A Machine Learning model for Early Depression Detection

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***Abstract*—Early depression is also referred to as early-onset depression. Depression is the most common and serious mental disorder that affects all age people. Identifying depression early on is crucial because we can provide help and support that significantly impacts the outcome for the better. In this study, we have introduced a detailed approach to detect depression early on. For this social media platforms are better than anything for getting the emotions of people. Our approach begins by collecting Twitter data from Kaggle with a dataset size of 1.6 million Twitter. But to filter data that has early depression we need to collect early depression keywords.to collect early depression we have used Google's Gemini AI API to fetch these keywords using PALM(pathway language model). subsequently, we filter the dataset to include only tweets that have early depression keywords ensuring the focus on relevant content. To prepare the data for analysis, we performed preprocessing techniques to clean and tokenize the text and machine learning algorithms. This approach combines Data science, natural language processing, and mental health care and helps for effective early depression detection and support for every individual who faces depression early on. [12]**

Keywords: *Machine learning, depression, Twitter data, natural language processing.*

I. Introduction and statement of the problem

Depression is a most common mental health condition that causes changes in the behavior of people in real life. It involves a depressed mood or loss of interest in daily activities for a long period. Depression can happen to anyone at any stage of life which is because of abuse, severe losses, or other stressful events that lead to developing depression. It can affect individuals in all aspects of life including home, work, school, and in the community. [3]

According to the World Health Organization(WHO), approximately 280 million people are depressed in the world. More than 0.7 million people die due to suicide every year. Although there are effective treatments for mental disorders more than 75% of people who have low income and less knowledge regarding depression receive no treatment.WHO introduced many programs to give awareness and support to people in different ways.

Traditionally depression is treated by psychotherapy and medication where therapists provide counseling and family health care providers provide medication. but so many people are not willing to express they have depression so it is difficult to predict whether that person has depression or not. so predicting whether the person has depression or not is difficult and sometimes identifying takes a long time which leads to suicide or self-harm for the people. For this, we are considering early to know the signs of depression which helps and gives support to that individual.

Our approach is to use social media platforms to know early depression signs in individuals. For the social media platform, we have taken Twitter where most people interact with others in the form of tweets, which is the best way to know a person's emotions at a particular stage. so we have collected Twitter data from Kaggle. kaggle is an open source to get datasets for any data science-related researchers. The dataset is collected from Kaggle with the size of 1.6 million tweets. This dataset would be pretty enough to know the individual behavior.However, we have to filter the dataset that has only early depression signs. For this, we need to fetch early depression keywords. [1]

To collect early depression keywords, one best way is to use the open platform. So we have used Google's Gemini AI API which is free to use for anyone.to use Gemini ai API we have to create our API key and after getting the API key we can use that in the source code. To interact with source Python code to open AI we have to use Google generative AI called PALM which is a pathway language model. This PALM works as the interaction between our Python code and Gemini AI. For this, we have used Python language which is easy to use and gives accurate results for machine learning algorithms. So after forming an interaction, it acts as a prompt and response way.so we have given input as "early depression keywords count of 100 unique", by giving this prompt we got a response as 100 unique early depression keywords. After getting this keyword we filtered the dataset which had these keywords. We have taken this subset of data for further analysis.

After collecting the subset data we have done preprocessing techniques. To standardize the data we have removed html, URLs, lowercasing, removing whitespaces, and special characters and then we have performed tokenization, stemming, and lemmatization. This preprocessing is briefly explained in the data preprocessing section. The data is further processed for data analysis. first tokenizing and encoding data. After that, we split data for training and testing and used machine learning algorithms such as logistic regression and convolutional neural networks(CNN).

After that, we evaluated by using evaluation techniques such as accuracy, precision, recall, and f1 score to know the performance of the model. [2]

A. Problem Statement

For the traditional approach to treating depression, relying on individuals seeking help from doctors leads to delaying and missing opportunities for interaction and some people are not willing to express they have depression which leads to suicide or self-harm. Detecting early depression early on helps individuals to survive this mental disorder. This study aims to use social media platforms such as Twitter. the Twitter data is collected and by using early depression keywords we take tweets that have early depression keywords and further analysis by machine learning techniques to develop a system that detects early depression cases early on and provides support to the people who are in need.

II. Review of the literature

The article "Depression detection from social network data using machine learning techniques" starts with explaining how social media is helping people to connect and share their experiences, emotions and feelings. This greatly helps professionals in health industry to look and analyze the mental health conditions of individuals based on their posts. This study employes various machine learning methodologies to detect patterns among users and their online interactions. Thus, getting to know users' mental conditions such as calm, anger, happy, sad, depressed etc. This research insists on building new techniques to analyze mental health condition of online users using their posts.

This study also outlines the research design and various methods used to detect depression among online users. They used classifiers like Decision tree, SVM, KNN, Ensemble etc. and achieved the accuracy of 60-80 percent for these models. Their study shows that the Decision Tree classifier performed better than all other classifiers used.

Furthermore, this study evaluates how good the proposed methods are by employing various factors. Their study is like a good foundation for future research on depression detection models and tries to provide a effective solution for analyzing mental health conditions.

[3] The article "Artificial intelligence assisted tools for the detection of anxiety and depression leading to suicidal ideation in adolescents: a review" employes deep learning models to try and get a combination of data to classify and identify people with anxiety and depression. This data may include voice (audio), images of face, medical history features. This greatly helps bring down the suicide numbers. [5]

The article "Depression detection using emotional artificial intelligence and machine learning: A closer review" tries to provide the overview of various machine learning and artificial intelligence algorithms which helps to analyze various emotions including depression as well as the associated research questions.

The article "A textual-based featuring approach for depression detection using machine learning classifiers and social media texts" aims to detect depression among users using social media texts. Despite the training data not having keywords like depression, diagnosis etc., the model in this study aims to detect depression. Furthermore, even when unrelated testing datasets are employed, this study tries to identify and classify depressed users.

The study by Chenhao Lin tries to use the social media posts of users, which has the potential to act as their mental condition, to detect depression and anxiety. These social media posts may include texts and images. This research designed a system dubbed SenseMood to indicate that the people having depression can be analyzed and detected with high accuracy. [4]

III. Objective of the study

The main objective of this project is to detect early signs of depression effectively among people so that we can have more time to address it. This project aims to:

- Employ Sentiment140 dataset from Kaggle which contains tweets data and filter those tweets using keywords generated by Gemini AI API.
- Develop a machine learning model using Logistic Regression and Convolutional Neural Networks to perform sentimental analysis on tweets data.
- Train the model to detect tweets that indicate early signs of depression.
- Test and evaluate the model by employing metrics like accuracy, precision, recall, F1-score and ROC-AUC using testing dataset.

IV. Data collection

A dataset comprising 1.6 million tweets has been collected from Kaggle's twitter data. click the link for the dataset

V. Exploratory data analysis and hypothesis of the study

A. Dataset Exploration:

Exploratory data analysis (EDA) In this case, data exploration entails learning about the composition and organization of the given dataset. Each row in the DataFrame df represents a tweet, and the columns include "target," "id," "date," "flag," "user," and "text."

Initially, summary statistics of numerical columns such as 'target' (which probably indicates sentiment, with '0' denoting negative sentiment and '4' denoting positive sentiment) and 'id' are usually examined as part of exploratory data analysis (EDA). This offers information on the range of tweet IDs and the distribution of sentiment labels. [16]

Exploration for categorical columns like as "date," "flag," and "user" may entail figuring out the distinct values, frequency counts, and patterns within each category. This can entail looking at how tweets are distributed over time, seeing any trends, and evaluating user interaction.

Exploring textual data is essential to comprehending the tweets' nature. Applying methods like sentiment analysis, word frequency analysis, and tokenization can help retrieve valuable information from the 'text' column.

[7]

B. Data Preprocessing:

Eliminating URLs and HTML tags: URLs are web addresses, whereas HTML tags are components used to organize web content. By eliminating these components from the text, it is ensured that just the tweets' has actual textual content without any formatting or links to external websites is taken into account. [11]

Text conversion to lowercase: By changing every letter in the text to lowercase, this step guarantees consistency.In this way, words like "Depression" and "depression" are used interchangeably while analyzing.

Eliminate all punctuation from the text: remove all commas, periods, exclamation points, and other punctuation. By taking this action, punctuated words are not treated as distinct entities and the text is made simpler.

Eliminating stop words: Stop words are regular terms that, in the context of analysis, frequently have little or no meaning, such as "and," "the," "is," etc. Eliminating stop words helps the data become less noisy and concentrate on terms with greater meaning. [6]

White space trimming: involves removing excess spaces between words and at the start and finish of phrases. This guarantees correctness and consistency while tokenizing and analyzing words.

handling special characters: Depending on their importance to the study, special characters such as hashtags, mentions, symbols, etc., may also be processed or eliminated.

Tokenization: The process of breaking up the text into distinct words, or tokens, is known as tokenization. The tokenization of the statement "depression causes loneliness" would be ["depression", "causes", "loneliness"].

Stemming: Removes suffixes and prefixes to return words to their basic form. For example, "happily" becomes "happy," "running" becomes "run," etc. This makes the writing simpler, although it might not always produce words.

Lemmatization: Parses words according to their part of speech and returns them to their base or dictionary form (lemma). "Better" becomes "good," "running" becomes "run," and so on. Compared to stemming, lemmatization preserves semantic meaning and grammatical accuracy better.

To improve the data's quality and applicability for tasks including analysis and modeling, preprocessing is necessary. Preprocessing stages are important for the given Twitter dataset for a number of reasons. First off, noise in the form of special characters, punctuation, and URLs is frequently included in the textual data in the 'text' column. This can negatively impact the efficiency of natural language processing (NLP) algorithms. By adopting methods like text cleaning and normalization, these artifacts can be replaced or removed, allowing the attention to be drawn to the tweets' valuable information. Second, to guarantee consistency and comparability between various tweets, textual data must be standardized. This is because differences in writing styles, capitalization, and abbreviations could prevent efficient analysis. [15] [8]

```
data['text']

0          [switchfoot, awww, that, bummer, shoulda, got,...
1          [upset, cant, updat, facebook, text, might, cr...
2          [kenichan, dive, mani, time, ball, manag, save...
3                       [whole, bodi, feel, itchi, like, fire]
4               [nationwideclass, behav, im, mad, cant, see]
                               ...
1599994    [cliffforst, yeah, work, better, wait, end, wo...
1599995                  [woke, school, best, feel, ever]
1599996        [thewdbcom, cool, hear, old, walt, interview]
1599997                 [readi, mojo, makeov, ask, detail]
1599998    [happi, 38th, birthday, boo, alll, time, tupac...
Name: text, Length: 1589938, dtype: object
```

Fig. 1. data preprocessing

C. Keywords Extraction

We generated answers to user queries using a pre-trained text generation model by using the Google Generative AI API. This AI can be used to extract keywords and insights from textual data in the context of early depression detection, allowing researchers to spot patterns and signs linked to depressive symptoms. Users can receive responses from the AI that may contain pertinent keywords or phrases that indicate sad behavior by asking it mental health-related inquiries. Afterwards, methods for early detection and intervention can be developed by analyzing and researching these terms further. The AI's capacity to produce language in response to prompts makes it easier to explore big databases, retrieve important information quickly, and build machine learning models focused at identifying early signs of depression.

```python
import google.generativeai as palm

# Configure the generative AI with your API key
palm.configure(api_key="AIzaSyAfnBPT2-xRULx-rP05QaHI4qRiQRttBvY")

# Define default generation parameters
defaults = {
  'model': 'models/text-bison-001',
  'temperature': 0.7,
  'candidate_count': 1,
  'top_k': 40,
  'top_p': 0.95,
  'max_output_tokens': 1024,
  'stop_sequences': [],
}

# Define the limit for the number of questions
question_limit = 1 # Change this to your desired limit

# Initialize a counter to keep track of the number of questions asked
question_count = 0

# Start the question-answering loop
while question_count < question_limit:
    # Take user input for the question
    prompt = input("Question: ")

    # Generate the response using the generative AI
    response = palm.generate_text(
        **defaults,
        prompt=prompt
    )

    # Print the answer
    print("Answer:", response.result)
```

Fig. 2. keywords extraction

```
Question: early depression keywords count 100 unique
Answer: 1. **sadness**
2. **grief**
3. **loneliness**
4. **hopelessness**
5. **worthlessness**
6. **isolation**
7. **emptiness**
8. **numbness**
9. **irritability**
10. **anger**
11. **anxiety**
12. **fear**
13. **worry**
14. **self-blame**
15. **guilt**
16. **shame**
17. **worthlessness**
18. **low self-esteem**
19. **poor self-image**
20. **hopelessness**
21. **pessimism**
22. **lack of motivation**
23. **fatigue**
24. **lack of energy**
25. **sleep problems**
26. **difficulty concentrating**
27. **memory problems**
28. **loss of appetite**
29. **weight loss**
30. **overeating**
31. **weight gain**
32. **aches and pains**
33. **headaches**
34. **gastrointestinal problems**
35. **sexual problems**
```

Fig. 3. keywords extraction

VI. Data Analytics

A. Machine Learning Models

Complex data can be predicted, categorized, and patterned by machine learning algorithms, which alters the way data is analyzed and interpreted. [17]

B. convolutional neural networks (CNNs):

When it comes to machine learning algorithms and how they are used with text data to identify depression in its early stages, we have covered a lot of area.

CNN: Text data is processed by convolutional neural networks (CNNs), which view the text as a series of word embeddings, with each word being represented by a dense vector.

Architecture: It is made up of convolutional layers that move over word embeddings to extract attributes associated with terms from the early depression.

Feature extraction: it is a hierarchical procedure that aids in the model's discovery of significant relationships and patterns in the text data. [9]

Classification: Using the learned patterns, the model predicts whether depression will be present or absent using the extracted attributes.

```
Epoch 1/5
19875/19875 [==============================] - 127s 6ms/step - loss: 0.5563 - accuracy: 0.7132 - val_loss: 0.5249 - val_accuracy: 0.7381
Epoch 2/5
19875/19875 [==============================] - 113s 6ms/step - loss: 0.5375 - accuracy: 0.7319 - val_loss: 0.5480 - val_accuracy: 0.7293
Epoch 3/5
19875/19875 [==============================] - 125s 6ms/step - loss: 0.5414 - accuracy: 0.7291 - val_loss: 0.5493 - val_accuracy: 0.7228
Epoch 4/5
19875/19875 [==============================] - 115s 6ms/step - loss: 0.5431 - accuracy: 0.7286 - val_loss: 0.5419 - val_accuracy: 0.7319
Epoch 5/5
19875/19875 [==============================] - 122s 6ms/step - loss: 0.5444 - accuracy: 0.7285 - val_loss: 0.5561 - val_accuracy: 0.7191
<keras.src.callbacks.History at 0x78fdc8efb9a0>
```

```
9938/9938 [==============================] - 26s 3ms/step - loss: 0.5561 - accuracy: 0.7191
Test Accuracy: [0.5561274886131287, 0.7190931439399719]
```

C. Logistic Regression

Text Representation: Using Count Vectorizer to tokenize and transform text input, a Bag-of-Words (BoW) representation is generated for logistic regression.

BoW features are used to measure the frequency of words in each document, which serves as the foundation for feature extraction.

Model Training: Because of its ease of use and interpretability, logistic regression is used as the classification model.

Prediction: Based on the presence or absence of particular phrases or patterns connected to depression keywords, the trained Logistic Regression model makes a prediction on depression. [13]

[10]

D. Model Evaluation

Model Evaluation: Performance Metrics: Recall, accuracy, precision, F1 score, and ROC AUC score are some of the metrics used to evaluate the model's performance.

Accuracy: Evaluates how well predictions are made overall.

Precision: Shows the percentage of actual positive forecasts among all made positive forecasts.

Recall: Calculates the percentage of real positive occurrences among all true positive forecasts.

F1 Score: A fair evaluation statistic that provides a harmonic mean of memory and precision.

ROC AUC Score: Assesses how well the model can differentiate across classes; especially helpful for datasets that are unbalanced. [10]

VII. Data Visualization and Results

This graphic is important for understanding the prevalence of positive and negative attitudes expressed in tweets in the context of early depression detection on Twitter. We can learn more about the general mood of Twitter users and spot any patterns that might be linked to depressed symptoms by examining this distribution. For example, a greater proportion of tweets expressing negative sentiment could suggest that the user base is more likely to have depressive experiences or thoughts. This visualization aids in the development of focused interventions or support networks for those at risk of depression as well as in the better understanding of the emotional terrain of social media platforms by researchers and mental health practitioners. [19]

The distribution of sentiment labels within the dataset is displayed in a bar chart created by this code. The two sentiment labels, "Positive" and "Negative," are represented by the x-axis, and the number of tweets connected with each sentiment is displayed on the y-axis. It is simple to visually compare the frequency of each sentiment category because the bars are colored red for negative sentiment and green for positive sentiment.

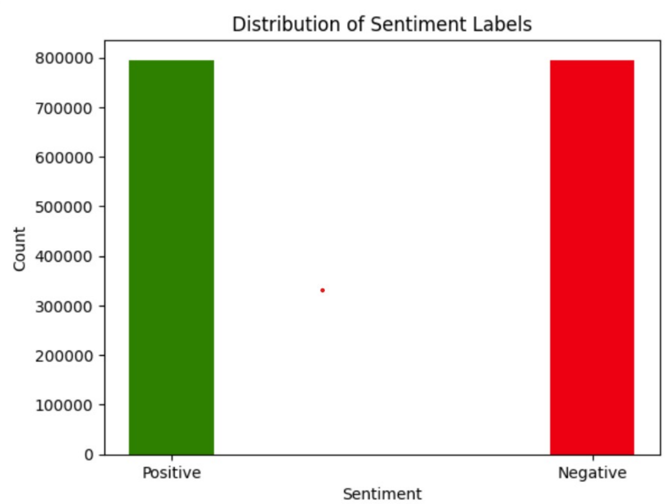

Fig. 4. Data Visualization

A. Results

The percentage of correctly identified examples out of the total is indicated by the accuracy of 0.778, indicating a relatively percentage of correctly categorized instances out of the total in the project mentioned above is indicated by the reported test accuracy of 0.719, indicating a reasonable level of general correctness in the model's predictions. Lower numbers indicate higher performance, while the error made during the training process is represented by the loss value of 0.5561. Even with the comparatively high accuracy, the loss value indicates that the model's performance can still be optimized. One important parameter for assessing how well the built model classifies tweets as positive or negative sentiment is the test accuracy score. good degree of overall correctness in the model's predictions. Precision, which is defined as the percentage of true positive predictions among all positive predictions, is 0.767. [18]

This suggests that the system can effectively identify tweets that convey depression behavior while reducing the number of false positives. The model's recall score of 0.801 indicates how well it captures the majority of real positive cases, which is important for thorough depression diagnosis. A balanced performance between precision and memory is shown by the F1 score, which is 0.784 and represents the harmonic mean of precision and recall. The percentage of correctly categorized instances out of the total in the project mentioned above is indicated by the reported test accuracy of 0.719, indicating a reasonable level of general correctness in the model's predictions. Lower numbers indicate higher performance, while the error made during the training process is represented by the loss value of 0.5561. Even with the comparatively high accuracy, the loss value indicates that the model's performance can still be optimized. One important parameter for assessing how well the built model classifies tweets as positive or negative sentiment is the test accuracy score. These findings suggest that although the model shows a respectable degree of accuracy, more improvement and optimization would be required to improve its functionality and dependability for the early identification of depression from Twitter data. [20]

Convolutional Neural Networks (CNNs) are used in this study to analyze textual data taken from Twitter in order to identify early indicators of depression. CNNs are very good at identifying spatial patterns in data, which makes them useful for examining text sequences like tweets. To begin with, the text data is preprocessed using techniques like tokenization and embedding to get it into a format that the CNN can use. Convolutional layers and pooling layers, which methodically build hierarchical representations of the text data and capture significant characteristics and patterns at various levels of abstraction, are the standard components of a CNN architecture. [14]

During the training phase, the CNN finds patterns indicative of depressive emotion or language by using backpropagation to adjust the weights of its neurons. After being trained, CNN classifies new tweets as either positive or negative, providing a predictive model for early depression identification. This strategy makes use of CNNs' innate capacity to identify intricate patterns in textual data, providing a viable means of automatically screening for depressed symptoms on social networking sites like Twitter. This has the potential to provide prompt intervention and assistance for those in need.

```
# Evaluate the model
accuracy = model.evaluate(X_test, y_test)
print("Test Accuracy:", accuracy)

9938/9938 [==============================] - 26s 3ms/step - loss: 0.5561 - accuracy: 0.7191
Test Accuracy: [0.5561274886131287, 0.7190931439399719]
```

Fig. 5. CNN

A key tool in this effort for early depression diagnosis using Twitter data is logistic regression. Logistic regression, as opposed to linear regression, is appropriate for problems involving binary classification, which makes it a good fit for identifying positive and negative sentiment in tweets. It works by combining the linear combination of input features with a logistic function to create an output that is a probability score that indicates the chance of a tweet falling into a specific mood category. Based on the variables taken from the textual input, logistic regression learns to differentiate between positive and negative attitudes by iteratively modifying the model parameters using methods like gradient descent.

```
# Evaluate model
accuracy = accuracy_score(y_test, y_pred)

accuracy

0.7779821880070946
```

Fig. 6. logistic regression

VIII. Conclusion

To sum up, this project shows how machine learning techniques may be used to use Twitter data for early depression identification. We learned about the features of tweets and found patterns suggestive of sad sentiment through exploratory data mining. Through the utilization of methods like logistic regression and convolutional neural networks, we were able to create models that could precisely categorize tweets as having a positive or negative sentiment, which would enable the early identification of depressed symptoms. These results have implications for the creation of automated screening instruments and intervention plans to help people with mental health issues. In order to improve mental health outcomes in online communities, more study and cooperation are required to develop these models and implement them in practical contexts.

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