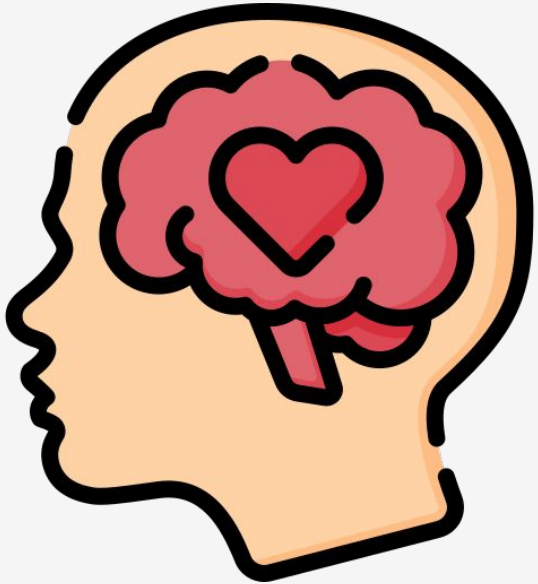
SC1015 Mini Project

Mental Health Predictor

REP2 group 1
Dion, Isaac, Ruiyun

Contents



01

Problem and Goals

1 in 8

people in the world live with a mental disorder

With the most common ones being:

Anxiety Disorder

Depression

Yet, approximately

50% goes

undiagnosed

Yet, approximately

Can we use machine learning to accurately predict the likelihood of depression and anxiety in University Students, given that many cases remain undiagnosed?

undiagnosed

MindScope

Mental Health Predictor app

General Information section

MindScope

Welcome to our Mental Health Predictor App, MindScope

This app is designed to support your mental well-being by helping you better understand potential indicators of anxiety and depression. By filling out a short questionnaire based on well-established predictive factors, you'll receive a personalized percentage estimate indicating the likelihood of experiencing symptoms related to anxiety or depression.

Please note: This tool is **not** a diagnostic instrument and should not replace professional mental health advice, diagnosis, or treatment. It is built on historical data and research to provide insight—not conclusions—into your mental health.

Your responses are handled with care and confidentiality. We hope this tool serves as a helpful starting point for reflection, awareness, and seeking further support if needed.

Gender

- ○ Male
- ○ Female

Age

Your answer

CGPA

Your answer

Work/Study Hours (per day)

Your answer

Next Clear form

MindScope

Rating Section

For each of the following questions, please give a rating from 1-5, with 1 being the least intense and 5 being the most intense

How pressured do you feel by academics?
put 0 if not applicable

	0	1	2	3	4	5	
Low pressure	○	○	○	○	○	○	High pressure

How pressured do you feel by work?
put 0 if not applicable

	0	1	2	3	4	5	
High pressure	○	○	○	○	○	○	Low pressure

How satisfied are you with your studies?
put 0 if not applicable

	0	1	2	3	4	5	
Low satisfaction	○	○	○	○	○	○	High satisfaction

How satisfied are you with your job?
put 0 if not applicable

	0	1	2	3	4	5	
Low satisfaction	○	○	○	○	○	○	High satisfaction

How stressed are you by finance related matters

	1	2	3	4	5	
Low stress	○	○	○	○	○	High stress

How satisfied are you by your social life?

	1	2	3	4	5	
Low satisfaction	○	○	○	○	○	High satisfaction

Would you say that your future is secure?

	1	2	3	4	5	
Low security	○	○	○	○	○	High security

How isolated would you say you are from friends and family?

	1	2	3	4	5	
Low isolation	○	○	○	○	○	High isolation

Back Next Clear form

Rating section

Categorical section

MindScope

Categorical section

What is your sleep duration?

- ◯ <5 hours
- ◯ 5-6 hours
- ◯ 7-8 hours
- ◯ >8 hours

How would you describe your dietary habits?

- ◯ Unhealthy
- ◯ Moderate
- ◯ Healthy

Have you ever had suicidal thoughts?

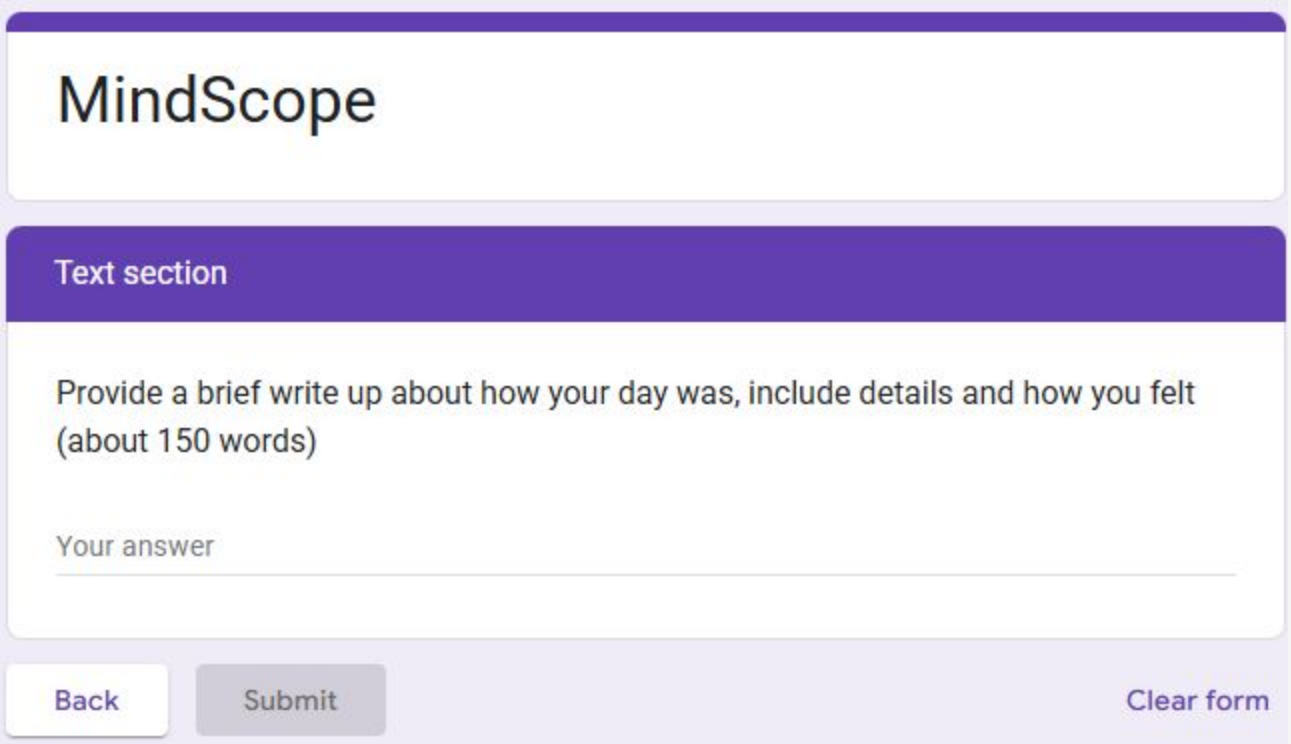
- ◯ Yes
- ◯ No

Any family history of mental illness?

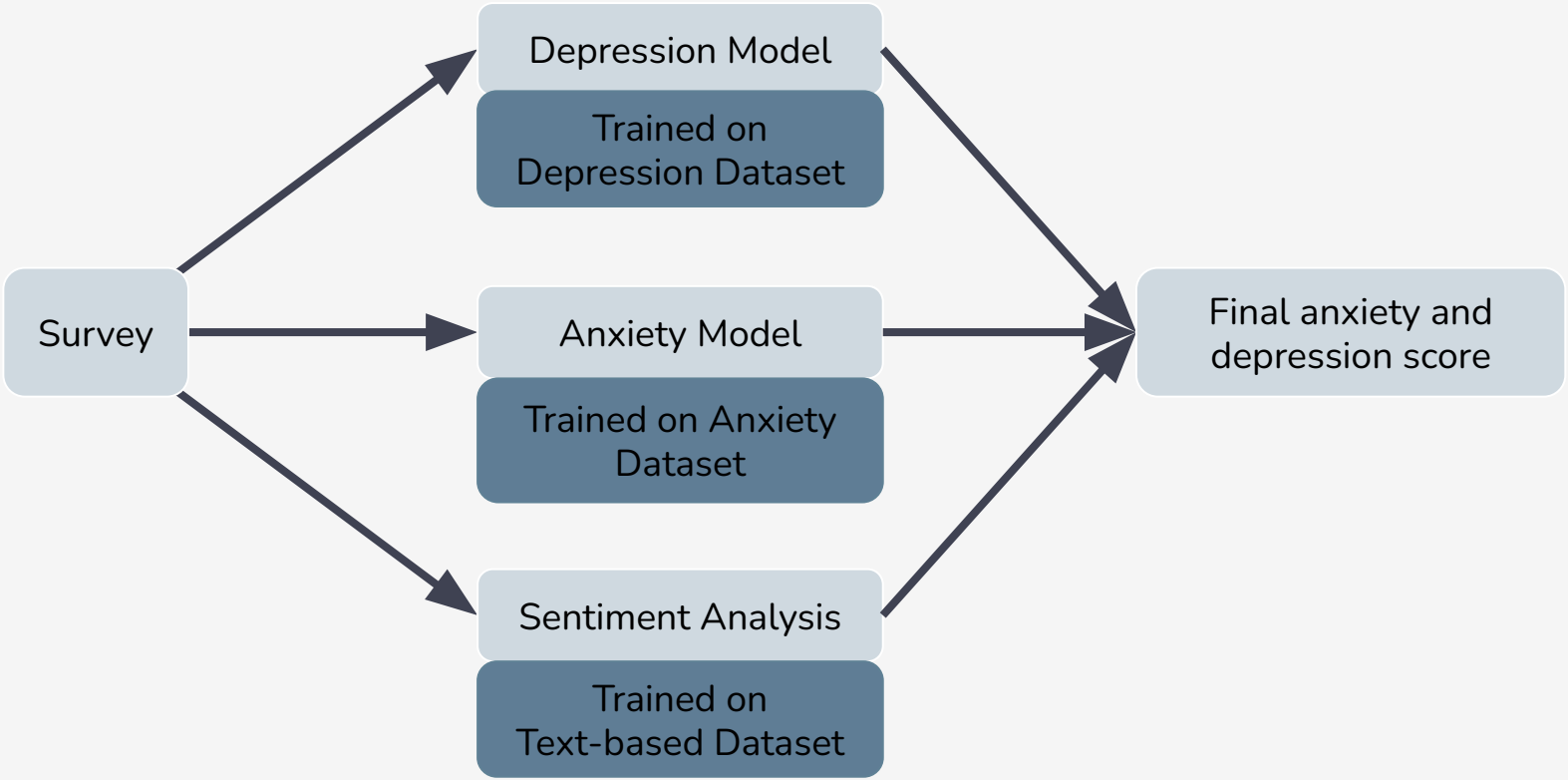
- ◯ Yes
- ◯ No

Back Next Clear form

Text based section



MindScope Overview



Dataset:

Targeting University students and young adults

kaggle

02

Dataset EDA

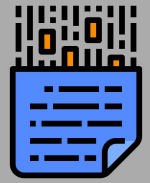
Depression dataset: Overview

Depression dataset: Understand Data

```
id                                      int64
Gender                                 object
Age                                   float64
City                                   object
Profession                             object
Academic Pressure                     float64
Work Pressure                         float64
CGPA                                  float64
Study Satisfaction                    float64
Job Satisfaction                      float64
Sleep Duration                         object
Dietary Habits                         object
Degree                                 object
Have you ever had suicidal thoughts ?  object
Work/Study Hours                      float64
Financial Stress                       object
Family History of Mental Illness       object
Depression                              int64
dtype: object
```

- Combination of numeric, categorical and binary columns
- 27901 values
- output column: Depression (binary)

Depression dataset: Correlation Analysis

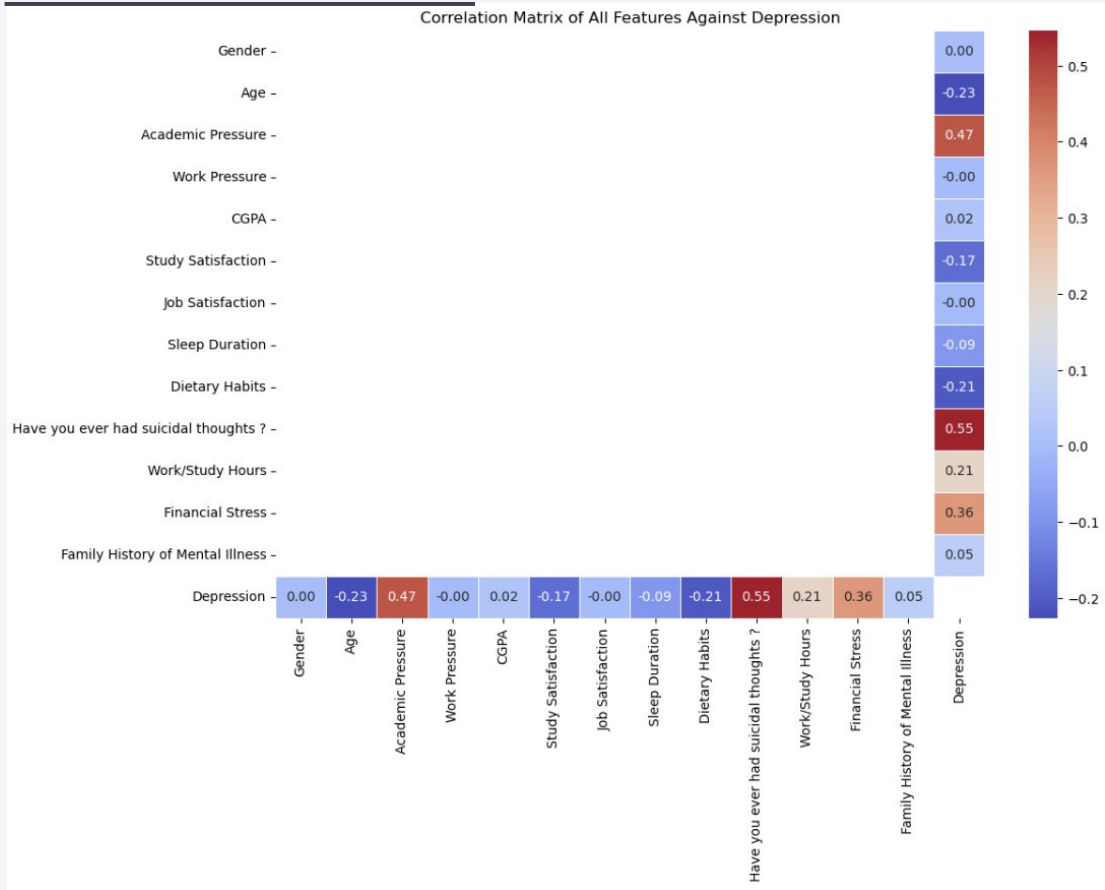


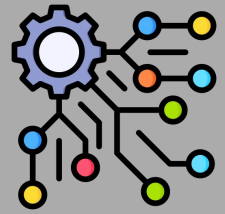
Categorical columns encoded

Numeric and categorical columns correlation with depression calculated using **point-biserial correlation**

Binary columns correlation with depression calculated with **phi-squared coefficient**

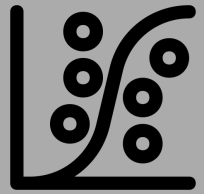
Depression dataset: Correlation Analysis





No one factor is very strongly correlated with depression- indicates complex relationship (multi-factor)

Depression dataset: Linearity Analysis

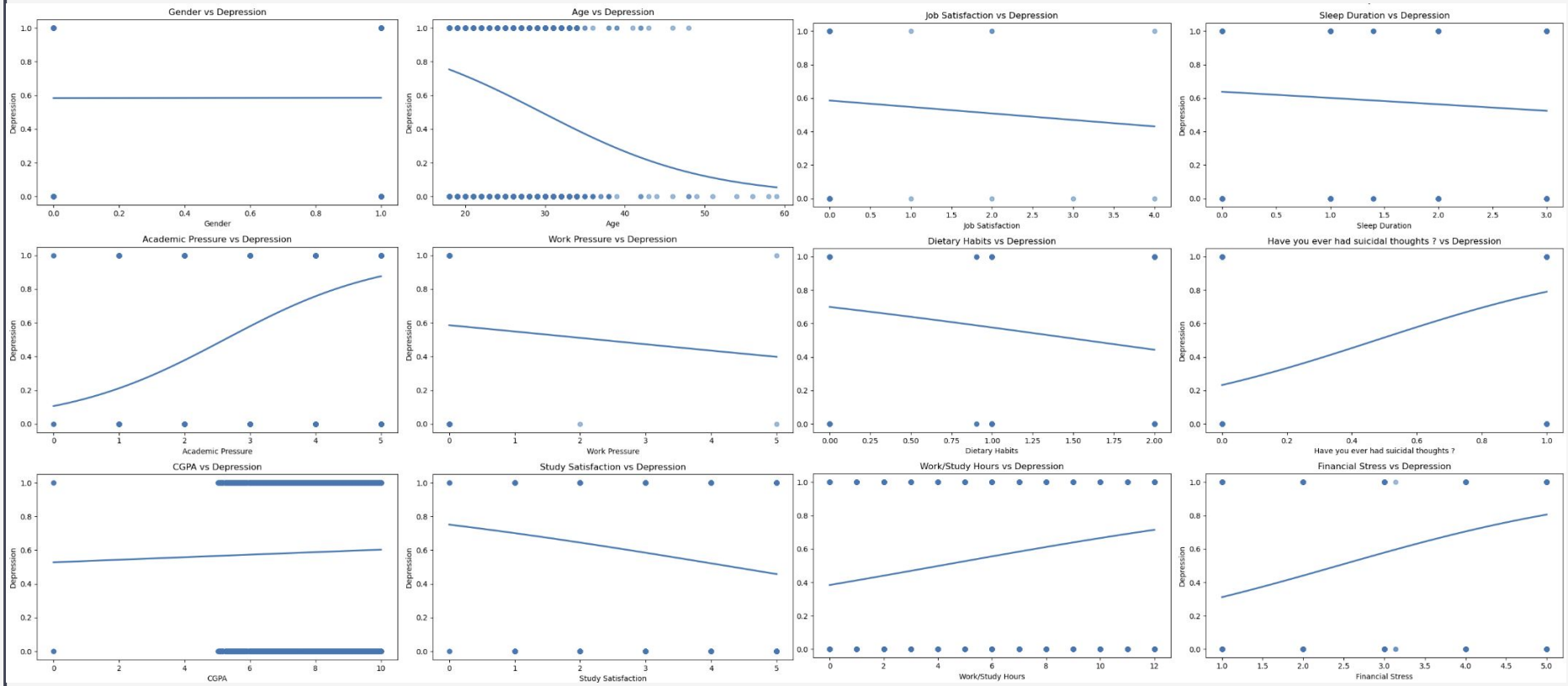


Regression plots plotted with logistic=True

Visualise correlation with depression (output)

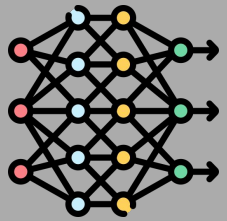
Sigmoid shapes indicate good fit for logistic regression model

Depression dataset: Linearity Analysis



Depression dataset: Model Selection

- Vast amount of data (27901)
- individually low correlation with depression
- combination of flat, linear and sigmoidal logistic relationships



Select ANN
Individual features may look weak or flat (non linear or complex relationship), but **combination could be highly predictive**

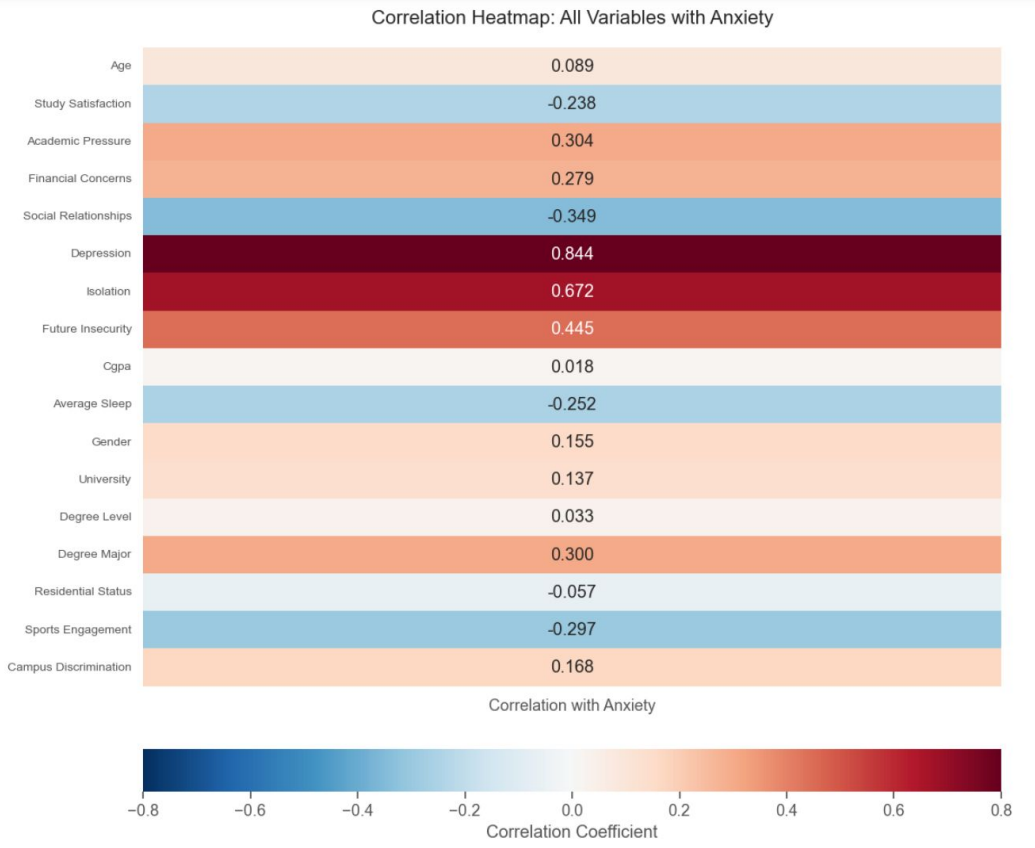
ANN can detect subtle, **multi-feature interactions** effectively

Anxiety dataset: Understand Data

```
Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 87 entries, 0 to 86
Data columns (total 21 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   gender                     87 non-null     object
 1   age                        87 non-null     int64
 2   university                 87 non-null     object
 3   degree_level               87 non-null     object
 4   degree_major               87 non-null     object
 5   academic_year              87 non-null     object
 6   cgpa                       87 non-null     object
 7   residential_status         87 non-null     object
 8   campus_discrimination      87 non-null     object
 9   sports_engagement          87 non-null     object
 10  average_sleep              87 non-null     object
 11  study_satisfaction         87 non-null     int64
 12  academic_workload          87 non-null     int64
 13  academic_pressure          87 non-null     int64
 14  financial_concerns         87 non-null     int64
 15  social_relationships       87 non-null     int64
 16  depression                 87 non-null     int64
 17  anxiety                    87 non-null     int64
 18  isolation                  87 non-null     int64
 19  future_insecurity          87 non-null     int64
 20  stress_relief_activities   87 non-null     object
dtypes: int64(10), object(11)
memory usage: 14.4+ KB
```

- Combination of numeric and categorical data
- 86 values

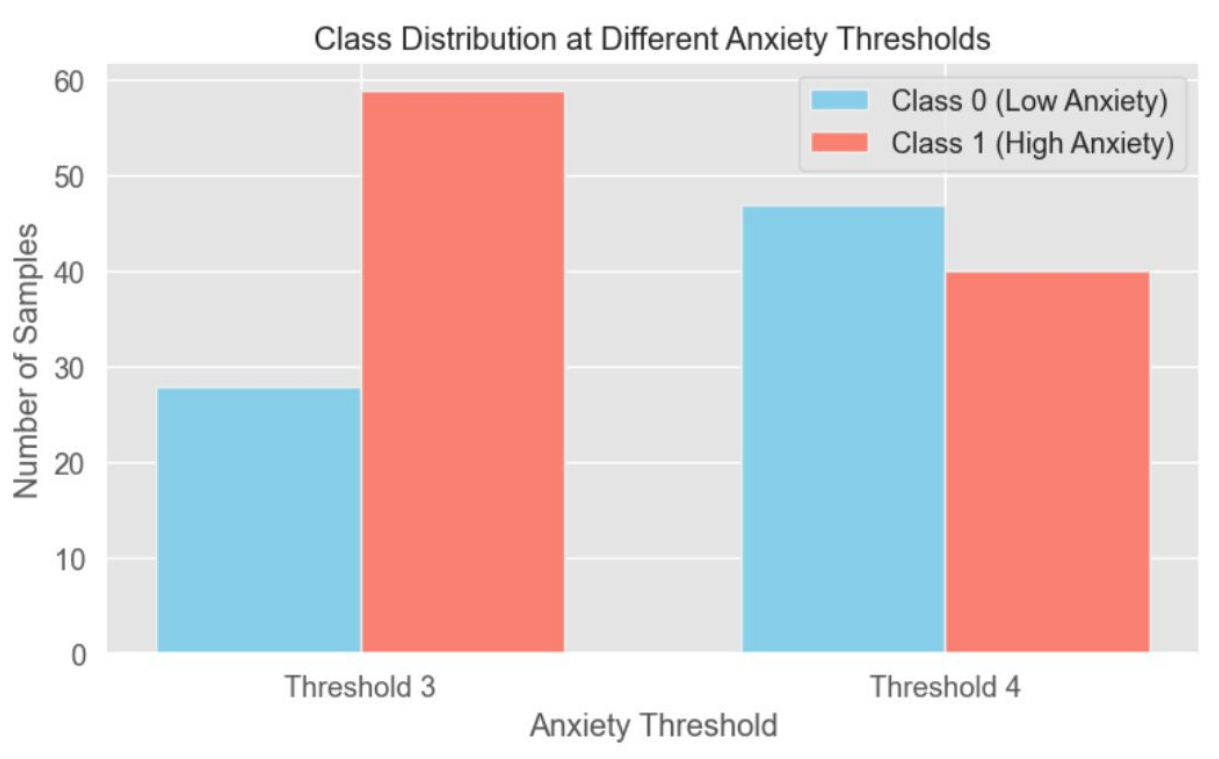
Anxiety dataset: Correlation Analysis



- Top 3 correlated variables with anxiety is
  1. Isolation
  2. Future Insecurity
  3. Social Relationship (negatively correlated)

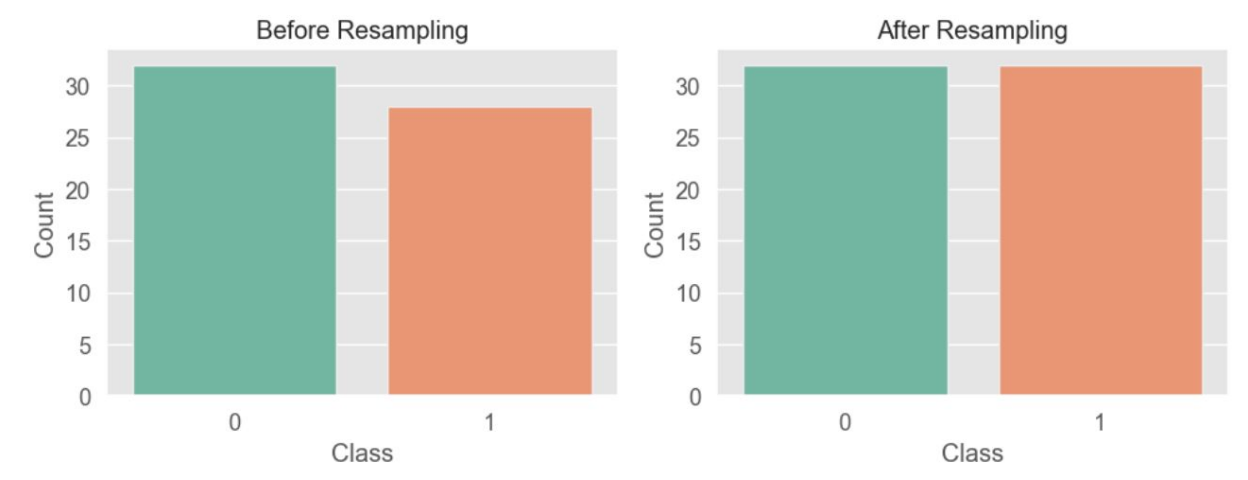
- Excluding depression despite high correlation to avoid circular logic (since we predicting depression separately)

Anxiety dataset: Data Preparation



- Reclassifying Anxiety as High or Low (for binary output)
- Threshold of 4 gives more balanced distribution

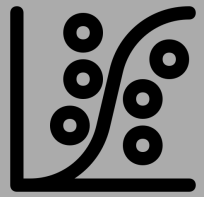
Anxiety dataset: Data Preparation



- Handled class imbalance after splitting
- Applied feature scaling
- Upsampled minority class

Anxiety dataset: Model Selection

- Small dataset (86 values)
- Binary Classification with Multivariate Input



Possible models:

- Logistic regression
- Random Forest
- SVM
- XGBoost

Selection Criteria:

- Performance on Validation set
- Resistance to overfitting

Sentiment Analysis Dataset: Understand Data

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 53043 entries, 0 to 53042
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   index      53043 non-null  int64 
 1   statement  52681 non-null  object
 2   status     53043 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.2+ MB


Nulls per column:
 index          0
statement    362
status         0
dtype: int64
Empty 'statement' entries: 0
```

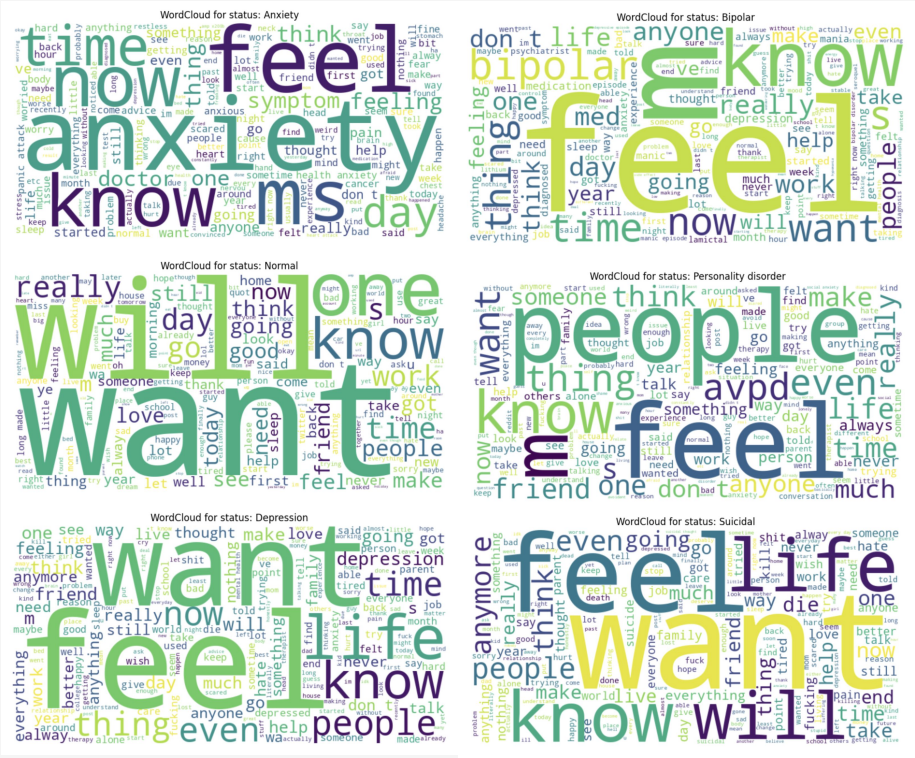
- Combination of textual and categorical data and columns.
- 53043 values / rows
- Index column: Index
- Statement column: Contains string of text
- Status column: Depression, Anxiety, Personality Disorder, Bipolar, Suicidal or Normal

Sentiment Analysis dataset: Understand Data

First look:

- Many common words across different statuses like i, to, and, my, that, the.
- These words do not help much to distinct statuses
- More needs to be to clean the dataset to make each group of text more unique.

Sentiment Analysis dataset: Understand Data

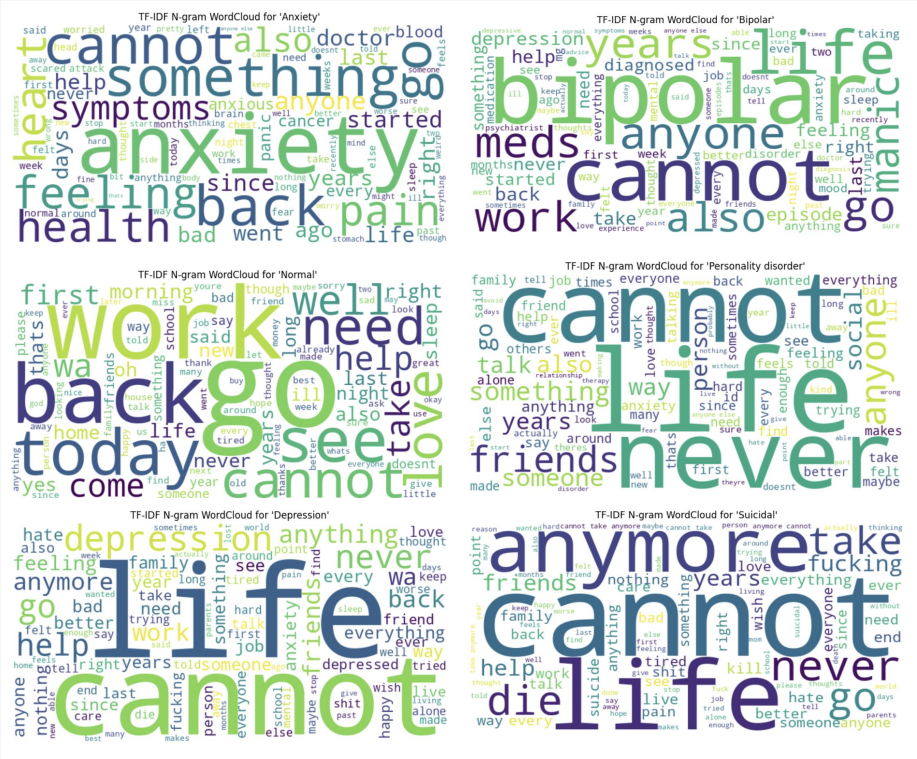


TF-IDF:

term freq - inverse document freq

- Use TF-IDF to find more important words in each status
- Many common words across different statuses still present like ‘feel’, ‘want’, ‘know’.
- More needs to be to clean the dataset to make each group of text more unique.

Sentiment Analysis dataset: Understand Data



TF-IDF + N-grams:

term freq - inverse document freq

- Use TF-IDF with N-grams to find more important words in each status
- We can see that the words across statuses are much more distinct.
- However, there are some that are groups of text that are still similar like Personality Disorder & Depression and Bipolar & Depression.

Sentiment Analysis dataset: Data Insights

- Common words used by people with Personality Disorder are significantly similar to words used by people with Depression (0.91). The next most similar pair would be words used by people with Bipolar and Depression (0.85).
- The dataset for people with Personality Disorder and Bipolar are the smallest at 1201 and 2877 statements.
- Might be better to drop these statements to minimise confusion for our model in discerning between mental health statuses.

Sentiment Analysis dataset: Insight Validation

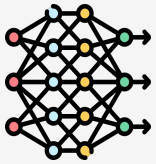
```
Status Classes Ranked by Similarity of Distinctive Words:
Rank 1: Normal and Personality disorder: 0.0546
Rank 2: Bipolar and Personality disorder: 0.0314
Rank 3: Normal and Bipolar: 0.0312
Rank 4: Depression and Personality disorder: 0.0225
Rank 5: Anxiety and Normal: 0.0000
Rank 6: Anxiety and Depression: 0.0000
Rank 7: Anxiety and Bipolar: 0.0000
Rank 8: Anxiety and Personality disorder: 0.0000
Rank 9: Normal and Depression: 0.0000
Rank 10: Depression and Bipolar: 0.0000


Cosine Similarity Matrix between Distinctive Word Sets:
                     Anxiety    Normal  Depression   Bipolar  \
Anxiety                  1.0  0.000000    0.000000  0.000000
Normal                   0.0  1.000000    0.000000  0.031231
Depression               0.0  0.000000    1.000000  0.000000
Bipolar                  0.0  0.031231    0.000000  1.000000
Personality disorder     0.0  0.054557    0.022511  0.031424

                     Personality disorder
Anxiety                          0.000000
Normal                           0.054557
Depression                       0.022511
Bipolar                          0.031424
Personality disorder             1.000000
```

- Conducted log-likelihood analysis to identify the most distinct word in each class
- Cosine similarity for the Distinctive words in each class and ranked pairs by similarity
- Most distinct words used by people with Personality Disorder are very similar to normal people (Rank 1), Bipolar Disorder (Rank 2) and Depression (Rank 4).
- It can also be seen that the most distinct words used by Bipolar people are very similar to normal people (Rank 3).
- With such considerations, this confirms our insights and we will remove both the statements for Personality Disorder and Bipolar statuses.

Sentiment Analysis dataset: Final Thoughts

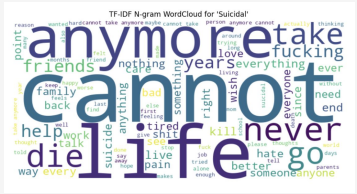
Observations

- While Anxiety, Depression, and Normal classes have some distinct top TF-IDF words, their overall language usage remains highly similar (as shown by cosine similarity scores).



Model Selection

- To go beyond surface-level word usage, we should use modern NLP approach like Large Language Models. This enables the model to learn semantic representations of entire statements, capturing context, tone, and subtle cues. As a result, we can achieve more accurate and meaningful classification of mental health statuses.



- Words used by people afflicted with Suicidal tendencies will be flagged. Most language models have safeguards that do not allow these words. Hence we shall drop the Suicidal status.

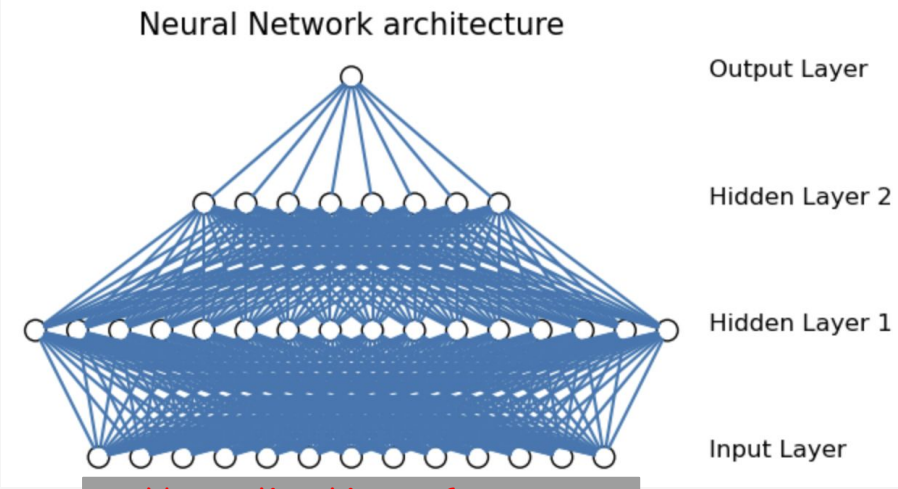
03

Machine Learning

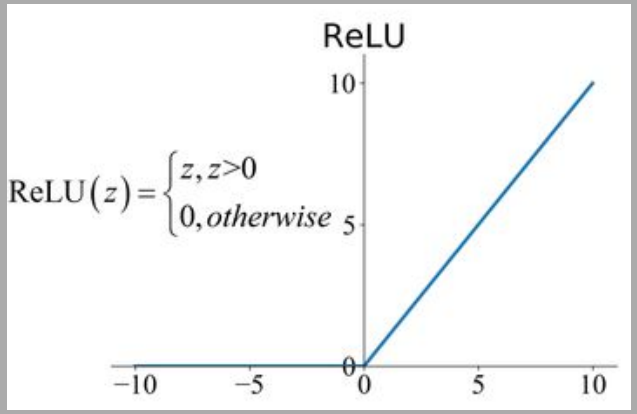
ANN (Depression dataset)

```
model = Sequential([
    Dense(16, input_dim=X.shape[1], activation='relu'),
    Dense(8, activation='relu'),
    Dense(1, activation='sigmoid')  # sigmoid outputs a probability between 0 and 1
])

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_3 (Dense)             (None, 16)                224

 dense_4 (Dense)             (None, 8)                 136

 dense_5 (Dense)             (None, 1)                 9

=================================================================
Total params: 369
Trainable params: 369
Non-trainable params: 0
_________________________________________________________________
```

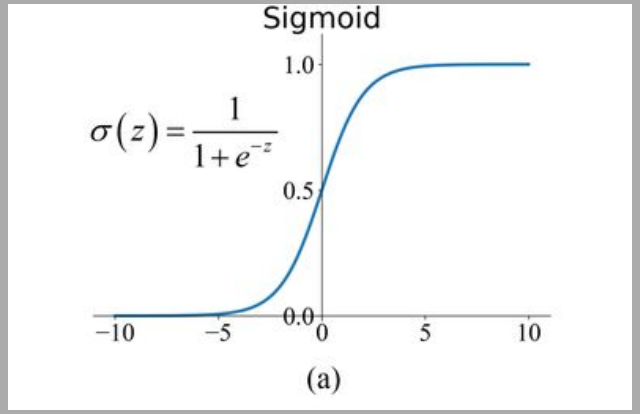


ANN (Depression dataset)



Hidden layers uses **RELU activation function**

- only allows x to pass through if x>0. 0 otherwise
- **capture piecewise linear patterns**
- **ignores flat features**, helps model to **focus on meaningful signals**

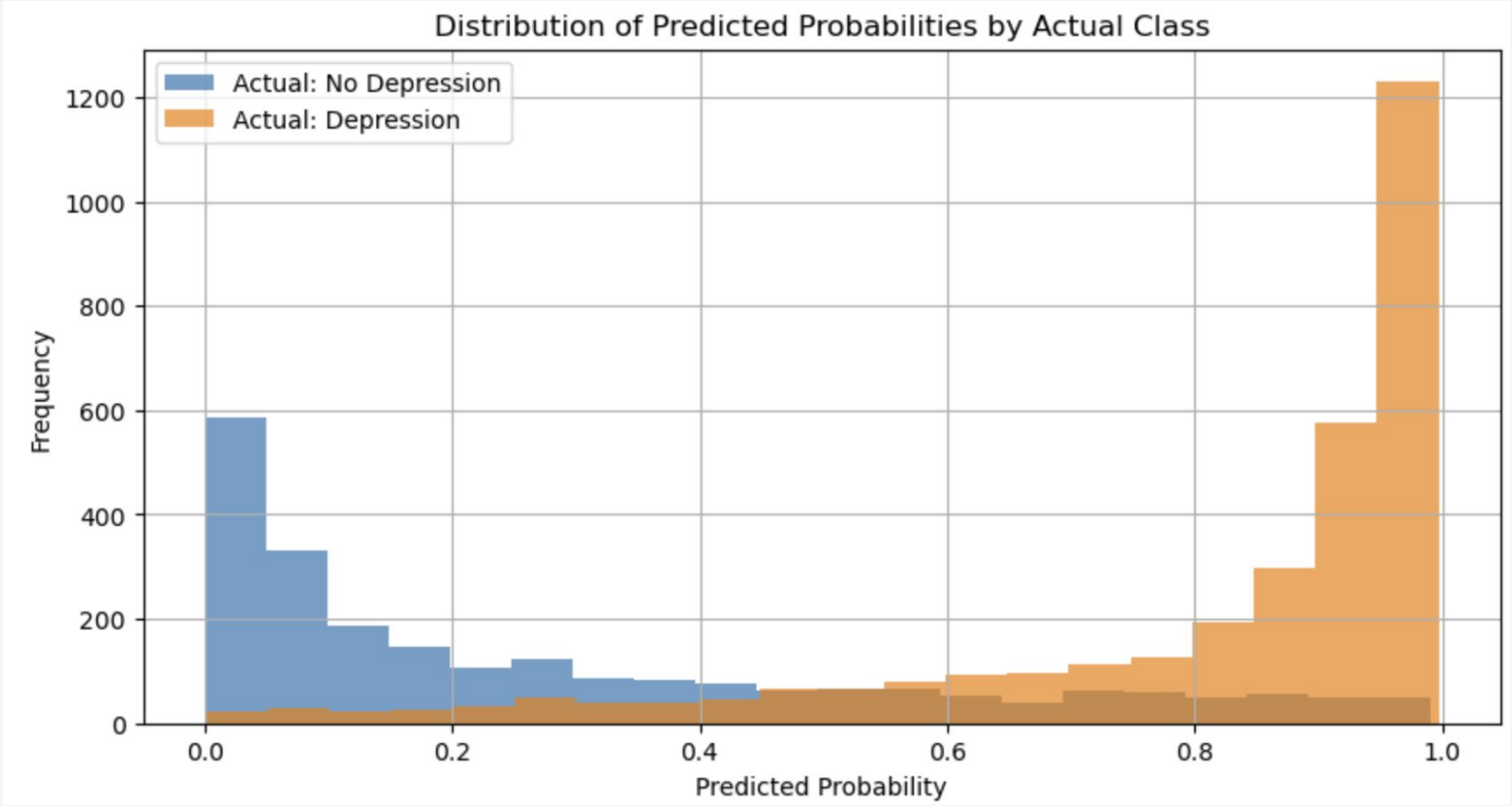


Output layer uses **Sigmoid activation function**

- sigmoid squashes final output into range [0,1]
- useful for probabilistic prediction

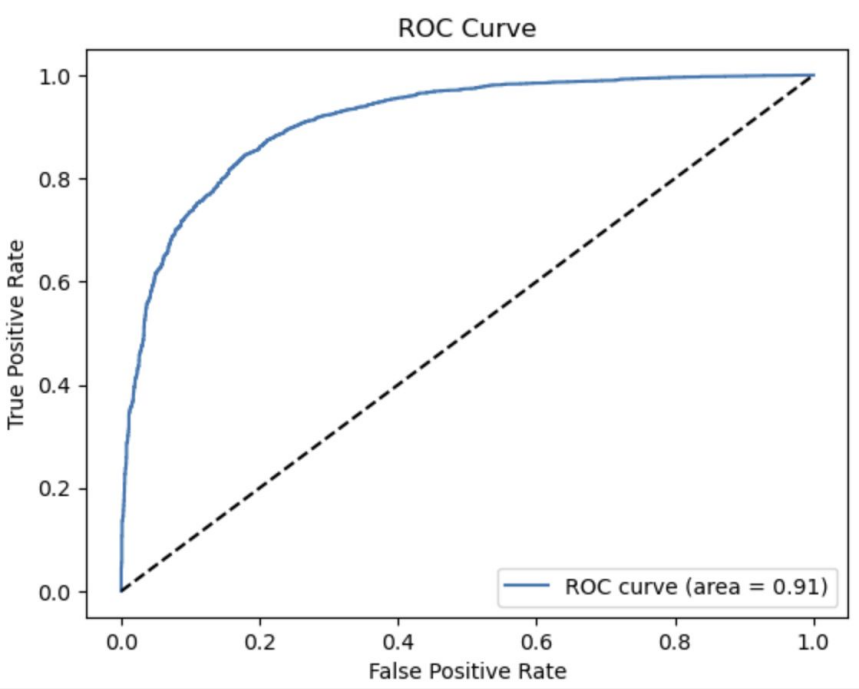
Loss calculated using **Binary cross entropy- backpropagation** to adjust weights using **adam optimiser**

ANN (Depression dataset)



ANN (Depression dataset)

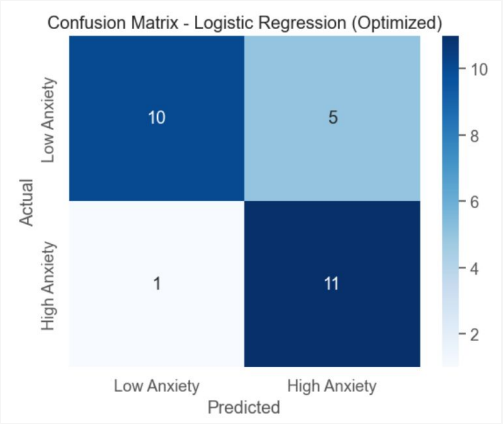
```
Classification Report:
              precision    recall  f1-score   support

           0       0.83      0.77      0.80      2343
           1       0.84      0.89      0.86      3238

    accuracy                           0.84      5581
   macro avg       0.84      0.83      0.83      5581
weighted avg       0.84      0.84      0.84      5581

Confusion Matrix:
 [[1800  543]
 [ 368 2870]]
ROC AUC Score: 0.91
```

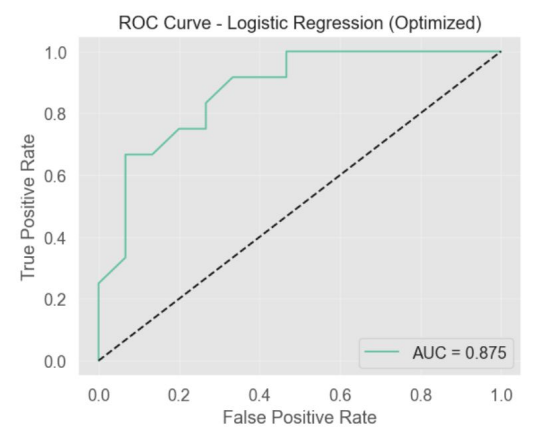


Model Performace (Anxiety Dataset)

1. Logistic Regression

```
--- Logistic Regression (Optimized) ---
Optimal threshold: 0.434
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.67      0.77        15
           1       0.69      0.92      0.79        12

    accuracy                           0.78        27
   macro avg       0.80      0.79      0.78        27
weighted avg       0.81      0.78      0.78        27
```

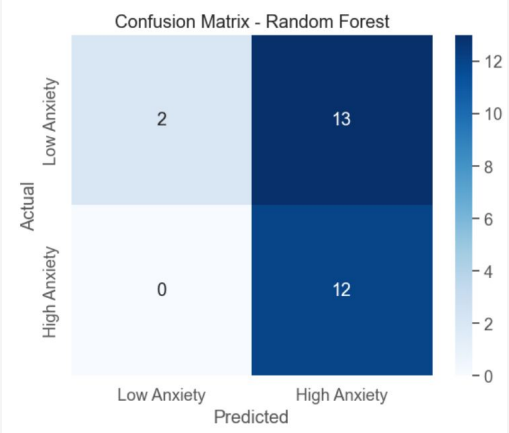


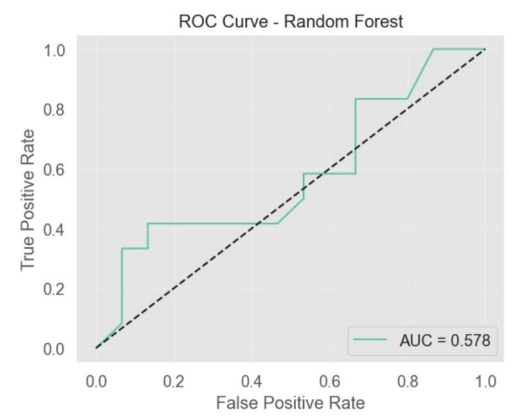


Model Performace (Anxiety Dataset)

2. Random Forest

```
--- Random Forest ---
Optimal threshold: 0.020
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.13      0.24        15
           1       0.48      1.00      0.65        12

    accuracy                           0.52        27
   macro avg       0.74      0.57      0.44        27
weighted avg       0.77      0.52      0.42        27
```

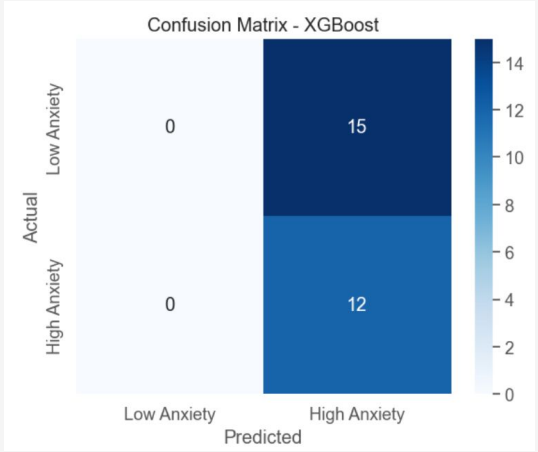


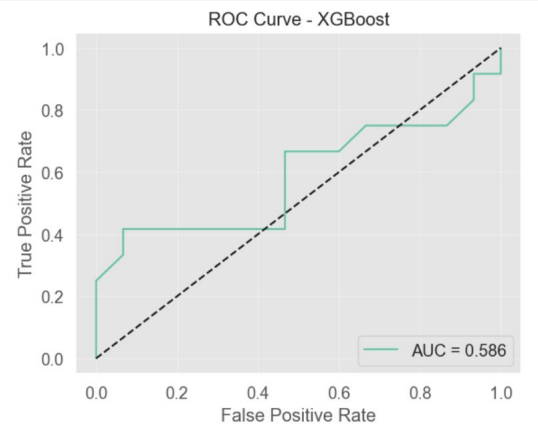


Model Performace (Anxiety Dataset)

3. XGBoost

```
--- XGBoost ---
Optimal threshold: 0.000
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        15
           1       0.44      1.00      0.62        12

    accuracy                           0.44        27
   macro avg       0.22      0.50      0.31        27
weighted avg       0.20      0.44      0.27        27
```

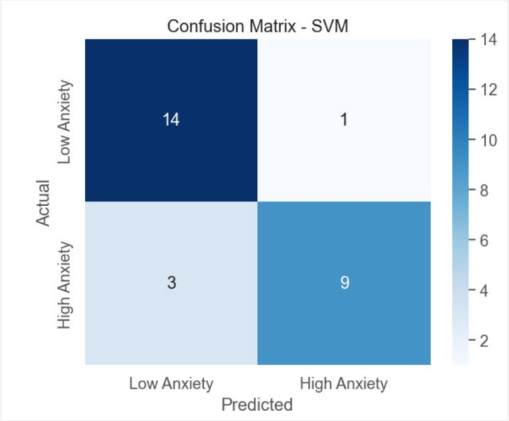


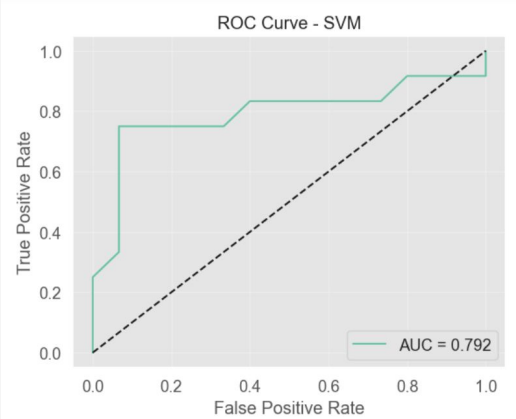


Model Performace (Anxiety Dataset)

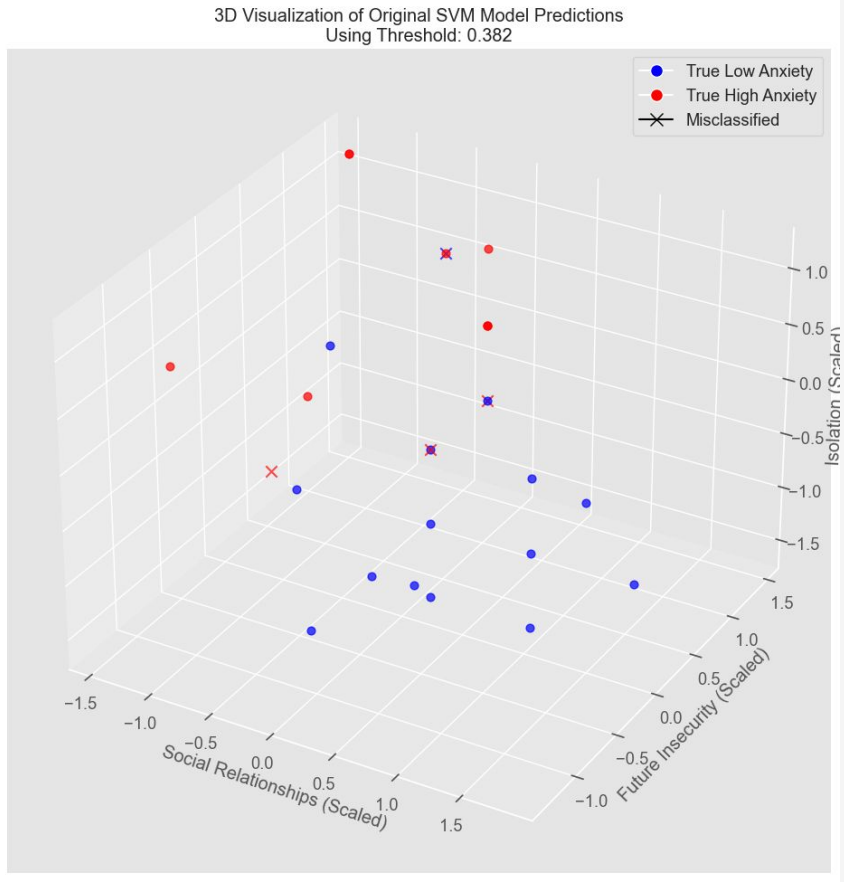
4. Best Model SVM

```
--- SVM ---
Optimal threshold: 0.382
Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.93      0.88        15
           1       0.90      0.75      0.82        12

    accuracy                           0.85        27
   macro avg       0.86      0.84      0.85        27
weighted avg       0.86      0.85      0.85        27
```





SVM (Anxiety Dataset)

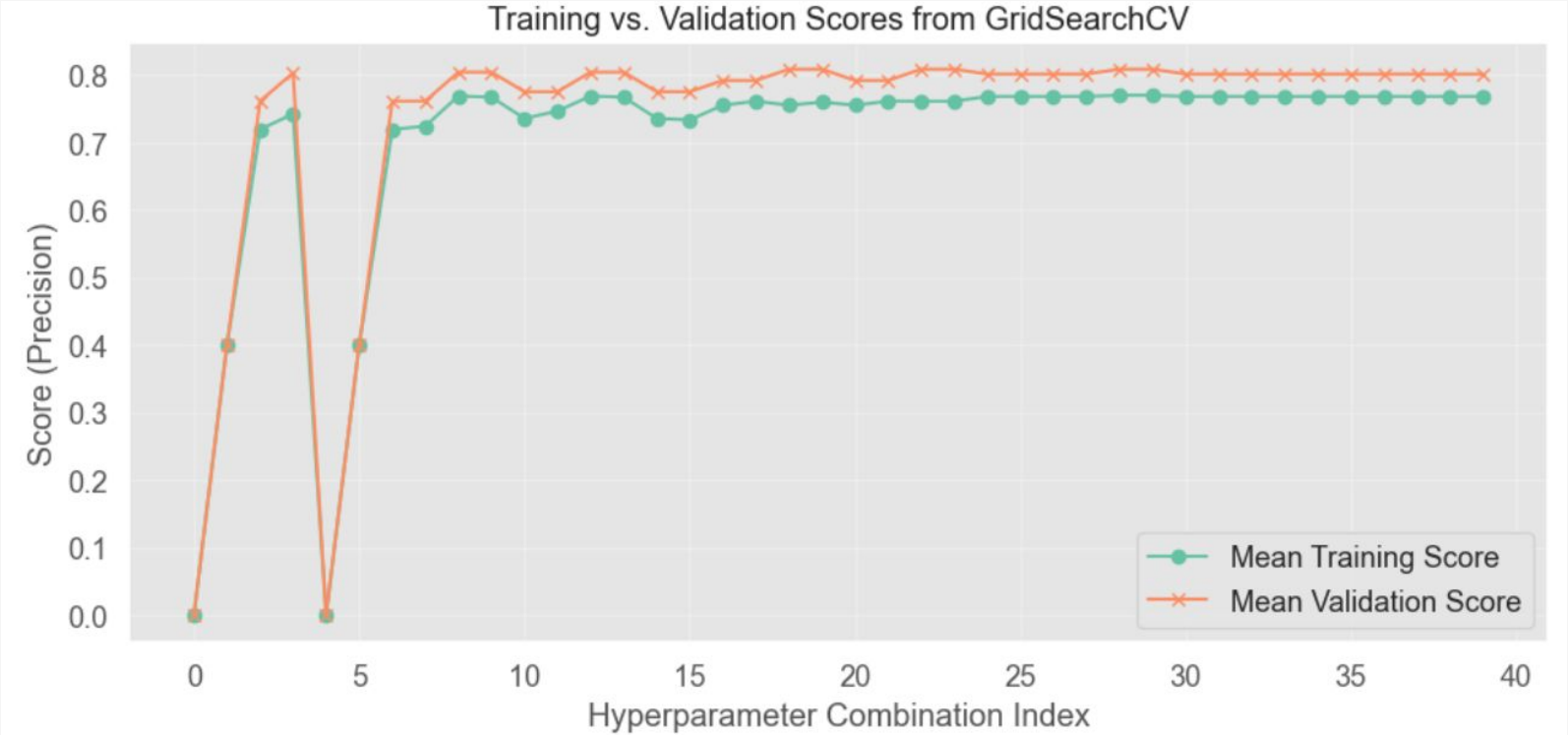


- Radial Basis Function (RBF) to create non-linear decision boundaries
- SVM finds the optimal hyperplane that maximises the margin between high and low anxiety cases

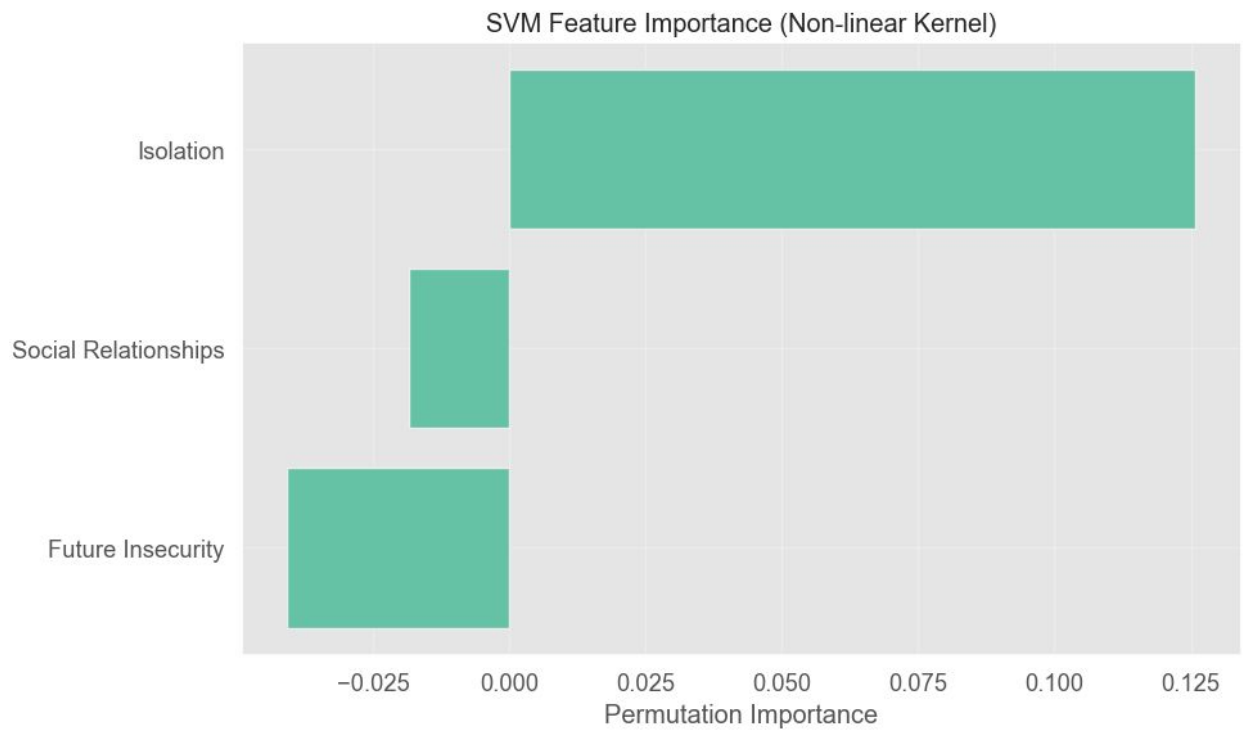
scaler = StandardScaler()

SVM with threshold 0.382

SVM Results (Anxiety Dataset)



SVM Data Insights (Anxiety Dataset)



Model Selection (Senti- Analysis Dataset)

Training VS Fine-Tuning a pre-trained Model

Leverage on powerful, pre-existing knowledge of language

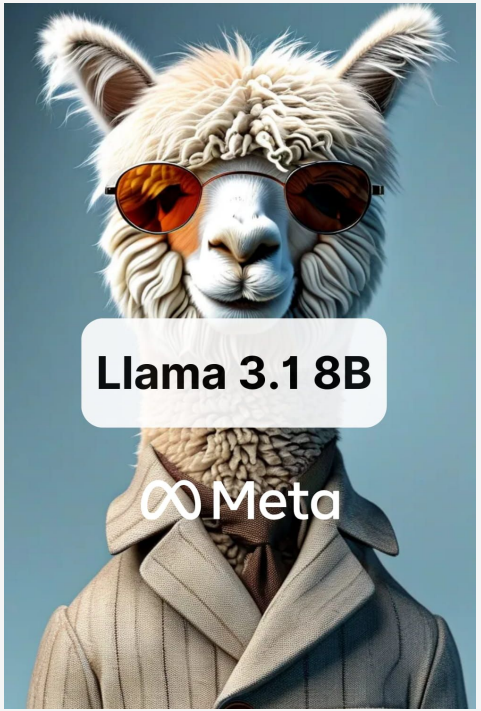
Use highly optimized and proven model architectures

Faster and less computationally intensive

Fine-Tuning LLM (Sentiment Analysis Dataset)

```python
from unsloth import FastLanguageModel

max_seq_length = 1024 # Choose any! We auto support RoPE Scaling internally!
dtype = None # None for auto detection. Float16 for Tesla T4, V100, Bfloat16 for Ampere+
load_in_4bit = True # Use 4bit quantization to reduce memory usage. Can be False.

model, tokenizer = FastLanguageModel.from_pretrained(
    model_name = "unsloth/Meta-Llama-3.1-8B-Instruct-bnb-4bit",
    max_seq_length = max_seq_length,
    dtype = dtype,
    load_in_4bit = load_in_4bit,
    token = HF_TOKEN, # use one if using gated models like meta-llama/Llama-2-7b-hf
)

# Set model configuration parameters similar to reference code
model.config.use_cache = False
model.config.pretraining_tp = 1

# Ensure pad token is set correctly
if tokenizer.pad_token_id is None:
    tokenizer.pad_token_id = tokenizer.eos_token_id
```

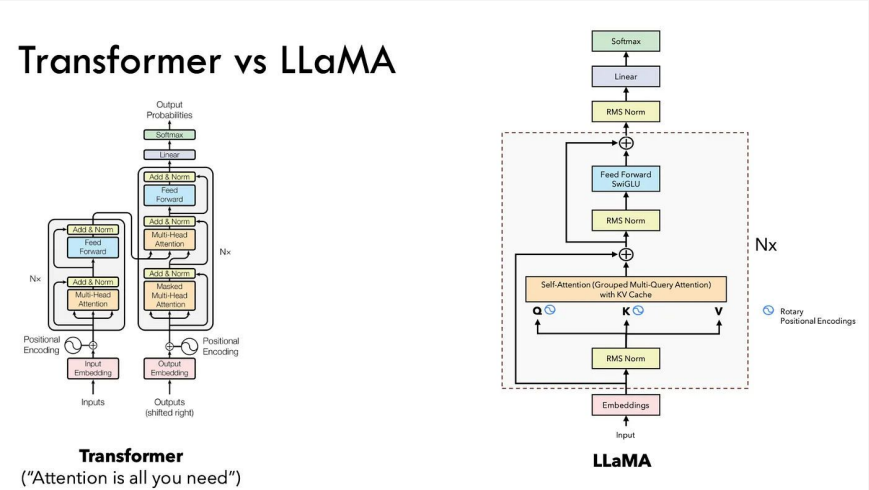
- Balance of computational computational efficiency and performance
- Suitable for deployment on normal consumer-grade hardware, but still delivers
- 4-bit quantized for memory efficiency



Model Overview

Model Differences

- **Encoder-Decoder vs. Decoder-only**
- LayerNorm vs. RMSNorm
- Absolute Sinusoidal vs. Rotary/RoPE
- Multi-Head Attention vs. Grouped-Query Attention
- Standard FFN + ReLU vs. SwiGLU



*(**In comparison with standard transformer proposed in the landmark paper, "Attention is all you need")*

Model Performance (Senti- Analysis Dataset)

Pre-Fine Tuning

- Already rather accurate having an accuracy of around 73%
- However, it is not very accurate when classifying people with anxiety.
- Some overfitting may exist, maybe just classifying anyone that sounds NOK to be Depressed.

```
Accuracy: 0.730
Accuracy for label Normal: 0.746
Accuracy for label Depression: 0.853
Accuracy for label Anxiety: 0.591

Classification Report:
              precision    recall  f1-score   support

      Normal       0.76      0.75      0.75       389
  Depression       0.67      0.85      0.75       389
     Anxiety       0.81      0.59      0.68       389

   micro avg       0.73      0.73      0.73      1167
   macro avg       0.75      0.73      0.73      1167
weighted avg       0.75      0.73      0.73      1167


Confusion Matrix:
[[290  82  17]
 [ 14 332  38]
 [ 76  83 230]]
```

Model Performance (Senti- Analysis Dataset)

Fine Tuning

- Trained the model for 1 epoch to save time
- Trained the model on the balanced dataset obtained from EDA.
- Split dataset into train-eval-test splits

```
Balanced class distribution:
 status
Anxiety       3888
Depression    3888
Normal        3888
Name: count, dtype: int64

Train set class distribution:
status
Anxiety       3111
Normal        3110
Depression    3110
Name: count, dtype: int64
```

```
Eval set class distribution:
status
Depression    389
Normal        389
Anxiety       388
Name: count, dtype: int64

Test set class distribution:
status
Normal        389
Anxiety       389
Depression    389
Name: count, dtype: int64
```

Run summary:

eval/loss	2.04277
eval/runtime	42.8131
eval/samples_per_second	27.235
eval/steps_per_second	6.82
total_flos	5.316330584776704e+16
train/epoch	0.99968
train/global_step	583
train/grad_norm	0.40559
train/learning_rate	0.0
train/loss	2.0802
train_loss	2.13006
train_runtime	3452.8734
train_samples_per_second	2.702
train_steps_per_second	0.169

Model Performance (Senti- Analysis Dataset)

Post-Fine Tuning

- Prediction accuracy increased significantly
- Achevies and average accuracy of 95.5% on prediction

```
Accuracy: 0.955
Accuracy for label Normal: 0.982
Accuracy for label Depression: 0.938
Accuracy for label Anxiety: 0.943

Classification Report:
              precision    recall  f1-score   support

      Normal       0.96      0.98      0.97       389
  Depression       0.94      0.94      0.94       389
     Anxiety       0.97      0.94      0.95       389

   micro avg       0.96      0.95      0.96      1167
   macro avg       0.96      0.95      0.96      1167
weighted avg       0.96      0.95      0.96      1167


Confusion Matrix:
[[382   6   1]
 [  9 365  12]
 [  5  17 367]]
```

Model Performance (Senti- Analysis Dataset)

Output

```
text = "I'm trapped in a storm of emotions that I can't control, and it feels like no one understands the chaos inside me"
prompt = f"""Classify the text into Normal, Depression, Anxiety, and return the answer as the corresponding mental health disorder label.
text: {text}
label: """.strip()

pipe = pipeline(
    "text-generation",
    model=merged_model,
    tokenizer=tokenizer,
    device_map="auto",
)

outputs = pipe(prompt, max_new_tokens=2, do_sample=True, temperature=0.1)
print(outputs[0]["generated_text"].split("label: ")[-1].strip())
```

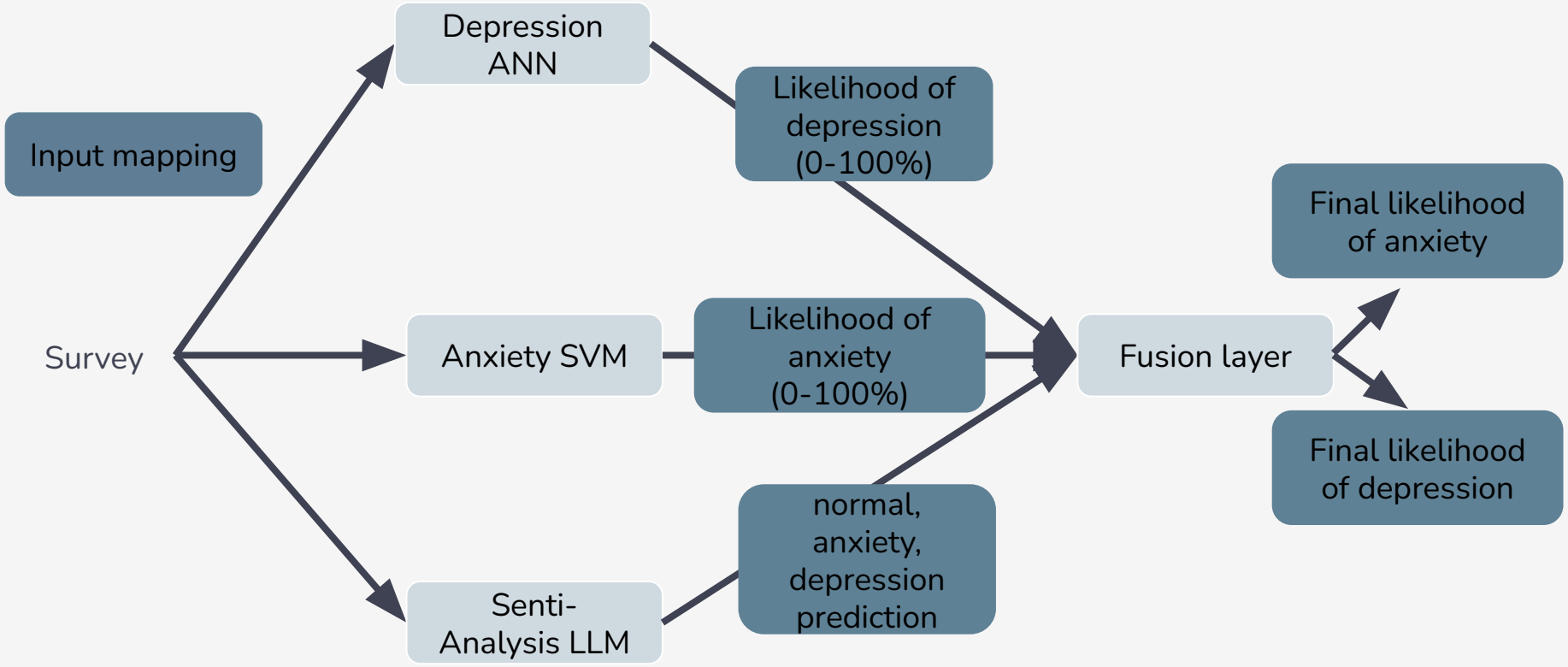
```
Device set to use cuda:0
The model 'PeftModelForCausalLM'
Depression
```

- Possible text input from a user and subsequent model output

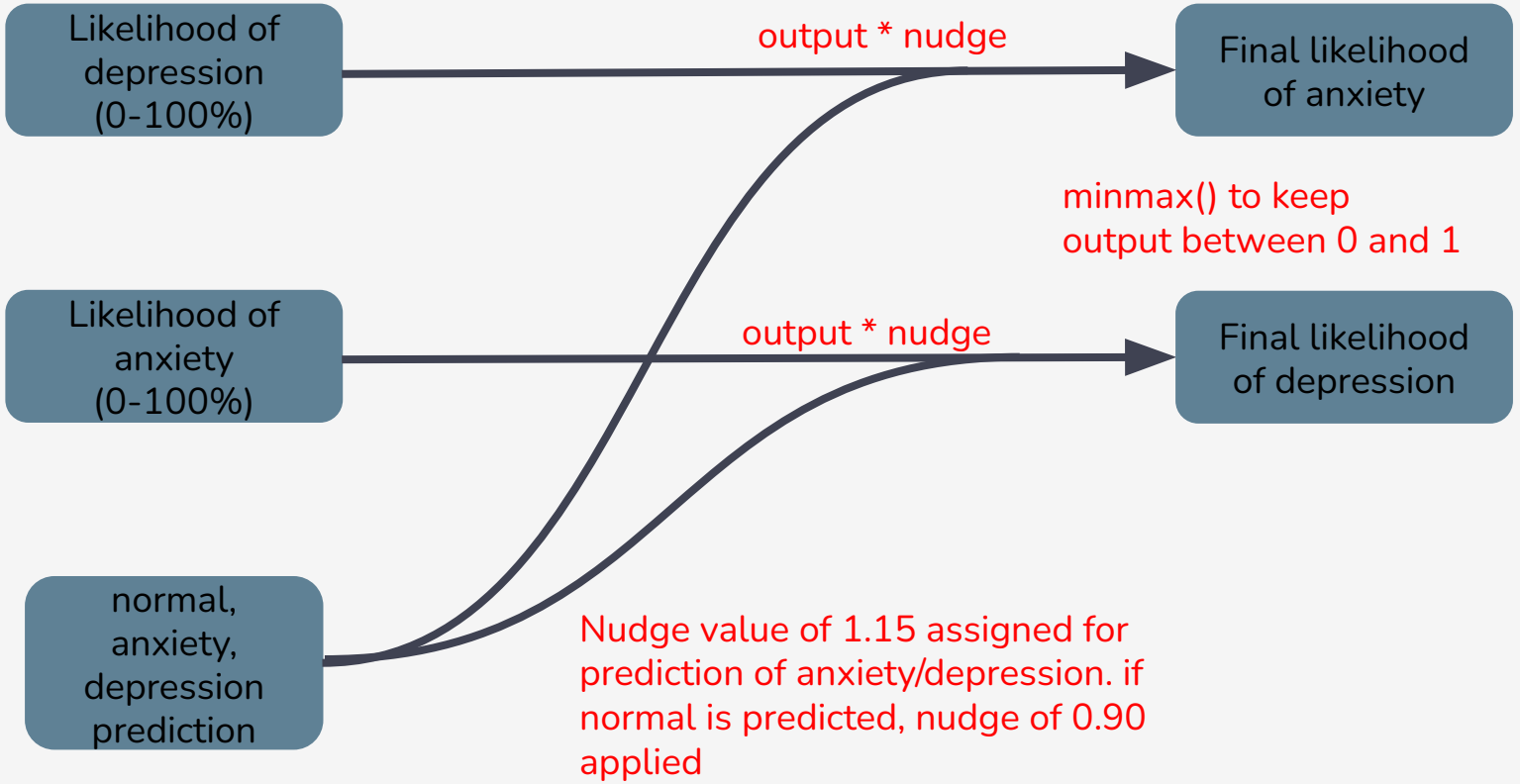
04

Recommendations

Recommendations: Output merging



Recommendations: fusion layer



Thank you!