#### V DATA LOADING

```
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
import nltk
import re
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import (Dense, Conv1D, MaxPooling1D, LSTM, Bidirectional,
                                                                                                                                        Embedding, Dropout, SpatialDropout1D, GlobalMaxPooling
from tensorflow.keras.regularizers import 12
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad sequences
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
data = pd.read_csv('/content/customer_service_sentiment - meaningful_customer_service_sentiment - meaningful_customer_service_sentiment_service_sentiment_service_sentiment_service_sentiment_service_sentiment_service_sentiment_service_sentime
```

## V DATA PROCESSING

```
nltk.download('punkt')
nltk.download('stopwords')
from nltk.corpus import stopwords
from nltk.tokenize import word tokenize
def preprocess_text(text):
    text = text.lower()
    text = re.sub(r'\W', ' '
    text = re.sub(r'\s+', ' ', text)
    tokens = word tokenize(text)
    tokens = [word for word in tokens if word not in stopwords.words('english')]
    return ' '.join(tokens)
# preprocessing
data['processed text'] = data['customer message'].apply(preprocess text)
#MAPPING sentiments
sentiment_mapping = {'Frustrated': 0, 'Neutral': 1, 'Satisfied': 2}
data['sentiment_label'] = data['sentiment_label'].map(sentiment_mapping)
```

## TEXT EMBEDDINGS

```
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer

# Bag of Words (BoW)
bow_vectorizer = CountVectorizer(max_features=5000)
X_train_bow = bow_vectorizer.fit_transform(train_data['processed_text']).toarray()
X_val_bow = bow_vectorizer.transform(val_data['processed_text']).toarray()
X_test_bow = bow_vectorizer.transform(test_data['processed_text']).toarray()

# TF-IDF
tfidf_vectorizer = TfidfVectorizer(max_features=5000)
X_train_tfidf = tfidf_vectorizer.fit_transform(train_data['processed_text']).toarray()
X_val_tfidf = tfidf_vectorizer.transform(val_data['processed_text']).toarray()
X_test_tfidf = tfidf_vectorizer.transform(test_data['processed_text']).toarray()
print("Embedding completed for BoW and TF-IDF.")
```

#### MODEL TRAINING WITH DIFFERENT ARCHITECTURES

## COMPARATIVE ANALYSIS OF MODELS

```
cnn_model.save('best_cnn_model.h5')
print("Best CNN model saved to best_cnn_model.h5")
```

# MODEL TRAINING AND COMAPRATIVE ANALYSIS

```
dropout_rate = 0.65
learning_rate = 0.0002
12 factor = 1e-4
batch size = 32
# ==========
# CNN Model
cnn model = Sequential([
   Embedding(input dim=max words, output dim=128),
   SpatialDropout1D(0.5), # Slightly reduced dropout on embeddings
   Conv1D(filters=32, kernel_size=5, activation='relu', kernel_regularizer=12(12_factor)),
   tf.keras.layers.BatchNormalization(),
   GlobalMaxPooling1D(),
   Dropout(dropout rate),
   Dense(16, activation='relu', kernel_regularizer=12(12_factor)),
   tf.keras.layers.BatchNormalization(),
   Dropout(dropout rate),
   Dense(3, activation='softmax')
1)
```

```
cnn_model.compile(loss='sparse_categorical_crossentropy', optimizer=Adam(learning_rate), me
```

```
# LSTM Model
lstm model = Sequential([
   Embedding(input dim=max words, output dim=128),
   SpatialDropout1D(0.8),
   LSTM(32, return_sequences=True, dropout=dropout_rate, recurrent_dropout=0.2, kernel_reg
   tf.keras.layers.BatchNormalization(),
   LSTM(16, dropout=dropout rate, kernel regularizer=12(1e-3)),
   tf.keras.layers.BatchNormalization(),
   Dense(16, activation='relu', kernel_regularizer=12(1e-3)),
   Dropout(dropout rate),
   Dense(3, activation='softmax')
1)
lstm_model.compile(loss='sparse_categorical_crossentropy', optimizer=Adam(learning_rate), m
# Revised BiLSTM Model
bilstm model = Sequential([
   Embedding(input_dim=max_words, output_dim=128),
   SpatialDropout1D(0.8),
   Bidirectional(LSTM(32, return_sequences=True, dropout=dropout_rate, recurrent_dropout=0
   tf.keras.layers.BatchNormalization(),
   Bidirectional(LSTM(16, dropout=dropout_rate, kernel_regularizer=12(1e-3))),
   tf.keras.layers.BatchNormalization(),
   Dense(16, activation='relu', kernel_regularizer=12(1e-3)),
   Dropout(dropout_rate),
   Dense(3, activation='softmax')
bilstm_model.compile(loss='sparse_categorical_crossentropy', optimizer=Adam(learning_rate),
# =============
# Train Models with individual epoch values
# ==============
print("Training CNN Model...")
history_cnn = cnn_model.fit(X_train, y_train,
                          validation_data=(X_val, y_val),
                          epochs=epochs_cnn,
                          batch size=batch size,
                          callbacks=[early_stop, reduce_lr],
                          verbose=1)
print("Training LSTM Model...")
history_lstm = lstm_model.fit(X_train, y_train,
                            validation_data=(X_val, y_val),
                            epochs=epochs lstm,
                            batch_size=batch_size,
                            callbacks=[early stop, reduce lr],
                            verbose=1)
print("Training BiLSTM Model...")
history_bilstm = bilstm_model.fit(X_train, y_train,
                               validation_data=(X_val, y_val),
                               epochs=epochs bilstm,
                               batch size=batch size,
                               callbacks=[early_stop, reduce_lr],
```

```
def evaluate_model(model, X, y, name):
   loss, acc = model.evaluate(X, y, verbose=0)
   print(f"{name} Model Accuracy on test data: {acc:.4f}")
print("\nEvaluating models on test data:")
evaluate_model(cnn_model, X_test, y_test, "CNN")
evaluate_model(lstm_model, X_test, y_test, "LSTM")
evaluate_model(bilstm_model, X_test, y_test, "BiLSTM")
[nltk_data] Downloading package punkt to /root/nltk_data...
                  Package punkt is already up-to-date!
    [nltk data]
    [nltk data] Downloading package stopwords to /root/nltk data...
                  Package stopwords is already up-to-date!
    [nltk_data]
    Training CNN Model...
    Epoch 1/10
    100/100 —
                                7s 13ms/step - accuracy: 0.3305 - loss: 1.7905 -
    Epoch 2/10
    100/100 -
                                    - 1s 5ms/step - accuracy: 0.3878 - loss: 1.5052 -
    Epoch 3/10
    100/100 —
                                    - 0s 5ms/step - accuracy: 0.4350 - loss: 1.3354 -
    Epoch 4/10
    100/100 -
                                    - 0s 5ms/step - accuracy: 0.4882 - loss: 1.1513 -
    Epoch 5/10
    100/100 —
                                    - 1s 6ms/step - accuracy: 0.5072 - loss: 1.0413 -
    Epoch 6/10
    100/100 -
                                    - 0s 5ms/step - accuracy: 0.5554 - loss: 1.0045 -
    Epoch 7/10
    100/100 -
                                    - 1s 5ms/step - accuracy: 0.5755 - loss: 0.8875 -
    Epoch 8/10
    100/100 -
                                    - 1s 5ms/step - accuracy: 0.6047 - loss: 0.8518 -
    Epoch 9/10
    100/100 -
                                    - 1s 5ms/step - accuracy: 0.6658 - loss: 0.7693 -
    Epoch 10/10
    100/100 —
                                    - 1s 4ms/step - accuracy: 0.6685 - loss: 0.7221 -
    Restoring model weights from the end of the best epoch: 10.
    Training LSTM Model...
    Epoch 1/12
    100/100 —
                                  —— 31s 247ms/step - accuracy: 0.3481 - loss: 1.718(
    Epoch 2/12
    100/100 -
                                    - 41s 249ms/step - accuracy: 0.3558 - loss: 1.621(
    Epoch 3/12
    100/100 -
                                    - 39s 233ms/step - accuracy: 0.3630 - loss: 1.488(
    Epoch 4/12
    100/100 -
                                    - 42s 240ms/step - accuracy: 0.3559 - loss: 1.4438
    Epoch 5/12
                                    - 42s 250ms/step - accuracy: 0.3593 - loss: 1.4314
    100/100 —
    Epoch 6/12
                                    - 41s 247ms/step - accuracy: 0.3753 - loss: 1.3736
    100/100 -
    Epoch 7/12
    100/100 —
                                    - 40s 233ms/step - accuracy: 0.3962 - loss: 1.3077
    Epoch 8/12
    100/100 -
                                    − 24s 236ms/step - accuracy: 0.3928 - loss: 1.295€
    Epoch 9/12
```

```
100/100 —
                    ______ 25s 250ms/step - accuracy: 0.3990 - loss: 1.282(
Epoch 10/12
100/100 ----
                           25s 248ms/step - accuracy: 0.4164 - loss: 1.2619
Epoch 11/12
                             - 41s 249ms/step - accuracy: 0.4261 - loss: 1.2356
100/100 -
Epoch 12/12
100/100 ——
                     41s 252ms/step - accuracy: 0.4695 - loss: 1.2003
Restoring model weights from the end of the best epoch: 12.
Training BiLSTM Model...
Epoch 1/15
100/100 ---
                    54s 433ms/step - accuracy: 0.3302 - loss: 2.0759
Epoch 2/15
100/100 -
                          42s 424ms/step - accuracy: 0.3318 - loss: 1.927
Epoch 3/15
```

#### SAVING THE BEST MODEL

```
cnn_model.save('best_cnn_model.h5')
print("Best CNN model saved to best_cnn_model.h5")
# predict sentiment for new text data
def predict_sentiment(text, model, tokenizer, max_length=100):
   # Preprocess the text using your existing function
   processed text = preprocess text(text)
    # Convert text to sequence and pad it
    sequence = tokenizer.texts_to_sequences([processed_text])
    padded sequence = pad sequences(sequence, maxlen=max length)
    prediction = model.predict(padded sequence)
    predicted_class = np.argmax(prediction, axis=1)[0]
    #mapping numeric prediction back to sentiment label
    sentiment_mapping = {0: 'Frustrated', 1: 'Neutral', 2: 'Satisfied'}
    predicted_sentiment = sentiment_mapping[predicted_class]
    return predicted sentiment, prediction
new text = "I am really happy with your service, everything was excellent."
sentiment, probabilities = predict_sentiment(new_text, cnn_model, tokenizer, max_length)
print("Predicted sentiment:", sentiment)
print("Prediction probabilities:", probabilities)
                    ----- 1s 1s/step
    Predicted sentiment: Satisfied
```

Prediction probabilities: [[0.24302487 0.2500682 0.50690687]]