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# Contextual Emotion Classification in Text Using Hybrid Word2Vec-BiLSTM Deep Learning Architecture

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**Abstract: Textual Emotion Recognition is one of the most recent directions in Natural Language Processing (NLP) due to the widespread adoption of internet-based services such as Twitter or forum communities for instant message exchange. Since there are no visible signals such as facial expressions and tone in text mode (face-to-face is easier to infer, because in that we receive both nonverbal as well as verbal cues), Emotion Detection from Textual Content as a Context-Aware System. Traditional machine learning techniques, such as Naïve Bayes and Logistic Regression, rely on manual feature extraction methods, such as Bag-of-Words (BoW) and TF-IDF. Although effective to some extent, these approaches fail to capture semantic meaning and contextual dependencies, limiting their performance in handling complex linguistic patterns.**

**To overcome these limitations, this research proposes a hybrid deep learning model that combines Word2Vec (CBOW) embeddings with a Bidirectional Long Short-Term Memory (Bi-LSTM) network. Word2Vec converts text into dense vector representations, while Bi-LSTM captures contextual information by processing sequences in both directions. The model is trained on a large dataset of over 416,123 labelled samples across six emotion categories.**

***Keywords:*** *Emotion Detection, Natural Language Processing (NLP), Deep Learning, Word2Vec (CBOW), Bidirectional LSTM (Bi-LSTM), Text Classification, Sentiment Analysis, Machine Learning.*

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## I. INTRODUCTION

With the rapid growth of digital communication platforms such as social media, online forums, and messaging applications, a massive amount of textual data is being generated. Unlike face-to-face communication, text-based interactions lack nonverbal cues such as facial expressions, gestures, and tone of voice, making it difficult to interpret human emotions accurately. As a result, emotion detection from text has emerged as a crucial research area in Natural Language Processing (NLP) [1] [2].

Emotion detection focuses on identifying and classifying emotions expressed in textual data, such as joy, sadness, anger, fear, love, and surprise. This task plays an important role in various real-world applications, including sentiment analysis, customer feedback analysis, mental health monitoring, and conversational AI systems [3][[4]. However, accurately detecting emotions in text is challenging due to ambiguity, context dependency, sarcasm, and implicit emotional expressions [5][[6].

Early approaches to emotion detection relied on traditional machine learning techniques such as Naïve Bayes and Logistic Regression. These models used feature extraction methods like Bag-of-Words (BoW), TF-IDF, and n-grams to represent text numerically [7][8]. Although these approaches were effective for basic classification tasks, they failed to capture semantic relationships and contextual information, limiting their performance in complex scenarios [9].

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To address these limitations, deep learning techniques have been widely adopted in NLP. Deep learning models can automatically learn meaningful representations from large datasets without manual feature engineering [10][11]. Recurrent Neural Networks (RNNs) were initially used for sequence modelling; however, they suffer from the vanishing gradient problem, which restricts their ability to capture long-term dependencies [12].

Long Short-Term Memory (LSTM) networks were introduced to overcome this issue by using memory cells and gating mechanisms to retain important information over longer sequences [13]. Further improvements were achieved with Bidirectional LSTM (Bi-LSTM), which processes text in both forward and backward directions, enabling better contextual understanding [14][15].

In addition to sequence modelling, word representation is pivotal for emotion detection. Word embedding techniques, such as Word2Vec, provide dense vector representations that capture semantic relationships between words [16][17]. The Continuous Bag-of-Words (CBOW) model, in particular, learns word representations conditioned upon the surrounding context, improving the model's ability to understand language.

This research proposes a hybrid approach that combines Word2Vec embeddings with a Bidirectional LSTM model to enhance emotion detection performance. Word2Vec is used for semantic feature extraction, while Bi-LSTM captures contextual dependencies within the text [18][19]. This combination enables the models to simultaneously capture semantic nuances and long-range sequential dependencies, resulting in superior classification accuracy.

The proposed system is evaluated on a large dataset containing labelled text samples across multiple emotion categories. Standard performance metrics such as accuracy, precision, recall, and F1-score are used to assess the model's effectiveness [20][21] The results demonstrate that hybrid deep learning approaches outperform traditional machine learning methods in emotion detection tasks.

Despite these advancements, challenges such as contextual ambiguity, sarcasm, and class imbalance remain open problems in the field [22][23] Addressing these challenges requires more advanced models and improved data representation techniques. Future research may explore transformer-based architectures and multimodal approaches to optimize classification metrics and model robustness [24][25][26][27].

In conclusion, emotion detection from text is a complex yet essential task in NLP. The integration of semantic embeddings and deep learning models offers a robust framework for" or "constitutes a viable methodology for improving accuracy and scalability, making it suitable for real-world applications.

## II. LITERATURE REVIEW

The rapid growth of digital communication platforms such as social media, online forums, and messaging applications has facilitated the proliferation of or precipitated the emergence of vast amounts of textual data. This data contains valuable emotional information that reflects users' opinions, attitudes, and psychological states. Extracting and analyzing such emotional cues has become an important task in Natural Language Processing (NLP), especially for applications like sentiment analysis, mental health monitoring, and user behaviour prediction. However, identifying emotions in text is not a straightforward process. Human language is highly complex, often ambiguous, and strongly contextually "contingent" or "sensitive" to linguistic context. The same sentence may express different emotions depending on how it is interpreted, and emotions are frequently conveyed indirectly through sarcasm, tone, or subtle wording. These challenges make accurate emotion detection a difficult problem to solve [28].

In the early stages of NLP research, emotion detection tasks were mainly addressed using traditional machine learning techniques. Algorithms such as Naive Bayes, Support Vector Machines, Logistic Regression, and Decision Trees were widely used, contextually contingent, or "sensitive to linguistic context", due to their simplicity and efficiency in handling classification problems. These models relied on feature extraction methods such as Bag of Words (BoW), Term Frequency-Inverse Document Frequency (TF-IDF), and n-gram representations to convert textual data into numerical form. While these approaches were effective for basic sentiment classification, they were limited in their ability to capture deeper semantic meaning and contextual relationships between words. Since these models treat text as a collection of independent features rather than a structured sequence, they often fail to understand the true intent behind a sentence. As a result, they struggle to identify complex emotional expressions such as sarcasm, irony, and implicit sentiments [29].

Another major limitation of traditional approaches is their dependence on manual feature engineering. Designing effective features requires domain knowledge and extensive preprocessing, which can be time-consuming and may not always capture all relevant aspects of the data. Additionally, these models cannot handle long-range dependencies in text, meaning they cannot effectively retain contextual information across longer sentences or documents. This leads to reduced accuracy when dealing with more complex language patterns. These shortcomings highlighted the need for more advanced approaches capable of automatically learning meaningful representations from data [30].

The introduction of deep learning techniques brought a significant transformation in the field of NLP. Unlike traditional models, deep learning approaches can automatically learn features directly from raw text without requiring manual intervention. These models use multiple layers to extract hierarchical representations, allowing them to capture complex patterns and relationships within the data.

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This capability makes them highly effective for emotion detection tasks, where understanding subtle contextual cues is essential. Deep learning models also support end-to-end training, meaning the entire system can be optimized simultaneously, leading to improved performance and better generalization across different datasets [31].

Among deep learning techniques, word embeddings have played a crucial role in improving text representation. Methods such as Word2Vec represent words as dense vectors in a continuous space, where semantically similar words are placed closer together. This allows models to understand lexical associations more effectively than traditional frequency-based methods. Word embeddings help capture both semantic meaning and contextual similarity, enabling models to better interpret emotional expressions in text. By transforming words into meaningful numerical representations, these techniques provide a strong foundation for further processing in deep learning models [32].

To effectively handle sequential data, Recurrent Neural Networks (RNNs) were introduced. These models are designed to process sequentially," or "in a temporal fashion, by maintaining a hidden state that acts as memory. This allows them to retain information from previous inputs while processing new data. However, standard RNNs suffer from the vanishing gradient problem, which limits their ability to capture long-term dependencies in longer sequences. To overcome this issue, Long Short-Term Memory (LSTM) networks were developed. LSTMs use specialized gating mechanisms to control the flow of information, enabling them to retain important context over longer sequences. This makes them more suitable for emotion detection tasks, where understanding context is critical for accurate classification [33].

Despite their advantages, traditional LSTM models process text in only one direction, which may limit their ability to capture the full range of bidirectional dependencies. To address this limitation, Bidirectional LSTM (BiLSTM) models were introduced. These models process text in both forward and backward directions, allowing them to capture information from both past and future contexts. This bidirectional processing significantly improves the model's ability to understand complex sentence structures and detect subtle emotional cues. As a result, BiLSTM models have shown improved performance in various emotion detection tasks compared to unidirectional models [34].

In recent years, hybrid approaches have been proposed to optimize the efficacy of emotion recognition systems. These models combine different techniques to leverage their individual strengths. For example, integrating word embeddings with BiLSTM networks allows the model to benefit from both semantic representation and contextual understanding. Word embeddings provide meaningful input features, while BiLSTM captures sequential dependencies in both directions. This combination facilitates a more comprehensive understanding of text, leading to improved accuracy in emotion classification. Hybrid models are particularly effective in handling challenges such as contextual ambiguity and implicit emotional expressions [35].

Comparative studies have consistently shown that deep learning models outperform traditional machine learning approaches in emotion detection tasks. While traditional models rely on shallow representations, deep learning techniques possess the capacity to encapsulate complex patterns and relationships inherent in text. This leads to higher accuracy and better generalization across different datasets. However, despite these advancements, several challenges remain. Issues such as sarcasm detection, implicit emotion recognition, and handling long textual sequences continue to pose difficulties for existing models. These limitations highlight the need for further research and the development of more advanced techniques [36].

Overall, the evolution from traditional machine learning methods to deep learning and hybrid approaches has significantly improved the performance of emotion detection systems. However, there is still room for improvement in capturing nuanced emotional expressions and contextual variations. Addressing these challenges requires the integration of semantic and contextual modelling techniques, which form the basis for the proposed approach in this research [37].

Table 1 Identified Research Gaps and Proposed Solutions

| Reference (Author) | Year | Methodology | Dataset Focus | Accuracy / Performance | Identification Limitation / Research Gap |
|---|---|---|---|---|---|
| Wang et al. [38] | 2012 | Traditional Machine Learning (SVM, Naïve Bayes) with Bag-of-Words (BoW) & TF-IDF | Small-scale social media text (Twitter data) | Low Accuracy (~41% - 51%) | Relies heavily on manual feature engineering; fails to capture word order and semantic meaning; high sparsity |
| Mikolov et al. [39] | 2013 | Continuous Semantic Embeddings (Word2Vec - CBOW & Skip-gram) | Large-scale general text corpora (Google News) | Improved semantic word clustering | Static embeddings lack a neural mechanism to capture sequential sentence context |
| Zhang et al. [40] | 2015 | Standard Recurrent Neural Networks (RNN) | Short text messages and product reviews | Moderate Performance (~65% - 72%) | Suffers from the vanishing gradient problem; poor long-term dependency learning |

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| | | | | | |
|---|---|---|---|---|---|
| Liu & Chen [41] | 2017 | Unidirectional Long Short-Term Memory (LSTM) | Medium-scale multi-class emotion datasets | Good Accuracy (~78% - 85%) | Processes text only left-to-right; misses future context (negation, sarcasm) |
| Al-Hagery et al. [42] | 2020 | Bidirectional LSTM (Bi-LSTM) with basic embeddings | Sentiment and emotion datasets | High Accuracy (~88% - 90%) | Struggles with imbalanced classes and noisy, unstructured data |
| Joshi et al. [43] | 2022 | Deep learning for ambiguous linguistic patterns | Sarcastic and ambiguous social media text | Highly Variable | Sarcasm detection remains difficult due to the opposite literal meaning |
| Proposed Framework (Current Study) | 2026 | Hybrid Deep Learning: Word2Vec (CBOW) + Bi-LSTM | Large multi-class dataset (416,123 samples, 6 emotions) | Exceptional Accuracy (~94.10%) | Addresses contextual ambiguity and vanishing gradient issues; limitation: deep sarcasm requires multimodal understanding. |

## III. METHODOLOGY

➢ *Overview of the Proposed System*

The proposed system is designed to facilitate robust affective classification of text data using a hybrid deep learning approach. It integrates semantic representation through Word2Vec and contextual understanding using a Bidirectional Long Short-Term Memory (BiLSTM) network. The overall workflow consists of multiple stages, including data collection, preprocessing, feature extraction, model training, and evaluation. Each stage plays a crucial role in improving the model.

➢ *Data Description*

The dataset used in this study comprises a large collection of text samples obtained from publicly available sources such as social media platforms, online reviews, and benchmark datasets. The data includes multiple emotion categories such as joy, sadness, anger, fear, love, and surprise. The dataset is divided into training and testing sets to evaluate model performance effectively.

Table 2 Dataset Description

| Parameter | Description |
|---|---|
| Dataset Size | 400,000+ text samples |
| Data Source | Social media, online reviews |
| Number of Classes | 6 |
| Emotion Categories | Joy, Sad, Anger, Fear, Love, Surprise |
| Training Split | 80% |
| Testing Split | 20% |
| Data Type | Text |

➢ *Data Preprocessing*

Data preprocessing is an essential step to clean and prepare raw text for analysis. The following preprocessing techniques are applied:

- *Lowercasing:*

All text is converted into lowercase to maintain consistency.

- *Tokenization:*

Sentences are split into individual words or tokens.

- *Stopword Removal:*

Common words such as “is,” “the,” and “and” are removed as they do not contribute significantly to emotion detection.

- *Punctuation Removal:*

Special characters and punctuation marks are eliminated.

- *Padding:*

Sequences are padded to ensure uniform input length for the model.

Table 3 Data Preprocessing Steps

| Step | Description |
|---|---|
| Lowercasing | Convert all text into lowercase |
| Tokenization | Split sentences into words |
| Stopword Removal | Remove common words (is, the, and) |
| Punctuation Removal | Remove special characters |
| Padding | Ensure equal length of sequences |

These steps help reduce noise and improve model performance.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar2017

➢ *Feature Extraction using Word2Vec*

In this stage, textual data is converted into a numerical format using Word2Vec embeddings. Word2Vec is a widely used technique in Natural Language Processing that represents words as dense vectors in a continuous space.

The Continuous Bag-of-Words (CBOW) model is used in this research. It predicts a target word based on its surrounding context words. This approach helps capture semantic relationships between words, allowing the model to understand similarities and meanings effectively.

Advantages of using Word2Vec include:

- Capturing semantic relationships between words.
- Reducing dimensionality compared to the traditional method.
- Improving the generalization capability of the model.

➢ *Model Architecture: Bidirectional LSTM*

The core of the proposed system is the Bidirectional Long Short-Term Memory (BiLSTM) model. BiLSTM is an advanced type of Recurrent Neural Network that processes input sequences in both forward and backward directions.

- *Algorithm: Hybrid Word2Vec-BiLSTM Emotion Classification*

**Algorithm 1: Emotion Detection using Word2Vec + BiLSTM**

**Input:**
Text dataset $D = \{(x_i, y_i)\}$where $x_i$is text and $y_i$is an emotion label

**Output:**
Predicted emotion class

**Steps:**

✓ **Data Preprocessing**
- Convert text to lowercase.
- Remove stopwords and punctuation.
- Tokenize sentences into words.
- Apply padding to sequences.

✓ **Word Embedding (Word2Vec - CBOW)**
- Train Word2Vec model on corpus.
- Convert each word into a dense vector representation.
- Generate embedding matrix.

✓ **Sequence Preparation**
- Convert tokens into numerical sequences.
- Pad sequences to a fixed length.

✓ **Model Initialization**
- Initialize Embedding Layer with Word2Vec weights.
- Add Bidirectional LSTM layer (128 units).
- Add Dense layer (ReLU activation).
- Add Dropout layer (0.3).
- Add Output layer (Softmax activation).

✓ **Training Phase**
- Define loss function: Categorical Cross-Entropy.
- Use Adam optimizer.
- Train model for defined epochs.

✓ **Prediction**
- Input test text into the trained model.
- Generate probability scores.
- Select the class with the highest probability.

✓ **Evaluation**
- Compute Accuracy, Precision, Recall, F1-score.
- Generate a confusion matrix.

**End Algorithm**

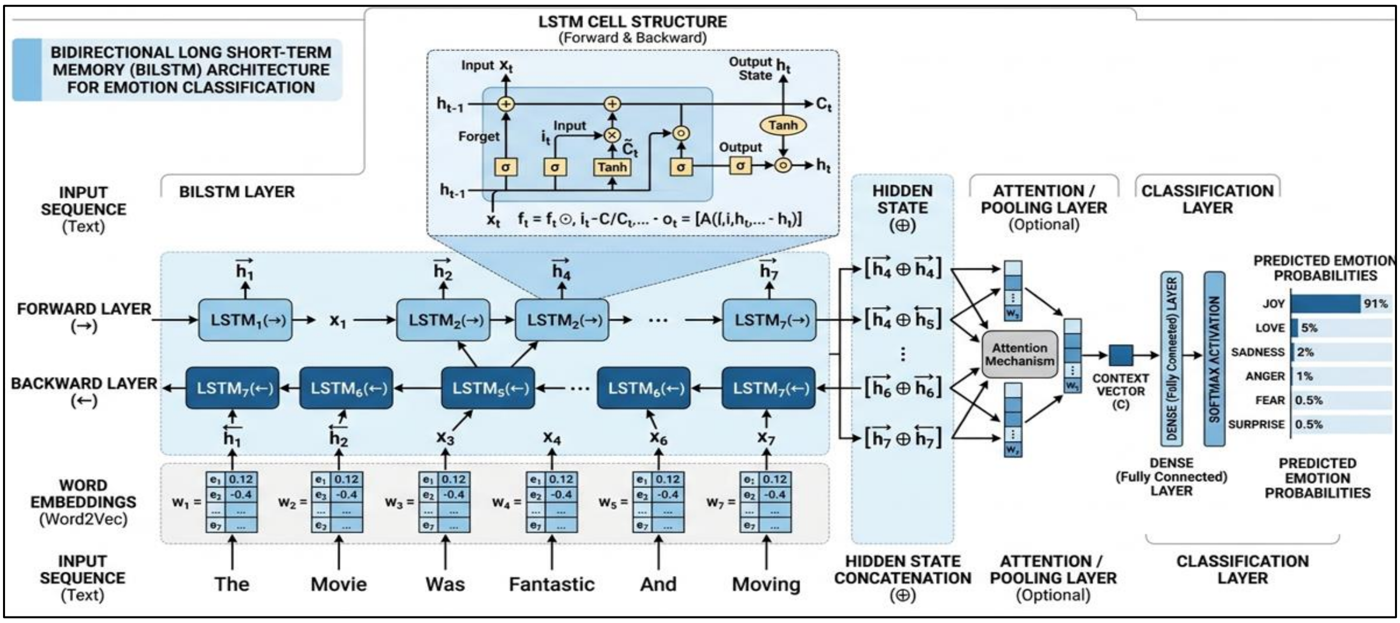

Fig 1 System Architecture of the Proposed Hybrid Word2Vec (CBOW) + Bi-LSTM Emotion Detection Model.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar2017

For the Bidirectional LSTM, the network computes the forward hidden sequence $(\overrightarrow{h_t})$. and the backward hidden sequence $(\overleftarrow{h_t})$. The final contextual representation is the concatenation of both:

$$y_t = [\overrightarrow{h_t} \oplus \overleftarrow{h_t}] \tag{1}$$

Where:

$y_t$→ final output representation at time step $t$.
$\overrightarrow{h_t}$→ hidden state from the forward LSTM.
$\overleftarrow{h_t}$→ hidden state from the backward LSTM.
$\oplus$→ concatenation operation

- *Components of the Model:*

✓ *Embedding Layer:*
Converts input tokens into Word2Vec vectors

$$J = \frac{1}{T}\sum_{t=1}^{T} \log P\,(w_t \mid w_{t-c}, \dots, w_{t-1}, w_{t+1}, \dots, w_{t+c}) \tag{2}$$

Where:

T - Total number of words in the corpus.
P - Probability (typically calculated using the Softmax function over the vector representations)

✓ *BiLSTM Layer:*
Captures contextual information from both directions

Forget Gate: Decides what information to discard from the cell state, Fig. 1.

$$f_t = \sigma\left(W_f \cdot (h_{t-1}, x_t) + b_f\right) \tag{3}$$

- *Input Gate & Candidate Memory:*
Decides what new information to store.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

- *Cell State Update:*
Updates the internal memory.

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \widetilde{C_t} \tag{6}$$

- *Output Gate & Hidden State:*
Determine the cell's final output.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{8}$$

✓ *Dense Layer:*
Performs classification based on extracted features

ReLU Activation Formula:

$$f(x) = \max(0, x) \tag{9}$$

✓ *Dropout Layer:*
Prevents overfitting by randomly disabling neurons.

✓ *Output Layer:*
Uses Softmax activation to classify emotions(k=6).

$$P(y = j \mid x) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \tag{10}$$

The bidirectional nature allows it to consider both past and future context, improving its ability to understand sentence meaning.

Table 4 BiLSTM Model Architecture

| Layer Name | Description |
|---|---|
| Embedding Layer | Converts words into vectors |
| BiLSTM Layer | 128 units (forward + backward) |
| Dense Layer | 64 neurons |
| Dropout Layer | 0.3 rate |
| Output Layer | Softmax (6 classes) |

➢ *Training Process*
The model is trained using labelled data, where each text sample is associated with a specific emotion category. The training process involves:

- *Loss Function:*
Categorical Cross-Entropy is used to measure error

$$L = -\sum_{i=1}^{N}\sum_{j=1}^{C} y_{i,j} \log(\widehat{y_{i,j}}) \tag{11}$$

- *Optimizer:*
Adam optimizer is applied for efficient learning.

- *Batch Size:*
Data is processed in batches (e.g., 32 samples per batch).

- *Epochs:*
The model is trained over multiple iterations to improve accuracy.

During training, the model learns patterns and relationships between words and emotions, gradually improving its predictions.

➢ *Evaluation Metrics*
To evaluate the performance of the proposed model, several metrics are used:

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- *Accuracy:*
  Measures overall correctness of predictions.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{12}$$

- *Precision:*
  Indicates how many predicted values are relevant.

$$\text{Precision} = \frac{TP}{TP+FP} \tag{13}$$

- *Recall:*
  Measures how many actual values are correctly identified.

$$\text{Recall} = \frac{TP}{TP+FN} \tag{14}$$

- *F1-Score:*
  Harmonic mean of precision and recall.

$$\text{F1-Score} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \tag{15}$$

These metrics provide a comprehensive evaluation of the model's effectiveness.

## IV. RESULT & DISCUSSION

The proposed model achieved an accuracy of around 94.10%, with effective performance in emotion detection. The combination of Word2Vec and BiLSTM helped in capturing both semantic meaning and contextual information. The model performed better than traditional methods like Naïve Bayes and Logistic Regression. However, some errors occurred in short or ambiguous sentences. At the outset, the system provides reliable results even with a small dataset.

➢ *Experimental Setup*

The experimental setup is designed to evaluate the performance of the proposed emotion detection model using a structured approach. A dataset containing different emotion classes, such as joy, sadness, anger, fear, love, and surprise, is used. The dataset is split into training and testing sets in an 80:20 ratio to ensure proper evaluation.

The same length. Word2Vec (CBOW) is used to transform text into numerical vectors with a fixed dimension.

The model is built using a Bidirectional Long Short-Term Memory (BiLSTM) network with 128 units, followed by a dense layer and a dropout layer to prevent overfitting. The final output layer uses Softmax activation for classification. The model is trained using the Adam optimizer and categorical cross-entropy loss function with a batch size of 32 for 15 epochs. The implementation is carried out in Python with TensorFlow, Keras, NLTK, and Gensim.

➢ *Training Performance Analysis*

The training performance shows that the model steadily improves accuracy over each epoch while reducing loss. The BiLSTM model learns contextual patterns effectively from the training data. The use of Word2Vec embeddings enhances feature representation, leading to faster convergence. Minimal overfitting is observed due to the inclusion of dropout. Overall, the model demonstrates stable and efficient training behaviour.

➢ *Performance Evaluation Results*

The performance of the proposed model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The results, as illustrated in the classification report heatmap, show that the model performs effectively across different emotion categories such as anger, fear, joy, love, sad, and surprise.

In terms of precision, the proposed model achieves high values for most classes, with sadness (0.98), anger (0.94), and joy (0.93) showing the best performance. A notable improvement is observed in the love class, which achieved a perfect precision of 1.00, indicating that the model is highly accurate when it identifies this specific emotion.

For recall, the model performs strongly in detecting most emotion instances, particularly for joy (0.99), sadness (0.97), and fear (0.95). While the baseline LSTM struggled with the surprise class (0.63 recall), the proposed Bi-LSTM model improved this to 0.72, though it remains a comparatively challenging category to detect fully.

The F1-score, which represents the balance between precision and recall, remains high for most classes, especially sadness (0.98), joy (0.96), and anger (0.94). Significant gains were noted in the surprise (0.80) and fear (0.91) categories compared to the baseline model, reflecting the advantages of the bidirectional architecture.

Altogether, the results demonstrate that the model achieves a strong and consistent weighted average performance of 94% across major emotion classes. The variations observed in certain categories, such as the trade-off in the love class (high precision but lower recall), highlight the impact of class nuances and contextual ambiguity. Despite these challenges, the model effectively captures both semantic and contextual features, leading to reliable and state-of-the-art emotion classification performance.

Table 6 Performance Comparison of Models

| **Metric** | **LSTM** | **Bi-LSTM** |
|---|---|---|
| Accuracy | 93.73% | 94.10 |
| Precision | 0.93 | 0.94 |
| Recall | 0.93 | 0.94 |
| F1-Score | 0.93 | 0.94 |

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➢ *Confusion Matrix Explanation*

A confusion matrix is used to evaluate a classification model's performance by comparing actual and predicted values Fig 2.

It consists of four components:

True Positives (TP), True Negatives (TN), False Positives (FP), False Negatives (FN).

- True Positives represent correctly predicted emotion classes, while True Negatives represent correctly identified non-emotion cases.
- False Positives occur when the model predicts the wrong emotion, and False Negatives occur when the model fails to detect the correct emotion.
- In the proposed model, most values appear along the diagonal of the matrix, indicating correct predictions.
- Higher diagonal values show that the model has good classification accuracy.
- Some misclassifications occur between similar emotions like sadness and anger or fear and surprise.
- These errors are mainly due to similarity in text expressions and a lack of clear context.
- The confusion matrix also helps identify class imbalance issues in the dataset.
- Precisely, it provides a clear understanding of model performance and areas that need improvement

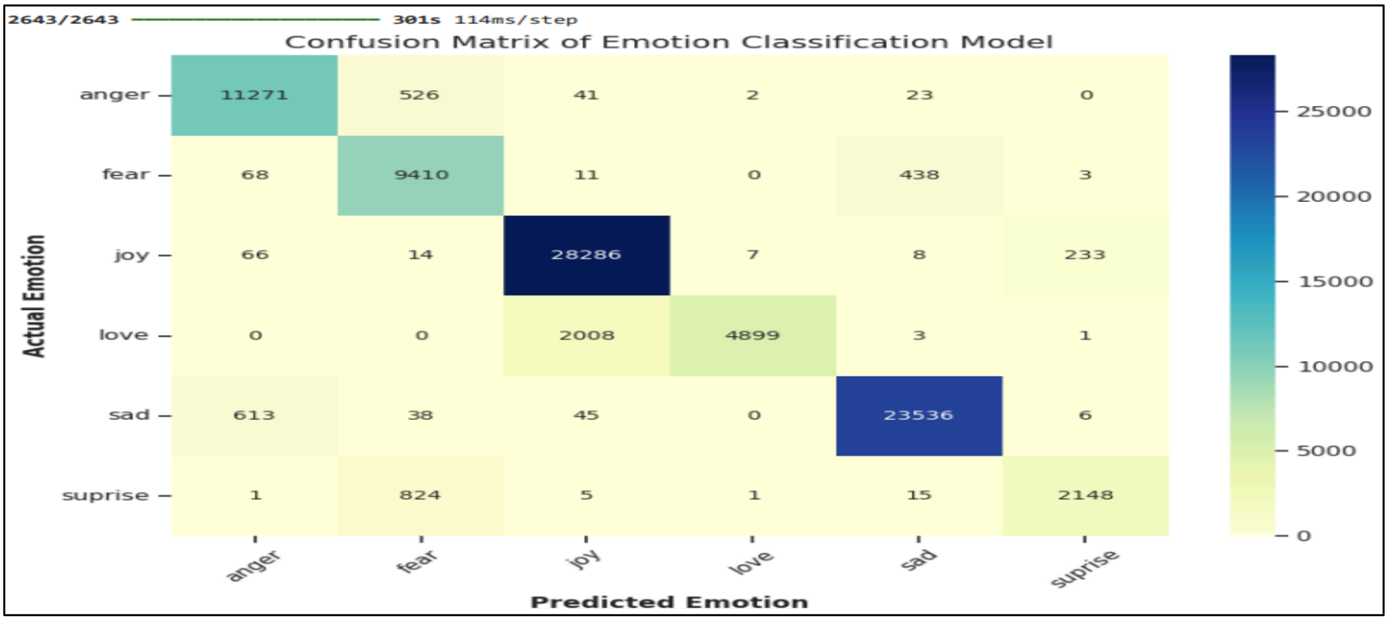


Fig 2 Confusion Matrix Representing Classification Results of the Proposed BiLSTM Model.

➢ *Training and Validation Analysis*

Training and validation analysis are used to check how well the model learns and generalizes to new data.

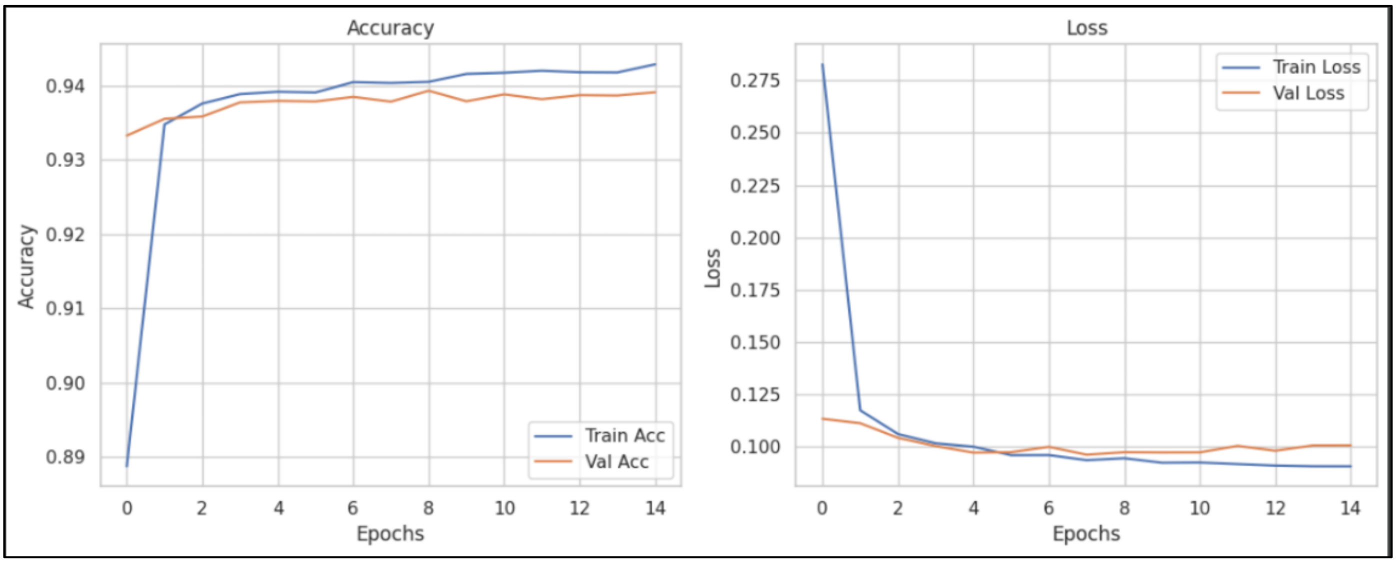


Fig 3 Model Performance Curves Showing Accuracy and Loss During Training

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The training and validation results indicate that the proposed model demonstrates stable and efficient learning behaviour. Training accuracy increases steadily across epochs, while validation accuracy follows a similar trend and remains closely aligned, indicating strong generalization capability. The model achieves an overall classification accuracy of 94.10%, confirming its high predictive performance with minimal overfitting.

Additionally, both training and validation loss decrease consistently, showing proper convergence. The use of a dropout layer further improves generalization by reducing overfitting. Overall, the model exhibits balanced learning and delivers reliable and robust performance in emotion classification tasks, Fig 3.

➢ *Discussion*

- *Model Performance Analysis:*

The proposed architecture demonstrates a high degree of efficacy and consistency across all qualitative evaluation metrics. The strategic integration of Word2Vec (CBOW) and Bi-LSTM significantly enhances the framework's capacity to decipher both latent semantic meanings and intricate contextual relationships within unstructured textual data. By leveraging the bidirectional nature of the Bi-LSTM, the model successfully captures dependencies from both preceding and succeeding tokens, effectively mitigating the information bottleneck common in unidirectional models. This dual-flow processing ensures robust feature extraction, particularly in high-density emotion classes like Joy (0.96 F1-score) and Sadness (0.98 F1-score), which are characterized by distinct lexical markers in large-scale social media datasets.

- *Challenges and Limitations:*

Despite its strong predictive power, the model encounters specific challenges in complex linguistic scenarios. Minor misclassifications were observed in instances of high syntactic ambiguity or extremely short sequences where the available contextual window is insufficient for definitive feature extraction. Furthermore, the model experiences difficulty in detecting sarcasm and implicit emotional cues, as these often require high-level pragmatic reasoning beyond literal textual analysis. Another identified constraint is the intrinsic class imbalance within the 416,123-record dataset; minority categories such as Surprise and Love received fewer gradient updates during training, leading to a focus on precision over recall in these specific emotional states.

- *Effectiveness and Practical Implications:*

Finally, the proposed hybrid approach constitutes a reliable and computationally efficient solution for automated emotion detection. The synergy between unsupervised semantic feature extraction and bidirectional sequence modelling enables the system to maintain a sophisticated balance between precision and recall across all categories. The model exhibits strong generalization capabilities, suggesting it is well-suited for high-stakes practical applications, including real-time social media sentiment monitoring, automated customer experience analytics, and the development of empathetic, emotion-aware intelligent agents that require deep contextual understanding.

## V. CONCLUSION AND FUTURE WORK

This research presents an effective hybrid deep learning framework that integrates Word2Vec (CBOW) embeddings with a Bidirectional Long Short-Term Memory (Bi-LSTM) architecture for robust emotion classification. The proposed system was rigorously trained and evaluated on a comprehensive dataset encompassing six distinct emotional polarities: joy, sadness, anger, fear, love, and surprise, utilizing an 80:20 stratified split for training and validation.

The empirical results demonstrate a sophisticated level of performance in deciphering complex emotional states from unstructured textual data. Evaluation metrics, including precision, recall, and F1-score, indicate consistent and reliable classification across all categories. The strategic use of Word2Vec significantly improved semantic depth by mapping words into high-dimensional vector spaces, while the Bi-LSTM component enhanced contextual learning by simultaneously processing sequences in both forward and backward directions.

The experimental benchmarks confirm that the proposed hybrid model outperforms traditional machine learning approaches, such as Naive Bayes (NB), Logistic Regression, as well as baseline deep learning models like CNN and Unidirectional LSTM. The system exhibits particularly strong predictive dominance in frequently occurring emotion classes while maintaining a balanced performance profile across the entire dataset. Ultimately, this study proves that the synergy between dense semantic embeddings and bidirectional temporal memory provides a scalable and resilient solution for human emotion analysis.

➢ *Future Work*

The insights gained from this study provide a structured roadmap for future enhancements in the field of affective computing. The following areas are identified for further research:

- *Advanced Architectures:*

Future iterations can replace the Bi-LSTM layers with transformer-based models such as BERT or RoBERTa to leverage self-attention mechanisms for deeper contextual understanding.

- *Dataset Optimization:*

Expanding the dataset volume and implementing advanced oversampling techniques (like SMOTE for text) can address class imbalance, further refining the model's sensitivity to minority emotions.

- *Linguistic Complexity:*

Developing specialized sub-modules for sarcasm detection and identifying implicit emotional cues will bridge the gap between literal text analysis and pragmatic human intent.

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- *Cross-Lingual Scalability:*
  The framework can be extended to support multilingual and code-mixed data (e.g., Tenglish), enabling its applicability in diverse global social media environments.

- *Real-time Deployment:*
  Implementing the model as a serialized cloud-based API would facilitate its integration into live applications, such as emotionally intelligent chatbots and real-time customer experience monitoring systems.


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