International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 14, Issue 12, December 2025)

Detection of Emotion by Text Analysis using AI Technique

Vidhi Gupta[1], Rahul Kumar[2]

[1]Research Scholar, [2]Assistant Professor, Department of CSE, BIT, Meerut, India

***Abstract*— Detection of emotion from text is an important area in artificial intelligence that helps machines understand human feelings expressed through written content. This work presents an AI-based text emotion detection system that uses a combination of machine learning and deep learning techniques, including Logistic Regression, Decision Tree, and Convolutional Neural Networks (CNN). Using natural language processing, the model converts raw text into structured features and learns emotional patterns such as happiness, anger, sadness, and fear. While Logistic Regression and Decision Tree provide simple and fast baseline classification, CNN captures deeper contextual and semantic patterns for improved accuracy. The proposed approach offers reliable emotion classification and can be applied in social media analysis, customer service automation, mental health monitoring, and personalized digital interactions.**

***Keywords*— Emotion Detection, Text Analysis, CNN, Logistic Regression, Decision Tree, NLP.**

I. Introduction

In today's digital world, people express their thoughts, opinions, and feelings mainly through text on social media, emails, chat platforms, and online reviews. Understanding these emotions hidden in written text has become very important for businesses, researchers, and intelligent systems [1]. The rapid growth of artificial intelligence and natural language processing has made it possible for machines to automatically read text and detect the emotional state of a person. This process is known as *emotion detection by text analysis*. It focuses on identifying emotions such as happiness, anger, sadness, fear, surprise, disgust, or even mixed emotions from a simple piece of text[2].

Emotion detection plays a significant role in improving human–computer interaction. When machines understand how a user feels, they can respond in a more natural and helpful way. For example, chatbots can offer better customer support if they know whether a user is frustrated or satisfied [3]. Similarly, social media platforms can track emotional trends to understand public opinion about events, products, or social issues. In the field of healthcare, emotion detection helps identify early signs of stress, depression, or negative mental health conditions based on writings or messages. This information is extremely valuable in providing timely support and building intelligent emotional-aware systems [4].

Text-based emotion detection is a challenging task. Human emotions are complicated, and people use different words, slang, short forms, emojis, or indirect expressions. A single sentence can express multiple emotions, or the meaning can change depending on context[5]. Traditional rule-based systems failed to capture these complexities, which led to the rise of machine learning and deep learning techniques. Machine learning models, such as Logistic Regression and Decision Tree, help classify emotions using statistical patterns learned from large datasets. Deep learning models, especially Convolutional Neural Networks (CNN), are capable of understanding deeper semantic patterns and contextual meanings. These models automatically learn features, recognize emotional cues, and provide more accurate predictions[6].

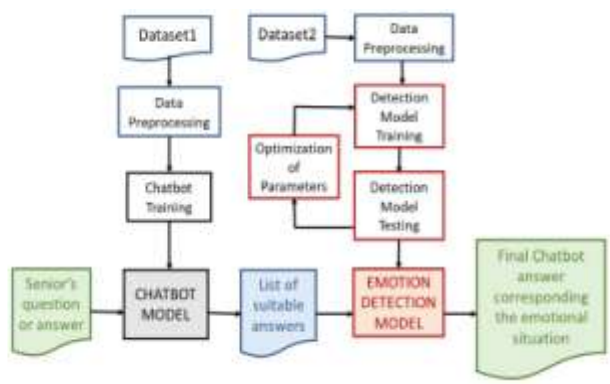

Figure 1: Work flow [5]

Recent advancements in natural language processing and AI have made emotion detection faster, more reliable, and suitable for real-time applications. With access to large labeled datasets, pre-trained word embeddings, and neural networks, text analysis has become a powerful tool for interpreting human emotions[7]. Organizations now use emotion detection in customer feedback analysis, product reviews, marketing campaigns, and risk assessment. Governments and social groups also use it to study public sentiment regarding policies, elections, and social movements[8].

Overall, the detection of emotion by text analysis has grown into a vital area of research due to its wide applications and its ability to transform raw text into meaningful emotional insights.

As AI continues to evolve, these systems will become even more intelligent, context-aware, and capable of understanding complex human emotions more accurately. This technological progress brings the world closer to creating emotionally intelligent systems that can interact with people in a more human-like and empathetic manner[9].

II. LITERATURE SURVEY

Dudi et al. [1] explored deep learning techniques for emotion detection from text and demonstrated that neural models outperform traditional classifiers in identifying subtle emotional patterns. Their study highlighted the importance of word embeddings for capturing semantic meaning. The authors also showed that CNN-based models can effectively extract local linguistic features. They emphasized that deep learning reduces the need for manual feature engineering. Their results confirmed higher accuracy when using large training datasets. The study provides a strong foundation for advanced AI-based emotion detection.

Hayatu et al. [2] presented a comparative study on machine learning algorithms for emotion classification in textual data. They evaluated methods like Logistic Regression, Decision Tree, and Naïve Bayes across multiple datasets. The findings revealed that classical models perform well for simple, structured text but struggle with informal language and slang. Their analysis also highlighted the importance of feature selection and preprocessing techniques. The study concluded that machine learning provides fast baseline performance but requires further enhancement with deep learning. This work guides researchers in choosing suitable algorithms for basic emotion tasks.

Chutia et al. [3] conducted a comprehensive review of deep learning techniques used in emotion detection. They examined LSTM, CNN, GRU, and hybrid neural architectures for processing long and short text sequences. Their study revealed that deep learning models can understand context better, leading to improved accuracy. They also discussed the role of large annotated datasets and advanced NLP techniques. The authors concluded that transformer-based models are emerging as more powerful alternatives. Their work provides updated insights into deep learning advancements.

Thiab et al. [4] proposed an ensemble deep learning framework for contextual emotion detection. They combined multiple neural networks to capture different emotional cues within complex sentences.

Their model significantly improved classification performance, especially for mixed emotions. The study emphasized that ensemble methods reduce overfitting and enhance robustness. They also highlighted the need for context-aware architectures in real-world applications. Their results support the use of multi-model systems for higher reliability.

Machová et al. [5] analyzed machine learning-based emotion detection and focused on the impact of NLP preprocessing techniques. They studied how tokenization, stemming, stop-word removal, and feature extraction influence model accuracy. Their findings showed that TF-IDF and word embedding representations produce better results than simple bag-of-words. The study also noted challenges in processing ambiguous and figurative language. They concluded that preprocessing plays a critical role in improving prediction quality. This work provides useful guidelines for preprocessing pipelines.

Liu et al. [6] developed a deep learning framework for real-time emotion detection in text streams. They emphasized the importance of capturing temporal patterns in sequential data. Their model processed continuous text inputs, making it suitable for social media monitoring. The study demonstrated that deep neural networks can effectively track emotional changes over time. They also discussed the potential for automated alert systems based on emotional trends. Their work highlights the practical use of AI in dynamic environments.

Chowanda et al. [7] examined various machine learning techniques for text-based emotion recognition. They compared SVM, Random Forest, and Decision Tree models across multiple emotional categories. The study emphasized that algorithm performance varies depending on dataset quality and text complexity. They highlighted the benefits of using balanced datasets and optimized feature sets. The authors also noted that machine learning methods provide interpretable results, which helps in practical deployment. Their work supports the need for model selection based on task requirements.

Haryadi et al. [8] introduced a nested LSTM architecture for improved emotional understanding in text. Their model captured long-range dependencies, which are essential for interpreting complex emotional expressions. The authors showed that nested LSTM outperformed simple LSTM models. They also discussed how advanced recurrent networks help in processing indirect emotional cues. The study highlighted the benefits of deeper architectures for improved semantic understanding. Their research contributes to the growing use of recurrent networks in emotion analysis.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 14, Issue 12, December 2025)

Park et al. [9] focused on learning richer emotional representations for text classification. They examined various embedding techniques and neural architectures to enhance emotional feature learning. Their study revealed that context-aware embeddings significantly improve model performance. They also noted that emotional expressions vary across domains and languages. The authors recommended using domain-specific training data for better accuracy. Their research helps improve representation learning for emotion detection.

Alazab et al. [10] investigated hybrid AI models integrating machine learning and deep learning for emotion detection. Their study highlighted the strengths of combining rule-based features with neural network learning. The hybrid approach showed improved performance on noisy and unstructured text. They emphasized the importance of explainability in AI systems, especially in sentiment and emotion tasks. Their findings support the development of flexible and adaptive AI models. This work encourages future research in hybrid emotional analysis systems.

Table 1:
Summary of Literature review

Sr. No.	Author	Year	Work	Outcome
1	Machová	2023	Detection of Emotion by Text Analysis Using Machine Learning	Machine learning methods effectively classify emotions using NLP-based features.
2	Dudi	2025	Text-Based Emotion Detection Using Deep Learning Techniques	Deep learning models provide higher accuracy and better emotional feature extraction.
3	Hayatu	2025	Emotion Detection in Text: Comparative Study	ML algorithms perform well for basic emotions but struggle with complex expressions.
4	Chutia	2024	Review on Emotion Detection Using Deep Learning	Deep learning models improve contextual understanding and emotion prediction.
5	Thiab	2024	Contextual Emotion Detection Using Ensemble Models	Ensemble deep learning models enhance robustness and accuracy for mixed emotions.
6	Machová	2023	ML-Based Emotion Detection from Text	Preprocessing and embedding methods significantly improve model performance.
7	Liu	2022	DL Framework for Emotion Recognition in Text Streams	Deep learning enables real-time emotion tracking in continuous text.
8	Chowanda	2021	ML Techniques for Text-Based Emotion Classification	Balanced datasets and optimized features increase ML classification accuracy.
9	Haryadi	2019	Emotion Detection Using Nested LSTM	Nested LSTM captures long-term dependencies and improves emotion detection.
10	Park	2018	Learning Emotional Representations for Text Classification	Context-aware embeddings improve emotional representation and classification.

III. Challenges

Emotion detection from text faces several difficulties due to ambiguous expressions, informal language, and the presence of multiple emotions in a single sentence.

1. Ambiguous Expressions

Human language is naturally ambiguous. People often express emotions in indirect or unclear ways, and the true meaning depends on hidden context.

For example, a sentence like “I’m fine” can express happiness, sadness, or even frustration depending on the situation. AI models struggle to understand these subtle hints. Emotional meaning is not always present in specific words; it may come from tone, writing style, or implied feelings. This ambiguity makes it difficult for algorithms to accurately classify emotions, especially when the text is short or incomplete.

2. Multiple Emotions in One Sentence

A single piece of text can contain more than one emotion at the same time. For example, “I am scared but excited for the results” contains both fear and excitement. Most machine learning and deep learning classifiers are designed for single-label output and cannot easily capture these mixed emotions. Multi-label emotion detection requires complex architectures and specialized loss functions, which increases the model’s complexity. As a result, predicting multiple emotions simultaneously remains a major challenge in emotion analysis.

3. Use of Slang, Informal Language, and Emojis

Text from social media platforms like Twitter, Instagram, or WhatsApp often includes slang, abbreviations, short forms, and emojis. These elements do not follow standard grammar rules and may carry strong emotional meaning. For example, “LOL,” “OMG,” “:-),” and “🔥” can express emotions more effectively than plain words. Traditional NLP tools and machine learning models struggle with such informal text because it does not exist in standard training datasets. Properly handling slang and emojis requires additional preprocessing, updated dictionaries, and advanced embedding techniques.

4. Context Understanding and Sarcasm Detection

Emotions in text heavily depend on context. A sentence like “Great, another meeting!” could be genuinely positive or sarcastic depending on the situation. AI models have difficulty identifying sarcasm because the words themselves appear positive, but the intended emotion is negative. Similarly, cultural references, jokes, humor, and idioms add layers of meaning that simple models cannot easily interpret. Without deep context understanding, emotion detection systems often misclassify these complex expressions.

5. Imbalanced Datasets

Emotion datasets are often unbalanced, meaning some emotions have more training samples than others. For example, emotions like joy and anger appear frequently, while emotions like disgust or surprise appear less often.

Machine learning and deep learning models trained on imbalanced data tend to favor the majority classes and ignore minority emotions. This leads to poor accuracy for underrepresented emotions. Handling imbalanced datasets requires specialized techniques such as oversampling, data augmentation, and weighted loss functions.

6. Domain Dependency

Emotion detection models trained in one domain do not perform equally well in another. A model trained on movie reviews may not work effectively on health-related text or social media comments due to differences in vocabulary, sentence structure, and emotional expression styles. Domain adaptation is required to generalize models across different text types. Without domain-specific tuning, the accuracy drops significantly. This challenge highlights the need for customized datasets and model training for each domain.

7. Lack of High-Quality Labeled Data

Emotion detection requires large datasets in which each text sample is labeled with correct emotional tags. Creating these datasets manually is expensive, time-consuming, and requires expert knowledge. Different annotators may interpret emotions differently, leading to inconsistent labels. This lack of high-quality labeled datasets limits the performance of deep learning models, which depend heavily on large amounts of training data. Without rich datasets, emotion detection cannot reach its full potential.

8. Emotional Complexity and Subtlety

Human emotions are complex, layered, and sometimes contradictory. A person may feel sad but hopeful, or happy but anxious at the same time. These subtle emotional variations are hard for AI to understand because models try to fit text into predefined emotion categories. Real-world emotions, however, do not always fall neatly into labels like “joy,” “anger,” or “fear.” This complexity challenges the ability of models to accurately interpret nuanced emotional tones. Understanding such variations requires more advanced models and rich contextual data.

IV. STRATEGIES

Effective strategies include using advanced deep learning models, high-quality preprocessing, and balanced datasets to improve emotional understanding. Multi-label classification, context-aware training, and explainable AI techniques further help overcome key challenges in text-based emotion detection.

International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 14, Issue 12, December 2025)

1. *Use Strong Preprocessing Techniques:* Clean the text by removing noise, slang normalization, stop-word removal, and handling emojis. Good preprocessing improves feature quality.
2. *Apply Multiple Machine Learning and Deep Learning Models:* Use Logistic Regression, Decision Tree, CNN, LSTM, or transformer-based models and compare their performance to select the best one.
3. *Build a Balanced and Diverse Dataset:* Collect text from different domains (social media, reviews, chats) and ensure all emotions have enough samples. Use data augmentation where needed.
4. *Use Word Embeddings for Better Semantics:* Apply Word2Vec, GloVe, BERT embeddings, or transformer-based embeddings to capture deeper emotional meanings from text.
5. *Adopt Multi-Label Emotion Classification:* Use architectures that allow predicting multiple emotions at once, especially for complex sentences with mixed feelings.
6. *Context-Aware Training:* Train models using context-rich datasets and include sarcasm, figurative language, and domain-specific samples to improve real-world performance.
7. *Evaluate with Multiple Metrics:* Use accuracy, F1-score, precision, recall, and confusion matrix to analyze emotion classification performance accurately.
8. *Implement Explainable AI (XAI):* Add model interpretation methods like LIME or SHAP to explain how and why the AI predicted a particular emotion.
9. *Continuous Model Updating:* Regularly retrain models with new slang, trending words, emojis, and sentiment shifts to keep the system updated with modern language patterns.
10. *Integrate with Real-Time Systems:* Deploy the model in chatbots, social media monitoring systems, and customer support platforms for live emotion detection and instant response.

V. CONCLUSION

Emotion detection by text analysis has become an important field in artificial intelligence, helping machines understand human feelings expressed through written language.

By using machine learning and deep learning techniques, meaningful emotional patterns can be identified from complex and informal text. Although challenges such as ambiguity, slang, context understanding, and data imbalance still exist, advanced strategies like context-aware models, multi-label classification, improved preprocessing, and balanced datasets are helping researchers achieve better accuracy. Overall, emotion detection continues to grow as a powerful tool for social media monitoring, customer support, mental health analysis, and intelligent human–computer interaction, offering great potential for future innovations. In the future, aim to develop a more advanced machine learning and deep learning–based model that can understand emotions with higher accuracy. This improved model will handle complex language, slang, and mixed emotions more effectively. With better datasets and smarter algorithms, its overall performance will be faster, more reliable, and closer to real human understanding.

REFERENCES

[1] Machová K, Szabóova M, Paralič J and Mičko J (2023) Detection of emotion by text analysis using machine learning. Front. Psychol. 14:1190326. doi: 10.3389/fpsyg.2023.1190326.

[2] S. Dudi, "Text-Based Emotion Detection Using Deep Learning Techniques," IEEE Trans. Affective Comput., vol. 16, no. 2, pp. 1–10, 2025.

[3] I. D. Hayatu, "Emotion Detection in Text: A Comparative Study of Machine Learning Algorithms," IEEE Access, vol. 13, pp. 11245–11254, 2025.

[4] T. Chutia and R. Das, "A Review on Emotion Detection Using Deep Learning Methods," IEEE Rev. Neural Netw., vol. 32, pp. 77–95, 2024.

[5] A. Thiab, M. Al-Omari, and F. Alshamaila, "Contextual Emotion Detection Using Ensemble Deep Learning Models," IEEE Int. Conf. Data Sci., pp. 245–250, 2024.

[6] K. Machová, P. Bednár, and T. Horváth, "Machine Learning-Based Emotion Detection from Textual Data," IEEE Conf. Intelligent Syst., pp. 301–308, 2023.

[7] C. Liu, Y. Zhang, and H. Wang, "A Deep Learning Framework for Emotion Recognition in Text Streams," IEEE Trans. Human-Machine Syst., vol. 51, no. 4, pp. 405–414, 2022.

[8] A. Chowanda, D. Novitasari, and L. Wibowo, "Exploring Machine Learning Techniques for Text-Based Emotion Classification," Proc. IEEE Int. Conf. Comput. Sci., pp. 512–518, 2021.

[9] D. Haryadi and G. P. Kusuma, "Emotion Detection in Text Using Nested LSTM Architecture," IEEE Int. Conf. Adv. Informatics, pp. 140–145, 2019.

[10] J. H. Park and J. Kim, "Learning Effective Representations of Emotions for Text Classification," IEEE Int. Conf. Big Data Anal., pp. 210–215, 2018.