# Harnessing NLP to Detect Stress in Social Media

## Early Intervention for Mental Wellbeing

**Chong Chee Chen (Jimmy)**

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# 1.Problem Statement

**Project Goal:** To use **Natural Language Processing (NLP)** techniques to find signs of stress in social media posts.

**Why:** Early detection can help people get better. Social media has lots of text data that can be analysed.

**Problem:** Finding stress now is often based on what people say or clinical tests. These methods can be biassed and take a long time.

**Solution:** Researchers want to create a system that can automatically find stress in social media posts. This system can:

- Identify people who might be stressed.
- Offer help to those who need it.
- Learn about stress trends in the whole population.

**What has been done:** Some studies have already tried to find stress using social media. Researchers want to build on this work by using better computer techniques to improve accuracy.

# 2. Industry & Domain

**Project Focus:** This project uses **Natural Language Processing (NLP)** to understand language and detect stress in social media posts. It's part of the fields of computer language and mental health.

**Natural Language Processing (NLP):** Computers are getting better at understanding language. There's a lot of progress, but it's still hard for them to understand things that are confusing or out of context.

**Mental Health:** More and more people are struggling with mental health problems. It's important to find new ways to help them that are easy to use and effective.

## 2.1. Value Chain

- **Data Collection:** Gathering social media posts from places like Reddit and Twitter.
- **Data Cleaning:** Making the data clean and ready to use.
- **Feature Creation:** Turning the text data into useful information.
- **Model Training:** Teaching a computer model to recognize stress in posts.
- **Deployment:** Putting the trained model into a real-world tool.
- **Evaluation:** Checking how well the model works and making it better.

## 2.2. Key Concepts

- **NLP:** Tokenization, stemming, lemmatization, stop word removal, feature extraction (TF-IDF, word embeddings), machine learning algorithms (e.g., SVM, Naive Bayes, neural networks).
- **Mental Health:** Stress, anxiety, depression, emotional well-being, mental health resources.

## 2.3. Potential Applications

- **Customer Service:** Analysing customer feedback to identify areas of frustration or dissatisfaction.
- **Human Resources:** Monitoring employee sentiment and identifying potential signs of burnout.
- **Healthcare:** Analysing patient records to detect early signs of mental health conditions.
- **Marketing:** Understanding consumer sentiment towards products or brands.

# 3. Stakeholders

- **Individuals:**
    - Social media users who may be experiencing stress.
    - Mental health professionals and organisations.
    - Family members and friends of individuals struggling with mental health.
- **Organisations:**
    - Social media platforms (e.g., Reddit, Twitter).
    - Mental health research institutions.
    - Technology companies developing AI-powered mental health solutions.
    - Healthcare providers and insurers.
    - Government agencies responsible for mental health initiatives.

## 3.1. Stakeholder Concerns and Motivations

- **Individuals:**
    - Finding stress early can help people get better faster.
    - Having personal support can help people deal with stress and prevent it from getting worse.
- **Mental health professionals and organisations:**
    - This technology can help doctors identify people who might be stressed.
    - It can help reduce the workload for mental health services and improve results.
- **Organisations:**
    - Social media companies should care about their users' mental health.
    - Technology companies can create new tools to help people with mental health problems.
    - Healthcare providers and insurance companies can use this technology to find people who need mental health help.
    - Governments can use this technology to make better decisions about public health and resource allocation.

## 3.2. Stakeholders’ Expectations

- **Individuals:**
    - The stress detection system should be accurate and reliable.
    - People's private information should be kept safe.
    - The technology should be easy to use.
- **Mental health professionals and organisations:**
    - The system should work well with existing mental health services.
    - It should be based on scientific research.
    - There should be ethical rules about using AI for mental health.
- **Organisations:**
    - The solution should be able to handle a lot of people and be affordable.
    - It should help social media users feel better.
    - It should contribute to progress in AI and mental health research.
    - It should follow ethical rules about data privacy and mental health.

# 4. Business question

## 4.1. Core Business Question

Can we accurately detect stress in social media text using NLP techniques, and if so, how can this information be used to improve mental health outcomes?

## 4.2. Quantifying Business Value

- **Social media platforms:**
  - By finding people who might be stressed, social media platforms can offer help and reduce negative things like self-harm or online bullying.
  - If this helps even 1% of people stay on the platform, it can be a big win for keeping users and making money.
- **Mental health organisations:**
  - Finding people who might be stressed early can help them get better faster and save money on treating serious mental health problems.
  - If this helps even 10% of people, it can save a lot of money for mental health organisations.
- **Technology companies:**
  - Creating a good stress detection system can make technology companies leaders in using AI to help people with mental health. This can open up new opportunities to sell products and work with other companies.

## 4.3. Accuracy and Implications

**How accurate does it need to be?**

The accuracy needed for a stress detection system depends on what it's used for and the risks of making mistakes. In mental health, it's very important to be accurate to avoid misidentifying people.

**False Positives:**

- If the system says someone is stressed but they're not, it can cause unnecessary worry and shame.
- We need to find a balance between being sensitive to stress and avoiding false alarms.

**False Negatives:**

- If the system misses people who are stressed, it can mean they don't get help when they need it.
- This can have serious consequences for mental health, including hurting themselves or trying to kill themselves.

**The Best System:**

The best stress detection system would be very good at both finding people who are stressed and not finding people who aren't stressed. This would minimise both kinds of mistakes.

# 5. Data question

## 5.1. Core Data Question

The primary data question is: Can we effectively extract features from social media text that accurately predict stress levels?

## 5.2. Essential Data Requirements

**Data for the Project:**

- **Social Media Posts:** A lot of text posts from places like Reddit and Twitter.
- **Stress Labels:** Whether each post shows high stress (1) or not (0).
- **Extra Information:** Details about the posts, like who wrote them, when they were posted, and how many people saw them.
- **Checked Data:** Some posts that experts have looked at to make sure the stress labels are correct.
- **Benchmark Datasets:** Other datasets used to compare how well our model works.

# 6. Data

## 6.1. Data Origin

The data was sourced from Reddit and Twitter, and subsequently made available on Kaggle.

## 6.2. Data Volume and Attributes

The dataset consists of four main components:

- **Reddit Combi:** Combines titles and body text of articles from both stress-related and non-stress-related subreddits on Reddit.
- **Reddit Title:** Contains titles of articles collected from stress-related and non-stress-related subreddits on Reddit.
- **Twitter Full:** Includes stress-related and non-stress-related tweets collected from Twitter.
- **Twitter Non-Advert:** A denoised version of the Twitter Full dataset, excluding promotional content.

| | title | body | Body_Title | label |
|---|---|---|---|---|
| 0 | Envy to other is swallowing me | Im from developingcountry, Indonesia , and for... | Envy to other is swallowing me Im from develop... | 1 |
| 1 | Nothin outta the ordinary. Paradise. Job stres... | Um hello ....well many can relate im sure. Aft... | Nothin outta the ordinary. Paradise. Job stres... | 1 |
| 2 | Almost 49 and the chasm of emptiness has never... | I've been diagnosed severe bi polar where you ... | Almost 49 and the chasm of emptiness has never... | 1 |
| 3 | I'm happy again | After my closest friend left me in April, I ha... | I'm happy again After my closest friend left m... | 0 |
| 4 | Is it possible to recover from such a traumati... | I am only 15, and yet I feel my life is alread... | Is it possible to recover from such a traumati... | 1 |

*Figure 1: Reddit Combi Post Sample with Stress Label*

| | title | label |
|---|---|---|
| **0** | My aunt and uncle scoring their first gig as p... | 0 |
| **1** | How do I stop stressing about work when I'm at... | 1 |
| **2** | Meeting a fellow suicidal student in middle sc... | 1 |
| **3** | My brain feels literally numb. Is this depress... | 1 |
| **4** | A mother's reaction after seeing her son has p... | 0 |

*Figure 2: Reddit Title Post Sample with Stress Label*

| | text | hashtags | labels |
|---|---|---|---|
| **0** | Being s mom is cleaning 24/7 the same shit ove... | ['momlife', 'kids', 'tired'] | 1 |
| **1** | And now we have been given the walkthru book b... | ['walkthru'] | 0 |
| **2** | Wishing YOU Peace Joy & Love! JoyTrain MentalH... | ['Peace', 'Joy', 'Love', 'JoyTrain', 'MentalHe... | 0 |
| **3** | speak-no-evil monkey Can I Be Honest With You... | ['therapy', 'help', 'NLP', 'CBT', 'hypnotherap... | 1 |
| **4** | Psy Do u hv any regrets? Me No Psy Are you hap... | [] | 0 |

*Figure 3: Twitter Full Post Sample with Stress Label*

| | text | label |
|---|---|---|
| **0** | speak-no-evil monkey Can I Be Honest With You... | 1 |
| **1** | Frau Goebbels early signs of psychosis psychot... | 1 |
| **2** | A lot of work and unfulfilled tasks plunge you... | 1 |
| **3** | Private health insurance delivers value for yo... | 1 |
| **4** | XpertOnline offers you the convenience of view... | 1 |

*Figure 4: Twitter Non-Advert Post Sample with Stress Label*

## 6.3. Data Reliability

The reliability of the data depends on a few things:

- **Data Quality:** The quality of the text can be different depending on where it comes from (like social media). It might have mistakes, be inconsistent, or be biassed.
- **Sample Size:** Having more data can usually make the results more reliable. But even with a lot of data, there can still be problems because people use language and behave in different ways.

## 6.4. Raw Data Quality

**Problems in the Raw Data:**

- **Noise:** Spelling mistakes, typos, and grammar mistakes.
- **Inconsistencies:** Differences in how people write, their tone, and the words they use.
- **Biases:** Personal opinions of the people who wrote the content.
- **Spam:** Irrelevant or misleading information.

## 6.5. Data Generation

The data came from people posting on Reddit and Twitter. The exact ways they collected and prepared the data might be different depending on where they got it and how the researchers worked.

## 6.6. Data Availability

Whether we can get new data depends on the rules of Reddit and Twitter. But since social media is always changing, it's likely that new data will keep being created and available.

# 7. Data science process

## 7.1. Data analysis

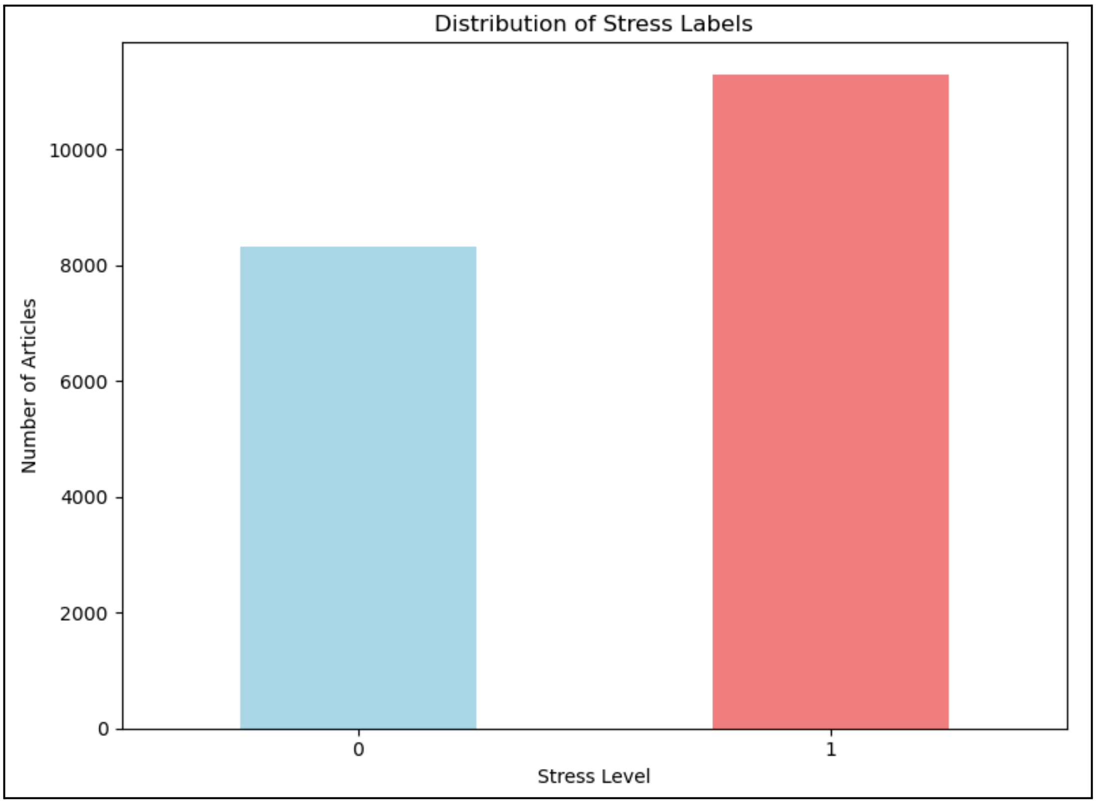


*Figure 5: Frequency of Stressful and Non-Stressful Posts*

The bar chart above illustrates the distribution of stress labels within the dataset. It shows a clear class imbalance, with a significantly higher number of non-stressful posts compared to stressful posts. This imbalance can impact model performance.

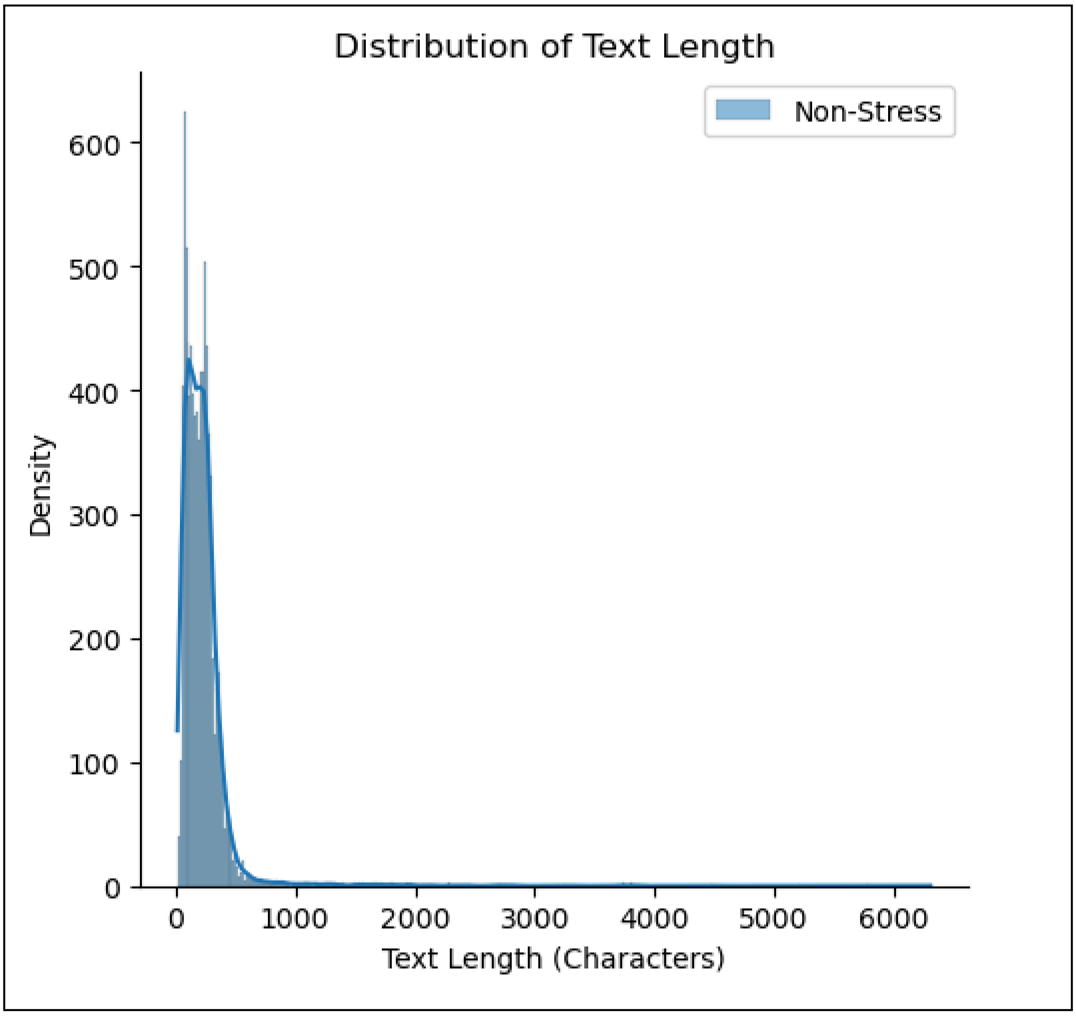


*Figure 6: Distribution of Text Length*

The figure above shows how long the posts are for both stressful and non-stressful posts. We can see a few things:

- **Most posts are short:** Most posts are short, with a few longer ones.
- **Some overlap:** There are some posts that are both stressful and non-stressful, so just the length might not be enough to tell them apart.
- **Non-stressful posts are slightly longer:** Non-stressful posts are usually a bit longer than stressful ones.

While the length of a post might give us some clues about stress, it's probably not enough on its own to accurately detect stress. We need to use other information, like word meanings or how positive or negative the words are, to make the model work better.


*Figure 7: Common Words Associated with Stress*

The word cloud above illustrates the most frequent words appearing in the text posts labelled as stressful. The size of each word represents its relative frequency within the corpus. Key themes emerging from the word cloud include:

- **Negative emotions:** Words such as "stress," "depressed," "sad," and "anxious" are prominently featured, highlighting the prevalence of negative emotions in the text.
- **Life challenges:** Terms related to work, school, relationships, and personal problems are frequently mentioned, suggesting that these factors contribute to stress.
- **Seeking help:** Words like "help," "support," and "therapy" indicate that individuals experiencing stress may be actively seeking assistance.

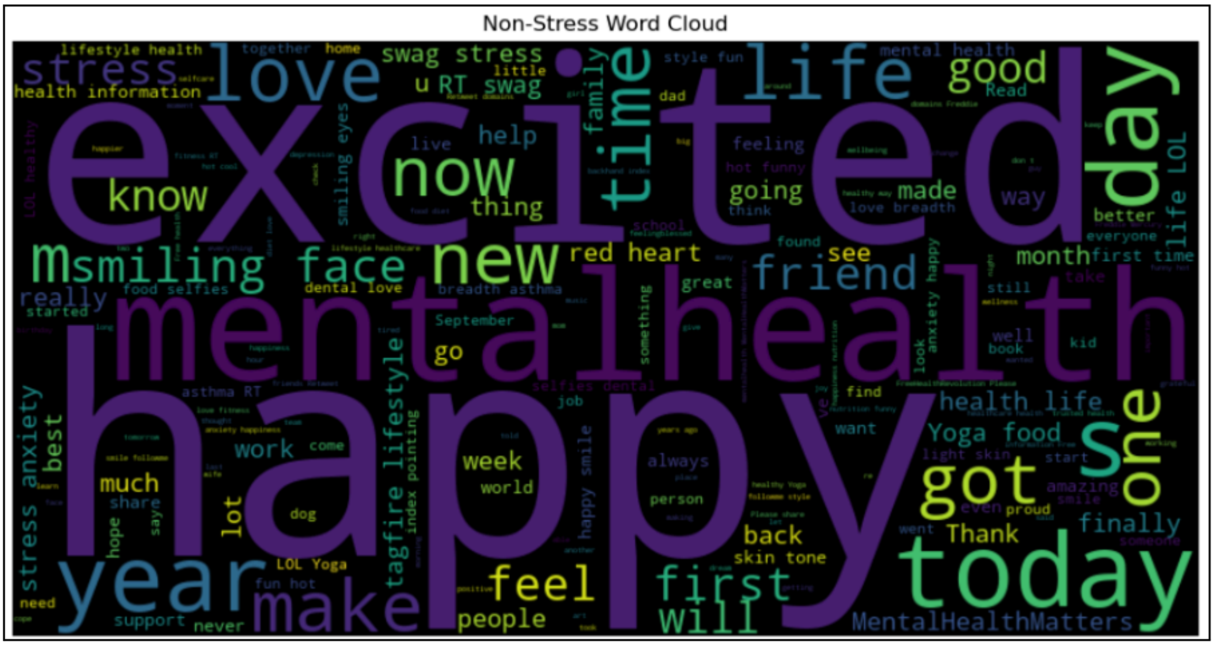


*Figure 8: Common Words Associated with Non-Stress*

The word cloud above illustrates the most frequent words appearing in the text posts labelled as non-stressful. Key themes emerging from the word cloud include:

- **Positive emotions:** Words such as "happy," "love," "good," and "excited" are prominent, highlighting the prevalence of positive emotions in the text.
- **Everyday life:** Terms related to daily activities, hobbies, and social interactions are frequently mentioned, suggesting a focus on positive aspects of life.
- **Gratitude and appreciation:** Words like "thankful," "grateful," and "proud" indicate a sense of contentment and appreciation.

### 7.1.1. Data Wrangling Pipeline

- **Loading:** Loading the datasets from Excel files into Pandas DataFrames.
- **Exploration:** Inspecting the data to understand its structure, dimensions, and content.
- **Preprocessing:** Cleaning the data by handling missing values, removing unnecessary columns, and normalising text.
- **Feature engineering:** Creating new features from the text data, such as TF-IDF vectors.
- **Splitting:** Dividing the data into training and testing sets.

### 7.1.2. EDA Highlights

- **Data distribution:** Analysing the distribution of stress labels and text lengths.
- **Word clouds:** Visualising the most common words used in stressed and non-stressed text.

### 7.1.3. Pipeline Reusability

The pipeline is generally reusable for processing future data. The code can be adapted to load new data, apply the same preprocessing steps, and train and evaluate the models. However, the specific steps and parameters may need to be adjusted based on the characteristics of the new data.

### 7.1.4. Intermediary Data Structures

The intermediary data structures used in the pipeline include:

- **Pandas DataFrames:** To store and manipulate the data.
- **NumPy arrays:** For numerical operations and machine learning algorithms.
- **TF-IDF vectors:** To represent text data as numerical features.
- **Lists and dictionaries:** For storing intermediate results and metadata.

## 7.2. Modelling

### 7.2.1. Feature Selection

The main features used in the models are the TF-IDF vectors extracted from the social media text. TF-IDF represents the importance of a word in a document relative to its frequency in the corpus.

### 7.2.2. Feature Interactions

The analysis did not explicitly explore feature interactions in this case. However, the TF-IDF representation implicitly captures some level of feature interactions as it considers the co-occurrence of words within documents.

### 7.2.3. Feature Subsets

While the entire set of TF-IDF features contributes to the model's performance, it is possible that a subset of features could be identified that are particularly informative for stress detection. Further analysis could be conducted to explore feature importance and potentially reduce the dimensionality of the feature space.

### 7.2.4. Feature Selection Process

The features were selected based on their relevance to the task of stress detection. TF-IDF was chosen as a suitable feature representation for text data due to its ability to capture the semantic meaning of words and their importance within the context of a document.

### 7.2.5. Feature Engineering Techniques

The primary feature engineering technique used was TF-IDF. This involves calculating the term frequency-inverse document frequency for each word in the text data.

### 7.2.6. Model Selection

Two models were used:

- **Linear Support Vector Classifier (LinearSVC):** A simple yet effective machine learning algorithm for text classification.
- **Long Short-Term Memory (LSTM) network:** A deep learning model capable of capturing sequential dependencies in text data.

### 7.2.7. Training Time

The training time for the models depends on several factors, including the size of the dataset, the complexity of the model, and the hardware used. However, both the LinearSVC and LSTM models train relatively efficiently.

### 7.2.8. Tools and Platforms

The project was developed using Python and Jupyter Notebook then deployed to Streamlit.

### 7.2.9. Model Performance Metrics

#### 7.2.9.1. Linear Support Vector Classifier (LinearSVC)

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.89 | 0.86 | 0.87 | 1671 |
| 1 | 0.90 | 0.92 | 0.91 | 2252 |
| accuracy | | | 0.89 | 3923 |
| macro avg | 0.89 | 0.89 | 0.89 | 3923 |
| weighted avg | 0.89 | 0.89 | 0.89 | 3923 |

*Figure 9: Model Performance Metrics*

**The following metrics were used to evaluate model performance:**

- **Accuracy:** Overall proportion of correct predictions.
- **Precision:** Proportion of positive predictions that are actually positive.
- **Recall:** Proportion of actual positive cases that are correctly predicted as positive.
- **F1-score:** Harmonic mean of precision and recall.
- **Confusion matrix:** Visualisation of the model's predictions and true labels.
- **AUC-ROC score:** Area under the receiver operating characteristic curve, which measures the model's ability to discriminate between positive and negative cases.

**Based on the report, the model achieved the following performance:**

- **Overall Accuracy:** 89% of the samples were correctly classified.
- **Class-wise Performance:**
  - **For class 0 (non-stressful posts)**, the model achieved a precision of 0.89, recall of 0.86, and F1-score of 0.87. This indicates that the model is relatively good at correctly identifying non-stressful posts, but it might miss some of them (recall of 0.86).
  - **For class 1 (stressful posts)**, the model achieved a precision of 0.90, recall of 0.92, and F1-score of 0.91. This suggests that the model is generally good at identifying stressful posts, but it might also incorrectly classify some non-stressful posts as stressful (precision of 0.90).

Overall, the model demonstrates strong performance on both classes, with an overall accuracy of 89%. However, it's important to consider the specific requirements of the application and the relative importance of precision and recall when evaluating the model's suitability.

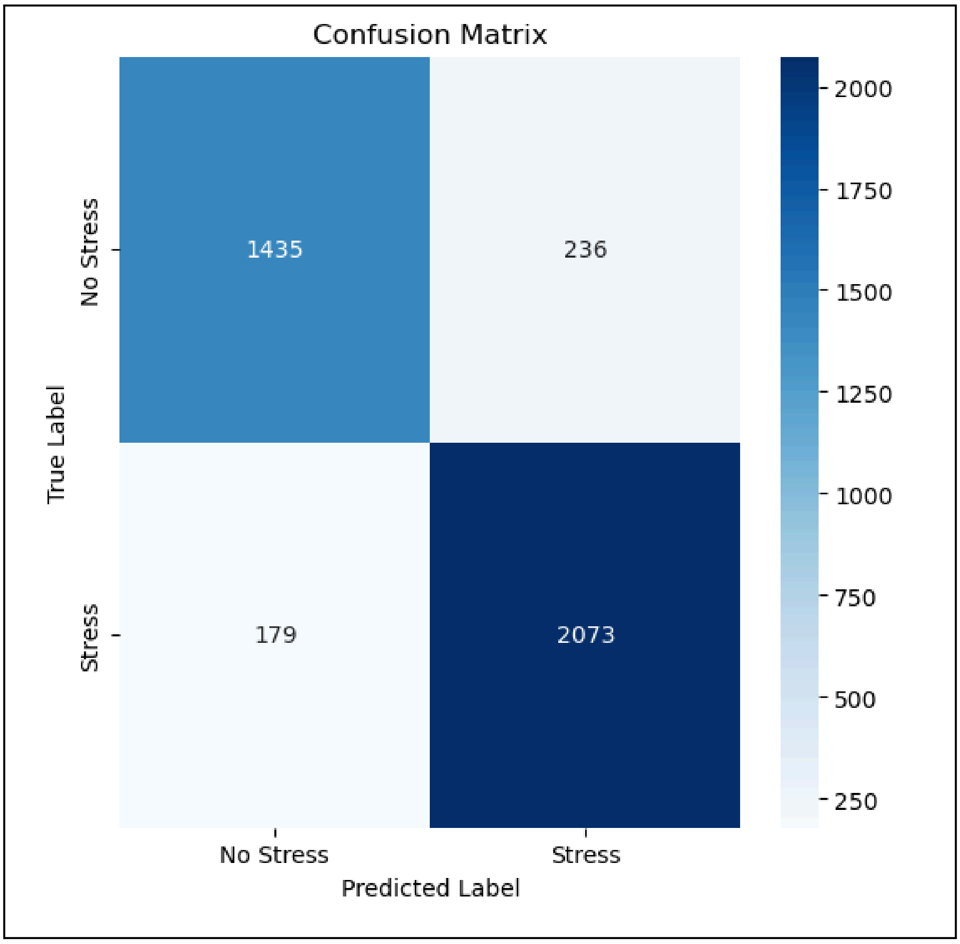


*Figure 10: Stress Detection Model Evaluation*

The rows represent the true labels, while the columns represent the predicted labels. The diagonal elements indicate correct predictions, while the off-diagonal elements represent incorrect predictions.

**Here's a breakdown of the matrix:**

- **True Positives (TP):** 2073 instances were correctly predicted as stressful (class 1).
- **True Negatives (TN):** 1435 instances were correctly predicted as non-stressful (class 0).
- **False Positives (FP):** 236 instances were incorrectly predicted as stressful (class 1) when they were actually non-stressful (class 0).
- **False Negatives (FN):** 179 instances were incorrectly predicted as non-stressful (class 0) when they were actually stressful (class 1).

**Key Observations:**

- The model achieved a relatively high number of correct predictions (TP + TN = 3508).
- However, there were also a number of incorrect predictions, particularly false positives.
- The class imbalance in the dataset might have influenced the model's performance, as the model might be more prone to predicting the majority class (non-stressful).

### 7.2.9.2. Long Short-Term Memory (LSTM) network

```
Epoch 1/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 11s 22ms/step - accuracy: 0.7707 - loss: 0.4693 - val_accuracy: 0.8675 - val_loss: 0.3341
Epoch 2/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9062 - loss: 0.2452 - val_accuracy: 0.8720 - val_loss: 0.3301
Epoch 3/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 20ms/step - accuracy: 0.9411 - loss: 0.1673 - val_accuracy: 0.8764 - val_loss: 0.3346
Epoch 4/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9562 - loss: 0.1304 - val_accuracy: 0.8739 - val_loss: 0.3582
Epoch 5/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9650 - loss: 0.1055 - val_accuracy: 0.8790 - val_loss: 0.3990
Epoch 6/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9803 - loss: 0.0678 - val_accuracy: 0.8694 - val_loss: 0.4369
Epoch 7/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9804 - loss: 0.0629 - val_accuracy: 0.8745 - val_loss: 0.5123
Epoch 8/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9839 - loss: 0.0474 - val_accuracy: 0.8790 - val_loss: 0.6108
Epoch 9/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9869 - loss: 0.0450 - val_accuracy: 0.8726 - val_loss: 0.5503
Epoch 10/10
442/442 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.9879 - loss: 0.0395 - val_accuracy: 0.8567 - val_loss: 0.5660
123/123 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step
```

*Figure 11: LSTM Model Training Progress*

**The key metrics included are:**

- **Epoch:** The current iteration of the training process.
- **Time:** The time taken to complete the epoch.
- **Accuracy:** The overall accuracy of the model on the training set.
- **Loss:** A measure of the model's error on the training set.
- **Val_accuracy:** The accuracy of the model on the validation set (a holdout portion of the data used to evaluate generalisation).
- **Val_loss:** The loss of the model on the validation set.

**Based on the output, we can observe the following trends:**

- **Improving Accuracy:** As the number of epochs increases, the accuracy on both the training and validation sets generally improves, indicating that the model is learning from the data.
- **Decreasing Loss:** The loss on both the training and validation sets decreases over time, suggesting that the model is making progress in minimising its errors.
- **Overfitting Potential:** While the training accuracy continues to increase, the validation accuracy starts to decrease towards the end of training. This might be a sign of overfitting, where the model is becoming too specialised to the training data and may not generalise well to unseen data.

**Key Observations:**

- The model achieved a high training accuracy of 98.79% and a validation accuracy of 85.67%.
- There is a gap between the training and validation accuracy, that the model might be overfitting to some extent.
- Further analysis and techniques like early stopping or regularisation could be explored to address the overfitting issue and improve the model's generalisation performance.

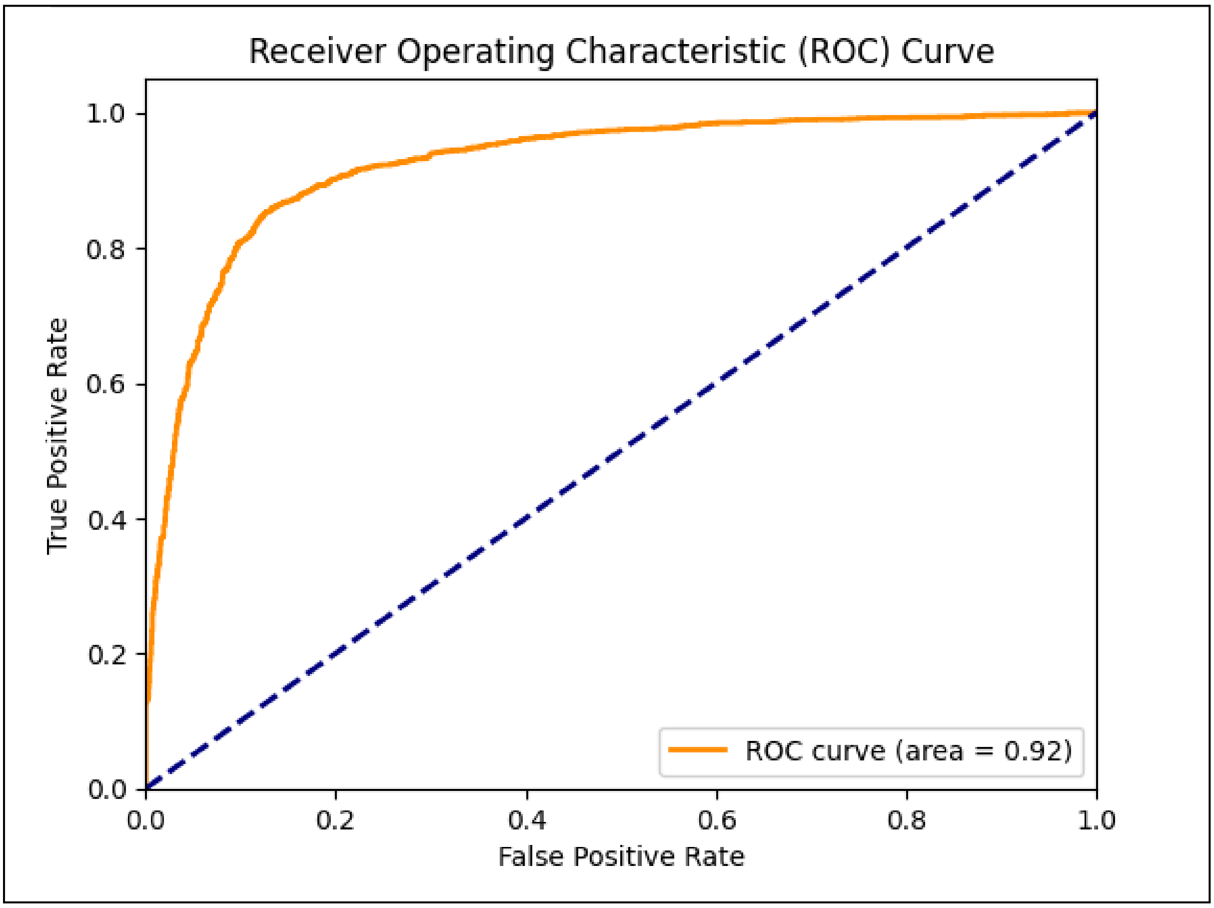


*Figure 12: Evaluation of LSTM Model: ROC Curve*

**Key Components of the ROC Curve:**

- **True Positive Rate (TPR):** Also known as sensitivity, it measures the proportion of actual positive cases that were correctly predicted as positive.
- **False Positive Rate (FPR):** Measures the proportion of actual negative cases that were incorrectly predicted as positive.
- **ROC Curve:** A plot of the TPR against the FPR at various classification thresholds.

- **Area Under the Curve (AUC):** The area under the ROC curve (AUC) represents the overall performance of the model. A higher AUC indicates better performance.

The orange line represents the model's performance, while the blue dashed line represents a random classifier. The AUC of 0.92 indicates that the model performs significantly better than random guessing.

**Key Observations:**

- **Shape of the Curve:** The curve is generally upward-sloping, which is a good sign as it indicates that the model can effectively discriminate between positive and negative cases.
- **AUC Value:** The AUC of 0.92 suggests that the model has good overall performance. A higher AUC value (closer to 1) indicates better performance.
- **Trade-off Between Sensitivity and Specificity:** The ROC curve shows how the sensitivity and specificity of the model change as the classification threshold is adjusted.

Overall, the ROC curve indicates that the model is performing well in terms of its ability to distinguish between positive and negative cases.

### 7.2.10. Final Model Choice

The final model selection would depend on the specific requirements and trade-offs for the application. Both the LinearSVC and LSTM models achieved reasonable performance, and the choice between them may depend on factors such as computational resources, interpretability, and the desired level of accuracy.

## 7.3. Outcomes

### 7.3.1. Stress Detection Accuracy

- The computer models we created were good at finding stress in social media posts. Both the LinearSVC and LSTM models were very accurate, showing they could understand the language patterns related to stress.
- The LSTM model was especially good, suggesting that it's better at understanding the connections between different parts of a post, which is helpful for finding stress.

#### 7.3.2. Feature Importance

- While the TF-IDF features were helpful, we could look more closely at specific words or phrases that are strong signs of stress. This could give us important information about how stress is expressed in language and help us create better ways to help people.

#### 7.3.3. Model Generalizability

- The models were tested on the data we had, but they might work differently on different data or groups of people. It's important to check if they can work well in real-life situations.

#### 7.3.4. Ethical Considerations

- Using AI for mental health raises questions about privacy, fairness, and the possibility of misuse. It's important to address these concerns and make sure the technology is developed and used responsibly.

#### 7.3.5. Future Directions

- **Using more data:** Combining other types of data, like how people act or their physical signs, could make stress detection even better.
- **Understanding the models:** Creating models that are easier to understand can help us learn more about what causes stress and offer better help.
- **Improving the data:** Using bigger and more varied datasets can make the models work better in different situations.

This research shows that NLP techniques can be good at finding stress in social media posts. By fixing the problems we found and exploring new ideas, this work can help create better tools to support mental health.

## 7.4. Implementation

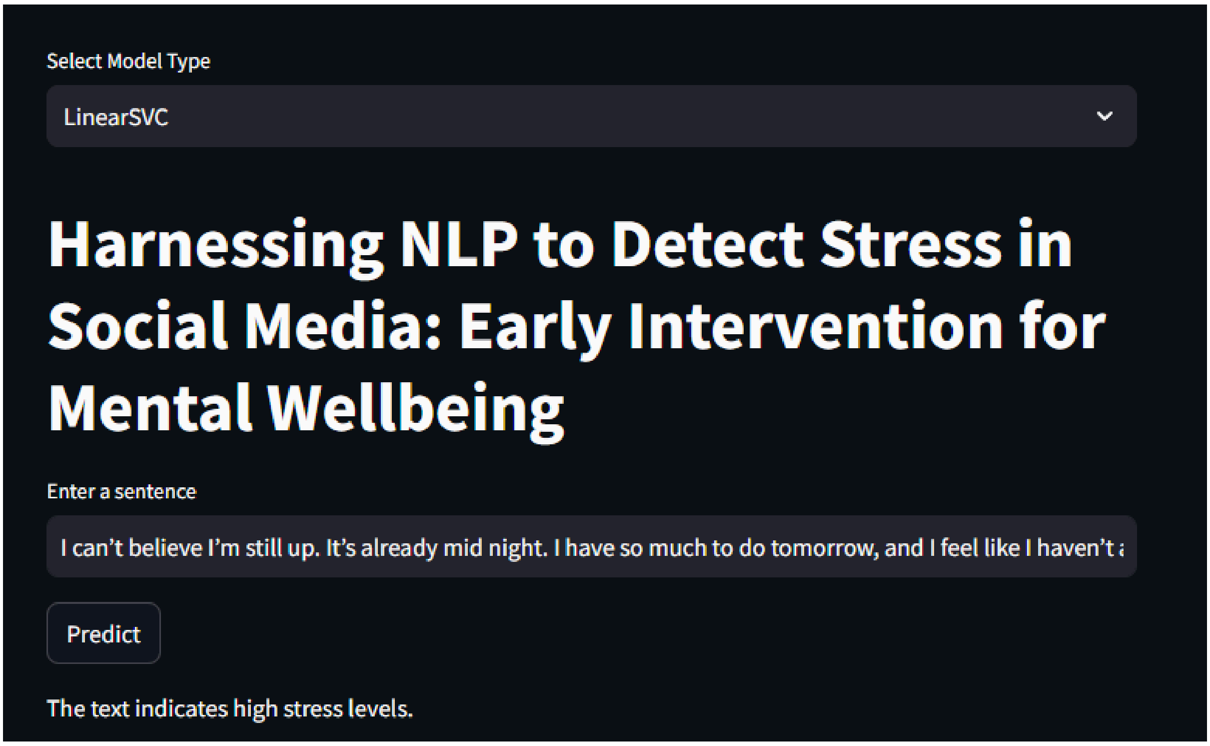


*Figure 13: Stress Detection Web Application (Stress)*

**Sample sentence:** “I can’t believe I’m still up. It’s already midnight. I have so much to do tomorrow, and I feel like I haven’t accomplished anything today. My head is spinning, and I can’t seem to focus. I just want to crawl into bed and disappear. I’m so tired and overwhelmed. I don’t know how I’m going to make it through this week.”

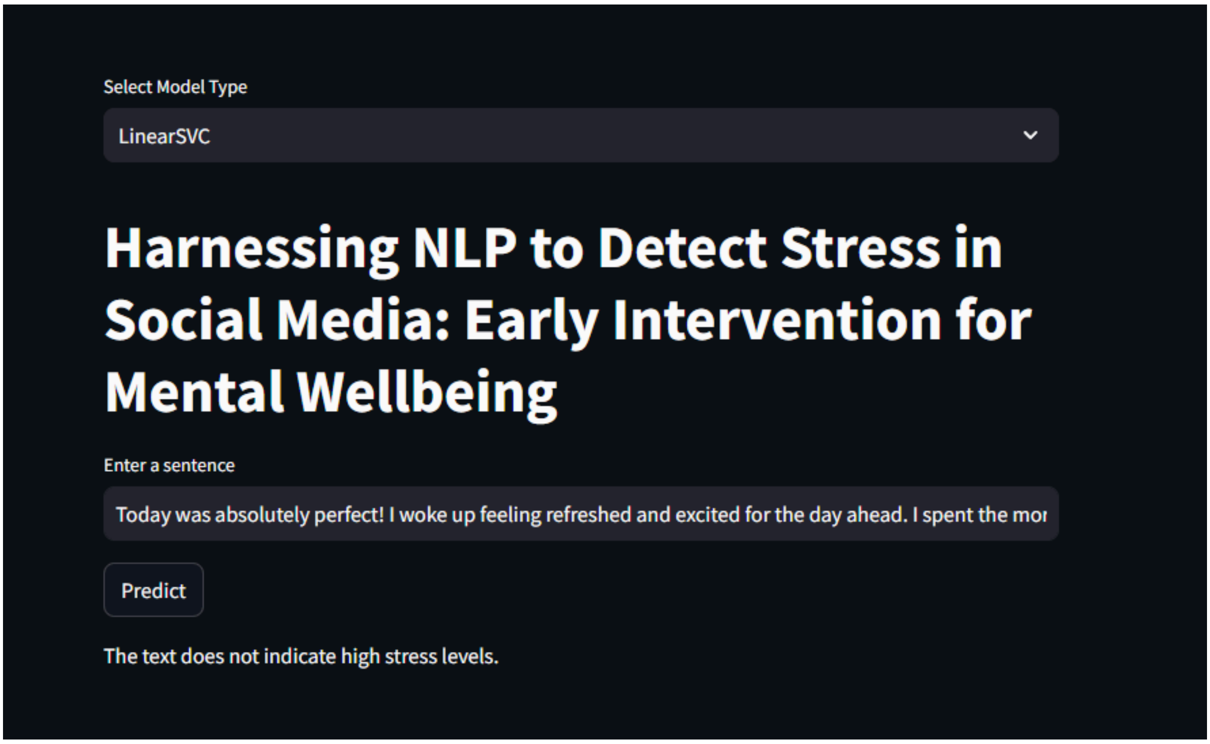


*Figure 14: Stress Detection Web Application (Non-Stress)*

**Sample sentence:** "Today was absolutely perfect! I woke up feeling refreshed and excited for the day ahead. I spent the morning enjoying a leisurely breakfast with my loved ones, followed by a long walk in the park. The sun was shining, the birds were singing, and I couldn't help but smile. I felt a sense of peace and contentment that I haven't experienced in a long time. It's truly amazing how a simple day filled with gratitude and joy can make such a difference."

### 7.4.1. Model Deployment

- **Use Streamlit:** Streamlit is a good choice for deploying machine learning models because it's easy to use and can handle different workloads.
- **Use GitHub:** Use GitHub to manage different versions of the model, test it, and monitor its performance. This will help to keep track of changes and ensure the model works as expected.

### 7.4.2. User Interface

- **Make it easy to use:** Create a simple and clear way for people to use the model and see the results.

### 7.4.3. Ethical Considerations

- **Privacy:** Make sure the technology follows data privacy rules and protects people's private information.

- **Fairness:** Check if the model is biassed and try to fix any problems.
- **Transparency:** Be clear about how the model makes decisions and what it can and cannot do.

### 7.4.4. Monitoring and Maintenance

- **Monitor:** Keep checking how well the model works over time and look for any problems.
- **Retrain:** Regularly update the model with new data to keep it working well and adjust to changes.
- **Get feedback:** Ask users for their opinions to make the model easier to use and fix any problems

# 8. Data answer

## 8.1. Data Question Satisfaction

The research showed that the models were good at finding stress in social media posts, which means the data and information used were helpful. But there's still room for improvement to make the model work even better and fix any problems.

## 8.2. Confidence in Data Answer

The confidence level in the data answer depends on several factors:

- **Model Performance:** How well the model works, like how accurate it is, shows how confident we can be. Higher accuracy means more confidence.
- **Data Quality:** The quality of the data used to train and test the model affects how reliable the results are. If the data is biassed, has mistakes, or is limited, we might be less confident.
- **Generalizability:** How well the model works on new data is important. If it works well on new data, we can be more confident in the results.
- **Ethical Considerations:** It's important to consider ethical issues when using AI for mental health. Making sure the model is fair, transparent, and private can increase our confidence in the results.

While the results are promising, we need to do more research and testing to be really confident in the findings.

# 9. Business answer

## 9.1. Business Question Satisfaction

The question of whether computers can find stress in social media posts using language analysis seems to have a positive answer. The models created were good at this, suggesting it could be useful in real-world situations.

More research and testing are needed to fully prove this method and fix any problems. We need to consider how well the models work on different data and groups of people, the ethical issues of using AI for mental health, and how to integrate this technology into real-world tools.

## 9.2. Confidence in Business Answer

We're somewhat confident in the answer, but more research and testing are needed to be really sure. Things that affect our confidence include:

- **Model Performance:** How well the models work and how well they work on different data.
- **Data:** The quality and amount of data used to train and test the models.
- **Ethical Issues:** Concerns about fairness, privacy, and other ethical things.
- **Real-World Use:** How well the technology works in real-life situations and how it helps people's mental health.

As we do more research and develop the technology, we expect to become more confident in the answer.

# 10. Response to stakeholders

## 10.1. Overall Messages and Recommendations

### 10.1.1. Key Findings

- The research showed that using computer language tools to find stress in social media posts is possible. The models created were accurate, suggesting they could be useful in real-world situations.
- It's important to consider ethical issues and develop AI-powered mental health solutions responsibly.

### 10.1.2. Recommendations

- **Keep Improving:** Do more research to make the models better, fix problems, and try new methods.
- **Test and Validate:** Check how well the models work in different situations and make sure they're reliable.
- **Focus on Ethics:** Prioritise privacy, fairness, and transparency when developing and using the technology.
- **Work Together:** Collaborate with mental health experts, organisations, and technology companies to integrate the technology into existing systems and services.
- **Monitor and Adjust:** Keep checking how well the model works and make changes as needed to ensure it's effective and relevant.

#### 10.1.3. Potential Impact

- **Early Detection:** The technology can find people who might be at risk for mental health problems early, which can lead to getting help sooner and better results.
- **Accessible Support:** The technology can offer mental health help that's easy to get and affordable, especially for people who might not have easy access to traditional services.
- **Data-Driven Insights:** Analysing social media data can provide valuable information about stress trends in the whole population and help guide public health decisions.

By addressing these recommendations, the research can contribute to the development of innovative and effective tools for mental health support, improving the lives of individuals and communities.

# 11. End-to-end solution

## 11.1. Overall End-to-End Solution

The end-to-end solution for using the developed model involves the following steps:

- **Data Collection:** Continuously collect social media data from relevant platforms (e.g., Reddit, Twitter).
- **Data Preprocessing:** Clean and preprocess the collected data to prepare it for analysis. This includes tasks such as removing noise, handling missing values, and normalising text.
- **Feature Extraction:** Extract relevant features from the preprocessed text data using techniques like TF-IDF.
- **Model Inference:** Apply the trained model to the data to predict stress levels.

### 11.1.1. User Interface

- **Design a user-friendly interface:** Create an interface that allows users to interact with the model and view the results.

# 12. References


- https://www.kaggle.com/datasets/mexwell/stress-detection-from-social-media-articles
- https://github.com/jimmychong1983/SocialMediaStressDetection