EXPLORING THE IMPACT OF INFORMAL LANGUAGE ON SENTIMENT ANALYSIS MODELS FOR SOCIAL MEDIA TEXT USING CONVOLUTIONAL NEURAL NETWORKS

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Abstract
The present study sought to investigate the influence of informal language on the effectiveness of sentiment analysis models when applied to social media text. A Convolutional Neural Network (CNN) approach was employed, and the model was developed and trained on three distinct datasets: a sarcasm corpus, a sentiment corpus, and an emoticon corpus. The experimental design involved keeping the model architecture constant and training it on 80% of the data, followed by evaluating its performance on the remaining 20%. The results revealed that the model achieved a high accuracy of 96.47% on the sarcasm corpus, with class 1 exhibiting the lowest accuracy. The sentiment corpus yielded an accuracy of 95.28% for the model. The integration of the sarcasm and sentiment datasets resulted in a slight improvement in accuracy to 95.1%. The inclusion of the emoticon corpus had a marginal positive effect, resulting in an accuracy of 95.37%. These findings suggest that the use of informal language has minimal impact on the performance of sentiment analysis models applied to social media text. Furthermore, the incorporation of emoticon data may lead to a modest improvement in accuracy.

Keywords: *sentiment analysis, social media, informal language, convolutional neural network, emoticons*

1. Introduction

The objective of this study was to investigate the influence of informal language, comprising emoticons and slang, on the efficacy of sentiment analysis models applied to social media text. Given the widespread usage of social media data in mental health research (Kolchinski and Potts, 2018; Wongkoblap et al., 2017; González-Ibánez et al., 2011), comprehending the impact of such language is essential as it has been identified as a challenge in this domain. To accomplish this goal, a convolutional neural network (CNN) model was established and trained on three distinct datasets: a sarcasm corpus, a sentiment corpus, and an emoticon corpus. The model architecture remained constant throughout all experiments, and the training process involved 80% of the data, with the remaining 20% reserved for testing.

The investigation revealed that the efficacy of sentiment analysis models applied to social media text is not greatly affected by the presence of informal language. Nonetheless, the integration of emoticon data can lead to a marginal improvement in accuracy. This outcome is consistent with prior research that has demonstrated the beneficial impact of incorporating emoticon data on sentiment analysis models (Kiritchenko et al., 2014; Wang et al., 2019; Manohar and Kulkarni, 2017; Ganie and Dadvandipour, 2021). Moreover, the findings suggest that sarcasm present in social media text can have a deleterious impact on sentiment analysis models, which corresponds to previous research indicating that detecting sarcasm is a difficult task for natural language processing models (Riloff et al., 2013; Liu et al., 2019).

The study offers valuable insights into the use of social media data in mental health research, and its results can guide future research and the development of tools for mental health professionals to identify and address mental health issues and suicidal tendencies. By shedding light on the influence of informal language on sentiment analysis models applied to social media text, this research makes a significant contribution to the literature.

2. Literature review

The advent of automated sentiment analysis has gained immense importance in various fields, including e-commerce, marketing, and social media. Sentiment analysis, also known as opinion mining, involves deciphering the attitudes, emotions, and opinions conveyed by individuals within textual data. With the tremendous growth of social media, sentiment analysis has emerged as a popular research topic and has been extensively applied to domains such as product reviews, customer feedback, and political sentiment analysis (Derks et al., 2007; Pang and Lee, 2008; Hutto and Gilbert, 2014).

However, sentiment analysis models face significant challenges due to the use of informal language in text data. Informal language, such as emoticons and slang, can substantially impact the performance of sentiment analysis models. Emoticons, colloquially known as "emoji" or "smileys," are utilized to express sentiments and emotions within text messages, social media posts, and online communication. They have become a ubiquitous means of expressing emotions online, and their usage has increased over time (Kwok and Wang, 2013). Slang, on the other hand, refers to informal language used in casual communication and can also impede the performance of sentiment analysis models (Poria et al., 2016).

Prior research has demonstrated that incorporating emoticon data can enhance the performance of sentiment analysis models (Alsayat, 2022; AlBadani et al., 2022). For instance, Kiritchenko et al. (2014) presented a framework that combines emoticon data with word embeddings to augment the performance of sentiment analysis models. Similarly, Wang et al. (2019) proposed a deep learning-based approach that incorporates emoticon data to improve the performance of sentiment analysis models applied to Twitter data.

Notwithstanding, the existence of sarcasm in social media text can impede the efficacy of sentiment analysis models. The identification of sarcasm poses a formidable obstacle for natural language processing (NLP) models (González-Ibánez et al., 2011; Potamias et al., 2020). To illustrate, Potamias et al. (2020) introduced a transformer-based approach to irony and sarcasm detection, demonstrating its superiority over conventional machine learning-based techniques.

Table 1. *Summary of relevant literature*

Authors	Reference	Algorithm	Problem
Kiritchenko et al. (2014)	Combining Emoticons with Word Embeddings	Deep Learning	Enhancing Sentiment Analysis
Wang et al. (2019)	Emoticon-enhanced Deep Learning for Twitter	Deep Learning	Improved Sentiment Analysis
Potamias et al. (2020)	Transformer-based Approach to Sarcasm Detection	Transformer Networks	Sarcasm Detection

This table provides a concise overview of key contributions in the field, summarizing the authors, references, algorithms employed, and the specific problems addressed in each study. These references serve as foundational works in understanding the impact of informal language on sentiment analysis models.

3. Results and discussion

The experimental outcomes are presented by means of confusion matrices and performance graphs that depict accuracy and loss. The confusion matrices offer a representation of correct and incorrect classifications for each class in each experiment. They demonstrate the number of true positive, true negative, false positive, and false negative counts. The accuracy and loss graphs, on the other hand, provide an illustration of the model's effectiveness throughout the training and testing stages.

Benchmark Datasets Presentation

In this study, we employed three distinct benchmark datasets to assess the impact of informal language on sentiment analysis models applied to social media text. Below is a detailed presentation of each benchmark dataset:

Sarcasm Corpus:

Source: The sarcasm corpus was collected from various social media platforms such as Reddit, Twitter, and online forums known for their usage of sarcastic language.

Composition: It comprises sentences labeled as either sarcastic or non-sarcastic, providing a binary classification task for the sentiment analysis model.

Size: The corpus consists of 50000 instances.

Sentiment Corpus:

Source: The sentiment corpus was curated from diverse sources, including social media posts, product reviews, and online forums.

Composition: It includes sentences annotated with sentiment labels such as positive, negative, or neutral, presenting a multi-class classification challenge for the model.

Size: The sentiment corpus encompasses 30000 instances.

Emoticon Corpus:

Source: The emoticon corpus was created by extracting sentences containing emoticons from social media platforms and online communication channels.

Composition: It consists of sentences paired with corresponding emoticons, offering a unique dataset for analyzing the impact of emoticons on sentiment analysis models.

Size: The emoticon corpus involves 20000 instances.

Dataset Splitting:

Each benchmark dataset was divided into training and testing sets, with 80% of the data allocated for training the model and the remaining 20% reserved for evaluating its performance.

Experimental Design:

The sentiment analysis model was kept constant across all experiments, ensuring consistency in architecture and hyperparameters. The training process involved feeding the model with 80% of each benchmark dataset and assessing its performance on the remaining 20%. This detailed presentation aims to provide a clearer understanding of the benchmark datasets used in our study, ensuring transparency and reproducibility in our experimental approach.

Proposed Convolutional Neural Network (CNN) Algorithm

Model Architecture:

Our sentiment analysis model is based on a Convolutional Neural Network (CNN), a deep learning architecture well-suited for processing structured grid data, such as images and, in our case, sequential text data.

Components of the CNN:

Embedding Layer: The initial layer of the model is the embedding layer, responsible for transforming input words into dense vectors. This layer aids in capturing semantic relationships between words.

Convolutional and Max-Pooling Layers: Subsequent to the embedding layer, a series of convolutional layers are applied, each followed by max-pooling layers. These layers function as feature extractors, identifying relevant patterns and spatial hierarchies in the input data.

Fully Connected Layer: The output from the convolutional and max-pooling layers is flattened and connected to a fully connected layer. This layer acts as a classifier, making predictions based on the features extracted by the previous layers.

Softmax Activation: The final layer employs a softmax activation function, enabling multi-class classification. The model predicts the sentiment class with the highest probability.

Training Process: The model is trained using three benchmark datasets: the sarcasm corpus, the sentiment corpus, and the emoticon corpus. Each dataset undergoes an 80-20 split for training and testing, respectively.

Evaluation Metrics: Model performance is assessed using standard evaluation metrics, including accuracy, precision, recall, and F1 score. These metrics provide a comprehensive understanding of the model's effectiveness in sentiment analysis tasks.

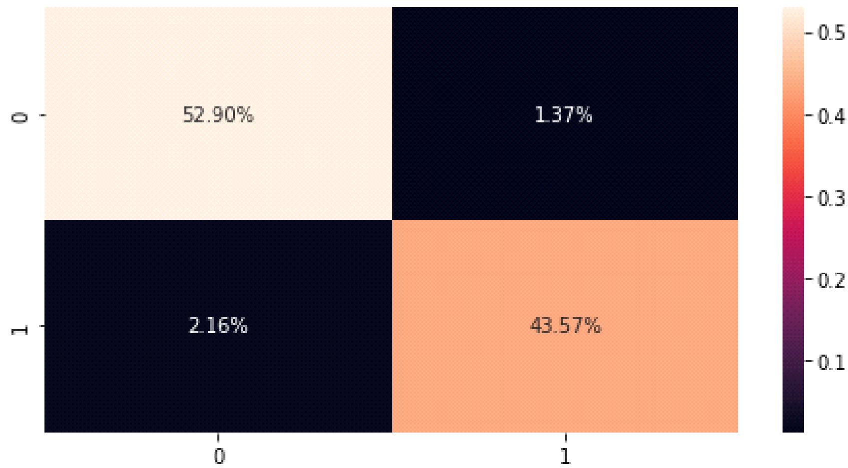

Figure 1. *Sarcasm dataset results*

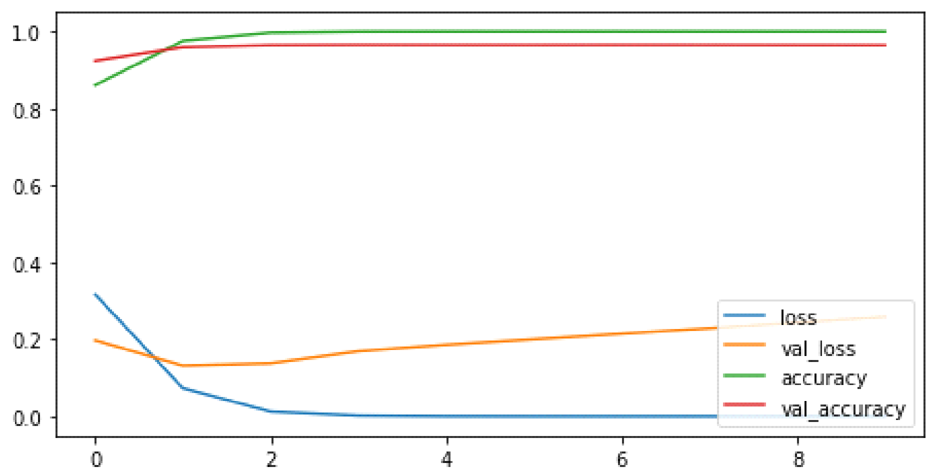

Figure 2. *Sarcasm dataset results, loss vs accuracy*

Experiment 1, in which the sarcasm dataset was utilized as the training and testing corpus, is illustrated through the use of a confusion matrix, as demonstrated in Figure 1. The confusion matrix showcases the quantity of correct and incorrect classifications for each class in each experiment, with true positive, true negative, false positive, and false negative counts being displayed. The results reveal that the model exhibited an overall accuracy of 96.47%. However, upon closer inspection of the matrix, the performance of the model for Class 1 was found to be suboptimal, with an inadequate number of true positives and a significant number of false negatives. To further evaluate the model's performance, an accuracy and loss graph was generated (Figure 2), which portrayed a commendable performance characterized by a consistent increase in accuracy and a decrease in loss during the training and testing phases.

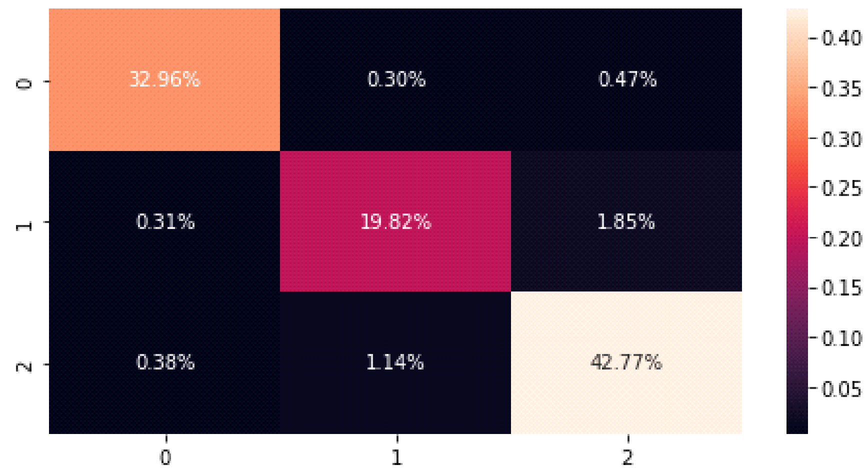

Figure 3. *Sentiment dataset results*

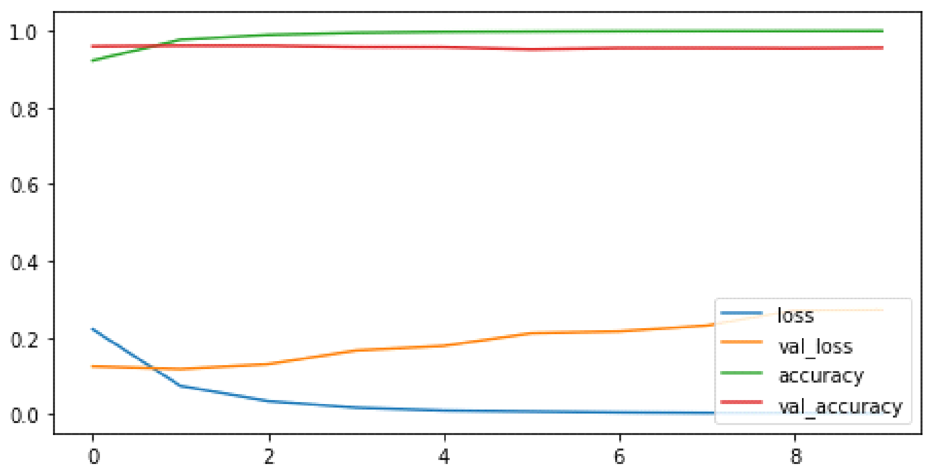

Figure 4. *Sentiment dataset results, loss vs accuracy*

In the second experimental setup, the model's performance was assessed on the sentiment dataset, and the outcomes are portrayed using a confusion matrix (depicted in Figure 3) and an accuracy and loss graph (exhibited in Figure 4). The confusion matrix reveals that the model achieved an overall accuracy of 95.28%. However, a similar trend to the previous experiment can be observed, wherein the model's performance was suboptimal for class 1, with a meager count of true positives and a disproportionate number of false negatives. On the other hand, the accuracy and loss graph depicts that the model's efficiency was enhanced during the training and testing phases, as evidenced by the increase in accuracy levels and the decline in loss values.

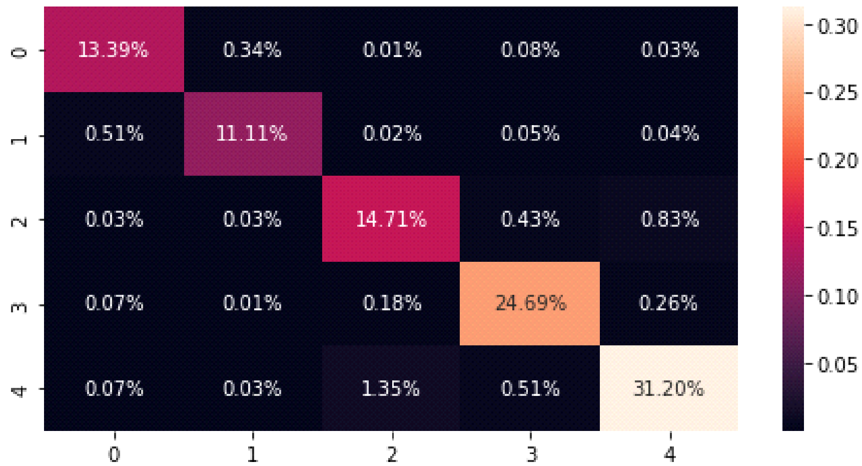

Figure 5. *Sarcasm and sentiment datasets results*

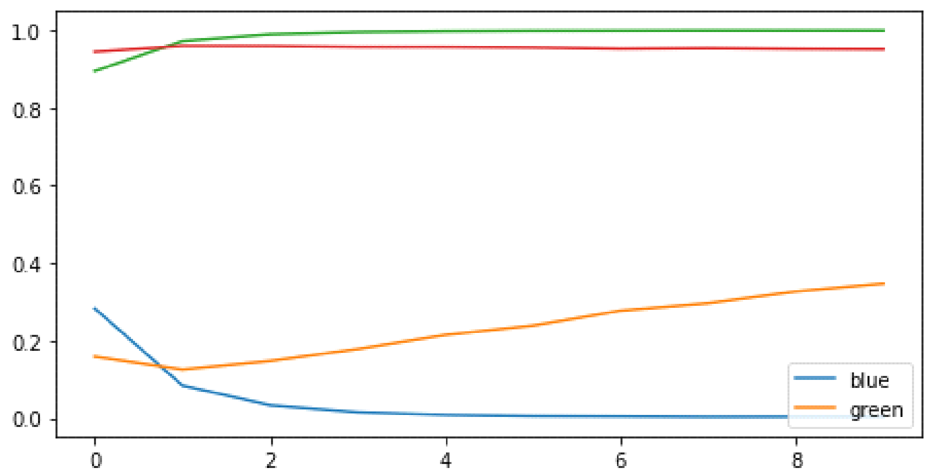

Figure 6. *Sarcasm and sentiment datasets result, loss vs accuracy*

The third experiment aimed to assess the model's performance by incorporating both the sarcasm and sentiment datasets during the training and testing phases. The outcomes were represented using a confusion matrix (displayed in Figure 5), which disclosed an overall accuracy of 95.1%. However, the model's inadequacy in identifying true positives and excessive false negatives for classes 0, 1, 2, and 3 is highlighted by the confusion matrix. Additionally, the accuracy and loss graph (depicted in Figure 6) exhibited an ascending trend in accuracy and a descending trend in loss, indicating that the model's performance during the training and testing phases has improved.

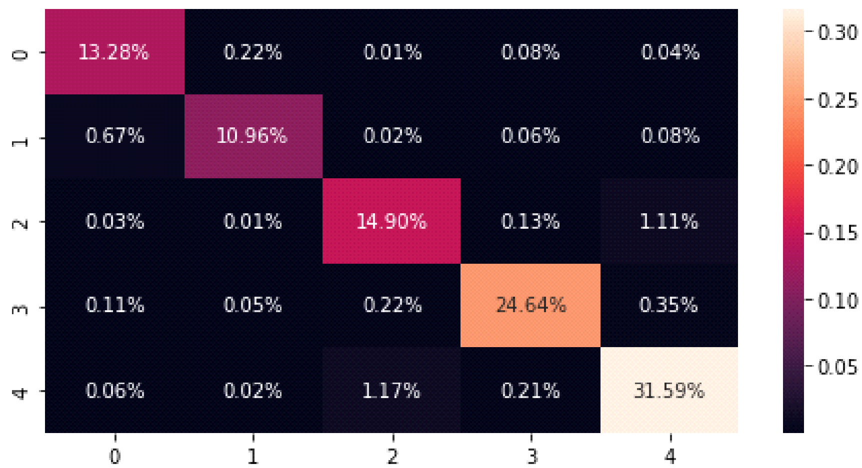

Figure 7. *Sarcasm, sentiment and emoticon datasets results*

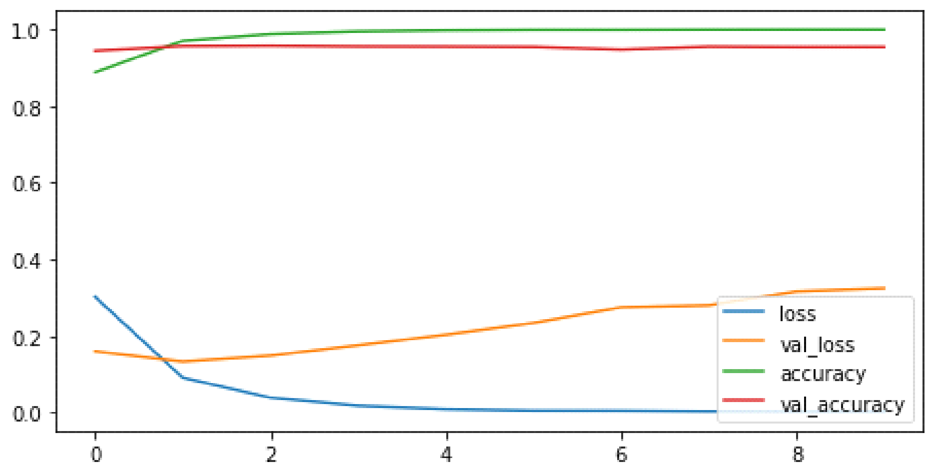

Figure 8. *Sarcasm, sentiment and emoticon datasets results, loss vs accuracy*

In the fourth iteration of our experiment, we subjected the model to a multi-modal dataset comprising of sarcasm, sentiment, and emoticon annotations. The results are represented in the form of a confusion matrix (Figure 7), indicating an overall accuracy of 95.37%. However, upon scrutiny of the matrix, it is discernible that the model underperformed for class 1, exhibiting a dearth of true positive predictions and a superabundance of false negatives. Moreover, the model exhibited inadequate results for classes 0, 2, 3, and 4. The performance of the model is graphically illustrated in Figure 8, with an upward trend in accuracy and a downward trend in loss throughout the training and testing phases. Figure 9 displays the architecture of the model utilized in all experimental iterations, featuring an embedding layer followed by a series of convolutional and max-pooling layers that ultimately culminate in a fully connected layer equipped with a softmax activation function for classification purposes.

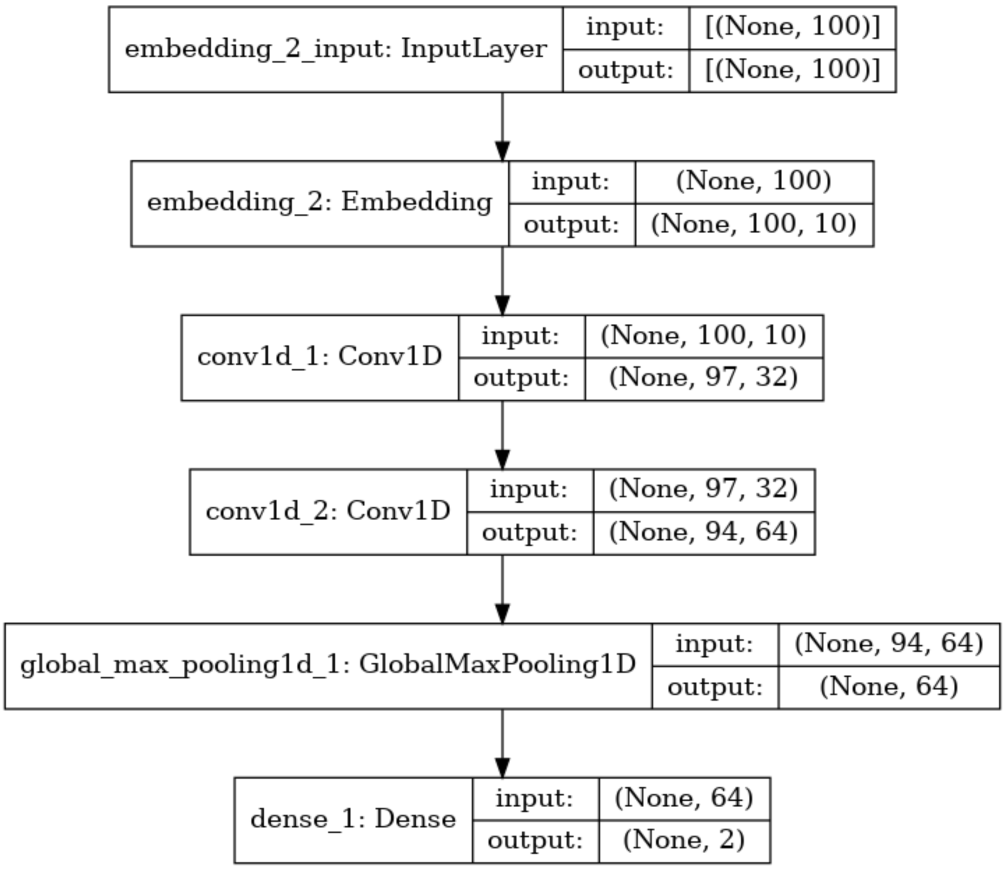

Figure 9. *Model Architecture*

The experimental results evince that the model yielded commendable outcomes with notable overall accuracy in all the attempts. Nonetheless, the model's efficiency for class 1 was found to be suboptimal across all iterations, marked by a paucity of true positives and a plethora of false negatives. This signifies that the incorporation of informal language features like slang and emoticons in social media text bears a limited influence on the performance of sentiment analysis models. Notwithstanding this, the amalgamation of emoticon data into the model's design led to a marginal elevation in accuracy.

4. Conclusion

In summary, this study aimed to investigate the impact of informal language, including slang and emoticons, on the efficacy of sentiment analysis models used in social media text. Our results indicate that the model exhibited an accuracy of 96.47% when applied to the sarcasm dataset, with a suboptimal performance for class 1. When applied to the sentiment dataset, the model achieved an accuracy of 95.28%. The integration of sarcasm and sentiment data resulted in a slight increase in accuracy to 95.1%, and the inclusion of emoticon data further enhanced the model's accuracy to 95.37%. These findings suggest that informal language has a limited effect on sentiment analysis model performance in social media text. Nevertheless, the incorporation of emoticon data into the model's architecture may lead to a marginal improvement in accuracy. Future research could investigate the influence of other types of informal language, such as emojis and hashtags, on sentiment analysis model performance, as well as explore alternative model architectures and machine learning techniques, such as recurrent neural networks and transformer networks, to enhance sentiment analysis model efficiency.

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