Assignment-4

Text and Sequence data

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Introduction:

The purpose of this assignment is to is to apply RNNs, or Transformers, to text and sequence data. We'll demonstrate each approach on a well-known text classification benchmark which is the IMDB movie review sentiment-classification dataset. Here we must apply RNNs or transformers to text and sequence data. Different NLP architectures handle word order differently. Bag-of-words models ignore order, recurrent models process words sequentially, and Transformers are order-agnostic yet incorporate positional information. So, both RNNs and Transformers are categorized as sequence models.

Goal of the project:

The goal of the assignment is to accomplish:

1. To apply RNNs or Transformers to text and sequence data
2. To improve the performance of network, especially when dealing with limited data
3. To determine which approaches are more suitable for prediction improvement.

Methodology:

Using google colab for our assignment, we have imported IMDB data source as our dataset. The IMDB dataset contains 50,00 reviews in total but only the top 10,000 words are considered. We took different ranges of training samples varying 100, 5000, 1000 & 10,000 and validation is done on 10,000 samples.

Our procedure had undergone two different approaches for generating word embeddings for the IMDB dataset which are:

1. Custom trained embedding layer
2. Pretrained word embedding layer using GloVe model.

GloVe model is a widely used pretrained word embedding model and it is trained on large amounts of textual data.

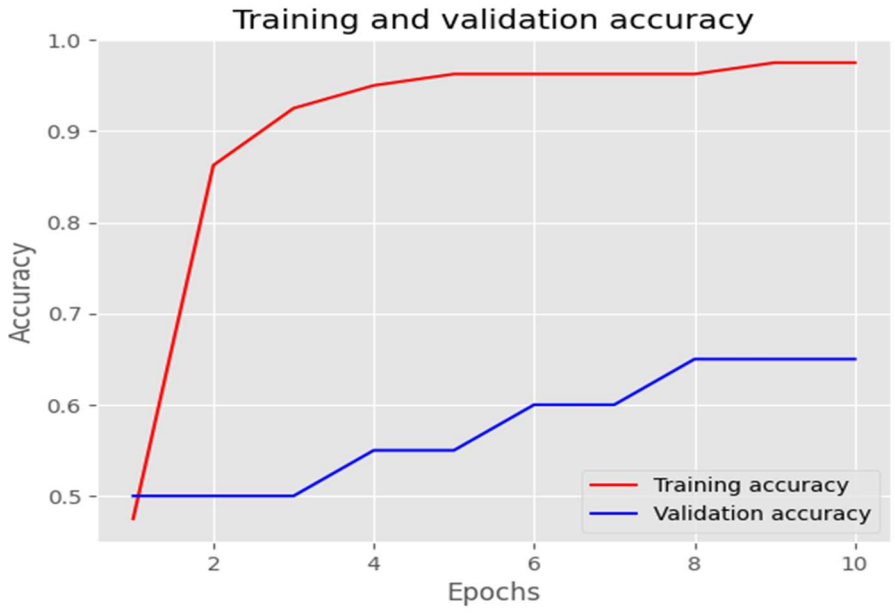
Here, I have compared the custom trained embedding layer with the pretrained word embedding using GloVe model to evaluate the effectiveness of those two different approaches. Comparison is done on different training sample sizes of 100, 5000, 1000 and 10,000.

Customed Trained Embedding Layer:

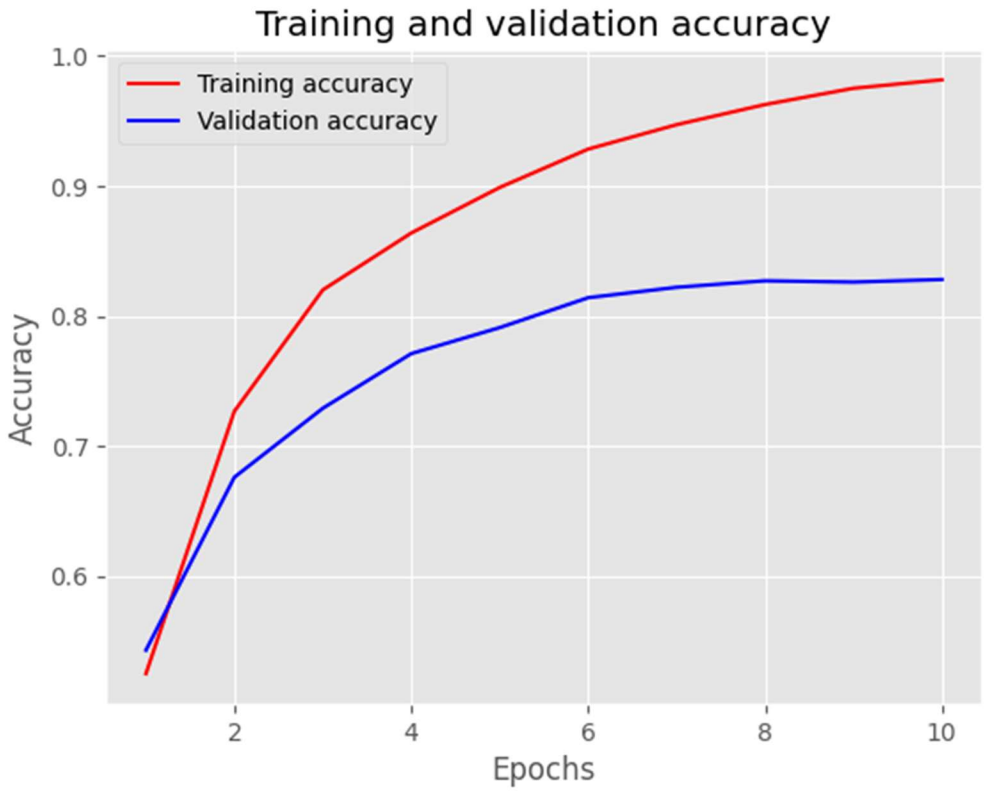
This custom trained embedding layer is an NN model where the embedding vectors are trained from scratch and is specific to the task and the dataset we are going to work with. They might capture nuances and details better than pre-trained embeddings because they are tailored to our specific situation.

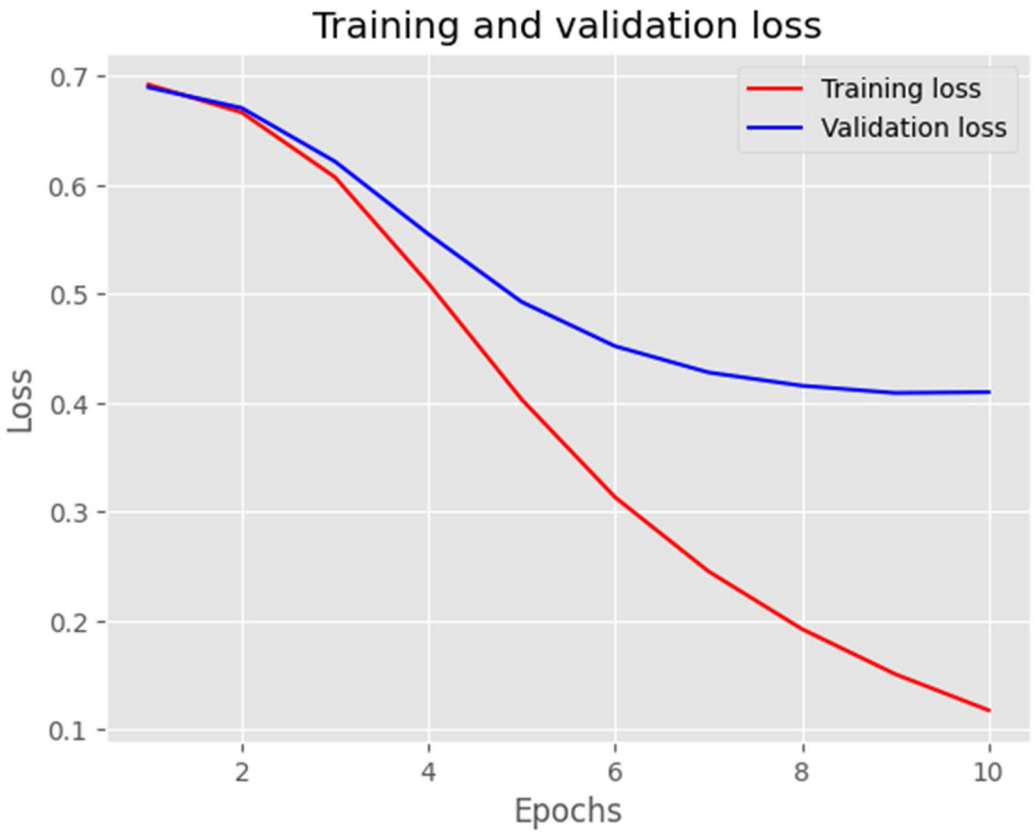
Here, we started creating a custom trained embedding layer by training each model on different sizes of training samples and measured its accuracy by evaluating the model with the test dataset.

1. Custom trained embedding layer with 100 training samples



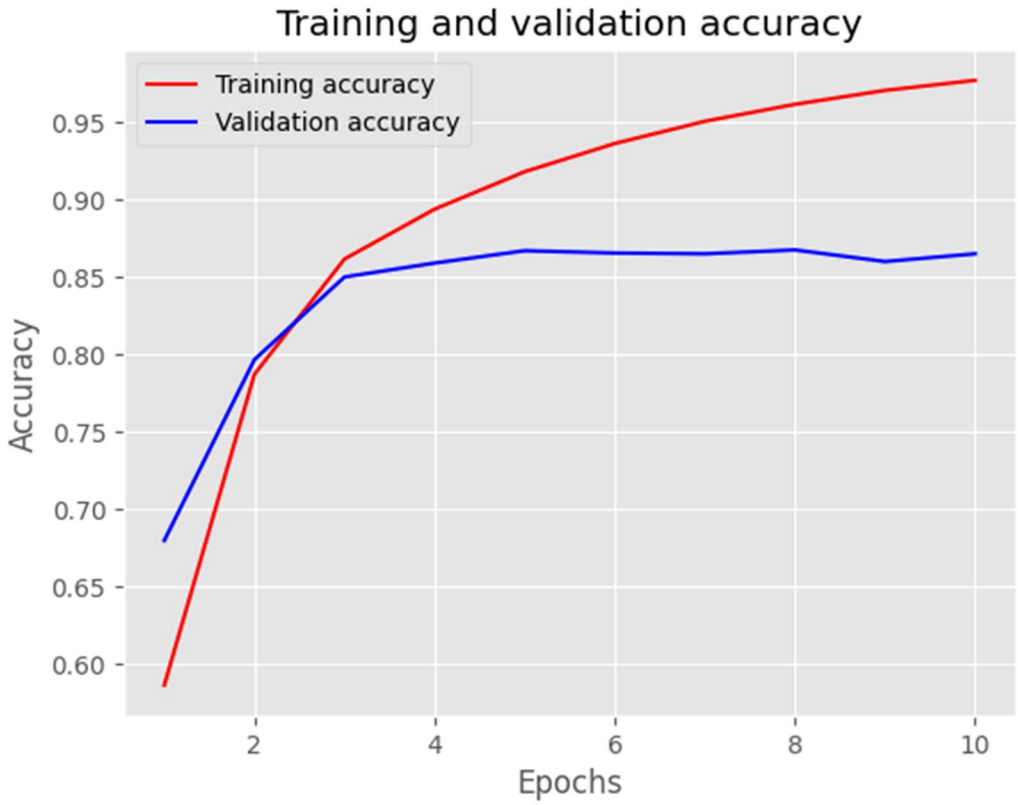
2. Custom trained embedding layer with 5000 training samples

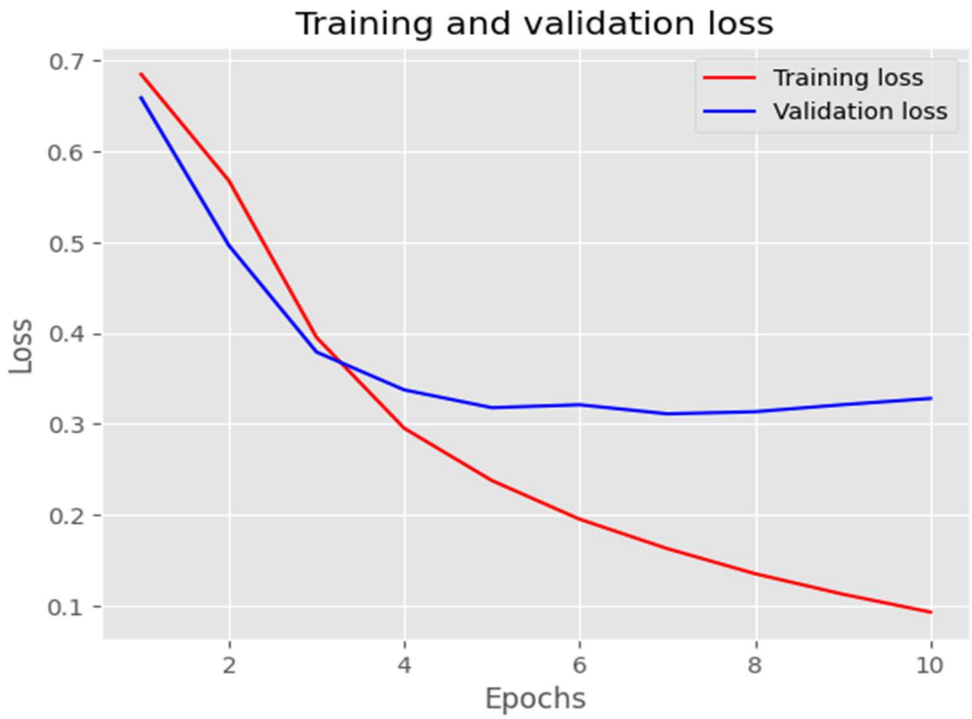




3. Custom trained embedding layer with 1000 training samples

4. Custom-trained embedding layer with 10000 training samples
   Images





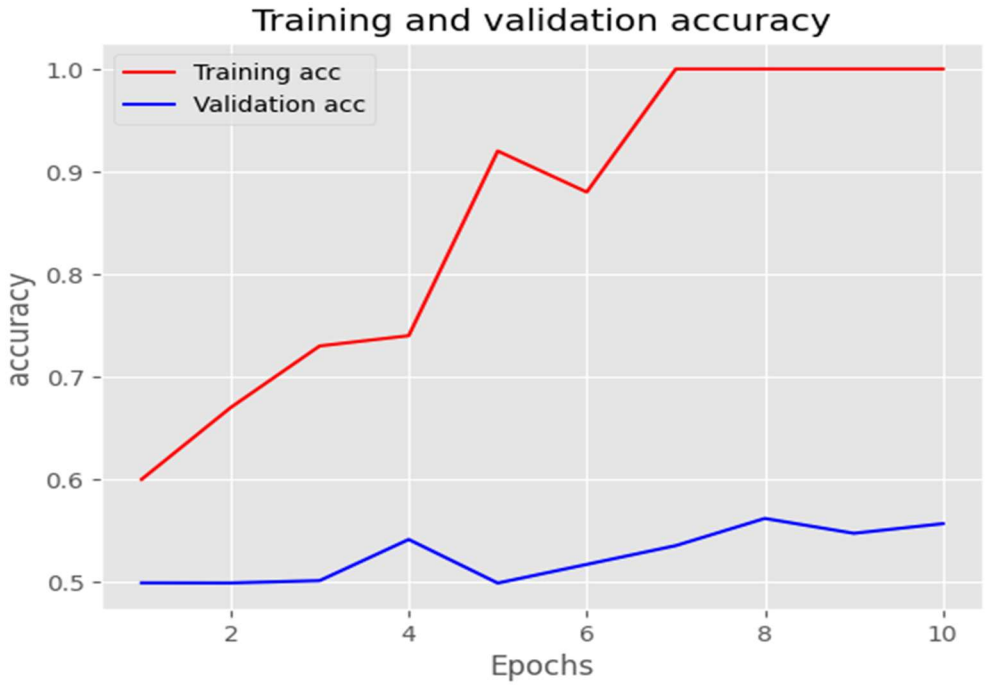
Pretrained Word Embedding Layer using GloVe model:

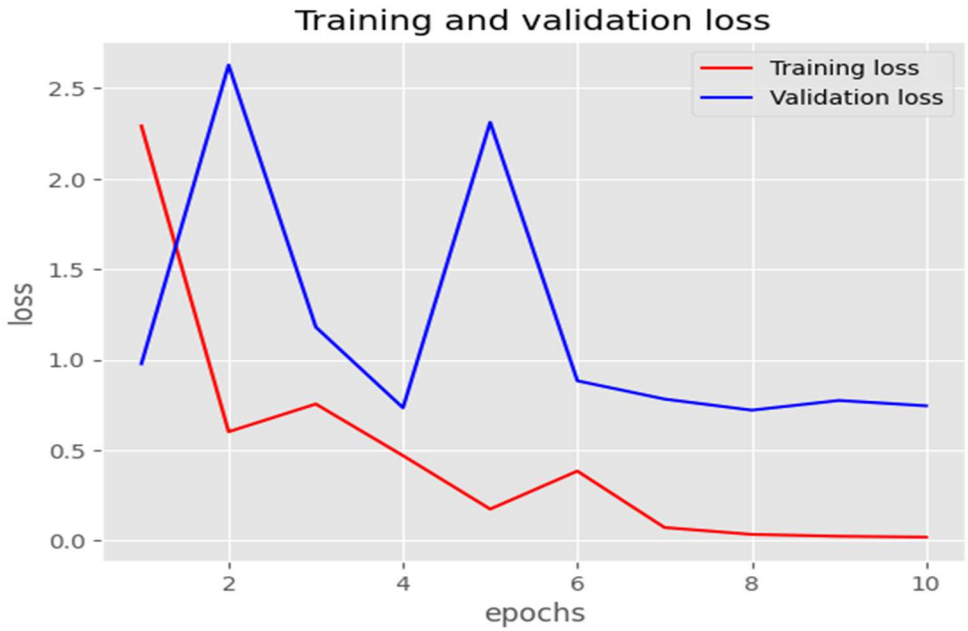
There are various precomputed databases of word embeddings that we can download and use in a Keras Embedding layer. Among them GloVe (Global Vectors of word representation is the most preferred one to use as a pretrained database. This is developed by Stanford researchers in 2014. This embedding technique is based on factorizing a matrix of word co-occurrence statistics.

- We have downloaded the GloVe word embeddings on 2014 English Wikipedia dataset. It is an 822 MB zip file containing 100-dimensional embedding vectors for 400,000 words (or non-word tokens)
- For building an index that maps words (as strings) to their vector representation, we parsed the unzipped file (a txt file).
- Next, we have built an embedding matrix that you can load into an Embedding layer.

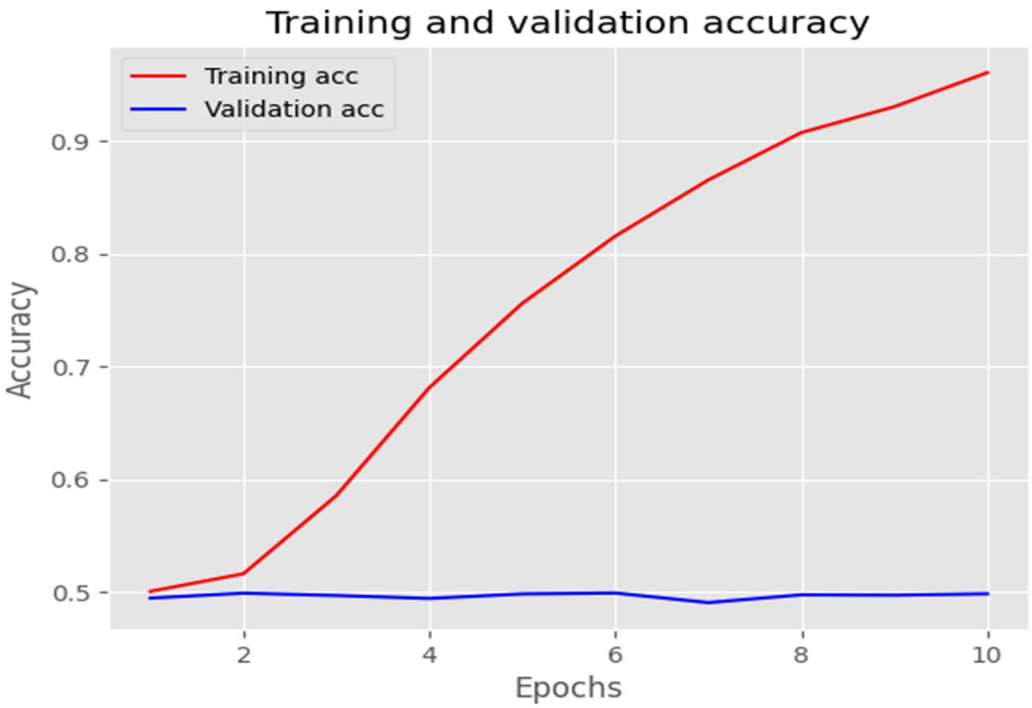
- Finally, we have used a constant initializer to load the pretrained embeddings in an Embedding layer. So as not to disrupt the pretrained representations during training, we have frozen the layer (trainable = false).
- Now, we're ready to train for a new model.

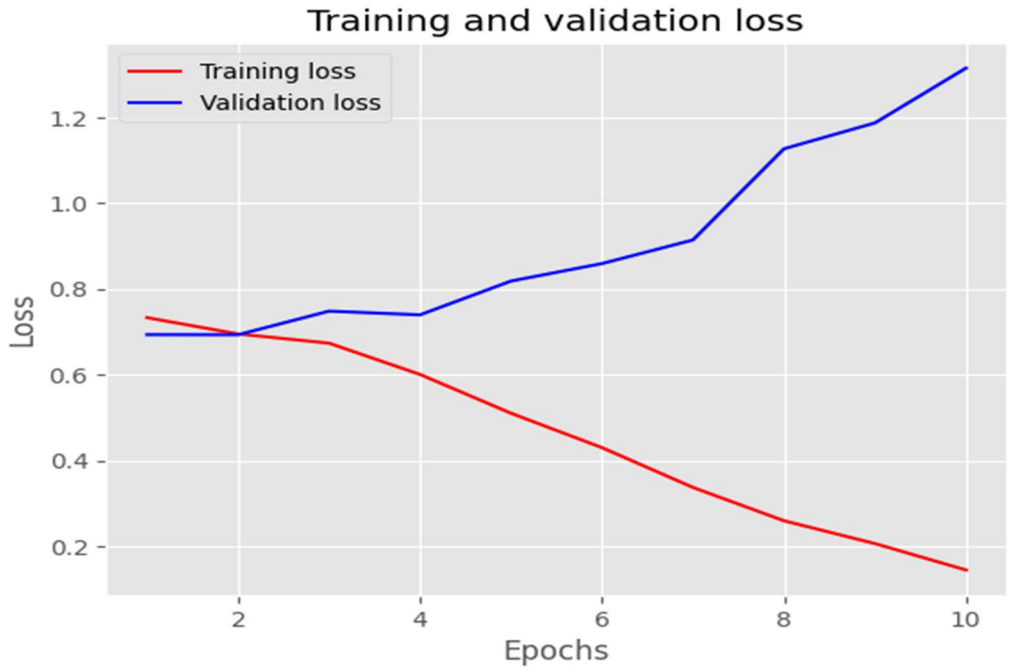
1. Pretrained word Embedding layer with 100 training sample



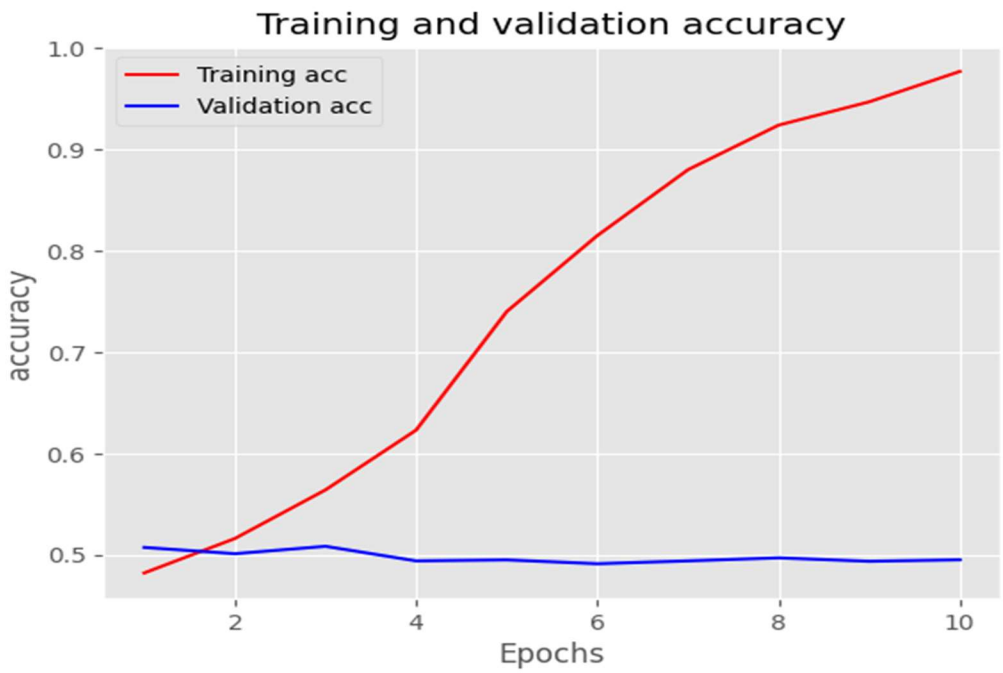


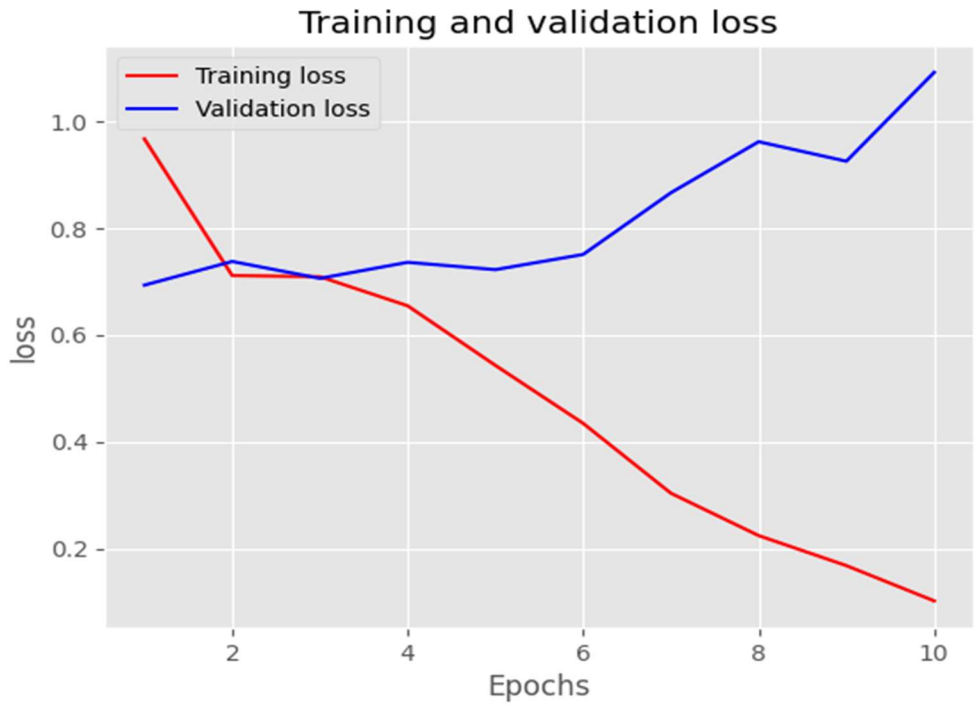
2. Pretrained word Embedding layer with 5000 training samples.



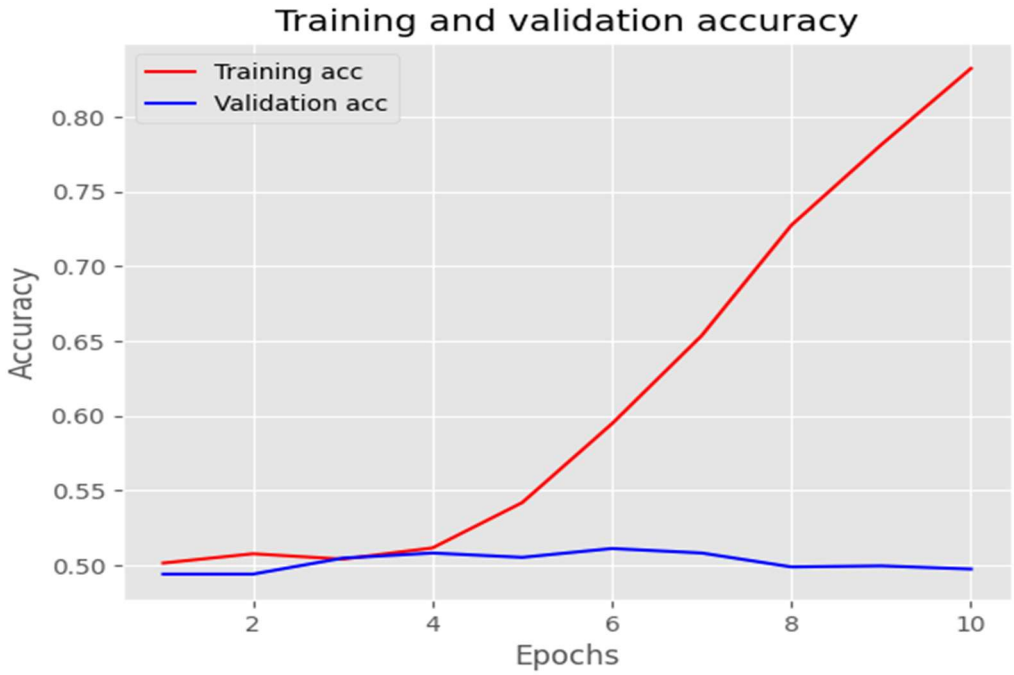


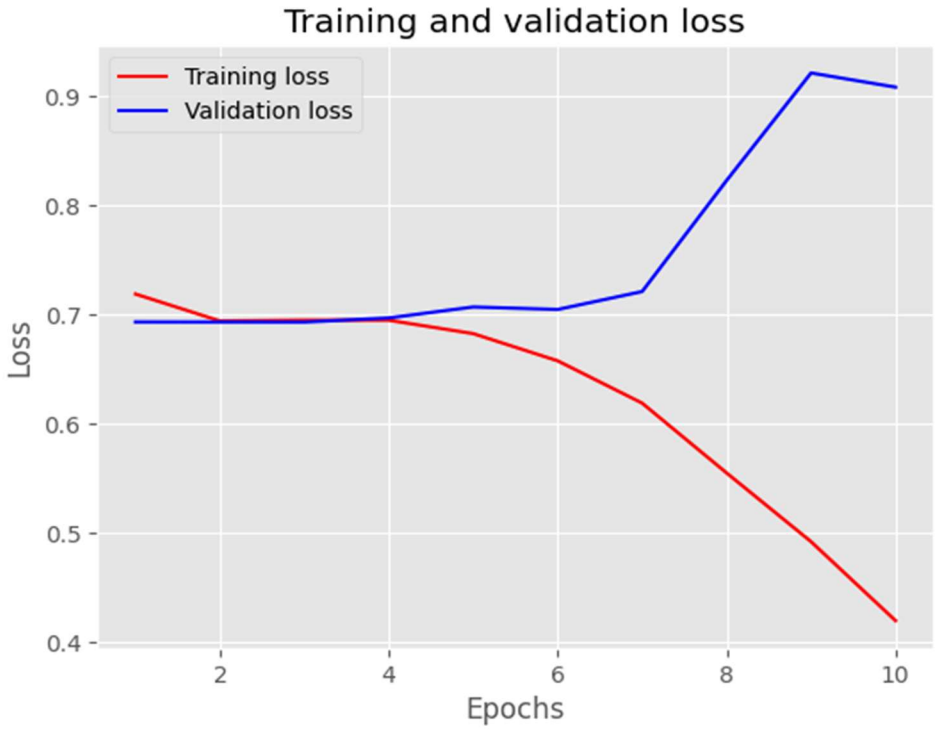
3. Pretrained word Embedding layer with 1000 training samples.





4. Pretrained word Embedding layer with 10000 training samples.





The pretrained word embedding layer (GloVe) exhibited varying degrees of accuracy, approximately from 92% to 100%, depending on the size of the training sample. Most accurate result was obtained with 100 training samples. In addition, the model quickly overfits when using the pretrained embeddings with bigger training sample sizes, which reduces accuracy. Because it depends on the needs and constraints of the task at hand, these findings make it difficult to determine which approach is the "best" to adopt with confidence.

Word Embedding Technique	**Training Sample Size**	**Test Accuracy**
Custom Trained word Embedding layer	100	50%
	5000	83.6%
	1000	58.2%
	10000	85.7%
Pretrained word embedding layer (GloVe Model)	100	50.7%
	5000	50.9%
	1000	50.3%
	10000	49.7%