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AUTOENCODERS AND GENDER-BASED APPROACH FOR DEPRESSION DETECTION USING BERT AND LSTM MODEL

Abstract: Depression is a austere medical ailment that upsets numerous people worldwide, causing a persistent decrease in mood and significantly impacting their emotions. The article focuses on utilizing BERT techniques and Autoencoders to detect depression from text data, considering gender differences. The work stresses on feature engineering of text data provided by benchmark dataset DAIC_WOZ. We experiment with BERT embeddings that encodes the meaning of text to derive text features. They are then fused with the help of Autoencoders with other parametric features from PHQ-8 survey responses, absolutist word count and gender information. The study found that incorporating this information significantly enhances the performance of the model. Our proposed method outperformed the baseline models. We emphasize the potential of machine learning for mental health research that considers gender differences. We report 98.6% accuracy demonstrated by our method.

We found the mean absolute error (MAE) as 0.19 and root mean squared error (RMSE) as 0.282 which signifies the high performance of our proposed method for binary depression classification.

Keywords: Depression Detection, Gender, Absolutist words, BERT, Deep Learning, Autoencoders, Feature Fusion, LSTM

1. Introduction: Depression is a familiar mental health ailment that distresses many people worldwide. Early detection and treatment of depression are crucial to prevent its negative impact on mental and physical health [1]. Recently, there has been growing interest in using artificial intelligence (AI) to detect depression from a combination of text and audio features and answers of the Patient Health Questionnaire-8 (PHQ-8) survey. A study by [2] used a combination of audio, text, and PHQ-8 features to develop a multimodal deep learning model that achieved high classification accuracy in detecting depression. There is ample evidence [3, 5] for text-based approach and have achieved high performance in detecting depression.

In recent years, the medical industry has incorporated machine learning (ML) to develop diagnostic tools that can improve precision and accuracy while reducing the need for manual intervention. There are studies that testify ML-powered technology can spot and enhance treatment of challenging mental disorders such as depression [4]. There are suggestions of usage of absolutist words used as a marker of depression [6]. The psychological patterns can be found from the linguistic patterns and their usage by depressive subjects [7]. The gender feature hides vibrant and visible patterns of difference in male and female depressive subjects. While using it for depression pattern detection and exploiting the significant differences in gender feature, we can accurately detect depression from text and audio data [8, 9]. This suggests utilizing the feature for depression detection [9].

While there are still limitations and challenges to be addressed in depression detection using AI, the potential benefits of early and accurate detection of depression are significant. It could aid in recovering the eminence of life for millions of people worldwide by enabling timely interventions and treatments. Thus, in this study we intend to detect depression using multimodal features from text and audio data [9], and deep learning models.

2. Objectives of the study:

There has been limited research conducted on the gender-dependent nature of depression and its distinctions between males and females [9]. We propose to study depression detection by exploiting absolutist word count features and gender feature for precise predictions.

We also apply feature fusion by autoencoders and denoise the fully fused features. This also helps in dimensionality reduction eliminating the need to apply another algorithm at the next step.

We then apply LSTM model for text-based depression detection since LSTM models perform well with the text data [10].

3. Literature Review: Depression causes a persistent decline in mood and significantly alters one's thought processes. Previous research has suggested that gender may be a useful predictor of depression. The article [4] describes the development of a framework called AiME that can detect depression with minimal human intervention. The article [6] describes three studies conducted on 63 internet forums with over to examine absolutist thinking in relation to anxiety, depression, and suicidal ideation. The linguistic characteristics analysis, found that forums containing anxiety, depression, and suicidal ideation had more absolutist words than control forums. The findings revealed an increased occurrence of absolutist words in depressed subjects, which advocates that absolutist thinking could be a vulnerability factor [6].

The article [9] aimed to investigate the influence of gender information on the estimation of depression. The study's findings reveal that a) including gender information in the analysis substantially enhances the accuracy of depression austerity approximation, and b) using adversarial learning to calculate precisely depression scores by gender further mends the precision of depression severity estimation.

Feature engineering on text data using BERT [16] (Bidirectional Encoder Representations from Transformers) involves several steps. BERT is a transformer-based language model [16] that utilizes an attention mechanism for learning contextual relationships between words in a sequence. The attention mechanism calculates the importance of each word in a sequence, allowing BERT to capture long-range dependencies in text. Thus, in the article [10], the authors used BERT features for depression spotting.

A new technique for fusing multisensory data is proposed with the aim of enhancing the reliability of fault diagnosis, as stated in [15]. Thus, we fuse the features using Autoencoders at the next level with Absolutist word counts, PHQ-8 responses, and Gender feature available in the dataset. This feature fusion is carried out using deep learning model called Autoencoders [14].

LSTMs achieved higher accuracy for depression detection in the work [10], which used standard dataset. Long Short-Term Memory (LSTM) [17] is a type of recurrent neural network (RNN) that is usually used in deep learning. LSTM networks are particularly suitable for processing sequential data [10, 17], due to their ability to capture enduring territories and mitigate the vanishing gradient problem.

4. Methodology:

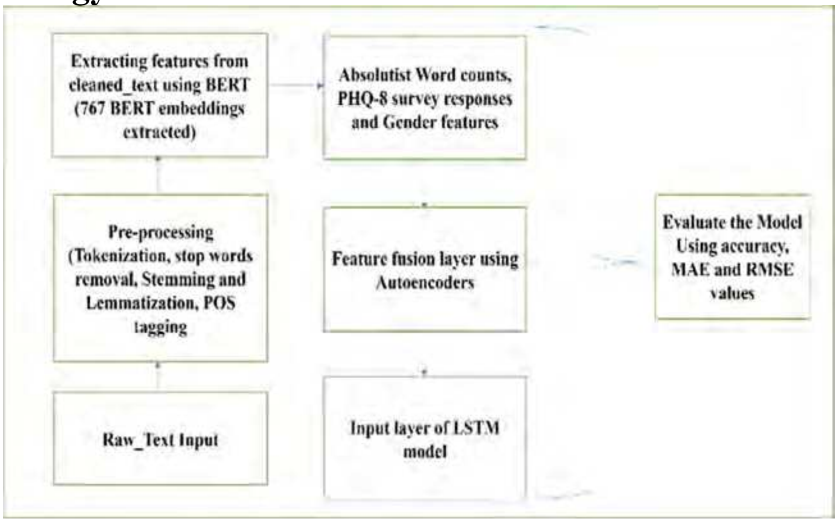

Fig. 1. Model Architecture

4.1 Data Used: The DAIC_WOZ dataset is a collection of audio and video footage records of patients spotted with depression during clinical interviews. The dataset includes self-reported ratings of depression severity, demographic information, and transcripts of the interviews. It was constructed to support the progress and assessment of automated systems for detecting depression in clinical settings.

4.2 Feature Engineering:

I) Preprocessing the Raw Transcript: Preprocessing the raw transcript using natural language processing (NLP) techniques involves a series of steps to prepare the text data for analysis. These preprocessing techniques can help to reduce noise and enhance the quality of the text data, enabling more accurate and meaningful analysis.

A) Tokenization: It [11] is the process of splitting a text into smaller elements known as tokens, which can include words, phrases, or sentences.

B) Stop words removal: Words, such as "and," "the," and "is," which do not convey important meaning, are typically removed from text data to reduce noise [12].

C) Stemming and lemmatization: These [11] practices are used to convert words to their basic form. Stemming removes word suffixes, while lemmatization uses a dictionary to convert the word to its base form.

D) Part-of-speech (POS) tagging: It is exercised to identify the grammatical structure of sentences by assigning each word a corresponding part of speech, as explained in "Speech and Language Processing" by [12].

II) BERT based feature extraction: By using BERT [16] for feature extraction, 767 embeddings were identified as essential for binary depression classification in the DAIC_WOZ corpus.

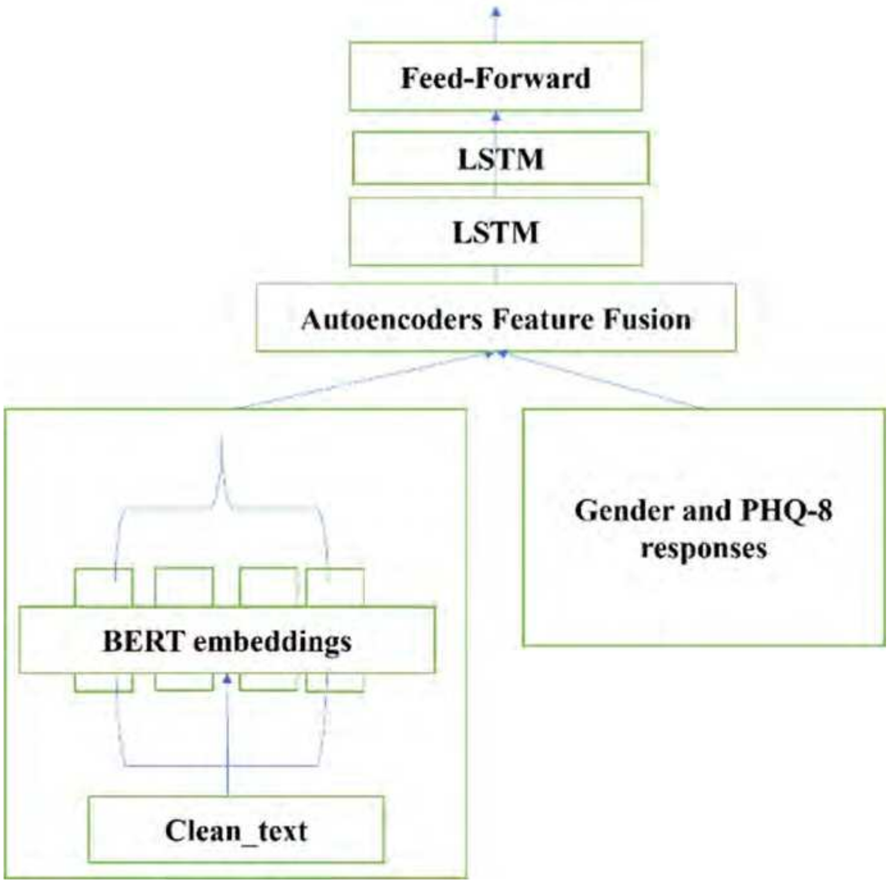

Fig. 2. Model Architecture

4.3 Feature fusion using Autoencoders: Autoencoders are neural networks that can be used for feature fusion and denoising of text features and fused gender features. In this process, the text features and gender features are supplied into the autoencoder network, which then compresses and reconstructs the input data to produce an output. This compressed data can then be used for feature fusion [14, 15], where the text features and gender features are combined to form a single set of features that can be used for further analysis. Autoencoders can also be used for denoising, where the network is trained to remove noise from the input data, resulting in cleaner and more accurate features.

4.4 LSTM: The LSTM [17] model used in this work for text-based depression analysis comprised of two layers of bi-directional LSTM, with each layer having four hidden nodes. The model utilized the concatenated merge mode and incorporated input and recurrent dropout rates of 0.1 and 0.8, respectively. The learning rate was 1e-01, and there was no decay, with a batch size of 32, and a momentum of 0.85.

4.5 Evaluation Metrics: We used Accuracy metrics, mean absolute error (MAE), root mean squared error (RMSE), and R-squared (R2) coefficient of the AI models used.

Results:

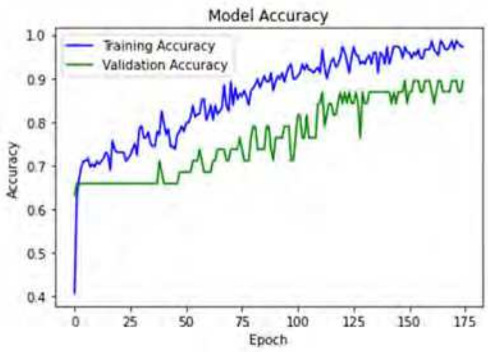

Fig. 3. Model Accuracy

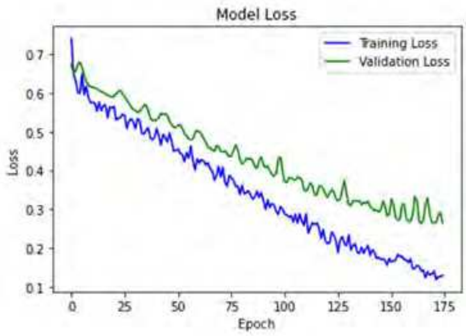

Fig. 4. Model Loss

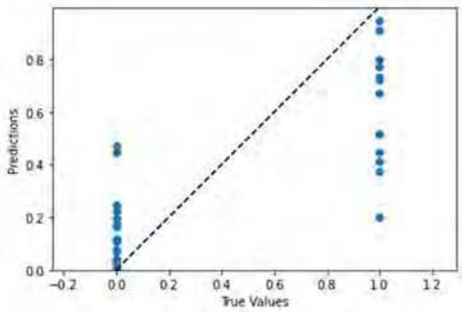

Fig. 5. Scatter Plot of True vs Predicted depression labels

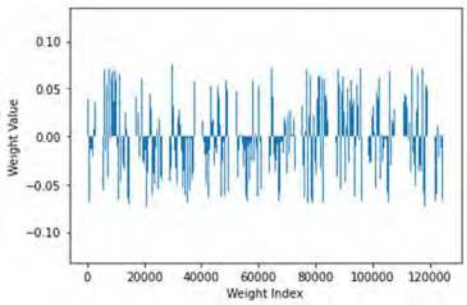

Fig. 6. BERT features visualization

Table 1

Model Evaluation

LSTM Model	Train Loss	Test Loss	Train Accuracy	Test Accuracy	MAE	RMSE	R^2
BERT features fused with Gender and Absolutist word count by Autoencoders	0.092	0.264	0.895	0.986	0.195	0.282	0.646

Discussion: We found that the methods we propose has outperformed all the baseline models as reported in [10]. Autoencoders based feature fusion is found to be effective in learning critical features and denoising the irrelevant ones. Our LSTM model has been trained on a dataset with 148 samples and 575 dimensionally reduced BERT features at the fusion step. We tested the model on a dataset with 41 samples. The performance of the model was assessed using evaluation metrics in section 4.5. The MAE of 0.195 and RMSE of 0.282 shows that on average, the predictions of the model are off by 0.195 units and 0.282 units respectively from the actual values. They give us a measure of the deviation of the errors. The R2 coefficient of 0.646 indicates that 64.6% of the variance in the dependent variable can be explained by the independent variables in the model. The value is closer to 1, indicating a better fit of the model to the data. Overall, the model seems to perform reasonably well, with a relatively low MAE and RMSE, and an R2 coefficient that indicates a moderate level of predictive power.

Conclusion and Future Works: We hypothesize that using gender and absolutist word count play crucial role for detecting depression from text data. By combining BERT embeddings and feature fusion by autoencoders can improve the prediction accuracy. Feature engineering of text data has high impact on prediction accuracy. The proposed method outperformed baseline models, considering gender differences and achieved a high accuracy of 98.6% in prediction.

This approach can be extended to larger datasets to test its robustness and generalizability. Further research could explore the use of this method in clinical settings to aid in the early detection and treatment of depression.

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METHODS OF CRITICAL HEAT FLUX PREDICTION IN SUB-COOLED WATER FLOW IN VVER-1200 FUEL RODS

Abstract. The prediction methods for critical heat flux (CHF) in sub-cooled boiling is presented with the aim of finding suitable model to use in the prediction of CHF in VVER-1200. Various models are available in literature, including; experimental data collected over the past 40 year for rod bundles