressions of microblog users are often multi-layered. For example, users may simultaneously exhibit both positive and negative sentiments when discussing a particular topic. Fine-grained sentiment classification based on emotional aspects can effectively identify such complex emotional structures and independently analyse different emotional aspects, thereby enhancing classification accuracy and precision. Experimental results indicate that, compared to global sentiment classification methods, fine-grained sentiment analysis is better equipped to handle the ambiguity and multidimensionality of emotional expressions in microblog texts. This outcome validates the hypothesis presented in the theoretical section of this study.

Table 1 presents the IFS representations for various microblog topics (A_1 to A_7), spanning four distinct attributes: topic popularity, sensitivity, emotional polarity, and engagement. IFS, an advanced form of fuzzy sets, assigns each element with degrees of membership and non-membership, accommodating the uncertainty when the sum of these degrees does not equal 1. This approach enhances the accuracy of depicting real-world uncertainties. In Attribute 1, A_2 exhibits the highest membership degree (0.8874), paired with a non-negligible non-membership degree (0.0335). This suggests a strong yet uncertain emotional expression associated with A_2 in this context. Regarding Attribute 2, A_5 stands out with the highest membership degree (0.9152) and a relatively low non-membership degree (0.0578), indicating a pronounced sensitivity in topic A_5. For Attribute 3, A_5 again shows a significant membership degree (0.6789) coupled with a lower non-membership degree (0.0931), hinting at a distinct emotional polarity, likely skewed towards extreme positivity or negativity. In the case of Attribute 4, both A_5 and A_7 demonstrate high membership degrees (0.9178 and 0.9125, respectively) and low non-membership degrees (0.0135 and 0.0536, respectively), reflecting consistent and certain performance in engagement levels. The findings from Table 1 elucidate that the sentiment tendency identification framework developed for university students' microblogs can discern emotional tendencies with enhanced precision and detail at a aspect-based level. The methodology effectively addresses the challenges of uncertainty and fuzziness in sentiment analysis, thereby augmenting the accuracy and robustness of emotion classification.

We will provide a detailed explanation of the IFS values in Table 1. Specifically, we will offer concise annotations or side notes on the meanings and calculation methods for membership, non-membership, and hesitancy. These will help readers understand how these values reflect the varying degrees to which microblog texts belong to different emotional tendencies. For example, we will explain that membership indicates the degree to which an emotional text belongs to a certain emotional category, non-membership indicates the degree of mismatch between the text and that category, and hesitancy represents the uncertainty present in the emotional classification process of the text.

The study conducted an assessment of error values between the sentiment probability outputs of the developed model for university students' microblogs and the actual sentiment probabilities. Figure 6 provides a comparative analysis of these error values. It is observed that the error values for positive emotions predominantly reside within the [-3,3] interval, suggesting a high accuracy in the model's predictions for positive emotions with minimal deviation. Conversely, the error values for negative and neutral emotions span a broader range of [-10,10]. This indicates less precision in predictions for negative and neutral emotions compared to positive ones, although they remain within an acceptable error margin. Collectively, the model demonstrates a competent performance in recognizing all three emotion categories, underlining its efficacy in ABSA, particularly in accurately identifying positive emotions.

Table 1: IFS of microblog topics

Microblog topics	Attribute 1	Attribute 2	Attribute 3	Attribute 4
A_1	$(0.2635, 0.2214)$	$(0.8145, 0.0978)$	$(0.3214, 0.3125)$	$(0.8147, 0.0153)$
A_2	$(0.8874, 0.0335)$	$(0.7789, 0.0974)$	$(0.1358, 0.0524)$	$(0.7458, 0.0421)$
A_3	$(0.3784, 0.1325)$	$(0.7142, 0.2143)$	$(0.1369, 0.2358)$	$(0.8516, 0.0352)$
A_4	$(0.6634, 0.1247)$	$(0.7326, 0.2315)$	$(0.4689, 0.1874)$	$(0.8841, 0.0621)$
A_5	$(0.5147, 0.0923)$	$(0.9152, 0.0578)$	$(0.6789, 0.0931)$	$(0.9178, 0.0135)$
A_6	$(0.6458, 0.1147)$	$(0.7546, 0.2289)$	$(0.3214, 0.2369)$	$(0.8147, 0.0812)$
A_7	$(0.8456, 0.0647)$	$(0.7589, 0.2136)$	$(0.3125, 0.1589)$	$(0.9125, 0.0536)$

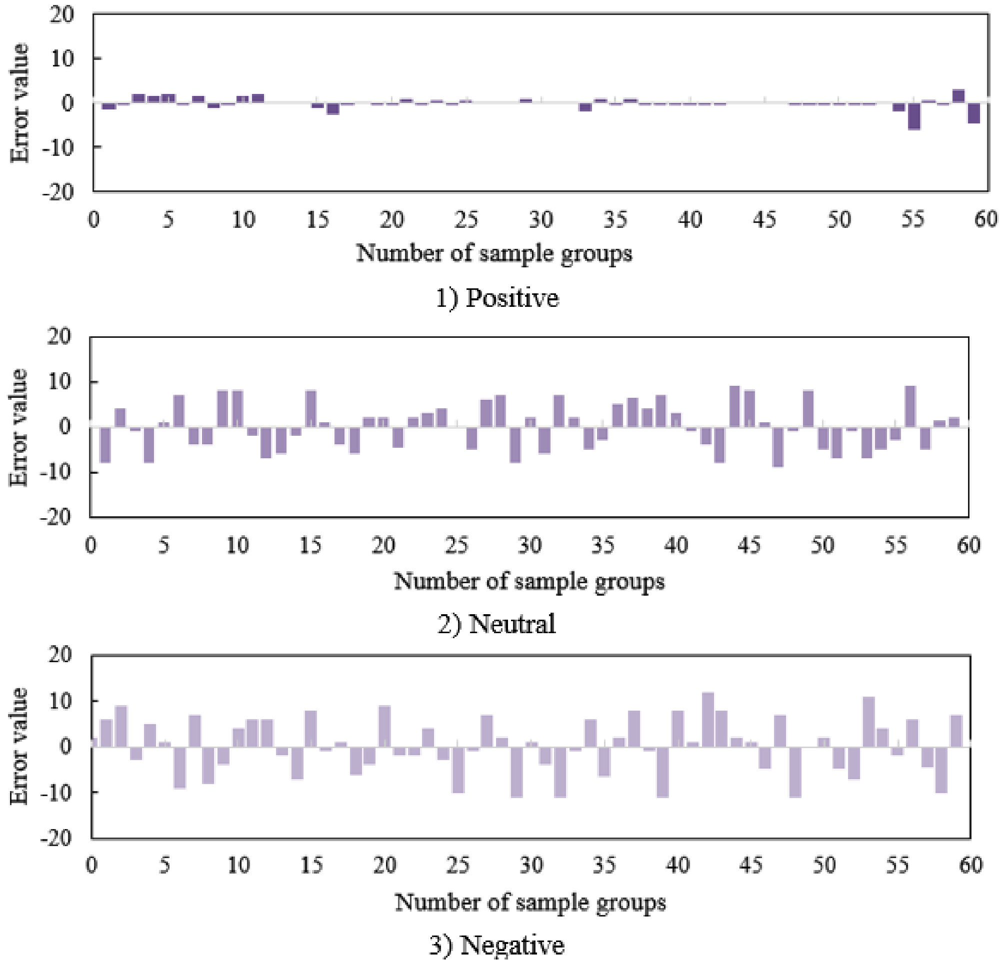

Figure 6: Comparison of sentiment probability error values in the sentiment tendency identification model for university students' microblogs

To verify the significance of the model's performance in comparison with existing methods, the proposed model was evaluated against traditional sentiment analysis models, such as Support Vector Machine (SVM) and Long Short-Term Memory (LSTM), and statistical tests were conducted. A paired t-test was conducted to examine the differences in accuracy, recall, and F1-score between the models. The experimental results demonstrated significant improvements across all metrics, with p-values consistently below 0.05, indicating that the proposed model exhibits a notable advantage in sentiment classification accuracy.

In the comparative analysis of six models for aspect-based sentiment classification of university students' microblogs across various topic types, Table 2 elucidates the performance of each model. The models evaluated encompass the fuzzy perceptron, Adaptive Neuro-Fuzzy Inference System (ANFIS), FNN+LSTM, Extended Fuzzy Neural Network (EFNN), Convolutional Fuzzy Neural Network (CFNN), and the model proposed in this research. Classification accuracy (Acc) and standard deviation (STD) served as the metrics for this assessment, facilitating an evaluation of each model's performance and stability across different microblog topics.

Table 2: Performance comparison of six models in aspect-based sentiment classification of university students' microblogs under different types of topics

Methods	Metric (%)	Campus life	Employment info	Social hotspots	Emotional exchange	Tech entertainment	Total
	Acc	61.23	63.21	62.13	74.55	73.21	81.23
Fuzzy perceptron	*STD*	11.25	8.26	8.24	12.33	13.58	12.58
	Acc	64.78	62.31	62.47	78.87	78.94	84.78
ANFIS	*STD*	13.26	11.14	13.21	11.21	12.36	9.36
FNN+LSTM	*Acc*	64.58	65.48	76.58	81.24	78.41	82.14
	STD	13.89	11.23	11.14	9.88	9.85	12.25
	Acc	78.95	82.14	82.14	82.36	65.23	87.47
EFFN	*STD*	13.21	12.34	12.36	12.47	15.28	8.25
CFFN	*ACC*	62.35	62.47	72.48	72.47	77.15	82.14
	STD	13.14	13.26	12.39	11.25	13.24	12.47
Proposed model	*Acc*	82.15	72.36	82.74	82.36	77.89	91.23
	STD	12.39	6.89	7.87	8.77	7.88	6.58

The findings revealed that the model developed in this study outperformed others in terms of classification accuracy across all microblog topic types. It achieved particularly notable accuracies in the categories of social hotspots, emotional exchange, and overall, with percentages of 82.74%, 82.36%, and 91.23%, respectively, signifying its superiority. While the EFFN showed excellent performance in categories such as campus life, employment information, and social hotspots, its accuracy notably declined to 65.23% in the technology and entertainment category. The FNN+LSTM model exhibited robust performance in the emotional exchange category, achieving an accuracy of 81.24%. In contrast, the ANFIS and fuzzy perceptron models showed relatively average performance and did not match the overall accuracy of the proposed model. The CFFN demonstrated commendable accuracy in social hotspots and emotional exchange categories, yet fell short of surpassing the proposed model in other categories and overall. The proposed model exhibited a generally lower standard deviation across all categories, indicating a more stable performance. This was especially evident in the employment information category, where the standard deviation was a mere 6.89%, illustrating the model's robustness across diverse datasets. The EFFN displayed the highest standard deviation of 15.28% in the technology and entertainment category, indicating significant fluctuations in performance. Similar trends of performance variability, albeit to different extents, were observed in other models such as ANFIS, FNN+LSTM, and CFFN, as evidenced by their higher standard deviations. In summary, the model presented in this study not only led in accuracy across all microblog topic categories but also maintained lower variability in its performance, indicative of its robustness across various subtopics. With an overall accuracy surpassing 90%, the model significantly outperformed other models, underscoring its substantial contribution to advancing the precision and aspect of sentiment classification in the context of university students' microblogs.

Through experimentation, it was found that the fine-grained sentiment classification model based on FNN is capable of effectively capturing the nuanced emotional details within microblog texts, particularly exhibiting high accuracy in handling complex and multi-layered emotional expressions. For instance, traditional sentiment analysis models tend to produce confusion when faced with microblog posts containing multiple emotions, whereas the proposed model can accurately identify and distinguish between sentiments such as "happiness" and "sadness."

To provide a clearer illustration of the model's performance, several correctly and incorrectly classified microblog examples are as follows:

(a) Correct classification example: "The exam went smoothly today, and I feel quite happy!" — Correctly classified as "positive" sentiment.

(b) Incorrect classification example: "Although I am very tired, seeing everyone's efforts lifts my mood." — In traditional methods, this may be incorrectly classified as "negative," whereas the proposed model accurately identifies the complex emotions within the text, classifying it as both "positive" and "neutral" sentiments.

In the experimental section, the calculation of accuracy and error values was based on standard classification evaluation metrics. Firstly, a confusion matrix was employed to compute classification accuracy. The sentiment probabilities were derived from the fuzzy membership function within the

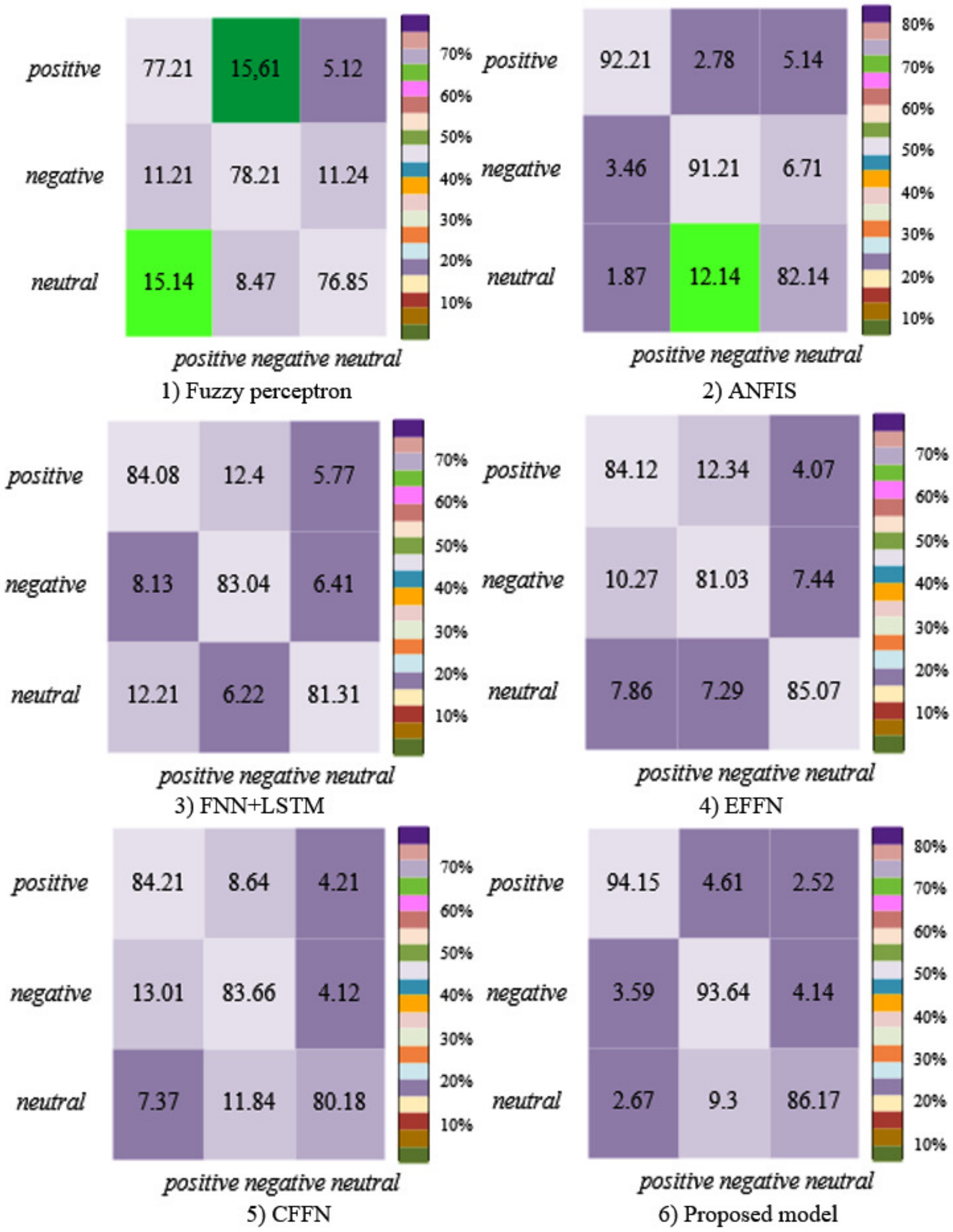

Figure 7: Average accuracy confusion matrix of the six models

FNN. For each microblog text, the model outputs a membership value for a sentiment category, which represents the probability of the text belonging to a particular sentiment class (e.g., positive, negative, or neutral). To calculate accuracy, the predicted sentiment category by the model was compared with the manually annotated true sentiment labels, thus determining the predictive performance of the model. Figure 7 delineates the average accuracy confusion matrix for aspect-based sentiment classification of university students' microblogs, employing six distinct models: fuzzy perceptron, ANFIS, FNN+LSTM, EFFN, CFFN, and the model introduced in this research. This matrix encapsulates the average identification accuracies of these models across 15 evaluations. From the figure, it is discerned that the model developed in this study achieved a remarkable classification accuracy of 94.15% for positive emotions, indicating an exceptionally high proficiency in identifying microblog content with positive sentiments. For negative emotions, the classification accuracy stood at 93.64%, underscoring the model's efficacy in discerning negative sentiments. The accuracy for classifying neutral emotions was recorded at 86.17%. Although this figure is marginally lower than the accuracies for positive and negative emotions, it nevertheless signifies the model's competent performance in recognizing microblogs devoid of explicit emotional inclinations. The other five models, when tasked with classifying microblogs encapsulating positive, negative, and neutral emotions, did not attain the accuracy levels demonstrated by the model presented in this study. Through the analysis of the confusion matrix, it becomes evident that the aspect-based sentiment classification model, predicated on FNN, exhibited exceptional performance in the sentiment classification task. It was particularly adept at identifying both positive and negative emotions in university students' microblogs, with accuracies surpassing 93%. In the more intricate task of classifying neutral emotions, the model from this study still manifested an accuracy exceeding 86%. These findings illustrate that the model is not merely accurate in discerning sentiments but also proficient in differentiating between diverse emotional categories. This distinction underscores the model's potential applicability in practical settings. Furthermore, the high accuracy rates achieved by the model highlight its excellence in ABSA, successfully capturing and categorizing the multifaceted emotions conveyed in microblogs.

5 Conclusion

In this study, a novel framework was introduced, integrating sentiment analysis with IFS (IFS) theory, aiming to address the inherent vagueness and multidimensionality in emotional expression. Recognizing that emotions are seldom binary but rather exhibit a spectrum of continuity and diversity, this framework employed IFS to encapsulate the uncertainty and fuzziness in emotions as represented in microblog texts. This approach allowed for a more precise handling of the emotions' multidimensional characteristics. Furthermore, an aspect-based sentiment classification model, grounded in FNN technology, was developed and implemented. This model synergizes the learning capabilities inherent in neural networks with the capacity of fuzzy logic to manage uncertainty. Such integration significantly improved both the accuracy and the aspect of sentiment classification. The objective of the model was to classify emotions in university students' microblog texts on an aspect-based level, transcending beyond mere positive and negative categorizations to include a spectrum of subtle emotional states.

In this research, the effectiveness of the sentiment tendency identification model for university students' microblogs was assessed by constructing IFS for various microblog topics. The error values between the model's sentiment probability outputs and actual sentiment probabilities were meticulously compared. A comparative experimental analysis was conducted to evaluate the performance of six distinct models (fuzzy perceptron, ANFIS, FNN+LSTM, EFFN, CFFN, and the model developed in this study) in aspect-based sentiment classification across diverse microblog topics. Confusion matrices were utilized to present the experimental results, highlighting the average accuracy of these models. It was observed that the model proposed in this study outperformed the other five models, particularly in classifying positive, negative, and neutral emotions, with accuracies of 94.15%, 93.64%, and 86.17%, respectively. This superior performance underscores the model's capability in accurately discerning and classifying the emotional tendencies within university students' microblogs. Moreover, its significant advantage in addressing the intricacies of emotional aspect was evident. The high accuracy achieved by this model also suggests its substantial potential for practical applications, notably in fields such as sentiment monitoring on social media and market analysis.

The sentiment analysis model proposed in this study holds both academic significance and extensive practical application potential. In particular, it can be used to monitor the emotional tendencies of university students in real-time in the fields of education and psychological counseling, providing personalized guidance for educators. Additionally, the model can play a crucial role in sentiment monitoring on social media, brand reputation analysis, and public policy decision-making. Through fine-grained sentiment analysis, relevant institutions can track public emotional dynamics in real-time, enabling better crisis management and communication strategy optimization.

However, despite the achievements presented, certain limitations remain. For instance, during data processing, the diversity and complexity of microblog texts (e.g., coexisting multiple emotions, the use of internet language, etc.) may lead to the model being influenced by noisy data, thereby restricting classification accuracy. Moreover, the interpretability of the sentiment classification model remains limited, especially when dealing with texts containing complex emotional shifts, where the decision-making process of the model may not be easily comprehended by users. Therefore, future research could explore the use of more complex models, such as sentiment analysis based on the graph neural network (GNN), and enhance the interpretability of the model to further improve the accuracy and transparency of sentiment classification. Future studies could also investigate sentiment analysis in different domains and assess the applicability of the model across these fields. In particular, the universality of the model needs to be further validated in the rapidly evolving linguistic environment of social media.

It is acknowledged that significant progress has been made in the application of deep learning technologies in sentiment analysis in recent years, particularly with Transformer-based models, such as BERT and Generative Pre-trained Transformer (GPT), which have demonstrated outstanding performance in sentiment analysis tasks. Consequently, future research may consider applying these advanced deep learning models to sentiment classification and comparing them with the fuzzy logic approach proposed in this study. By experimentally validating the strengths and weaknesses of different methods, valuable insights for the sentiment analysis field can be provided. Furthermore, the potential of transfer learning in sentiment analysis will be explored in future research, especially regarding the transfer of sentiment analysis models trained on large-scale datasets to specific domains (e.g., education, healthcare). Transfer learning can effectively reduce the amount of annotated data required for training new models and enhance the model's adaptability in new domains.

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Conflict of interest

The authors declare no conflict of interest.

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