A Review of Emotion Detection Techniques for Hindi Language

Tapesh Kumar, Mehul Mahrishi
Department of Computer Science Engineering, Swami Keshvanand Institute of Technology, Management & Gramothan, Jaipur, India
Email: tapesh945@gmail.com, mehul@skit.ac.in

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***Abstract*- Emotions are a necessary and fundamental component of our existence. Everything we say, do, or do not say, and body language exhibit some of our emotions, albeit not immediately. To understand a person's most basic behaviour, we must examine their emotions using emotional data, also known as affect data. For this purpose, speech, text, facial expressions, and other data types may be used. Affective (Emotional) Computing, which analyses emotions using emotional data, is an interdisciplinary field. Emotion recognition from text is a challenging task in the field of natural language processing (NLP). While there has been great development, there is still potential for improvement. This analysis is used in a variety of applications to understand human thoughts based on their conversation. Deep learning advances have greatly improved algorithms' capability to understand text. Text classification into several groups is now being researched extensively. However, the application of these research is very limited in local and regional languages such as Hindi. This study will focus on text emotion analysis, specifically for the Hindi language.**

Keywords– Emotion Recognition, Text Analysis, Machine learning, Deep learning, BERT Transformer.

1. INTRODUCTION

Many scholars have developed theories and techniques for text sentiment and emotion analysis in recent years. Affective computing researchers have aspired to create computer systems that perceive, analyse, and represent users' various affective states (moods and emotions). Emotions may be communicated in various ways, including the face, voice, body language, physiology, brain imaging, and writing. Textual emotion has recently piqued the interest of academics in natural language processing who aim to discern sentiment, subjectivity, and emotions. Textual data comprises several components such as words, phrases, clauses, sentences, paragraphs, and documents. Emotion recognition research has been conducted at various levels, most notably at the word and phrase levels. Language is a very effective tool for communicating and conveying information. It also serves as a technique for expressing feelings. Natural Language Processing (NLP) techniques have long been used to determine information content in text. Summarisation, Topic-based text classification, information retrieval systems, question-answering systems, etc., are a few examples of applications that focus on the information contained in the text [1].

The technique of detecting feelings and emotions is known as emotion recognition. People's ability to recognise the emotions of others varies greatly. Implementing technology to help identify a person's emotions or text is a rapidly developing area of research. The technology works best when various modalities are used in context. Until now, most research has concentrated on automating the recognition of written expressions in text, spoken expressions in speech or audio, physiology as accessed by wearables, and facial expressions in video [2].

1.1 Basic of Emotion Recognition

Since its outset in 1950 and rebirth in the twentieth century, Artificial intelligence has made essential contributions in various sectors, including natural language processing (NLP), by providing acceptable answers for real-world personal and social challenges. The NLP uses linguistic and computational techniques to help machines understand and occasionally produce linguistic information in the form of audio and text. Sentiment analysis (SA), translation systems, questions and answers systems, information retrieval (IR), text generation system, and others are notable accomplishments. Emotion Detection is the process of determining the emotion behind any text or voice. It is a more advanced form of sentiment analysis (SA). As a result, ED is a synergistic combination of emotions. Emotions can be discrete or multidimensional. ED is also known as affective computing [3], and it derives its core from the use of emotion-based technologies in a variety of industries to facilitate smooth decision making. Different thinkers suggest various collections of fundamental emotions, Tomkins describes the basic units as affects. However, it is accepted that each fundamental emotion may have varying intensity levels, eliciting somewhat more complex feelings and allowing for more accurate terminology. Furthermore, scholars believe that each emotion activates a specific brain circuit, resulting in a specific response pattern in various bodily systems.

This area of emotional theory is frequently discussed in the study of emotion recognition. This is due to its suitability for mapping various bodily reactions to particular emotions in a one-to-one interaction. The notion of core emotions as opposed to the doctrine of different emotions. Lisa Barrett contributed to this idea by focusing on categorising core effects. This is what she refers to as a conceptual act. Barrett has done much work in recent years to undercut the credibility of her search for a unique universal response to individual emotions, pursuing a more individualised approach to emotion detection. However, there appear to be continuous efforts to categorise distinct motor and physical responses towards various emotions, particularly in ANS and face recognition. The link between these factors remains ambiguous, as evidenced by the extensive range of empirical data, emotion recognition systems, and theories. Arthur Samuel, a researcher in artificial intelligence and computer gaming, invented the phrase Machine Learning. Machine learning is a "field of research that permits computers to learn without being explicitly taught," according to him. In a word, Machine Learning is the process of automating and refining the learning process of computers based on their experiences, without the need for human intervention. The process starts with supplying high-quality data to our computers and training using the data and various methods to create machine learning models. The type of data and the task to automate define the algorithms. In traditional programming, DATA (input) is fed into a machine and a defined PROGRAM (logic), which is then run to produce output. In Machine Learning, only Data (Input) is fed into the machine to generate output. The machine, in training, creates a logic that can be evaluated during testing. Machine learning is of three types: unsupervised, supervised, and reinforcement learning.

1.2 Applications

In the last two years, emotion AI companies have expanded into entirely new domains and industries, assisting enterprises in providing a better customer experience while realising significant cost savings. Among these applications are: In video games: During the game, the game console/video game recognises and adjusts to emotions via facial expression using computer vision.

Medical evaluation: Using speech analysis, the software can assist clinicians in identifying disorders such as depression and dementia.

Education: Prototypes of learning software have been created to adjust to children's emotions. When a youngster expresses irritation because a job is too difficult or too simple, the software adjusts the activity to make it easier or more difficult. Another learning system assists autistic children in recognising the emotions of others.

Employee security: According to Gartner client queries, the need for employee safety solutions is increasing. Emotion AI can assist in analysing the stress and anxiety levels of people with high-stress occupations, such as first responders.

Concern for the patient: A 'nurse bot' reminds elderly patients on long-term medical programs to take their medications and communicates daily to assess their general well-being.

Car security: Automotive providers can utilise computer vision technology to track the emotional condition of the driver. An excessive emotional condition or tiredness may cause the driver to be alerted.

Autonomous vehicle: In the future, the inside of self-driving vehicles will be equipped with several sensors, including cameras and microphones, to monitor what is going on and to learn how people perceive the driving experience.

Detection of fraud: When a consumer submits a claim, insurance firms utilise voice analysis to determine whether or not the customer is speaking the truth. According to independent polls, up to 30% of consumers have acknowledged lying to their vehicle insurance provider to obtain coverage.

Recruiting: The software is utilised to assess a candidate's believability during employment interviews.

Service to the public: Partnerships have formed between emotion AI technology manufacturers and security camera providers. In the United Arab Emirates, cameras in public locations can identify people's facial expressions and comprehend the community's general mood. The Ministry of Happiness in the government spearheaded this effort.

Retail: Retailers have begun to investigate the installation of computer vision emotion AI technologies in stores to record demographic information and people's moods and emotions.

Intelligent call centre: Routing, a furious consumer, may be identified from the start and directed to a well-trained employee, who can also monitor and change the dialogue in real-time.

Intelligent Home: A VPA-enabled speaker can detect and respond to the person's mood by engaging with it.

1.3 Challenges

Emotion Recognition in Text Tasks presents several unanswered questions for NLP researchers. Beyond the efficiency of the Emotion Classification in Text algorithm, the difficulty of Emotion Recognition in Text may be linked to various issues. This section discusses present difficulties and future possibilities from various perspectives:

Emotional boundaries that are hazy: Emotions expressed by humans are complicated. There is no apparent distinction between feelings like love and happiness. Furthermore, emotions may change even within the same statement owing to people's individual experiences and present sensations. This difficulty inspired the multi-label emotion recognition task. As a result, by assigning numerous emotional labels to a written phrase, the embedded emotions may be articulated in more detail.

A scarcity of high-quality datasets: A high-performance Text Emotion Recognition (TER) system is guaranteed by high-quality emotional datasets. Even though various open-source emotion databases have been presented, they are primarily small. There is no standardised emotional annotation system, resulting in incompatibility across various corpora. Furthermore, the TER model's effectiveness is influenced by the unequal data distribution among emotion categories.

Textual emotion detection in conversation: Textual emotion detection is a critical component of an effective and intelligent conversation system. Most TER is done under the presumption that the statement is isolated from its context and communicates static emotion. On the other hand, Textual emotion is dynamic and significantly associated with contextual information, making the emotion recognition task more difficult.

Insufficient Emotional Information: There is insufficient emotional information in written expressiveness. Human emotional displays are more introverted in genuine emotional exchanges and based purely on textual information; emotion prediction is insufficient. As a result, several researchers concentrate on emotion identification utilising multi-modal information to alleviate the difficulty of emotional information in textual modal.

Casual Writing on the Internet: People generate many data. These difficulties make text-based analysis by models complicated. One does not always convey his feelings properly. For instance, use "Y" instead of "Why", and so on.

Language Barrier: Another issue with materials is that most are only available in English. As a result, sentiment analysis and emotion identification in languages other than English, particularly regional languages, present a significant challenge and potential for academics. Furthermore, specific lexicons and corpora are area/domain-specific, restricting their use in other domains.

Web slang: Consider an example, the youngest adults and upcoming generation in a society utilise phrases like 'ROFL', which stands for rolling on the floor out loud.

Sarcasm and Irony: People generally convey their rage or dissatisfaction through sarcastic and ironic words, which are difficult to discern. For example, in the statement "This narrative is fantastic to put you to slumber," the term excellent denotes a good attitude, although the reviewer found it highly uninteresting. As a result, detecting sarcasm has become a time-consuming problem in mood and emotion detection.

Embedded Emotions in Single Statement: The other difficulty is expressing numerous emotions in a single statement. The multi-opinionated statement makes it difficult to discern numerous features and accompanying attitudes or emotions. For example, the line "view at this spot is so tranquil and quiet, yet this area smells" demonstrates two feelings, 'bafflement' and 'soothing,' in different ways.

2. DISCUSSIONS ON VARIOUS METHODS OF EMOTION DETECTION

Wang et al. [4] proposed a CNN-LSTM architecture. Unlike a standard CNN, which examines the entire text as input. An area division technique is proposed to increase performance even further to find task-relevant words and sentences to add structured information to VA prediction. Dataset: Four emotional corpora were utilised in this experiment: Stanford Sentiment Treebank, EmoBank, The Valence and Arousal Facebook Posts, Chinese Valence-Arousal Texts. Data sets were randomly divided for 5- fold cross-validation using a 7:2:1 ratio of training, development, and test sets. Both word vectors have a dimensionality of 300. Results: On the testing dataset, the model has a Pearson correlation coefficient (r) of 0.809 on SST, 0.626-0.504 (valence-arousal) on EB (reader), 0.566-0.499 (valence-arousal) on FB, and 0.793-0.580 (valence-arousal) on CVAT. Suggested Regional CNN-LSTM (Tree) beat the LSTM (HAN) with ρ less than 0.05.

Zhang et al. [5] proposed KGCapsAN. Previous research has shown the effectiveness of an attention-based technique, still confronts several challenges in the actual world. Most studies simply employ one vector to represent the backdrop and the target. Traditional methods fail to detect sentiment in statements with distinctive sentence forms, such as double negatives. However, because natural languages are delicate and complicated, using only one vector to describe the phrase is restricted. Proposed approach: They suggested KGCapsAN overcome the limitations listed above. A capsule attention network and a Bi-LSTM network are the two components of this technique. The capsule attention network uses the attention mechanism to implement the routing strategy. Furthermore, they used two previous knowledge. Dataset: Used 6 datasets: the Twitter corpus, Rest15 (from SemEval-15 Task 12), Rest16 (from SemEval-16 Task 5), SpATSA, Lap14, and Rest14 (from SemEval-14 Task 4). Results: They achieved accuracy of 74.28%, 76.28%, 81.96%, 81.12%, 73.18%, and 88.47% on twitter, lap14, Res14, Res15, SpATSA and Res16 dataset repectively. The experimental findings showed that the KGCapsAN model beat state-of-the-art approaches for aspect-based sentiment analysis substantially.

Lu et al. [6] used RNN with self-attention. Problem Statement: The main problem in audio sentiment analysis is determining how to discover a decent representation that captures the emotional signals. It is unaffected by changing speakers, acoustic settings, or other natural speech variances. Acoustic characteristics such as band-energies were used in traditional techniques. To anticipate sentiment, use filter banks, MFCC characteristics [7], or raw waveform. Models that have been trained on Low-level characteristics are prone to overfitting noise or sentimentally irrelevant signals. Proposed approach: They proposed pre-training with end-to-end automated speech recognition and solving the audio sentiment as a downstream challenge. Furthermore, the end-to-end model incorporates both the acoustic and language models of classic ASR, allowing for the seamless integration of acoustic and text elements into a single representation. Dataset was made up of 140 hours of speech with 49,500 classified utterances, making it ten times larger than the current biggest, IEMOCAP. Results: They enhance the state-of-the-art sentiment analysis accuracy on IEMOCAP from 66.6% to 71.7%. They outperformed strong baselines on the SWBD sentiment dataset, achieving 70.10% accuracy.

Yin et al. [8] worked on a Feeling (Emotion) vocabulary based on the pos chunks, specifically CP chunks and proposed this FCP-Lex method. Problem Statement: In sentiment analysis, most emotion dictionaries currently have one polarity for each term and ignore sen timental ambiguity. Proposed approach: They notice that (1) the Sentiment Lexicon's surrounding words, with the same meaning, can be different, (2) the Part of Speech can be utilised to identify feelings. If they consider the context of the present term when building a lexicon, they will get vast results and information redundancy. As a result, they consider the POS of surrounding words. It indicates that researchers determine the emotion of a word by considering the POS of its preceding and succeeding words. The classification step follows them. Dataset: They used two movie review datasets: the long movie review dataset, which contains 100000 sentences (25000 negative labelled, 25000 positives labelled, 50000 unlabeled sentences). Another movie review data is labelled corpora with 5331 positive and an equal number of negative labels. Results: They achieved an accuracy of 71.34% and 82.10% on MRD and LMRD, respectively. Experiments revealed that FCP-Lex is more successful than other sentiment lexicons.

Ahmad et al [9] proposed Transfer Learning for ED. Problem Statement: The quantity of resources available in a specific language or domain considerably influences the performance of any NLP system. As a result, while tackling an issue in a low-resource environment, it is critical to research strategies: They present an effective strategy for overcoming resource constraints in Hindi emotion recognition. This solution employs a transfer learning architecture. They employ CNN with Bi-LSTM. Researchers constructed a novel data because there is no known emotion labelled datasets in Hindi. They use transfer learning to harness resources available in related areas to improve the performance of emotion categorization in Hindi. This technique is based on transfer learning algorithms for emotion categorisation in Hindi. Dataset: From the ground up, they constructed a dataset called Emo-Dis-HI. They monitor famous Hindi news websites for disaster-related news documents (both natural and artificial). They did emotion annotation at the sentence level, labelling each sentence with emotion categories like sadness, pensiveness, optimism, anxiety, joy, contempt, rage, and astonishment, some of the emotions expressed in class. The annotators had a Kappa agreement score (k) of 0.80, indicating strong consistency. Because the dataset originates from the disaster field, they found it biased toward negativity. There are 3336 sentences (2,668 train + 668 test) in dataset. Results: The baseline models are evaluated using two datasets, Emo-Dis-HI and EmoSemEval-EN. An F1-Score(micro) of 86.3% on Emo-SemEval-EN data was achieved. On their dataset, the F1-score was 53.0%.

Matla et al. [10] performed emotional analysis on Twitter data. Problem Statement: Performing emotion analysis using publicly available online data significantly decreases the work and time necessary to execute large- scale surveys and questionnaires. According to the researchers, Tweets generally communicate relevant information about the user's emotional states. Using Twitter covers a wide range of topics, resulting in a wide range of possible word exchanges. Proposed approach: In prior work, they produced labelled data using a rule-based method, referencing Russell's Circumplex model. They utilised the supervised lazy learning classifier (k-nearest neighbour) and supervised eager learning classifier (Naive Bayes) algorithms. Dataset: The sentiment140 dataset was collected. Although the dataset contains several properties such as a tweet, label, and so on, they were only interested in the text. Results: They achieved an accuracy of 72.60% by using Na¨ive Bayes and 55.50% using KNN.

Seal et al. [11] presents a practical emotion identification approach at the sentence level from the text by searching direct emotional terms from a pre-defined emotion keyword library. Problem Statement: They examined recognising these six emotions from phrases that are meant to include emotional terms. To fine-tune the outcome, phrasal verbs and negative words were thoroughly examined. Proposed approach: They used python and C# pro gramming language to implement their emotion detection algorithm. Dataset: They utilised the 'ISEAR' standard big emotion dataset. Around 7500 phrases in the dataset deal with anger, joy, sadness, fear, contempt, and guilt. The dataset is a collection of writings that have been accurately classified with emotion. They built an individual emotion dataset with emotion keywords that correspond to the individual feelings. Results: Accuracy obtained was 65%, Precession value was 70.11%, Recall value of 62.67%, and F1 score of 66.18%.

Seo et al. [12] proposed "Heterogeneous modality transfer learning" (HMTL). Problem Statement: Multimodal sentiment analysis is a broader approach that incorporates data from additional relevant modality sources. Multi modal sentiment analysis often employs textual, visual, and audio representations for sentiment prediction. Several data fusion approaches for multimodal sentiment analysis have recently been developed. The textual modality is the most important in most situations, with visual and audio modalities serving as supplemental sources for multimodal sentiment analysis. Text transcripts of an individual's speech, on the other hand, are not available in generic multimedia such as video. Therefore, the approach that does not rely on text data/modality becomes critical. Proposed approach: They proposed integrating knowledge from a source modality of textual data and have three stages. The first stage is to train the source model to extract helpful data. The Second stage make use of the "Heterogeneous Modality Transfer Module" (HMTM). Dataset: Two multimodal datasets, CMU-MOSI and IEMOCAP, were used. We can test a multinomial classification problem with these datasets because it contains nine emotions. Results: On CMU-MOSI data, the Baseline + HMTL model performs best, with 62.6% accuracy and 60.8% F1 score for the auditory data and 64.8% accuracy and 61.7% F1 score for the visual modality. Unimodal performance on the IEMOCAP was 51% for auditory data and 51.6% for visual data, respectively.

Feng et al. [13] proposed MCNN-MA. Problem Statement: Given the restricted text features of short messages, short text features should be mined from numerous viewpoints, and several sentiment feature combinations should be employed to acquire the hidden sentiment information. Proposed approach: A unique model called MCNN-MA is developed. This was developed for sentiment analysis. This model individually integrates word features(W), position features(P), dependency syntax features (Ps), and part of speech (T) features to generate three new combined features, which are then input into the proposed model to understand the sentiment information in the text more comprehensively. Dataset: The performance of the MCNN-MA model is validated using 2 data sets in this research." TanSongbo's Chinese" hotel review dataset and "Taobao Chinese" review data set. Each data sample is classified with positive or negative labels in both data sets. Both sets of data are imbalanced. Tan Songbo's dataset includes 10,000 ratings (7,000 good + 3,000 bad). While Taobao dataset includes 18,875 feedbacks from customers (9,549 good + 9,326 bad). Results: On the two data sets, the three-channel feature combination attained the highest accuracy (86.32%, 85.29%), demonstrating that the three-channel setup is both essential and effective.

Luo et al. [14] proposed "Sequence Generative Adversarial Networks" (SeqGAN). Problem Statement: Training generative ML models have two major issues, including training on long texts and generating erroneous sentiment information. It is challenging to increase sentiment analysis accuracy successfully. Proposed approach: SeqGAN is used to increase the quality of data and make it diverse. Long short-term memory (LSTM) networks with attention techniques compress sentences for SeqGAN training data. A sentiment dictionary is utilised to save the sentiment terms for compressed data. In addition, they presented a data screening approach for obtaining more reliable data from created data. Dataset: The two datasets were used- (1) Hate Speech (HS) Dataset collects tweets obtained by accessing the Twitter API. It is divided into three categories: "hate", "offensive", and "clean." The training and testing datasets are 21,000 and 4020 tweets, respectively. (2) Stanford Sentiment Treebank (SST) Dataset is a publicly available movie review dataset. It has two types of sentiments: "good" and "negative". There are 6,920 training texts and 1,821 test texts in this dataset. Results: It provides an average of 80.1% and 75.6% accuracy on the SST dataset and HS dataset, respectively. The recommended phrase shortening improves usability by 24.6% and increases novelty by 4.8%. Compared to the usual technique of EDA, the suggested framework improves the diversity of the produced data by an average of 58.4%. On other benchmark datasets, the data provided by the proposed approach improves classification accuracy by 1%.

Table:

S. No.	Authors	Method	Dataset
1	Wang et al. [4]	CNN-LSTM	Facebook Posts
2	Zhang et al. [5]	KGCapsAN	Twitter corpus, Rest15, Rest16, SpATSA, Lap14 & Rest14
3	Lu et al. [6]	RNN with self-attention	SWBD Sentiments
4	Yin et al. [8]	FCP-Lex	MRD and LMRD
5	Ahmad et al [9]	CNN + Bi-LSTM	Emo-Dis-HI and Emo Sem Eval-EN
6	Matla et al. [10]	KNN and Naïve Bayes	Twitter data
7	Seal et al. [11]	Word Based approach	ISEAR
8	Seo et al. [12]	HMTL	CMU-MOSI and IEMOCAP
9	Feng et al. [13]	MCNN-MA	TanSongbo's & Taobao Chinese review dataset
10	Luo et al. [14]	SeqGAN	HS and SST dataset

3. DISCUSSION AND CONCLUSION

Emotion recognition from text is a fascinating problem with numerous dimensions of e-Learning, market research, social media analysis, genre predictions etc. This research investigates the challenges of emotion recognition. The work presented in this research can be expanded in several ways. One of the tasks is to investigate the relationship between emotion categories and intensity. Since punctuation in chatting has increased, the relationship between punctuation and emotion classes can be examined. According to a recent study [15], there are 27 different types of emotions. Increasing the number of classes will thus aid in better emotion classification. Cross-lingual emotion classification will be another area of future research. Examining cross-lingual implementation may be an additional dimension for future research.

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