Universitat Pompeu Fabra Barcelona

Deep Learning Final Project

Sentiment Analysis with LSTMs for Mental Health Detection

05/06/2025

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01

Introduction

Problem definition

Problem

- Identify potential mental health issues based on text inputs.
- LSTM-based model to classify into mental health categories

Motivation

- Critical issue nowadays
- Exploration of AI in a clinical environment
- Positive social impact

Dataset characteristics

- **Columns** = [Unique ID, Statement, Mental Health Status]
- 53.042 data entries with 51.704 unique values

1	trouble sleeping, confused mind, restless heart. All out of tune	Anxiety

Figure 1: Screenshot of a dataset entry

- Mental health status:

1 Normal

2 Suicidal

3 Anxiety

4 Personality Disorder

5 Depression

6 Bipolar

7 Stress

02

State of the Art

State of the Art

- RNNs (LSTMs, GRUs, BiLSTMs)
- Transformers (BERT-based)
- CNNs + RNNs

- Pre-trained embeddings
- Dropout
- Accuracy and F1-score

Model	Classification	Accuracy
LSTM	7 classes	75-88%
MentalBERT	4 classes	93%
CNN+GRU	3 classes	93%

Table 1: State of the Art comparison.

Benchmark

Transformers

- Transformer used= *nateraw/bert-base-uncased-emotion*
- Accuracy = 0.849

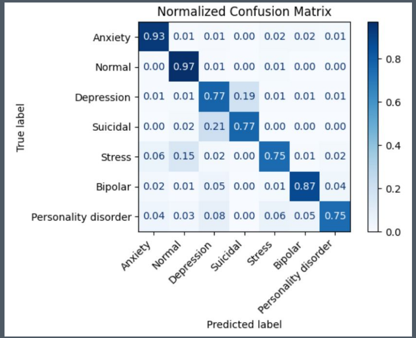


Figure 2: Transformer-based confusion matrix [1]

LSTM

- LSTM + ReLu + Softmax
- Accuracy = 0.723

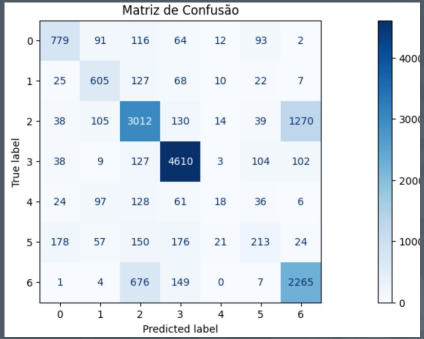


Figure 3: LSTM confusion matrix [2]

Machine Learning

- Model = XGBoost
- Accuracy = 0.808

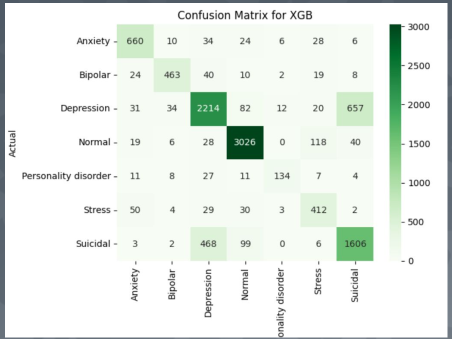


Figure 4: XGBoost confusion matrix [3]

03

Methodology

Exploratory Data Analysis (EDA)

1 Class Distribution

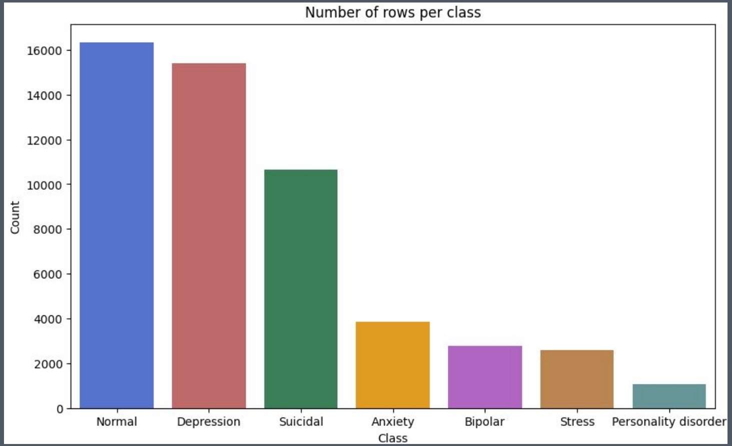


Figure 5: Barplot showing class distribution

2 Statement length

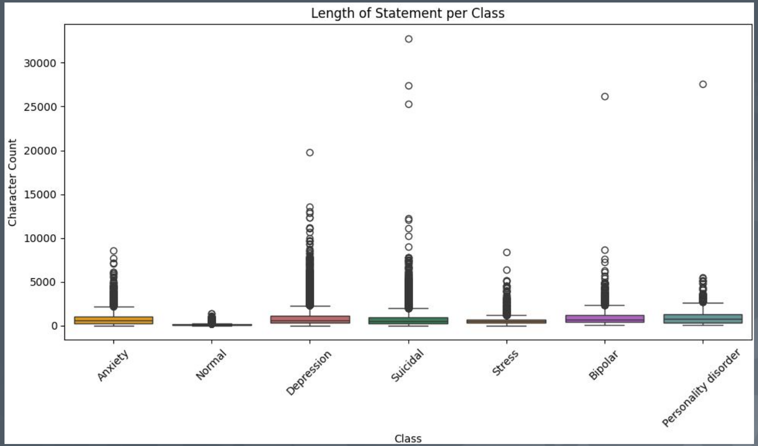


Figure 6: Boxplot showing statements' length

3 Text noise

	0
hashtag	1754
mention	1094
url	902
emoji	539952

Figure 7: Text noise count

Exploratory Data Analysis (EDA)

4 Top 20 words per class

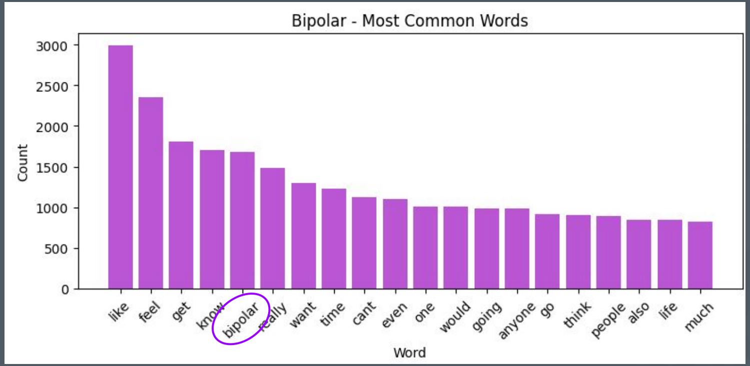


Figure 8(1): Barplot showing top 20 words in bipolar class

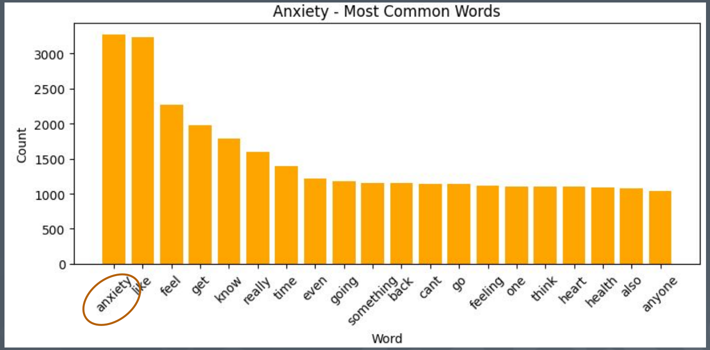


Figure 8(2): Barplot showing top 20 words in anxiety class

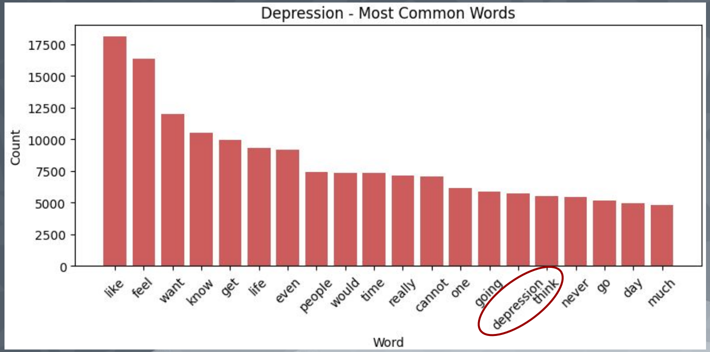
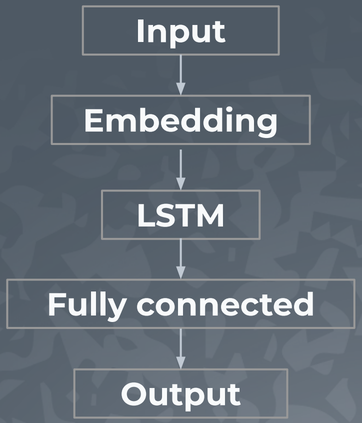


Figure 8(3): Barplot showing top 20 words in depression class

Baseline Model

- Single layer LSTM
- Trained with **raw text**
- Good performance but improvable
- Poor generalisation



Model optimization through input data preprocessing

1. Data cleaning
2. Stopword removal
3. Embedding Selection
4. Data augmentation
5. Grid search

Data processing models

Model 1: Data Cleaning

1. Length outlier removal
2. Text noise removal:

URL

HTML

Emojis

\n
Newlines

#
Hashtags

@
Mentions

a b
Extra spaces

! ?
Basic punctuation

Model 2: Stopword removal

- Articles (a, an, the)
- Prepositions (of, in, for, through)
- Pronouns (it, their, his)

NLTK

Data processing models

Model 3: Embedding selection

Word2Vec

- Easiest and simplest
- Does not improve baseline

GloVe

- State-of-the-art embedder
- Improves baseline

Model 4: Data augmentation

1. **Back translation**

   English → French → English

2. **Synonym replacement**

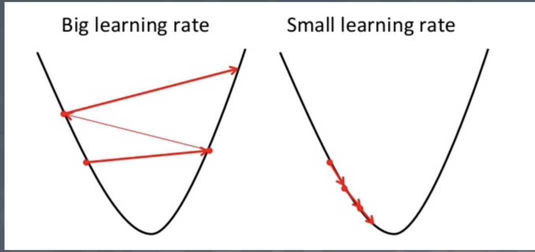
   WORD → SYNONYM
   stress → pressure

Data processing models

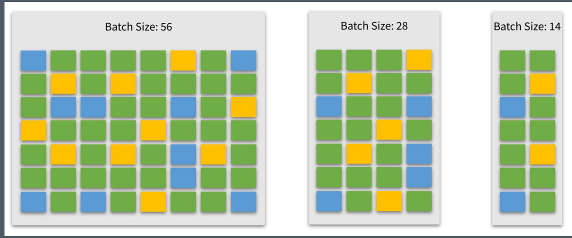
Model 5: Grid Search

- Maximize performance
- Brute-force

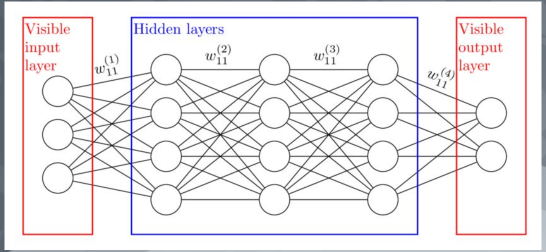
Learning rate



Batch size



Hidden layers



Model optimization through architecture refinement

6 Dropout

7 Stacked LSTM

8 Attention layer

9 GRU

Architecture refinement models

Model 6: Dropout

Input
↓
Embedding
↓
LSTM with dropout
↓
Fully connected
↓
Output

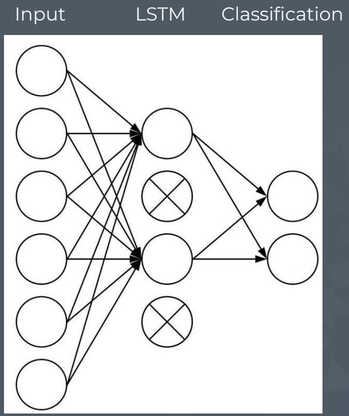


Figure 9: Dropout representation

Model 7: Stacked LSTM

Architecture refinement models

Model 8: Attention Layer

Input

↓

Embedding

↓

LSTM

↓

Attention

↓

Fully connected

↓

Output

Model 9: GRU

LSTM gates		GRU gates
Input gate Output gate Forget gate	→	Reset gate Update gate

04

Results

Baseline model

- Final accuracy = 0.7332
- Weighted F1-score = 0.7355

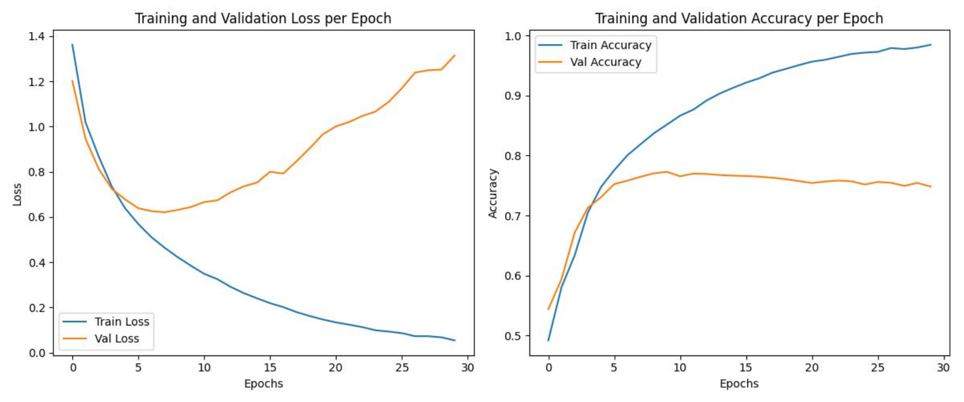


Figure 10: Baseline LSTM Training and Validation Loss and Accuracy plots

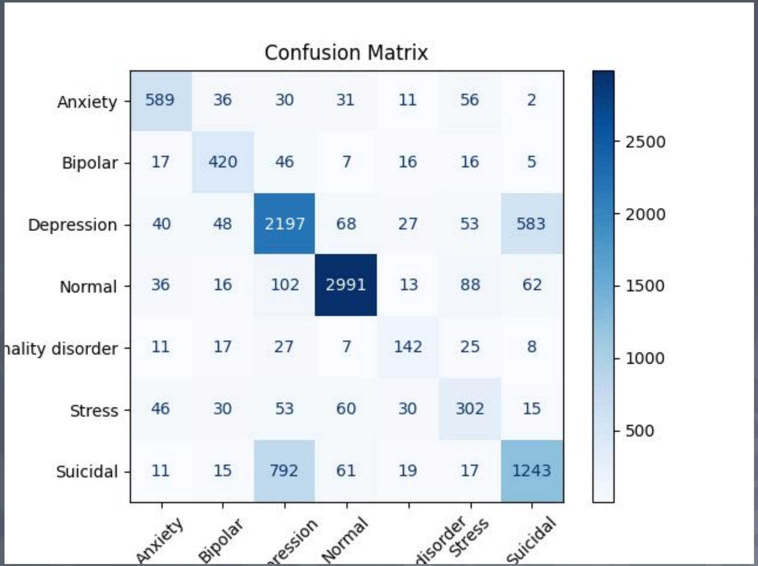


Figure 11: Baseline LSTM Confusion Matrix

Data preprocessing experiments

Model	Name	Best validation accuracy	Final validation accuracy	Final validation loss	Weighted F1-score
0	Baseline	0.7524	0.7332	1.5110	0.7355
1	Data cleaning	0.7566	0.7408	1.3936	0.7412
2	Stopword removal	0.7539	0.7394	1.4413	0.7384
3	Embedding Selection	0.7779	0.7744	0.6665	0.7753
4	Data Augmentation	0.7590	0.7442	0.8882	0.7476
5	Grid Search	0.7818	0.7735	0.6010	0.7769

Table 2: Results of the data preprocessing models

Data preprocessing experiments

	Baseline	Data cleaning
Anxiety	**0.78**	0.75
Bipolar	0.73	**0.75**
Depression	0.67	**0.69**
Normal	0.91	**0.92**
Personality Disorder	0.48	**0.52**
Stress	0.53	**0.54**
Suicidal	**0.62**	0.61

Data preprocessing experiments

Data cleaning

Embedding Selection

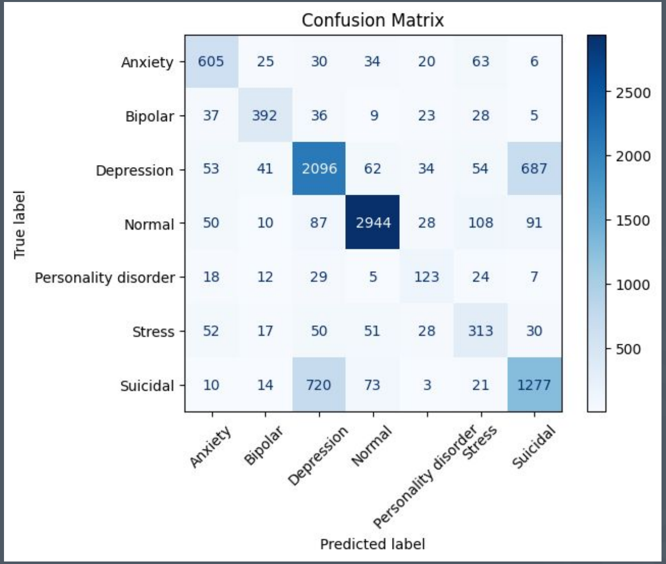


Figure 13: Data cleaning model. Confusion matrix.

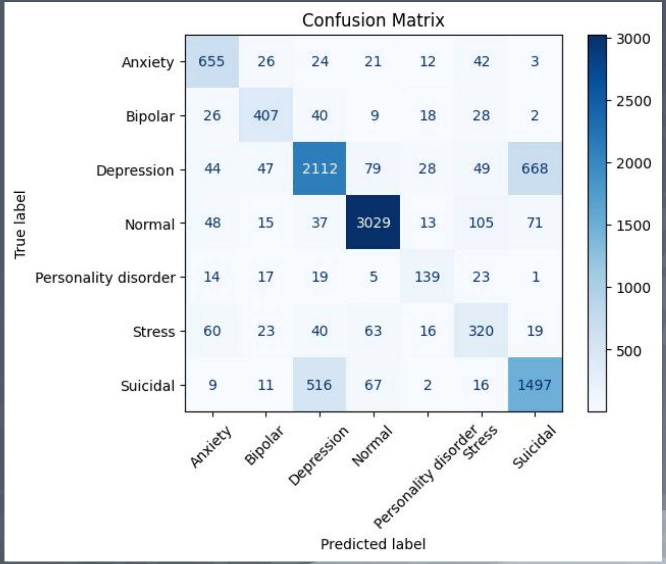


Figure 15: Embedding Selection model. Confusion matrix.

Data preprocessing experiments

Embedding Selection → **Grid Search**

- Less overfitting
- Better accuracy

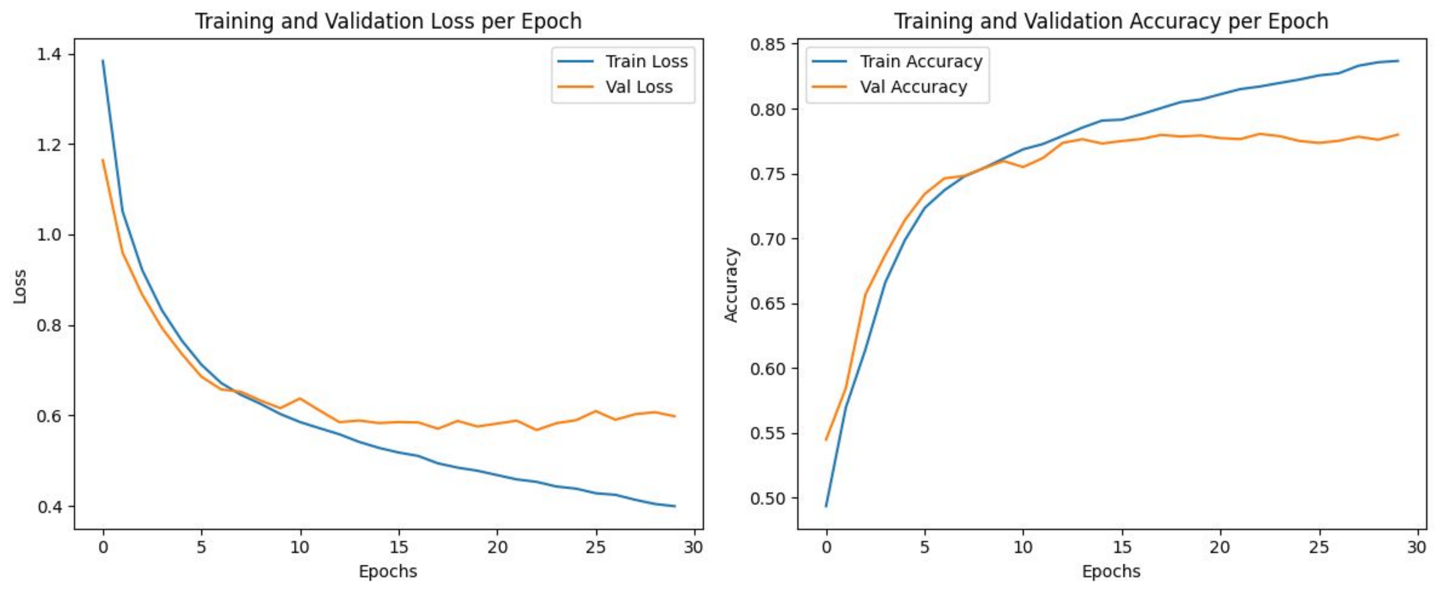


Figure 17: Grid Search model. Loss and accuracy curves.

Architecture optimization experiments

Model	Name	Best validation accuracy	Final validation accuracy	Final validation loss	Weighted F1-score
0	Baseline	0.7524	0.7332	1.5110	0.7355
5	Grid Search	0.7818	0.7735	0.6010	0.7769
6	Dropout	0.7790	0.7773	0.5892	0.7774
7	Stacked LSTM	0.7820	0.7789	0.5835	0.7795
8	Attention	0.7804	0.7715	0.6420	0.7732
9	Baseline GRU	0.7627	0.7388	1.7622	0.7376
10	Improved GRU	0.7932	0.7684	0.9345	0.7682

Architecture optimization experiments

Grid Search → Dropout

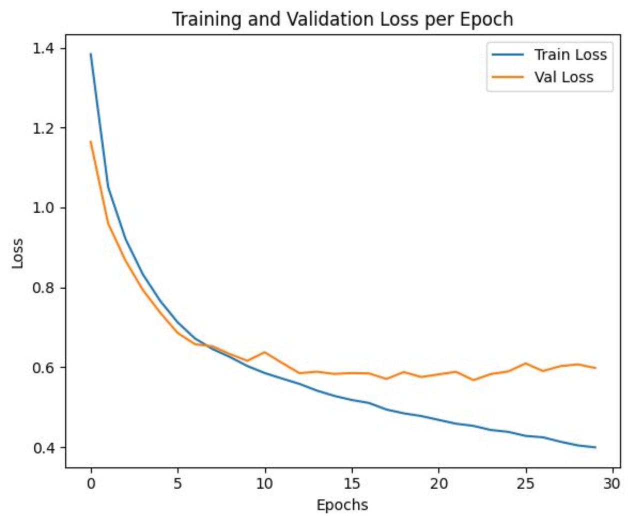


Figure 18: Grid Search model. Loss curve.

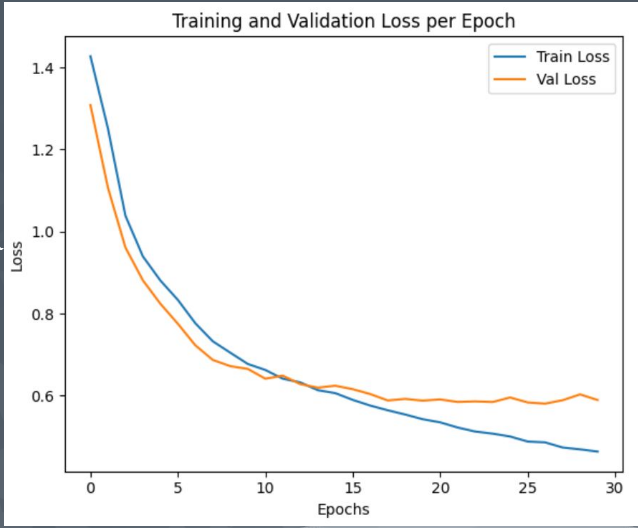


Figure 19: Dropout model. Loss curve.

Architecture optimization experiments

Dropout → Stacked LSTM

	Dropout	Stacked LSTM
Anxiety	0.81	**0.82**
Bipolar	0.77	**0.79**
Depression	**0.73**	0.72
Normal	0.92	**0.93**
Personality Disorder	**0.62**	0.60
Stress	0.57	**0.61**
Suicidal	0.68	0.68

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Conclusions

Conclusions

1. Raw baseline model limited by noisy data and simple features.

2. Data cleaning and using embeddings like GloVe raise accuracy.

3. **Final best model:** Stacked LSTM with dropout. Accuracy = 0.7789. Weighted F1-score = 0.7795

4. Outperformed benchmark models, with exception of transformers.

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Future work

Future work

1. Bidirectional LSTMs (BiLSTM)

2. **Transformer Models:** Experiment with SotA transformers (BERT, RoBERTa, etc)

3. **Ensembling models**: Combination of multiple models like LSTM and transformer classifiers. **CNNs + RNNs, like seen in SotA**

Resources

[1]
https://www.kaggle.com/code/grantgonnerman/mental-health-sentiment-analysis-eda-modeling

[2] https://www.kaggle.com/code/rafaeldrago/lstm-sentiment-prediction/notebook

[3] https://www.kaggle.com/code/hnfrmdhni/klasifikasi-jenis-depresi

Thank you!

Any question?

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