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Novel Deep Neural Network Approach for the Sarcasm Detection in Hindi Language

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Abstract: Sentiment analysis, also known as opinion mining, is a computational technique used to determine and classify sentiments expressed in text data. With the increasing popularity of social media platforms and the vast amount of user-generated content in Hindi, there is a growing need for effective sentiment analysis tools specifically designed for the Hindi language. As more individuals from diverse age groups and languages start using the internet, we need it in regional languages. Up until now, the majority of SA research has been done in English. However, very little study has been done on Indian languages, with the exception of a few. One of the Indian languages, Hindi, is the focus of this study on SA.

The work on sentiments like positive, negative, and neutral has been done previously here in this research one more very complex sentiment is detected which is sarcasm. Sarcasm is a complex linguistic phenomenon that involves expressing irony or mockery through words or phrases that convey the opposite meaning of the intended message. Accurate detection of sarcasm in textual data is a challenging task, especially in languages like Hindi, which possess rich contextual nuances and linguistic intricacies. The novel neural network along with their results are presented in the paper.

Keywords**:** *Sentiment Analysis (SA), Natural Language Processing (NLP), BiLSTM, Neural Network (NN)*

1. Introduction

People in today's environment routinely ask for opinions and advice from others to help them with their perseverance and decision-making. These feelings (or judgments) support marketing and business operations in creating goods or services. Client-produced content is increasingly being emphasized on the World Wide Web because users are the most likely to benefit from substances. Similar to this, there are several comments and blog posts about the tendency for web-based media to drift. People may now produce, share, and transmit free-streaming messages and data, enabling online networks to flourish. This has been made possible by the quick expansion of microblogging and new websites like Twitter. An exciting area in text analysis known as assumption mining, idea examination, assessment extraction, and subjectivity investigation has been produced by this surge of stubborn content.

Based on customer feedback, a lot of advertising agencies and recommendation engines try to determine what consumers like and dislike. The fourth most extensively used language worldwide is Hindi. The rise of user-generated content on the Internet serves as a driving force behind SA research. Most existing research on this subject is written in English. The Hindi version of SA hasn't gotten much notice. For government and industrial purposes, it is crucial to analyse Hindi information content.

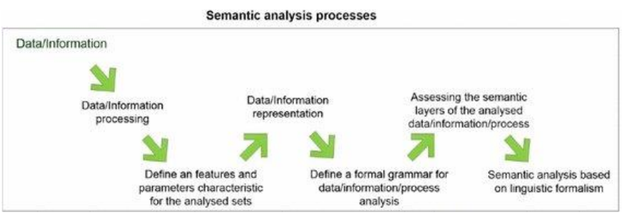

Fig 1: Process of Semantic Analysis [7]

According to Ishu Gupta et al.'s [1] studies, using machine learning models to perform sentiment analysis on user behavior affected by conflicting environmental factors can improve forecasting accuracy for a company's financial equities. People have been making stock market investments for many years in an effort to increase the return on their capital. In their essay, people recommend leveraging historical and sentimental data to accurately predict stock values using LSTM. Existing research in the field of SA indicates that there is a strong correlation between stock price movement and news story publishing.[3][8][14][18].

The assignment known as conversational aspect sentiment analysis (CASA) modifies the standard aspect-based SA to fit the conversational context. A 200-dialogue out-of-domain test set should also be annotated for robustness validation. Additionally, they establish several baselines based on either persistent BERT or self-attention for the purposes of the preliminary study.

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Experiments demonstrate that our BERT-based model performs well for both in-domain and out-of-domain datasets, and a thorough analysis by Linfeng Song et al. [2][5] identifies a number of potential areas for development.

In order to identify user issues and lay the foundation for future, extensive, automated review analysis, Kaavya Rekanar et al. [4] look at user reviews of the HSE's Contact Tracker app. Although it might seem like this is only applicable to Ireland, the HSE app is the model for many other US and European countries' apps. Methods To ascertain which app features individuals were most interested in, as well as the positive and negative attitudes conveyed, a manual study of user reviews from the Google/Apple Play shops was done.

Lack of oversight is used by compliant detection and sentiment classification to add sentiment labels to the corpus. They provide a robust multitask framework with a knowledge component that uses Affective Space to include parts of common-sense information into the learning process. The method simultaneously mimics Apoorva Singh et al. [6]'s work on emotion classification and complaint identification.

SA can be used by Marouane Birjali et al. [7] to gather and analyze data on public sentiment and viewpoints, get business-related information, and make better judgments. In order to give academics a global perspective on SA and associated topics, this article offers a thorough study of SA methodology, issues, and trends. The overall SA approach is described in detail, along with SA's applications. The various approaches are then examined, contrasted, and investigated in order to develop a thorough grasp of both their advantages and disadvantages. The challenges of SA are then emphasized in order to clarify future directions. A benchmark resource for academics evaluating multimodal SA algorithms in Persian is included in the paper's proposal, which is a first-of-its-kind dataset with over 800 utterances. In order to more precisely assess the sentiment being sent, they also outline a novel context-aware multimodal SA framework that makes use of audio, visual, and textual inputs. They employ both the decision-level and feature-level fusion techniques of Kia Dashtipour et al [9] to incorporate emotional cross-modal information.

Lukas Stappen looks into lexical knowledge-based extraction techniques to obtain such comprehension from video transcriptions of a sizable multimodal dataset. SenticNet is used to refine various feature categories and extract NLP ideas from a subset of MuSe-CAR. traits to develop when learning to predict speaker subject classes, arousal, and emotional valence, as well as when analyzing video footage. For the prediction of valence on the specified challenge metric, our best model outperforms a variety of baseline systems that need far more processing power than the one provided here, raising the linguistic baseline from the MuSe-Topic 2020 sub-challenge by around 3%[10][17].

Findings and analysis of the feelings and behaviors of Twitter users have been made by László Nemes et al. [11] based on the key developments in NLP and Sentiment Classification using Recurrent Neural Networks. For further processing, they assess, compile, illustrate, and summarise statistics. The trained model performs noticeably more accurately, with a smaller margin of error, in detecting emotional polarity in today's "modern" world, where ambiguous tweets are frequent [12][13][16].

Traditional word vector learning is less effective than the relevant language model designed to teach contextual representation. The two most popular approaches for implementing relevant language models in downstream activities, feature-based and fine-tuning methods, are often discussed separately. A single task-specific contextual representation cannot manage several SA tasks, in addition. They propose the use of a broad multitask transformer network (BMT-Net) to address these challenges in light of these benefits and drawbacks. Both feature-based and fine-tuning approaches are used by BMT-Net. It was developed with the intention of examining high-level information from a reliable and contextual representation. Our suggested structure can make learned representations universal across tasks by using multitask transformers [15].

Finding the polarity of text-based opinions is the process of SA. The paper offers a technique for figuring out tweet sentiments in a language spoken in India. The optimal parameter choices were used to build 39 sequential models using three different NN layers. These sequential models for the three languages were investigated. We evaluate the suggested sequential models and investigate the performance impact of the hidden layers. To determine whether neural networks have an edge over traditional machine learning methods, current methods were compared as well [19].

It is challenging to keep up with all of the work because SA is one of the computer science research topics that is expanding the fastest. They provide user feedback reviews of items in which they employ sentiment analysis, text mining, and opinion mining to alter public perceptions of a certain product. Online product reviews on Amazon.com provided the information for this study [20]. The reviews that were retrieved underwent a SA. This study article provides a SA of many smartphone opinions, classifying them into three groups: neutral behavior, unfavorable behavior, and favorable behavior [21].

Users of social media sites like Facebook and Twitter routinely express their thoughts on a wide range of subjects, including television, the news, and food. Politics, fashion, and a lot more Reviews and opinions are significant. The data are then used to locate the positive, negative, and neutral polarity an examination of the approach to SA in Hindi film reviews, which plays a significant role in defining the amount of user satisfaction in regard to a particular entity. NLP is used by the author Charu Nanda [22][23] to identify SA.

Since it is vital to extract sentiment from this data, research into extracting sentiment from regional languages like Hindi is encouraged. The goal is to use neural networks to analyze sentiment from Hindi data. Nikita Kolambe, Yashashree Belkhede, and Nikhil Wagh will train the model to categorize Hindi data into good and negative feelings using a deep belief network (DBN) [24]. The feature selection approach and mathematical model for classification [28] are extremely beneficial and easy to implement in the feature extraction text [27].

Contextual mining is a computer technique for locating and classifying the opinions expressed in a text to determine if the author has a favorable, negative, or neutral attitude toward the subject.SA provides word polarity, which enables us to determine whether the text has a favorable or unfavorable impact. Various techniques are used to carry out SA. In South Africa, there has been a lot of research on the English language but little on the Hindi language. In this paper [25], the research on the Hindi language SA is reviewed and examined.

2. Proposed Methodology

As seen in Figure 2, the suggested system architecture (PCA) combines two distinct methods. Bi-LSTM text feature extraction is suggested in the first section. The classification process is then carried out using a feedforward neural network.

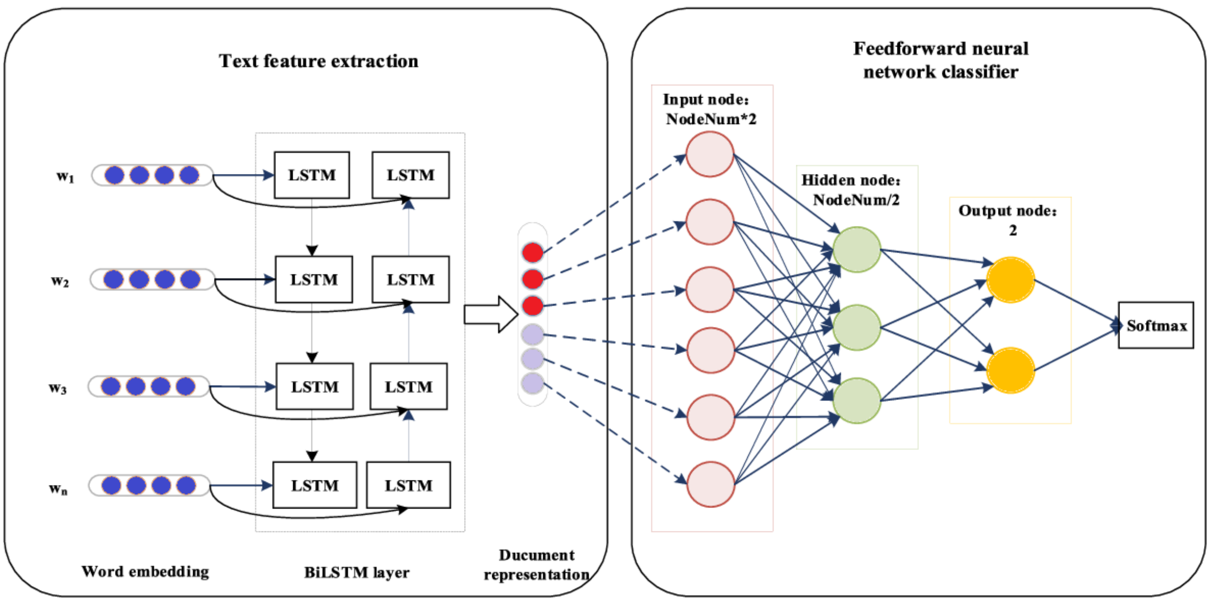

Fig 2. Proposed system architecture for the classification of the liver cancer

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

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

… equation (1)

The i_t, f_t, c_t, o_t representes the input gate, forgetting gate, cell memory unit, and output gate. 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).

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

… equation (2)

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

$$f_t = \sigma\big(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f$$
… equation (4)

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

$$h_t = o_t \Theta \tanh\,(c_t)$$
… equation (6)

Text vectorization should be completed prior to submitting the dataset as input to the PSA. Text vectorization is the process of converting textual information into numeric format. Textual input must be transformed into numeric or vector format since machine learning algorithms often work with numeric data. The most common method of vectorization is bag of words. By mapping words or phrases from a lexicon to a corresponding vector of real numbers, an NLP approach called word embeddings, often referred to as word vectorization, can be used to extract word predictions and semantics.

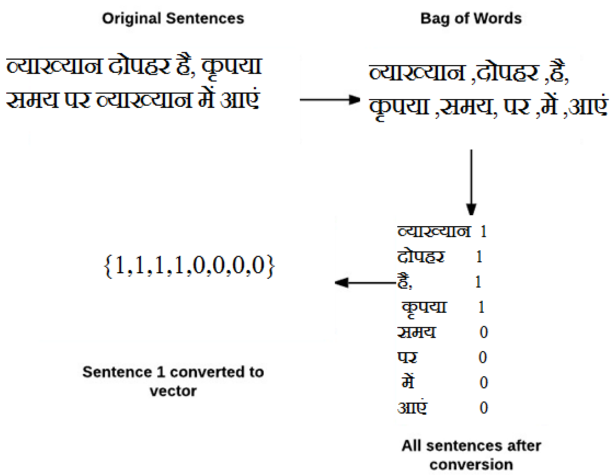

Fig 4: text vectorization for the Hindi language sentiment analysis

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

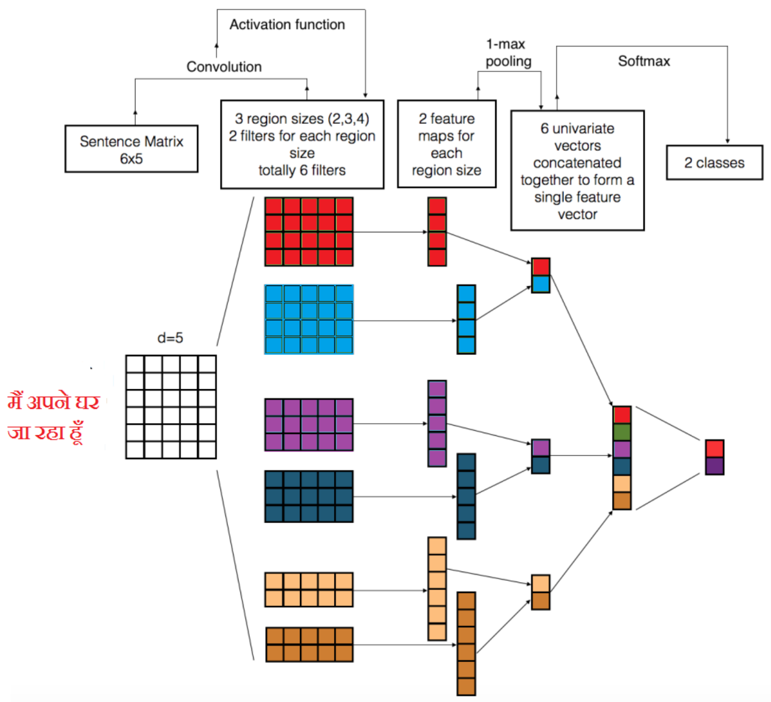

Fig 5. Detailed structure of getting sentiment of Hindi language sentences

Dataset is get 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 is represented in next session.

3. Result and Discussion

A sentence, paragraph, book, or other text-based composition is analyzed by sentiment analysis software, which then produces numerical scores or classifications that indicate whether the computer believes the content to be positive or negative. It involves analyzing text from websites to identify whether it has a positive, negative, sarcastic or neutral. Sentiment analysis looks at the emotional expression in a text. It is frequently used for customer feedback, survey responses, and product reviews. Sentiment analysis is useful for a variety of tasks, including customer service, reputation management, and social media monitoring. For instance, reviewing tens of thousands of product reviews could yield valuable information about the cost and characteristics of the product.

Total 12800 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 [29] is presented in table 1.

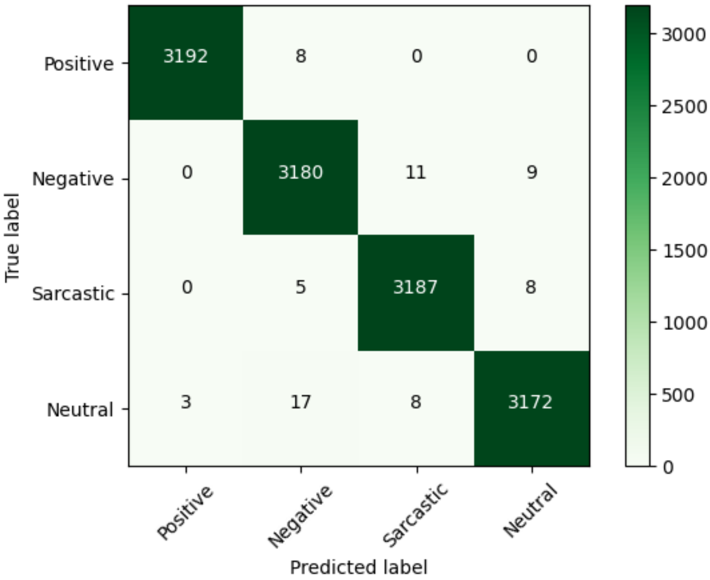

Fig 6. Confusion matrix of PSA

Table 1. the performance parameters of the classification using PSA

Parameters	Sentiment				Overall
	Positive	Negative	Sarcastic	Neutral	
Accuracy	99.91%	99.61%	99.75%	99.65%	99.73%
Precision	100%	99%	100%	99%	99.50%
Recall	100%	99%	99%	99%	99.25%
F1 score	100%	99%	100%	99%	99.50%

The graphical representation of the performance parameters is shown in figure 7 which only shows that every performance parameter higher that 97%.

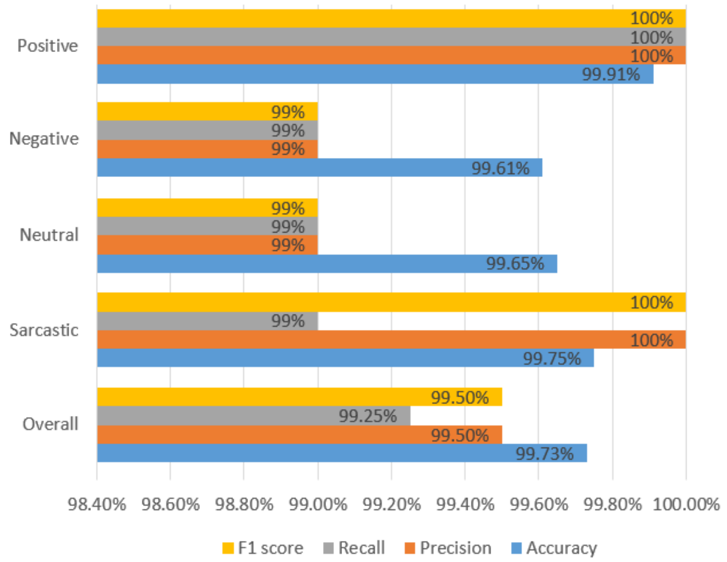

Fig 7. Graphical representation of the performance parameters of the PSA

The PSA is compared with the CNN with respect to performance parameters which are as shown in figure 8.

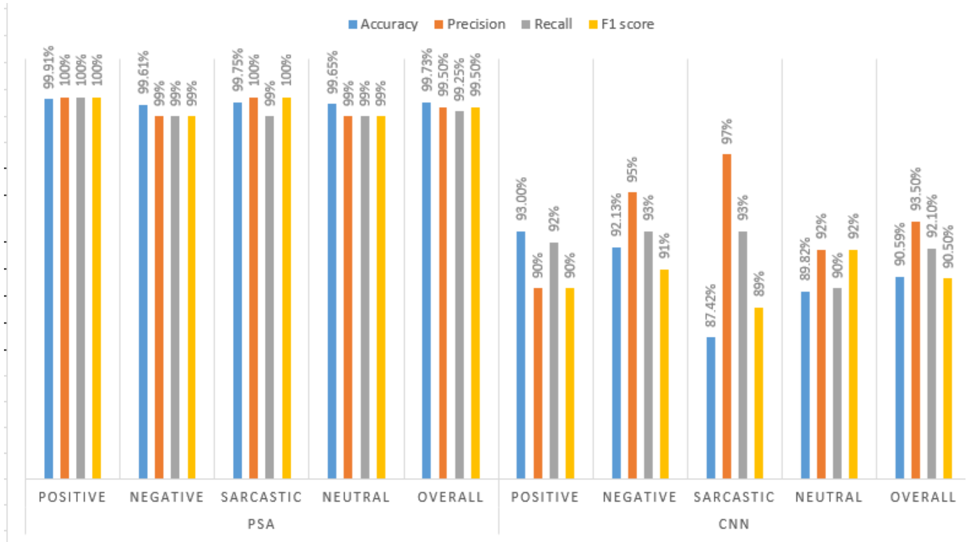

Fig 8. comparison of performance parameters of different algorithms

The results presented in figure 8 gives the better idea about how PSA is better than CNN algorithms. Every performance parameter of the PSA is superior.

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	0.018
CPU, i5 processor, 8GB RAM	0.012
CPU, I7 processor, 8GB RAM	0.009
GPU, Nvidia K80	0.0003

When testing on a GPU, there is a significant difference in the amount of time needed to obtain the results compared to using a CPU with an i5 or i7.

4. Conclusion

Sarcasm detection in the Hindi language presents a unique set of challenges due to the linguistic complexities and cultural nuances involved. However, it holds immense potential in understanding sarcastic communication patterns and their impact on various applications. The PSA gives 99.75% accuracy for the sarcasm detection and overall accuracy of the architecture is 99.73%. The PSA is also compared with well-known CNN classifier. The performance of the PSA is superior than that of the CNN classifier. The time complexity of the PSA is also presented in the paper on average on CPU it comes out as 13 milliseconds.

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