Comparing Deep Learning Transformers To Naive Bayes and Random Forest Models in the Context of Emotion Detection

Graduate Project Proposal

Richard Hoehn*

Middle Tennessee State University

CSCI 6350

Prof. Dr. Sal Barbosa

March 4, 2024

*Electronic address: rhoehn@mtmail.mtsu.edu; corresponding author

1 Introduction

In the CSCI 6350 graduate project[1], the focus of research and student learning is on implementing a Deep Learning Transformer model for Emotion Detection (ED) and comparing its prediction accuracy with the previous work by Hoehn et al.[3] that employed Naive Bayes and Random Forest ML models for ED analysis. Additionally, we intend to compare our transformer model with the transfer learning-based ED model proposed by Lim[5] et al., ensuring a thorough comparative analysis of built transformers.

2 Background

Emotion detection (ED) has garnered significant interest and investment in recent years, emerging as a pivotal tool for understanding human behavior and enhancing communication effectiveness[7, 3]. Through the analysis of text, speech, or facial expressions, ED processes, and the underlying machine learning (ML) models, aim to accurately identify and classify emotions expressed by individuals or groups, often in real-time.

ED ML models, incorporating natural language processing (NLP) and deep learning, can detect emotions with high precision given sufficient data[1]. The introduction of the transformer model by Vaswani et al. in 2017 through the seminal paper "Attention is All You Need"[8] marked a significant advancement, establishing it as the state-of-the-art for various natural language tasks including machine translation, text summarizing, and question answering. Moreover, ED systems are applied across diverse fields such as sentiment analysis, customer feedback analysis, voting and news stance prediction, and mental health monitoring, all contributing to a deeper understanding of human emotions and their impacts on different life aspects.

3 Motivation & Specific Aims

The motivation for the this CSCI 6350 graduate project is twofold. **Firstly**, building upon previous work that Hoehn[3] completed for the qualifying exam of the COMS[2] PhD program is a superb expansion of that research focused on ML (Naive Bayes & Random Forest) models. **Secondly**, building on previous projects in CSCI 6350 allows for continuation of NLP[3] branching into an interesting area of the use of Deep Learning for NLP tasks.

In order to complete the project, data from Hoehn's[3] paper that uses a labeled emotions will be the basis for comparison. The dataset[4] itself is from 2021 Twitter, which is basically a collection of tweets annotated with the emotions. There are 13 different labeled emotion and corresponding text with over 40,000 rows in a `csv` file.

The aim for this Graduate Project using a Transformer for Emotion Detection has three (3) main goals.

- Build, Train, and Validate a Transformer for Emotion Detection. This will be don by use of PyTorch[6]
- Using Plots display the learning rates and validation results in graphical forms
- Evaluate the Transformer's results with that of Hoehn et. al's [3] Naive Bayes & Random Forest Results
- Compare the constructed transformer to Lim et al. on Transformer's transfer learning emotion detection model[5] to ensure comparative results in ED

An important part of research into transformers involves the utilization of visual aids, such as plots, to display the learning rates and validation results throughout the model's training phase. These visual representations are important for understanding the transformer's learning and making necessary adjustments to hyperparameters in order to enhance performance.

[1] The purpose of the graduate project is to afford students the opportunity to research modern technologies in use in the natural language processing (NLP) field.
[2] COMS - Computational Data & Science Department
[3] NLP - Natural Language Processing

A comprehensive evaluation of the transformer model's capabilities by comparing its performance against the findings of Hoehn[3] et al., who employed Naive Bayes and Random Forest models for ED. This comparison will not only validate the effectiveness of transformer models in capturing complex emotional nuances in text but also highlight their superiority in understanding contextual dependencies over traditional machine learning approaches.

Additionally, we intend to compare our transformer model with the transfer learning-based ED model proposed by Lim[5] et al., ensuring a thorough comparative analysis of built transformers. This approach will enable us to ascertain the comparative results of our model in the context of emotion detection.

4 Proposed Methods

The methodology to achieve the objectives outlined involves three primary components. Initially, the dataset will undergo preprocessing to cleanse the tweets by eliminating irrelevant characters or words. Subsequently, tokenization will be employed to transform the tweets into a format comprehensible by the model, utilizing BERT-Tokenization[2] for this purpose.

Upon completion of tokenization, the transformer model, likely BERT[2] due to its proven efficacy in comprehending human language context, will be deployed. The dataset, consisting of labeled records, will be divided using an 80/20% split to create training, validation, and test sets.

The model training on the training set will facilitate learning the mapping of input text to accurate emotion labels. Optimization of the model's parameters will be achieved through back-propagation and gradient descent techniques.

Model performance will be evaluated on the validation set, focusing on accuracy and F1 score to assess its effectiveness in emotion prediction. Performance metrics will guide necessary adjustments to the model's configuration or training methodology.

Finally, the transformer model's predictive outcomes will be juxtaposed with the Naive Bayes and Random Forest results from Hoehn's study[3] to establish comparative efficacy.

5 Expected Results

In the context of this Graduate Project on Emotion Detection from text data, it is anticipated that a Deep Learning Transformer model will outperform the Naive Bayes and Random Forest Machine Learning (ML) approaches described in Hoehn's paper[3].

This expectation is based on the premise that transformers, designed to capture the contextual nuances of human language through their attention mechanisms, are more adept at recognizing the intricacies of spoken and written language, such as sarcasm and idioms. Therefore, when applied to a dataset of labeled records for emotion detection, the Transformer is likely to achieve higher accuracy rates than the Naive Bayes and Random Forest approaches, showcasing its robustness and effectiveness in capturing the emotions conveyed in text, surpassing the capabilities of traditional ML classifiers.

References

[1] Mengnan Chen et al. “Research on Emotion Recognition for Online Learning in a Novel Computing Model”. In: *Applied Sciences* 12.9 (2022). ISSN: 2076-3417. DOI: 10.3390/app12094236. URL: https://www.mdpi.com/2076-3417/12/9/4236.

[2] Jacob Devlin et al. “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding”. In: *CoRR* abs/1810.04805 (2018). arXiv: 1810.04805. URL: http://arxiv.org/abs/1810.04805.

[3] Richard Hoehn and Jaishree Ranganathan. *Improving Emotion Detection through Translation of Text to ML Models Trained in Different Languages*. Version 1.0.1. https://github.com/richardhoehn/mtsu.coms.qualifying-exam. Aug. 2023. URL: https://github.com/richardhoehn/mtsu.coms.qualifying-exam.

[4] Kaggle and data.world. *Emotion Detection from Text*. 2021. URL: https://www.kaggle.com/datasets/pashupatigupta/emotion-detection-from-text.

[5] Sanghyub John Lee et al. “Transformer transfer learning emotion detection model: synchronizing socially agreed and self-reported emotions in big data”. In: *Neural Computing and Applications* 35.15 (2023), pp. 10945–10956. DOI: 10.1007/s00521-023-08276-8. URL: https://doi.org/10.1007/s00521-023-08276-8.

[6] Adam Paszke et al. “PyTorch: An Imperative Style, High-Performance Deep Learning Library”. In: *Advances in Neural Information Processing Systems 32*. Ed. by H. Wallach et al. Curran Associates, Inc., 2019, pp. 8024–8035. URL: http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf.

[7] Iqbal H. Sarker. “Machine Learning: Algorithms, Real-World Applications and Research Directions”. In: *SN Computer Science* 2.3 (Mar. 2021), p. 160. ISSN: 2661-8907. DOI: 10.1007/s42979-021-00592-x. URL: https://doi.org/10.1007/s42979-021-00592-x.

[8] Ashish Vaswani et al. “Attention is All you Need”. In: *Advances in Neural Information Processing Systems*. Ed. by I. Guyon et al. Vol. 30. Curran Associates, Inc., 2017. URL: https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.