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Sarcasm Detection with A New CNN+BiLSTM Hybrid Neural Network and BERT Classification Model

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ABSTRACT

One of the most common effects in the use of social media today is that people constantly make fun of each other or certain issues or do not take them seriously. Some comments made by sarcastic people in this widespread effect are misunderstood or taken seriously by other users. Some sarcastic comments, especially in the news headlines, create false effects on the readers and create some misunderstandings for people who do not have this sense of humor. Although there are numerous studies on the problem of sarcasm detection, even low performance increment in automatic sarcasm detection is very important and popular task. In this paper, a new hybrid deep neural model is proposed for more efficient automatic detection of sarcastic context. It is aimed to detect sarcasm using a hybrid neural network model CNN+BILSTM and BERT models with bidirectional language processing in a dataset consisting of headlines of The Onion News, which made such sarcastic headlines, and professionally prepared headlines without any sarcastic comments. When the results of this study were examined, it was seen that the model that gave the best results was BERT. In addition, accuracy, precision, recall and F1 score values were checked without using Glove embeddings in the CNN+BiLSTM model, and then the results were compared by applying Glove embeddings. In this comparison, the CNN+BiLSTM model without Glove embeddings gave relatively better results.

Keywords – **Sarcasm Detection, BERT, CNN+BiLSTM, Deep Learning, Hybrid Model**

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I. INTRODUCTION

Sarcasm involves creating and showing contradictions between the initial meaning of the expression and its intended meaning. In a way, we can say that irony is a way of speaking. That is, it allows the person to say what is not really there, and we often use it as a humorous form of rejection or humiliation. Contrary to what we want to say, it is a kind of humor tool used to make fun of a situation or person, by using expressions or making analogies [1]. It is like a verbal caricature [2]. Sarcastic expressions are funny but thought-provoking, sometimes based on allusions and sometimes metaphors. Given such difficulties, when someone sees a sarcastic comment on a topic on social media, they probably won't be able to understand the contradiction and irony if they are not well-versed in that topic. In such cases, it is necessary to make an application that can understand these sarcastic sentences. Because sometimes, even if a person has a good command of the subject, a sentence is so cleverly constructed that many people may not be able to understand whether this sentence contains real feelings or is meant to make fun of it. For this reason, it is very important to be able to understand who is making fun of what on social media or who shares their true feelings on social media by making applications that learn much better and have a low margin of error.

The vast majority of people use social media to have fun and have a good time [3]. Others may be inclined to make fun of people with their own sense of humor and make ironic comments about certain subjects [4]. This diversity of users in social media creates some problems and can cause people to misunderstand each other. Just as each person's sense of humor is different, some do not have this feeling [5]. For this reason, they may have difficulty understanding many of the sarcasm.

So why is it so important whether a comment contains sarcasm? For example, on social media, when viewing posts and comments on a topic that is very important to a user, if he does not have a high sense of humor or does not like to be teased and teased, he may not understand many comments containing sarcasm and may think it true. Thus, by participating in these comments, he may think that the other people have the same feelings as him, and then he may feel humiliated among sarcastic people. It will be a disappointment for many people to think that they are being teased, to be ridiculed and to realize that they have been humiliated, and this will probably start to lay some bad foundations psychologically [6]. When we look around, most of the people do not even comment on social media anymore, they are afraid of being ridiculed and exposed [7]. One of the reasons for this is to not fully understand many of the sarcastic sentences and to confuse them with real emotions.

Looking at these two types of users, detecting sarcastic and mocking comments will make the use of social media much comfortable for both users, and it will be easier to find out which comment is real and which comment is meant to mock. It will also be possible to put an end to the semantic complexity about the subjects that will give rise to sarcastic comments on social media.

The aim of this study is to detect sarcastic sentences in tweets and comments on Twitter, one of the social networks, and the Transformer deep learning method was used for this detection. The main contributions of this study are listed below:

- A new hybrid methodology based on CNN+BiLSTM neural networks with BERT bidirectional language processing model is proposed in order to obtain more efficient results for the problem of automatic sarcasm detection.
- The proposed system is checked and compared with and without Glove embeddings for a hybrid CNN+BiLSTM neural network model.
- More effective and accurate results were achieved with BERT model, which can be adapted with additional preprocessing steps to handle different types of social media and networks problems.

II. Literature Review

Detection of sarcasm is a crucial component of text classification that has implications for a variety of fields, including health, security, and sales [8]. Using sarcasm detection techniques, businesses can analyze customers' opinions of their products. This provides essential assistance for these companies to enhance product quality [9]. As stated in the introduction, sarcasm detection has a very important place in text classification. For this reason, more than one research has been done on this subject so far and the majority of them have used Twitter data as the primary data source.

A fundamental problem in implementing supervised learning on sarcastic texts is marking the corpus as sarcastic or non-sarcastic beforehand. Cornell University's Dr. Mathieu Cliche classified tweets as sarcastic or non-sarcastic based on the presence of the hashtag #sarcasm, arguing that tweets with #sarcasm are more likely to be genuine sarcastic tweets, whereas tweets without the tag contain such a large corpus of regular tweets that the sarcastic samples can be considered noise [10].

Liebrecht and her colleagues at Radboud University Nijmegen [11] and Drs. David Bamman and Noah A. Smith of Carnegie Mellon University created their datasets using comparable methods [12].

Gonzalez-Ibanez and his colleagues from Rutgers University also used #sarcasm to identify sarcastic tweets, but instead of choosing non-sarcastic tweets as tweets without sarcastic hashtags, he used tweets with positive or negative tags (#happy, #sadness, #angry, etc.) on the premise that tweets with tags representing pure emotions are less likely to be sarcastic [13]. Although this strategy caused the non-sarcastic dataset to be less representative of general tweets, we considered that it is a preferable alternative since it decreases the noise associated with the non-sarcastic set if it were obtained by merely choosing tweets without "#sarcasm"

Studies on sarcasm identification in Indonesian-language social media have been conducted [14] using interjection and negative word count data. SentiWordNet is used in this study to classify sentiment, and the accuracy result is less than 60%. According to a review study from 2010, the Supervised Sarcasm Identification function had an accuracy and precision value of more than 90% when it came to recognizing sarcasm. This study used English-language content and data from Twitter and Amazon [15].

Sarcasm detection will be necessary for public personalities, political gatherings, product manufacturers, and organizations that use social media as a communication tool with their voters, clients, or customers. Sarcasm is difficult to interpret, which may make natural language processing concepts for online news evaluations, politician debate, institution websites, or product monitoring feedback problematic. Wicana and his colleagues have studied the technique that is most frequently used to identify sarcasm [16].

In order to classify statements as sarcastic or non-sarcastic, A. K. Jena et al. [17] suggested a C-Net model that employs contextual information gathered from a statement in a serial approach. Contextual Network is used to display prospective results when a comparison is made between a traditional machine learning approach and u-to-the-minute transformer models.

An overview of text representation methods and tools for sentiment analysis was provided by A.R. Pathak et al. It carried out a comparative analysis of deep learning approaches for sentiment analysis based on the neural network, dataset, text portrayal, and individual method's core.

Researchers provide a summary of text representation methods and sentiment analysis tools in [18]. It carries out a comparative analysis of deep learning approaches for sentiment analysis based on the neural network, dataset, text portrayal, and individual method's core.

Recurrent CNN-RoBERTA model was developed by R. A. Potamias et al. [19] to discover sarcastic statements in a given dataset. The outcomes from SemEval [20], Reddit's Political Sarcastic Statements [21], and Riloff's Sarcastic dataset [22] were compared.

K. Nimala et al. [23] tested the sentiment topic sarcasm mixture (STSM) method. Its fundamental premise is that, absent human interference, some topics tend to elicit sarcasm more frequently than others. The model includes a number of elements, including pragmatic, incongruity-based, subjective, and lexicon-based aspects.

S. Minaee [24] studied several text mining datasets and over 150 deep learning models. The RNNs, Capsule networks, CNN-based, Graph neural networks, attention mechanisms, Siamese networks, Memory augmented networks, Transformers, Hybrid models, and unsupervised methods were put together. The unsupervised learning techniques make use of adversarial training, reinforcement learning, and autoencoders.

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In [25], researchers conducted an assessment of Deep Learning approaches for various coarse-grain, cross-domain, and fine-grain sentiment domain evaluations. It was discovered that CNN, GRU, LSTM, and attention are the most effective approaches.

index	article_link	headline	is_sarcastic
0	https://www.huffingtonpost.com/entry/versace-black-code_us_5861fbefe4b0de3a08f600d5	former versace store clerk sues over secret 'black code' for minority shoppers	0
1	https://www.huffingtonpost.com/entry/roseanne-revival-review_us_5ab3a497e4b054d118e04365	the 'roseanne' revival catches up to our thorny political mood, for better and worse	0
2	https://local.theonion.com/mom-starting-to-fear-son-s-web-series-closest-thing-she-1819576697	mom starting to fear son's web series closest thing she will have to grandchild	1
3	https://politics.theonion.com/boehner-just-wants-wife-to-listen-not-come-up-with-alt-1819574302	boehner just wants wife to listen, not come up with alternative debt-reduction ideas	1
4	https://www.huffingtonpost.com/entry/jk-rowling-wishes-snape-happy-birthday_us_569117c4e4b0cad15e64fdcb	j.k. rowling wishes snape happy birthday in the most magical way	0

Table 1 Sample Data from the Dataset

Misra and Arora published an article titled 'Sarcasm Detection using Hybrid Neural Network' in 2019 [27]. They initialized the missing words uniformly at random in both models and represented the words using pre-trained embeddings from the word2vec model. The training procedure then fine-tunes these. By randomly dividing the data in an 80:10:10 ratio, they formed the train, validation, and test sets. Using grid search, they adjust the hyper-parameters learning rate, regularization constant, output channels, filter width, hidden units, and dropout fraction

III. DATASET AND PREPROCESSING

When the data set created by Rishabh Misra and Prahal Arora in 2019 and used in this study is examined, it is seen that the source is TheOnion and HuffPost news sites [26]. The Onion news site edits news headlines from a sarcastic perspective, mostly producing sarcastic versions of current events. These headlines, taken from the News in Shorts and News in Photos categories, constitute the sarcastic content. On the other hand, non-sarcastic, real news headlines were collected from the HuffPost news site. A dataset was created with these titles and made available for use. The advantages of this dataset over existing Twitter datasets are:

— There are no typos, as the news headlines are written officially by professionals.
— Since TheOnion's sole purpose is to publish news with sarcastic headlines, it has a lot less noise compared to Twitter datasets and also has high quality tags.
— Unlike the responses to some tweets, especially in Twitter data, news headlines are independent in this dataset. This way it will be much easier to separate content that contains sarcasm.

Looking at each label, it is seen that there are 3 features.

— sarcastic if is_sarcastic:1, 0 otherwise
— headline: the title of the news article
— article_link: The link to the original news article. (This information may be useful for collecting additional data)

In total, there are 26,709 pieces of data in the data set when we look at it closely. 11,725 of these data had the label "1" (Sarcastic) while 14,984 had the label "0" (Non-sarcastic). Because it is a more balanced and recent data set in the study area, this data set was chosen. Other datasets exist in this field, however they are both more dated and unreliable than the one being used.

Some of the data in the dataset are shown in Table 1 together with the index, article_link, headline and is_sarcastic tags. If we come to the data pre-processing step, first of all, the data under the article_link column has been deleted, since it will not be of any use to us in this study. Then, all of the data under the headline column was converted to lowercase and punctuation was removed. After all these processes were completed, English stop words were removed.

When the data in the dataset are examined, the noise ratio is very low compared to social media data such as Twitter, since all of the data consists of professional titles. For this reason, it was sufficient to apply a few preprocessing steps on the data in the article_link column on the dataset [28]. All these steps are shown in Figure 1.

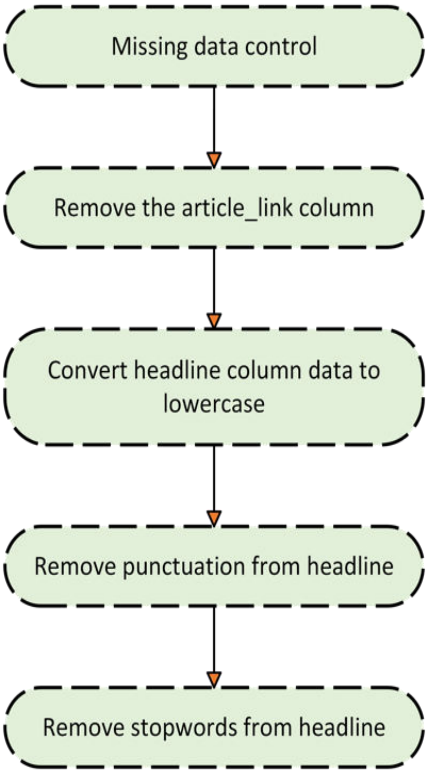

Figure 1 Preprocessing Steps on Dataset

IV. EXPERIMENTAL RESULTS

In this study, it was determined whether the data in the above-mentioned dataset has sarcastic content. There are two types of classification approaches used in making this detection: CNN-BiLSTM and BERT. 'Adam Optimizer' is used in both models.

CNN-BiLSTM

After the CNN layer, the CNN-BiLSTM model has a bidirectional LSTM layer. ReLU serves as the activation function for the CNN layer, which recognizes 128 features. A dense neural network with 64 nodes makes up the LSTM layer, which is followed by 1 hidden layer. The hidden layer comprises an L1 arrangement and has 100 nodes. The dropout layer is specified as 0.1.

A single node and sigmoid activation function are utilized in the final output layer since binary categorization is necessary. Without GloVe embeddings, the Model 10 epoch produced an accuracy of 9.22%, whereas with GloVe embeddings, it produced an accuracy of 92.06%. Figure 2 depicts the architecture without glove embeddings, while Figure 3 depicts the architecture after glove embeddings.

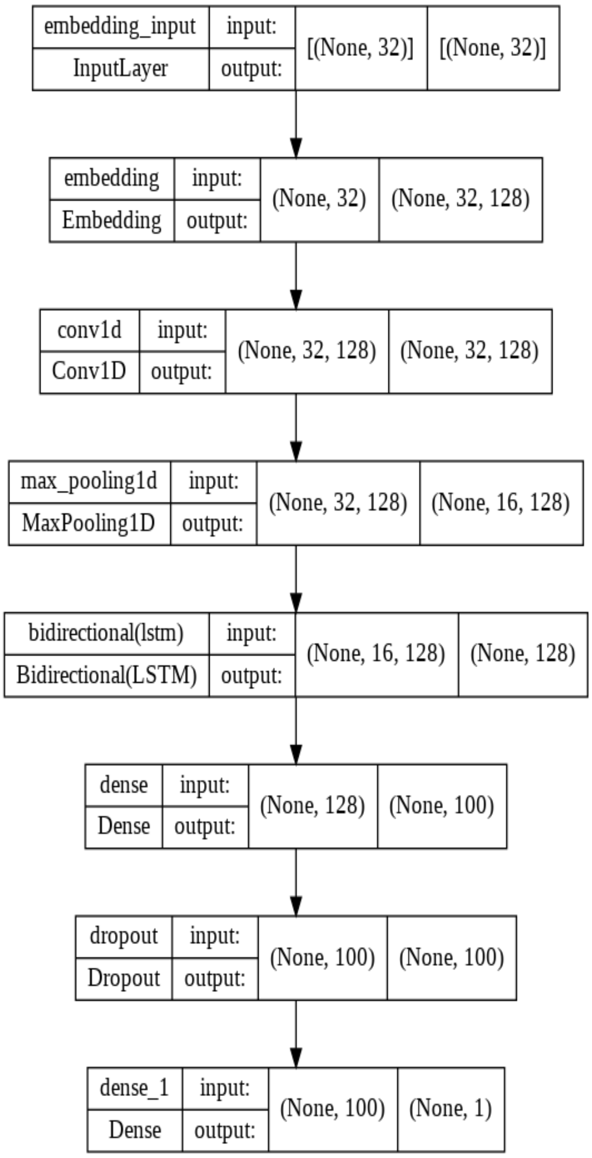

Figure 2 CNN-BiLSTM Architecture Before Glove Embeddings

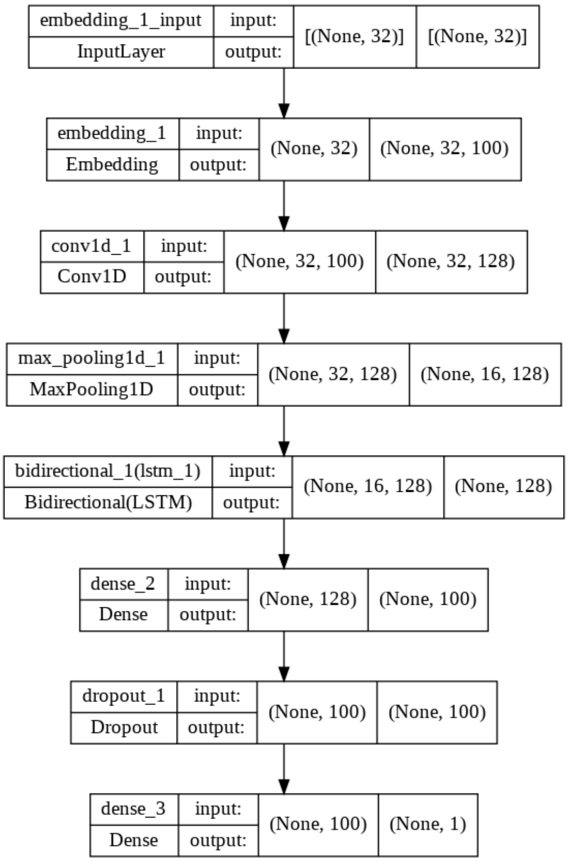

Figure 3 CNN-BiLSTM Architecture After Glove Embeddings

BERT

The BERT model in this work uses a pre-trained encoder known as "bert-case-uncased." On the BERT encoder, a neural network with a single hidden layer is used. 128 nodes with the ReLu activation function make up the hidden layer. A dropout layer of 0.1 was used. Because binary classification is necessary, there is just one node in the output layer and the sigmoid activation function is used. The model's accuracy rate was 93.87% after 10 training iterations were done. Figure 4 depicts the BERT model's architecture, which was used in this study.

If the experimental findings are looked at, the CNN+BiLSTM classification model's accuracy rate has produced a very pleasing outcome. This accuracy rate, which was 93.22% before the application of Glove embeddings, as seen in Table 2, decreased to 92.06% after the application of Glove embeddings, as shown in Table 3. Likewise, while the recall value was 92.91% in Table 2, this value decreased to 92.13% after applying Glove embeddings. These values give lower values when compared to the results of the BERT classification model in Table 4. For example, while the accuracy rate was 94.39% in the BERT model, the recall value was 92.80%. Although this value gives a lower result in CNN+BiLSTM than the model without Glove embeddings, the BERT model gave a much better result when the accuracy rates were compared. When Table 4 is examined, precision and F1-Score values of BERT model gave much better results than the other model (CNN+BiLSTM with and without Glove Embeddings).

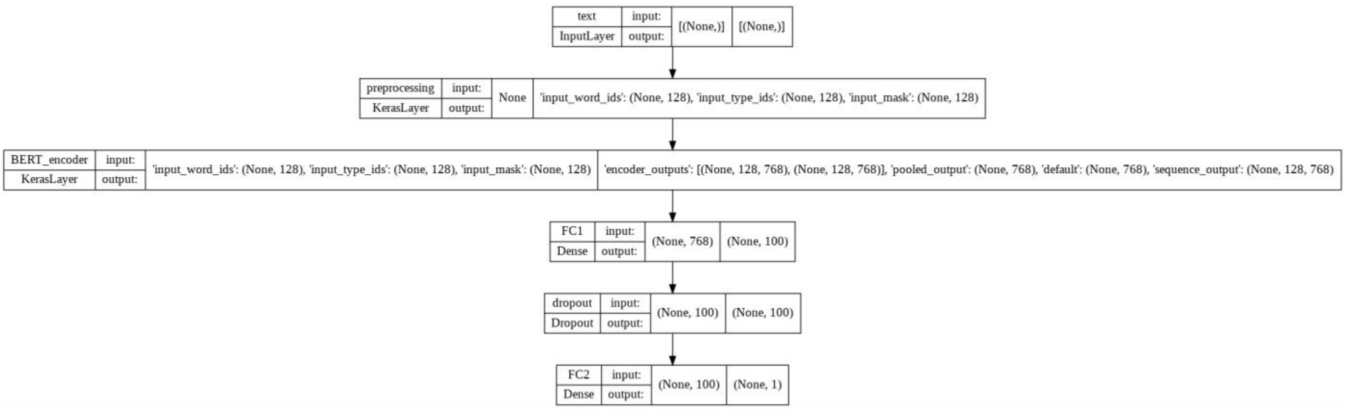

Figure 4 BERT Architecture

Table 2 CNN+BiLSTM Model Before Glove Embeddings Results

CNN+BiLSTM Model Before Glove Embeddings	
F1-Score	0.9271703243348223
Accuracy	0.9322248328212543
Recall	0.9291553133514986
Precision	0.9251937984496124

Table 3 CNN+BiLSTM Model After Glove Embeddings Results

CNN+BiLSTM Model After Glove Embeddings	
F1-Score	0.9151362845544171
Accuracy	0.9206578709560816
Recall	0.9213701829505644
Precision	0.9089861751152074

Table 4 BERT Model Results

	BERT Model
F1-Score	0.9383942766295708
Accuracy	0.9439725284655702
Recall	0.9280660377358491
Precision	0.9489549839228296

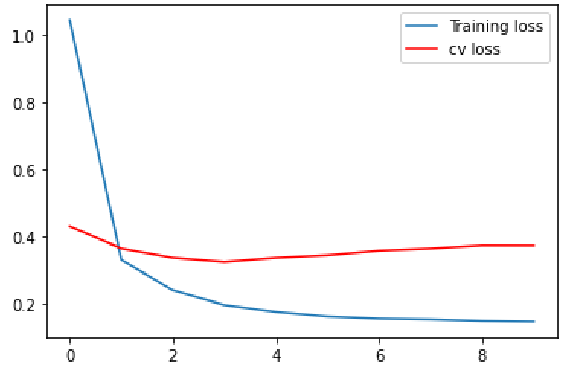

Figure 5 CNN+BiLSTM Loss Graph Before Glove Embeddings

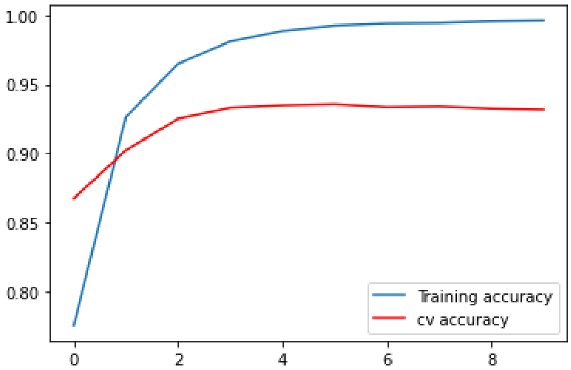

Figure 6 CNN+BiLSTM Accuracy Graph Before Glove Embeddings

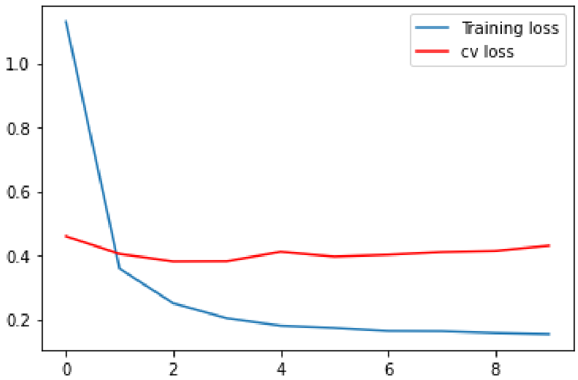

Figure 7 CNN+BiLSTM Loss Graph After Glove Embeddings

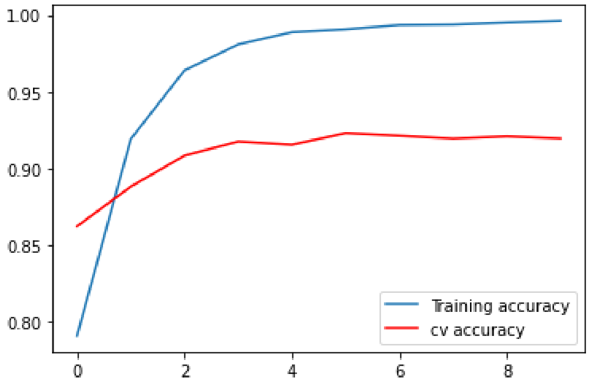

Figure 8 CNN+BiLSTM Accuracy Graph After Glove Embeddings

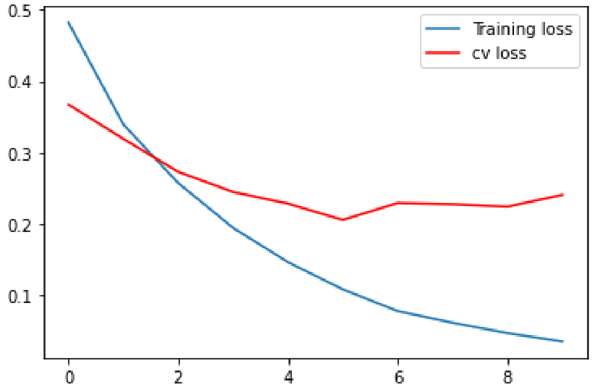

Figure 9 BERT Loss Graph

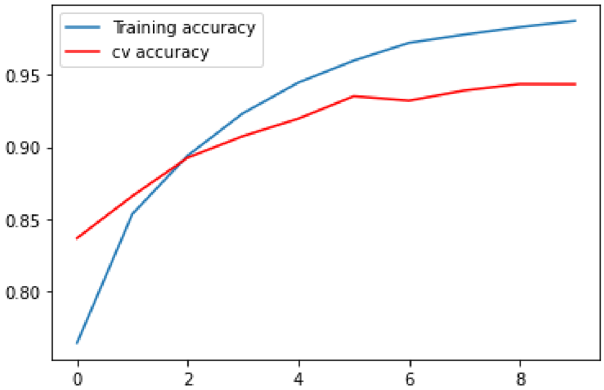

Figure 10 BERT Accuracy Graph

The difference between training and cross validation loss increased when glove embeddings were applied, as seen in Figures 5 and 7, the CNN+BiLSTM model's loss chart before and after applying glove embeddings. In the same way, when the accuracy graph is examined, it is seen that the difference has increased.

Figures 6 and 8 show accuracy graphs for the CNN+BiLSTM hybrid model with and without glove embeddings applied. It can be shown that training accuracy values outperform cross validation accuracy values in terms of accuracy rate.

There is a greater than expected disparity between the training and cross validation values, as can be observed when the loss graph of the BERT model in Figure 9 is inspected. However, it can be observed from Figure 10 that the accuracy graph of the BERT model declines when this difference is contrasted with that of the other model (CNN+BiLSTM).

V. Conclusion

The purpose of this study is to identify whether social media and internet headlines contain sarcasm. For this purpose, sarcasm detection was made with CNN+BiLSTM, a hybrid neural network model, and BERT, a pre-training model of natural language processing, using the dataset created by Misra and Arora in 2019 and shared for use in Kaggle.

Before anything further, it should be noted that when the data set is inspected, the data gathered from Twitter or other social networking sites can be quite noisy, poorly written, and occasionally even written in a way that is incomprehensible. However, the data set used in this study was prepared by collecting the titles of two professionally written news sites. In short, the data were collected as far away from noise as possible and intelligible. For this reason, data preprocessing has become much easier and more accurate results can be obtained.

If we look at the results of this study, the BERT model gave a much better result than the CNN+BILSTM model. In addition, metrics were checked without using Glove embeddings in the CNN+BiLSTM model, and then the results were compared by applying Glove embeddings. CNN+BiLSTM artificial neural network model, which is a hybrid model applied without glove embeddings, gave relatively better results.

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