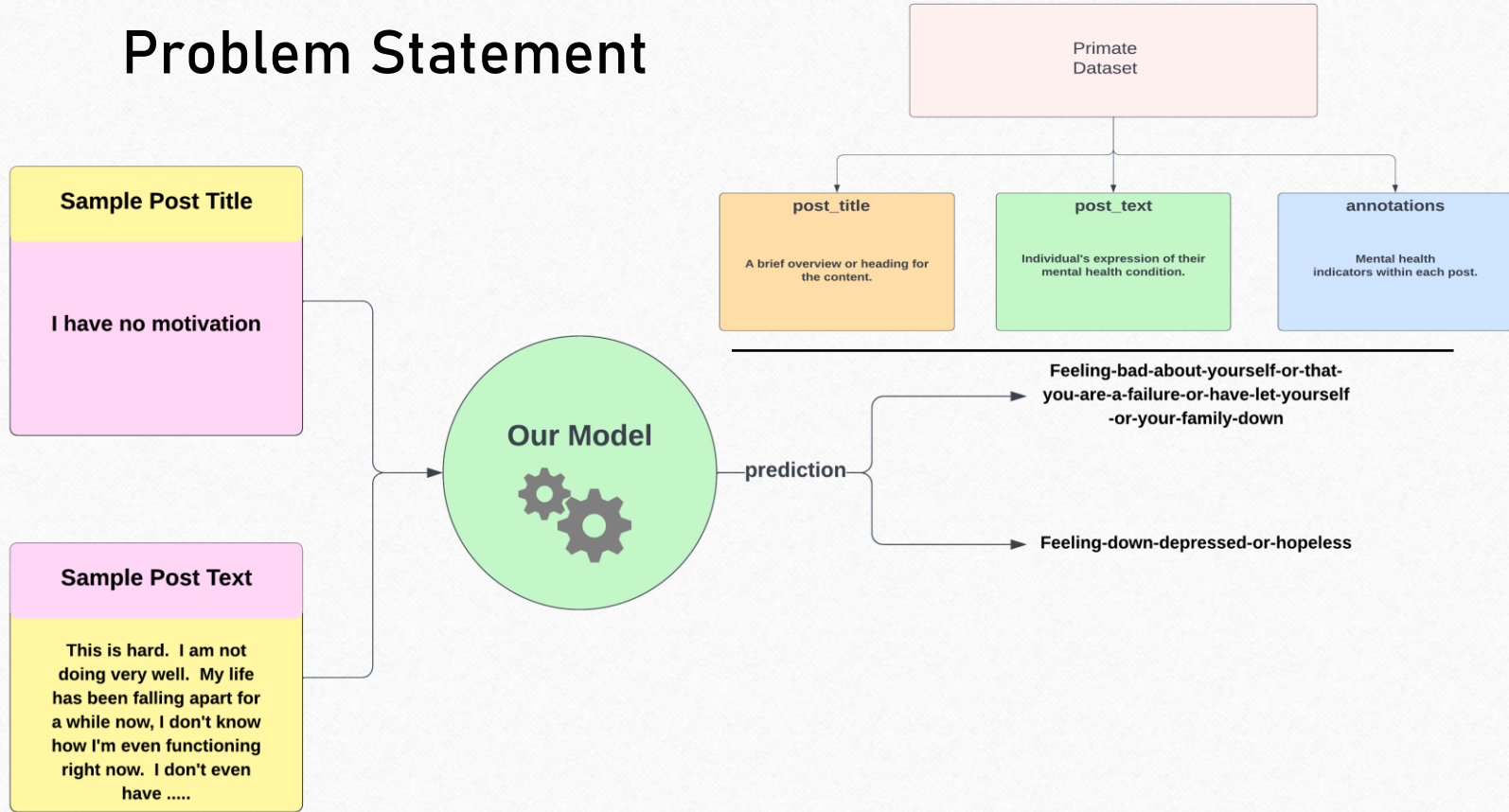


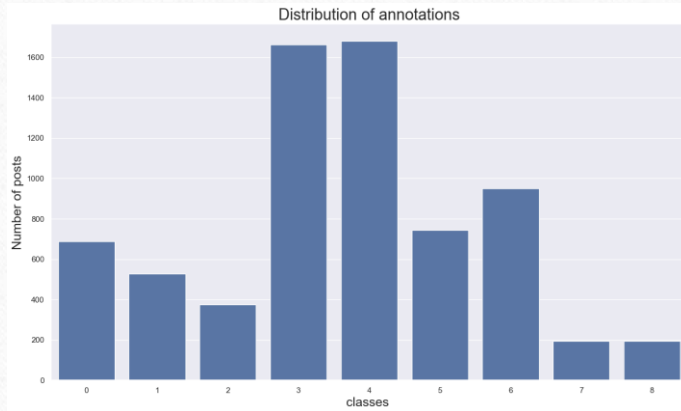
TEAM DETAILS AND PROBLEM STATEMENT

- **Problem Statement** : categorizes paragraphs based on the dataset's presence or absence of specific mental health indicators.
- **Team Name** : bHUC
- **Team Leader Details (Name, Phone Number, Email)** : Drishtant Singh Sengar , 9044400879
bt22cse012@iiitn.ac.in
- **Institution Name** : IIIT Nagpur
- **Course Enrolled** : Btech CSE

Problem Statement



Observations : Class imbalance



1.Imbalanced Classes: When the classes are imbalanced, meaning some classes have significantly more instances than others, the model may become **biased towards the majority class**. This can lead to **poor performance** on the minority classes and inaccurate predictions.

2.Limited Representation: Annotations with fewer instances may not have enough data to accurately learn their patterns and characteristics. As a result, the model may struggle to make accurate predictions for these annotations.

3.Evaluation Metrics: When evaluating the model's performance, metrics such as **accuracy may not provide an accurate representation of its effectiveness**. For imbalanced datasets, metrics like precision, recall, and F1-score are more informative in assessing the model's performance on individual classes.

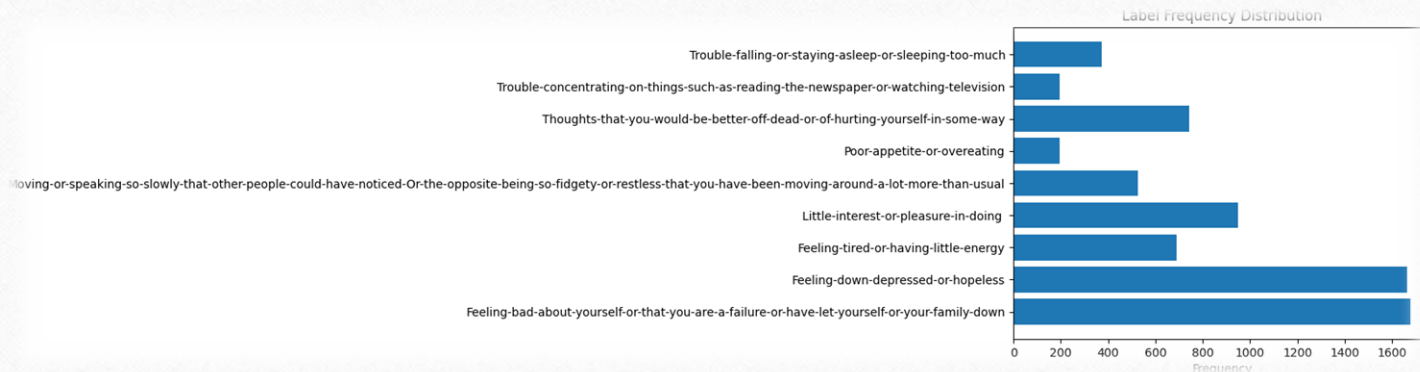
Our Approach

To solve the problem of **label/class imbalance** we assigned different **weights** to each label to improve the precision and recall of our model.

```
sample_weights = sample_weights[:-401]  
sample_weights
```

✓ 0.0s

```
array([0.27509327, 0.07394186, 0.09504036, ..., 0.07394186, 0.26618515,  
       0.32206228])
```



Our workflow(addressing class imbalance)

```
['Feeling-down-depressed-or-hopeless', 'no'],  
['Feeling-tired-or-having-little-energy', 'yes'],  
['Little-interest-or-pleasure-in-doing ', 'yes'],  
['Moving-or-speaking-so-slowly-that-other-people-could-have-noticed-Or-the-opposite-being',  
 'no'],  
['Poor-appetite-or-overeating', 'no'],  
['Thoughts-that-you-would-be-better-off-dead-or-of-hurting-yourself-in-some-way',  
 'no'],  
['Trouble-concentrating-on-things-such-as-reading-the-newspaper-or-watching-television',  
 'no'],  
['Trouble-falling-or-staying-asleep-or-sleeping-too-much', 'no']]
```

Binarizer

```
array([[1, 0, 1, ..., 0, 0, 0],  
       [1, 1, 0, ..., 0, 0, 0],  
       [1, 1, 1, ..., 1, 0, 0],  
       ...,  
       [1, 1, 0, ..., 0, 1, 0],  
       [1, 1, 1, ..., 1, 0, 0],  
       [0, 1, 0, ..., 0, 0, 0]])
```

encoded_labels

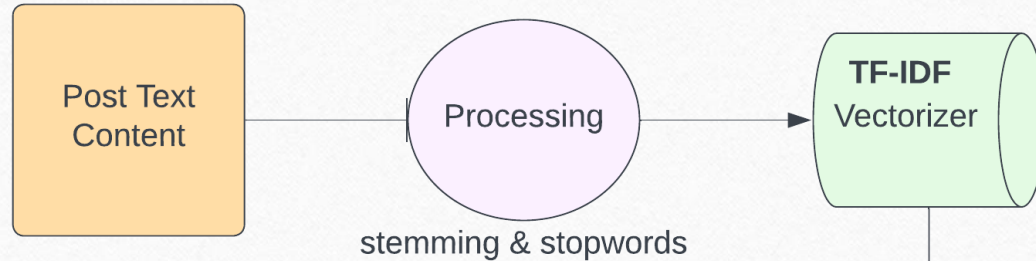
sample weights

```
array([0.27509327, 0.07394186, 0.09504036, ..., 0.24478142, 0.08557239,  
       0.13731608])
```

computing
sample weights

These are extremely black boxed explanations of the ML models to know how they were really implemented check out the Jupyter notebooks [here!](#)

Our workflow(vectorizing data)



TF-IDF Matrix

```
array([[0.      , 0.      , 0.      , ..., 0.      , 0.      ,
        0.      ],
       [0.      , 0.      , 0.10303694, ..., 0.      , 0.      ,
        0.      ],
       [0.      , 0.03807011, 0.      , ..., 0.      , 0.      ,
        0.      ],
       ...,
       [0.      , 0.      , 0.      , ..., 0.      , 0.      ,
        0.      ],
       [0.      , 0.      , 0.      , ..., 0.      , 0.      ,
        0.      ],
       [0.      , 0.      , 0.      , ..., 0.      , 0.      ,
        0.      ]])
```

These are extremely black boxed explanations of the ML models to know how they were really implemented check out the Jupyter notebooks [here!](#)

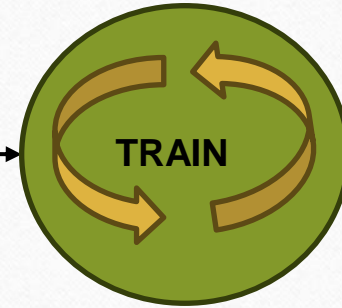
Our workflow(neural network define and train)

```
model = Sequential([
    Dense(128, activation='relu', input_shape=(X_train.shape[1],)),
    Dropout(0.5),
    Dense(64, activation='relu'),
    Dropout(0.5),
    Dense(y_train.shape[1], activation='sigmoid')
])
```

Dense layer with **128 units**

Dropout : to avoid overfitting

Final Dense layer → Num of **target classes**



10 EPOCHS

These are extremely black boxed explanations of the ML models to know how they were really implemented check out the Jupyter notebooks [here!](#)

Evaluation metrics

	precision	recall	f1-score	support
0	0.81	1.00	0.89	162
1	0.83	1.00	0.90	166
2	0.61	0.19	0.29	72
3	0.56	0.47	0.51	93
4	0.83	0.18	0.29	56
5	1.00	0.05	0.10	19
6	0.88	0.53	0.66	81
7	1.00	0.05	0.09	21
8	0.50	0.05	0.09	39
micro avg	0.78	0.62	0.69	709
macro avg	0.78	0.39	0.43	709
weighted avg	0.76	0.62	0.62	709
samples avg	0.78	0.67	0.69	709

```
# Calculate the number of correct predictions
correct_predictions = sum(y_test == y_pred)

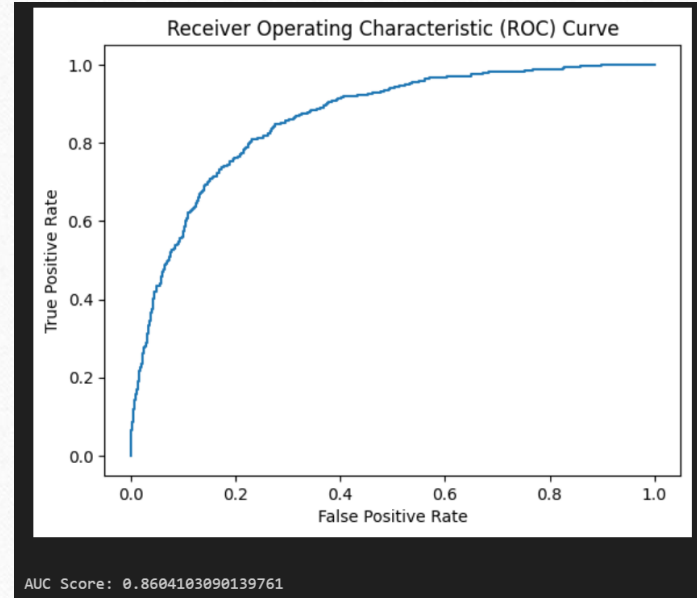
# Calculate the total number of predictions
total_predictions = len(y_pred)

# Calculate the accuracy
accuracy = correct_predictions / total_predictions

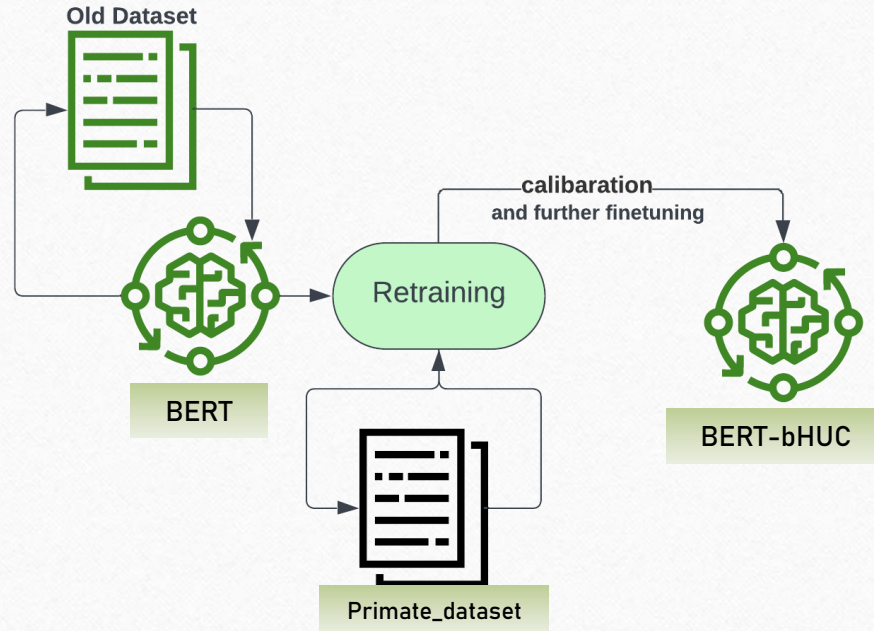
# Print the accuracy
print("Accuracy:", accuracy)
```

```
Accuracy: [0.80597015 0.82587065 0.66666667 0.58706468 0.76119403 0.91044776
0.78109453 0.90049751 0.80597015]
```

Accuracy of each label



Our Second Approach(Transfer learning)



These are extremely black boxed explanations of the ML models to know how they were really implemented check out the Jupyter notebooks [here!](#)

Evaluation metrics

Classification Report:				
	precision	recall	f1-score	support
0	0.84	1.00	0.91	338
1	0.82	1.00	0.90	329
2	0.53	0.62	0.57	148
3	0.51	0.86	0.64	190
4	0.43	0.48	0.45	88
5	0.71	0.24	0.36	42
6	0.58	0.72	0.64	154
7	0.57	0.09	0.15	47
8	0.60	0.42	0.50	78
micro avg	0.68	0.79	0.73	1414
macro avg	0.62	0.60	0.57	1414
weighted avg	0.68	0.79	0.72	1414
samples avg	0.68	0.81	0.71	1414
Overall Accuracy: 10.47				

As accuracy is not a great metric in multi-label classification with class imbalance we decided to choose this model as it performs better on other metrics

