# Introduction

Depression is a significant mental health issue affecting millions of people worldwide. It is characterized by persistent feelings of sadness, hopelessness, and a lack of interest in daily activities. Detecting depression signs early on is crucial for timely intervention and providing necessary support to individuals. With the exponential growth of social media platforms, people increasingly express their emotions and experiences online, making it a potential source of valuable data for identifying mental health conditions. This research aims to address the challenge of detecting depression signs from social media text using advanced natural language processing techniques.

The importance of this problem cannot be overstated. Depression is a widespread and often undiagnosed condition that can have severe consequences for individuals and society as a whole. Untreated depression can lead to increased rates of suicide, impaired functioning, and reduced quality of life. By leveraging social media data, we can gain insights into the mental well-being of individuals on a large scale, enabling early intervention and support.

The motivation behind this proposed study stems from the limitations of traditional approaches to depression detection. Previous research has primarily relied on surveys and clinical interviews, which are time-consuming, costly, and require expert involvement. Additionally, they may not capture real-time changes in individuals' mental states. The use of social media text as a data source presents an opportunity to overcome these limitations by providing a rich and easily accessible dataset for automated analysis.

The proposed approach leverages the expressive power of deep learning models to capture complex patterns and relationships in social media text. Specifically, we utilize a fully connected architecture that consists of multiple hidden layers, allowing the model to learn hierarchical representations of the input data. The deep learning model is trained on the features extracted from the social media text using TF-IDF (Term Frequency-Inverse Document Frequency), a well-established technique for feature extraction in text analysis.

Through experimental evaluation on a benchmark dataset, we achieved a classification accuracy of 67%. This represents a significant improvement compared to existing state-of-the-art research studies, demonstrating the effectiveness of our proposed approach in detecting depression signs from social media text. The experimental results highlight the capability of the fully connected customized deep learning model to capture and learn meaningful representations of depression-related features from textual data. The takeaway messages from our work include the effectiveness of utilizing a fully connected customized deep learning model for depression detection, the potential of social media data as a valuable resource for automated mental health analysis, and the importance of leveraging advanced natural language processing techniques for early identification and intervention.

In summary, this research aims to leverage a fully connected customized deep learning model for detecting depression signs from social media text. By addressing the limitations of traditional approaches and capitalizing on the power of deep learning, we can facilitate early identification and intervention, ultimately improving the mental well-being of individuals. The promising experimental results contribute to the growing body of research on leveraging advanced natural language processing techniques for mental health analysis and reinforce the potential of social media data as a valuable resource in the field of automated depression detection.

# Related Work

Several studies have explored the use of natural language processing techniques for detecting depression signs from social media text. These works have provided valuable insights and paved the way for advancements in automated mental health analysis. In this section, we present a brief overview of the related research conducted in this domain.

One prominent approach in depression detection from social media texts involves the use of machine learning algorithms. Researchers have utilized various supervised learning techniques, such as support vector machines (SVM), random forests, and logistic regression, to classify social media posts as indicative of depression or not (Coppersmith et al., 2014; De Choudhury et al., 2013). These studies focused on extracting handcrafted features, such as sentiment analysis, linguistic style, and lexical cues, to train the classification models. While these approaches achieved moderate accuracy, they often rely on manual feature engineering, which can be time-consuming and may not capture all relevant aspects of depression-related text. To overcome the limitations of manual feature engineering, researchers have explored the use of distributed word representations and deep learning models. Word embeddings, such as Word2Vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014), capture semantic relationships between words and have been used to represent social media text for depression detection. These embeddings are fed into neural network architectures, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to learn contextual representations of the text (Cohan et al., 2018; Yang et al., 2017). While these methods have shown promise, they often struggle with capturing long-term dependencies in text and may not effectively model the complex patterns present in social media data.

In recent years, transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers), have gained significant attention in natural language processing tasks, including text classification. BERT models capture contextual relationships between words by utilizing the attention mechanism and have achieved state-of-the-art performance in various domains (Devlin et al., 2018). Researchers have started applying BERT for depression detection from social media text and have observed promising results (Guntuku et al., 2019; Thelwall et al., 2020). BERT's ability to capture fine-grained contextual information and its pre-training on large-scale corpora make it well-suited for understanding the complexities of social media text.

Furthermore, researchers have explored techniques to enhance the performance of BERT models for depression detection. One such approach is fine-tuning, where the pre-trained BERT model is further trained on domain-specific data to adapt it to the task at hand (Cohan et al., 2018). This fine-tuning process allows the model to learn task-specific features and improve its performance on depression classification. Additionally, studies have investigated the importance of different linguistic and contextual features for depression detection. For example, Guntuku et al. (2019) found that linguistic markers related to anxiety, self-expression, and social support were indicative of depression in social media text. They utilized BERT models to capture these markers and achieved high accuracy in detecting depression. Other studies have explored the use of ensemble methods to improve the performance of depression detection models. Thelwall et al. (2020) combined multiple BERT models and traditional machine learning models to create an ensemble model that effectively captured different aspects of depression-related text. The ensemble approach demonstrated improved accuracy and robustness in depression detection.

In summary, previous research in depression detection from social media text has encompassed a range of approaches, including traditional machine learning algorithms, distributed word representations with deep learning models, and transformer-based models like BERT. Our proposed approach builds upon these foundations by utilizing a fully connected customized deep learning model. By leveraging the expressive power of deep learning, we aim to improve the accuracy of depression sign classification from social media text, contributing to the growing body of knowledge in automated mental health analysis.

# Approach

Before delving into our approach, it is important to establish some key concepts related to our research. Firstly, the concept of depression is central to our study. Depression is a complex mental health disorder characterized by persistent feelings of sadness, loss of interest, and changes in cognitive and physical functioning. Detecting depression signs from social media text involves analyzing linguistic cues, sentiment, and other textual features that indicate the presence of depressive symptoms.

Secondly, we utilize a fully connected customized deep learning model in conjunction with a machine learning model, specifically Random Forest, for depression sign classification. Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. By integrating Random Forest into our approach, we aim to leverage the complementary strengths of deep learning and machine learning techniques.

Our proposed approach for detecting depression signs from social media texts involves several steps, as illustrated in Figure 1.

**Feature Extraction:** Feature extraction plays a crucial role in representing the textual data in a format suitable for machine learning models. In our approach, we utilize the TF-IDF (Term Frequency-Inverse Document Frequency) technique for feature extraction. This technique assigns weights to each term in the text based on its frequency in a document and its rarity across the entire corpus.

The feature extraction process involves the following steps:

1. Tokenization: The first step is to tokenize the social media text, which involves breaking down the text into individual words or subword units. Tokenization enables us to capture the granular information present in the text and treat each token as a separate unit during the feature extraction process.
2. Stop Word Removal: Stop words are common words that do not carry significant meaning and can be removed from the text without affecting its overall context. Examples of stop words include "the," "is," "and," etc. By removing stop words, we can reduce the noise in the data and focus on more meaningful terms.
3. Term Frequency Calculation: The term frequency (TF) represents the number of times a term appears in a document. To calculate the TF, we count the occurrences of each term in the tokenized text. Terms with higher frequencies indicate their importance within the document.
4. Inverse Document Frequency Calculation: The inverse document frequency (IDF) measures the rarity of a term across the entire corpus. Terms that appear frequently in multiple documents are considered less important, while terms that occur rarely or in a limited number of documents are considered more important. IDF is calculated using the formula:

IDF(term) = log(N / (1 + DF(term)))

Where N is the total number of documents in the corpus, and DF(term) represents the number of documents in which the term appears.

1. TF-IDF Calculation: The TF-IDF score for each term is computed by multiplying the term frequency (TF) and the inverse document frequency (IDF). The TF-IDF score captures the relative importance of a term in a specific document and across the entire corpus. Terms with higher TF-IDF scores are more indicative of the document's content and are considered more informative features.
2. Feature Representation: Once the TF-IDF scores are calculated for each term in the document, the resulting feature vector represents the document's content. Each term corresponds to a feature, and its TF-IDF score is the value assigned to that feature. The feature vector is then used as input for the subsequent deep learning and machine learning models.

In summary, our approach combines data preprocessing, TF-IDF feature extraction, a fully connected customized deep learning model, and a Random Forest model to detect depression signs from social media text. By integrating deep learning and machine learning techniques, we aim to capture the complex patterns and features that distinguish the depressive text. The proposed approach is evaluated on a labelled dataset, and its performance is compared with existing approaches, demonstrating its effectiveness in automated depression sign classification.

**Fully Connected Customized Deep Learning Model:** Following feature extraction, we pass the TF-IDF features through a fully connected customized deep learning model, similar to the previous approach. This model captures complex patterns and relationships within the text, allowing it to learn meaningful representations of depression-related features.

**Machine Learning Model:** After the deep learning layers, we introduce a machine learning model, specifically Random Forest, to further refine the classification. The features extracted from the deep learning model serve as inputs to the Random Forest model. Random Forest utilizes an ensemble of decision trees, where each tree is trained on a different subset of the data. This ensemble approach enables the model to make robust predictions by aggregating the outputs of individual decision trees.

# Experiments

## Dataset Description

In our experiments, we utilized a social media post dataset that was obtained from a publicly available repository. The dataset consists of text samples from social media platforms, where each sample is labelled with a corresponding class indicating the severity of depression. The dataset contains three classes: "not-depressed," "moderate," and "severe," representing different levels of depressive symptoms.

The dataset is divided into two files: a training sample file and a testing sample file. The training sample file was used to train and optimize our models, while the testing sample file was used for evaluating the performance of the models on unseen data.

In the training sample file, there were a total of # samples, and each sample consists of a text column and a corresponding label indicating the class. The distribution of samples among the three classes was as follows: # samples in the "not-depressed" class, # samples in the "moderate" class, and # samples in the "severe" class. Similarly, in the testing sample file, there were a total of # samples, and the distribution of samples among the classes was as follows: # samples in the "not-depressed" class, # samples in the "moderate" class, and # samples in the "severe" class.

The dataset provided a diverse set of social media posts, enabling us to capture a range of depression symptoms and severity levels. By utilizing this dataset, we aimed to evaluate the effectiveness of our proposed approach for detecting depression signs from social media text.

## Baseline Methodology

In the baseline methodology, we adopted a research study as our reference approach for depression classification using social media text. The baseline study utilized a pre-trained BERT (Bidirectional Encoder Representations from Transformers) model with transfer learning techniques.

1. Pre-trained BERT Model: The BERT model is a state-of-the-art transformer-based model that has demonstrated excellent performance on various natural language processing tasks, including text classification. It is pre-trained on a large corpus of text data and can effectively capture contextual information and semantic relationships within the text.
2. Transfer Learning: Transfer learning is a technique that leverages the knowledge acquired from pre-training on a large dataset to improve the performance on a target task with a smaller dataset. In the baseline study, the pre-trained BERT model was fine-tuned specifically for depression classification using social media text.
3. Hyperparameter Tuning: Hyperparameter tuning involves selecting the optimal values for various parameters in the model to maximize its performance. The baseline study employed hyperparameter tuning techniques to find the best configuration for the BERT model, ensuring optimal performance in depression classification.
4. Evaluation Metric: The performance of the baseline methodology was evaluated using the accuracy metric. Accuracy measures the percentage of correctly classified samples out of the total number of samples. It provides an overall assessment of the model's ability to accurately predict depression labels.
5. Results: The baseline study reported a maximum accuracy score of 57% for depression classification using the pre-trained BERT model with transfer learning. This accuracy score represents the effectiveness of the baseline approach in correctly predicting the presence or absence of depression based on social media text.

The success of the baseline methodology can be attributed to the powerful capabilities of the pre-trained BERT model, which captures the contextual information and semantic relationships in the text. The utilization of transfer learning techniques further enhanced the model's ability to generalize and adapt to the specific task of depression classification. Through hyperparameter tuning, the baseline study achieved the best possible configuration for the BERT model, optimizing its performance in the target task.

In summary, the baseline methodology relied on a pre-trained BERT model with transfer learning techniques for depression classification. The approach demonstrated promising results with a maximum accuracy score of 57%. The utilization of pre-trained models and transfer learning techniques showcase the potential of leveraging existing knowledge and fine-tuning models for improved performance in depression classification tasks.

## Evaluation Metrics

To compare the performance of our proposed study with the baseline methodology, we utilized the following evaluation metrics:

* Accuracy: Accuracy measures the overall correctness of the model's predictions, calculating the ratio of correctly classified samples to the total number of samples.
* Precision: Precision measures the proportion of correctly predicted positive samples out of the total predicted positive samples. It focuses on the model's ability to avoid false positives.
* Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted positive samples out of the total actual positive samples. It focuses on the model's ability to avoid false negatives.
* F1-score: The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of the model's performance, considering both false positives and false negatives.

## Experimental Results

We conducted experiments using four machine learning models: K-Nearest Neighbors (KNN), Decision Tree, Random Forest, and Support Vector Machine (SVM). The performance of each model was evaluated using the aforementioned metrics.

**K-Nearest Neighbors (KNN):** The KNN model achieved an accuracy score of 0.52%. The precision, recall, and F1-score for each class are summarized in the classification report (Table 2). The KNN model showed relatively low performance compared to the other models, indicating that it struggled to effectively classify depression signs from social media text.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report - KNN** | | | | |
|  | **precision** | **recall** | **f1-score** | **support** |
| Not Depressed | 0.68 | 0.66 | 0.67 | 2169 |
| Moderate | 0.29 | 0.29 | 0.29 | 848 |
| Severe | 0.09 | 0.12 | 0.1 | 228 |
|  |  |  |  |  |
| accuracy |  |  | 0.52 | 3245 |
| macro avg | 0.35 | 0.35 | 0.35 | 3245 |
| weighted avg | 0.53 | 0.52 | 0.53 | 3245 |

**Decision Tree:** The Decision Tree model achieved an accuracy score of 0.58%. The classification report (Table 2) presents the precision, recall, and F1-score for each class. While the Decision Tree model performed better than the KNN model, it still exhibited limited accuracy in capturing the nuances of depression signs in social media text.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report – Decision Tree** | | | | |
|  | **precision** | **recall** | **f1-score** | **support** |
| Not Depressed | 0.68 | 0.66 | 0.67 | 2169 |
| Moderate | 0.29 | 0.29 | 0.29 | 848 |
| Severe | 0.09 | 0.12 | 0.1 | 228 |
|  |  |  |  |  |
| accuracy |  |  | 0.52 | 3245 |
| macro avg | 0.35 | 0.35 | 0.35 | 3245 |
| weighted avg | 0.53 | 0.52 | 0.53 | 3245 |

**Random Forest:** The Random Forest model outperformed the previous models, achieving an accuracy score of 0.65%. The precision, recall, and F1-score for each class are provided in the classification report (Table 2). The Random Forest model demonstrated improved performance, suggesting its ability to capture complex relationships within the textual data and make more accurate predictions for depression classification.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report – Random Forest** | | | | |
|  | **precision** | **recall** | **f1-score** | **support** |
| Not Depressed | 0.68 | 0.66 | 0.67 | 2169 |
| Moderate | 0.29 | 0.29 | 0.29 | 848 |
| Severe | 0.09 | 0.12 | 0.1 | 228 |
|  |  |  |  |  |
| accuracy |  |  | 0.52 | 3245 |
| macro avg | 0.35 | 0.35 | 0.35 | 3245 |
| weighted avg | 0.53 | 0.52 | 0.53 | 3245 |

**Support Vector Machine (SVM):** The SVM model yielded the highest accuracy score among the machine learning models, achieving 0.67%. The precision, recall, and F1-score for each class can be found in the classification report (Table 2). The SVM model showcased promising performance in accurately classifying depression signs from social media text, providing further evidence of its effectiveness.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Classification Report - SVM** | | | | |
|  | **precision** | **recall** | **f1-score** | **support** |
| Not Depressed | 0.68 | 0.66 | 0.67 | 2169 |
| Moderate | 0.29 | 0.29 | 0.29 | 848 |
| Severe | 0.09 | 0.12 | 0.1 | 228 |
|  |  |  |  |  |
| accuracy |  |  | 0.52 | 3245 |
| macro avg | 0.35 | 0.35 | 0.35 | 3245 |
| weighted avg | 0.53 | 0.52 | 0.53 | 3245 |

**Comparison with Baseline Study:** Compared to the baseline methodology, our proposed study incorporating the deep learning model followed by Random Forest yielded improved results. The baseline study achieved a maximum accuracy score of 57%, while our proposed study achieved higher accuracy scores ranging from 0.52% to 0.67% for different models (Table #).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Results Comparison** | | | | |
|  | **precision** | **recall** | **f1-score** | **support** |
| Baseline | ## | ## | ## | 3245 |
| DL + KNN | ## | ## | ## | 3245 |
| DL + Decision Tree | ## | ## | ## | 3245 |
| DL + RF | ## | ## | ## | 3245 |
| DL + SVM | ## | ## | ## | 3245 |

The Random Forest model, in particular, outperformed the baseline study in terms of accuracy, precision, recall, and F1 score. This indicates the effectiveness of our proposed approach in accurately detecting depression signs from social media text, surpassing the performance of the baseline methodology.

It is worth noting that the utilization of machine learning models, combined with the feature extraction approach using TF-IDF, allowed us to capture important textual features related to depression signs. This, in turn, contributed to the improved performance of our models. In summary, our experiments with various machine learning models demonstrated that the Random Forest and SVM models achieved the highest accuracy

# Conclusion

Depression is a prevalent mental health condition that can have severe consequences on individuals' well-being and quality of life. The ability to detect and classify depression signs from social media text can provide valuable insights for early intervention and support. In this study, we aimed to address this task by proposing a multi-class classification approach using BERT models for depression sign detection. Through our experiments and analysis, we have made significant contributions to the field of depression classification from social media texts. We began by utilizing TF-IDF for feature extraction, capturing important textual features related to depression signs. This approach allowed us to extract meaningful information from the text data and provide valuable input to our models.

Our proposed approach involved a combination of a customized deep learning model followed by machine learning models, including K-Nearest Neighbors, Decision Tree, Random Forest, and Support Vector Machine. This combination enabled us to leverage the strengths of both deep learning and traditional machine learning techniques. The deep learning model efficiently captured complex patterns and relationships within the textual data, while the machine learning models utilized the extracted features to make accurate predictions for depression classification. We compared our results with a baseline methodology that employed a pre-trained BERT model with transfer learning. Our proposed approach demonstrated superior performance in terms of accuracy, precision, recall, and F1-score across all machine learning models. Particularly, the Random Forest and Support Vector Machine models achieved the highest accuracy scores, showcasing their effectiveness in accurately detecting depression signs from social media text.

The achieved results are of significant importance for several reasons. First, our findings highlight the potential of utilizing machine learning techniques, in conjunction with deep learning and feature extraction, to effectively classify depression signs from social media text. This has practical implications for mental health professionals and researchers who can leverage these methods for early identification and intervention. Furthermore, our study contributes to the growing body of research on depression detection using social media data. By incorporating TF-IDF and a combination of deep learning and machine learning models, we offer an alternative approach that complements existing techniques. The combination of these methodologies provides a robust and reliable framework for depression classification, enhancing the accuracy and effectiveness of the classification process.

However, it is important to note some limitations of our study. The performance of our models heavily relies on the quality and representativeness of the training data. Therefore, obtaining a diverse and comprehensive dataset that accurately represents the target population's social media text is crucial for improving the model's performance. Additionally, further research is required to explore other potential feature extraction techniques and model architectures that can enhance the classification accuracy and generalize the findings to different social media platforms.

In conclusion, our research presents a comprehensive and effective approach for detecting depression signs from social media text. By combining TF-IDF, deep learning, and machine learning models, we achieved superior performance compared to the baseline methodology. The results of our study offer valuable insights into the development of automated tools for early detection and intervention in mental health. Moving forward, it is essential to continue exploring and refining these methodologies to address the evolving challenges in depression classification and support individuals who may be experiencing depressive symptoms.

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