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Construction of Hybrid Model for English News Headline Sarcasm Detection by Word Embedding Technique

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Abstract

People often use sarcasm to taunt, anger, or amuse one another. Scathing undertones can't be missed, even when using a simple sentiment analysis tool. Sarcasm may be detected using a variety of machine learning techniques, including rule-based approaches, statistical approaches, and classifiers. Since English is a widely used language on the internet, most of these terms were created to help people recognize sarcasm in written material. Convolutional Neural Networks (CNNs) are used to extract features, and Naive Bayes (NBs) are trained and evaluated on those features using a probability function. This suggested approach gives a more accurate forecast of sarcasm detection based on probability prediction. This hybrid machine learning technique is evaluated according to the stretching component in frequency inverse domain, the cluster of the words and word vectors with embedding. Based on the findings, the proposed model surpasses many advanced algorithms for sarcasm detection, including accuracy, recall, and F1 scores. It is possible to identify sarcasm in a multi-domain dataset using the suggested model, which is accurate and resilient.

Keywords: Sarcasm detect, deep learning, natural language processing, word embedding, text classification, sentimental analysis

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1. Introduction

Natural Language Processing (NLP) research includes sarcasm detection. Emotion analysis includes a unique instance in which sarcasm is the primary focus rather than determining if a statement expresses positive or negative sentiment. In sentiment analysis, the views, ideas, and sentiments of a person towards a certain target are analysed. Since sarcasm changes the text's polarity, performing sentiment analysis on it is difficult. Due to the rise of social media and microblogging services, sarcasm detection has become a major study topic [1-5] and hence, sarcasm detection from text data has been studied extensively in the literature.

When it comes to expressing one's thoughts and feelings, social media has emerged as a powerful tool. There is an enormous quantity of data collected each day from social media sites like Twitter and Facebook. This data is used by a wide number of corporations and governments to gauge public opinion on a particular person, idea, product, or organisation [6- 8].

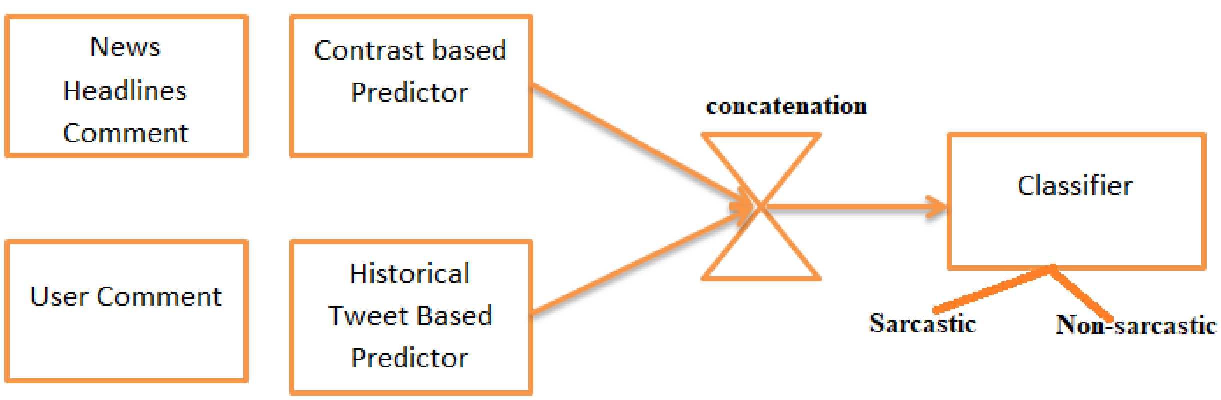

Figure 1. Simplified block diagram for sarcasm detection

Using data to identify the polarity of feelings or emotions, sentiment analysis seeks to categorise the sentiments or emotions as positives, negatives, or neutrals. Customers' reactions to

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a product are determined by the polarity of their feelings toward it, and this information is used by business owners to take proactive and remedial efforts to satisfy their customers' expectations. It is also crucial for governments to examine the demands of the public and make critical choices based on public feedback on public service [9]. Figure 1 shows simplified block diagram for sarcasm detection.

For these reasons, there are a lot of studies on sentiment analysis. There are a number of issues that need to be addressed before a sarcasm detector can be developed. It's crucial to be aware of both the literal and metaphorical connotations of social media comments. There are many nice phrases and feelings that may be found in tweets that are used to express bad or undesirable attributes [10- 13].

Satire is the use of words that are in direct contradiction to what the speaker intends to convey. Sarcasm is also said to occur when a pleasant attitude is paired with a terrible scenario [14]. Waiting for the bus is one of my favorite activities. "Love" connotes a good attitude; however, "nobody loves to wait for lengthy hours" is a negative sentiment in this scenario. There is a caustic connotation to the given scenario. Sarcasm may be detected by the use of grammar, lexical structures, and context information in the text. Detecting sarcasm in written communication is more difficult than watching it in conversation. The rest of the study paper is organized as follows: Section 2 provides past research work about sarcasm detection. Section 3 discusses an innovative approach for detecting sarcasm. Section 4 discusses several performance measurements. Section 5 discusses the conclusion and next tasks.

2. Related Works

The importance of sarcasm identification in sentiment analysis was shown by Diana Maynard and Mark A Greenwood. Using a sarcasm detector in a sentiment analyser system

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resulted in a significant improvement in this experiment, according to the researchers. Sarcasm may be detected using hashtags, however relying only on this method is inefficient since there may be instances when no hashtags appear in the statement [15].

Researchers P. Dharwal et al. looked at the methods that are used to identify sarcasm automatically. They have shown that n-grams alone are not sufficient for good classification, but when combined with other approaches, they may increase the accuracy of classification. SVM is shown to be more effective than Logistic regression and Naive Bayes [16].

A pattern-based technique was utilized to identify sarcasm in tweets and classify them as either sarcastic or non-sarcastic. There are three ways sarcasm may be used: when a person is trying to be amusing, when he or she is angry, and when he or she doesn't feel like answering a question. The feature set is obtained from the given assumptions. Classifiers such as "SVM," "Random forest," and "maximum entropy" have been employed [17].

Random Forest and Naive Bayes were used by Yessi Yunitasari et al. [18] to classify Indonesian tweets. Unigrams, TF-IDF methods, and Boazizi four feature sets have all been utilized to extract features from the data. Accuracy in detecting sarcasm in sentiments was improved by using this model [17].

Naive Bayes multinominal text method and Weka classifier features were used by D. Ghadhban et al. [11] to train an Arabic Twitter dataset for detecting sarcasm. Using hashtags, they've amassed a large number of tweets. Precision was 0.659, the recall was 0.710, and the f-score for this model was 0.676 [19].

In Hindi tweets, Santosh Kumar Bharti et al. developed a context-based framework for detecting sarcasm. They've taken into account the Hindi social media news from Twitter sources

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as the background of the tweet at the same time. Using this strategy, an accuracy rate of 87 percent was achieved [20].

Gupta et al. proposed the scathing analysis on the textual statistics using practical and verbal aspects, to the extent possible. For example, the chi-square test was used to narrow down the recovered structures, which aids the polling based classifier for sarcasm detection [21].

According to Ren et al., sarcasm is strongly linked to negative emotions and in emotion semantics for sarcasm recognition on many social media such as Twitter, Internet Argument Corpus (IAC-V1, IAC-V2) datasets were used to collect a wide range of sarcastic expression features [22].

3. Proposed Method

3.1 CNN for sarcasm detection

There are layers in convolutional neural networks that aid in extracting the characteristics from the text. A dataset is used to train the network so that the layers can learn the features, and then a phrase may be used as an input. The network generates probabilities. Using these probabilities, the kind of class a phrase falls into in the text is determined. The error is calculated after the output has been evaluated. Backpropagation of the mistake over the network is used to change the settings to lessen the error. Figure 2 shows the proposed working model. This process is repeated until a working model is obtained. The work is executed by connecting a few layers together [23].

3.1.1 Convolution Layer

This layer is critical to CNN since it does a bulk of work. Word embedding matrix is built through analysing text. Slides over embeddings to produce convolutions are a filter/kernel (may

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be used interchangeably). Feature extraction relies on this. Several feature maps are generated after applying the filter to the complete embedding matrix.

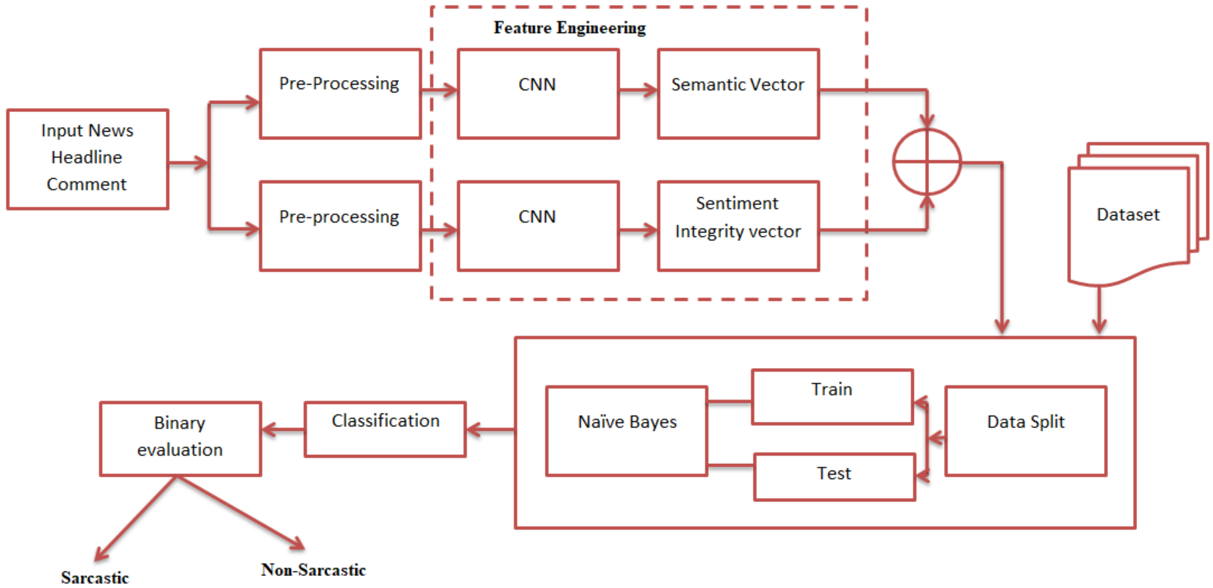

Figure 2. Overall proposed architecture for sarcasm detection

3.1.2 Max-Pooling Layer

The purpose of this layer is to lower the dimensionality of the feature maps acquired from the convolutional layer while retaining the crucial information. Pooling also reduces computational complexity. It's possible to reduce the output matrix to only a third of the input matrix's size by using pooling of 3.

3.1.3 Activation Layer

A non-linear output is produced by this layer. Neural networks benefit greatly from this non-linearity, which makes training more precise and quicker. The Softmax, Tanh, Identity, and

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Rectified Linear unit are some of the activation functions that may be used in CNN's. Generally, this activation function can convert all negative values to zero in the network [24- 28].

3.2 NB for training network

The Naive Bayes technique is used to train the neural network from the CNN structure. The feature engineering work has been completed using the CNN model in order to get additional features from one layer to the next. Incorporating the word embedding process for real-time classification, is implemented using the proposed framework.

3.2.1 Word embedding procedure

A neural network can't process text strings directly, therefore it has to transform them at first. An initial process known as "tokenization" is used to turn each word in the dataset into an integer and then feed that data into the neural network. To guarantee that all sequences in the dataset have the same length as input, padding is done. When working with a large amount of data, neural networks are unable to handle sequences of varying durations. The next stage is to employ word embedding that has been pre-trained. Then, the tokenizer is "tuned" to match the dataset. The tokenizer is asked to utilize just the dataset's 10400 most frequently occurring terms. To construct the vocabulary, the function fit is invoked on all the text in the dataset and is run through the tokenizer. Tokens are the integers that represent each word in the data collection.

3.2.2 Fully connected layer

All neurons in the network are linked to each other at this layer, which is the last stage of the process. As a result of the softmax activation on top of the Dense (completely connected) layer, the final single vector for classification is generated (sarcastic or non-sarcastic) and the binary cross-entropy error is minimized during network training. In order to optimize parameters, ADAM

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is employed. If a neural network is used to train a model, it is necessary to define how many times the model has to be trained until it's ready [28-32]. Epochs refer to the number of times a process repeats itself (25 - 30 epochs are considered in this model). Batch size (32 batch size is used in the proposed work) is another option that tells the number of samples utilized in a single epoch.

4. Results and Discussion

Totally there are 26k news headlines in this collection. Each record is made up of three different qualities. The first variable is a Boolean variable that indicates whether or not the headline is sarcastic. The second point to mention is the news story's headline. The third piece of information is the article's URL. The URL is not included in this analysis to assess if a news title is intended to be humorous or sarcastic. The benchmark dataset is downloaded from the website: https://www.kaggle.com/rmisra/news-headlines-dataset-for-sarcasm-detection.

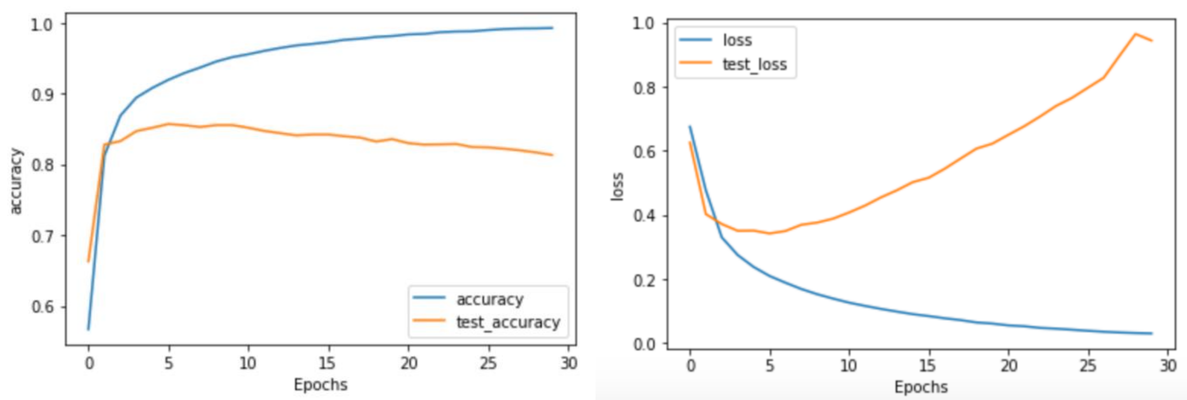

Figure 3. Testing accuracy and loss of the network

Figure 3 shows the testing accuracy and model loss of testing procedure. A Python script is used to classify the training sets, which is developed in the Python programming language [33-35]. It is necessary to refer to the feature maps to classify the data, which suggests that more the

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features are extracted, the better the result. However, doing so increases the amount of time required to train the model. The overall performance of the proposed model is measured by the following metrics,

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\ score = \frac{2 * (precision * recall)}{precision + recall}$$

Table 1. Computed performance metrics of various methods

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**False detection rate**
LSTM (Pre-trained)	88.9%	82%	78%	92%	0.4%
CNN (Pre-trained)	90.76%	74.67%	87.9%	87.45%	0.7%
CNN+LSTM	91.9%	82.51%	77.89%	90%	0.21%
Proposed hybrid approach	94.8%	93.1%	93.81%	93.07%	0.08%

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Table 1 contains the computed performance metrics. The operating flow of proposed sarcasm classifier is shown in Figure 2. Because of probability prediction, CNN is employed for feature extraction in the suggested model, while NB is used for classification. Figure 4 shows overall performance chart for various sarcasm detection model.

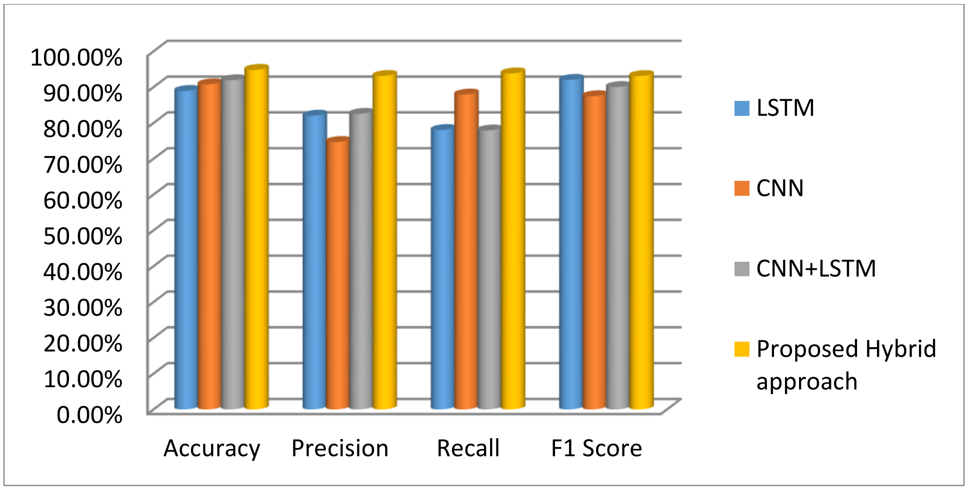

Figure 4. Overall performance measures of various techniques

Regardless of the application, this approach delivers a solid forecast for detection. Finally, it is completed with the activation of Softmax. At the conclusion, they are split into two groups: those who were sardonic and those who were not. The false detection rate of the proposed model is lower than that of the existing techniques.

5. Conclusion

Thus, the proposed work succeeds with semantic word embedding that is used to train the neural network, and it is considered a feature. The first step in spotting sarcasm in English news headlines is to submit the headline to the model, which is a computer program. Then, TensorFlow is used as a front-end and Keras as a back-end to apply the classifiers. In comparison to previous

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techniques, this new approach has a success rate of 96 percent. Due to the lack of available data, it was unable to conduct the study to full potential. In addition to improving the present model's accuracy, additional data might lead to the creation of newer and more powerful designs. Moreover, pre-trained word embeddings were not used in this experiment. Word2vec and other pre-trained models might provide significant benefits in practise. Scamming data sets from multiple languages to give local sarcasm detection is the way of the future of the art. This suggested method may be enhanced by incorporating pragmatics (emoji) in the text as sarcastic attributes. A better corpus is needed for local languages like Tamil, Malayalam, or Telugu, which is difficult to train using deep-learning methods.

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