Title: Deep Learning Approach for Depression Classification and Prediction from User Tweets

TOPIC ANAYSIS REPORT BY:

**VIVEK PANDEY**

AKTU

**COMOUTER SCIENCE AND TECHNOLOGY**

**18-11-2024**

Title: Deep Learning Approach for Depression Classification and Prediction from User Tweets

***Justification for the Topic:***

The proposed topic, addresses a critical issue in mental health care—early detection and intervention for depression. Depression is a global mental health concern, with millions of people affected, yet many individuals do not seek help due to stigma, lack of resources, or unawareness of their condition. Early identification of depressive symptoms can significantly improve outcomes by enabling timely support and intervention. However, traditional diagnostic methods, such as clinical interviews or self-reports, have limitations, including subjectivity, time constraints, and accessibility challenges.

With the rise of social media, platforms like Twitter have become primary spaces where individuals express their emotions, experiences, and thoughts in real-time. Tweets, often reflective of users' moods and mental states, provide an invaluable source of unfiltered psychological data. Analyzing this data for signs of depression offers a novel and scalable approach to mental health monitoring.

Deep learning models particularly those used in Natural Language Processing (NLP) have demonstrated exceptional capabilities in understanding and interpreting unstructured text. These models can learn complex patterns from large volumes of data, allowing them to identify subtle linguistic cues, sentiment, and emotional context in tweets. By applying deep learning to Twitter data, it is possible to build systems that classify tweets based on depressive content and even predict the likelihood of depression, providing an early warning system that can be used by mental health professionals for further assessment or intervention.

This topic is timely and relevant due to the increasing interest in using AI to support mental health initiatives. By harnessing the power of deep learning, this research can help bridge the gap in early detection of depression, complementing traditional clinical approaches and contributing to mental health care at scale. Additionally, it opens the door to more personalized, real-time interventions, potentially improving the lives of individuals affected by depression.

**Understanding Depression: Key Features, Causes, and Symptoms**

***Key Features of Depression:***

Depression is a serious mental health condition that affects how a person feels, thinks, and handles daily activities. It is more than just feeling sad or going through a rough patch; it requires clinical attention. Key features of depression include:

* **Persistent Sadness:** Prolonged periods of feeling hopeless or empty.
* **Loss of Interest:** Diminished interest or pleasure in activities that were once enjoyed.
* **Fatigue:** Decreased energy and increased fatigue, often leading to reduced physical activity.
* **Changes in Appetite and Weight:** Significant weight loss or gain, or changes in appetite.
* **Sleep Disturbances:** Insomnia or excessive sleeping.
* **Cognitive Impairment:** Difficulty concentrating, remembering, or making decisions.
* **Physical Symptoms:** Aches, pains, or digestive problems without a clear physical cause.
* **Thoughts of Death or Suicide:** Recurrent thoughts of death, suicidal ideation, or suicide attempts.

***Causes of Depression:***

Depression can be caused by a combination of genetic, biological, environmental, and psychological factors:

* **Genetics:** A family history of depression increases the likelihood of developing the condition.
* **Brain Chemistry:** Imbalances in neurotransmitters (such as serotonin, dopamine, and norepinephrine) play a significant role in mood regulation and can contribute to depression.
* **Hormonal Changes:** Changes in hormones, such as during pregnancy, postpartum, menopause, or thyroid problems, can trigger depression.
* **Life Events:** Traumatic or stressful events, such as the death of a loved one, divorce, job loss, or financial problems, can lead to depression.
* **Medical Conditions:** Chronic illnesses, severe pain, and certain medications can contribute to depression.
* **Personality:** Individuals with low self-esteem, who are easily overwhelmed by stress, or who are generally pessimistic, may be more prone to depression.
* **Environmental Factors:** Exposure to violence, neglect, abuse, or poverty can increase the risk of developing depression.

***Behaviour of People with Depression on Social Media Platforms like Twitter:***

Social media platforms like Twitter have become an important space where people express their feelings and share their experiences. Individuals with depression may exhibit distinct patterns of behaviour on these platforms:

* **Negative Language:** Increased use of negative words or phrases, expressing sadness, loneliness, or hopelessness.
* **Frequent Posting:** More frequent posts about personal struggles, often seeking support or understanding from followers.
* **Emotional Content:** Sharing content that reflects their emotional state, such as quotes, songs, or articles about depression.
* **Isolation:** Tweets indicating withdrawal from social activities or a sense of isolation from friends and family.
* **Help-Seeking Behaviour:** Explicit or implicit calls for help, support, or advice from their online community.
* **Reduced Interaction:** Decreased engagement with others' posts, including likes, comments, or retweets, reflecting their reduced interest in social interactions.
* **Inconsistent Activity:** Periods of high activity followed by long silences, mirroring their fluctuating energy levels and interest in engaging with the world.

# Data Sets Used In The Topic

For the **" Depression Classification and Prediction from User Tweets and Comments on Social Media,"** several publicly available datasets can be utilized to evaluate, and test deep learning models. ***These datasets consist of labeled text data, including tweets, posts, and comments***, which contain both depressive and non-depressive content.

***A list of relevant datasets that can be used for the task:***

**1. Depression Tweets Dataset**:

This dataset includes tweets annotated with labels indicating whether the tweet contains depressive or non-depressive language. It focuses specifically on social media content related to depression.

* **Size**: Contains thousands of tweets labelled for depressive content. The size can vary based on the dataset version.
* **Use**: Ideal for training deep learning models focused on depression classification using Twitter data.
* **Access**: Available on platforms like Kaggle or GitHub, often used in depression-related research.

**2. CLPsych 2015-2020 Datasets:**

The **CLPsych** (Computational Linguistics and Clinical Psychology) challenge datasets are specifically designed for the detection of mental health issues (including depression) from text. These datasets consist of tweets, forum posts, and social media data labelled for depressive and other mental health disorders.

* **Use**: Commonly used for mental health classification, sentiment analysis, and depression prediction tasks in NLP.
* **Access**: Available through the official CLPsych website or linked repositories like GitHub. Access requires registration for the challenge.

**3. TwiBot-20 Dataset:**

***TwiBot-20*** is a large dataset that contains tweets from users with and without depression. The dataset includes demographic information and emotional content, useful for training and predicting depression based on social media posts.

* **Use**: Suitable for training deep learning models to detect depression in real-time social media data, specifically on Twitter.
* **Access**: Available through research papers or GitHub repositories focused on mental health prediction.

**4. Reddit Depression Dataset:**

This dataset is focused on Reddit rather than Twitter, it contains valuable data from users discussing their depression, mental health challenges, and related topics in subreddits such as r/depression.

* **Use**: This dataset is ideal for fine-tuning models trained on Twitter data, offering more in-depth discussions of mental health.
* **Access**: Available on GitHub or through research papers in the field of computational psychiatry.

**5. Mental Health on Twitter (MHOT) Dataset:**

This dataset includes tweets from users discussing mental health conditions, including depression, anxiety, and stress. It is annotated to indicate whether a tweet expresses signs of mental distress.

**6. Sentiment140 Dataset:**

Although not specifically designed for depression, the **Sentiment140** dataset contains 1.6 million tweets labelled for sentiment (positive, negative, or neutral). Negative sentiment can often correlate with depressive symptoms.

* **Use**: The dataset can be used to pretrain sentiment analysis models, which can later be fine-tuned for depression detection tasks.
* **Access**: Available on the Sentiment140 website or Kaggle.

**7. The i2b2 Depression Dataset:**

The **i2b2** (Informatics for Integrating Biology and the Bedside) challenge dataset includes clinical text data that has been used in depression-related NLP tasks. Although the dataset primarily focuses on clinical notes, it can be adapted for social media text by fine-tuning models trained on similar data.

* **Use**: Can be adapted for transfer learning or for fine-tuning deep learning models trained on Twitter or Reddit data.
* **Access**: Available through the official i2b2 website for academic research.

**8. Twitter Mental Health Dataset (TweetEval):**

The **TweetEval** dataset contains a set of labelled tweets specifically focused on evaluating the performance of NLP models for mental health topics. It includes categories for various mental health conditions, including depression.

**9. EmoReact Dataset:**

The **EmoReact** dataset is a collection of posts from different social media platforms (including Twitter, Reddit, and Instagram) that have been labelled with emotional reactions. It includes a category for depression-related emotions and can be used for training models focused on emotional and psychological distress.

**10. Social Media Mental Health Dataset (SMMH):**

This dataset contains social media posts from Twitter, Facebook, and Instagram, annotated for mental health issues such as depression and anxiety. It includes posts and comments that reflect a range of emotional and psychological states. **Use**: Can be used to train models on cross-platform social media data, making it ideal for models that aim to detect depression across different platforms

### RESEARCH PAPER (BASE PAPER) ANALYSIS

*Research paper used as a base*:

**A hybrid deep learning approach for depression**

**prediction from user tweets using feature-rich CNN**

**and bi-directional LSTM**

***Harnain Kour & Manoj K. Gupta***

Received: 20 April 2021 /Revised: 2 January 2022 /Accepted: 9 February 2022 /

Published online: 18 March 2022

© The Author(s), under exclusive licence to Springer Science + Business Media, LLC, part of Springer Nature 2022

**Writer’s OBJECTIVE:**

The study aims to see if it's possible to predict a person's mental state by identifying depressive versus non-depressive tweets. To do this, ***it uses a hybrid deep learning model combining a Convolutional Neural Network (CNN) and a bi-directional Long Short-Term Memory (biLSTM) network***, which ***achieves 94.28% accuracy on a dataset of tweets related to depression***. This CNN-biLSTM model outperforms other models, like standard Recurrent Neural Networks (RNNs) and CNNs alone, as well as traditional baseline methods.

The **main objective** of This study was to develop a hybrid DL model for depression prediction, and compare its performance to the related DL models namely, CNN and RNN. Our hypothesis is that the proposed DL model should outperform DL-based CNN and RNN models, state-of-the-art studies, and baseline models in both accuracy and robustness.

**Technologies Proposed By the Authors:**

Natural Language Processing (NLP) is a method for analyzing text and speech that has evolved from traditional grammar-focused studies to complex computer algorithms. Originally, NLP focused on well-structured text, like books, but now it’s used to analyze diverse, less structured content, including emails, web content, reviews, comments, and social media posts, which are much harder to interpret.

Sentiment Analysis (SA) is a part of NLP that examines positive and negative sentiments in text. With people sharing thoughts and experiences on social media, SA can help assess emotions, including signs of depression. While social media now includes videos, text-based content remains valuable for understanding users’ emotions. However, analyzing text on social media comes with challenges, like interpreting emojis, hashtags, and multilingual content.

NLP, combined with machine learning (ML) and deep learning (DL), is useful for detecting mental health patterns early on. Traditional ML methods like Random Forest (RF), Support Vector Machines (SVM), and Decision Trees (DT) have been used, but they struggle with larger, complex datasets. DL techniques, especially Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), have improved text analysis by using neural word embeddings, which capture the meaning and structure of text more effectively.

CNNs, initially designed for image recognition, can also work with text by focusing on essential features within words. RNNs, designed for sequential data, are great for tasks involving language structure, while ***Long Short-Term Memory (LSTM) networks*** are ideal for retaining important information over long sequences, avoiding common issues like the “vanishing gradient” problem.

***In this research, they combined DL techniques in a hybrid model to improve the accuracy of detecting depressive content in social media posts, comparing it with traditional methods to show its effectiveness***.

**Problem Statement**:

This study addresses the challenge of distinguishing between depressed and non-depressed individuals on social media by analyzing linguistic patterns. Unlike ***previous studies that often use unsupervised methods***, ***this research applies a supervised approach to classify depressed users based on psycho-linguistic features***. Handling Twitter data is complex due to its large volume and unstructured nature, making user and text classification a challenging task.

Some of the most common issues encountered while working with Twitter data are:

1. A huge number of images and video transactions were done parallelly with text.

2. Unstructured data with significant usage of emojis and GIFs.

3. Usage of foreign languages etc.

4. Labelling tweets that require professionals to label data and are very time-consuming.

***This study focuses on using English text only, excluding emojis, videos, and foreign languages, with noisy data cleaned through pre-processing.*** The problem of labelling data is solved by using an authenticate Twitter dataset that is released for the use of psychology and computer science researchers.

**Proposed Model*:***

***The main objective is to develop a hybrid deep learning model for predicting depression, hypothesizing that it will outperform CNN & RNN.***

Their hypothesis is that the proposed DL model should ***outperform DL-based CNN*** and ***RNN models***, ***state-of-the-art studies, and baseline models in both accuracy and robustness.***

OUR APPROCH AND OBJECTIVE TO INCREASE THE ACCURACY AND PERFORMANCE:

***Our main objective is to develop a Deep Learning Approach for Depression Classification and Prediction from User Tweets focusing not only on using English text but also including videos, and foreign languages.***

Technologies we’ll work upon:

To enhance the accuracy and predict depression using **images**, **videos**, and **foreign languages** in tweets, we can do this by incorporating the following technologies along with **NLP**, **CNN**, and **RNN**:

**1.Multimodal Deep Learning:**

- Multimodal deep learning integrates text, images, and videos, allowing the model to learn from multiple data sources. Depression indicators may appear in both text and visuals (e.g., dark-themed images, expressive videos), so combining these inputs can improve prediction accuracy.

- Use separate CNNs or RNNs for each modality (text, image, video) and fuse the learned representations at a later stage (e.g., using concatenation or attention mechanisms) to make a final prediction.

**2. Vision Transformers (ViT) for Image Analysis:**

- Vision Transformers have shown state-of-the-art performance in image classification tasks. They handle large image datasets well and can capture detailed visual cues that might indicate mood or emotional state.

- Apply a ViT model to analyse visual content associated with tweets, which can be helpful for capturing depressive themes in images shared by users.

**3. Convolutional 3D (Conv3D) or Recurrent Convolutional Networks (RCN) for Video Processing:**

**-**Conv3D and RCNs are designed for video data, as they can capture temporal changes across frames, which is crucial for understanding mood or sentiment in video content.

- Use Conv3D or RCN models on video frames from tweets to capture visual and temporal cues, which can add context to the depression prediction when combined with text-based analysis.

**4. Multilingual NLP Models (e.g., mBERT, XLM-R):**

**-** Multilingual models like **mBERT (Multilingual BERT)** or **XLM-R (XLM-Roberta)** are pre-trained on multiple languages and can capture cross-linguistic semantics, making them ideal for handling tweets in different languages.

**-** Use multilingual transformers to process non-English tweets and then combine these embeddings with English text features, allowing the model to capture depression-related language across multiple languages.

**5. Multimodal Attention Mechanisms:**

**-** Attention mechanisms highlight important parts of each input (text, image, video) and can help focus on depression-relevant aspects in complex, multimodal content.

**-** Implement attention layers that weigh key features across modalities, helping the model prioritize depressive signals in text, imagery, and video content for improved prediction.

**6. Sentiment and Emotion Analysis for Multimodal Content:**

**-** Analysing sentiment and emotions across text, images, and videos can provide a clearer picture of a user’s mental state.

**-** Use sentiment analysis tools (e.g., VADER, TextBlob for text) and emotion recognition models (e.g., FER for facial expressions in images and videos) to add sentiment and emotion scores as features. This will allow the model to assess emotional signals in both verbal and non-verbal content.

**7. Graph Neural Networks (GNN) for Contextual User Information**:

- GNNs can analyse social network structure and user interactions, offering additional context that may be relevant for understanding depression.

- Build a GNN on a user's social interactions and relationships, as depressed individuals may exhibit unique social patterns (e.g., isolation, types of interactions) that could be predictive when combined with multimodal content.

**8. Advanced Data Augmentation Techniques for Multimodal Content:**

**-** Multimodal data can be scarce and diverse, so augmenting images, video frames, and text can improve model generalization.

**-** Use tools like GANs (Generative Adversarial Networks) for synthetic image and video generation, and NLP-based models (e.g., GPT-3) for generating additional text to enhance the multimodal dataset.

**9. Hyperparameter Tuning and Model Assembling:**

**-** Tuning parameters across multiple modalities can significantly improve performance, as different configurations might be optimal for text, images, or video.

**-** Perform hyperparameter optimization on each component and consider assembling different architectures (e.g., text-only model, image-only model, multimodal model) to make the final prediction more robust.

RESEARCH GAP:

Existing 2022 system **developed a hybrid deep learning approach for depression prediction from user tweets using feature-rich CNN and bi-directional LSTM *focusing on using English text only, excluding emojis, videos, and foreign languages, with noisy data cleaned through pre-processing.***

***What we are proposing in 2025*** is ***to develop a Deep Learning Approach for Depression Classification and Prediction from User Tweets and social media focusing not only on using English text but also including videos, and foreign languages***