

A CONTEXTUAL EMBEDDING FRAMEWORK WITH GRAPH RECURRENT MODELING FOR EMOTION DETECTION AND CLASSIFICATION ON SOCIAL MEDIA DATA

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ABSTRACT

In the modern era, a majority of users are accessing the internet globally for communication through text, images, audio, and video. People from various backgrounds share data on discussing current events and projecting their personal views on social media. There is a necessity for identifying and understanding the behaviours of massive textual data on people by examining their emotions. People expressing their feelings through tweeter real reactions, Facebook posts, and more. Nevertheless, handling large-scale data generated across diverse social media platforms is challenging. In Natural Language Processing (NLP), emotion recognition is a frequently studied task that can identify these kinds of emotions. Deep learning (DL) approaches are widely used for single-modal text-based emotion analysis. In this paper, we design a Contextual Embedding Framework with Graph Recurrent Modeling for Emotion Detection in Social Media (CEGRM-EDSM) approach. The main purpose of the CEGRM-EDSM system is to develop an effectual and intelligent framework for social media data classification and emotion detection by leveraging advanced deep learning approaches. At primary stage, a comprehensive text pre-processing pipeline is implemented to enhance data quality and semantic consistency, comprising elimination of URLs, noise, and hashtags, hashtag segmentation through word partitioning, substitution of slang and abbreviations, spelling correction, emoji interpretation, and removal of unwanted numerals. Following this, the high-quality contextual representations are generated using the DeBERTa V3-base word embedding model to capture rich semantic and syntactic dependencies within social media text. For classification and emotion recognition, a hybrid graph attention network with bidirectional long short-term memory architecture has been deployed to model both relational word dependencies and sequential contextual patterns effectively. A wide range of simulation analyses were conducted on two benchmark datasets. The comparative outcomes exhibit the superiority of proposed CEGRM-EDSM methodology over recent approaches in terms of various evaluation metrics.

Keywords: *Social Media, Emotion Detection, Data Classification, Graph Attention Network, Contextual Embedding*

1. INTRODUCTION

Globally, people are strongly connected with social media network such as Facebook and Twitter for expressing themselves through various subjects [1]. These platforms became popular in textual data and unlocked numerous research concerns in the area of natural language processing (NLP) [2]. Among these, identifying emotions in text is vital in many domains. To examine the feelings specified in social media text content is

highly beneficial to calculate human apprehension in applications, namely verdict of a movie, the review of a product, reception of a recently announced government policy by recognizing it [3]. In social media, people are willing to employ an easier way for depicting a standard syntactic framework, which is not followed, making classification a challenging task. Emotions are cognitive/mental states determined by neurophysiological changes in humans [4]. Behavioral responses are driven by mental and

psychological states; they could be unhappiness, pleasure, or other features that substantially affect our daily activities. Anger, Fear, sadness, and joy are instances of emotional states that impact our mental health and decision-making capability [5]. Consequently, emotion analysis is essential to understand an individual's emotional state of mind because it exhibits a person's true voice and perspective, recognizes any probable upcoming concerns, and provides solutions for supporting an individual with anxiety [6]. Likewise, it is employed to decide a person's emotional or mental state by assessing his or her behaviors over time and identifying depression risks.

Emotional analysis has consistently been a major research topic in NLP [7]. It investigates, processes, and summarizes the data with intrinsic emotional color and judges the emotional tendency of consumers. By facilitating natural language, microblog emotional analysis became one of the existing investigation hotspots [8]. Machine learning (ML) is one of the most investigated approaches for the exploration of linguistic data by recognizing the personality that is presented by investigators in the task of NLP. Recently, the quick progression of deep learning (DL) approaches can result in significant development in emotion analysis [9]. The convolutional neural network (CNN), recurrent neural network (RNN), and pre-trained language models have shown effective performance in NLP tasks. These methodologies automatically acquire features from data, decreasing the requirement for manually intended attributes, which are highly dependent on conventional emotion analysis models [10]. Usually, the conventional methods neglect the relational structure among consumers, resulting in sub-optimum performance while managing large-scale emotion propagation in social networks [11].

Yet a closer look at this body of work reveals a persistent gap: most deep learning pipelines for emotion detection process tokens largely in isolation through a sequential encoder, or lean on a single embedding source, so the relational cues linking emotionally loaded words within a sentence are rarely modelled explicitly. This weakness is magnified in social media text, where grammar is loose and meaning often hinges on how a handful of charged words interact rather than on the sentence as a whole. Few of the approaches reviewed above combine a disentangled, context-sensitive embedding with an explicit graph-based relational encoder, and this is the gap the present study sets out to close. The novelty of the proposed

CEGRM-EDSM framework lies in coupling DeBERTa V3-base contextual embeddings with a hybrid GAT-BiLSTM encoder so that word-level relational structure and sequential context are learned jointly rather than separately. This combination is expected to raise classification performance on imbalanced, multi-class social media corpora and to yield a pre-processing-to-classification pipeline that can be carried over, with only minor adjustment, to related text-mining tasks such as hate-speech or stance detection.

This manuscript designs a Contextual Embedding Framework with Graph Recurrent Modeling for Emotion Detection in Social Media (CEGRM-EDSM) approach. Initially, a text pre-processing phase can be executed to enhance data quality, including URL removal, noise, and hashtags, hashtag segmentation by word partitioning, exchange of slang and abbreviations, spelling correction, emoji interpretation, and elimination of unwanted numerals. Next, the high-quality contextual representations are produced by the DeBERTa V3-base vector embedding method to capture rich semantic and syntactic dependencies from the social media text. For the emotion classification process, a hybrid graph attention network with bi-directional long short-term memory (GAT-BiLSTM) network was utilized to model both relational word dependencies and sequential contextual patterns effectively. A wide range of simulation results was conducted on two benchmark datasets with respect to several evaluation measures.

2. REVIEW OF LITERATURE WORKS

This section provides a comprehensive comparison of existing studies on social media data classification and emotion detection. Saadi et al. [12] propose an emotion recognition approach employed on Apache Spark, an open-source stage for distributed big data processing. The projected approach incorporates ML approaches with an NLP task and utilizes Spark's MLlib library for categorizing emotions stated in YouTube comment. To effectively manage the difficulty and noise inherent in extensive multi-media data, numerous pre-processing and representation stages were recommended. Yan et al. [13] project an Emotion-RGC Net, a novel DL methodology that combines RoBERTa, GNN, and CRF for improving the robustness of emotion identification. RoBERTa has been utilized for effectual feature learning from unstructured text, GNN acquires the dissemination and impact of emotions with user communication,

and CRF acquires global constancy in emotion label classification. In [14], EmoNet is an innovative DL methodology inspected for managing these problematic circumstances effectively. EmoNet integrates CNN and Bi-LSTM layers for acquiring hierarchical depictions from text, allowing it to recognize intricate emotional indicators in communications. EmoNet views language patterns in social media because it does not necessitate function engineering.

Saadi et al. [15] inspected an ensemble clustering model that automatic creates an emotion label from Twitter data, without human interference. This model integrates 3 emoji-handling approaches in the pre-processing stage, permitting numerous semantical depictions of emoji's. The authors employed BERT embedding integrated with PCA for dimension reduction with a similar empirical module. An ensemble clustering approach incorporates with GMM, K-means, and agglomerative clustering models is accepted utilizing numerous ensemble formations. Hussain et al. [16] suggest an innovative knowledge distillation module that conveys knowledge from modified BERT-base teacher module to lightweight DistilBERT and ALBERT student approach, enhanced for effectual emotion identification.

Shi et al. [17] propose a novel method, called deviation rule markov model, for predicting the emotional modification trends of internet consumers in online public opinion by examining the correlation among emotional classes of Internet users. Basically, the projected DRMM follows several processes like pre-processing, data mining, transfer prediction, and emotion categorization. The presented approach undertakes pre-processing to remove unwanted data. In addition, a prolonged association rule mining model is leveraged from the emotion identification procedure by attaining the transfer likelihood among emotion categories. Additionally, a Markov chain has been employed to build an emotional state transition matrix for predicting the transition likelihood of negative or positive emotions. Jadon and Kumar [18] recommended LexiRoBERTaNet, a new hybrid approach that integrates the RoBERTa transformer with lexicon-based aspects and a hybrid loss function for upgrading the precision of multi-class emotion identification. The authors utilized hybrid loss function depend on Focal Loss and CrossEntropy Loss for optimizing the model through training.

3. METHODOLOGY FRAMEWORKS

This study introduces an innovative CEGRM-EDSM approach designed for intelligent social media emotion detection using a DL framework. Unlike conventional approaches, the proposed methodology integrates advanced contextual embedding with graph-based recurrent modeling to enhance semantic understanding. A novel pre-processing strategy tailored for noisy social media text enhances data representation quality. The integration of DeBERTa V3-base ensures richer contextual awareness, but the hybrid GAT-BiLSTM frameworks capture both structural word relationships and sequential dependencies. Fig. 1 demonstrates the entire process flow of the CEGRM-EDSM algorithm.

Design and Framework: the choice of this three-stage design is deliberate rather than incidental. Pre-processing alone cannot resolve the ambiguity of short, informally written posts, and a transformer embedding alone cannot represent how individual words relate to one another once they are reduced to a feature vector; a graph-based encoder is therefore placed between the embedding stage and the classifier so that word-to-word relationships are learned explicitly rather than left implicit in a purely sequential model. The BiLSTM layer, in turn, restores the ordering information that a graph structure alone does not preserve. Each component is chosen to compensate for a specific limitation of the one before it; Section 3.4 sets out how the data supporting this pipeline were obtained and how the pipeline was executed and evaluated.

3.1. Text Preprocessing Pipelines

Text preprocessing plays an essential part in the processes of text classification. The efficiency of different pre-processing methods in automatic text classification tasks has been emphasized by numerous research workers in previous research [19]. The implications of preprocessing methods are noticed in various real-world applications, such as Twitter sentiment classification and movie reviews. An inspection is used to increase the quality of short text and also consider the influence of pre-processing methods before using the models. This work relates to text pre-processing techniques, which are explained, and the respective instances of tweets are used by using a hate speech dataset.

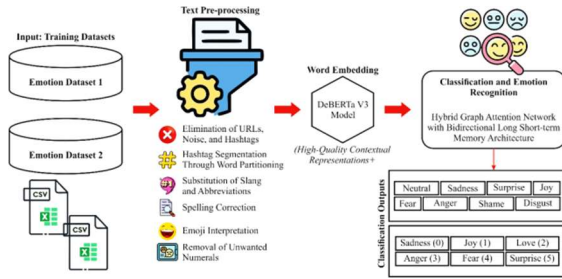


Figure 1: Overall Flow Of CEGRM-EDSM Algorithm

Elimination of URLs, noise, and hashtags: The removal process is used to remove the noise from the data. Similarly, the majority of the tweets are located by users like URLs that can indicate additional content to the user. The hashtag symbol also offers any supplementary data, occasionally communicating sentiments. Hence, this data must be known as noise, which has been required to be controlled. Numerous research works have been previously explored. As stated by a survey, these noisy effects need to be replaced with alternative words, while additional studies are required to eliminate such noisy data.

Word partition: It is the process of separating the words or contents employed in a hashtag, like #usedbytrendypeople, which is separated as 4 words: used + by + trendy + people. This process can be more useful to machines for separating the sentences into words with no human participation.

Substitute slang and abbreviations: Each social network website restricts the word counts in the comments. This limitation encourages online users to utilize short phrases and slang. Abbreviations include letters that are gained from the comprehensive word, like VIP remains an important person, BTW, which denotes by the way, BFN, which refers to a bye for now, and more. Slang has also been employed as a casual mode of signifying concepts and occasionally its point to a specific set of persons. Later, it can be vital to handle informal words within the comments by replacing them with its correct word meanings. Therefore, the performance of the classifier is enhanced with no data loss. The text must be effectively analyzed with a normal text analytical device, so that slang and abbreviation could be replaced with its meanings.

Incorrect spelling and grammatical errors: They are generally presented in social network commentaries. Textblob2 and Norvig's spell

correction technique are mainly utilized for correcting grammar and spelling.

Emoji handling comprises the conversion of emojis into their respective textual descriptions previous to model training. As emojis are robust emotional indications in social media texts, substituting them with meaningful words supports maintaining the sentiment and emotional contexts. This expands the capability of the classifier for precisely detecting emotions with no loss of semantic data.

Delete unwanted numerals: Inappropriate numeric tokens must be eliminated, whereas contextually meaningful numbers are maintained.

3.2. Vector Representation Model

In this section, the DeBERTa V3-base model is utilized for rich contextual feature extraction. This method utilizes the DeBERTa V3-base encoding that employs disentangled self-attention for separating content and representing position, critical to capture contextual dependency and semantic variations in social media text [20]. All inputs post S is tokenization into a series as in Eq. (1).

$$C = t_1, t_2, \dots, t_n, n \leq 256 \quad (1)$$

This sequence is embedded as Eq. (2).

$$X \in \mathbb{R}^{n \times d}, d = 768 \quad (2)$$

Leveraging a WordPiece tokenization with a vocabulary size of 128,001, given by the DeBERTaV3Preprocessor in the keras-nlp library. The results embedded are fed to 12 transformer layers, creating a contextual outcome as in Eq. (3).

$$H \in \mathbb{R}^{n \times d} \quad (3)$$

By extracting the representation of initial token (analogous to [CLS] token) as in Eq. (4).

$$h_{cls} = H_1 \in \mathbb{R}^d \quad (4)$$

The outcome of the [CLS] token, h_{cls} , is fed to a layer of dropout to yield h_1 that is then a linear transformation employing $W_1 \in \mathbb{R}^{768 \times 768}$ denotes the weight matrix and bias b_1 , accomplished by an activation function of ReLU for producing h_2 . Another dropout is used to h_2 , leads to h_3 , which is fed to the final linear layer parameter by $W_2 \in \mathbb{R}^{768 \times K}$ and bias b_2 , accomplished by an activation function of sigmoid

to create the outcome vector $\hat{y} \in \mathbb{R}^K$. It encodes the forecasted probability for all of the K emotion categorizes. The method has trained employing the binary cross-entropy losses as described in Eq. (5).

$$\mathcal{L} = -\frac{1}{K} \sum_{i=1}^K [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (5)$$

3.3. Hybrid Graph Recurrent Modeling

For emotion detection, a hybrid GAT-BiLSTM classifier is used to capture relational and sequential dependencies. GAT is a neural network intended specially to process structural information of the graph; it completely assumes the relations among data once processing input data and automatic learns the connections among nodes [21]. This method depends on an attention mechanism (AM) that dynamically regulates the connection weighted among diverse nodes and adaptively collections the data of adjacent nodes, thereby accomplishing a more effective and precise model on the structural information of the graph. Related to conventional graph NN (GNN) techniques, GAT provides the succeeding benefits: primarily, it could adaptively learn the data significance of all nodes and more correctly state the interrelations among nodes; next, it could efficiently improve the noise and sparsity issues in graph data and manage larger-scale graphical information.

Among them, the primary considers the feature of node $V = \{v_1, v_2, \dots, v_N\}$, here $v_i \in \mathbb{R}^F$, and the causal relation matrix at time t as input. Especially, N signifies the count of channels, and F implies the data dimension of all nodes. During this layer, the self-AM is used for all nodes in the graph to assign diverse weights based on their significance. Then, it aggregated the node and its neighboring nodes depends on the weighted size. For two nodes with v_i denotes the input feature vectors signify the node influences i and v_j implies the input feature vectors represent the influence of node j , which is signified as e_{ij} , as:

$$e_{ij} = a(Wv_i, Wv_j) \quad (6)$$

where W denotes the weight matrix that is utilized for establishing the relations among the output and input attributes, thus obtaining the alteration of node attributes. The feed-forward NN $a(\cdot)$ feature mapped to the original numbers. It computes the nodes' significance j to i without allowing for the graph-structured data. By combining the coefficient of correlation among

nodes and its 1st-order neighbor set, the computation of e_{ij} is restricted to node $j \in G_i$, let G_i signifies the adjacent node i . Afterwards, using the softmax function for normalizing the weighted of each neighboring node.

$$\alpha_{ij} = \text{softmax}_j(e_{ij}) = \frac{\exp(e_{ij})}{\sum_{l \in V_i} \exp(e_{il})} \quad (7)$$

The coefficient of attention α_{ij} denotes the attention among the nodes i and j , whereas l denotes the node from the 1st-order neighborhood of i . To introduce the activation function of LeakyReLU and expand the formula, the co-efficient of attention computed by the AM could be represented as follows:

$$\alpha_{ij} = \frac{\exp(\text{Leaky_ReLU}(a^T[Wv_i \| Wv_j]))}{\sum_{l \in G_i} \exp(\text{Leaky_ReLU}(a^T[Wv_i \| Wv_l]))} \quad (8)$$

Here, $\|$ signifies the contact operating.

The capability of single-layer AM for learning from neighboring nodes can comparatively restricted. To enhance the precision of learning data, it integrates multi-AMs. For leveraging a multiple-head AM to compute the attention coefficient of neighboring nodes, the learning procedure of model is increasingly steady. The fused feature outcome attained, signified as v'_i , could be represented as below:

$$v'_i = \sigma\left(\frac{1}{k} \sum_{k=1}^k \sum_{j \in G_i} \alpha_{ij}^k W^k v_j\right) \quad (9)$$

In this formula k denotes the head, W^k implies the weighted matrix of k , σ represents the activation function, and v' signifies the model outcomes.

The AM in the method learned and parameterized the relations among nodes, enabling diverse weights to be assigned for all edges. Moreover, every head from the multiple head AM is used separately and in parallel, removing the necessity for an intricate matrix function. Attention shares weights only among surrounding nodes, to ensure robustness and capture spatial relations even if connections are lost.

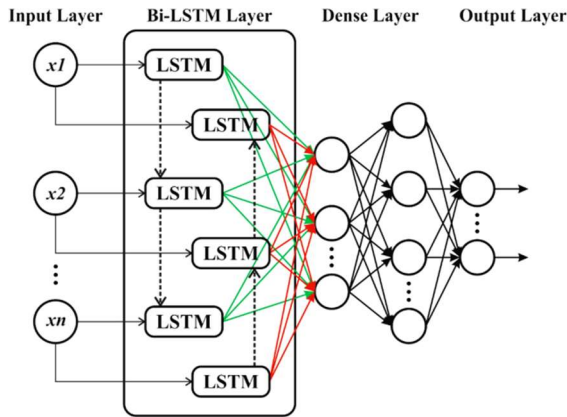


Figure 2: Structure Of Bi-LSTM Module

BiLSTM Component: Spatial features from the GAT are passed into the BiLSTM model for capturing the temporal dependency, creating spatial- temporal and causal features for signal identification. LSTM is a RNN that addresses the gradient explosion issues in conventional RNN to introduce gate processes. The main elements of LSTM are cell conditions and several gate processes, such as i_t denote the gate of input, o_t denote the gate of output, and f_t denote the gate of forget that controls the degree of data flow over the activation purpose of sigmoid for a provided time step t

$$f_t = \sigma(W_{f,m}m_t + W_{f,h}h_{t-1} + b_f) \quad (10)$$

$$i_t = \sigma(W_{i,m}m_t + W_{i,h}h_{t-1} + b_i) \quad (11)$$

$$\tilde{c}_t = \tanh(W_{\tilde{c},m}m_t + W_{\tilde{c},h}h_{t-1} + b_{\tilde{c}}) \quad (12)$$

$$o_t = \sigma(W_{o,m}m_t + W_{o,h}h_{t-1} + b_o) \quad (13)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (14)$$

$$h_t = o_t \odot \tanh(c_t) \quad (15)$$

In this formula, m_t denotes the vector of input, b signifies the biased term, c_t implies the cell layer, c_t denotes the vector of candidate performance, h_t implies the vector of output, and W signifies the weight matrix.

The LSTM only processes previous data and ignores future context. Meanwhile, detecting signals needs complete contextual understand, the model utilizes a BiLSTM that calculates hidden states $\vec{h}_{t+1}$ and $\overleftarrow{h}_{t+1}$ to run the LSTM backward and forward along the time axis and then integrate them into a last bi-directional hidden state. Fig. 2 depicts the infrastructure of the Bi-LSTM module.

3.4. Data Collection and Execution Protocol

Data Collection: the two corpora used to evaluate CEGRM-EDSM were both obtained from Kaggle's public dataset repository rather than collected directly by the authors, a choice made so that results could be compared against the wide body of prior work that already reports figures on the same corpora. Emotion Detection Dataset 1 [22] consists of short, informally written posts labelled with eight emotion categories, and Emotion Dataset 2 [23] consists of Twitter-style messages labelled with six categories; full class distributions are given in Tables 1 and 5. Both corpora were downloaded in their original CSV form, retaining the text and emotion-label columns only, and no additional manual annotation was performed. Because the two datasets differ in class count and in the degree of class imbalance, evaluating the framework on both allows its robustness to be judged under two distinct label distributions rather than a single one.

Execution Protocol: each dataset was processed through the pipeline described in Sections 3.1 to 3.3 and then split into a 70% training and 30% testing partition, with the split applied independently to each dataset. Model training was carried out in a Python-based deep learning environment using a Keras/TensorFlow backend: DeBERTa V3-base was used to extract the contextual embeddings described in Section 3.2, and the GAT-BiLSTM classifier built on top of these embeddings was trained using the Adam optimiser against the binary cross-entropy objective in Eq. (5). Training was run for 25 epochs on both datasets, with training and validation accuracy and loss logged after every epoch to produce Figs. 4, 5, 7 and 8; the same hyperparameter configuration was kept fixed across both datasets so that the comparison between them reflects the data rather than a difference in tuning. Model performance was scored using accuracy, precision, recall, F1-score and AUC, computed per class and then averaged, since accuracy alone is not informative on datasets where some classes (such as Shame in Dataset 1) contain only a few hundred samples.

4. EXPERIMENTAL ASSESSMENTS

The performance validation of the proposed CEGRM-EDSM methodology has comprehensively conducted using two widely recognized benchmark datasets, namely Emotion Detection Dataset 1 [22] and Emotions Dataset 2 [23], to ensure rigorous evaluation across diverse emotional categories and textual variations.

4.1. Result Analysis of Emotion Dataset 1

The Emotion Detection Dataset comprises short text samples labeled with human emotions like sadness, joy, fear, and neutral. These texts mimic real-world, informal interaction usually found on social media platforms such as chat apps, Twitter, or online forums. The dataset comprises 34792 samples with 8 classes are shown in Table 1. Table 2 represents the sample text of the emotion dataset 1.

Table 1: Details On Emotion Dataset 1

Emotion	No. of Samples
Neutral	2254
Joy	11045
Sadness	6722
Fear	5410
Surprise	4062
Anger	4297
Shame	146
Disgust	856
Total Samples	34792

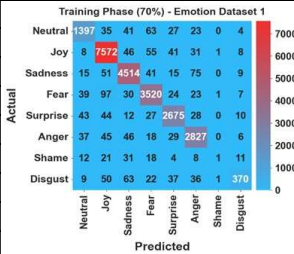
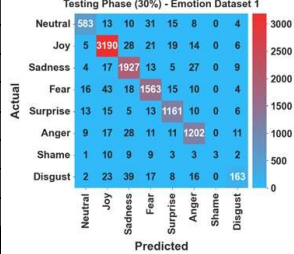
Table 2: Sample Text Of Emotion Dataset 1

S. No	Sample Text	Emotions
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1	"You'd better prepare for the examination. "	Neutral
2	"Sage Act upgrade on my to do list for tommorow."	Joy
3	"People hide their behind a #fake smile."	Sadness
4	"Is a friend that you misunderstood but I know the #heartoflife is good."	Fear
5	"I almost forgot my hair was red until I looked in the mirror"	Surprise
6	"With everything, with everybody, with all this!"	Anger
7	"Nobody doubted him, or failed to recognise his temporary financial embarrassment."	Shame
8	"SMHim really sad. the only basketball i have to look forward too is march madness????"	Disgust

Table 3 signifies the confusion matrices and classification outcomes of the CEGRM-EDSM model with 70 and 30 splits in emotion dataset 1. On confusion matrices, the outcome represents that the CEGRM-EDSM model has effective recognition of each 8 classes on a 70:30 split. Additionally, with classification results, the outcomes demonstrate that the CEGRM-EDSM approach provides correctly identified varied class labels.

Table 3: Confusion Matrices And Classifier Outcome Of Emotion Dataset 1

Confusion Matrix		Classes	$Accu_r$	$Preci_n$	$Recal_l$	$F1_{score}$	AUC_{score}
	Actual \ Predicted	Neutral	98.54	89.55	87.86	88.70	93.57
		Joy	97.81	95.67	97.55	96.60	97.74
		Sadness	98.05	94.38	95.64	95.00	97.13
		Fear	98.09	93.52	94.09	93.80	96.45
		Surprise	98.60	93.79	94.22	94.01	96.70
		Anger	98.34	92.66	93.98	93.32	96.47
		Shame	99.56	25.00	00.94	01.82	50.47
		Disgust	98.88	87.06	62.93	73.05	81.35
		Average	98.48	83.95	78.40	79.54	88.74
		Neutral	98.74	92.10	87.80	89.90	93.64
	Actual \ Predicted	Joy	97.79	95.85	97.17	96.51	97.62
		Sadness	97.97	93.36	96.25	94.79	97.31
		Fear	97.88	93.15	93.65	93.40	96.17
		Surprise	98.68	93.86	94.93	94.39	97.05
		Anger	98.32	93.18	93.25	93.21	96.14
		Shame	99.65	100.00	07.50	13.95	53.75
		Disgust	98.59	79.51	60.82	68.92	80.20
		Average	98.45	92.63	78.92	80.63	88.99

Emotion Dataset 1

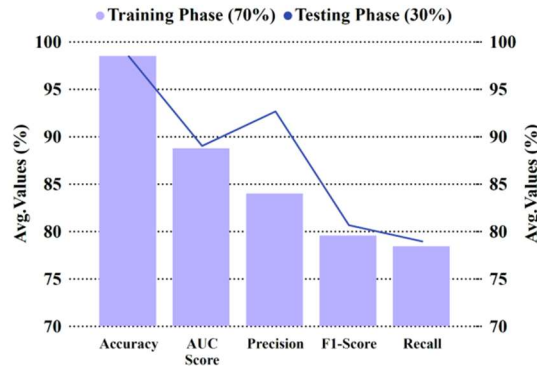


Figure 3: Average Of CEGRM-EDSM Approach Under Emotion Dataset 1

Fig. 3 represents the overall average classification outcomes of the CEGRM-EDSM approach with emotion dataset 1. With 70%TRPA, the CEGRM-EDSM approach attains average $accu_r$ of 98.48%, $preci_n$ of 83.95%, $recal_l$ of 78.40%, $F1_{score}$ of 79.54%, and AUC_{score} of 88.74%. At the same time, with 30%TEPA, the CEGRM-EDSM model gains an average $accu_r$ of 98.45%, $preci_n$ of 92.63%, $recal_l$ of 78.92%, $F1_{score}$ of 80.63%, and AUC_{score} of 88.99%, correspondingly.

Fig. 4 represents the training $accu_r$ and validation $accu_r$ of CEGRM-EDSM method on Emotion Dataset 1 through 25 epochs. Both curves reveal a constant rise in accuracy as the epoch counts upsurges, depicting that the method is learning effectively. Around epochs, the accuracy curves start to plateau, recommending that the method is approaching its optimum solutions. Considerably, the training and validation curves are nearly aligned throughout, depicting minimum overfitting and improved generality on unseen data.

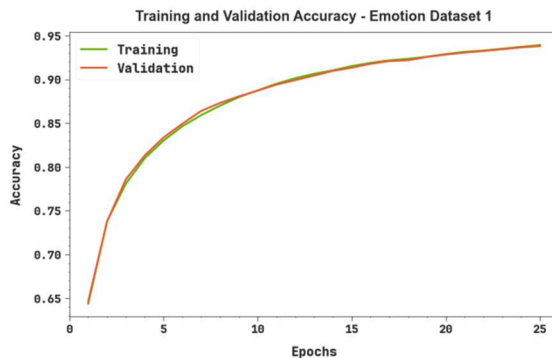


Figure 4: Accuracy Curve Of CEGRM-EDSM Approach Under Emotion Dataset 1



Figure 5: Loss Curve Of CEGRM-EDSM Approach Under Emotion Dataset 1

Fig. 5 portrays the training and validation loss of CEGRM-EDSM method on Emotion Dataset 1 around 25 epochs. Both losses lessen consistently through the epochs, representing that the method is effectively learning the essential patterns in the data. A quick drop in loss is identified in the initial epochs, showcasing that the method rapidly adapts to the data. The consistent overlap among training and validation loss over the training process depicts minimum overfitting and better generality to unseen data.

To exhibit the capability of the CEGRM-EDSM model with emotion dataset 1, a detailed comparative study is specified in Table 4 [24-27]. The outcome depicts that SVM-Unigrams, Bnet, Transformer, and NTUA-SLP approaches have attained ineffective values. Likewise, the AdaBoost and LR approaches have moderately enhanced outcomes. Simultaneously, the BiLSTM and TextCNN approach are gained closer performance. However, the CEGRM-EDSM model accomplishes enhanced solution with $accu_r$ of 98.48%, $preci_n$ of 83.95%, $recal_l$ of 78.40%, and $F1_{score}$ of 79.54%, respectively.

Table 4: Comparative Analysis Of CEGRM-EDSM System With Other Approaches Under Emotion Dataset 1

Emotion Dataset 1				
Methods	$Accu_r$	$preci_n$	$recal_l$	$F1_{score}$
LR Model	70.11	71.47	78.37	76.81
AdaBoost	68.94	68.20	79.72	69.94
BiLSTM	85.02	78.54	71.22	71.66
TextCNN	84.23	75.16	68.11	77.37
Bnet	59.00	70.29	68.16	66.69
SVM-Unigrams	44.20	65.92	67.48	75.13
Transformer	57.70	70.14	78.30	76.09
NTUA-SLP	58.80	79.74	72.54	79.22
CEGRM-EDSM	98.48	83.95	78.40	79.54

A pattern worth flagging in Table 4 is that overall accuracy and F1-score do not move together for every baseline: NTUA-SLP, for instance, reaches a relatively high recall yet a modest F1-score, pointing to a precision cost that a single accuracy figure would hide. CEGRM-EDSM avoids this trade-off, posting its highest scores on precision and F1 rather than on accuracy alone, which is the more meaningful signal on an eight-class, heavily imbalanced dataset such as this one, where a model can reach a high accuracy simply by favouring the majority classes.

4.2. Result Analysis of Emotion Dataset 2

This Emotion Classification dataset is intended to assist research and experimentation in the task of NLP and emotion identification. It comprises various collections of text instances, and all classes are labelled with the consistent emotion it conveys. Emotions could range from happiness and excitement to sadness, anger, and more. Every entry in this dataset comprises a text segment depicting a Twitter message and equivalent label depicting the predominantly conveyed emotion. The emotions were categorized into 6 classes with 80000 instances are represented in Table 5. Whether you're concerned with sentiment analysis, text mining, or emotion classification, this dataset presents a better foundation for examining the nuanced emotional landscape in social media platforms. Table 6 defines the sample text of the emotion dataset 2.

Table 5: Details On Emotion Dataset 2

Emotion	No. of Samples
"Sadness (0)"	20000
"Joy (1)"	20000
"Love (2)"	10000
"Anger (3)"	10000
"Fear (4)"	10000
"Surprise (5)"	10000
Total Samples	80000

Table 6: Sample Text Of Emotion Dataset 2

S. no	Sample Text	Emotions
1	"im feeling a little like a damaged tree and that my roots are a little out of wack"	Sadness (0)
2	"i have officially graduated im not feeling as ecstatic as i thought i would"	Joy (1)
3	"i guess that feeling is what im really getting all nostalgic about"	Love (2)
4	"this emotion has never been an intense one"	Anger (3)

5	"i feel a bit intimidated and out of my league due to his experience"	Fear (4)
6	"i was feeling really overwhelmed"	Surprise (5)

Table 7 denotes the confusion matrices and classification outcomes of CEGRM-EDSM model with 70 and 30 splits in the emotion dataset 2. On confusion matrices, the solution represents that the CEGRM-EDSM method has effective recognition of 8 classes on a 70:30 split. Additionally, with classification solutions, the outcomes demonstrate that the CEGRM-EDSM model provides appropriately identified, varied class labels.

Table 7: Confusion Matrices And Classifier Outcome Of Emotion Dataset 2

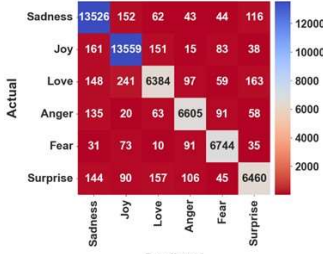
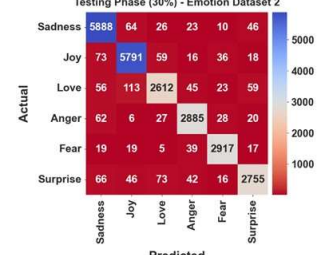
Confusion Matrix		Classes	$Accu_r$	$Preci_n$	$Recal_l$	$F1_{score}$	AUC_{score}
		Sadness	98.15	95.62	97.01	96.31	97.77
		Joy	98.17	95.93	96.80	96.36	97.71
		Love	97.94	93.51	90.02	91.73	94.56
		Anger	98.72	94.94	94.74	94.84	97.01
		Fear	99.00	95.44	96.56	96.00	97.95
		Surprise	98.30	94.03	92.26	93.14	95.71
		Average	98.38	94.91	94.56	94.73	96.79
		Sadness	98.15	95.52	97.21	96.36	97.84
		Joy	98.12	95.89	96.63	96.26	97.63
		Love	97.98	93.22	89.82	91.49	94.46
		Anger	98.72	94.59	95.28	94.93	97.25
		Fear	99.12	96.27	96.72	96.49	98.09
		Surprise	98.32	94.51	91.89	93.18	95.57
		Average	98.40	95.00	94.59	94.79	96.80

Fig. 6 illustrates the overall average classification performance of CEGRM-EDSM model in emotion dataset 2. With 70%TRPA, the CEGRM-EDSM method gains an average $accu_r$ of 98.38%, $preci_n$ of 94.91%, $recal_l$ of 94.56%, $F1_{score}$ of 94.73%, and AUC_{score} of 96.79%, respectively. At the same time, with 30%TEPA, the CEGRM-EDSM technique gains an average $accu_r$ of 98.40%, $preci_n$ of 95.00%, $recal_l$ of 94.59%, $F1_{score}$ of 94.79%, and AUC_{score} of 96.80%, respectively.

Fig. 7 portrays the training and validation accuracy of CEGRM-EDSM approach on Emotion dataset 2 around 25 epochs. Both curves exhibit a consistent growth in accuracy as the counts of epoch's progression, depicting that the method is learning efficiently. Around epochs, the accuracy curves start to plateau, recommending that the method is approaching its optimum solutions. Considerably, the training and validation curves are strongly united, representing minimum overfitting and better generality on unseen data.

Emotion Dataset 2

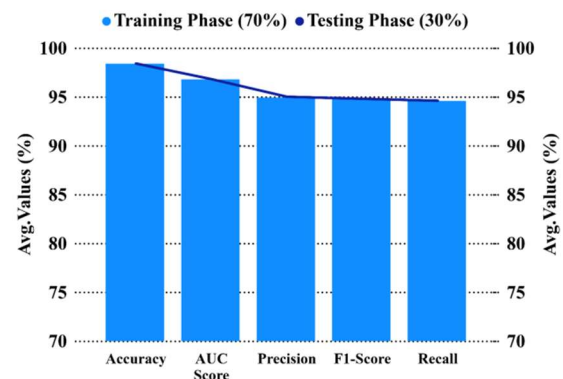


Figure 6: Average Of CEGRM-EDSM Approach Under Emotion Dataset 2

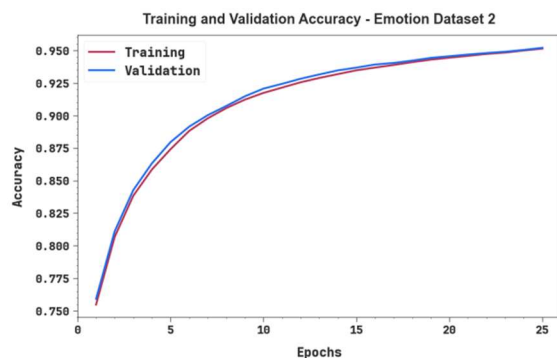
Figure 7: $Accu_r$ Accuracy Curve Of CEGRM-EDSM Approach Under Emotion Dataset 2

Fig. 8 demonstrates the training and validation loss of CEGRM-EDSM method on

Emotion dataset 2 under 25 epochs. Both losses diminish gradually through the epochs, denoting that the method is effectually learning the essential patterns in the data. A quick drop in loss is identified in the initial epochs, demonstrating that the method rapidly adapts to the data. The constant overlap among training and validation loss during the training process represents minimum overfitting and enhanced generality to unseen data.

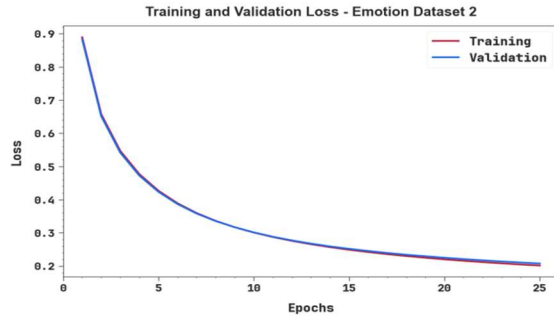


Figure 8: Loss Curve Of CEGRM-EDSM Approach Under Emotion Dataset 2

To show the capability of the CEGRM-EDSM model with emotion dataset 2, a detailed experimental investigation is specified in Table 8. The outcome depicts that the BERT, PlusEmo2Vec, TCS, and RoBERTa+MA approaches are gaining the worst outcomes with $accu_y$ of 57.215, 57.60%, 58.20%, and 62.40%, correspondingly. Simultaneously, the CNN and ANN techniques have gained moderately enhanced outcomes with $accu_y$ of 89.93% and 88.05%. Concurrently, the DNN and LRA-DNN approaches have revealed nearer outcomes with $accu_y$ of 92.08% and 94.48%. Finally, the CEGRM-EDSM approach attains enhanced outcomes with $accu_y$ of 98.40%, $preci_n$ of 95.00%, $recal_l$ of 94.59%, and $F1_{score}$ of 94.79%, respectively.

Table 8: Comparative Analysis Of CEGRM-EDSM System With Other Approaches Under Emotion Dataset 2

Emotion Dataset 2				
Methods	$Accu_y$	$Preci_n$	$Recal_l$	$F1_{score}$
TCS	58.20	66.99	76.42	69.34
PlusEmo2Vec	57.60	72.04	65.03	76.84
LRA-DNN	94.48	87.96	91.70	91.67
Deep Neural Network	92.08	86.74	90.53	88.39
CNN	89.93	80.47	87.59	86.10
ANN	88.05	78.43	84.75	83.93
BERT	57.21	79.79	71.41	76.36
RoBERTa+MA	62.40	76.26	75.17	74.79
CEGRM-EDSM	98.40	95.00	94.59	94.79

The comparison in Table 8 follows the same pattern seen with Dataset 1: models built on a single representation, whether classical (BERT, TCS) or a single transformer variant (RoBERTa+MA), plateau well below the ensemble-style methods (CNN, ANN, DNN, LRA-DNN), and CEGRM-EDSM extends that trend further by combining a contextual embedding with a relational encoder rather than relying on either alone. The margin between LRA-DNN, the strongest baseline, and CEGRM-EDSM (94.48% vs. 98.40% accuracy) is wider than the margin separating LRA-DNN from the next-best baseline, DNN, suggesting that the gain comes from the graph-based relational component rather than from incremental tuning of an existing architecture.

Therefore, the proposed CEGRM-EDSM technique demonstrates strong potential for improving emotion recognition performance in social media networks.

5. DISCUSSION

Taken together, the results in Section 4 confirm that combining a disentangled contextual embedding with a relational graph encoder offers a genuine advantage over both purely sequential and purely transformer-based baselines, and this is consistent with, rather than contradicted by, related work. Yan et al. [13] reported similar gains from pairing RoBERTa with a graph neural network and a CRF layer, and Sankari and Priscila [14] found that combining a CNN with a Bi-LSTM improved on either component used alone; CEGRM-EDSM extends this line of reasoning by replacing the CNN/GNN pairing with a graph attention mechanism specifically, which lets the model weight neighbouring words unevenly rather than treating every relation as equally important. Hussain et al.'s [16] distillation-based approach and Shi et al.'s [17] Markov-based DRMM model take a different route, trading some accuracy for a lighter or more interpretable model, which suggests that the choice between CEGRM-EDSM and these alternatives should depend on whether accuracy or deployment cost is the priority for a given application.

Practically, a framework that reaches this level of accuracy on noisy, informally written text has a direct bearing on tasks such as monitoring public sentiment during a crisis, flagging distressed users for early mental-health outreach, or filtering emotionally manipulative content – tasks in which the input text resembles the two benchmark corpora

used here far more than it resembles clean, edited prose.

These results should, however, be read alongside several limitations. First, both benchmark corpora are English-language and drawn from a similar register of informal social media text; how the framework performs on other languages, scripts, or more formal text genres has not been tested. Second, severe class imbalance limits what the headline accuracy figures can tell us: the Shame class in Dataset 1 contains only 146 of 34,792 samples, and its F1-score (1.82% and 13.95% across the two splits) is far below the model's average, showing that a high overall accuracy can coexist with poor performance on rare but potentially important classes. Third, the evaluation reports a single 70:30 split rather than repeated cross-validation, so the variance of the reported metrics is not established, and no ablation study isolates how much of the improvement is attributable to the GAT component, the BiLSTM component, or the DeBERTa embedding individually. Finally, the computational cost and inference latency of running a transformer embedding, a graph attention layer, and a BiLSTM in sequence were not measured, which would matter for any real-time deployment of the framework.

6. CONCLUSION

In this study, we have designed a CEGRM-EDSM algorithm to develop an effective and intelligent framework for social network data classification and emotion recognition by leveraging advanced DL systems. Primarily, a comprehensive text pre-processing pipeline has been executed to improve data quality, comprising removal of URLs, noise, and hashtags, hashtag segmentation over word partitioning, exchange of slang and abbreviations, spelling correction, emoji interpretation, and elimination of unwanted numerals. Afterwards, the high-quality contextual representations are created utilizing the DeBERTa V3-base word embedding method to capture rich semantic and syntactic dependencies in the social media network text. For emotion recognition, a hybrid GAT with BiLSTM framework can be employed to model both relational word dependencies and sequential contextual patterns efficiently. An extensive range of simulation outcome were conducted on two benchmark datasets. The comparative analysis exhibits the superiority of the presented CEGRM-EDSM

algorithm over recent systems with respect to numerous performance metrics.

Beyond the performance figures reported here, several directions could extend this work. Future studies could evaluate CEGRM-EDSM on multilingual or code-mixed social media corpora, where emotion cues are expressed differently across languages, and could incorporate multimodal signals such as accompanying images, rather than relying on emoji-to-text substitution alone. Addressing the class-imbalance limitation noted in Section 5 – through targeted oversampling, class-weighted losses, or few-shot techniques for rare emotion categories such as Shame – is a natural next step. A lighter, distilled version of the GAT-BiLSTM classifier would also be worth exploring for applications that need near real-time emotion tagging, such as live content moderation or crisis-response dashboards, and an ablation study quantifying the individual contribution of the embedding, graph, and recurrent components would help clarify which part of the pipeline drives the reported gains.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

ETHICAL CONSIDERATIONS

This study did not involve human participants, human tissue, or animal subjects, and no new data were collected from individuals by the authors. Both benchmark corpora used for evaluation, Emotion Detection Dataset 1 [22] and Emotion Dataset 2 [23], are third-party datasets that were already public and de-identified at the point of release on the Kaggle platform, and they were used strictly under the terms attached to their original publication. Consequently, no additional ethical approval was required for this work.

FUNDING STATEMENT

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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