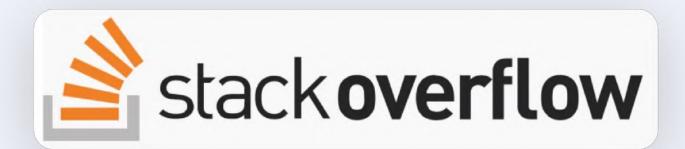
COURSE: MET CS 664 ARTIFICIAL INTELLIGENCE BOSTON UNIVERSITY METROPOLITAN COLLEGE

DATE: DECEMBER 18TH 2024

Artificial Intelligence Final Project

Course Instructor: Suresh Kalathur





Predicting Closed Questions on Stack Overflow

USING NEURAL NETWORK AND NATURAL LANGUAGE PROCESSING MODELS - (MACHINE LEARNING + ARTIFICIAL INTELLIGENCE)



Meet the team



Shreni Singh
TEAM MEMBER 1



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TEAM MEMBER 2

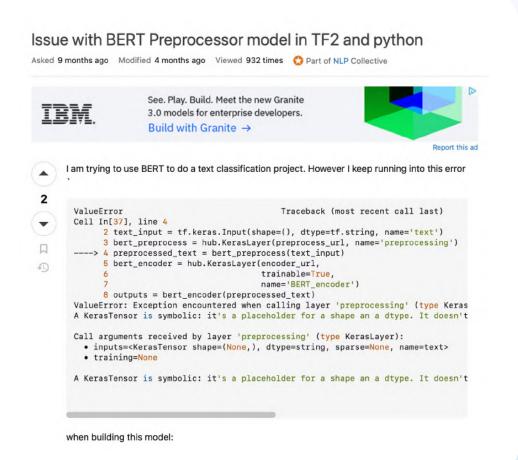


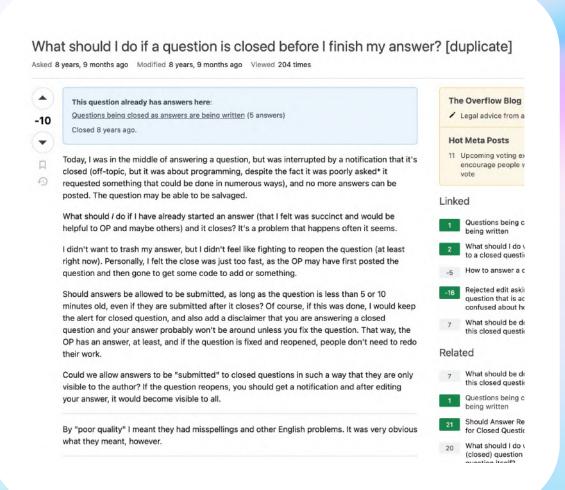
Stack Overflow is an *invaluable resource for programmers*, serving as a global forum for coding questions and answers. However, not all questions meet the *platform's quality and relevance standards*. Questions may be closed for reasons such as duplication, lack of detail, opinion-based content, or being off-topic.

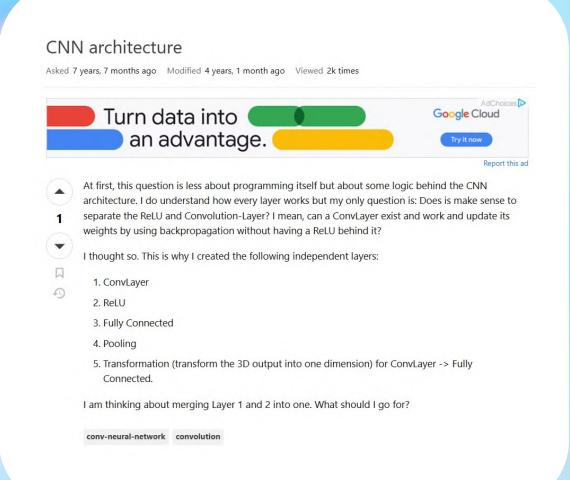
Identifying such questions at the time of submission can help improve the platform's efficiency and user experience.

This project aims to build an Al-driven predictive system that determines whether a newly posted question on Stack Overflow will be closed, as well as identifying the likely reason for closure. By addressing this issue, we can contribute to enhancing the community's effectiveness and the quality of knowledge shared.









Problem Statement

The increasing volume of questions on Stack Overflow necessitates a system to automatically flag questions that are likely to be closed. This project focuses on:

- Predicting whether a question will be closed.
- Classifying the closure reason (e.g., not a real question, off-topic, too localized).

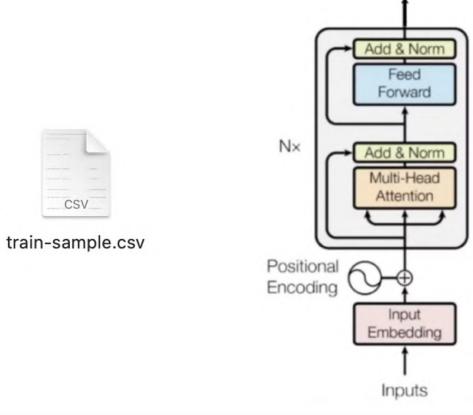


Dataset and Approach

- Dataset: The Kaggle dataset comprises a rich set of features derived from questions posted on Stack Overflow, including:
 - Question Title: A short description of the question.
 - Question Body: Detailed text of the question.
 - Tags: Metadata describing topics related to the question.
 - Post Creation Date: Date and time the question was created.
 - Closure Reason (or Open Status): Labels such as "duplicate," "off-topic," etc.
 - No.of data point ~ 15 lakh

Approach:

- Use a BERT, FNN, DNN model for text classification.
- Fine-tune BERT for predicting Stack Overflow questions' status.
- Use Basic Neural Network and Deep Neural Network for predicting Stack Overflow questions status.



Column Name	Description	
PostId	Unique identifier for the post	
PostCreationDate	Date when the post was created	
OwnerUserId	ID of the user who posted it	
OwnerCreationDate	Date the user account was created	
ReputationAtPostCreation	User's reputation at post creation	
OwnerUndeletedAnswerCountAtPostTime	Number of answers by the user at that time	
Title	Title of the post	
BodyMarkdown	Content of the post	
Tag1, Tag2, Tag3, Tag4, Tag5	Tags assigned to the post	
PostClosedDate	Date the post was closed	
OpenStatus	Indicates if the post is open or closed	



Data Preprocessing

Preprocessing Steps:

- Combining multiple text columns(e.g., TItle, BodyMarkdown) into a single text field
- Label encoding of the OpenStatus categories to numerical values.
- Transforming the text data into numerical features using TF-IDF vectorizer
- Tokenize the question text using BERT's preprocessing layer.
- Handle missing values, drop irrelevant columns.
- Encode target labels using custom mapping.

Define the columns to be
removed

columns_to_remove = ['Title',
'BodyMarkdown']

Drop the specified

columns from each

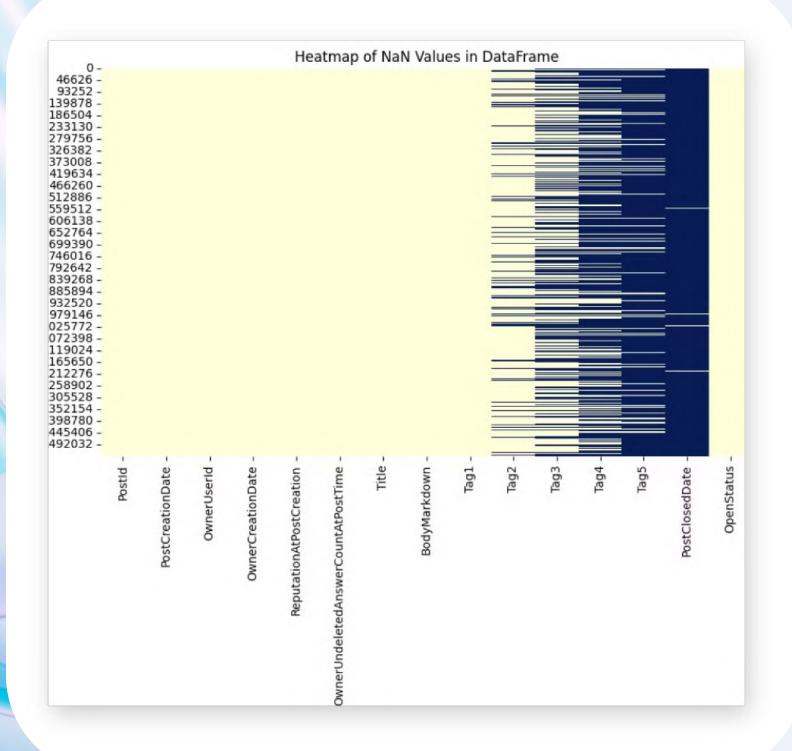
DataFrameso_train_df.drop(

columns=columns_to_remov

e, implace = True)

Tokenize input text using
BERT preprocessing layer
preprocessor =
hub.KerasLayer("https://kaggl
e.com/models/tensorflow/be
rt/frameworks/TensorFlow2/v
ariations/en-uncasedpreprocess/versions/3")
tokenized_output =
preprocessor(input_text)

46%

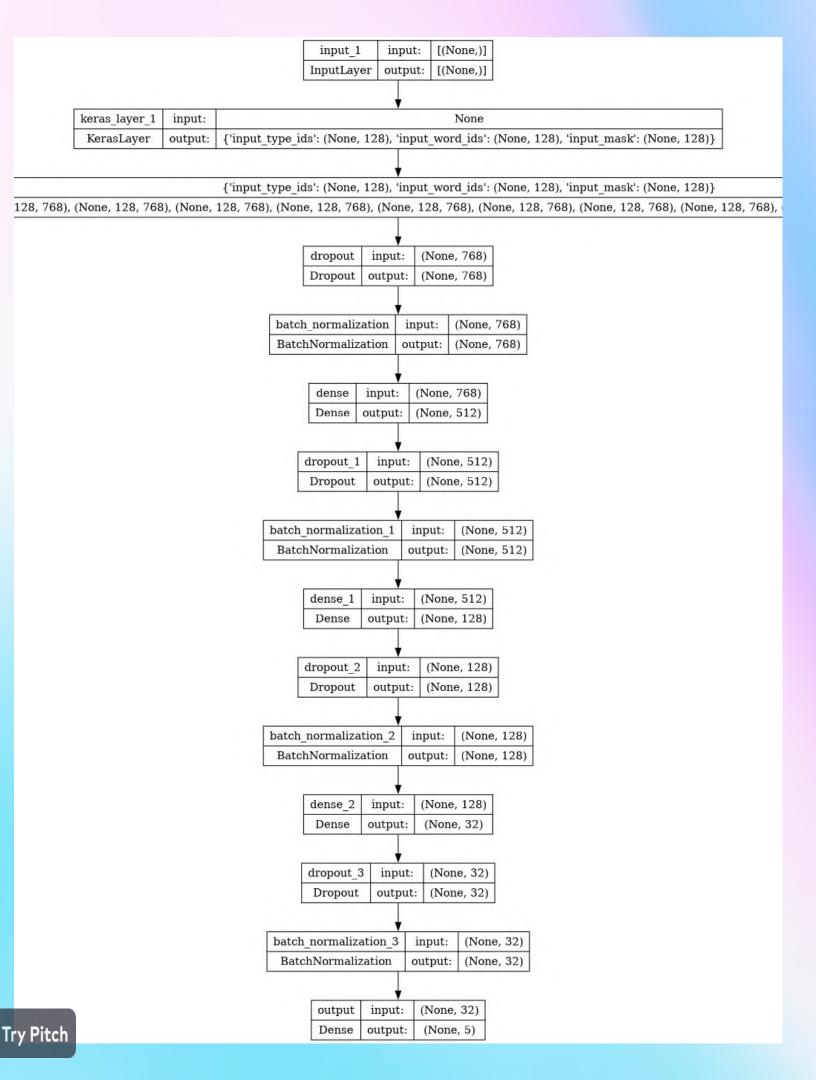


Data Preprocessing

HEATMAP

We have decided to utilize only the "Title," "BodyMarkdown," and "OpenStatus" columns from the DataFrame. The "Title" and "BodyMarkdown" columns will be combined to form the text input, while the "OpenStatus" column will serve as the target variable.





Model Architecture

Model Overview:

- BERT encoder layer to understand contextual relationships in the text.
- Dense layers with dropout and batch normalization for classification.

Key Layers:

- BERT encoder layer.
- Dense hidden layers (512, 128, 32 units).
- Output layer with softmax activation (5 classes for Stack Overflow question types).

Component	Туре	Description	
Text Processing	BERT Preprocessor	Tokenization and text processing	
Main Model	BERT Encoder	Transformer-based model (not RNN, LSTM, CNN)	
Classification Head	Feedforward Neural Network (MLP)	Custom dense layers for classification	

Model Architecture

Summary of NN Architecture:

- Input Layer: 10000 features (from TF-IDF).
- Hidden Layer 1: 128 neurons, ReLU activation.
- Dropout Layer: 50% dropout rate.
- Hidden Layer 2: 64 neurons, ReLU activation.
- Output Layer: 5 neurons, Softmax activation.

Summary of DNN Architecture:

- Input Layer: 10000 features (from TF-IDF).
- Hidden Layer 1: 512 neurons, ReLU activation.
- **Hidden Layer 2**: 256 neurons, ReLU activation.
- **Hidden Layer 3**: 128 neurons, ReLU activation.
- Dropout Layer: 50% dropout rate.
- Output Layer: 5 neurons, Softmax activation.

```
Try Pitcl
```

```
# TF-IDF Vectorizer for text processing
vectorizer = TfidfVectorizer(max_features=10000)
# Fit and transform the text data
X_train_tfidf = vectorizer.fit_transform(X_train)
X_valid_tfidf = vectorizer.transform(X_valid)
X_test_tfidf = vectorizer.transform(X_test)
# Save the vectorizer for later use
with open('vectorizer.pkl', 'wb') as f:
    pickle.dump(vectorizer, f)
# Label Encoder for OpenStatus encoding
encoder = LabelEncoder()
y_train_encoded = encoder.fit_transform(y_train)
y_valid_encoded = encoder.transform(y_valid)
y_test_encoded = encoder.transform(y_test)
# Save the encoder for later use
with open('encoder.pkl', 'wb') as f:
    pickle.dump(encoder, f)
```

```
#f create_nn_model(input_dim):
    model = Sequential()
    model.add(Dense(128, input_dim=input_dim, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(64, activation='relu'))
    model.add(Dense(54, activation='relu'))
    model.add(Dense(5, activation='softmax')) # 5 classes in OpenStatus
    model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
    return model

l_model = create_nn_model(X_train_tfidf.shape[1])
    model.summary()

Train the model
    l_model.fit(X_train_tfidf, y_train_encoded, validation_data=(X_valid_tfidf, y_valid_encoded), epochs=5, batch_size=32

Save the model
    l_model.save('nn_model.h5')
```

Model Training

- Training Strategy:
 - Optimizer: Adam with a learning rate of 2e-5.
 - Loss Function: Sparse categorical cross-entropy.
 - Metrics: Accuracy

```
# Classification layers
# Add dropout and batch normalization layers
drop1 = tf.keras.layers.Dropout(0.5)(pooled_output)
batch_norm1 = tf.keras.layers.BatchNormalization()(drop1)
# Add hidden dense layers
hidden1 = tf.keras.layers.Dense(512, activation='relu')(batch_norm1)
drop2 = tf.keras.layers.Dropout(0.4)(hidden1)
batch_norm2 = tf.keras.layers.BatchNormalization()(drop2)
hidden2 = tf.keras.layers.Dense(128, activation='relu')(batch_norm2)
drop3 = tf.keras.layers.Dropout(0.3)(hidden2)
batch_norm3 = tf.keras.layers.BatchNormalization()(drop3)
hidden3 = tf.keras.layers.Dense(32, activation='relu')(batch_norm3)
drop4 = tf.keras.layers.Dropout(0.2)(hidden3)
batch_norm4 = tf.keras.layers.BatchNormalization()(drop4)
# Output layer with 5 classes
output_layer = tf.keras.layers.Dense(5, activation='softmax', name='output')(batch_norm4)
# Model definition
model = tf.keras.Model(inputs=[text_input], outputs=[output_layer])
# Model Compilation
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=2e-5), # Adam optimizer with a small
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=False), # Sparse categoricalCrossentropy
              metrics=['accuracy']) # Tracking accuracy
```



Model: "model"

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None,)]	0	[]
keras_layer_1 (KerasLayer)	<pre>{'input_type_ids': (None, 128), 'input_word_ids': (None, 128), 'input_mask': (None, 128) }</pre>	0	['input_1[0][0]']
keras_layer_2 (KerasLayer)	{'encoder_outputs': [(None, 128, 768), (None, 128, 768)], 'pooled_output': (None, 768), 'sequence_output': (None, 128, 768), 'default': (None, 768)}	1094822	['keras_layer_1[0][0]', 'keras_layer_1[0][1]', 'keras_layer_1[0][2]']
dropout (Dropout)	(None, 768)	0	['keras_layer_2[0][13]']
batch_normalization (Batch Normalization)	(None, 768)	3072	['dropout[0][0]']
dense (Dense)	(None, 512)	393728	['batch_normalization[0][0]']
dropout_1 (Dropout)	(None, 512)	0	['dense[0][0]']
<pre>batch_normalization_1 (Bat chNormalization)</pre>	(None, 512)	2048	['dropout_1[0][0]']
dense_1 (Dense)	(None, 128)	65664	<pre>['batch_normalization_1[0][0]]</pre>
dropout_2 (Dropout)	(None, 128)	0	['dense_1[0][0]']
<pre>batch_normalization_2 (Bat chNormalization)</pre>	(None, 128)	512	['dropout_2[0][0]']
dense_2 (Dense)	(None, 32)	4128	<pre>['batch_normalization_2[0][0]]</pre>
dropout_3 (Dropout)	(None, 32)	0	['dense_2[0][0]']
<pre>batch_normalization_3 (Bat chNormalization)</pre>	(None, 32)	128	['dropout_3[0][0]']
output (Dense)	(None, 5)	165	['batch_normalization_3[0][0]

Total params: 109951686 (419.43 MB)
Trainable params: 109948805 (419.42 MB)
Non-trainable params: 2881 (11.25 KB)

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	1,280,128
dropout (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 64)	8,256
dense_2 (Dense)	(None, 5)	325

Total params: 1,288,709 (4.92 MB)

Trainable params: 1,288,709 (4.92 MB)

Non-trainable params: 0 (0.00 B)

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	(None, 512)	5,120,512
dropout_1 (Dropout)	(None, 512)	0
dense_4 (Dense)	(None, 256)	131,328
dense_5 (Dense)	(None, 128)	32,896
dense_6 (Dense)	(None, 5)	645

Total params: 5,285,381 (20.16 MB)

Trainable params: 5,285,381 (20.16 MB)

Non-trainable params: 0 (0.00 B)



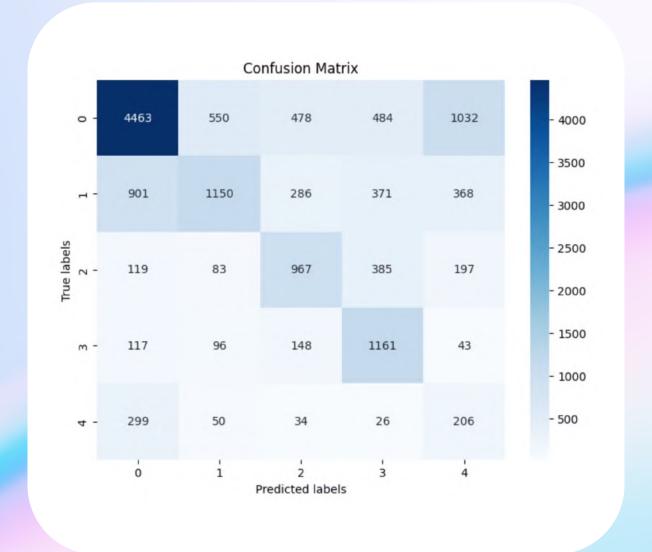
Model Training

Model Creation:

- Two different types of neural network models are created:
 Feedforward Neural Network (NN) and Deep Neural Network (DNN).
- Both models use the **ReLU activation function** for hidden layers and **softmax activation** for the output layer (5 classes).
- The models are trained using sparse categorical crossentropy loss and Adam optimizer.
- After training, the models are saved as .h5 files for later use.

Training and Saving Models:

- The NN model is trained for 5 epochs with a batch size of 32.
- Similarly, the **DNN model** is trained using the same parameters.
- Both models are saved for future use.



```
141/141 ----- 3s 16ms/step
```

accuracy: 0.9364 - loss: 0.2564 - val_accuracy: 0.4875 - val_loss: 1.6017

141/141 7s 52ms/step

accuracy: 0.9926 - loss: 0.0305 - val_accuracy: 0.4589 - val_loss: 2.6909

Accuracy: 56.7076 %

Sparse Categorical Cross-Entropy Loss: 1.1826568035936256

Model Evaluation & Results

Performance Metrics:

- **Accuracy**: Measures the overall correctness of the model.
- **Confusion Matrix**: Helps to understand misclassifications and the model's performance for each class.

Sample Output:

- **Accuracy**: 57-61%
- Confusion matrix highlighting prediction correctness across classes.



TEXT:

Title: 'Hardware. What is the difference between a port and a bank?'

For example, NVidia's shared memory is 32-banked, so what they say i then what is port ? also same issues to cache structure

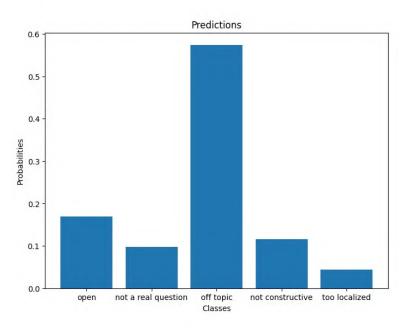
Could anyone clarify on this ? Thanks!

GROUND TRUTH:

off topic

1/1 [======] - 0s 38ms/step

PREDICTION:



PREDICTED CLASS: off topic

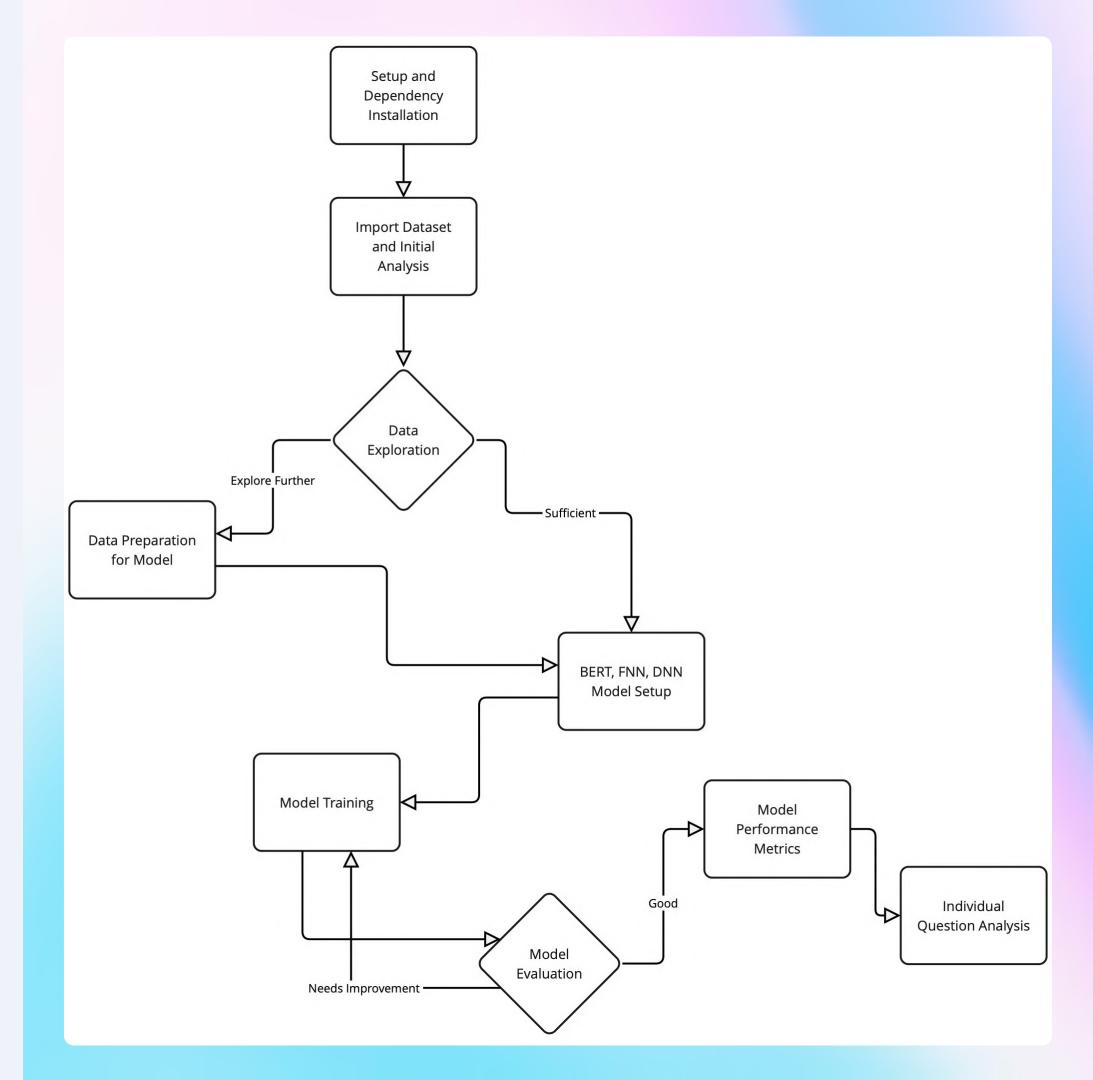
CORRECT PREDICTION !!!

Prediction Demonstration

- Random Test Case:
 - Input Question: Example of a Stack Overflow question.
 - Predicted Class: The model's predicted class (closed, off-topic, etc.).
 - Ground Truth: Actual label for the question.
- **Visualization**: Bar chart showing the prediction probabilities for each class.



Flowchart



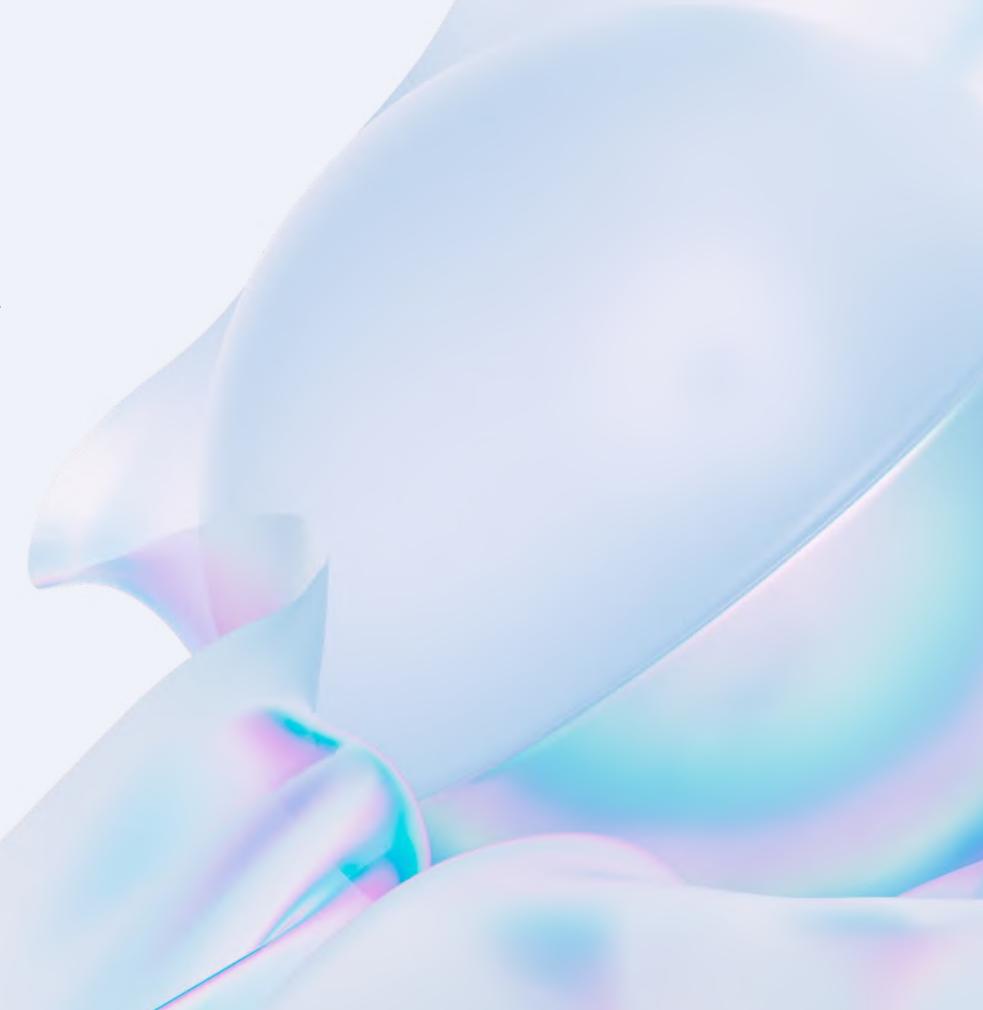
Challenges and Future Work

Challenges:

- Handling unbalanced classes and making predictions on noisy text.
- Fine-tuning BERT effectively to achieve optimal results.

• Future Work:

- Experimenting with other models like **RoBERTa** or **DistilBERT**.
- Incorporating more features (e.g., user reputation, question history).





Conclusion

By leveraging **neural networks** and **advanced NLP techniques**, this project seeks to assist Stack Overflow users and moderators in identifying and addressing low-quality or inappropriate questions promptly.

The anticipated system will streamline moderation efforts and improve user experience, contributing to the platform's overall quality.





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