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Unveiling Sarcasm in Hindi: Cutting-Edge Deep Learning Framework for Sarcasm Detection

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Abstract:

Opinion mining, also known as sentiment analysis (SA), is a pivotal computer-based approach for discerning and categorizing sentiments within textual data. With the burgeoning popularity of social media platforms and the proliferation of user-generated content in Hindi, there is an escalating need for proficient sentiment analysis techniques tailored specifically for this language. The internet's accessibility in regional languages has become imperative to accommodate a diverse user base irrespective of age or linguistic inclination. While a significant portion of SA research has been conducted in English, there exists a dearth of comprehensive studies focusing on Indian languages, notably Hindi. This paper addresses this gap by investigating sentiment analysis within the context of Hindi, delving into various sentiment categories including positive, negative, neutral, and the notably complex sentiment of sarcasm. Sarcasm, characterized by its subtle irony and ridicule, poses a formidable challenge in sentiment analysis, particularly in languages like Hindi, which boast intricate grammatical structures and nuanced contextual cues. This study aims to enhance sentiment analysis methodologies by unraveling the intricacies of sarcasm detection in Hindi textual data.

Keywords: Sentiment Analysis (SA), Natural Language Processing (NLP), CNN, Neural Network (NN);

1. Introduction

Blogs, forums, and online social networks that let users talk and share their thoughts on any subject have become more popular as a result of Web 2.0. For instance, people might discuss current events, voice their political opinions, or complain about a product they have purchased. The functioning of numerous apps (such recommender systems), organisation survey studies, and political campaign planning all depend on the utilization of such user data. Furthermore, governments find great value in examining public opinion analysis as it provides an explanation for human behaviour and activity, as well as how opinions of others shape it. To compensate for the absence of clear user input on a service, the inference of user sentiment can be particularly helpful in the fields of recommender systems and personalisation. Apart from machine learning, alternative techniques including similarity-based approaches can also be applied here [1]. Online social media users produce an ever-increasing volume of data, which is the source of data for sentiment analysis (SA). These kinds of data sources must therefore be taken into account when using the big data strategy, since there are other matters that need to be resolved in order to accomplish effective data processing, storage, and access as well as to guarantee the accuracy of the outcomes that are produced [2]. In today's society, people often ask other people for opinions and guidance in order to improve their resilience and decision-making. When creating new goods or services, marketing and commercial tasks benefit from these feelings (or conclusions). Given that clients are the most likely recipients of substance, there has been a significant increase in the number of websites that highlight content created by clients. Likewise, a number of blog entries and comments discuss the way web-based media tends to stray. Online networks have flourished as a result of people being able to generate, share, and distribute free-streaming messages and data, thanks to the quick development of microblogging and new websites like Twitter. An exciting new area of text analysis characterised with several names including assumption mining, idea examination, assessment extraction, and subjectivity investigation has been generated by this explosion of unyielding content.

Determining a book's objectivity or emotionality is the aim of SA. Subjectivity is the degree to which the content has feeling, whereas objectivity is the degree to which there is no evaluation. As an illustration of objectivity, the sentence "This celebrity Amir Khan and Kajol" expresses truth rather than emotion or personal opinion and provides a wide overview of the subject matter. Moreover, the remark "Amir Khan and Kajol's film is excellent." also addresses subjectivity because it expresses the essayist's opinions on the movie. The abstract material can also be placed into generic groups according to the evaluations that are conveyed within the content. Take the phrases "I love to watch Star TV arrangement." and "The film was terrible." The adjective "horrible" suggests a negative attitude towards films, whereas the essayist's positive attitude towards "star TV arrangement" is shown in the use of the word "love." Similar to the last example, the statement "I usually get excited by early afternoon." is abstract and denotes an objective assessment since it expresses opinions and feelings about the customer without going to either extreme.

Deep Learning

Deep learning applies a multilayer strategy to the neural network's hidden layers. Conventional machine learning techniques involve the human definition and extraction of features using feature selection techniques. Deep learning models, on the other hand, achieve higher accuracy and performance since features are automatically learned and extracted. Generally speaking, classifier models' hyperparameters are also automatically measured. Figure 1 illustrates how classical machine learning (Support Vector Machine (SVM), Bayesian networks, or decision trees) and deep learning differ in their ability to classify sentiment polarity. For many picture and audio recognition, natural language processing, and other challenges, artificial neural networks and deep learning offer the best current solutions.

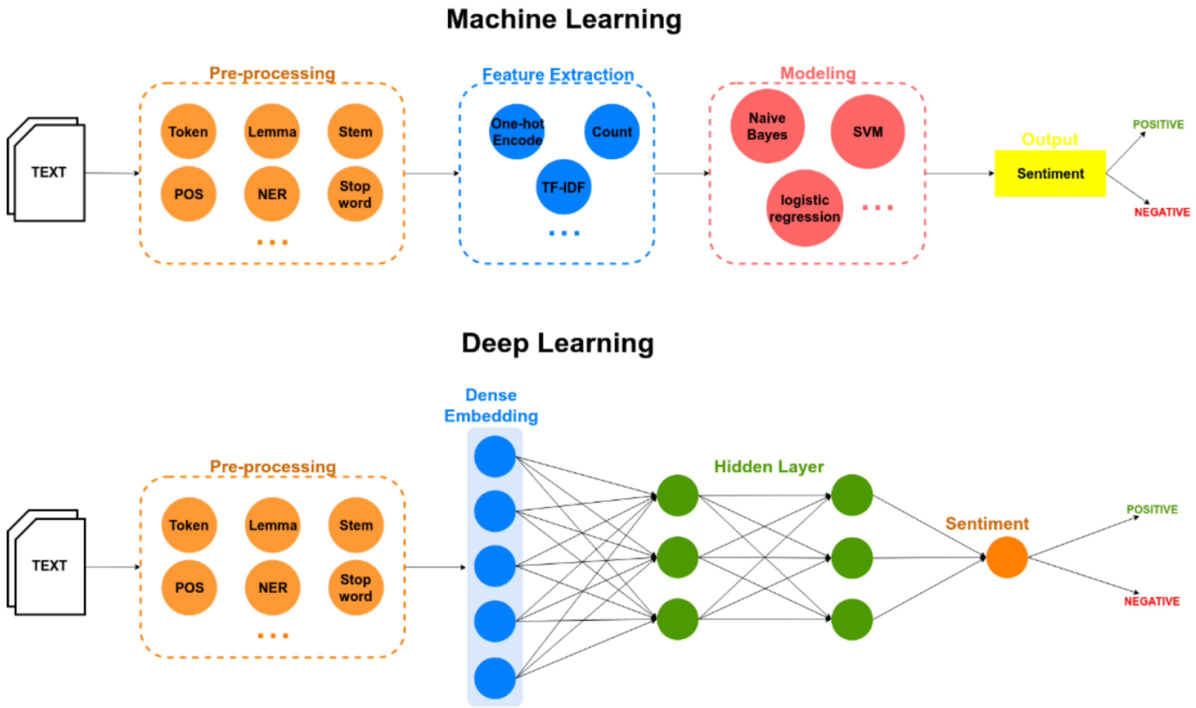

Figure 1: Disparities between machine learning (top) and deep learning (bottom) as two sentiment polarity classification methods. Recognition of Named Entities (NER); Part of Speech (POS); Inverse Document Frequency Term Frequency.

2. Literature Survey

According to Ishu Gupta et al.'s research [1], using machine learning models to perform sentiment analysis on user behavior impacted by conflict environmental variables can improve the accuracy of financial stock forecasts. For years, people have been investing in the stock market to get the most return on their money. In their paper, they propose leveraging sentiment and historical data to forecast stock prices with LSTM in an efficient manner. Previous research in the field of SA indicates that there is a strong correlation between changes in stock prices and the publication of news articles.[3][8][14][18].

Sentiment analysis based on conversational aspects (CASA) assignments modify standard aspect-based SA to fit the context of a discussion. For robustness validation, further annotate a 200-dialogue out-of-domain test set. Moreover, they establish several baselines using either self-attention or sustained BERT for exploratory studies. Tests demonstrate the effectiveness of our BERT-based model for both in-domain and out-of-domain datasets, and a thorough analysis points up several potential areas for development by Linfeng Song et al. [2][5]

User evaluations of the HSE's Contact Tracker app are examined by Kaavya Rekanar et al. [4] to find user issues and provide the framework for upcoming, extensive, automated review analysis. Although this seems to be exclusive to the Irish context, several US and European jurisdictions base their apps on the HSE app. Methods: A manual analysis of user reviews from the Google and Apple play stores was done to find out what aspects of the app users were most interested in, as well as what kind of feedback users had to provide.

In order to contribute sentiment labels to the corpus, complaint identification and sentiment classification rely on unsupervised learning. They provide a rich multitask framework with a knowledge component that uses Affective Space to integrate components of common sense information into the learning process. The method mimics Apoorva Singh et al.'s complaint detection and emotion categorization concurrently [6].

Using SA, Marouane Birjali et al. [7] may gather and analyze public sentiment and viewpoints, gather corporate intelligence, and improve decision-making. In order to give scholars a worldwide overview of SA and associated themes, this article offers a thorough assessment of SA methodology, issues, and trends. The generic SA approach is described, and its applications are discussed. After that, the study looks at, contrasts, and explores the different strategies to get a thorough grasp of their advantages and disadvantages. The challenges of SA are then emphasized in order to clarify future directions.

A first-of-its-kind multimodal Persian dataset including more than 800 utterances is proposed as a benchmark resource for scholars assessing multimodal SA algorithms in Persian. Second, they provide a unique context-aware multimodal SA framework that more accurately determines the transmitted sentiment by utilizing textual, visual, and audio information. They employ both the feature-level and decision-level fusion techniques of Kia Dashtipour et al. to include emotional cross-modal in- formation [9].

In this article, Lukas Stammen explores an extraction technique based on lexical knowledge to obtain such understanding from video transcriptions of a large-scale multimodal dataset. SenticNet is used to extract NLP concepts and refine several feature categories on a subset of MuSe-CAR. Qualities to acquire the ability to predict speaker topic classes, emotional valence, and arousal in addition to analyzing video information. Our best model improves the linguistic baseline from the MuSe-Topic 2020 sub challenge by around 3%[10][17], outperforming a variety of baseline systems that need significantly more computing power than the one provided herein for the prediction of valence on the specified challenge measure.

The analysis of Twitter users' attitudes and manifestations, based on the primary trends in NLP and Sentiment Classification using Recurrent Neural Networks, has been concluded by László Nemes et al. [11]. They compile, organize, present, and summarize data for additional processing. The trained model performs significantly better, with a smaller margin of error, in predicting emotional polarity in the "modern" world of today, where ambiguous tweets are typical [12][13][16]. The pertained language model designed to learn contextual representation outperforms traditional learning word vectors in terms of performance. Nonetheless, the two most popular approaches for using pertained language models in downstream tasks—feature-based and fine-tuning—are often handled separately. Moreover, several SA tasks cannot be handled by a single task-specific contextual representation. Given these benefits and drawbacks, they recommend a broad multitask transformer network (BMT-Net) to address these problems. Both feature-based and fine-tuning approaches are used by BMT-Net. Its creation was to explore the high-level information of contextual and robust representation. Our suggested structure can make learned representations ubiquitous across tasks by using multitask transformers [15].

Finding the polarity of text-based views is the process of SA. The study offers a way to ascertain the feelings expressed in tweets in one of the Indian languages. Using three distinct NN layers, thirty-nine sequential models were built using the optimal parameter choices. These sequential models for all three languages were examined. The effect of the hidden layers on the overall performance of the suggested sequential models is investigated. Neural networks were also compared with other methods to determine if they could outperform traditional machine learning methods [19].It's challenging to keep up with everything going on in SA, one of the computer science research fields that is expanding the fastest. They display user evaluations of items and employ sentiment analysis, opinion mining, and text mining to alter public perceptions of the products in question. Online product reviews on Amazon.com provided the study's data [20]. The collected reviews underwent a SA. This research paper provides a SA of several smart phone viewpoints, classifying them as either good, bad, or neutral behavior [21].

Social media users often express their thoughts on a wide range of subjects, including news, entertainment, and cuisine, on sites like Facebook and Twitter. Politics, fashion, and a lot more Reviews and opinions have weight. An examination of the approach to SA in Hindi cinema reviews uses the data to identify the positive, negative, and neutral polarity, which plays a significant role in determining the degree of user satisfaction in regard to a certain entity. NLP is used by author Charu Nanda [22][23-27] to identify SA.

Determining sentiment from such data becomes vital, which motivates research into sentiment analysis of regional languages like Hindi. The goal is to use neural networks to analyze sentiment from Hindi data. Nikita Kolambe, Yashashree Belkhede, and Nikhil Wagh will use a deep belief network (DBN) to train the model [28-31] to categorize Hindi data into good and negative sentiments [24]. Contextual mining is a computer technique that finds and groups the viewpoints expressed in a text to determine if the author is favorable, negative, or neutral about the subject.With the help of word polarity provided by SA, we can determine if the text has a positive or negative affect. A range of techniques are used in SA. In South Africa, a lot of study has been done on the English language, but not as much on the Hindi language. This paper reviews and analyzes the studies on Hindi language SA [25].

3. Methodology of the Proposed Research

Proposed system architecture (PCA) is the combination of two different algorithms as shown in figure 2. In the first part there is a text feature extraction using Bi-LSTM is proposed. Then the feedforward neural network is used for the classification.

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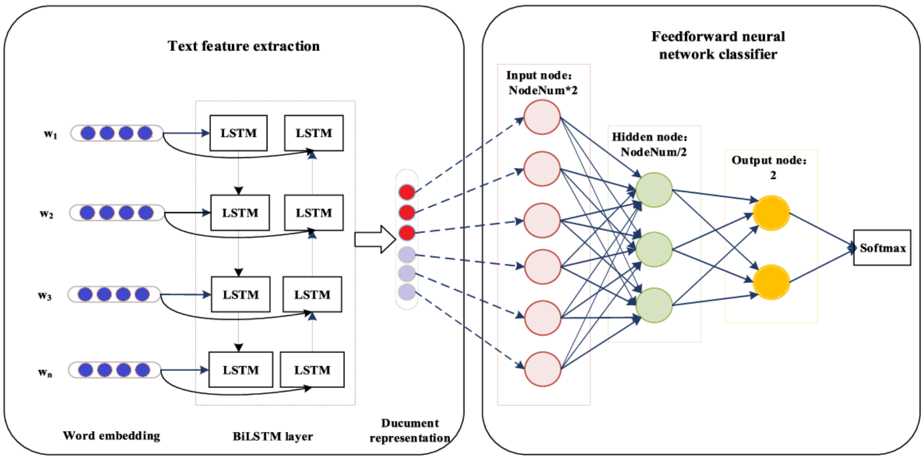

Figure 2. Proposed system architecture for the classification of the liver cancer

Assume that at the n^{th} moment, the current input of the neural network is x_n , and the hidden value of the previous time is h_{n-1} . The current hidden value h_n is calculated by the Eq. (1). Where W_{nh} is the matrix parameter input to the hidden layer, W_{hh} is the matrix parameter of the hidden layer to the hidden layer, b_n is the bias vector parameter of the hidden layer, and σ is the sigmoid function

$$h_n = f(x_n, h_{n-1}) = \sigma\left(W_{nh_{sn}} + W_{hh}h_{n-1} + b_n\right) \qquad \ldots \text{ equation (1)}$$

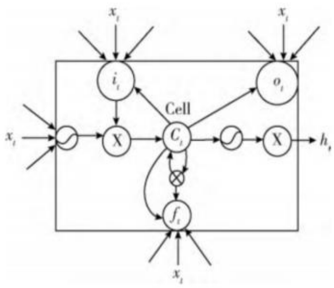

Figure 3. Long-short term memory cell

The i_t, f_t, c_t, o_t in Figure 3, the input gate, forgetting gate, cell memory unit, and output gate are all represented. How much of the previous sample is kept in memory depends on the input gate. The forgetting gate controls the pace of loss of stored memory and decides what data is removed from the cell's state while the output gate controls the quantity of data passed to the following layer. The input gate, forgetting gate, and output gate are used to change the weight of the LSTM, preventing gradient disappearance or explosion. The following equations, equation (2) through equation (3), are used to determine input gate, forgetting gate, output gate, and state cell (6).

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{cj}c_{t-1} + b_i\right) \qquad \ldots \text{ equation (2)}$$

$$\tilde{C}_t = f_t \Theta c_{t-1} + i_t \Theta \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c)$$
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \qquad \ldots \text{ equation (3)}$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right. \qquad \ldots \text{ equation (4)}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_0 \qquad \ldots \text{ equation (5)}$$

$$h_t = o_t \Theta \tanh\,(c_t) \qquad \ldots \text{ equation (6)}$$

Before passing dataset as input to the PSA the text vectorization is the process which should have to be done. The technique of translating textual attributes into numeric format is known as text vectorization. Because machine learning algorithms typically operate with numeric data, it's necessary to convert textual input to numeric or vector representation. Bag of words is the most frequent vectorization approach. Word Embeddings, also known as Word Vectorization, is an NLP technique for mapping words or phrases from a lexicon to a corresponding vector of real numbers, which can then be used to derive word predictions and semantics.

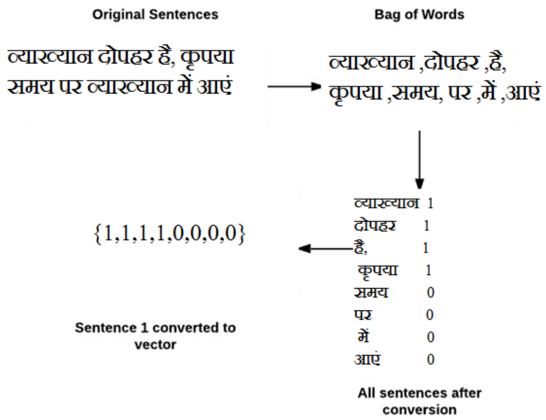

Figure 4: text vectorization for the Hindi language sentiment analysis

The text vectorization result is passed to the neural network as shown in figure 5.

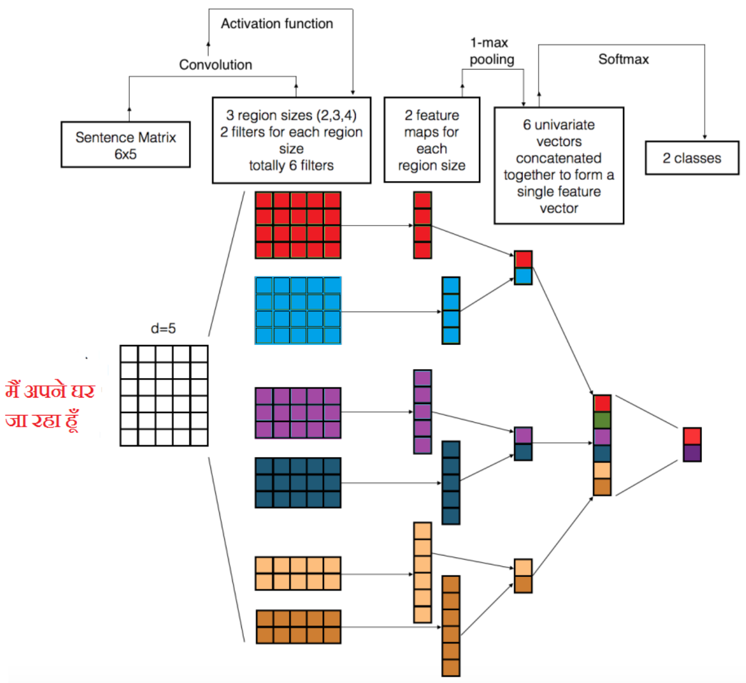

Figure 5. Detailed structure of getting sentiment of Hindi language sentences

Dataset is getting passed through the PSA for training purpose. The 70% data of the dataset is used for training and 30% data is used for testing. The results of the PSA are represented in next session.

4. **Result and Discussion**

Sentiment analysis software functions by scrutinizing textual data, such as sentences, paragraphs, or entire documents, and generating numerical scores or classifications to denote the perceived emotional tone, whether positive or negative. It involves the evaluation of online textual content to discern Happy, Sad, or Angry emotional tones. This analytical process investigates the emotional expression within the text. Common applications include the analysis of customer feedback, survey responses, and product reviews. Sentiment analysis contributes to various tasks including social media monitoring, reputation management, and enhancing customer experience. For instance, scrutinizing a vast array of product reviews can yield valuable insights into pricing strategies and product attributes.

Total 35,000 sentences are tested by using PSA. The figure 6 shows confusion matrix of the result of classification. Also the performance parameters calculated from confusion matrix is presented in table 1.

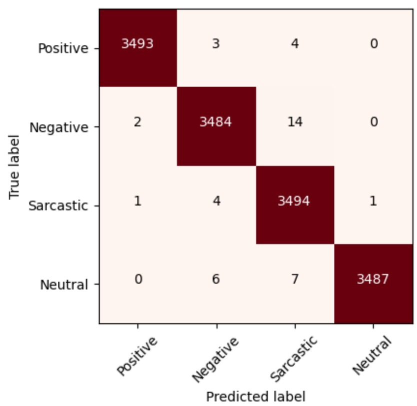

Figure 6. Confusion matrix of PSA

Table 1. the performance parameters of the classification using PSA

Parameters	Sentiment			
	Positive	Negative	Sarcastic	Neutral
Accuracy	99.91%	99.63%	99.29%	99.97%
Precision	99.80%	99.54%	99.83%	99.63%
Recall	99.91%	99.63%	99.29%	99.97%
F1 score	99.86%	99.59%	99.56%	99.80%

The graphical representation of the performance parameters is shown in figure 7 which only shows that every performance parameter higher that 99%.

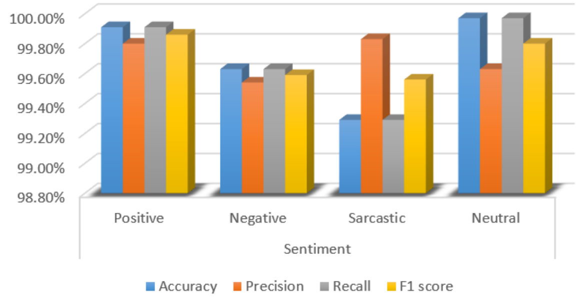

Figure 7. Graphical representation of the performance parameters of the PSA

Additionally, the time complexity of the various processors is examined. The average turnaround time for various hardware systems is compiled in table 2.

Table 2. The time it takes to get the result by using PSA on different hardware platforms [26]

Platform	Time required to get result (in seconds)
CPU, i3 processor, 8GB RAM	0.0123
CPU, i5 processor, 8GB RAM	0.0091
CPU, I7 processor, 8GB RAM	0.0088
GPU, Nvidia K80	0.0002

The use of CPU, i5 and the i7 gives almost same time complexity, but when the system is tested on GPU then there is huge difference in time required to get the results.

5. Conclusion

Various research papers are examined to learn how various strategies function and how they affect SA in various situations. The project necessitates data analysis in Hindi. Processing data in Hindi is a little more complex because it is an NLP with little research on the subject. The results show that words that aren't in the database are classified as neutral, even though they are sentiment terms. As a result, for efficient results, the database should be as large as possible. As a result, not only strategies but also resources are more vital for improved outcomes. In our system input is a sentence and output will be the emotions or expression that is about user behavior our system basically check the user sentiment using sentences write by user in different platform. In output or system results include the sentiment as positive, negative, sarcastic or neutral.

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