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ORIGINAL

Developing a Novel Method for Emotion Detection through Natural Language Processing

Desarrollo de un nuevo método de detección de emociones mediante el procesamiento del lenguaje natural

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ABSTRACT

The analysis of audience emotional responses to textual content is vital across various fields, including politics, entertainment, industry, and research. Sentiment Analysis (SA), a branch of Natural Language Processing (NLP), employs statistical, lexical, and machine learning methods to predict audience emotions—neutral, positive, or negative—in response to diverse social media content. However, a notable research gap persists due to the lack of robust tools capable of quantifying features and independent text essential for assessing primary audience emotions within large-scale social media datasets. This study addresses the gap by introducing a novel approach to analyse the relationships within social media texts and evaluate audience emotions. A Dense Layer Graph (DLG-TF) model is proposed for textual feature analysis, enabling the exploration of intricate interconnections in the media landscape and enhancing emotion prediction capabilities. Social media data is processed using advanced convolutional network models, with emotion predictions derived from analysing textual features. Experimental results reveal that the DLG-TF model outperforms traditional emotion prediction techniques by delivering more accurate predictions across a broader emotional spectrum. Performance metrics, including accuracy, precision, recall, and F-measure, are assessed and compared against existing methodologies, demonstrating the superiority of the proposed model in utilizing social media datasets effectively.

Keywords: Social Platforms; Sentiment Analysis; Feature Encoding; Forecasting; Intricate Network.

RESUMEN

El análisis de las respuestas emocionales de la audiencia a contenidos textuales es vital en diversos campos, como la política, el entretenimiento, la industria y la investigación. El análisis de sentimientos, una rama del procesamiento del lenguaje natural (PLN), emplea métodos estadísticos, léxicos y de aprendizaje automático para predecir las emociones del público -neutrales, positivas o negativas- en respuesta a diversos contenidos de redes sociales. Sin embargo, persiste una notable laguna en la investigación debido a la falta de herramientas robustas capaces de cuantificar características y textos independientes esenciales para evaluar las emociones primarias de la audiencia en conjuntos de datos de medios sociales a gran escala. Este estudio aborda esta carencia introduciendo un novedoso enfoque para analizar las relaciones dentro de los textos de los medios sociales y evaluar las emociones de la audiencia. Se propone un modelo de gráfico de capas densas (DLG-TF) para el análisis de características textuales, que permite explorar las intrincadas interconexiones en el paisaje mediático y mejorar las capacidades de predicción de emociones. Los datos de las redes sociales se procesan mediante modelos avanzados de redes convolucionales, con predicciones de emociones derivadas del análisis de características textuales. Los resultados experimentales revelan que el modelo DLG-TF supera a las técnicas tradicionales de predicción de emociones al ofrecer predicciones más precisas en un espectro emocional más amplio. Las métricas de rendimiento, como la exactitud, la precisión, la recuperación y la medida F, se evalúan y comparan con las metodologías existentes, lo que demuestra la superioridad del modelo propuesto a la hora de utilizar eficazmente los conjuntos de datos de las redes sociales.

Palabras clave: Plataformas Sociales; Análisis de Sentimientos; Codificación de Características; Predicción; Red Intrincada.

INTRODUCTION

Social media has rapidly attracted billions of users, becoming a global phenomenon in recent years.[1] As a result of widespread consumer use of these platforms, the amount of subjective content on Web 2.0 has grown exponentially. Given the significant potential benefits for business, society, politics, and education, there has been a surge of interest among researchers to develop methods for extracting insights from the vast, unstructured data that has emerged alongside this new form of digital communication.[2] Consequently, new tools, resources, and techniques in natural language processing (NLP) are required to effectively analyse and process this data.

Sentiment analysis (SA) is an NLP task focused on processing subjective data. Within this field, two primary tasks are distinguished: Opinion Mining (OM), which involves automatically classifying and identifying opinions in text as neutral, positive, or negative[3] and Emotion Recognition (ER), which focuses on more complex emotional expressions, such as anger, contempt, or fear. Emotion recognition is a more intricate task than opinion mining due to its nuanced approach in identifying emotional categories. The growing interest in ER stems from its potential applications across various industries, including suicide prevention[4] detecting instances of cyberbullying, and improving student engagement and performance. To address the challenges of textual ER, NLP researchers employ diverse techniques, including lexical methods, rule-based approaches, and machine learning (ML) models.[5] Given the scalability, learning capacity, and rapid advancements in machine learning algorithms, supervised learning has become a predominant technique in emotion recognition tasks.[7]

The quality and quantity of training data play a crucial role in the performance of supervised models. Therefore, the training dataset is critical to developing accurate emotion recognition algorithms. Furthermore, the emergence of Deep Learning (DL) has further emphasized the importance of large training datasets.[8] Creating a labelled corpus for emotion recognition remains challenging, as even human annotators may struggle to convey emotions through text, influenced by personal circumstances and interpretations. Past research highlights the difficulties in creating reliable emotion-labelled datasets, including the time required to achieve effective Inter-Annotator Agreement (IAA).[9,10] As a result, acquiring accurate emotional data has become one of the biggest challenges in ER.

To address the challenges of emotion annotation, this study introduces EmoLabel, a semi-automated approach designed to generate large, high-quality English emotion corpora from a variety of genres. EmoLabel follows a two-step process: First, an automatic method pre-annotates the text with fewer emotional categories, and second, a manual refinement phase where human annotators select the dominant emotion from a predefined set of options. With a large number of emotion categories, this study suggests that automating the pre-annotation with fewer emotional categories can improve the reliability of the final corpus. By limiting the number of categories, human annotators can more accurately identify the dominant emotion in the second phase, thereby enhancing the overall dependability of the system.

This study employs a pre-annotation technique utilizing a Dense Layer Graph model (DLG-TF) for textual feature analysis, combined with a deep learning-based supervised pre-annotation approach. The effectiveness of these methods is evaluated in a subsequent phase. The model examines both global and local textual features through window connections at various levels. Multiple experimental setups are designed to measure the impact of pre-annotation on the final corpus annotation process and the time required for human annotation. Results indicate that pre-annotation significantly enhances efficiency, reducing annotation time and improving the accuracy of emotion labeling. Performance improved by over 20 % with pre-annotation compared to alternative methods, particularly aiding contributors who face challenges with annotation precision.

The paper is structured as follows: Section 2 reviews existing approaches and highlights associated challenges. Section 3 details the methodology, focusing on the Dense Layer Graph model (DLG-TF) for textual feature analysis. Section 4 presents the experimental results, and Section 5 concludes the study.

Related Works

Textual Emotion Analysis (TEA) is extensively used to understand and interpret emotional states from text. While serving as an independent information extraction tool, TEA is integral to numerous Natural Language

Processing (NLP) applications. These applications include areas like e-commerce, public sentiment analysis, large-scale search engines, predictive analytics, personalized recommendations, healthcare, and digital education. The framework of the "seven emotions and six desires," encompassing happiness, love, anger, sadness, fear, evil, and desire, underscores the complexity of human emotions.(12) Studies indicate that individuals are generally more susceptible to negative emotions, with most emotions being unpleasant and only a few associated with mild positivity. In practical settings, negative emotions tend to spread more quickly than positive ones.(13) The 2011 Annual Report of China's Internet Public Opinion Index(14) revealed that over 80 % of analysed topics were associated with negative events. Social media platforms like Microblog and Tianya Forum exhibited even higher negativity rates, at 75,6 % and 95,8 %, respectively.(15)

The rapid growth of social networks has transformed users from passive consumers to active information processors.(16) A report on China's internet development states that the country has 710 million internet users, with a 52 % utilization rate. Among them, 656 million accessed the internet via mobile devices, over 100 million regularly updated blogs, and 242 million used Microblogs. The majority of these interactions are saturated with negative sentiments. TEA enables the automatic extraction of users' emotional states from these interactions, including blog posts and tweets. Earlier studies primarily focused on binary (positive/negative) or ternary (positive/negative/neutral) sentiment classification.(17) However, these approaches fail to capture the nuanced psychological states and variations in user emotions, limiting the representation of complex emotional expressions. To address this, a more comprehensive approach termed "fine-grained sentiment analysis" was introduced, distinguishing it from the traditional "sentiment analysis" based on binary classification.(18)

Following the success of object recognition using ImageNet,(19) Deep Learning (DL) techniques(20,21,22) were integrated into NLP, leading to significant advancements in tasks such as machine translation, sentiment analysis, and question-answering systems. Techniques like Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), Bi-directional LSTM, attention mechanisms, and Multi-Head Attention (MHA) networks(23) are commonly utilized to model data. Researchers often combine these methods into unified models to enhance the effectiveness of emotion analysis.(24) For instance,(25) proposed using G-RNN for fine-grained emotion detection, while(26) developed a hybrid model integrating GRNN trained on multi-genre emotional corpora. Another approach, LE-PC-DNNs,(27) combines CNN layers with fully connected layers in non-sequential configurations to improve performance by extracting contextual features to detect emotions.

Several models leverage embeddings like Glove and Elmo, along with POS tagging, SVM classifiers, neural network classifiers, and recurrent architectures like LSTM and GRU. Techniques such as attention-based RNNs and skip-gram-based LSTM models have also been applied for short-text emotion classification.(28) Rathnayaka et al.(29) introduced Sentylic for implicit emotion recognition using a capsule network and bidirectional GRUs. Additionally(30) proposed the Semantic-emotion Neural Network (SENN), which integrates semantic/syntactic features and emotional information through auxiliary networks leveraging Bi-LSTM and CNN layers. A multi-task CNN model for emotion distribution learning was suggested by Zhang et al.(31), and ConvLex LSTM was introduced for emotion recognition in online health communities by combining CNN outputs with lexicon-based features fed into an LSTM network. Furthermore, interpretable neural networks have been developed using multi-layer feed-forward architectures.(32) Sent2affect, an RNN-based emotion recognition method tailored for affective computing, incorporates transfer learning techniques. Another method, Interpretable Relevant Emotion Ranking with Event-driven Attention (IRER-EA), combines attention mechanisms and RNNs for emotion recognition but struggles to deliver optimal results.

METHOD

This section offers a comprehensive explanation of the Dense Layer Graph (DLG-TF) model architecture. Initially, the process of constructing the graph is detailed, followed by an explanation of the bottom-level message-forwarding technique. Next, the development of the graph-based network model (GNM) is outlined, including how the graph structure refines mid-level node representations. Subsequently, the use of the scaled dot-product attention mechanism is described to further enhance top-level node representations. Finally, the output of the DLG-TF model and the associated loss functions are presented. Figure 1 illustrates the DLG-TF model architecture.

This study begins by constructing the graph from the ground up, following the approach of a previous study. For a text consisting of lll words, the graph is defined as:

$$G(0) = \{v1(0), \dots, vk(0), \dots, vn(0)\}G(0) = \{v_1^{\{(0)\}}, \dots, v_k^{\{(0)\}}, \dots, v_n^{\{(0)\}\}G(0)} \\ = \{v1(0), \dots, vk(0), \dots, vn(0)\}$$

Where:

ri(0)$r_i^{\{(0)\}}$ri(0) represents the initial embedding of the ithi\text{th}ith word.

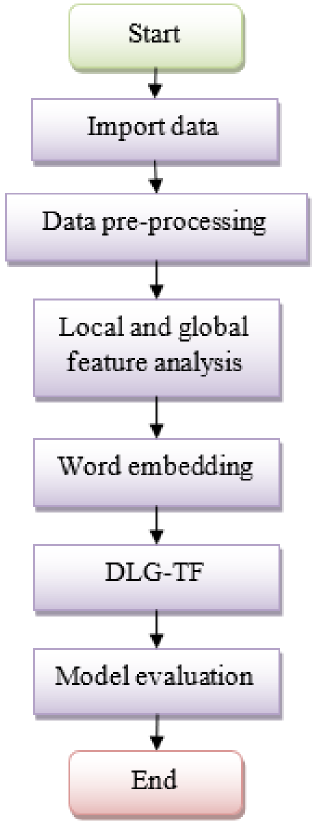

Figure 1. Flowchart of the proposed DLG-TF model

The starting value of ri(0)$r_i^{\{(0)\}}$ri(0) is determined by a d0d0d0-dimensional word embedding, which is adjusted during the training process. Words within the text are treated as nodes in the graph, with edges connecting each word to the next. If ppp denotes the number of words linking each node to its neighbors, the graph can be defined accordingly. Node set:

$$V(0) = \{vk(0) \mid k \in [1, n]\}$$

Edge set:

$$F(0) = \{ fkl(0) \mid k \in [1, n]; l \in [k - w, k + w] \}$$

Representations are updated using a message-passing approach, aggregating information from neighboring nodes. Representations for the words within this window are aggregated as:

$$v^{k(1)} = \mid Vkw \mid 1b \in Vkw \sum vb(0)$$
$$vk(1) = g(Ulowv{\sim}k(1) + clow)$$

Here:
α is a parameter controlling how much of vk(0) $v_k^{\{(0)\}vk(0)}$ is retained.
g is a nonlinear activation function.

Ulow and Clow are trainable matrices. The updated representation focuses on local features. After this step, the node set is represented as:

$$G(1) = \{v1(1), \ldots, vk(1), \ldots, vn(1)\}$$

Intermediate Level

At this level, a larger connection window is used, represented as:
Nodeset:

$$V(1) = \{vk(1) \mid k \in [1,n]\}V\hat{}\{(1)\} = \{v\_k\hat{}\{(1)\},|,k \in [1,n]\}V(1) = \{vk(1) \mid k \in [1,n]\}$$

Edge set:

$$F(1) = \{fkl(1) \mid k \in [1,n]; l \in [k-z,k+z]\}F\hat{}\{(1)\} = \{f\_\{kl\}\hat{}\{(1)\},|,k \in [1,n];$$
$$l \in [k-z,k+z]\}F(1) = \{fkl(1) \mid k \in [1,n]; l \in [k-z,k+z]\}$$

Here, z≥wz \geq wz≥w, allowing the model to capture long-range correlations. The Graph Neural Mechanism (GNM).

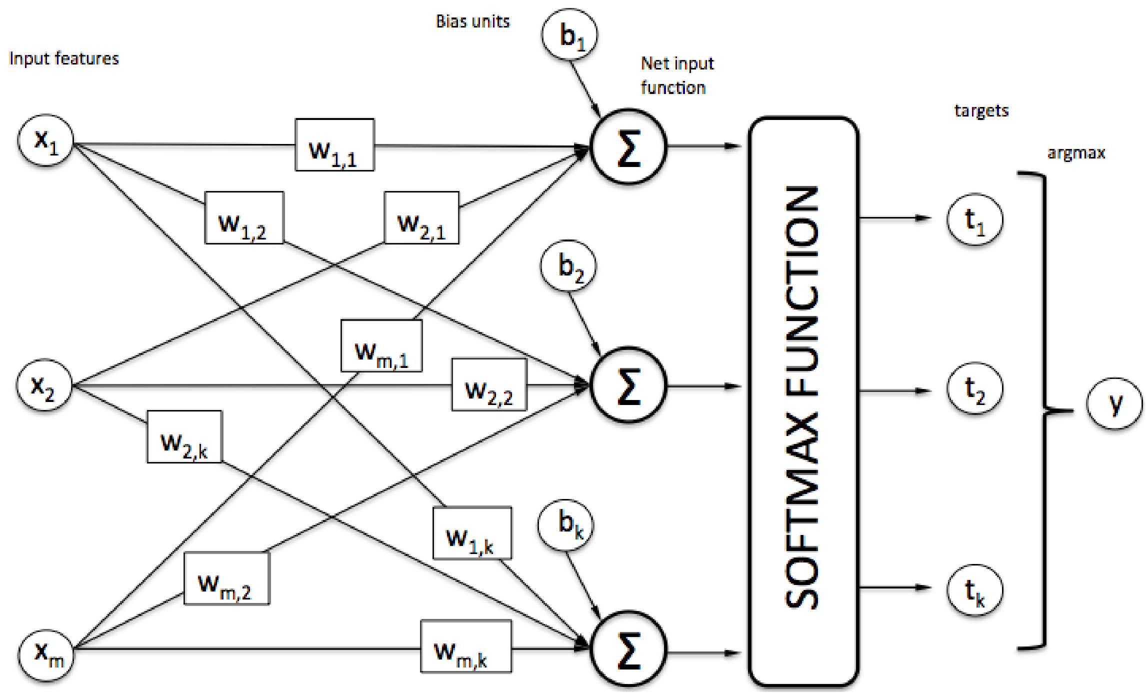

Figure 2. Graph-based network model

The trainable parameters include:

$$WQ \in Rd2 \times d3W_Q \backslash in \backslash mathbb\{R\}^{\{d_2 \backslash times\ d_3\}WQ} \in Rd2 \times d3, WK \in Rd2 \times d3W_K \backslash in \backslash$$
$$mathbb\{R\}^{\{d_2 \backslash times\ d_3\}WK} \in Rd2 \times d3$$
$$WV \in Rd2 \times d3W\_V \backslash in \backslash mathbb\{R\}\hat{}\{d\_2 \backslash times\ d\_3\}WV \in Rd2 \times d3.$$

Computes the correlation coefficient between the ithi{th}ith node and all other nodes. For the multi-head attention mechanism to operate, H-scaled dot-product attention is required.

$$W0 \in Rhd3 \times d3W_0 \backslash in \backslash mathbb\{R\}^{\{h\ d_3 \backslash times\ d_3\}W0} \in Rhd3 \times d3$$

Here is a trainable weight matrix and:

$$r^i, h(3)\backslash hat\{r\}_{\{i,h\}}^{\{(3)\}r^i}, h(3)$$

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Represents the ithi$^{\{th\}ith}$ node's hthh$^{\{th\}hth}$ scaled dot-product attention result. The concatenation operation is represented by ||| |||. The node representations at the top level can be concatenated to form:

$$r = r1(3) \parallel \cdots \parallel ri(3) \parallel \cdots \parallel rl(3)r \;=\; r_1^{\{(3)\}|} \;|\; \ldots | \quad |r_i^{\{(3)\}|} \;|\; \ldots | \quad |r_l^{\{(3)\}r}$$
$$= r1(3) \parallel \cdots \parallel ri(3) \parallel \cdots \parallel rl(3)$$

Where:
N is the overall sample count and y_i is the ith ground-truth label.

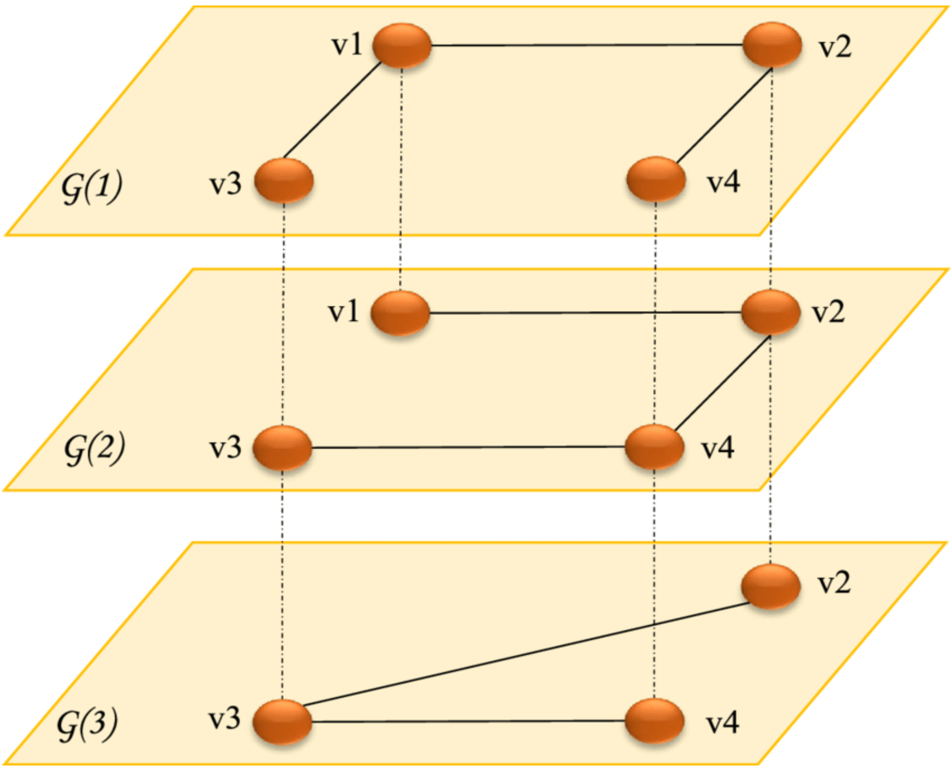

Figure 3. Dense layered network model

Numerical analysis

The evaluation of EmoLabel involves both intrinsic and extrinsic analyses. Intrinsic evaluation examines the pre-annotation process, while extrinsic evaluation measures annotator performance during the second phase of the methodology. To test their versatility across different genres, these techniques are applied to two emotion datasets: the Aman corpus and the EmoTweet-28 corpus.

- Aman Corpus: this dataset consists of 4000 sentences extracted directly from blog posts on the web, with annotations provided at the sentence level. Emotions are classified into six categories as defined by Ekman, alongside intensity levels (low, medium, or high). The distribution of the dataset is presented in table 1.

Table 1. Emotion categories

Anger	Disgust	Fear	Joy	Sad	Surprise	Neutral	Total
180	170	120	540	175	116	2804	4100

An excerpt from EmoTweet-28: this dataset contains 15 553 tweets, each annotated with one of 28 unique emotion categories. It includes labels for valence, arousal, emotion category, and emotion cues, capturing the four dimensions of emotion. A condensed version, EmoTweet-5, is used due to its emphasis on the basic emotions defined by Ekman. This subset retains the same number of neutral tweets as the original dataset, along with tweets categorized as angry, fearful, joyful, sad, or surprised. The final EmoTweet-5 dataset comprises 5931 tweets, with their distribution across emotions maintained.

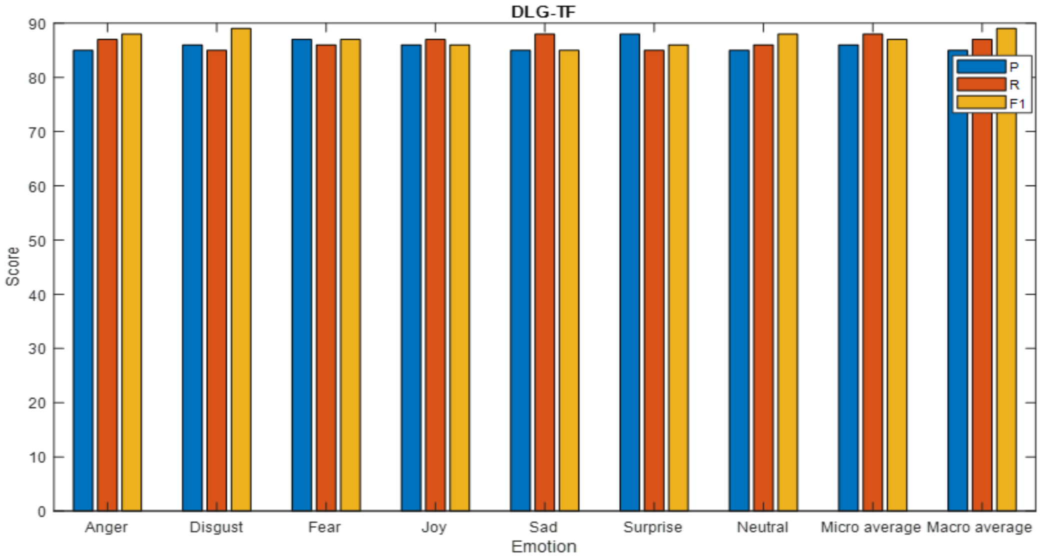

Figure 4. Aman corpus based unsupervised model

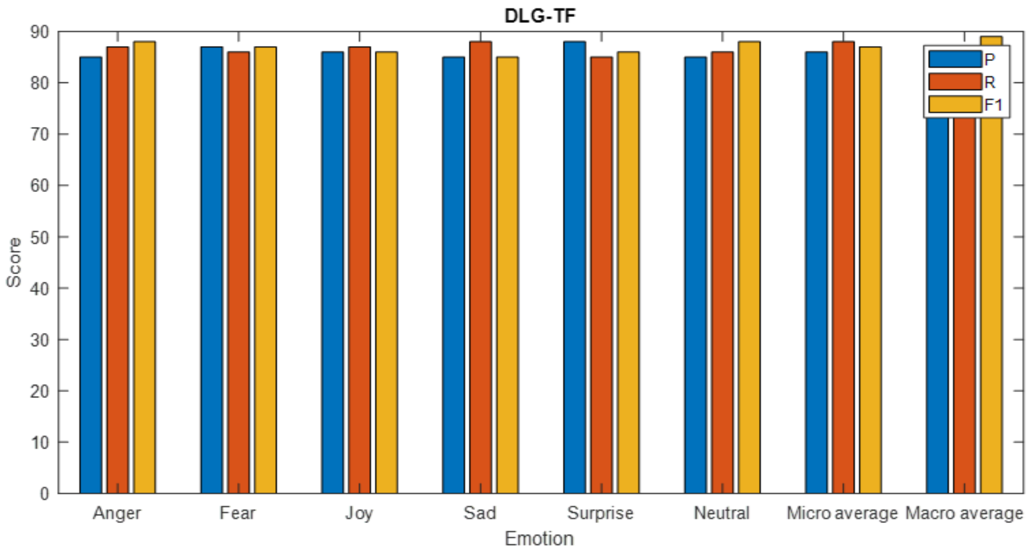

Figure 5. EmoTweet based unsupervised model

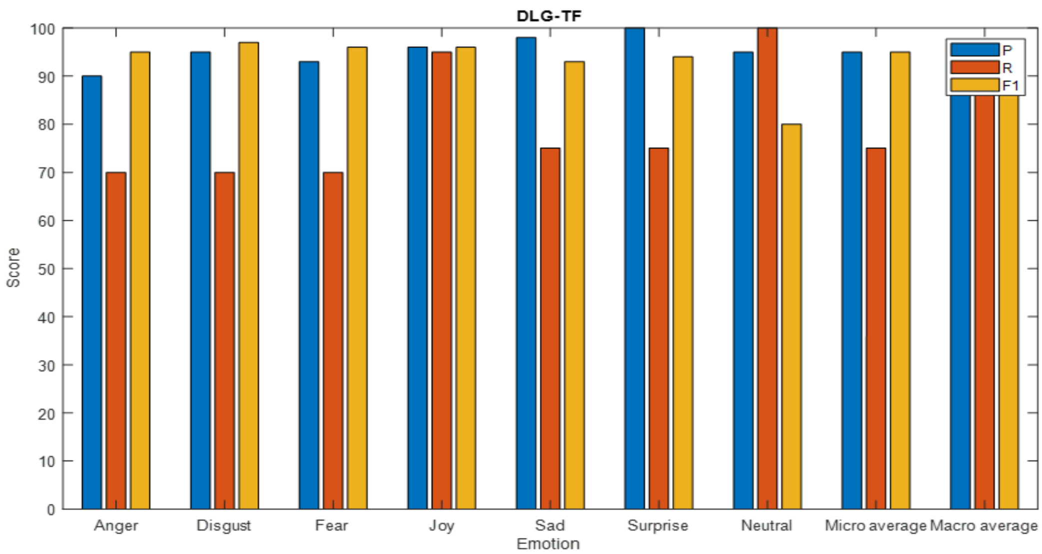

Figure 6. Aman corpus based supervised model

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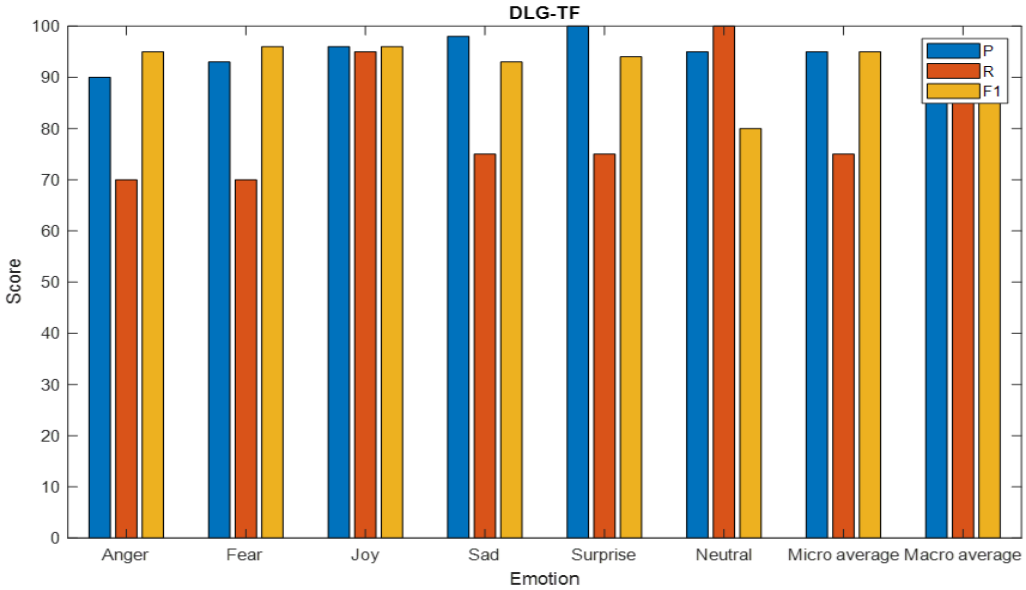

Figure 7. EmoTweet5 based supervised model

These datasets were selected for two primary reasons: (i) they are widely recognized benchmarks in emotion recognition (ER) research, and (ii) they enable an assessment of the pre-annotation process across diverse social media formats, such as blogs and tweets, where users express opinions, share information, and convey emotions.

Twitter GloVe and Ultradense SA models outperform unsupervised pre-annotation techniques on EmoTweet-5, illustrating a distinct difference with Affective Space, which diverges from the baseline. This could be attributed to the professional language in Affective Space compared to the informal, often ungrammatical English prevalent on Twitter. These findings underscore the importance of employing DSMs tailored to specific genres when processing social media texts. For the Ultradense SA model, the improvements in recall for emotions like joy, sadness, and surprise are evident in this dataset (refer to figure 6 and figure 7). Additionally, intriguing results for anger and disgust remain observable with EmoTweet-5. The Twitter GloVe model shows strong performance for joy and sadness, driven by high recall scores. These outcomes further highlight the critical role of lexical coverage in unsupervised techniques. For instance, while the Affective Space model lacks adaptation for this genre, it excels in joy due to its extensive lexical representation. Conversely, the limited coverage of surprise, yielding an F1-score of only 13 %, likely hampers the unsupervised pre-annotation method's success in identifying this emotion.

A comparison of evaluation results reveals that the Twitter GloVe and Ultradense SA models perform best. This emphasizes the need for embeddings with specific characteristics: the semantic space must be representative, embeddings should be derived from extensive datasets to cover a wide vocabulary, and they should encode high-dimensional semantic information to ensure better performance. Moreover, embeddings should align with the target content type. The findings also stress the importance of the vocabulary used in lexicon coverage for unsupervised pre-annotation. Notably, the improvements in identifying anger and disgust emotions by Ultradense SA are genre-independent.

SVM Models and Features: the EmoLexicon, Unigrams (1-grams), and CountWordEmo feature sets were applied to construct SVM models with multiple classifiers, as described in Section 3.2. To evaluate the supervised technique, datasets were split into 70 % training and 30 % testing subsets. After a thorough 10-fold cross-validation process, optimal hyperparameters for each SVM were determined. For the Aman corpus, CountWordEmo used a linear kernel with a C value of 1, while EmoLexicon adopted an RBF kernel with gamma = 0,001. For unigrams, a linear kernel with a C value of 1 was applied. For EmoTweet-5, CountWordEmo used an RBF kernel with gamma = 0,001 and a C value of 10, while a linear kernel was used for the unigram model.

Tables 6 and 7 display the supervised pre-annotation outcomes for the Aman corpus and EmoTweet-5, respectively. The results demonstrate that the unigram model achieved the highest macro-average F1-scores, exceeding 75 %. However, CountWordEmo and EmoLexicon struggled to detect emotions such as fear and surprise due to reliance on lexicon coverage. The findings for the Aman corpus align with EmoTweet-5, where 1-grams performed better than other features. Yet, the performance on EmoTweet-5 was lower, largely due to prevalent grammatical errors and unstructured language on Twitter. This genre's limited lexical coverage significantly impacted results, especially for lexicon-reliant aspects. The study concludes that effective features must extract detailed textual information rather than relying solely on emotion lexicons. Integrating advanced feature selection or genre-specific classifiers could further enhance supervised emotion recognition. However, such complex feature engineering was avoided to evaluate the practicality of a pre-annotation-driven emotion model.

Extrinsic Evaluation: the second phase of EmoLabel focuses on assessing annotator performance. This phase utilized the Aman corpus dataset, where the previously used 30 % test data was divided into three subsets (D1, D2, D3), each containing 100 sentences. The subsets were fairly distributed to ensure balanced representation of emotions. Manual annotation involved three annotators labeling the datasets under three configurations: pre-WE (unsupervised annotation with GloVe), pre-ML (supervised annotation with 1-grams), and no-pre (without pre-annotation). Based on intrinsic evaluation findings, pre-WE and pre-ML configurations utilized the best pre-annotation models. Annotation quality was measured using kappa coefficients, which quantify agreement beyond chance, and macro-average scores for all tasks reached 0,60, indicating "substantial agreement."

Efficiency of Pre-Annotation: the annotation process significantly reduced time, with pre-ML accelerating annotations by 24,8 % compared to pre-WE. This demonstrates that improper pre-annotation methods could hinder rather than assist annotation tasks, as pre-ML generalizes better, benefiting annotators with more useful emotion cues. While pre-WE relies heavily on lexicon coverage and semantic representation, its performance is comparable to pre-ML only for straightforward sentences. For complex ones, pre-ML outperforms. Annotator 3 faced challenges comprehending the task, but pre-ML yielded the best agreement and efficiency scores, suggesting pre-annotation could aid less-experienced annotators. This has implications for crowdsourcing platforms like AMT or F8, where annotator expertise is unknown.

CONCLUSIONS

This study aimed to streamline emotion annotation for improved efficiency and accuracy. The DLG-TF approach comprises two stages: unsupervised automatic pre-annotation of unlabeled phrases and manual fine-tuning by annotators. Two pre-annotation methods were evaluated: an unsupervised approach to minimize human input and a supervised approach leveraging existing models or corpora. The supervised method proved faster and more effective, reducing annotation time by over 20 %. Results confirm that pre-annotation improves emotion labeling without compromising quality, with all tasks achieving substantial agreement. Supervised pre-annotation is advantageous as it simplifies annotator tasks and facilitates the use of existing supervised emotion recognition systems for new data. The benefits of pre-annotation are particularly significant on crowdsourcing platforms where annotator expertise is limited. These findings highlight the potential of pre-annotation as a practical solution for efficient emotion annotation.

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