Create Model

```
In [ ]: # Clear session
        K.clear session()
        # Model configuration
        dropout1 = 0.5
        dropout2 = 0.2
        dropout3 = 0.1
        initial learning rate = 0.001
        # Define the model
        model lstm = Sequential()
        model lstm.add(Bidirectional(LSTM(64, return sequences=True), input shape
        model lstm.add(BatchNormalization())
        model lstm.add(Dropout(dropout1))
        model_lstm.add(Bidirectional(LSTM(64, return_sequences=False)))
        model lstm.add(BatchNormalization())
        model_lstm.add(Dropout(dropout2))
        model lstm.add(Dense(64, activation='relu'))
        model lstm.add(BatchNormalization())
        model_lstm.add(Dropout(dropout3))
        model lstm.add(Dense(12, activation='sigmoid'))
        # Compile the model
        model lstm.compile(loss='binary crossentropy',optimizer='adam',metrics=['
```

Train Model

Train the model with the training data and validate it with the test data.

Training configuration:

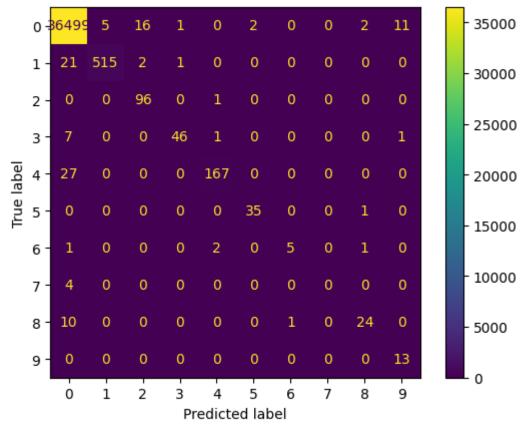
- 30 epochs
- Batch size of 64
- Early stopping to prevent overfitting
- Learning rate reduction on plateau
- Model checkpoint to save the best model based on validation loss

```
In []: # Define callbacks
    early_stopping = EarlyStopping(monitor='val_loss', patience=3, restore_be
    reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.2, patience=5,
    model_checkpoint = ModelCheckpoint('best_models/best_model_BILSTM.keras',

# Train the model
    model_lstm_output = model_lstm.fit(train, y_train, epochs=30, batch_size)
```

```
Epoch 1/30
2024-06-18 07:21:56.023662: I external/local xla/xla/stream executor/cuda/
cuda dnn.cc:465] Loaded cuDNN version 8907
                25s 11ms/step - accuracy: 0.0993 - loss: 0.
2120 - val accuracy: 0.2156 - val loss: 0.0041 - learning rate: 0.0010
Epoch 2/30
             21s 12ms/step - accuracy: 0.1781 - loss: 0.
1759/1759 -
0058 - val_accuracy: 0.2757 - val_loss: 0.0027 - learning_rate: 0.0010
Epoch 3/30
044 - val accuracy: 0.2210 - val loss: 0.0025 - learning rate: 0.0010
Epoch 4/30
                       — 15s 8ms/step - accuracy: 0.2180 - loss: 0.0
1759/1759 -
034 - val accuracy: 0.2295 - val loss: 0.0026 - learning rate: 0.0010
Epoch 5/30
                       15s 8ms/step - accuracy: 0.2266 - loss: 0.0
1759/1759 -
030 - val accuracy: 0.1664 - val loss: 0.0019 - learning rate: 0.0010
Epoch 6/30
          16s 9ms/step - accuracy: 0.2518 - loss: 0.0
1759/1759 —
028 - val accuracy: 0.2284 - val loss: 0.0020 - learning rate: 0.0010
Epoch 7/30
                   23s 10ms/step - accuracy: 0.2339 - loss: 0.
1759/1759 -
0024 - val accuracy: 0.2698 - val loss: 0.0025 - learning rate: 0.0010
Epoch 8/30
1759/1759 —
                        — 22s 11ms/step - accuracy: 0.2113 - loss: 0.
0023 - val accuracy: 0.1696 - val loss: 0.0016 - learning rate: 0.0010
Epoch 9/30
1759/1759 17s 10ms/step - accuracy: 0.2194 - loss: 0.
0021 - val accuracy: 0.2974 - val loss: 0.0015 - learning rate: 0.0010
Epoch 10/30
0019 - val accuracy: 0.2889 - val loss: 0.0018 - learning rate: 0.0010
Epoch 11/30
                   18s 10ms/step - accuracy: 0.2206 - loss: 0.
1759/1759 -
0019 - val accuracy: 0.3382 - val loss: 0.0021 - learning rate: 0.0010
Epoch 12/30
1759/1759 -
                        — 17s 9ms/step - accuracy: 0.2089 - loss: 0.0
018 - val accuracy: 0.1427 - val loss: 0.0014 - learning rate: 0.0010
Epoch 13/30
0018 - val accuracy: 0.4554 - val loss: 0.0015 - learning rate: 0.0010
Epoch 14/30
                   18s 10ms/step - accuracy: 0.1848 - loss: 0.
1759/1759 -
0017 - val accuracy: 0.3518 - val loss: 0.0014 - learning rate: 0.0010
Epoch 15/30
                         17s 10ms/step - accuracy: 0.1458 - loss: 0.
1759/1759 -
0018 - val accuracy: 0.3367 - val loss: 0.0015 - learning rate: 0.0010
```

RESULTS



Performance Metrics

• Accuracy =
$$=$$
 $\frac{Correct\ Predictions}{All\ Predictions}$

$$ullet$$
 Precision for a given class = $=$ $\dfrac{Correct\ Predictions\ for\ the\ Class}{All\ Predictions\ for\ the\ Class}$

$$ullet$$
 Recall for a given class = $\dfrac{Correct\ Predictions\ for\ the\ Class}{All\ Instances\ of\ the\ Class}$

- Averaging is a way to get a single number for multiclass. Depending on the importance one wants to give to minority classes:
 - Macro average: Compute the metric for each class, and returns the average without considering the proportion for each class in the dataset. For instance:

$$\text{Precision} = = \frac{P_{class1} + P_{class2} + ... + P_{classn}}{N}$$

 Weighted average: Compute the metric for each class, and returns the average considering the proportion (weighted) for each class in the dataset. For

instance:

```
Precision = \frac{N_1 * P_{class1} + N_2 * P_{class2} + ... + N_n * P_{classn}}{N}
```

```
In [ ]: # Calculates performance metrics
        acc = accuracy_score(y_true = y_test, y_pred = pred)
        print(f'Accuracy : {np.round(acc*100,2)}%')
        precision = precision_score(y_true = y_test, y_pred = pred, average='mac
        print(f'Precision - Macro: {np.round(precision*100,2)}%')
        recall = recall_score(y_true = y_test, y_pred = pred, average='macro')
        print(f'Recall - Macro: {np.round(recall*100,2)}%')
        f1 = f1_score(y_true = y_test, y_pred = pred, average='macro')
        print(f'F1-score - Macro: {np.round(f1*100,2)}%')
        precision = precision_score(y_true = y_test, y_pred = pred, average='wei
        print(f'Precision - Weighted: {np.round(precision*100,2)}%')
        recall = recall_score(y_true = y_test, y_pred = pred, average='weighted'
        print(f'Recall - Weighted: {np.round(recall*100,2)}%')
        f1 = f1 score(y true = y test, y pred = pred, average='weighted')
        print(f'F1-score - Weighted: {np.round(f1*100,2)}%')
       Accuracy : 99.69%
       Precision - Macro: 79.22%
```

Precision - Macro: 79.22% Recall - Macro: 78.55% F1-score - Macro: 77.61% Precision - Weighted: 99.69% Recall - Weighted: 99.69% F1-score - Weighted: 99.68%

TEST THE NETWORK

```
In [ ]:
```