Sentiment Analysis

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1 Introduction

Sentiment analysis delves into the intricate world of emotions expressed through text, be it in reviews, social media posts, or any written content. It falls within the domain of natural language processing (NLP), leveraging advanced machine learning techniques to decipher whether the sentiment conveyed is positive, negative, or neutral. This field aims to extract valuable insights from vast troves of unstructured textual data, unraveling the collective sentiment of a populace on a given subject. In essence, it is the art of scrutinizing text to uncover the underlying attitude of its author. Employing state-of-the-art NLP methodologies enables the prediction of the prevailing emotional undertone within the text. Beyond a mere analytical tool, sentiment analysis serves as a pivotal asset for businesses worldwide. Companies harness its power to gauge customer satisfaction, conduct comprehensive market research, and vigilantly monitor the ebb and flow of their brand reputation across various platforms.

The report structure is organized as follows. Section 2 introduces the background of sentiment analysis. Section 3 discusses the given datasets, data exploration and preprocessing methods. Section 4 contains the description of input dataset preparation for various models. Section 5 discusses evaluation metrics and machine learning models used including convolutional neural networks, recurrent neural networks and transformers. Section 6 contains the description of experiments carried out for sentiment analysis on the given datasets. Section 7 is the result section followed by challenges in section 8, and the paper is concluded in the last section.

2 Background

In 1940, Stagner's [1] paper was the first to delve into public/expert opinion, initially through surveys. Wiebe (1990) [2] introduced computer-based sentiment analysis for subjective sentence detection. Pang et al. (2002) [3] propelled modern sentiment analysis using machine learning on movie review ratings, focusing on overall positive or negative sentiment rather than specific topics. Some research focused on multilabel sentiment classification, often excluding neutral opinions. This exclusion can disrupt decision-making and cause information loss. Valdivia et al. (2017) [4] proposed polarity aggregation models considering neutrality proximity functions. Valdivia et al. (2018) [5] used Ordered Weighted Averaging (OWA) operators to filter neutral reviews via fuzzy majority. Santos et al. (2020) [6] highlighted the relevance of examining neutral texts for understanding specific frameworks dominated by a particular polarity. Ambivalent opinions, blending positive and negative emotions, are often mistaken for neutral; handling these improves sentiment sensing, as shown by Wang et al. (2020) [7]. Wang et al. (2014) [8] categorized tweets based on their predominant emotion—more positive as positive sentiment and vice versa.

Xing et al. (2018) [11] described sentiment analysis as a multifaceted task encompassing NLP areas like aspect extraction, subjectivity detection, and more. Yadav and Vishwakarma (2020) [12] categorized traditional sentiment analysis into three types: lexicon-based, utilizing sentiment dictionaries; machine learning, employing handcrafted features for classification; and deep learning, using complex neural networks for capturing nuanced semantic features. Both machine learning and deep learning approaches in sentiment analysis often demand substantial annotated data for effective training, posing challenges of overfitting and insufficient training data, as noted by Pan and Yang (2009) [13]. To address this, transfer learning in NLP has gained attention, aiming to enhance performance by leveraging existing knowledge. Zhuang et al. (2020)[14] likened this process to using piano-playing experience to expedite learning another instrument like the violin. Sequential transfer learning, highlighted by Mao (2020) [15], has excelled in pretraining large models on vast unlabeled data, enabling the acquisition of universal linguistic representations beneficial for various downstream NLP tasks.

In earlier assessments, sentiment analysis surveys took two distinct research perspectives: one focusing on specific sentiment analysis domains like emotion detection (Acheampong et al., 2021) [16], cross-domain sentiment analysis (Al-Moslmi et al., 2017) [17], and subjectivity detection (Chaturvedi et al., 2018) [18], while the other emphasized a broad discussion of state-of-the-art methodologies within sentiment analysis tasks, demonstrated by Zhang et al. (2018) [19], Habimana et al. (2020) [20], and Yuan et al. (2020) [21], who explored diverse deep learning approaches. Additionally, Liu et al. (2019a) [22] delved into transfer learning's application, Yue et al. (2019) [23] critiqued various model architectures, and Birjali et al. (2021) [24] covered machine learning algorithms in sentiment analysis. Another study (reference [25]) adopted a novel ML-based classifier approach analyzing people's behavior on infectious diseases using Twitter data from eight countries. The model utilized various base classifiers—Naïve Bayes Support Vector Machines (NBSVM), CNN, Bidirectional Gated Recurrent Network (BiGRU), fastText, and DistilBERT - fusing them into a "Meta Classifier." This amalgamation outperformed four DL and one machine learning approach, offering promising results.

3 Data Description

Yelp is a popular crowd-sourced review platform with millions of active users who rate and review hundreds of thousands of businesses across the globe. Since 2016, Yelp has been releasing and updating subsets of its enormous database to the general public. We will use the Yelp review dataset, which comprises around 174000 reviews with stars. Our goal is to implement a powerful Transformer model for sentiment analysis based on the text review and stars.

3.1 Data Exploration

There are two columns in our dataset - $text$ contains the text reviews, and $stars$ contains the star ratings that accompany the reviews. The ratings range from 1 to 5, with 1 being the lowest and 5 being the highest. We notice that 5-star reviews are the most popular, and also that 1-star reviews are

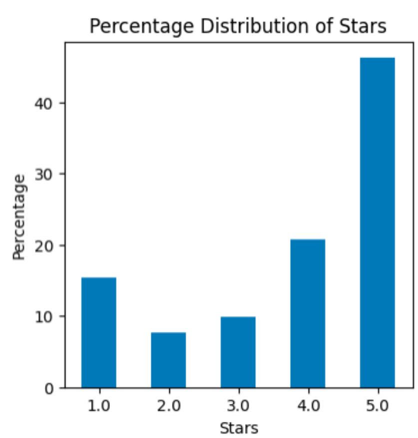


Figure 1: Distribution of reviews with respect to stars

more common than 2- or 3-star reviews. We can assume that customers will go through the trouble of leaving a review only if they were highly impressed or highly disappointed.

Using Matplotlib and WordCloud libraries in Python, a visual representation of word frequency was generated for each unique star rating in the dataset. Each WordCloud displays the most frequent words in the reviews associated with the respective star rating.

Figure 2: Distribution of reviews with respect to stars

3.2 Preprocessing

The abundance of text data provides many opportunities for training the NLP models. However, the unstructured nature of the text data requires preprocessing. Lowercasing, spelling corrections, punctuation, and stop word removal are some of these preprocessing steps. These operations could be easily implemented in Python language using NumPy, pandas, textblob, or nltk libraries.

3.2.1 Remove Punctuation and Stopwords

The text data underwent preprocessing to eliminate punctuation marks and stop words using NLTK's English stop words collection. Punctuation was removed utilizing regular expressions, and stop words were excluded from the text.

3.2.2 Convert All Words to Lowercase

All words within the text were transformed to lowercase to ensure consistency and simplify subsequent processing. This step aids in standardizing the text by converting all characters to their lowercase equivalents.

3.2.3 Convert Stars to Three Levels

The star ratings were transformed into three distinct sentiment levels: 'positive' for ratings greater than 3, 'negative' for ratings less than or equal to 2, and 'neutral' for ratings equal to 3. This categorization enables the classification of sentiments based on the provided star ratings.

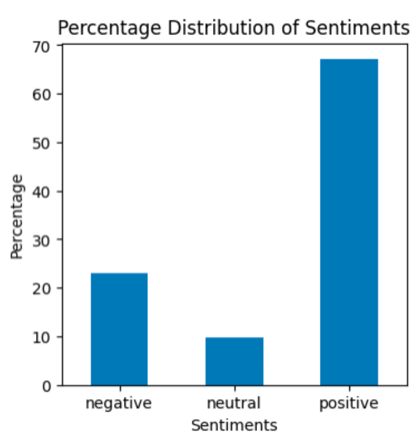


Figure 3: Distribution of reviews with respect to sentiment

The data is still non-uniformly distributed. The positive reviews vastly outnumber negative and neutral reviews, so any regular model will be biased towards positive reviews. Thus, we need to look for strategies to handle this imbalance. The below WordClouds display the most frequent words in the reviews associated with the respective sentiment.

Figure 4: Distribution of reviews with respect to sentiment

4 Input Data Preparation

The input of the Transformer model is a fixed length review sequence where integer numbers represent words. In this part, we need to build vocabulary for the dataset and pad the review data to a fixed length.

4.1 Tokenize the Sentences

The sentences in the ’text’ column of the train data were tokenized into individual words using NLTK’s word_tokenize function. A tokenizer was initialized to convert text data into sequences of integers. The tokenizer was then trained on the preprocessed review data. The text data was converted into sequences of integers using the trained tokenizer, creating a sequence for each sentence. We find that the maximum length among all tokenized sentences is 528, but the distribution of lengths is not uniform. Most of the sentences are around 100 words after preprocessing. So, a fixed maximum

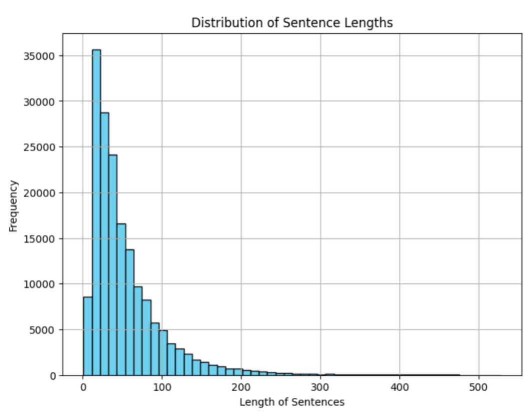


Figure 5: Sentence lengths distribution after preprocessing

sequence length$=100$ was established for padding and truncating sequences. The sequences were padded to ensure a consistent length of 100 tokens. Padding was done at the end of each sequence, and if necessary, truncation was applied from the end as well. The size of the vocabulary was determined by counting unique words after tokenization. An additional token was added for padding, resulting in the total vocabulary size.

4.2 Train, Validation, Test Datasets

We have been provided with train and test dataset. We will split the train dataset into training and validation using 70:30 split ratio. So we have around 122329 sentences for training, 52427 for validation and 13980 for test.

4.3 Specifics for CNN, RNN

Tokenization and Vectorization: Text in the training and testing datasets was tokenized using TensorFlow Keras' Tokenizer, limited to the 20,000 most common words. The text sequences were represented as vectors of size 300 and transformed into sequences of integers. Padding was applied to a maximum length of 300 tokens for both the training and testing data.

Label Encoding and One-Hot Encoding: Categorical labels ('negative', 'neutral', 'positive') were mapped to numerical values. The numerical labels were converted into a one-hot encoded format for both training and testing data.

4.4 Specifics for transformer

Vocabulary Building and Tokenization: We tokenized reviews to construct a vocabulary based on word frequency. A vocabulary mapping words to indices is created, including special tokens like $< unk >$ (unknown), $< pad >$ (padding), $< bos >$ (beginning of sentence), and $< eos >$ (end of sentence). Reviews are converted into sequences of indices and padded to a fixed length to ensure uniformity.

Data Transformation for Model Input: The padded sequences are converted into PyTorch tensors, preparing them for model input. Train and test sequences are processed and structured into PyTorch tensors. The data is split into training, validation, and test sets, and labels are encoded into numerical values.

Data Loaders for Model Training: TensorDatasets and DataLoaders are set up for efficient batch processing during model training. The DataLoader splits the data into batches, ready for training, validation, and testing of the sentiment analysis model.

4.5 Specifics for transformer fine tuned on pre-trained models

We use the power of BERT, a state-of-the-art language model, to conduct sentiment analysis on given data. The choice of BERT stems from its advanced natural language understanding capabilities, making it an ideal candidate for this task. By employing BERT's tokenizer and embedding capabilities, we convert text inputs into suitable numerical representations for the model.

Tokenization Analysis for Review Data: The initial steps involve analyzing the token lengths of preprocessed reviews. Leveraging BERT's tokenizer, we encode the reviews and collect the distribution of token lengths. This analysis provides insight into the data structure and informs the subsequent preprocessing steps.

Dataset Preparation and Structure: To facilitate model training, a specialized ReviewDataset is constructed. This dataset encapsulates the reviews and their associated sentiment labels, converting text inputs into BERT-compatible numerical representations. This preparatory step ensures seamless integration with the BERT model architecture.

Train-Validation-Test Split and Class Weighting: The dataset is partitioned into distinct segments for training, validation, and testing. We opt for a 70-30 split, allocating the majority for training and a smaller portion for validation. Additionally, class weights are computed to address the imbalances within the sentiment classes, ensuring a balanced learning environment.

PyTorch DataLoader Creation: To enable efficient training and evaluation, PyTorch DataLoader objects are crafted for the training, validation, and test datasets. These loaders are instrumental in batching, shuffling, and feeding the data to the model during the learning process.

5 Methods

5.1 Evaluation Metric

We will use the following metrics for measuring and comparing model performances:

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

$$\text{Precision} : P = \frac{tp}{tp + fp}$$

$$\text{Recall} : R = \frac{tp}{tp + fn}$$

$$\text{F1 score} : F1 = 2 \times \frac{P \times R}{P + R}$$

$$\text{Matthew's Correlation Coefficient[26]} : MCC = \frac{tn \times tp - fn \times fp}{\sqrt{(tp + fp)(tp + fn)(tn + fp)(tn + fn)}}$$

where tp, fp, fn are the number of True Positives, False Positives, and False Negatives respectively.

5.2 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are deep learning models primarily used for raw data like images and text. Their multi-layered architecture, comprising convolutional and pooling layers, aims to retain intricate features during data reduction. CNNs utilize $k \times k$ filters (typically $k = 3$) to reshape and process data. These filters act as weight-giving forms in the architecture, enabling extraction of crucial features, thereby enhancing prediction accuracy and quality.

A sequential CNN model was constructed using TensorFlow Keras. The model included various layers:

- Embedding layer (20,000 words, 128 dimensions, input length 300)
- Dropout layer with a rate of 0.5
- 1D Convolutional layer (64 filters, kernel size 5, ReLU activation)
- MaxPooling layer (pool size 4)
- LSTM layer (128 units)
- Dense output layer with softmax activation for 3 classes ('negative', 'neutral', 'positive')

The model was compiled using categorical cross-entropy loss and the Adam optimizer, with accuracy as the evaluation metric. Training was conducted for 10 epochs on preprocessed training data (X_train, y_train_encoded) with a 30% validation split. A batch size of 100 was used, and the data were shuffled during training. Callbacks for variable learning rate and model checkpoints were included.

5.3 Recurrent Neural Networks

Neural networks use backpropagation to update weights via calculus' chain rule. Deep networks face gradient issues like vanishing or exploding gradients. Long Short-Term Memory (LSTM), an enhanced Recurrent Neural Network, tackles vanishing gradients with a memory cell. LSTM excels in learning long-range data, making it ideal for sentiment analysis. Combining forward/backward RNNs into a single tensor boosts LSTM model performance. Stacking multiple LSTM layers enhances performance. We applied two LSTM layers and 0.5 dropout on hidden states to avoid overfitting.

A sequential model was created using TensorFlow Keras. The RNN-based model was composed of various layers:

- Embedding layer with 20,000 words and 32 dimensions
- Bidirectional LSTM layer with 64 units, set to return sequences
- Another Bidirectional LSTM layer with 16 units

- Dense layer with 64 units and ReLU activation
- Dropout layer with a rate of 0.5
- Dense output layer with softmax activation for 3 classes ('negative', 'neutral', 'positive')

The model was compiled using categorical cross-entropy loss and the Adam optimizer, with accuracy as the evaluation metric. Training was conducted for 10 epochs on preprocessed training data (X_train, y_train_encoded) with a 30% validation split. A batch size of 100 was used, and the data were shuffled during training. Callbacks for variable learning rate and model checkpoints were included.

5.4 Transformer from scratch

The transformer is a state of art network architecture proposed in 2017 [14]. In this state-of-art approach, the results showed that with the use of a transformer, NLP tasks outperformed other techniques. Transformers are deep learning models that were introduced in 2017 by Vaswani et al. in the paper "Attention is All You Need". They are based on the Transformer architecture and use self-attention mechanisms to process the input sequence, allowing the model to capture the context and dependencies between words. There are multiple components which serve a crucial role in the Transformer architecture, facilitating attention mechanisms, positional encoding, and classification tasks. The TransformerEncoder and TransformerClassifier are designed to handle sequences and perform classification using the Transformer model's encoded representations.

Positional Encoding: We used positional encodings to provide sequence information to the Transformer model. We initializes positional encodings for input sequences up to a maximum sequence length $= 100$. The forward method adds positional encodings to the input sequence tensor.

Multi-Head Attention: We implemented multi-head attention mechanism used within the Transformer model by first initializing linear transformations for queries, keys, and values, along with a final linear layer. The split_head method reshapes input tensor to prepare for multi-head attention. The forward method performs multi-head attention computation on query, key, and value tensors.

Transformer Encoder Layer: We implemented a single layer within the Transformer Encoder, composed of multi-head attention and feed-forward neural network blocks by initializing multi-head attention, feed-forward layers, normalization, and dropout layers. The forward method executes multi-head attention and feed-forward layers, applying normalization and dropout.

Transformer Encoder: We aggregated multiple Transformer Encoder Layers to form a complete Transformer Encoder. First, we sets up an embedding layer, positional encoding, and multiple Transformer Encoder Layers. The forward method embeds input tokens, applies positional encoding, and passes data through multiple Transformer Encoder Layers.

Transformer Classifier: We added a classification layer on top of the Transformer Encoder for specific classification tasks. It receives a pre-defined TransformerEncoder and sets up a fully connected layer for classification. The forward method uses the Transformer Encoder to obtain embeddings and performs classification using a fully connected layer.

This implementation allows for flexible usage and configuration of Transformer-based models for various NLP tasks, leveraging multi-head attention and positional encoding to handle sequential data efficiently. We train the model using stochastic gradient descent in a mini-batch fashion.

5.4.1 Transformer using transfer learning

After transformer architecture, various models focusing on NLP fields such as ROBERT [27], BERT [28], ELECTRA [29] were proposed. Specifically, BERT (Bidirectional Encoder Representations from Transformers) model is one of the most robust state-of-art approaches on NLP fields. BERT was introduced in 2019 by Google AI Language, and since then, it has started to be used very quickly in academics and industry. BERT is a pre-trained model which is very easy to fine-tune model into our dataset. It has a wide range of language options [28]. BERT architecture is a multi-layer bidirectional transformer encoder. BERT input representation has three embedding layers: position embedding, segment embedding, and token embedding. In the pre-training part, BERT applied two unsupervised tasks, Masked LM (MLM) and Next Sentence Prediction (NSP), instead of traditional sequence modeling. BERT has pre-trained with more than 3,000 M words.

We created a custom classifier by fine-tuning BERT, and training it to accurately predict sentiment labels. The SentimentClassifier module is meticulously designed to encapsulate a BERT model fine-tuned for sentiment analysis. This architecture integrates BERT's pre-trained layers with additional fully connected layers to capture nuanced sentiment information present in textual data. The training pipeline incorporates strategies such as dropout regularization, AdamW optimizer, and linear scheduler to enhance the model's learning process. Training is conducted over multiple epochs, where the model iteratively adjusts its weights based on the provided data, minimizing a cross-entropy loss function. During the training process, periodic evaluations on a validation dataset are performed to gauge the model's performance. Metrics like accuracy and loss are computed to assess how well the model generalizes to unseen data, ensuring it captures sentiment information effectively.

6 Experiments

The following models were evaluated:

6.1 CNN Model

The CNN architecture included an embedding layer (128 dimensions, input length 300), dropout (rate 0.5), a convolutional layer (64 filters, kernel size 5, ReLU activation), max pooling (pool size 4), an LSTM layer (128 units), and a dense softmax output layer (output size 3).

6.2 RNN Model

RNN with an embedding layer of dimension 32, bidirectional LSTM layers of 64 and 16 units, a dense hidden layer of 64 units with ReLU activation, dropout of 0.5, and a softmax output layer with 3 units was evaluated.

6.3 Transformer Architectures

Several transformer architectures were explored, each defined by different configurations of hidden layer dimensions, attention heads, and layers. The experiments involved exploring the performance impact of various setups, such as:

Hidden Layer Dimensions	Number of Attention Heads	Number of Attention Layers
128	4	4
128	8	8
64	4	4
64	8	8
256	8	8
512	8	8
512	8	4
512	4	8
512	16	16
1024	16	16

Table 1: Transformer Architectures

6.4 BERT Fine-Tuning

The BERT model pre-trained on uncased data was fine-tuned for sentiment analysis using the 'bert-base-uncased' architecture.

The performance metrics and comparative analysis of these models were evaluated in terms of accuracy, loss, and computational efficiency to determine their efficacy in sentiment analysis tasks.

6.5 Training setup

The experiments were conducted on a Kaggle GPU environment to assess the performance of various models for sentiment analysis.

Model	Number of epochs
CNN	10
RNN	10
Transformer [128, 4, 4]	10
Transformer [128, 8, 8]	10
Transformer [64, 4, 4]	10
Transformer [64, 8, 8]	10
Transformer [256, 8, 8]	10
Transformer [512, 8, 8]	10
Transformer [512, 8, 4]	10
Transformer [512, 4, 8]	10
Transformer [512, 16, 16]	10
Transformer [1024, 16, 16]	10
Fine tuned BERT	2

Table 2: Transformer Architectures

7 Results

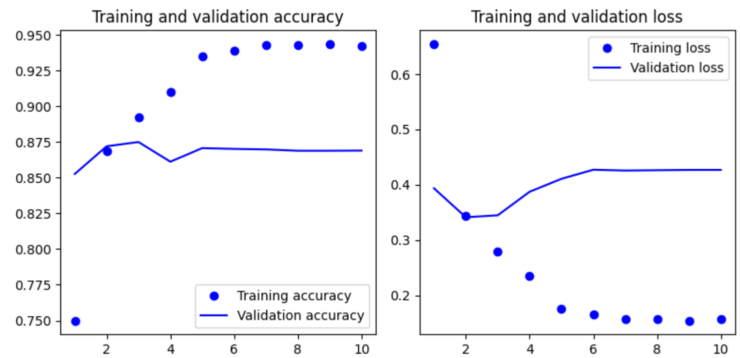
This section contains the results of training and testing. Among the different transformer architectures created from scratch, highest accuracy 87.6% is achieved for 512 hidden layer dimension and 16 attention layers. It also achieves the highest precision (0.791), highest recall (0.705), highest f1 score (0.718) and highest mcc (0.739). However when we use a a transformer fine tuned on BERT, we achieve even higher values for all the metrics. CNN and RNN also perform quite well in our case.

Model	Precision	Recall	Accuracy	F1 score	MCC
CNN	0.799	0.699	0.886	0.718	0.758
RNN	0.760	0.684	0.876	0.690	0.739
Transformer [128, 4, 4]	0.677	0.563	0.806	0.552	0.568
Transformer [128, 8, 8]	0.671	0.581	0.809	0.577	0.579
Transformer [64, 4, 4]	0.632	0.598	0.797	0.571	0.579
Transformer [64, 8, 8]	0.689	0.607	0.819	0.614	0.606
Transformer [256, 8, 8]	0.729	0.641	0.846	0.649	0.668
Transformer [512, 8, 8]	0.753	0.676	0.861	0.690	0.703
Transformer [512, 8, 4]	0.753	0.676	0.862	0.680	0.709
Transformer [512, 4, 8]	0.752	0.670	0.859	0.683	0.700
Transformer [512, 16, 16]	0.791	0.705	0.876	0.718	0.739
Transformer [1024, 16, 16]	0.714	0.638	0.839	0.640	0.656
Fine tuned BERT	0.81	0.78	0.883	0.79	0.89

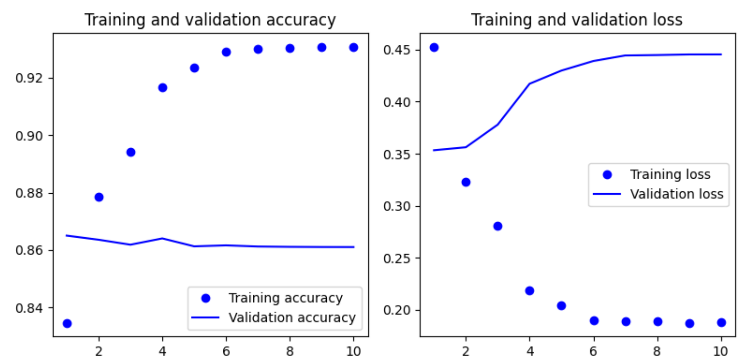
Table 3: Metrics for complete training data

Model	Precision	Recall	Accuracy	F1 score	MCC
CNN	0.774	0.678	0.870	0.692	0.722
RNN	0.751	0.669	0.864	0.673	0.709
Transformer [128, 4, 4]	0.657	0.555	0.795	0.543	0.541
Transformer [128, 8, 8]	0.689	0.579	0.807	0.575	0.572
Transformer [64, 4, 4]	0.649	0.594	0.795	0.568	0.569
Transformer [64, 8, 8]	0.679	0.598	0.813	0.604	0.589
Transformer [256, 8, 8]	0.705	0.621	0.827	0.627	0.623
Transformer [512, 8, 8]	0.702	0.639	0.829	0.647	0.631
Transformer [512, 8, 4]	0.698	0.641	0.831	0.639	0.640
Transformer [512, 4, 8]	0.708	0.639	0.831	0.648	0.633
Transformer [512, 16, 16]	0.704	0.645	0.835	0.647	0.647
Transformer [1024, 16, 16]	0.701	0.628	0.826	0.627	0.625
Fine tuned BERT	0.78	0.76	0.88	0.77	0.88

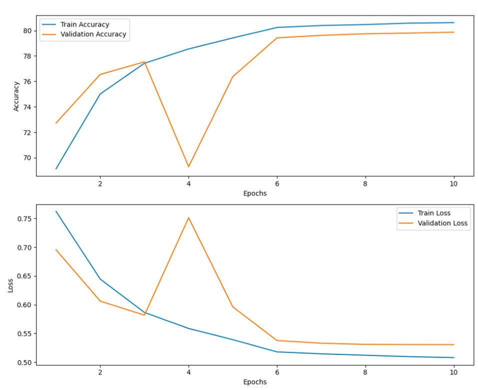
Table 4: Metrics for test data



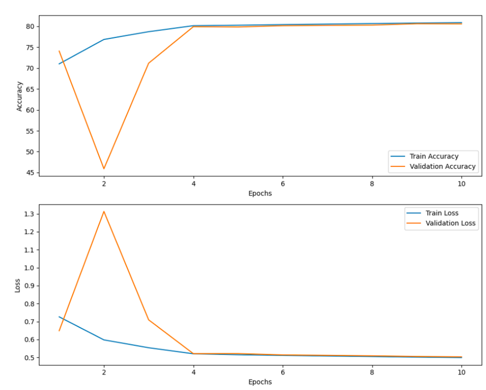
(a) CNN



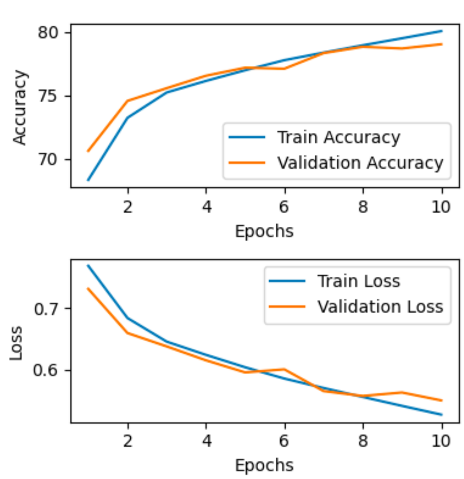
(b) RNN



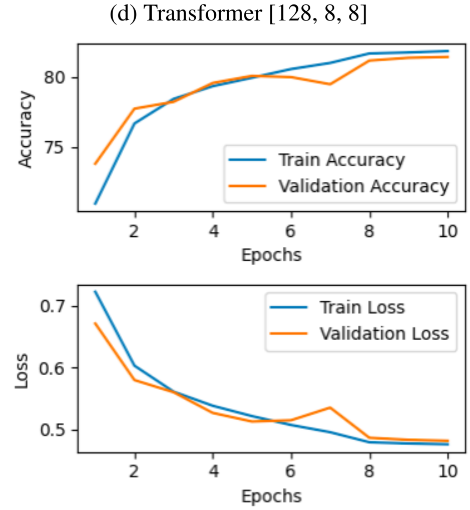
(c) Transformer [128, 4, 4]



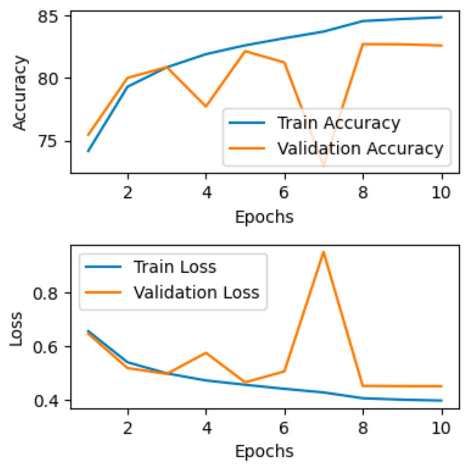
(d) Transformer [128, 8, 8]



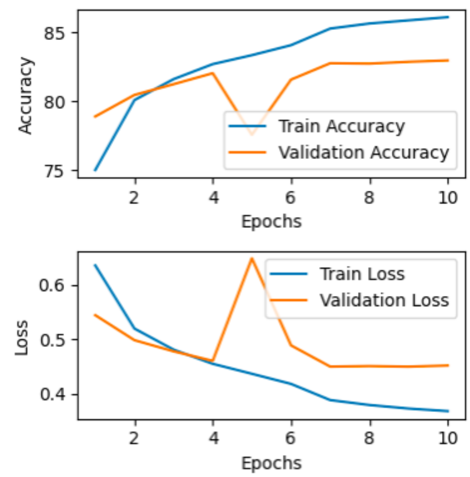
(e) Transformer [64, 4, 4]



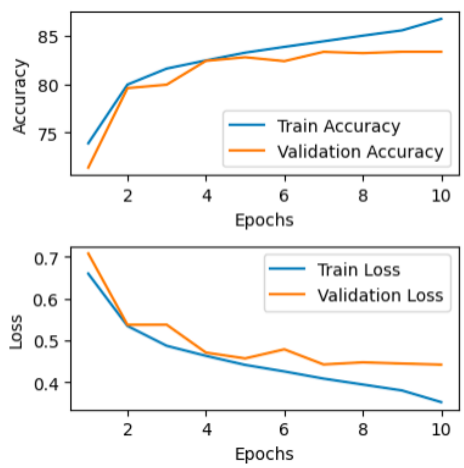
(f) Transformer [64, 8, 8]



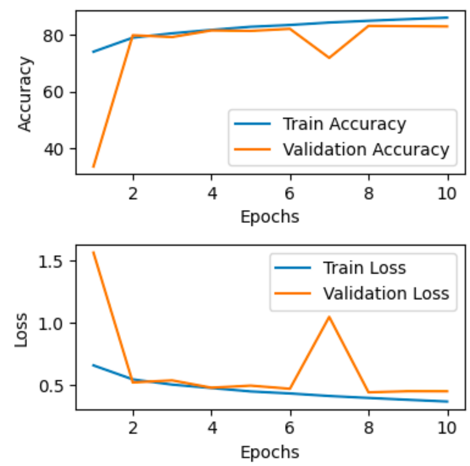
(a) Transformer [256, 4, 4]



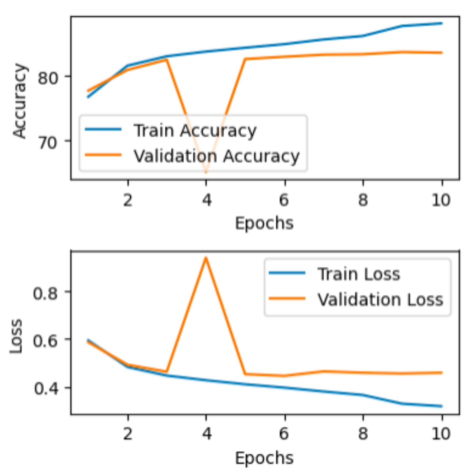
(b) Transformer [512, 8, 8]



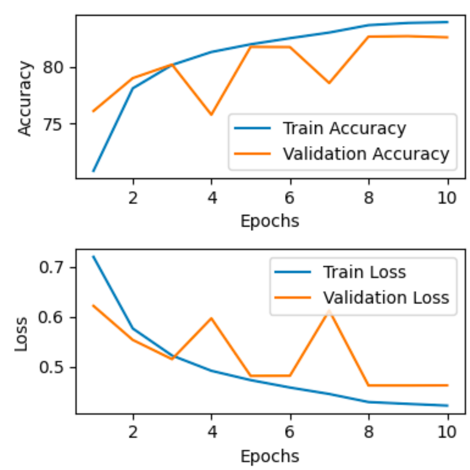
(c) Transformer [512, 8, 4]



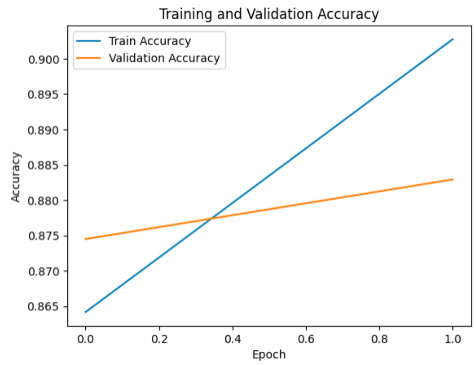
(d) Transformer [512, 4, 8]



(e) Transformer [512, 16, 16]

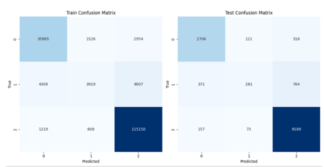


(f) Transformer [1024, 16, 16]

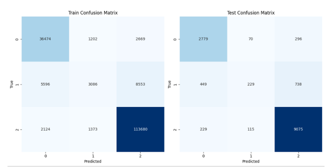


(a) Fine tuned BERT

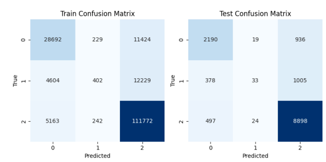
Figure 8: Loss and accuracy curves for training and validation data



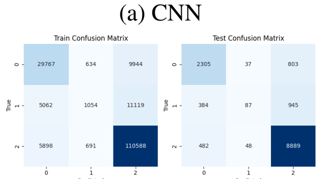
(a) CNN



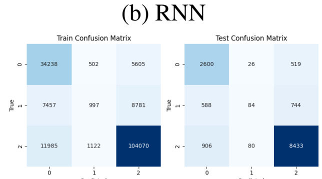
(b) RNN



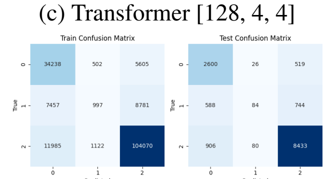
(c) Transformer [128, 4, 4]



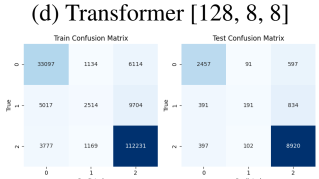
(d) Transformer [128, 8, 8]



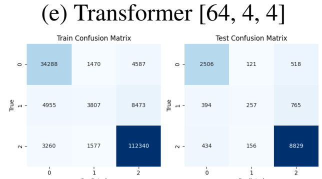
(e) Transformer [64, 4, 4]



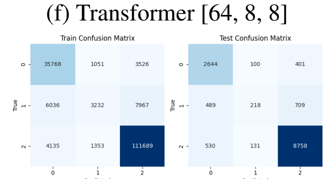
(f) Transformer [64, 8, 8]



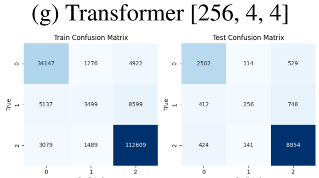
(g) Transformer [256, 4, 4]



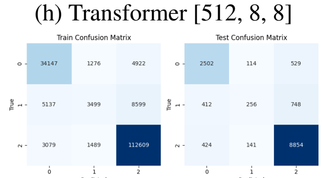
(h) Transformer [512, 8, 8]



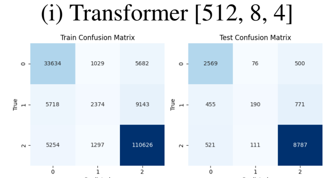
(i) Transformer [512, 8, 4]



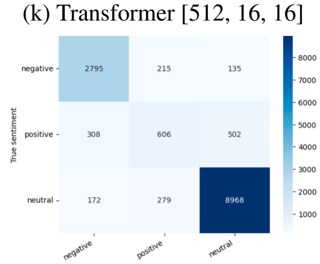
(j) Transformer [512, 4, 8]



(k) Transformer [512, 16, 16]



(l) Transformer [1024, 16, 16]



(m) Fine tuned BERT

Figure 9: Confusion metrics for train and test data

8 Challenges

The dataset exhibits a non-uniform distribution across sentiment classes, leading to challenges in model training and potential biases in predictions. The computational resources available for training and experimenting with complex models are restricted, affecting the exploration of larger architectures or extensive hyperparameter tuning.

9 Conclusion

In conclusion, we have experimented with various supervised learning algorithms to predict sentiment of the Yelp reviews dataset based using review text alone. We evaluated the effectiveness of different algorithms based on accuracy, precision, recall, f1 score and mcc measures. We concluded that as we increase the number of hidden layers in transformer, model performance improves to a certain extent and then starts decreasing. Increasing the number of attention heads and number of attention layers show significant improvement for all the metrics in general. Using transfer learning also proved to be helpful in our case which might indicate that our dataset was small to train a very powerful transformer from scratch. Nevertheless, we achieve 83.5% accuracy on test dataset with our final transformer model.

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