# Mental Health Prediction For Kenyan University Students

### PRESENTED BY:

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### Overview

The project aims to create a machine learning model that can classify statements and questions related to mental health challenges expressed by university students in Kenya.



### Problem Statement

Kenyan universities lack support services for mental health despite resource growth.

Research shows high levels of mental health problems among university students in Kenya, particularly for those from poor backgrounds, resulting in dropouts and unrealized potential.

Africa Mental Health Foundation conducts mental health research and develops innovative practices for mental health services in Africa.

In 2023, they are partnering with the Ministry of Education in Kenya to develop a chatbot.

The chatbot will allow students to input their thoughts and feelings and classify their problems to provide fitting resources.

### Objectives

To develop a machine learning model that classifies statements and questions expressed by university students in Kenya related to their mental health challenges.

To help universities establish mental health support and wellness services to their students.

To help university students in Kenya that are facing mental health problems to find resources and support services that will enable them to get better.

#### Data

The data used in the project is from the Tech4MentalHealth competition by Zindi Africa. The data comprises statements and questions expressed by Kenyan university students who reported experiencing various mental health challenges. The prompts were based on the question, "What is on your mind?".

| Text  | Mental<br>Health<br>Problem |
|---|-----------------------------|
| Why is everything so hard to deal with in this life | Depression                  |
| How to avoid drug abuse?                            | Drugs                       |
| Why is life important?                              | Suicide                     |

## Modeling

|                                   | Ham Accuracy Score (%)   | Test Accuracy Score(%)  | Train Log_loss   | Test Log_loss   |
|-----------------------------------|--|---|--|---|
| Baseline Decision Tree            | 99   | 83  | 0.012334   | 5.590810  |
| Baseline KNN Classifier           | 81   | 67  | 0.499348   | 3.116017  |
| Baseline Random Forest Classifier | 99   | 81  | 0.106574   | 0.775972  |
| Baseline Adaboost Classifier      | 85   | 77  | 1.031080   | 1.059045  |
| Baseline Gradient Boost           | 97   | 83  | 0.163581   | 0.509805  |
| baseline XGBoost Classifier       | 93   | 85  | 0.219129   | 0.451154  |
| XGBoost Classifier-Grid Search    | 92   | 85  | 0.241682   | 0.439006  |
|                                   | Baseline KNN Classifier Baseline Random Forest Classifier Baseline Adaboost Classifier Baseline Gradient Boost baseline XGBoost Classifier | Baseline KNN Classifier 99 Baseline Random Forest Classifier 99 Baseline Adaboost Classifier 85 Baseline Gradient Boost 97 baseline XGBoost Classifier 93 | Baseline KNN Classifier 81 67 Baseline Random Forest Classifier 99 81 Baseline Adaboost Classifier 85 77 Baseline Gradient Boost 97 83 baseline XGBoost Classifier 93 85 | Baseline KNN Classifier       81       67       0.499348         Baseline Random Forest Classifier       99       81       0.106574         Baseline Adaboost Classifier       85       77       1.031080         Baseline Gradient Boost       97       83       0.163581         baseline XGBoost Classifier       93       85       0.219129 |

### Evaluation

The XGBoost Classifier-Grid Search model had a train accuracy score of 92% and test accuracy of 85%.

Log loss was used as a performance metric because it takes into account the probabilities underlying in the model, not only the final output of the classification.

The XGBoost classifier had the lowest log loss score, making it the chosen best model.

The prior models had high training and test data accuracy but were not chosen due to their log loss scores.

### Limitations

Due to the imbalance in the dataset the F1score for drug and alcohol was notably lower than depression and suicide.



Due to a relatively small dataset we could not achieve high score as desired.

### Conclusion

The final model had an accuracy of around 85% and a log score of 0.52.

AMHF can integrate the model into a chatbot prototype and test it on actual university students to predict their mental state and offer appropriate assistance.

The chatbot will correctly identify and classify mental health problems to match students with suitable resources, while also reducing stigma around seeking help.

### Recommendations

AMHF should collect more data on drug and alcohol related problems and other mental health issues not covered in the current data.

The model should be integrated into the chatbot prototype and tested on actual university students to collect performance data.

The chatbot should have a database of resources and services based on the problem identified by the model to ensure users receive appropriate help.

