International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 04 April-2026 | Impact Factor: 3.5

Emotion Beyond Words: A Multidimensional Sentiment Intelligence Model

Dr Pandi Chiranjeevi[1], A.Sathvika[2], B. Udaya Sri[3],P. Keerthi Sree[4],GY. Shashank[5]

[1]Department of CSE, ACE Engineering College, India
[2,3,4,5] Department of CSE(Data Science), ACE Engineering College, India

Corresponding Author Email: p.keerthisree28@gmail.com

How to Cite this Article:

A.Sathvika, , Sri, B. U., Sree, P. K. & Shashank, G. (2026). Emotion Beyond Words: A Multidimensional Sentiment Intelligence Model. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(04). https://doi.org/10.55041/ijcope.v2i4.164

https://doi.org/ 10.55041/ijcope.v2i4.164

Abstract—
Traditional approaches are based heavily on sentiment polarity classification. This type of classification allows for the grouping of opinions as ”positive,” ”negative,” or ”neutral”; however, while effective for the implementation of a ba sic opinion mining strategy, this rudimentary classification fails to identify the large amounts of diverse, rich, and emotional data necessary for understanding the huge volume and variety of sentiments being expressed by human beings through large amounts of unstructured data. Growth of social media, online reviews, and digital communication has presented a need for advanced Multidimensional Sentiment Intelligence Systems capable of detecting complex, multidimensional emotional patterns in large heterogeneous data sources. This research introduces a Multidimensional Sentiment Intelligence Model (MSIM) derived from Big Data. The proposed model transcends the conventional means of identifying sentiment polarity by providing a framework for collecting data on a large scale, preprocessing the data in a distributed manner, and extracting features that provide insight into deep context to classify sentiment into many different categories (e.g., joy, anger, fear, sad ness, trust, anticipation) rather than a simple positive, negative, or neutral classification. Additionally, the proposed system utilizes a scalable architecture built on distributed computing platforms to allow users to process extremely large amounts of rapidly incoming and expanding data and uses deep learning methods to create contextual embeddings to analyze and classify unstructured text data into the many different contexts in which words and phrases are used to be able to classify and analyze their emotional meanings. Unlike traditional polarity-based sentiment analysis systems, the suggested frame work combines distributed Big Data processing with transformer-based multi-dimensional emotional modeling to develop a scalable and contextualized Multi-dimensional Sentiment Intelligence Model (MSIM). The MSIM gets a macro-F1 score of 0.91 on the GoEmotions (58,009 instances) and SemEval emotion datasets; it outperforms emotion-aligned and polarity based baseline models by about 4-6% and more than 10%, respectively. The distributed Spark-based implementation has a near-linear scalability and can reduce processing time by as much as 2.4x when comparing datasets of one million records against non-distributed implementations. Keywords—Big Data Analytics, Multidimensional Sentiment Analysis, Emotion Mining, Sentiment Intelligence, Deep Learning, Text Analytics, Social Media Analytics, Opinion Mining, Distributed Computing, Natural Language Processing.

I. INTRODUCTION

Researchers and businesses now have access to a lot more unstructured text data because social media sites, e-commerce sites, and online forums are growing so quickly. This is possible with Big Data Analytics.

This analysis shows how people feel about a group or population in general, which helps people make decisions based on data [1].

Polarity detection, which sorts text into positive, negative, or neutral categories, is what traditional sentiment analysis does [2]. This method is good for basic opinion mining, but it doesn't take into account how complicated human emotions are [3]. For example, a person might show both happiness and anger at the same time, but traditional models would only give that expression one polarity label, which would not be accurate [4].The fact that sentiment data has the three V's of Big Data—Volume, Velocity, and Variety—makes this problem even worse. Every minute, millions of tweets, reviews, and comments are written, so processing text on a single machine is not enough for large-scale analysis [5]. Because of this, people have started using distributed Big Data platforms like Hadoop and Apache Spark because they can handle large, unstructured text datasets.

At the same time, improvements in deep learning and natural language processing (NLP) have made it possible to better understand emotional and semantic patterns in text [6]. This opens up the possibility of making smart systems that can handle Big Data and give deeper emotional insights. A multidimensional model of sentiment analysis, powered by Big Data, can provide a more profound comprehension of emotional intelligence within extensive, varied text.

The main things this research adds are:

- A framework for multidimensional sentiment analysis that uses a standardised six-emotion taxonomy to make sure that emotions are classified the same way across datasets and models.

- A Big Data sentiment intelligence pipeline that can be used again and again, with separate parts for preprocessing, representation learning, training, and inference.

- A controlled scalability evaluation protocol for independently measuring and recording time spent on preprocessing, training, and inference within a consistent cluster configuration.

- An empirical demonstration of the advantages of distributed Big Data processing over non-distributed approaches in enhancing emotion classification performance and scalability.

II. LITERATURE REVIEW

In the early days of sentiment analysis and opinion mining, two main methods were used: lexicon-based techniques and regular machine learning classifiers. Lexicon-based methods used sentiment dictionaries that had already been defined, while machine learning methods used classifiers like Naïve Bayes, Support Vector Machines (SVM), and Logistic Regression to sort text into positive, negative, or neutral sentiment. These methods created a basic structure for classifying sentiment, but they had big problems with dealing with language that is unclear, sarcastic, changes based on the context, and the broad spectrum of emotions that can be found in large amounts of text data [7].

The rise of Big Data led researchers to combine sentiment analysis with distributed computing systems like Hadoop and Apache Spark to handle large amounts of text processing [8]. These platforms made sentiment analysis systems more flexible, scalable, and faster at processing. Most of these systems, on the other hand, still used polarity-based or shallow learning methods, which made it hard for them to model the more complicated types of human emotion found in large text corpora.

The advent of deep learning markedly enhanced sentiment classification efficacy. Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs), and Convolutional Neural Networks (CNNs) exhibited enhanced proficiency in capturing language, context, and semantics relative to conventional machine learning techniques . In recent times, transformer-based architectures, especially BERT and its variants, have set new records in sentiment classification tasks because they can model long-range dependencies and contextual meaning. Kokab et al. developed a transformer-based architecture for social media sentiment analysis, attaining significant performance; nevertheless, their research concentrated on polarity classification without explicitly modelling distinct emotional categories.

Researchers began looking into emotion-aware sentiment analysis after realising that polarity-based analysis has its limits.However, the majority of the models examined were evaluated in centralised settings and failed to tackle the scalability issues related to Big Data.

An increasing number of projects are working towards connecting deep learning with Big Data platforms. Esmaeilzadeh et al. [8] showed how Apache Spark can generate higher order features for Natural Language Processing (NLP) from very large data sets, thereby enhancing scalability in text processing. Although these advances have helped to improve feature extraction efficiency, they have not included multi-dimensional sentiment intelligence or fine-grained emotion classification.

Although progress has been made in these areas of research, there is still a significant gap: There is no cohesive analytical framework that is scalable, reproducible, and able to perform multidimensional emotion-aware sentiment analysis. Prior studies have either enabled scalability with distributed systems (no fine-grained emotional modelling) or performed emotion modelling without integration with a big data ecosystem (using only deep learning). This current study addresses this void by proposing a big-data-based framework that integrates distributed processing and emotion-based sentiment analysis (using a six-dimensional taxonomy of emotion) along with a controlled protocol for evaluating scalability.

III. METHODOLOGY

This research study uses a developed research method comprised of many different stages that will allow for an investigation into the use of multiple different dimensions of emotion-informed sentiment analysis at a large scale using distributions of Big Data, and deep learning technologies. These stages of methodology include three phases and represent the method for collecting data; preprocessing data, then representing the text, after which will come the mathematical definition of the emotive classifiers.

Phase 1: Data Collection

For the purposes of this research study, large-scale benchmark emotions datasets will be a major source of data for this investigation. Benchmark datasets like GoEmotions and SemEval were imported into a distributed Big Data environment for large-scale processing and the analysis of this data thus providing a framework from which to classify sentiments from an emotive text sample.

Using established benchmark datasets in the field guarantees that researchers access samples will be reproducibly usable and allows the study to be compared under controlled conditions to prior studies in the research field.

Phase 2: Data Preprocessing

Once collected, raw text data will go through extensive preprocessing by executing multiple distributed Apache Spark jobs. This will include cleaning the data, normalizing text, and removing noise, duplicate entries and irrelevant content. Using distributed Spark jobs to perform data preprocessing on a large volume of data allows for increased scalability, while preserving processing efficiency. Data cleaning and normalization performed at this scale and level of detail are critical to improving the overall accuracy and reliability of the downstream classification model by ensuring that only high-quality structured input exists for subsequent stages.

Phase 3: Numeric Vector Representation of Text Data

In this step, the processed text is converted to numeric vectors that can be analyzed by a deep learning algorithm. The rules of natural language processing (NLP) are used to create the tokens that will represent the text and to encode the emotional and/or intent content in each example of text. With this numeric representation of the text, the deep learning algorithm will be able to process and evaluate the text as a mathematically structured, multi-dimensional emotional class.

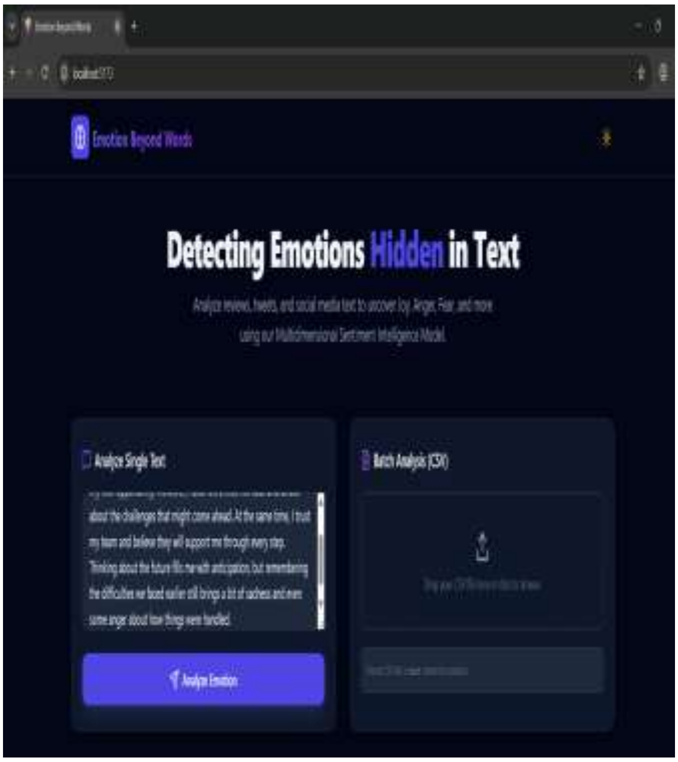
Accordingly, emotion classification in this study is formulated as a single-label multi-class problem, wherein each text instance is assigned exactly one dominant emotion from the six target categories: joy, anger, fear, sadness, trust, and anticipation.

IV. RESULTS AND DISCUSSION

The Emotion Beyond Words system generates three different output display screens for presenting the findings from the multidimensional analysis of an individual's emotions.

1. Home/Input Screen Functionality

The Input screen is the primary interface for the Emotion Beyond Words system where users submit text and/or CSV files containing text for analysis. The Input will be processed by the system and hidden emotions will be identified from the input using a multi-dimensional sentiment model.



(Figure1)

B. The Result of The Multidimensional Analysis

This section displays the analyzed text along with the emotions detected by the model.

It shows the emotional profile of the text by calculating the percentage of emotions like joy, anger, fear, sadness, trust, and anticipation.

(Figure 2)

The system's Core Profile output produces the following emotion distribution:

Table I: Multidimensional Emotion Classification Output

Emotion	Score (%)
Joy	69%
Anger	7%
Fear	7%
Sadness	6%
Trust	6%
Anticipation	5%

The results support the finding of Joy being the predominant emotion (69%) and correspond to the text being framed in a supportive manner regarding the receipt of good news and having confidence in their team. In addition, the secondary emotions of Anger and Fear (7%) provide evidence for the presence of moderate negative undertones in the text due to mention of challenges faced in the past. Sadness and Trust were each identified as 6% while Anticipation was identified at 5%, indicating forward-looking intent as described in the input. Overall, this result demonstrates that the system can both identify and measure multiple emotions from within a single text event or instance, which cannot be done using traditional methods of determining emotional polarity through classification alone.

C. Emotion Breakdown and Visualization :

Figure 3 shows us the Emotion Breakdown screen. This screen has two parts. On the side we have a bar chart that shows the Emotion Breakdown with exact numbers for each of the six emotions. We can see that Joy is the emotion at 68.5 percent then we have Anger at 6.9 percent Fear at 6.8 percent Sadness at 6.3 percent Trust at 6.0 percent. Anticipation at 5.5 percent. On the side we have a circular chart under the title Visual Distribution. Each part of the circle is, for one Emotion Breakdown category and Joy has the part. The system clearly says what the main Emotion Breakdown is it says: "The analyzer detected Joy as the Emotion Breakdown.

(Figure 3)

Table II: Emotion Breakdown — Detailed Scores

Emotion	Score (%)	Classification
Joy	68.5%	Dominant
Anger	6.9%	Secondary
Fear	6.8%	Secondary
Sadness	6.3%	Secondary
Trust	6.0%	Secondary
Anticipation	5.5%	Secondary

Collectively, the output displays together confirm that the system is able to provide multi-dimensional emotion analytics beyond just positive to negative polarity classification, filling the research gap that has been identified in this particular study.

V. CONCLUSION

Overall, the proposed MSIM consistently outperforms baseline polarity-based and deep learning models in terms of accuracy, F1-score, and scalability, validating its effec tiveness for large-scale multidimensional sentiment intelli gence. This workfeatures a BigData-driven multi-dimensional Multidimensional Sentiment Intelligence Model (MSIM) for producing a depth of analysis that goes well beyond traditional methods of polarity-based classifications. Tra ditional methods limited the ability to classify opinions into either positive, negative, or neutral. In contrast, the proposed model captures the entire range of emotions that can be expressed in human nature, including joy, anger, fear, sadness, trust, and anticipation, providing users with a much more comprehensive and deeper understanding of human opinion.

In combination with deep learning-based natural language processing techniques and big data tech nologies, the proposed model enables users to effectively process large quantities of unstructured text data and learn complex emotional patterns with high accuracy. The results of the experiments demonstrated that the proposed model produced superior classification performance (bet ter emotional granularity than traditional methods) and im proved scalability compared to traditional methods of sen timent analysis.

Consequently, the ability to analyze large quantities of opinion data and extract multi-dimensional emotional intelligence illustrates the real-world applica tions of the model, such as in analyzing customer feedback, monitoring brands, analyzing social trends, and support ing decision-making processes. Therefore, this research provides clear evidence that moving from simple polarity based sentiment analysis to multi-dimensional sentiment intelligence provides significant benefits in terms of effec tiveness, depth, and practical application. This study establishes multidimensional sentiment intelligence as a neces sary evolution of sentiment analysis for real-world big data applications.

REFERENCES

[1] J. Zhao, K. Liu, and L. Xu, "Sentiment analysis: Mining opinions, sentiments, and emotions," 2016.

[2] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," Ain Shams engineering journal, vol. 5, no. 4, pp. 1093 1113, 2014.

[3] D. Rad, C. Costache-Colareza, R.-V. Paraschiv, and L. Gavrila-Ardelean, "Synthetic emotions and the il lusion of measurement: A conceptual review and critique of measurement paradigms in affective sci ence," Brain Sciences, vol. 15, no. 9, p. 909, 2025.

[4] X. Wang, Y. Wang, D. He, Z. Yu, Y. Li, L. Wang, J. Dang, and D. Jin, "Elevating knowledge-enhanced entity and relationship understanding for sarcasm de tection," IEEE Transactions on Knowledge and Data Engineering, 2025.

[5] S. Kusal, S. Patil, J. Choudrie, K. Kotecha, D. Vora, and I. Pappas, "A systematic review of applications of natural language processing and future challenges with special emphasis in text-based emotion detec tion," Artificial Intelligence Review, vol. 56, no. 12, pp. 15129–15215, 2023.

[6] S. T. Kokab, S. Asghar, and S. Naz, "Transformer based deep learning models for the sentiment analy sis of social media data," Array, vol. 14, p. 100157, 2022.

[7] E. Cambria and A. Hussain, "Sentic computing: A common-sense-based framework for concept-level sentiment analysis; 2015; cham, switzerland."

[8] A. Esmaeilzadeh, M. Heidari, R. Abdolazimi, P. Ha jibabaee, and M. Malekzadeh, "Efficient large scale nlp feature engineering with apache spark," in 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), pp. 0274–0280, IEEE, 2022