ANALYSIS THE EFFECTIVENESS OF TEXT AUGMENTATION BACK TRANSLATION AND SYNONYM REPLACEMENT IN MENTAL HEALTH STATUS CLASSIFICATION USING DISTILLED-BERT (DISTILBERT)

(Research Results)

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OUTLINE

1. Introduction
2. Literatur Review
3. Research Methodology
4. Results and Discussion
5. Conclusion
6. Bibliography

Background and Issues

- MENTAL HEALTH DISORDERS
- SOCIAL MEDIA AS A MEANS OF SELF-EXPRESSION
- DATA IMBALANCES
- TEXT AUGMENTATION
- CLASSIFICATION USING DISTILBERT MODEL

Problem Statement

1 **Performing text classification on mental health status data to predict the type of mental disorder experienced by an individual.**

2 **Assesses whether differences in data quantity can affect the predictive performance of classification models.**

Research Objectives

1. Build a DistilBERT model to classify types of mental health disorders based on texts expressed by individuals.

2. Applying text augmentation techniques, back translation and synonym replacement, to assess the impact of increased data quantity on the predictive performance of a classification model.

Research Benefits

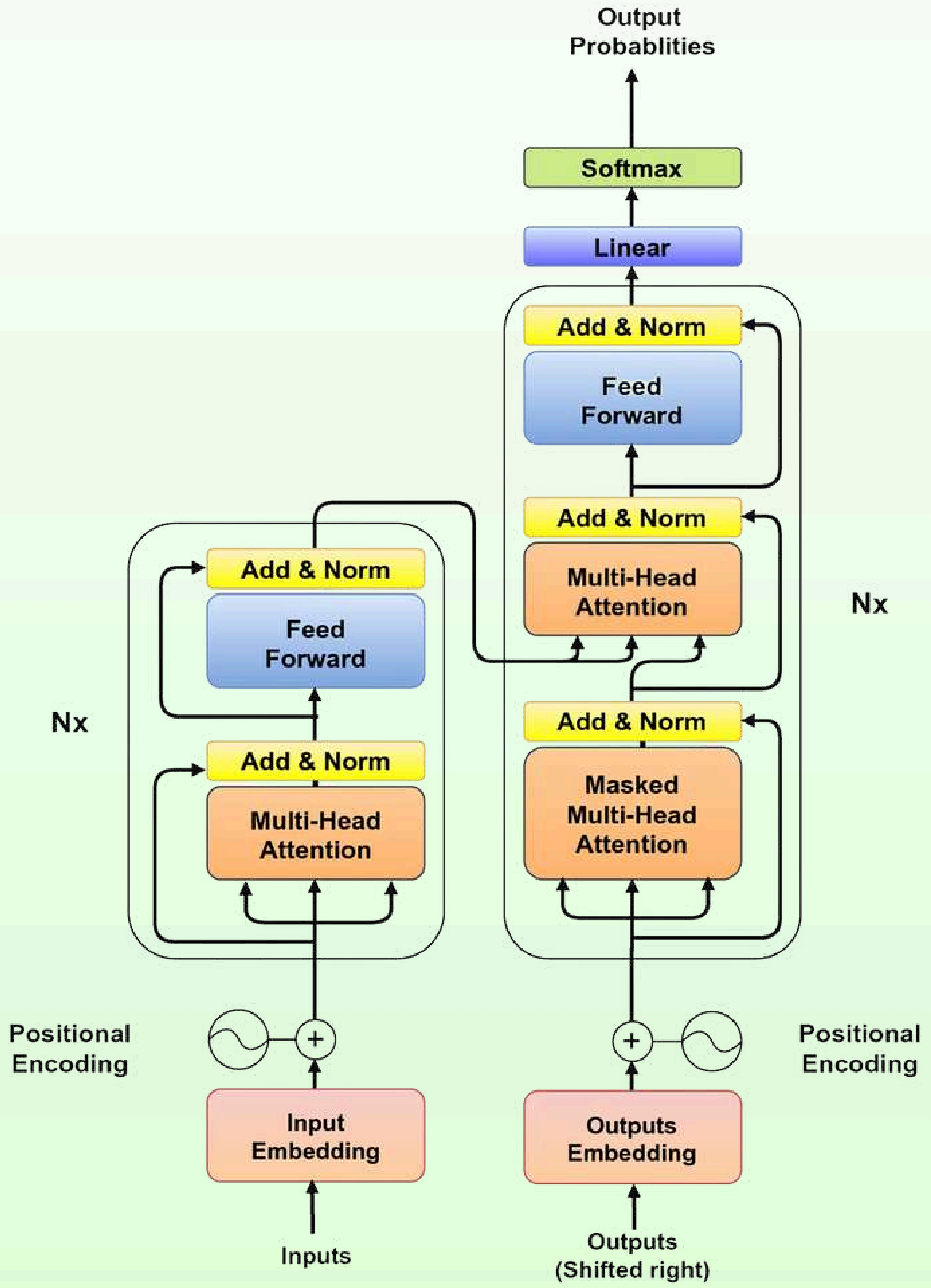
1. Supporting the development of an early detection system for types of mental health disorders through text analysis.

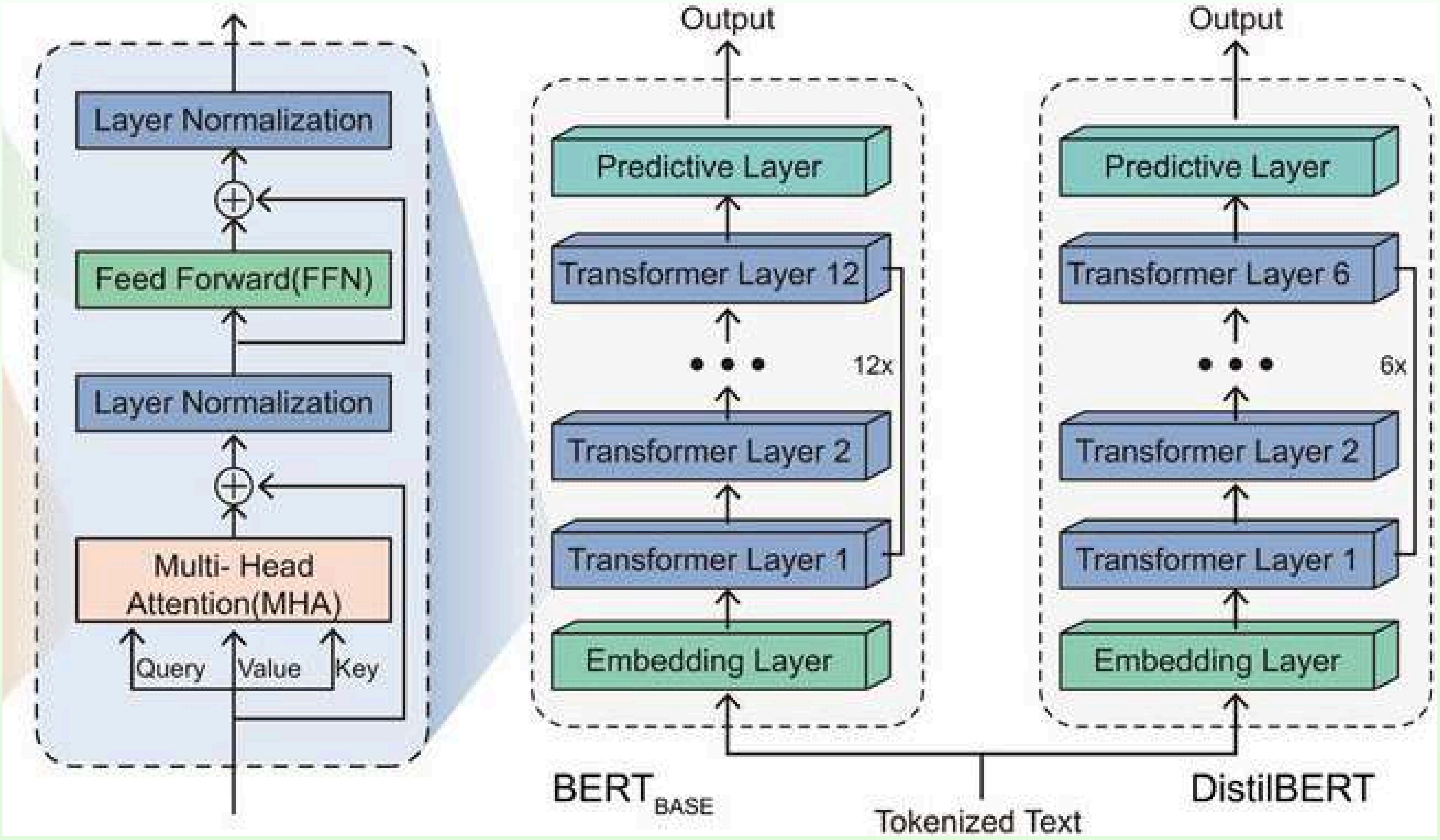
2. Helping to identify effective data augmentation techniques can improve model performance and facilitate the increase of data volume without the need for manually collecting additional data.

Related Research

Research	Data	Text Augmentation Technique	Method	Result	Increased Accuracy
Penerapan Text Augmentation Untuk Mengatasi Data Yang Tidak Seimbang Pada Klasifikasi Teks Berbahsa Indonesia. Studi Kasus: Deteksi Judul Clickbait Dan Komentar Hate Speech Pada Berita Online.(Rahma & Suadaa, 2023)	Data Teks Formal Clickbait: 3.316 Non-clickbait: 5.927 Data Teks Informal Hate Speech: 263 Non-Hate Speech: 1.307	Synonym Replacement Back Translation	IndoBERT Support Vector Machine (SVM)	Model Indo-BERT Data clickbait WA: 83,51% SR: 83,23% BT: 84,04%	Back Translation(Clickbait): +0,53% Akurasi tidak meningkat pada data clickbait
Klasifikasi Sentimen Untuk Mengetahui Kecenderungan Politik Pengguna X Pada calon Presiden Indonesia 2024 Menggunakan Metode IndoBERT (oktariansyah dkk., 2024)	Data Tweet Pengguna X Positif Anies: 1901 Positif Prabowo: 888 Positif Ganjar: 1525 Negatif Anies: 264 Negatif Prabowo: 971 Negatif Ganjar: 93 Netral: 708	Synonym Replacement Back Translation	IndoBERT	Tanpa Augmentasi: 75% Augmentasi Sinonim: 82% Augmentasi Back Translation: 78%	Synonym Replacement: +7% Back Translation:+3%
Text Data Augmentation Techniques for Word Embeddings in Fake News Classification (Kapusta dkk., 2024)	Dataset WELFake : dengan label berita palsu (35.028) dan berita asli (37.106)	• Synonym Replacement • Back Translation • Reduction of Function Words	• Random Forest • Logistic Regression • BernouliNB • Support Vector Classifier (SVC)	SVC Original: 82,90% SR: 85,75% FWD: 85,93% BT:85,96%	SVC: SR: +3,43% FWD: +3,71% BT: +3,71%

DistilBERT


Output
Probablities
Softmax
Linear
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Add & Norm
Masked
Multi-Head
Attention
Nx
Add & Norm
Feed
Forward
Add & Norm
Multi-Head
Attention
Nx
Positional
Encoding
Input
Embedding
Inputs
Positional
Encoding
Outputs
Embedding
Outputs
(Shifted right)


Layer Normalization
Feed Forward(FFN)
Layer Normalization
Multi- Head
Attention(MHA)
Query
Value
Key
Output
Predictive Layer
Transformer Layer 12
12x
Transformer Layer 2
Transformer Layer 1
Embedding Layer
BERT BASE
Output
Predictive Layer
Transformer Layer 6
6x
Transformer Layer 2
Transformer Layer 1
Embedding Layer
DistilBERT
Tokenized Text

Model Performance Evaluation

Accuracy

$$\text{Accuracy} = \frac{\sum_{i=0} C_{ii}}{\sum_{i=0} \sum_{j=0} C_{ij}}$$

Sensitivity

$$\textit{Sensitivity class } C_i = TPR(C_i) = \frac{TP(C_i)}{TP(C_i) + FN(C_i)}$$

$$\textit{Sensitivity}_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} TPR(C_i)$$

F1-Score

$$F1\text{-}Score \text{ class } C_i = 2 \times \frac{TPR(C_i) \times PPV(C_i)}{TPR(C_i) + PPV(C_i)}$$

$$F1\text{-}Score_{\text{avg}} = 2 \times \frac{TPR(\text{Macro}) \times PPV(\text{Macro})}{TPR(\text{Macro}) + PPV(\text{Macro})}$$

Precision

$$\textit{Precision class } C_i = PPV(C_i) = \frac{TP(C_i)}{TP(C_i) + FP(C_i)}$$

$$\textit{Precision}_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} PPV(C_i)$$

Specificity

$$\textit{Specificity class } C_i = TNR(C_i) = \frac{TN(C_i)}{TN(C_i) + FP(C_i)}$$

$$\textit{Specificity}_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} TNR(C_i)$$

AUC

$$AUC \text{ class } C_i = \frac{TPR(C_i) - FPR(C_i) + 1}{2} = \frac{TPR(C_i) + TNR(C_i)}{2}$$

$$AUC_{\text{avg}} = \frac{1}{N} \sum_{i=1}^{N} AUC(C_i)$$

Research Data

Data

Source : Kaggle
Total : 24.393 Text
Label : 6

Label	Total	Percentage
Normal	7754	31,8%
Depression	7061	28,9%
Anxiety	3600	14,8%
Bipolar	2535	10,4%
Stress	2455	10,1%
Personality disorder	988	4,1%

Sample Data

	statement	status
0	could you imagine angel eva fight against tita...	Depression
1	i am on week on prozac and experiencing no rea...	Depression
2	i hope so. i have to go to the bathroom.	Normal
3	I feel like I never stood a chance I was made...	Depression
4	but of course the document with the important ...	Normal
...	...	...
24389	A"Fuck you bitch, I can make your life hell and...	Stress
24390	IYou've only been playing for a while, don't be...	Normal
24391	My mom [54F] has catered to his every need sin...	Normal
24392	[Kinda Gross] Hey what is this in my throat, I...	Anxiety

Research Tools

Hardware

Processor : Intel® Core™ i3-7020U CPU @ 2.30GHz (4 CPUs), ~2.3GHz

Installed RAM : 4 GB

Software

Sistem Operasi Windows 10 Pro 64-bit

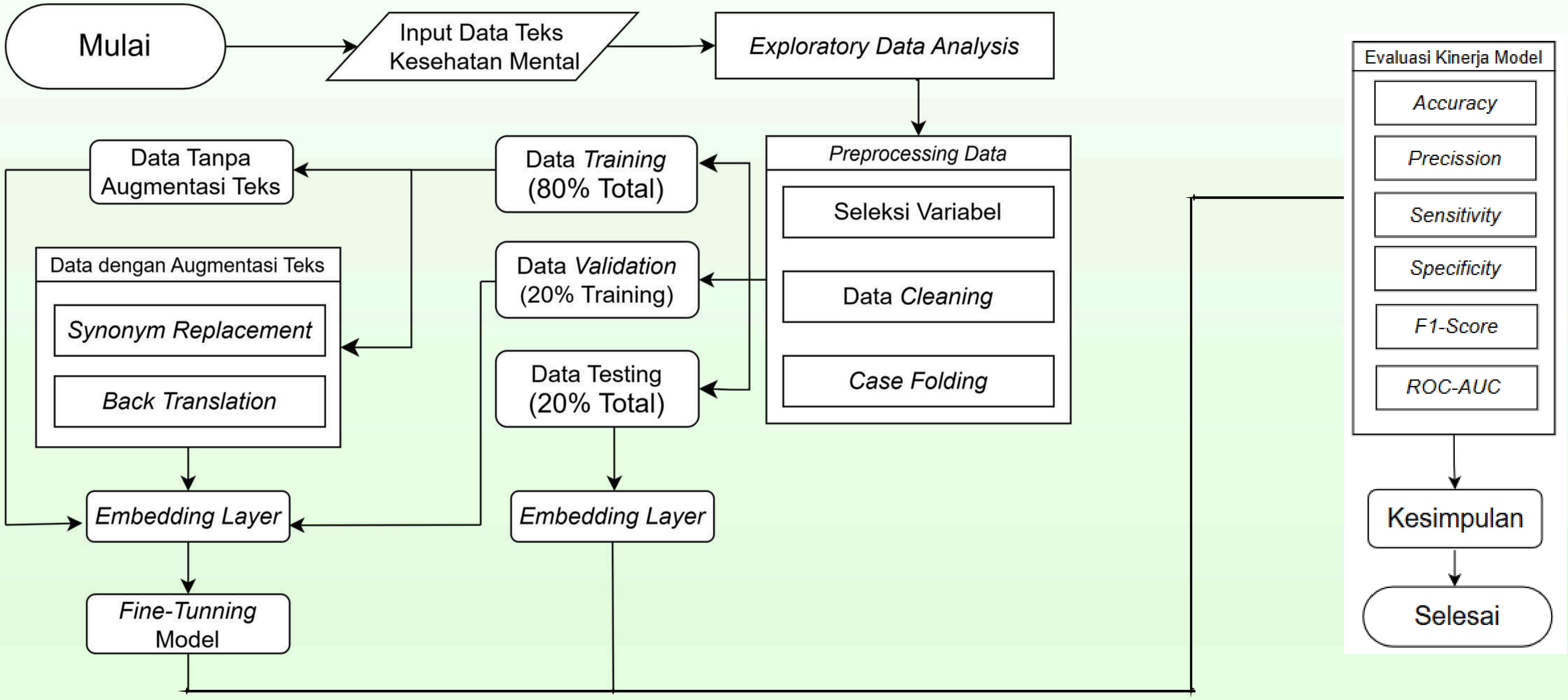
Google Colaboratory

Kaggle

Package

- Pandas 2.2.2
- Numpy 1.26.4
- Matplotlib 3.7.5
- Seaborn 0.12.2
- NLTK 3.2.4
- Transformers 4.44.2
- Sklearn 1.2.2
- PyTorch 2.4.0
- WordCloud 1.9.3

Research Methods



Input Data

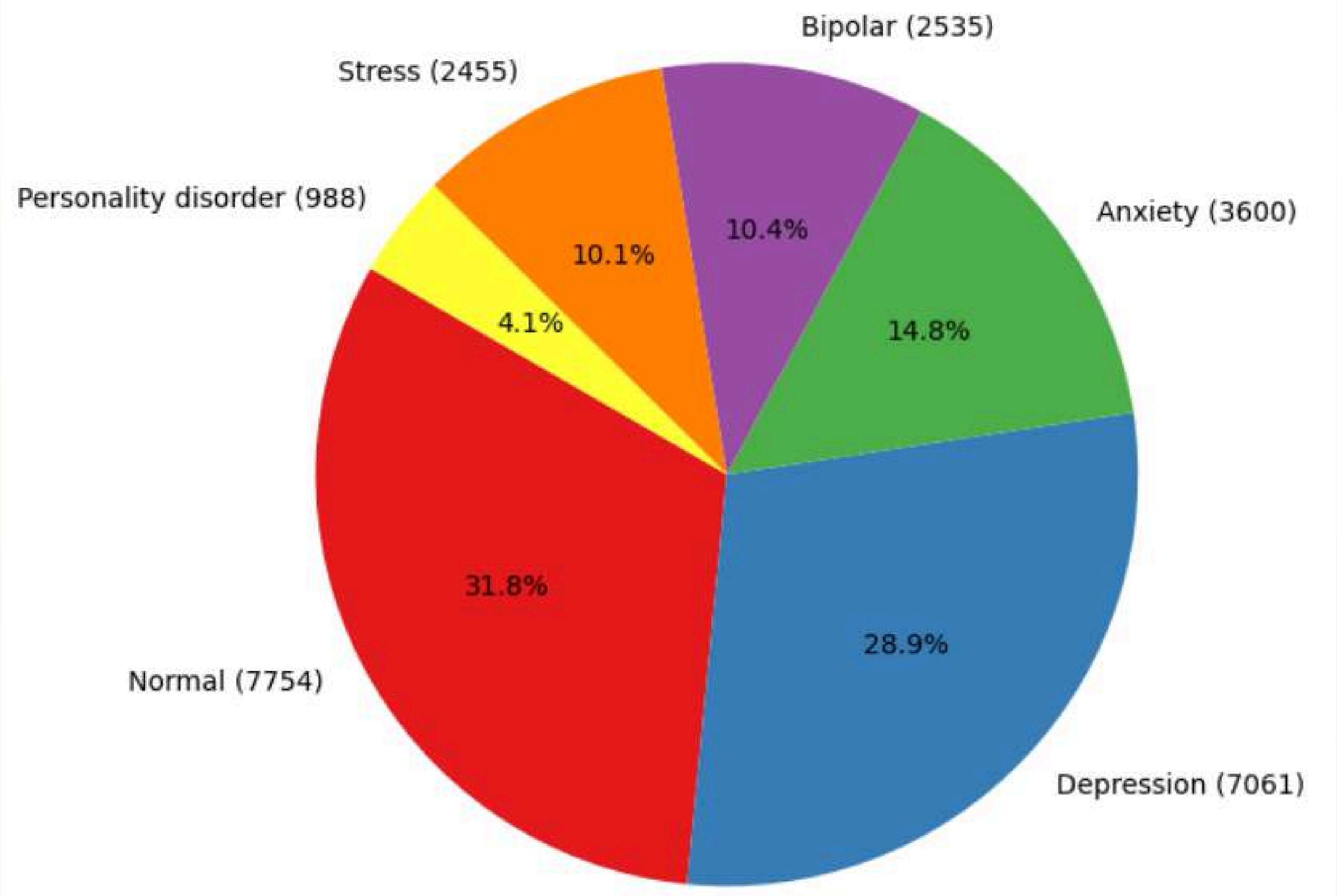
Data

	Unnamed: 0	statement	status
0	1	could you imagine angel eva fight against tita...	Depression
1	2	i am on week on prozac and experiencing no rea...	Depression
2	3	i hope so. i have to go to the bathroom.	Normal
3	4	I feel like I never stood a chance I was made ...	Depression
4	5	but of course the document with the important ...	Normal
...	...	...	...
24388	24389	Hey reddit. I do not know what is wrong with m...	Depression
24389	24390	"Fuck you bitch, I can make your life hell and...	Stress
24390	24391	You've only been playing for a while, don't be...	Normal
24391	24392	My mom [54F] has catered to his every need sin...	Normal
24392	24393	[Kinda Gross] Hey what is this in my throat, I...	Anxiety

24393 rows × 3 columns

Exploratory Data Analysis

Data Distribution

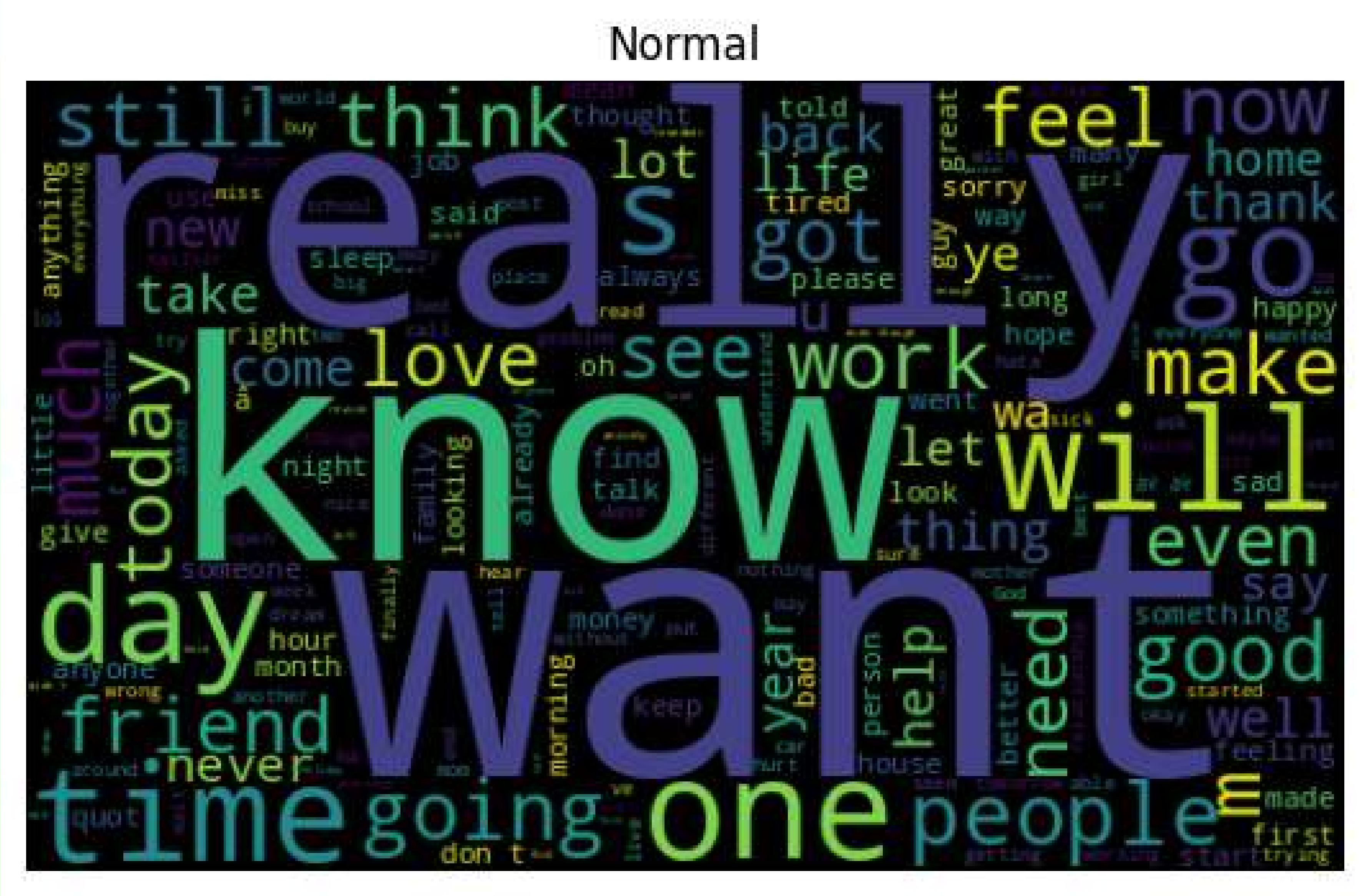


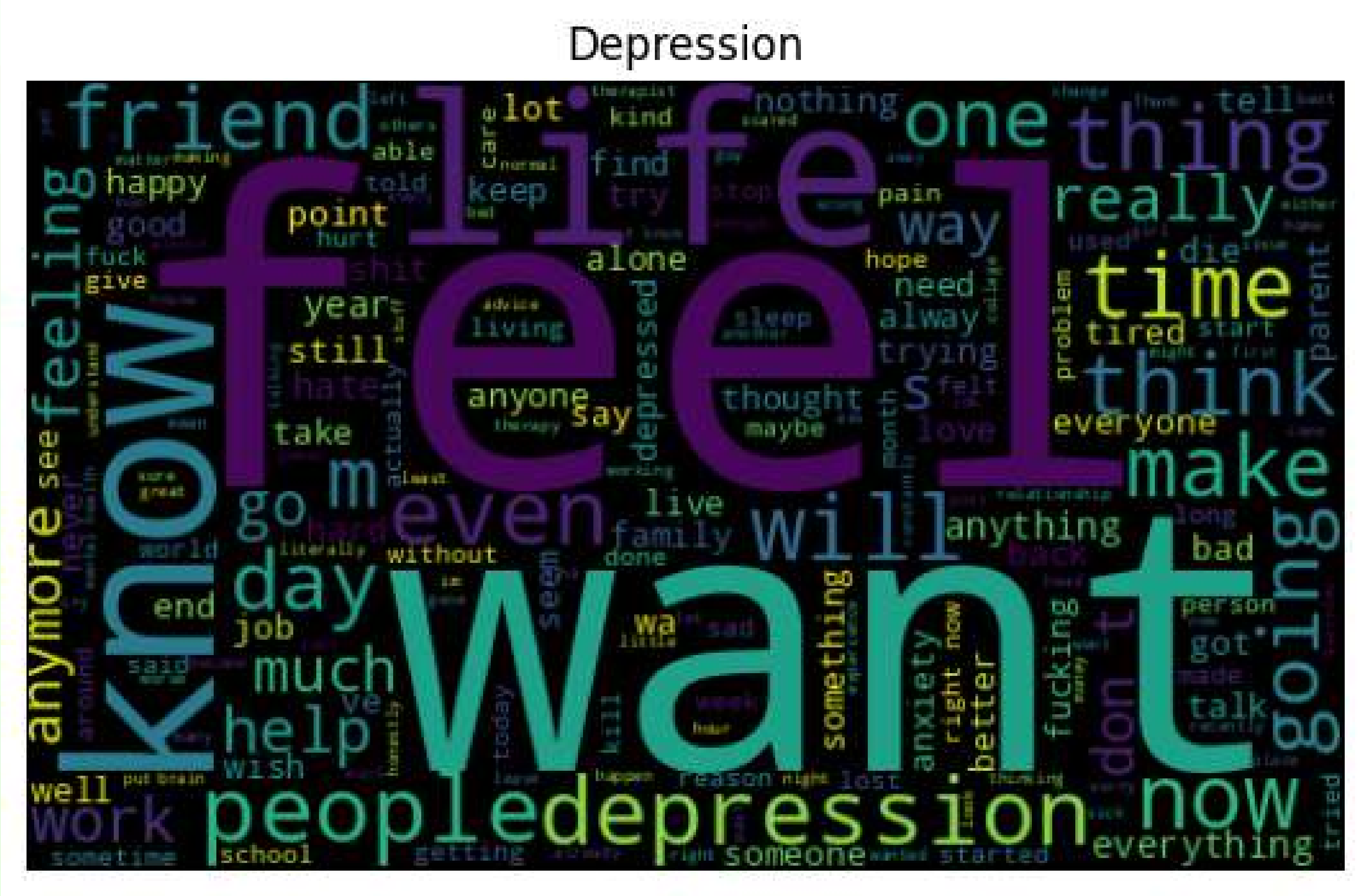
Word Length Distribution

status	count	mean	std	min	25%	50%	75%	max
Anxiety	3600.0	133.276944	107.130515	1.0	44.00	110.0	198.00	450.0
Bipolar	2535.0	161.725444	99.795511	7.0	82.00	139.0	222.00	448.0
Depression	7061.0	142.861918	106.845793	6.0	56.00	115.0	206.00	450.0
Normal	7754.0	20.575445	26.263545	3.0	7.00	12.0	21.00	311.0
Personality disorder	988.0	163.782389	109.174596	6.0	71.75	141.5	241.25	448.0
Stress	2455.0	120.014664	71.298549	16.0	76.00	100.0	141.00	450.0

Exploratory Data Analysis

WordCloud



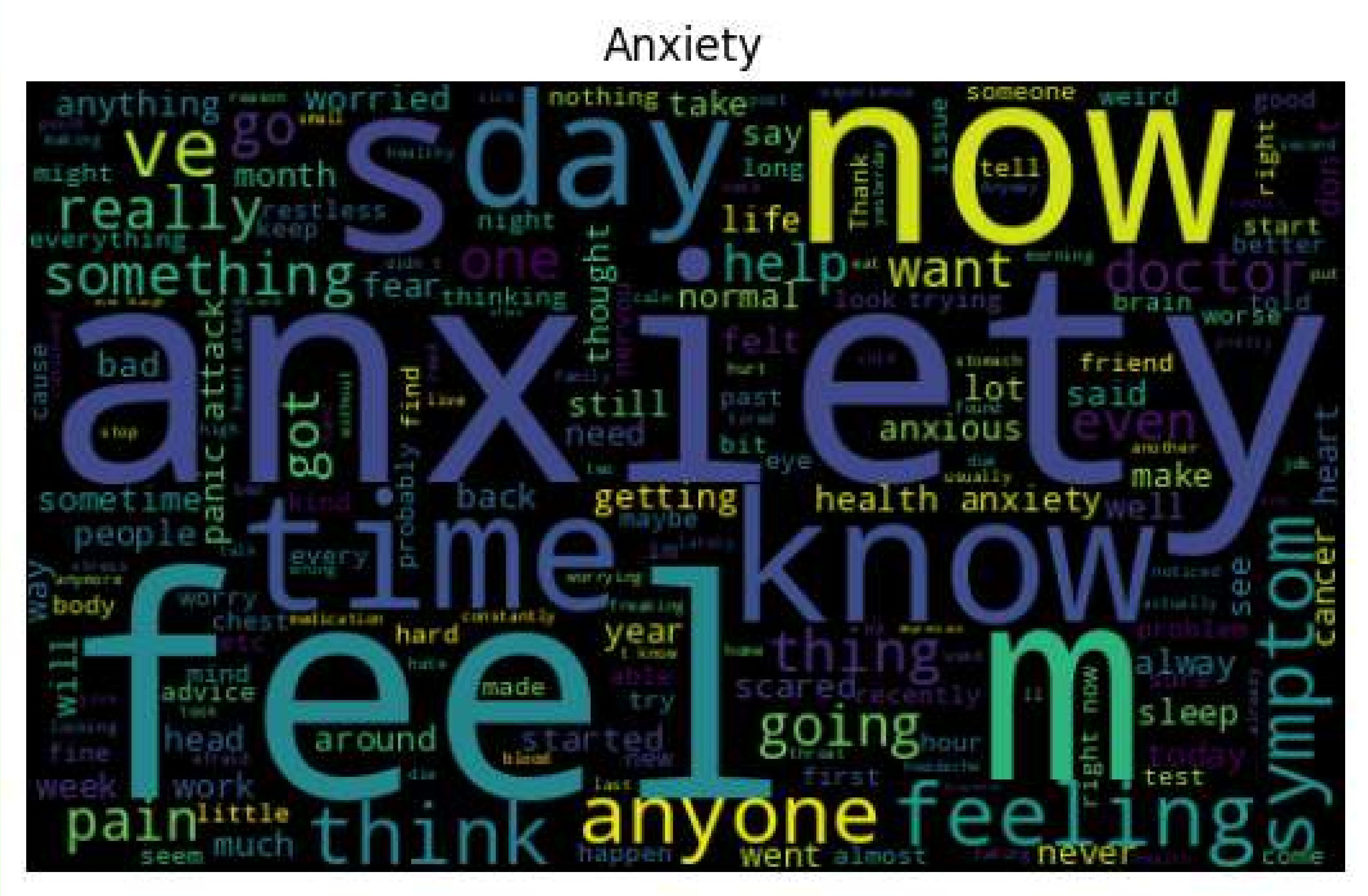


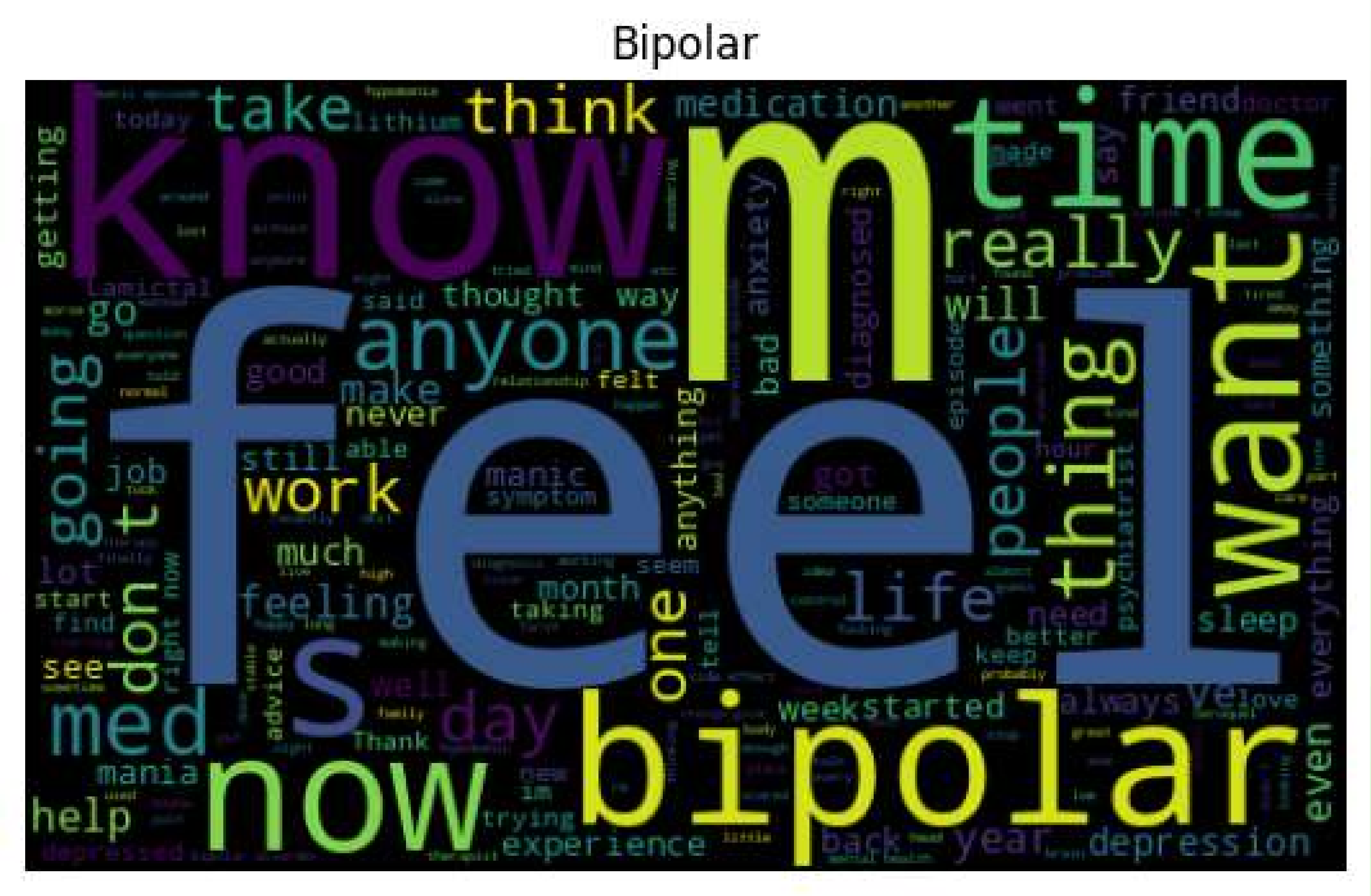
Love, friend, happy, good, help, and, tired

Feel, want, depression, help, alone, and hurt

Exploratory Data Analysis

WordCloud



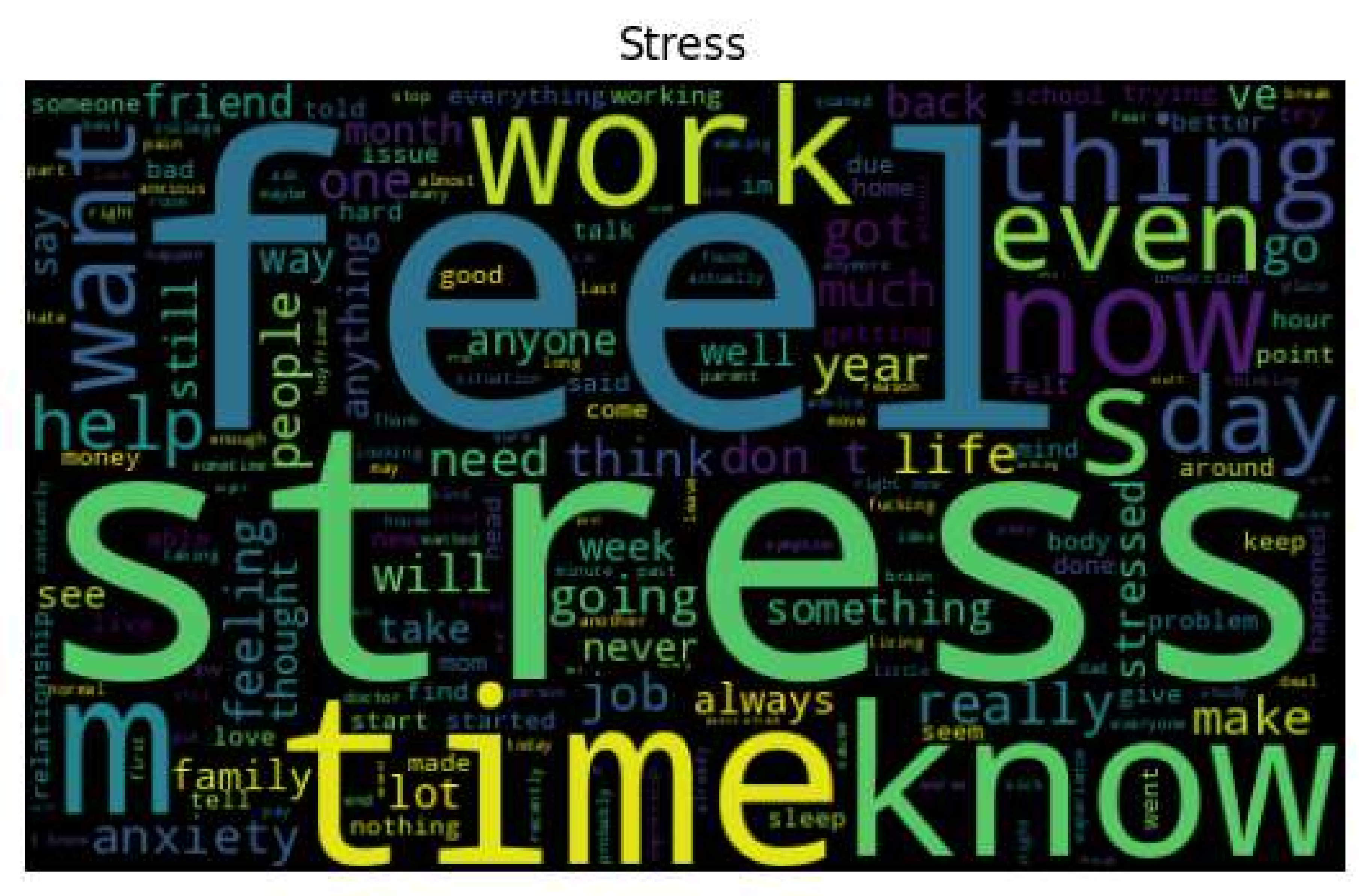


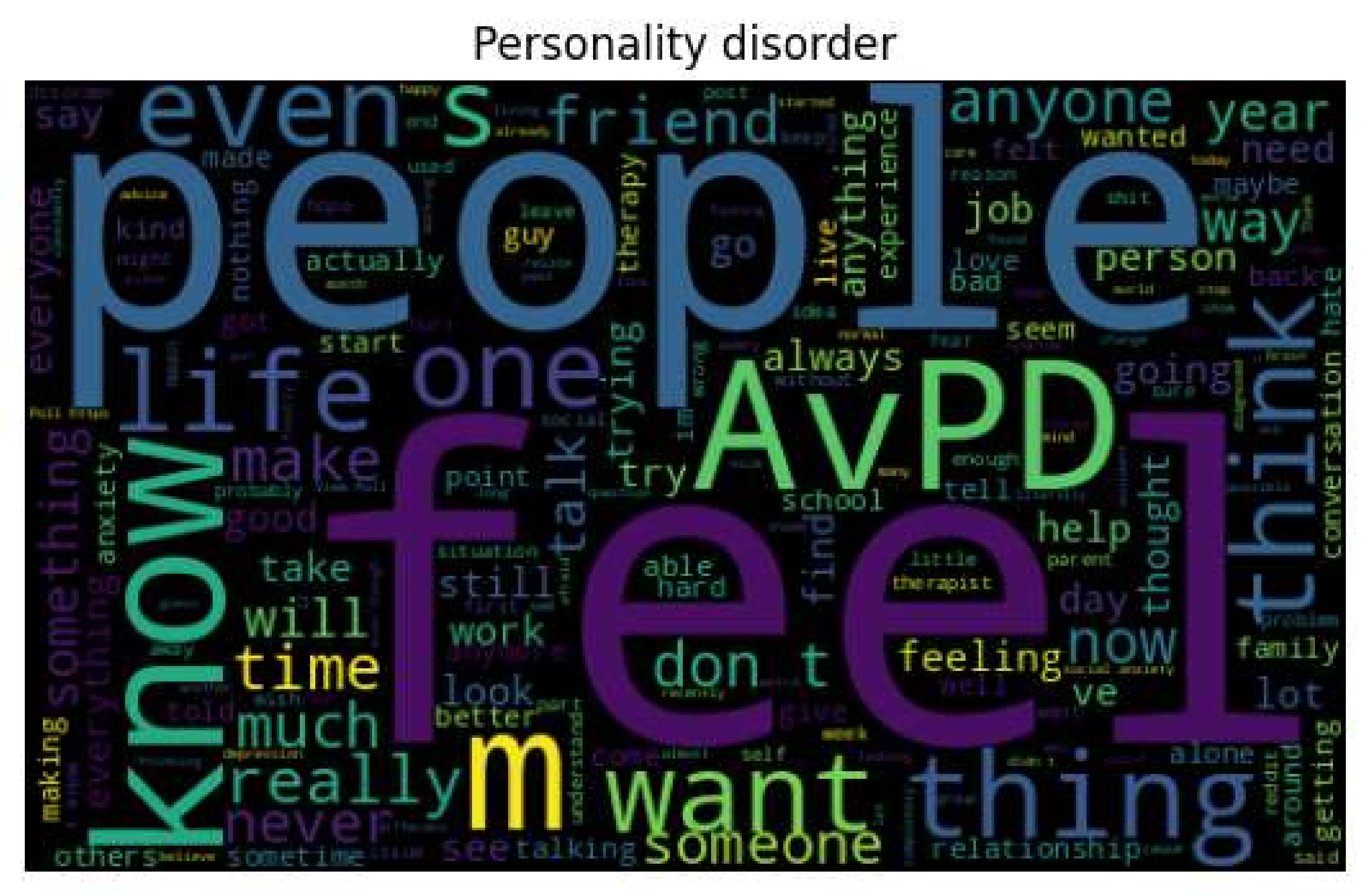
Anxiety, feel, panic attack, worried, scared, and help

Bipolar, feel, manic, and depression

Exploratory Data Analysis

WordCloud





Stress, feel, and anxiety

Feel, people, AvPD

Pre-processing Data

Selection of Variable

	statement	status
0	could you imagine angel eva fight against tita...	Depression
1	i am on week on prozac and experiencing no rea...	Depression
2	i hope so. i have to go to the bathroom.	Normal
3	I feel like I never stood a chance I was made ...	Depression
4	but of course the document with the important ...	Normal
...	...	...
24388	Hey reddit. I do not know what is wrong with m...	Depression
24389	"Fuck you bitch, I can make your life hell and...	Stress
24390	You've only been playing for a while, don't be...	Normal
24391	My mom [54F] has catered to his every need sin...	Normal
24392	[Kinda Gross] Hey what is this in my throat, I...	Anxiety

24393 rows × 2 columns

Data Cleaning

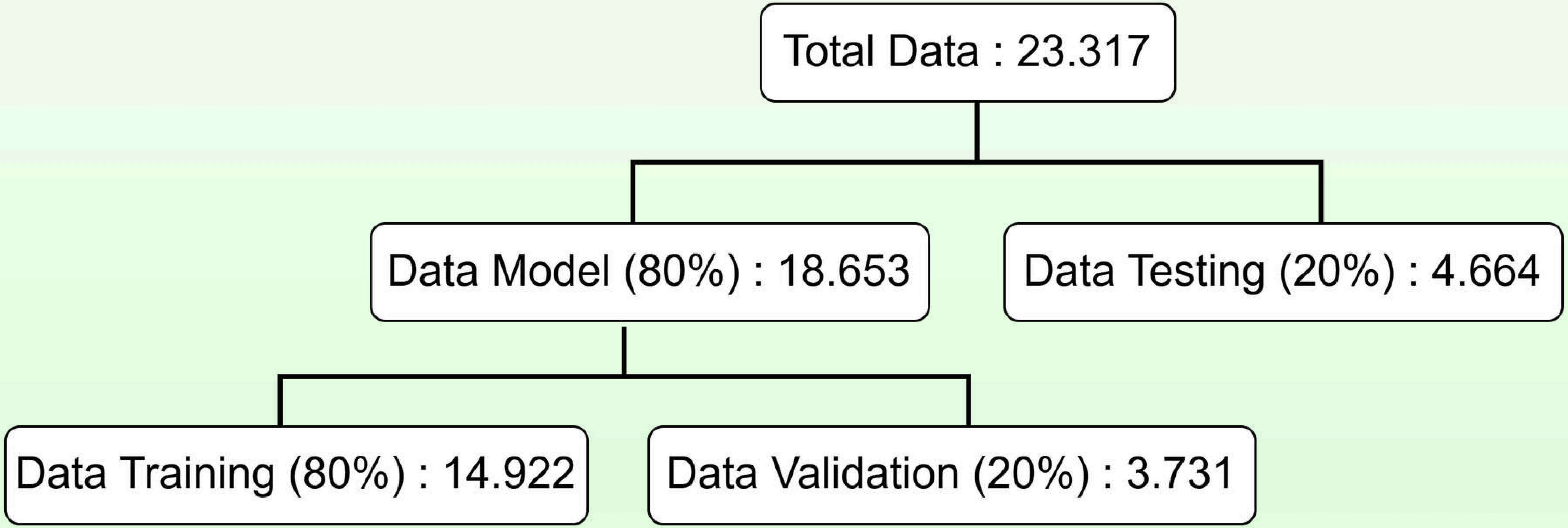
Missing Value : 0

Duplicate Data : 1.076

Before Pre-processing	I don’t know... I don’t know what to do. I just want out of here. It’s too hard. With this house and school work.
After Pre-Processing	i dont know i dont know what to do i just want out of here its too hard with this house and school work

Spliting Data

Spliting Data



Data Augmentation

Back Translation

Indonesian Language

Original Text	i do not even remember what happiness even feels like anymore i cannot even cry anymore i am feeling so numb
Temporary Translation	Aku bahkan tidak ingat lagi bagaimana rasanya kebahagiaan aku bahkan tidak bisa menangis lagi aku merasa begitu mati rasa
Back Translation Result	i can't even remember what it feels like to be happy. i can't even cry anymore. i feel so numb.

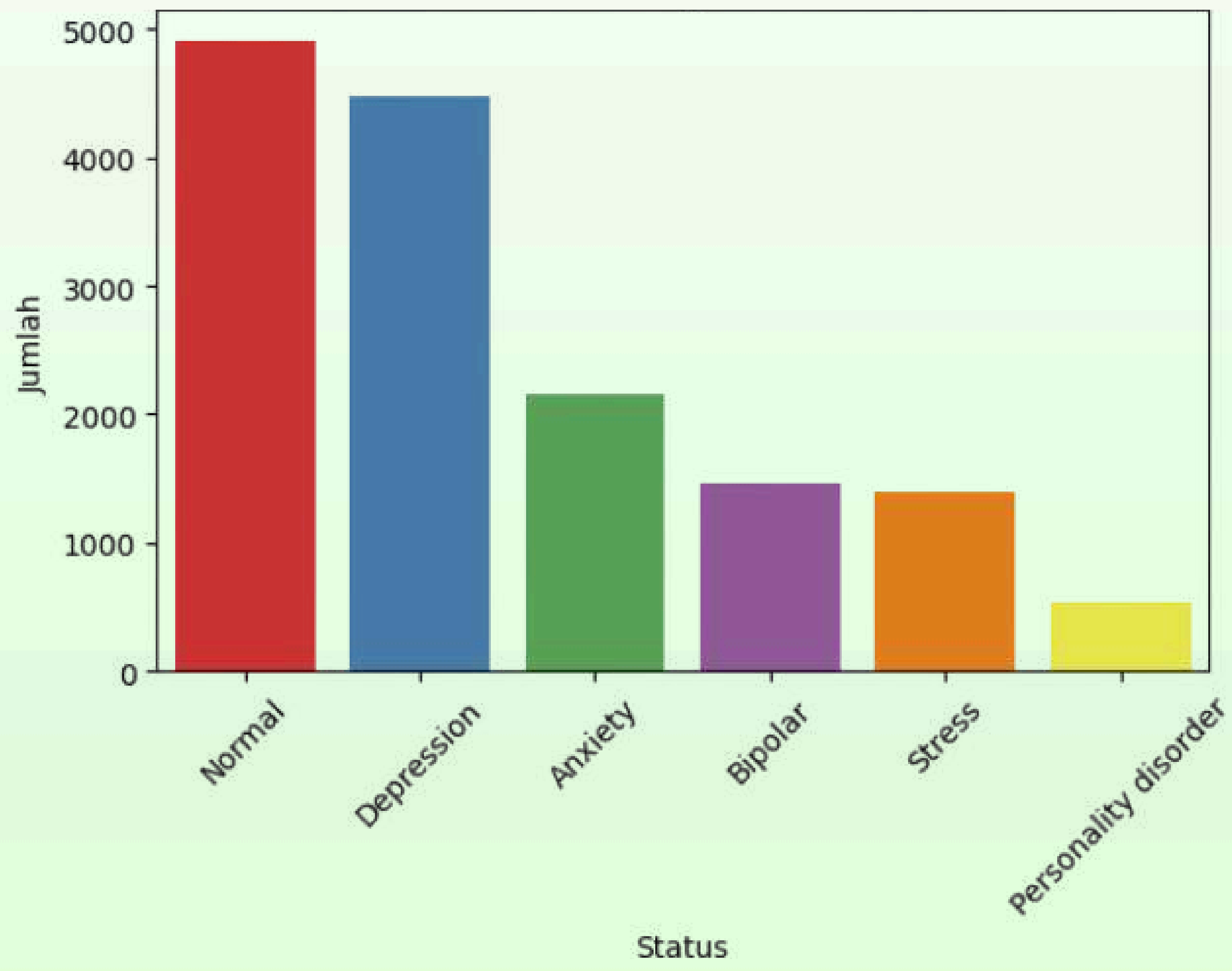
Back Translation

French Language

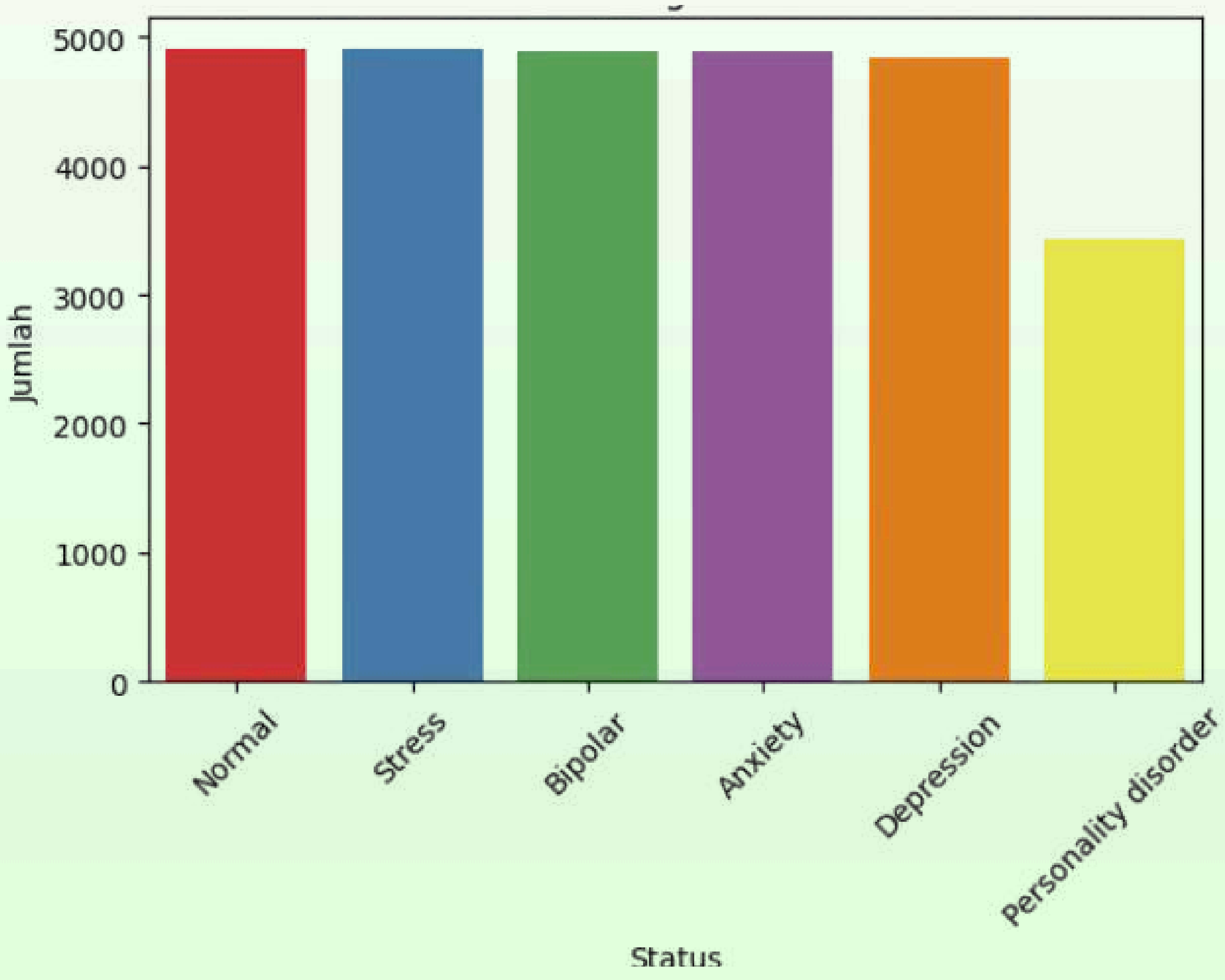
Original Text	first of all im really sorry that this account doesnt work as expected i dont know why im sad now im nervous i dont want to give up i often panic i know time is running i really try so hard but im sorry again cin failed sorry everyone i cant tell you positive things
Temporary Translation	Tout d'abord im vraiment desol ´e que ce compte ne ´ fonctionne pas comme prevu je ne sais pas ´ pourquoi im triste maintenant im nerveux je ne veux pas abandonner je panique souvent je sais que le temps est en cours d'execution j'essaie ´ vraiment si dur mais im desol ´ e´ a nouveau cin ` echou ´ e d ´ esol ´ e tout le ´ monde je ne peux pas vous dire des choses positives
Back Translation Result	first of all im really sorry that this account doesn't work as expected i don't know why im sad now im nervous i don't want to give up i panic often i know that the time is running i really try so hard but im sorry again cin failed sorry everyone i can't tell you positive things

Data Augmentation

Original Data Distribution



After Back Translation

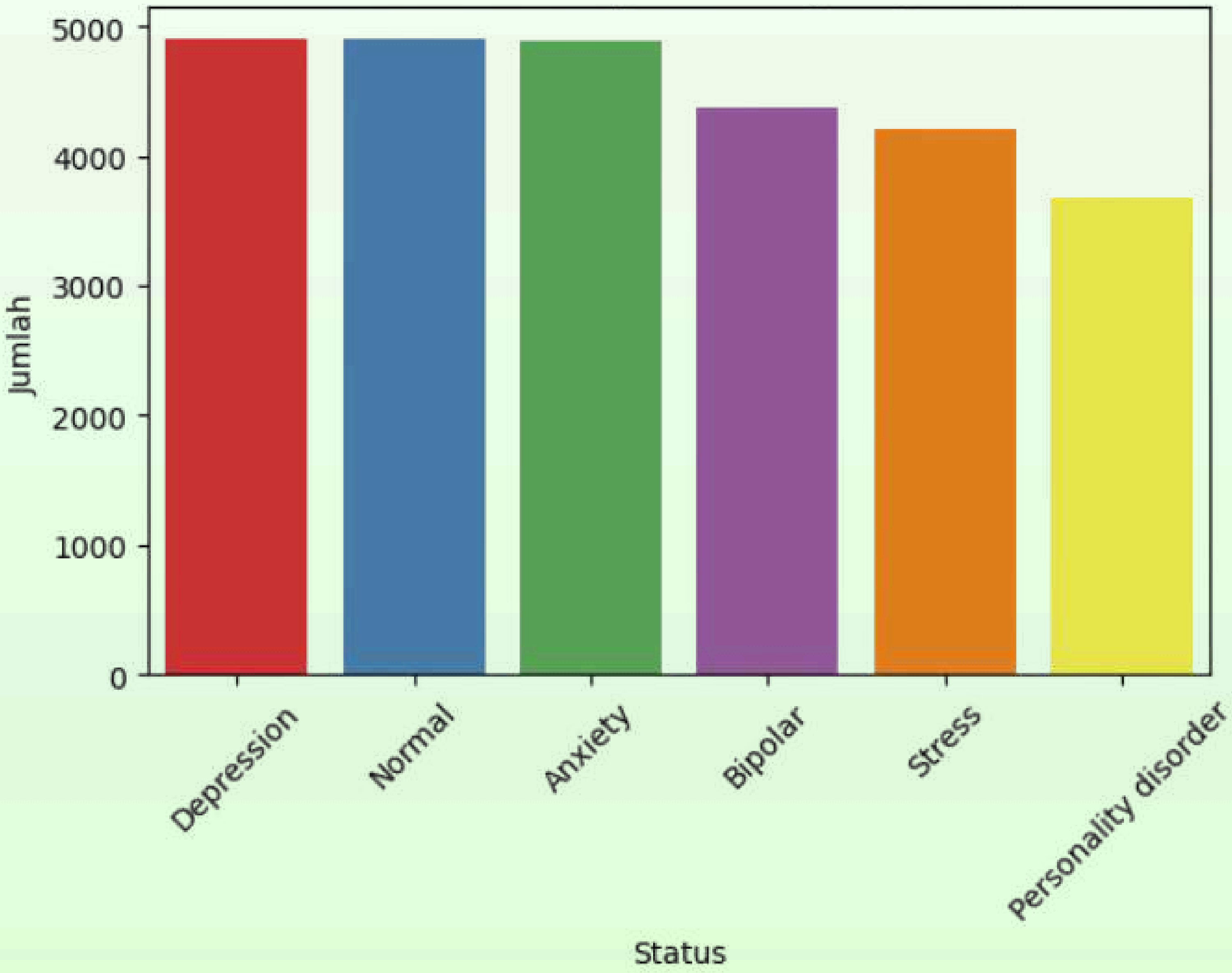


Data Augmentation

Synonym Replacement

Original Text	Synonym Replacement Result
what is your personal experience during highs and lows what changes do you notice when going into each of them we all know the textbook symptoms but every person has their own unique experience with bipolar disorder whats yours	what is your personal experience during highs and lows what changes do you acknowledge when pass into each of them we all know the textbook symptom but every person has their own unique experience with bipolar disorder whats yours
if youre blank and restless your typing will be random	if youre blank and restless your typewriting will be random

After Synonym Replacement



Embedding

DistilBERT Embedding

Original Text	i ve thought of ending my life so many time but i never end up doing it i just wish there wa a peaceful purposeful way to go out that would be a benefit to others but i suppose life isn t that kind so the next best thing is to donate a body to science right or i hope so ive been thinking that it would benefit my mother with financial trouble she said i m just getting in the way so i think insurance should give her some money i think right now that s my only plausible solution but i just am too chicken
DistilBERT Tokenization	'[CLS]', 'i', 've', 'thought', 'of', 'ending', 'my', 'life', 'so', 'many', 'time', 'but', 'i', 'never', 'end', 'up', 'doing', 'it', 'i', 'just', 'wish', 'there', 'wa', 'a', 'peaceful', 'purpose', '##ful', 'way', 'to', 'go', 'out', 'that', 'would', 'be', 'a', 'benefit', 'to', 'others', 'but', 'i', 'suppose', 'life', 'isn', 't', 'that', 'kind', 'so', 'the', 'next', 'best', 'thing', 'is', 'to', 'donate', 'a', 'body', 'to', 'science', 'right', 'or', 'i', 'hope', 'so', 'iv', '##e', 'been', 'thinking', 'that', 'it', 'would', 'benefit', 'my', 'mother', 'with', 'financial', 'trouble', 'she', 'said', 'i', 'm', 'just', 'getting', 'in', 'the', 'way', 'so', 'i', 'think', 'insurance', 'should', 'give', 'her', 'some', 'money', 'i', 'think', 'right', 'now', 'that', 's', 'my', 'only', 'plausible', 'solution', 'but', 'i', 'just', 'am', 'too', 'chicken', '[SEP]'

Token IDS	101, 1045, 2310, 2245, 1997, 4566, 2026, 2166, 2061, 2116, 2051, 2021, 1045, 2196, 2203, 2039, 2725, 2009, 1045, 2074, 4299, 2045, 11333, 1037, 9379, 3800, 3993, 2126, 2000, 2175, 2041, 2008, 2052, 2022, 1037, 5770, 2000, 2500, 2021, 1045, 6814, 2166, 3475, 1056, 2008, 2785, 2061, 1996, 2279, 2190, 2518, 2003, 2000, 21357, 1037, 2303, 2000, 2671, 2157, 2030, 1045, 3246, 2061, 4921, 2063, 2042, 3241, 2008, 2009, 2052, 5770, 2026, 2388, 2007, 3361, 4390, 2016, 2056, 1045, 1049, 2074, 2893, 1999, 1996, 2126, 2061, 1045, 2228, 5427, 2323, 2507, 2014, 2070, 2769, 1045, 2228, 2157, 2085, 2008, 1055, 2026, 2069, 24286, 5576, 2021, 1045, 2074, 2572, 2205, 7975, 102

Embedding

DistilBERT Embedding

Input IDS	101, 1045, 2310, 2245, 1997, 4566, 2026, 2166, 2061, 2116, 2051, 2021, 1045, 2196, 2203, 2039, 2725, 2009, 1045, 2074, 4299, 2045, 11333, 1037, 9379, 3800, 3993, 2126, 2000, 2175, 2041, 2008, 2052, 2022, 1037, 5770, 2000, 2500, 2021, 1045, 6814, 2166, 3475, 1056, 2008, 2785, 2061, 1996, 2279, 2190, 2518, 2003, 2000, 21357, 1037, 2303, 2000, 2671, 2157, 2030, 1045, 3246, 2061, 4921, 2063, 2042, 3241, 2008, 2009, 2052, 5770, 2026, 2388, 2007, 3361, 4390, 2016, 2056, 1045, 1049, 2074, 2893, 1999, 1996, 2126, 2061, 1045, 2228, 5427, 2323, 2507, 2014, 2070, 2769, 1045, 2228, 2157, 2085, 2008, 1055, 2026, 2069, 24286, 5576, 2021, 1045, 2074, 2572, 2205, 7975, 102, 0

Attention Mask	1, 0, 0

Development a Classification Model

Fine Tuning Model

Hyperparameters	Values
Learning Rate	1 × 10−6
Weight Decay	0.001
Epoch	15
Batch Size	{16, 32, 64}
Dropout	{0.1, 0.2}

Hyperparameters Combination

Hyperparameters	Values
Learning Rate	1 × 10−6
Weight Decay	0.001
Epoch	15
Batch Size	64
Dropout	0.1

Best Hyperparameters Combination

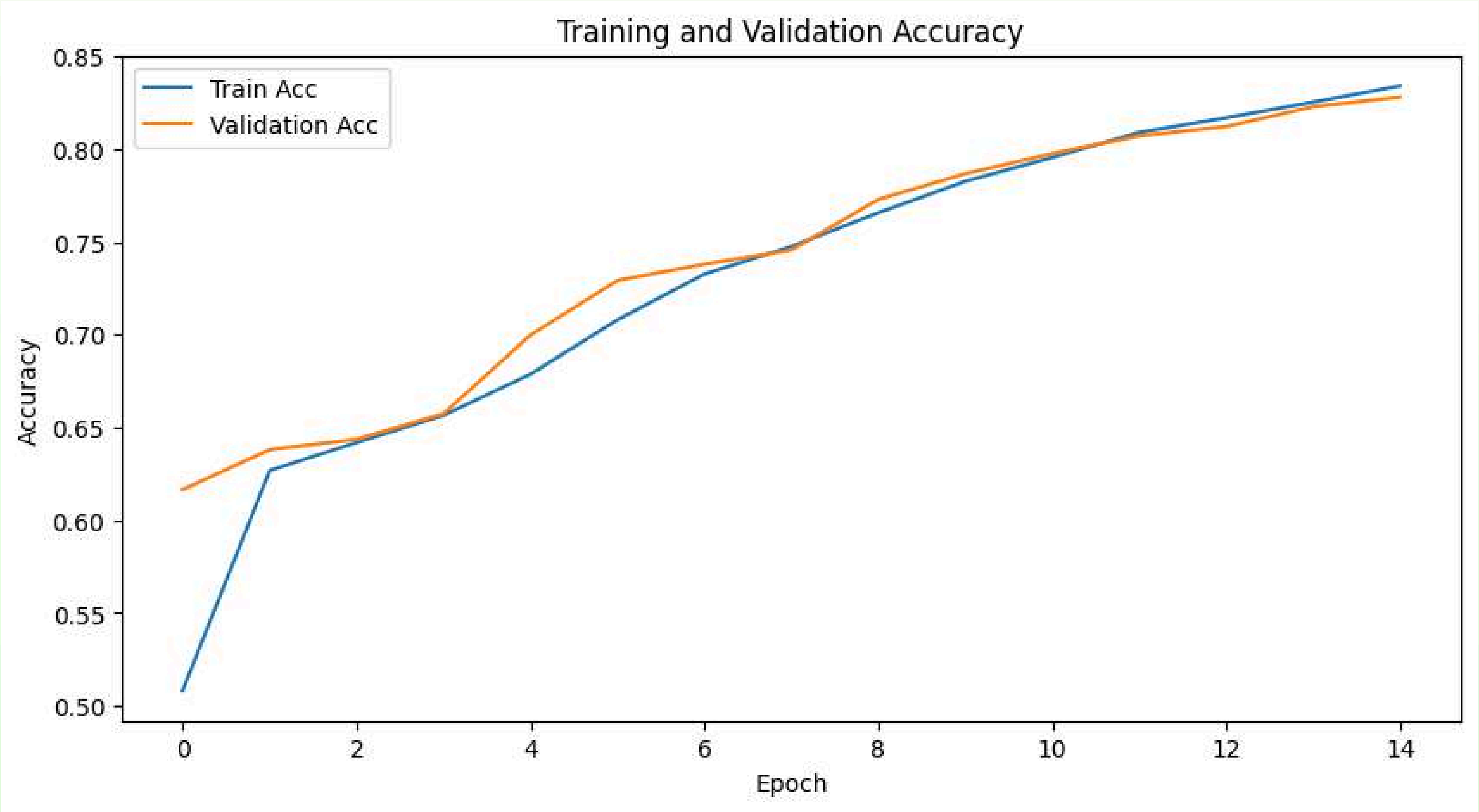
Development a Classification Model

Structure of the Model

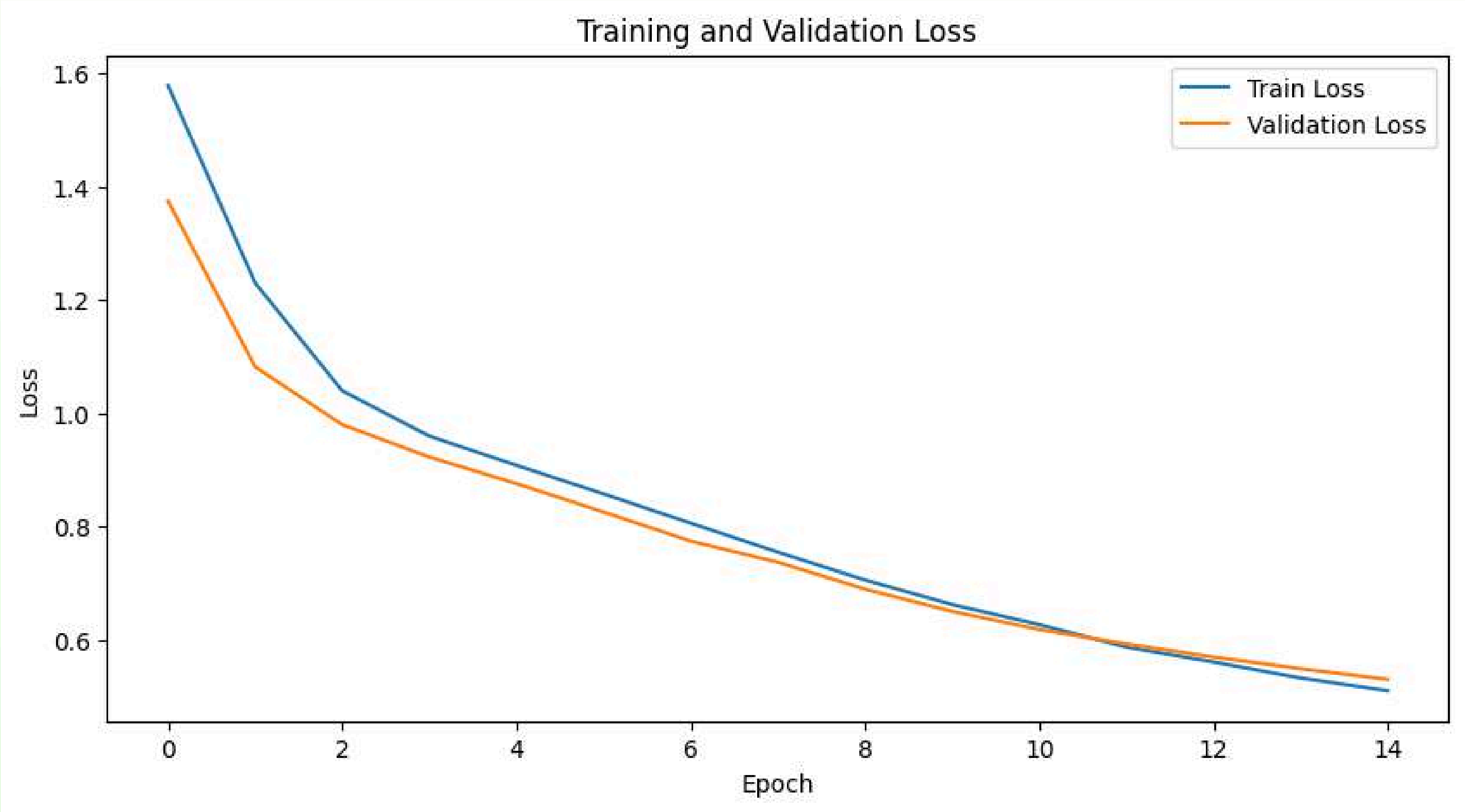
```
DistilBertForSequenceClassification(
  (distilbert): DistilBertModel(
    (embeddings): Embeddings(
      (word_embeddings): Embedding(30522, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (transformer): Transformer(
      (layer): ModuleList(
        (0-5): 6 x TransformerBlock(
          (attention): DistilBertSdpaAttention(
            (dropout): Dropout(p=0.1, inplace=False)
            (q_lin): Linear(in_features=768, out_features=768, bias=True)
            (k_lin): Linear(in_features=768, out_features=768, bias=True)
            (v_lin): Linear(in_features=768, out_features=768, bias=True)
            (out_lin): Linear(in_features=768, out_features=768, bias=True)
          )
          (sa_layer_norm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
          (ffn): FFN(
            (dropout): Dropout(p=0.1, inplace=False)
            (lin1): Linear(in_features=768, out_features=3072, bias=True)
            (lin2): Linear(in_features=3072, out_features=768, bias=True)
           (activation): GELUActivation()
                   )
                   (output_layer_norm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
                 )
               )
             )
           )
           (pre_classifier): Linear(in_features=768, out_features=768, bias=True)
           (classifier): Linear(in_features=768, out_features=6, bias=True)
           (dropout): Dropout(p=0.1, inplace=False)
          )
```

Model Performance Evaluation

Accuracy Graph of Original Data

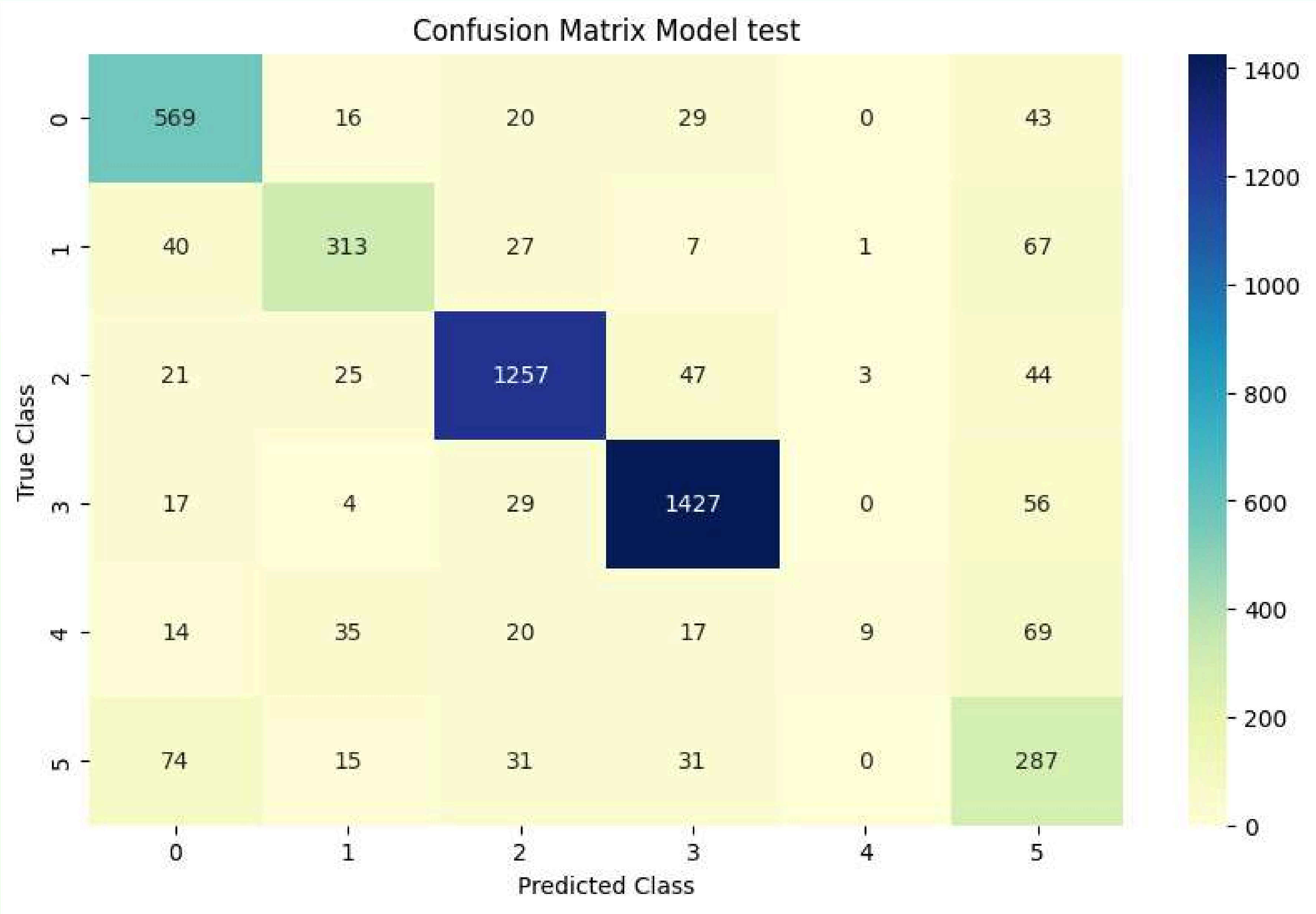


Loss Graph of Original Data



Model Performance Evaluation

Confusion Matrix of Original Data

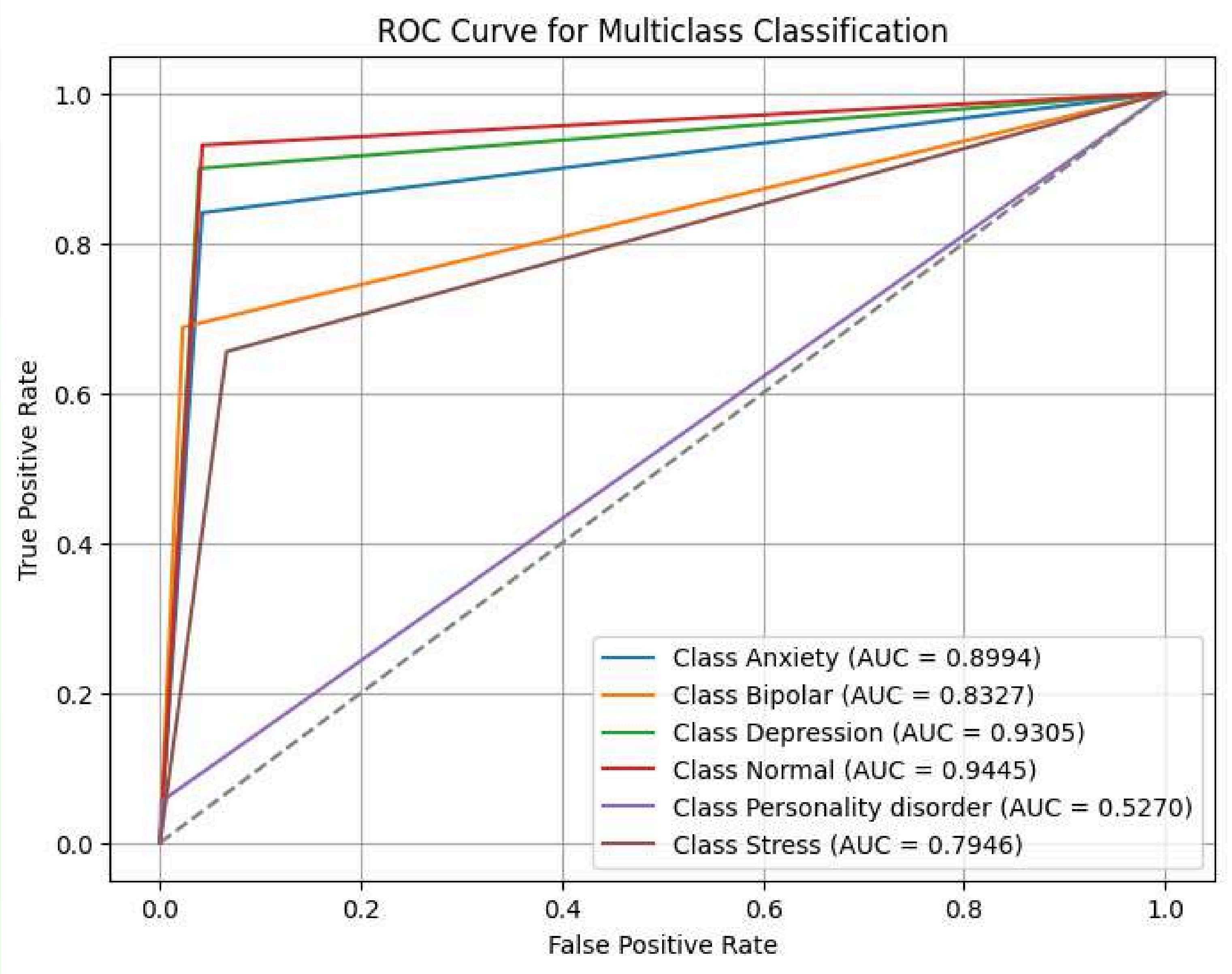


Classification Report

Classes	Precision C_i	Sensitivity C_i	Specificity C_i	*F1-Score* C_i
Anxiety	77,41%	84,04%	95,83%	80,58%
Bipolar	76,71%	68,79%	97,74%	72,53%
Depression	90,82%	89,97%	96,11%	90,34%
Normal	91,59%	93,08%	95,81%	92,33%
Personality disorder	69,23%	5,49%	99,91%	10,71%
Stress	50,70%	65,53%	93,39%	57,16%
Average	76,07%	67,81%	96,46%	67,18%
Accuracy				82,80%

Model Performance Evaluation

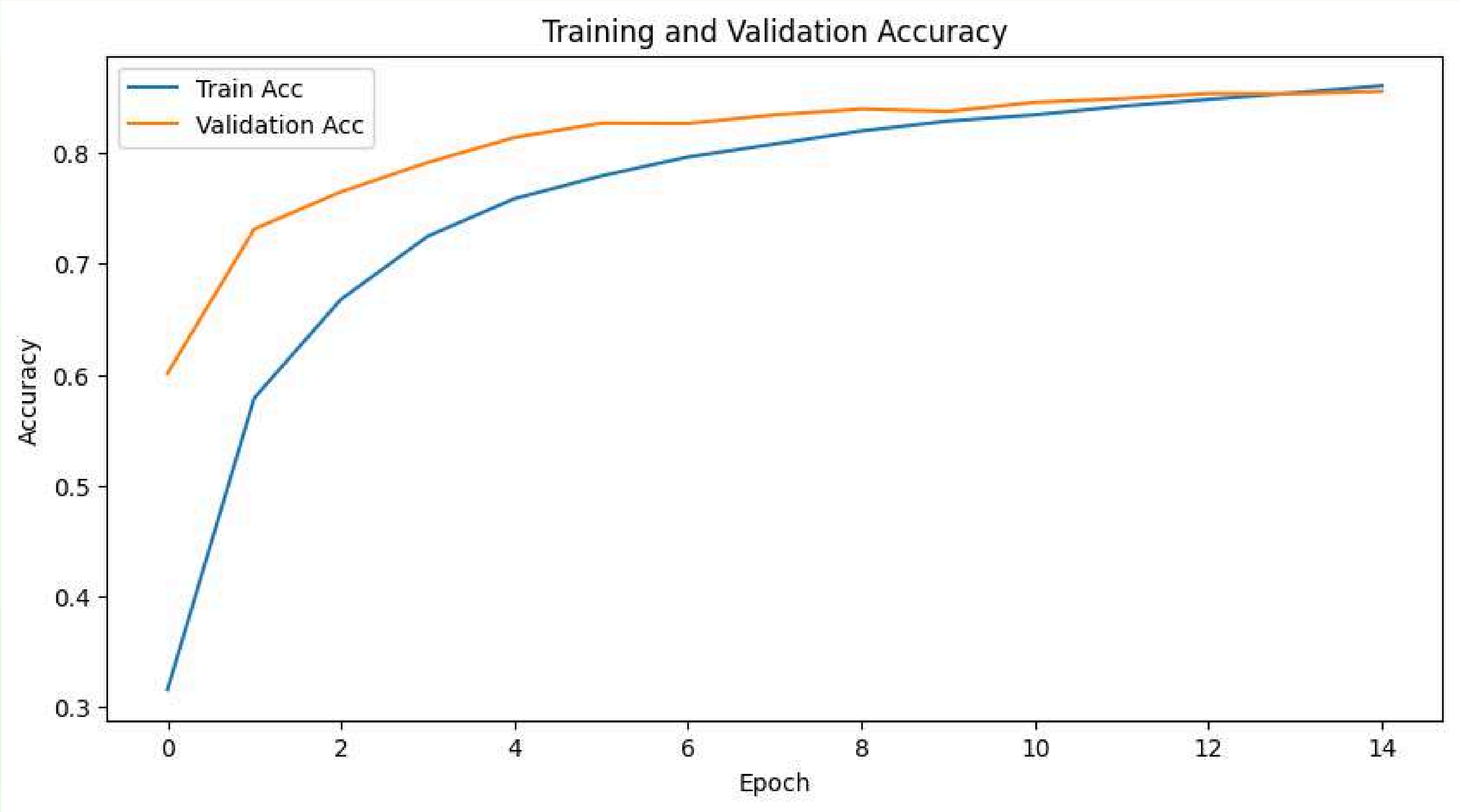
ROC-AUC Curves of Original Data



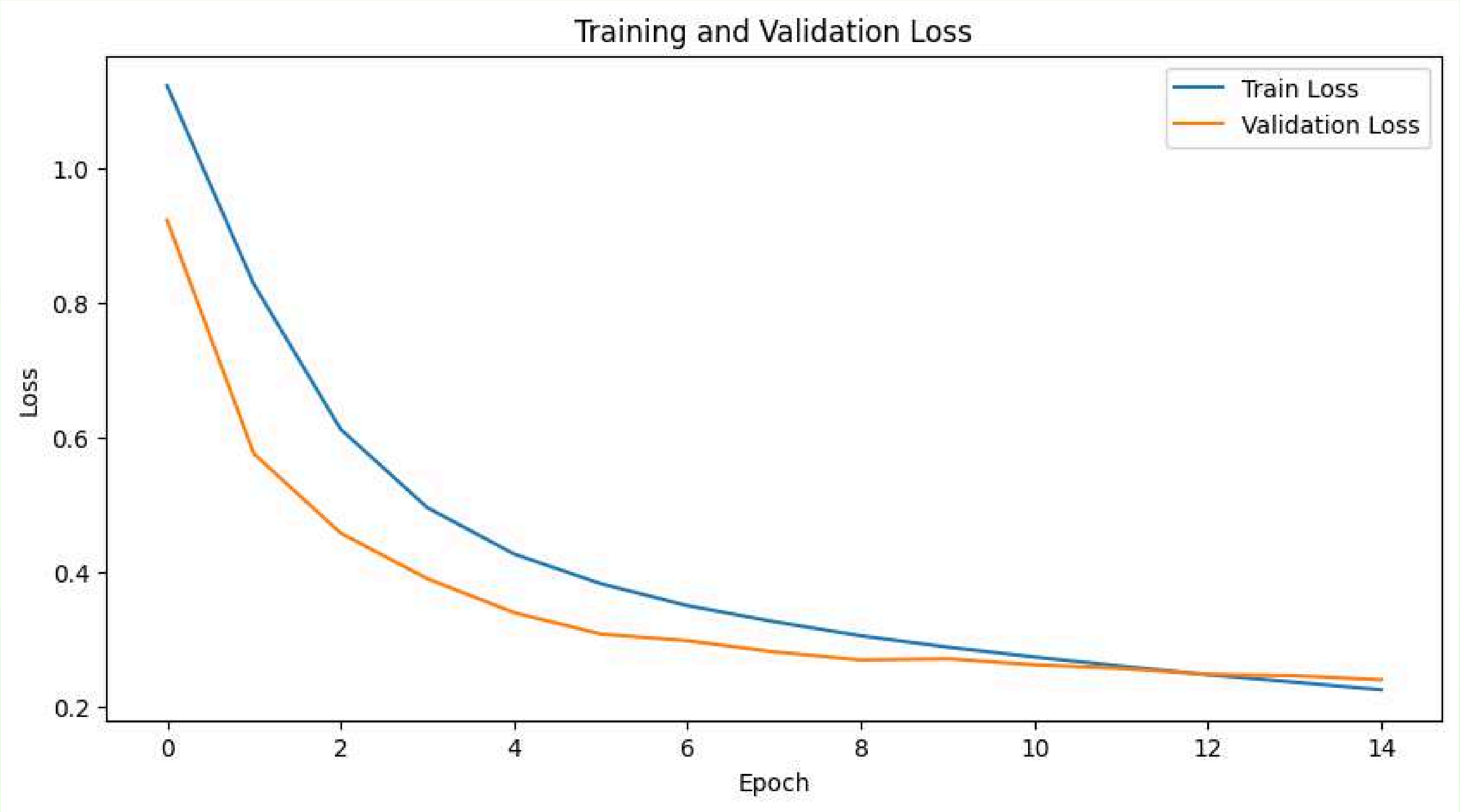
AUC Average: 0,8214

Model Performance Evaluation

Accuracy Graph of Back Translation Data

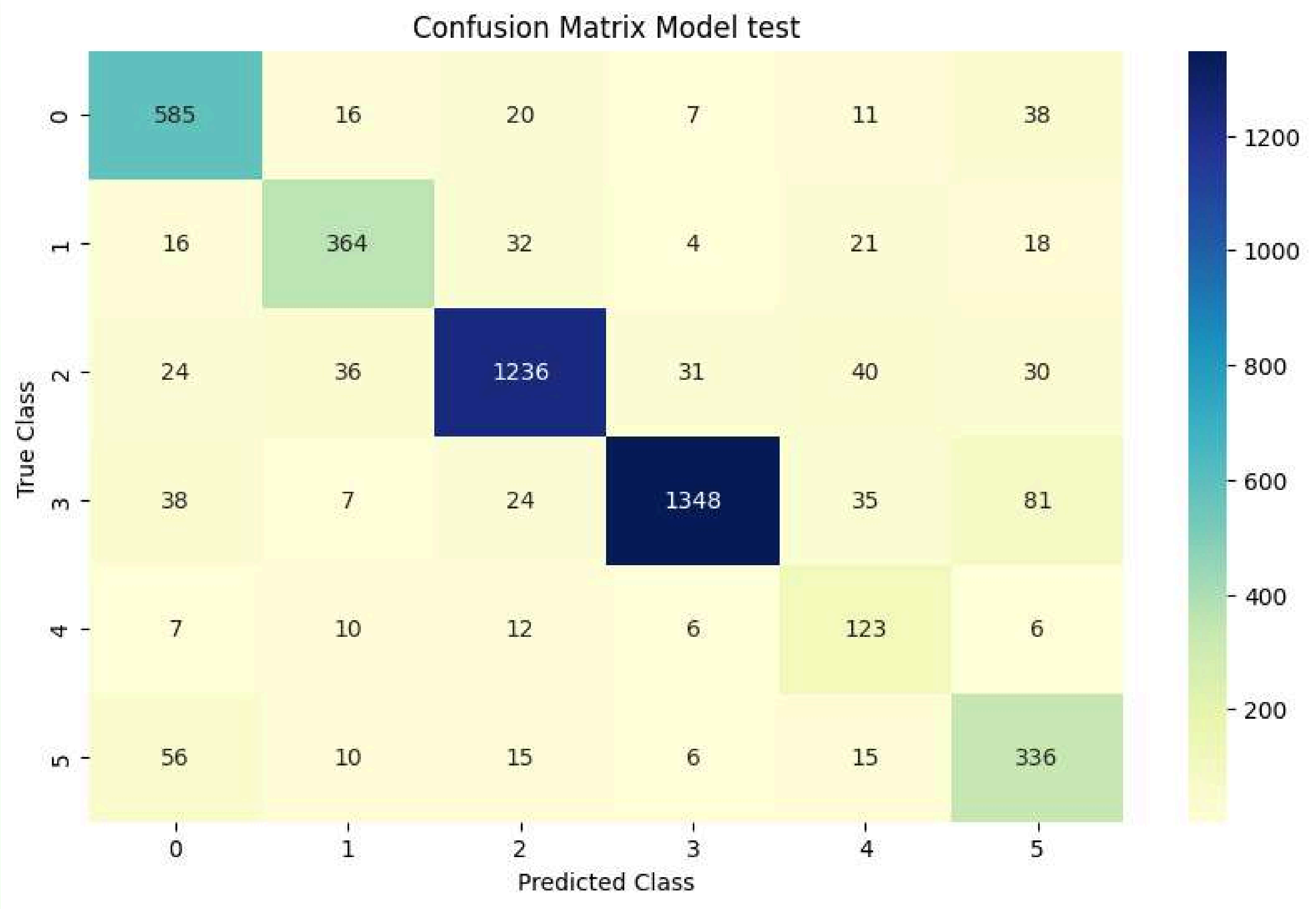


Loss Graph of Back Translation Data



Model Performance Evaluation

Confusion Matrix of Back Translation Data

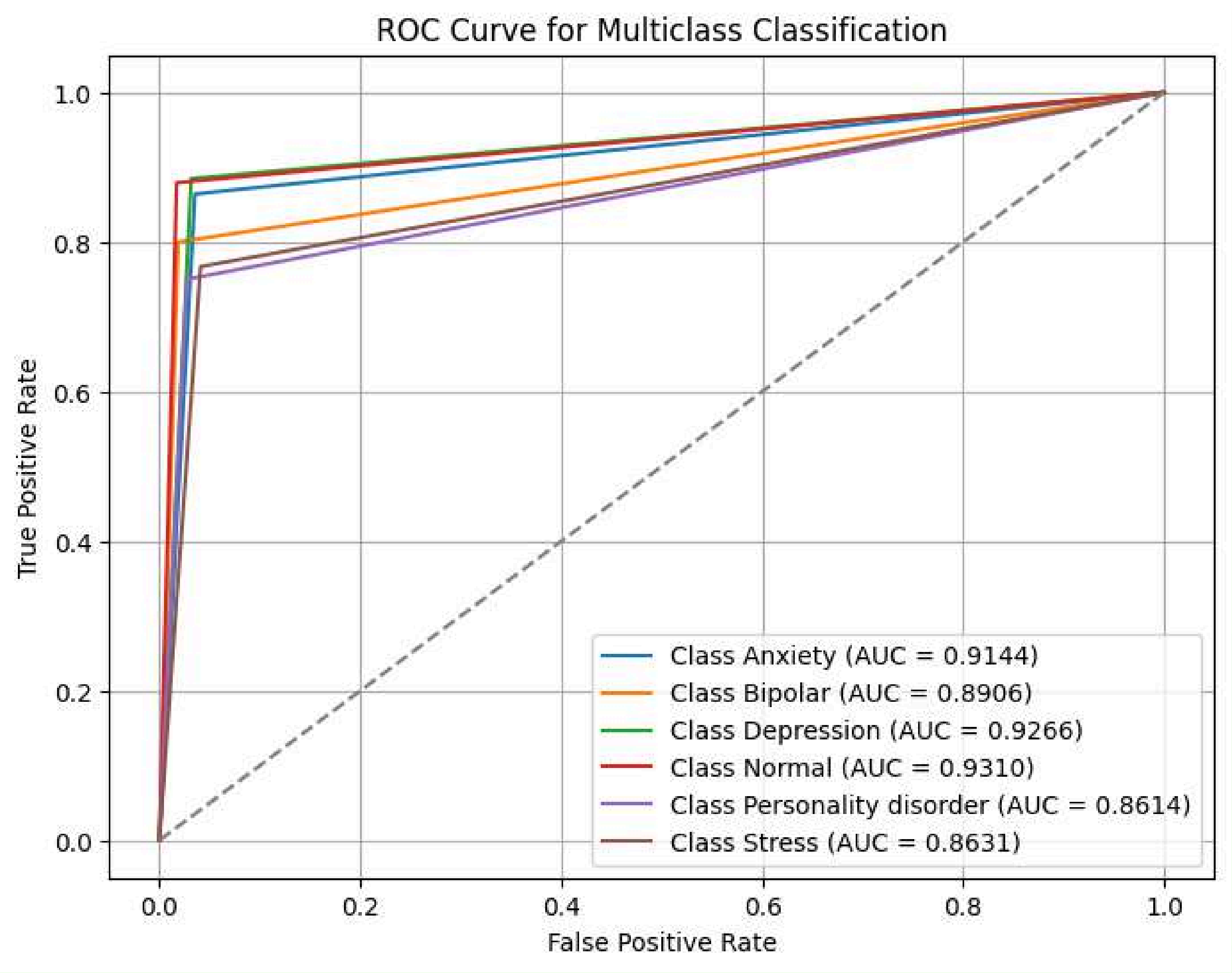


Classification Report

Classes	Precision C_i	Sensitivity C_i	Specificity C_i	*F1-Score* C_i
Anxiety	80,57%	86,41%	96,46%	83,38%
Bipolar	82,16%	80%	98,12%	81,06%
Depression	92,30%	88,47%	96,84%	90,34%
Normal	96,14%	87,93%	98,27%	91,85%
Personality disorder	50,20%	75%	97,28%	60,14%
Stress	66,01%	76,71%	95,90%	71,30%
Average	77,89%	82,42%	97,15%	79,67%
Accuracy				85,59%

Model Performance Evaluation

ROC-AUC Curves of Back Translation Data

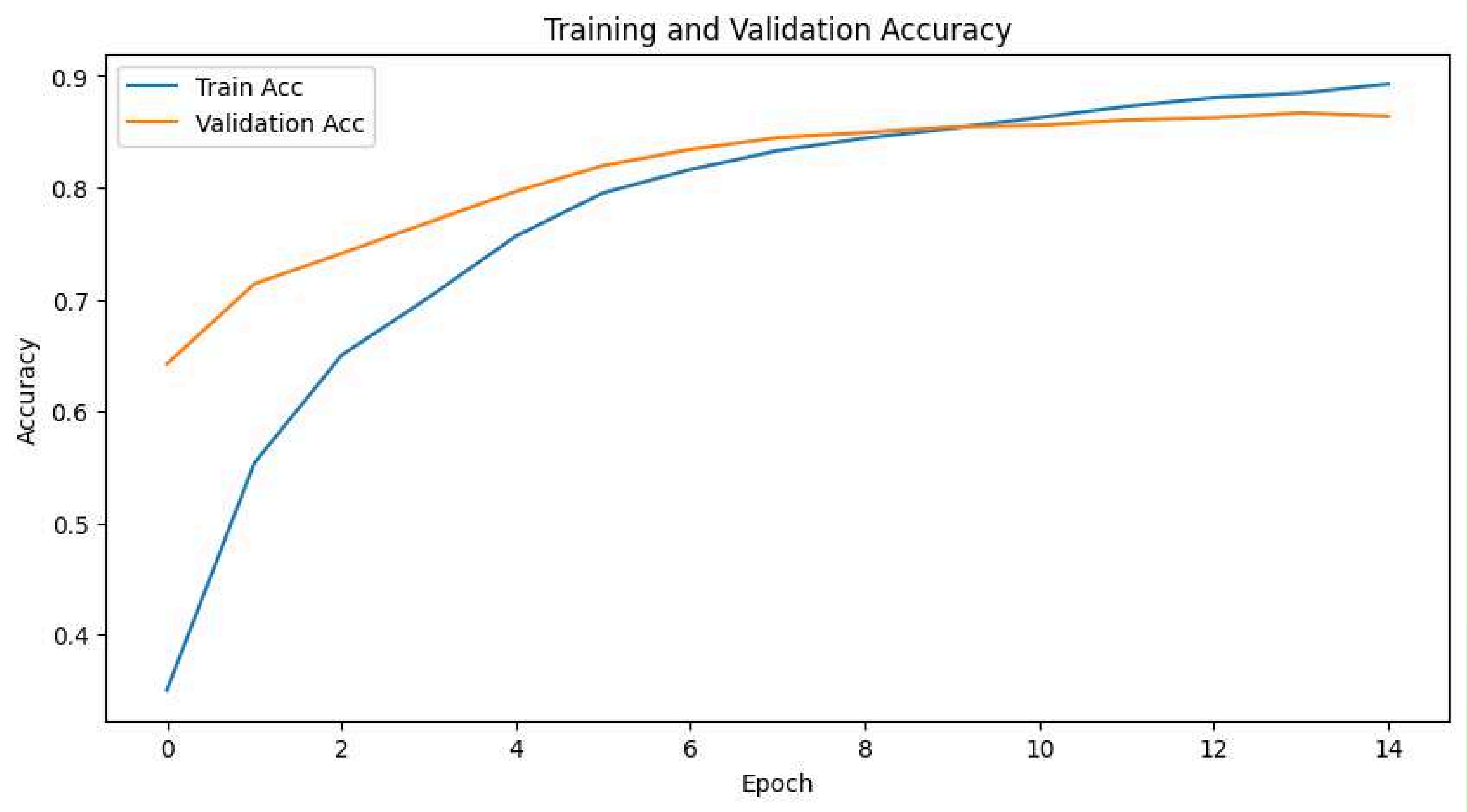


AUC Values

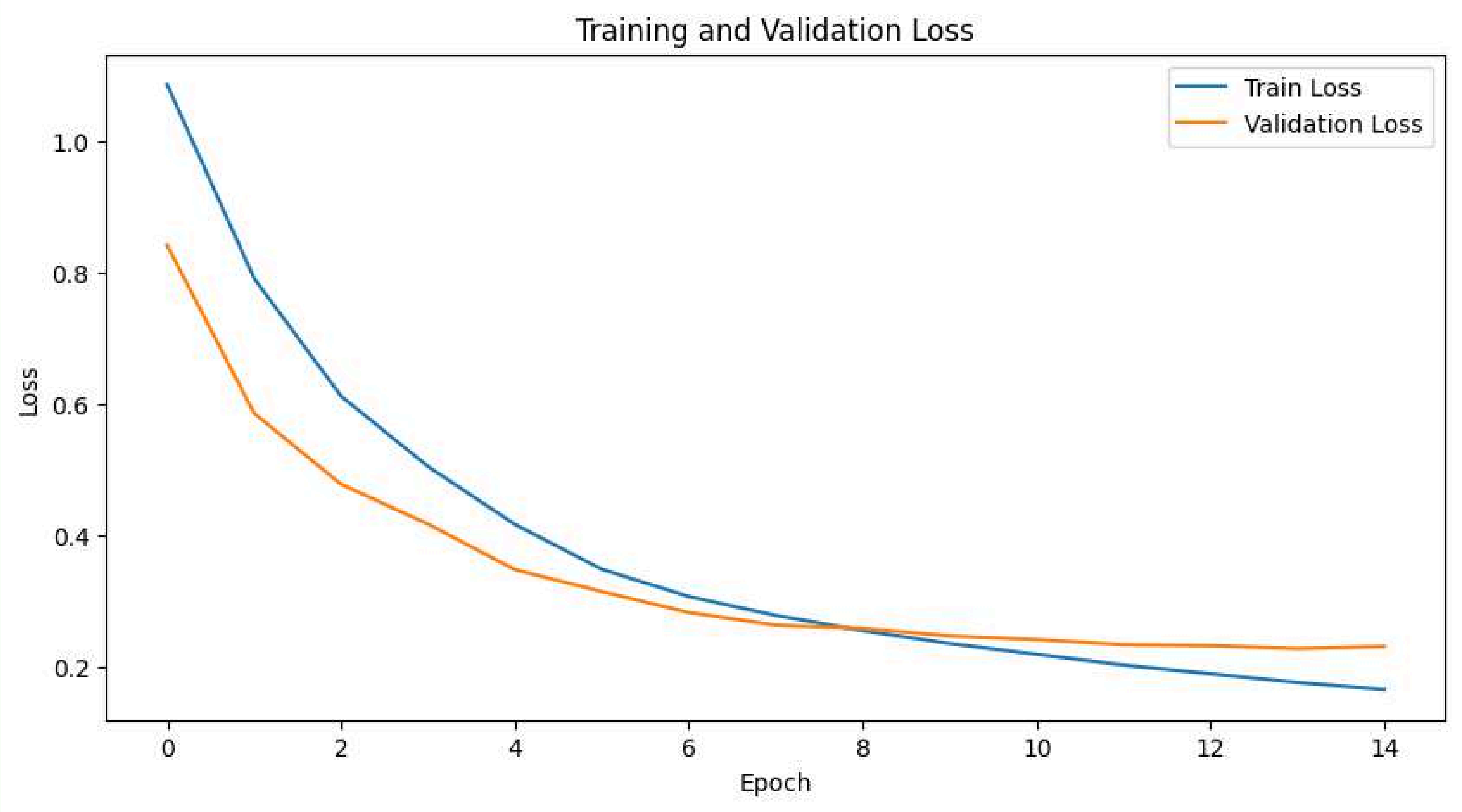
Classes	FPR	AUC
Anxiety	0,0354	0,9144
Bipolar	0,0188	0,8906
Depression	0,0316	0,9266
Normal	0,0173	0,9310
Personality Disorder	0,0272	0,8614
Stress	0,0403	0,8631
Average		0,8978

Model Performance Evaluation

Accuracy Graph of Synonym Replacement Data

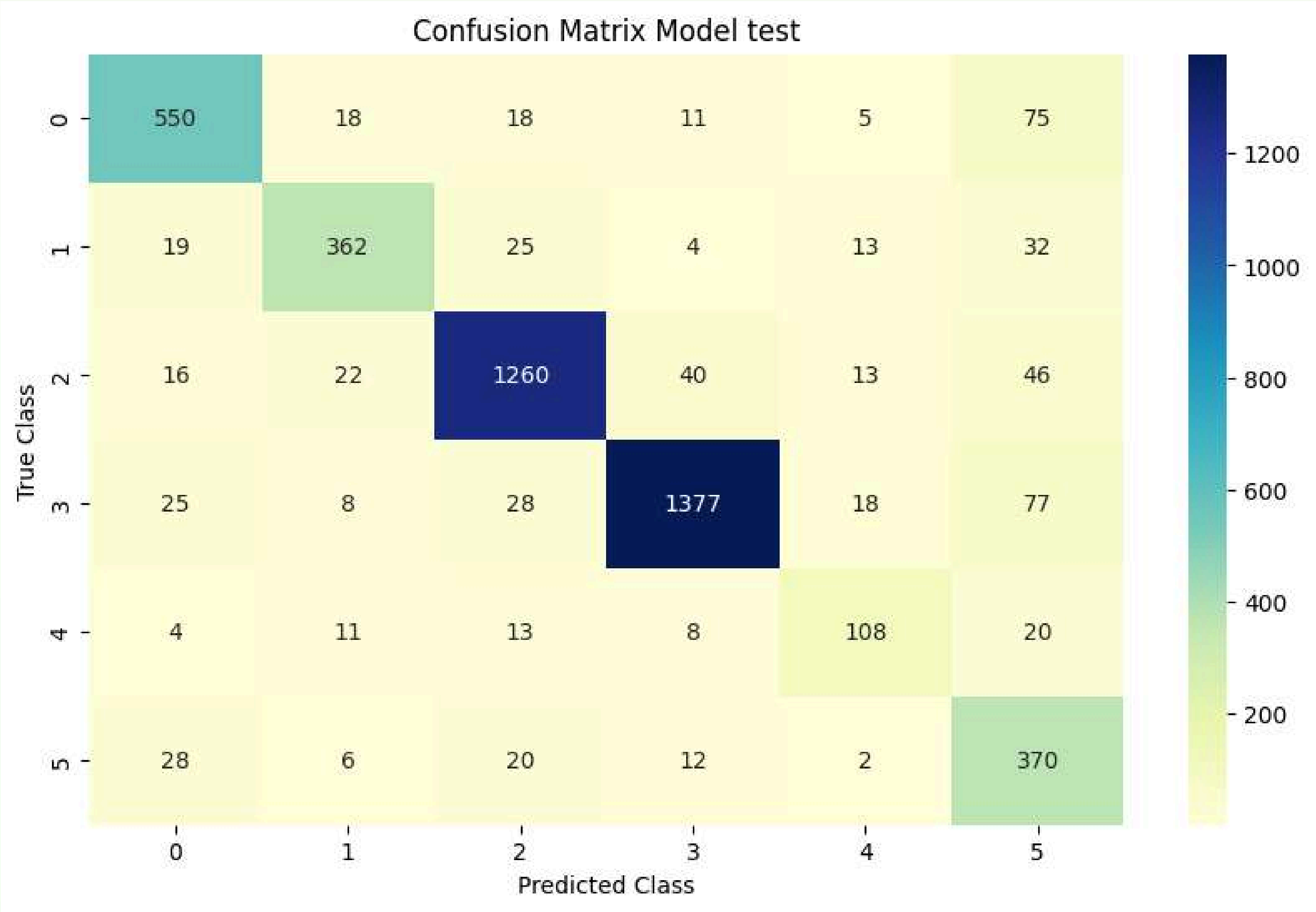


Loss Graph of Synonym Replacement Data



Model Performance Evaluation

Confusion Matrix of Synonym Replacement Data

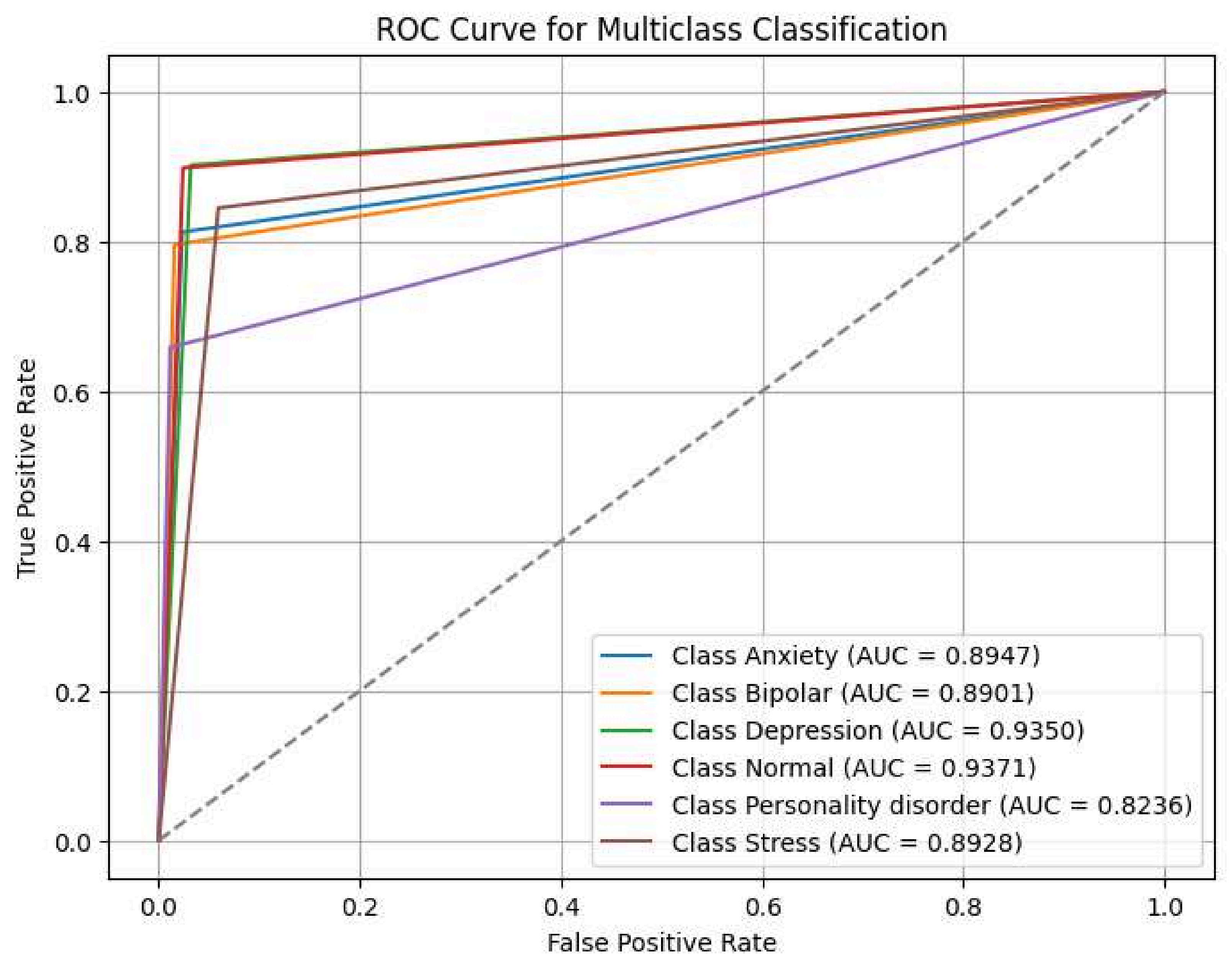


Classification Report

Classes	Precision C_i	Sensitivity C_i	Specificity C_i	*F1-Score* C_i
Anxiety	85,66%	81,24%	97,69%	83,39%
Bipolar	84,77%	79,56%	98,45%	82,08%
Depression	92,37%	90,19%	96,81%	91,26%
Normal	94,83%	89,82%	97,60%	92,25%
Personality disorder	67,92%	65,85%	98,86%	66,86%
Stress	59,67%	84,47%	94,08%	69,93%
Average	80,87%	81,85%	97,24%	80,96%
Accuracy				86,34%

Model Performance Evaluation

ROC-AUC Curves of Synonym Replacement Data



AUC Values

Classes	FPR	AUC
Anxiety	0,0232	0,8947
Bipolar	0,0155	0,8901
Depression	0,0319	0,9350
Normal	0,0243	0,9371
Personality Disorder	0,0114	0,8236
Stress	0,0592	0,8928
Average		0,8955

Comparison of DistilBERT Model Performance on Each Data

DistilBERT Model

Type of Data	$Akurasi_{avg}$	$Presisi_{avg}$	$Sensitivitas_{avg}$	$Spesifisitas_{avg}$	$F1\text{-}score_{avg}$	AUC_{avg}
Without Augmentation	82,60%	76,07%	67,81%	96,46%	67,18%	0,8214
Augmentation *Back Translation*	85,59%	77,89%	82,42%	97,15%	79,67%	0,8978
Augmentation *Synonym Replacement*	86,34%	80,87%	81,85%	97,24%	80,96%	0,8955

Benchmarking of Research Results

Research Results

Research	Accuracy			Accuracy Improvement
	Without Augmentation	Back Translation Augmentation	Synonym Replacement Augmentation	
Deteksi Judul Clickbait Dan Komentar Hate Speech Pada Berita Online. (Rahma & Suadaa, 2023)	IndoBERT (Data Clickbait): 83,51% IndoBERT (Data Hate Speech): 61,78%	IndoBERT (Data Clickbait): 84,04% IndoBERT (Data Hate Speech): 66,97%	IndoBERT (Data Clickbait): 83,23% IndoBERT (Data Hate Speech): 64,50%\	Data ClickBait Back Translation: +0,53% Synonym Replacement: -0,28% Data Hate Speech Back Translation: +5,19% Synonym Replacement: +2,71%
Klasifikasi sentimen tweet Pengguna Media Sosial X. (oktariansyah dkk., 2024)	IndoBERT: 75%	IndoBERT: 78%	IndoBERT: 82%	Back Translation: +3% Synonym Replacement: +7%
Klasifikasi Berita Palsu (Kapusta dkk., 2024)	Support Vector Classifer: 82,90%	Support Vector Classifer: 85,96%	Support Vector Classifer: 85,75%	Back Translation: +3,71% Synonym Replacement: +3,43%
Klasifikasi Teks status kesehatan mental. (Penelitian ini, 2025)	DistilBERT 82,60%	DistilBERT 85,59%	DistilBERT 86,34%	Back Translation: +2,99% Synonym Replacement: +3,74%

Conclusion

1

The DistilBERT model was applied for classifying mental health status texts through several stages, including data pre-processing, data augmentation (back translation and synonym replacement), and hyperparameter tuning.

2

In this study, the DistilBERT model combined with synonym replacement augmentation proved to be more effective than back translation, achieving the highest accuracy of 86.34% with an accuracy improvement of 3.74%.

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THANK YOU