Assignment 4: Intent Classification With Neural Networks

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The task is to build an intent classifier with neural networks.

Dataset: https://www.kaggle.com/datasets/hassanamin/atis-airlinetravelinformationsystem

References: https://www.tensorflow.org/text/tutorials/classify_text_with_bert

In [ ]:
```
!pip install scikit-plot
!pip install tensorflow-text
!pip install contractions
#!pip install tensorflow-gpu
```

In [3]:
```
# Import Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import nltk
import re
from nltk.corpus import stopwords
from wordcloud import WordCloud
from nltk.stem import  WordNetLemmatizer
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, roc_auc_score, classification_report
from sklearn.model_selection import train_test_split, GridSearchCV
import scikitplot as skplt
from keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras.layers.core import Activation, Dropout, Dense
from keras.layers import Flatten, LSTM, Bidirectional, CuDNNLSTM
from keras.layers import GlobalMaxPooling1D
from tensorflow.keras.layers import Embedding
from keras.models import Sequential
from gensim.models.keyedvectors import KeyedVectors
from keras import Model
from keras.layers import Layer
import keras.backend as K
from keras.layers import Input, Dense, SimpleRNN
from keras.layers.pooling import GlobalAveragePooling1D
import logging
from numpy import array
from numpy import asarray
from numpy import zeros
#import fasttext
import tensorflow as tf
import tensorflow_hub as hub
import tensorflow_text as text
import seaborn as sns
import contractions
%matplotlib inline
```

In [4]:
```
nltk.download('stopwords')
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

Out[4]: True

Data Load and EDA

In [7]:
```
# read train data
train_df = pd.read_csv("atis_intents_train.csv", header = None)
train_df.columns = ['intent','text']
train_df.head()
```

Out[7]:

	intent	text
0	atis_flight	i want to fly from boston at 838 am and arriv...
1	atis_flight	what flights are available from pittsburgh to...
2	atis_flight_time	what is the arrival time in san francisco for...
3	atis_airfare	cheapest airfare from tacoma to orlando
4	atis_airfare	round trip fares from pittsburgh to philadelp...

In [8]:
```
test_df = pd.read_csv("atis_intents_test.csv", header = None)
test_df.columns = ['intent','text']
test_df.head()
```

Out[8]:

	intent	text
0	atis_flight	i would like to find a flight from charlotte ...
1	atis_airfare	on april first i need a ticket from tacoma to...
2	atis_flight	on april first i need a flight going from pho...
3	atis_flight	i would like a flight traveling one way from ...
4	atis_flight	i would like a flight from orlando to salt la...

Let us check the distribution of classes. We see there is some class imbalance in the data.

In [24]:
```
train_df.groupby('intent').describe()
```

Out[24]:

	text			
	count	unique	top	freq
intent				
atis_abbreviation	147	108	what is fare code h	8
atis_aircraft	81	78	show me the aircraft that canadian airlines uses	2
atis_airfare	423	403	round trip fares from baltimore to philadelph...	4
atis_airline	157	148	show me the airlines for flights to or from l...	2
atis_flight	3666	3426	show me the flights from san francisco to boston	5
atis_flight_time	54	52	please list the flight times from pittsburgh ...	2
atis_ground_service	255	235	what ground transportation is available in sa...	4
atis_quantity	51	49	how many fares are there one way from tacoma ...	2

```
Error: Runtime no longer has a reference to this dataframe, please re-run this cell and try again.
```

In [22]:
```
train_df['intent'].value_counts(normalize = True)
```

Out[22]:
```
atis_flight            0.758378
atis_airfare           0.087505
atis_ground_service    0.052751
atis_airline           0.032478
atis_abbreviation      0.030410
atis_aircraft          0.016756
atis_flight_time       0.011171
atis_quantity          0.010550
Name: intent, dtype: float64
```

In [25]:
```
test_df.groupby('intent').describe()
```

Out[25]:

	text			
	count	unique	top	freq
intent				
atis_abbreviation	33	26	what does fare code bh mean	5
atis_aircraft	9	8	tell me about the m80 aircraft	2
atis_airfare	48	48	on april first i need a ticket from tacoma to...	1
atis_airline	38	28	which airline is us	4
atis_flight	632	613	what is the earliest arriving flight from hou...	2
atis_flight_time	1	1	what are the departure times from detroit to ...	1
atis_ground_service	36	36	does tacoma airport offer transportation from...	1
atis_quantity	3	3	how many canadian airlines international flig...	1

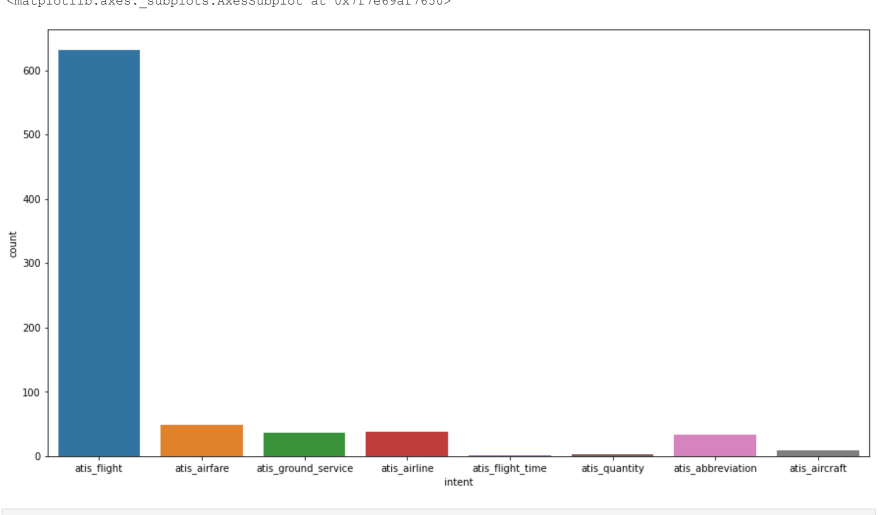
In [23]:
```
test_df['intent'].value_counts(normalize = True)
```

Out[23]:
```
atis_flight            0.79000
atis_airfare           0.06000
atis_airline           0.04750
atis_ground_service    0.04500
atis_abbreviation      0.04125
atis_aircraft          0.01125
atis_quantity          0.00375
atis_flight_time       0.00125
Name: intent, dtype: float64
```

Checking distribution of classes in the dataset.

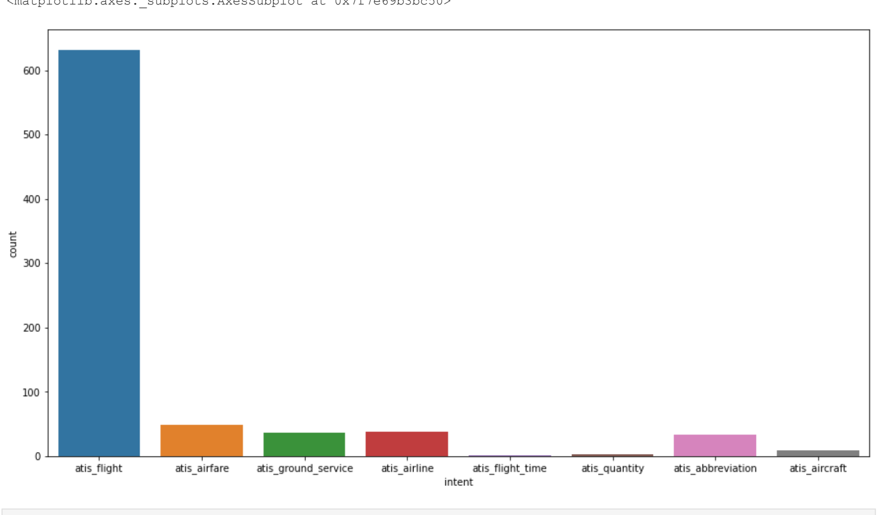
In [29]:
```
plt.figure(figsize = (15,8))
sns.countplot(data = train_df, x = test_df['intent'])
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7e69af7650>



In [28]:
```
plt.figure(figsize = (15,8))
sns.countplot(data = test_df, x = test_df['intent'])
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7e69b3bc50>



In [9]:
```
# Mount data
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

Since there is no Keras wrapper for Attention layer, I have used a custom Attention class.

Reference: https://machinelearningmastery.com/adding-a-custom-attention-layer-to-recurrent-neural-network-in-keras/

In [10]:
```
# Custom Attention Layer
class attention(Layer):
    def __init__(self,**kwargs):
        super(attention,self).__init__(**kwargs)

    def build(self,input_shape):
        self.W=self.add_weight(name='attention_weight', shape=(input_shape[-1],1),
                               initializer='random_normal', trainable=True)
        self.b=self.add_weight(name='attention_bias', shape=(input_shape[1],1),
                               initializer='zeros', trainable=True)
        super(attention, self).build(input_shape)

    def call(self,x):
        e = K.tanh(K.dot(x,self.W)+self.b)
        e = K.squeeze(e, axis=-1)
        alpha = K.softmax(e)
        alpha = K.expand_dims(alpha, axis=-1)
        context = x * alpha
        context = K.sum(context, axis=1)
        return context
```

Deep Learning Pipeline Class

I have included all the functions for preprocessing and training different neural networks in a class.

In [12]:
```
class DLPipeline():
  def __init__(self):
    pass

  def removeStopwords(self, sentence):
    '''Removes stopwords from a sentence'''
    stop_words = stopwords.words('english')
    tokens = [token for token in sentence.split() if token not in stop_words]
    return tokens

  def preprocess(self, text):
    '''Preprocesses text, removes punctuation and extra spaces'''
    special_characters = re.compile("[^A-Za-z0-9 ]")
    # fix contractions
    text = contractions.fix(text)
    # remove punctuation
    s = re.sub(special_characters, " ", text)
    s = re.sub(r"\s+[a-zA-Z]\s+", ' ', s)
    s = re.sub(r'\s+', ' ', s)
    # remove stopwords
    s = self.removeStopwords(s)
    return s

  def generate_wordcloud(self, text):
    word_cloud = WordCloud(collocations = False, background_color = 'white').generate(text)
    plt.figure(figsize=(15,8))
    plt.imshow(word_cloud, interpolation='bilinear')
    plt.axis("off")
    plt.show()

  def tokenize(self, X_train, X_test):
    '''Tokenize text in format required by Keras models'''
    tokenizer = Tokenizer(num_words=5000)
    tokenizer.fit_on_texts(X_train)
    # Convert text to token sequences
    X_train = tokenizer.texts_to_sequences(X_train)
    X_test = tokenizer.texts_to_sequences(X_test)
    # Vocab size plus 1 because 0 index is reserved
    vocab_size = len(tokenizer.word_index) + 1
    return (X_train, X_test, tokenizer, vocab_size)

  def create_padding(self, X_train, X_test, maxlen = 100):
    '''Pads input sentences to length maxlen'''
    X_train = pad_sequences(X_train, padding='post', maxlen=maxlen)
    X_test = pad_sequences(X_test, padding='post', maxlen=maxlen)
    return (X_train, X_test)

  def load_glove_embedding_dictionary(self, root, glove_file_name = 'glove.6B.100d.txt'):
    '''Loads pretrained Glove vectors from downloaded file'''
    glove_embeddings_dict = dict()
    glove_file = open(root + glove_file_name, encoding="utf8")
    for line in glove_file:
        records = line.split()
        word = records[0]
        word_vector = asarray(records[1:], dtype='float32')
        glove_embeddings_dict[word] = word_vector
    glove_file.close()
    return glove_embeddings_dict

  def load_fasttext_embedding_dictionary(self, root, filename):
    ft = fasttext.load_model(root+filename)
    return ft

  def create_glove_embedding_matrix(self, tokenizer, embeddings_dict, vocab_size, embedding_dim = 100):
    '''Creates Embedding matrix from pretrained Glove vectors'''
    # Create an empty embedding matrix of dimensions vocab_size x embedding_dim
    # Each row corresponds to embedding of a word in the vocab
    embedding_matrix = zeros((vocab_size, embedding_dim))
    # retrieve pretrained Glove embedding for all words of our vocab
    for word, index in tokenizer.word_index.items():
        embedding_vector = embeddings_dict.get(word)
        if embedding_vector is not None:
            embedding_matrix[index] = embedding_vector
    return embedding_matrix

  def load_w2vec_embedding_dictionary(self, root, w2vec_file_name = 'GoogleNews-vectors-negative300.bin'):
    '''Loads pretrained Word2vec vectors from downloaded file'''
    w2vec_file_name = root + w2vec_file_name
    logging.basicConfig(format='%(asctime)s : %(levelname)s : %(message)s', level=logging.INFO)
    print("Loading word2vec model")
    word2vec_model = KeyedVectors.load_word2vec_format(w2vec_file_name, binary=True)
    return word2vec_model

  def create_embedding_matrix(self, tokenizer, w2vec_embeddings_dict, vocab_size, embedding_dim):
    '''Creates Embedding matrix from pretrained Word2Vec vectors'''
    embedding_matrix = np.zeros((vocab_size, embedding_dim))
    for word, i in tokenizer.word_index.items():
      if word in w2vec_embeddings_dict:
        embedding_vector = w2vec_embeddings_dict[word]
      else:
        embedding_vector = None
      if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
    return embedding_matrix

  def plot_accuracy_loss(self, history):
    '''Creates loss and accuracy plot of training and validation from training history'''
    # Plot accuracy
    plt.figure(figsize = (15,8))
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train','test'], loc='upper left')
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.show()

    # Plot loss
    plt.figure(figsize = (15,8))
    plt.title('model loss')
    plt.ylabel('loss')
    plt.xlabel('epoch')
    plt.legend(['train','test'], loc='upper left')
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.show()


  def create_BiLSTM_nn_model(self, embedding_matrix, vocab_size, maxlen, embedding_dim, dense):
    '''Creates an BiLSTM model with given parameters'''
    model = Sequential()
    # Create embedding layer, with non trainable parameters
    embedding_layer = Embedding(input_dim = vocab_size,
                                output_dim = embedding_dim,
                                weights=[embedding_matrix],
                                input_length=maxlen ,
                                trainable=False)
    model.add(embedding_layer)
    # Add a BiLSTM layer
    model.add(Bidirectional(LSTM(128)))
    # Add the final Dense layer for classification with softmax
    model.add(Dense(dense, activation = 'softmax'))
    METRICS = [
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Precision(name='precision'),
        tf.keras.metrics.Recall(name='recall')
    ]
    # compile model with categorical cross entropy
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=METRICS)
    return model


  def create_BiLSTM_Attention_nn_model(self, lstm_units, embedding_matrix, vocab_size, max_len, embedding_dim,
    '''Creates an BiLSTM model with Attention and given parameters'''
    x=Input(shape=(max_len,))
    # Create embedding layer, with non trainable parameters
    embedding_layer = Embedding(input_dim = vocab_size,
                                output_dim = embedding_dim,
                                weights=[embedding_matrix],
                                input_length=max_len ,
                                trainable=False)(x)
    # Add a BiLSTM layer
    lstm_layer = Bidirectional(LSTM(lstm_units, return_sequences=True))(embedding_layer)
    # Add an Attention layer
    attention_layer = attention()(lstm_layer)
    # Add the final Dense layer for classification with softmax
    outputs=Dense(dense, trainable=True, activation='softmax')(attention_layer)
    model = Model(x,outputs)
    METRICS = [
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Precision(name='precision'),
        tf.keras.metrics.Recall(name='recall')
    ]
    # compile model with categorical cross entropy
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=METRICS)
    return model

  def create_bert_model(self,bert_preprocess, bert_encoder, dense):
    '''Creates a BERT model for classification'''
    lstm_units = 2
    text_input = tf.keras.layers.Input(shape=(), dtype=tf.string, name='text')
    # PReprocess input according to BERT
    preprocessed_text = bert_preprocess(text_input)
    outputs = bert_encoder(preprocessed_text)
    l = outputs['pooled_output']
    # Add dropout layer to prevent overfitting
    x = tf.keras.layers.Dropout(0.1, name="dropout")(l)
    out = tf.keras.layers.Dense(dense, activation='softmax', name="output")(x)
    model = tf.keras.Model(inputs=[text_input], outputs = [out])

    METRICS = [
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Precision(name='precision'),
        tf.keras.metrics.Recall(name='recall')
    ]
    # compile model with categorical cross entropy
    model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=METRICS)
    return model

  def train_evaluate_model(self, model, X_train, y_train, X_test, y_test,
                           epochs = 10, batch_size = 128):
    '''Trains and evaluates a model'''
    history = model.fit(X_train,
                        y_train,
                        batch_size=batch_size,
                        epochs=epochs,
                        verbose=1,
                        validation_split=0.2)
    score = model.evaluate(X_test, y_test, verbose=1)
    print("Test loss, Test Accuracy, Test Precision, Test Recall: ", score)
    return history


  def evaluate_model(self, model, X_test, y_test):
    '''Evaluates a model with different metrics'''
    y_pred = model.predict(X_test, verbose = 1, batch_size=64)
    y_pred_bool = np.argmax(y_pred, axis = 1)
    y_test = np.argmax(y_test,axis = 1)
    print(classification_report(y_test, y_pred_bool))
    skplt.metrics.plot_confusion_matrix(y_test, y_pred_bool, title="Confusion Matrix",
                    text_fontsize="large")
    plt.show()
```

In [13]:
```
# Instantiate DL Pipeline
dl_pipeline = DLPipeline()
```

Wordcloud

Let us check the frequently appearing words in the dataset. We see flight, denver, atlanta, francisco, boston appear very frequently, probably because there are many passengers traveling from these cities.

In [32]:
```
all_text = ' '.join(train_df['text'])
dl_pipeline.generate_wordcloud(all_text)
```

Data Preprocessing

We will preprocess the data and label encode the target variable.

In [14]:
```
# Preprocess X
X_train = list(train_df['text'].apply(lambda x: dl_pipeline.preprocess(x)))
X_test = list(test_df['text'].apply(lambda x: dl_pipeline.preprocess(x)))

# Onehot Encode the y variable
y_train = pd.get_dummies(train_df['intent']).values
y_test = pd.get_dummies(test_df['intent']).values
```

In [56]:
```
len(X_train), y_train.shape, len(X_test), y_test.shape
```

Out[56]: (4834, (4834, 8), 800, (800, 8))

Tokenize Data

Let us tokenize the data in the format required by Keras models.

In [15]:
```
X_train, X_test, tokenizer, vocab_size = dl_pipeline.tokenize(X_train, X_test)
len(X_train), len(tokenizer.word_index)
```

Out[15]: (4834, 763)

Padding Data

We will pad the data to max_len, to make all sentences of the same length for inputting to the neural networks.

In [16]:
```
max_len = 100
X_train, X_test = dl_pipeline.create_padding(X_train, X_test, max_len)
X_train.shape, X_test.shape,X_test.shape
```

Out[16]: ((4834, 100), (800, 100), (800, 100))

Neural Networks with Glove Embeddings

I have trained following models with pre trained Glove Embeddings:

- BiLSTM
- BiLSTM with Attention

Loading Glove Vectors

Let us load the pretrained Glove embeddings in a dictionary.

In [58]:
```
root = "/content/drive/MyDrive/"
glove_file_name = 'glove.6B.100d.txt'

glove_embeddings_dict = dl_pipeline.load_glove_embedding_dictionary(root, glove_file_name)
```

Creating Embedding Matrix

We will create an embedding matrix from the GloVe vectors that will be used as weights in the embedding layer of our neural networks. The embedding dimension for Glove vectors is 100.

In [59]:
```
embedding_dim = 100
embedding_matrix = dl_pipeline.create_glove_embedding_matrix(tokenizer, glove_embeddings_dict, vocab_size, embe

embedding_matrix.shape
```

Out[59]: (764, 100)

BiLSTM

Let us create a BiLSTM model with the embeddings from Glove.

In [70]:
```
dense = 8
bilstm_model = dl_pipeline.create_BiLSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim, dense)
```

In [71]:
```
bilstm_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_4 (Embedding)     (None, 100, 100)          76400

 bidirectional_4 (Bidirectio  (None, 256)              234496
 nal)

 dense_4 (Dense)             (None, 8)                 2056

=================================================================
Total params: 312,952
Trainable params: 236,552
Non-trainable params: 76,400
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [72]:
```
epochs = 10
batch_size = 128
history = dl_pipeline.train_evaluate_model(bilstm_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/10
31/31 [==============================] - 32s 887ms/step - loss: 0.9998 - accuracy: 0.9329 - precision: 0.8059 -
recall: 0.6100 - val_loss: 0.6941 - val_accuracy: 0.9470 - val_precision: 0.8147 - val_recall: 0.7456
Epoch 2/10
31/31 [==============================] - 28s 904ms/step - loss: 0.5548 - accuracy: 0.9601 - precision: 0.8773 -
recall: 0.7916 - val_loss: 0.3833 - val_accuracy: 0.9719 - val_precision: 0.9204 - val_recall: 0.8490
Epoch 3/10
31/31 [==============================] - 19s 626ms/step - loss: 0.3395 - accuracy: 0.9746 - precision: 0.9312 -
recall: 0.8606 - val_loss: 0.2396 - val_accuracy: 0.9833 - val_precision: 0.9525 - val_recall: 0.9121
Epoch 4/10
31/31 [==============================] - 19s 623ms/step - loss: 0.2299 - accuracy: 0.9831 - precision: 0.9504 -
recall: 0.9123 - val_loss: 0.1715 - val_accuracy: 0.9885 - val_precision: 0.9670 - val_recall: 0.9400
Epoch 5/10
31/31 [==============================] - 19s 619ms/step - loss: 0.1675 - accuracy: 0.9889 - precision: 0.9649 -
recall: 0.9454 - val_loss: 0.1395 - val_accuracy: 0.9902 - val_precision: 0.9675 - val_recall: 0.9535
Epoch 6/10
31/31 [==============================] - 21s 672ms/step - loss: 0.1303 - accuracy: 0.9911 - precision: 0.9699 -
recall: 0.9589 - val_loss: 0.1277 - val_accuracy: 0.9894 - val_precision: 0.9614 - val_recall: 0.9535
Epoch 7/10
31/31 [==============================] - 19s 626ms/step - loss: 0.1086 - accuracy: 0.9930 - precision: 0.9748 -
recall: 0.9692 - val_loss: 0.0892 - val_accuracy: 0.9943 - val_precision: 0.9812 - val_recall: 0.9731
Epoch 8/10
31/31 [==============================] - 22s 723ms/step - loss: 0.0850 - accuracy: 0.9941 - precision: 0.9782 -
recall: 0.9741 - val_loss: 0.0812 - val_accuracy: 0.9931 - val_precision: 0.9751 - val_recall: 0.9700
Epoch 9/10
31/31 [==============================] - 19s 619ms/step - loss: 0.0747 - accuracy: 0.9951 - precision: 0.9823 -
recall: 0.9780 - val_loss: 0.0697 - val_accuracy: 0.9952 - val_precision: 0.9844 - val_recall: 0.9772
Epoch 10/10
31/31 [==============================] - 19s 614ms/step - loss: 0.0577 - accuracy: 0.9961 - precision: 0.9860 -
recall: 0.9829 - val_loss: 0.0648 - val_accuracy: 0.9951 - val_precision: 0.9823 - val_recall: 0.9783
25/25 [==============================] - 2s 95ms/step - loss: 0.0445 - accuracy: 0.9966 - precision: 0.9875 - r
ecall: 0.9850
Test loss, Test Accuracy, Test Precision, Test Recall:  [0.044473763555288315, 0.9965624809265137, 0.9874686598
777771, 0.9850000143051147]
```

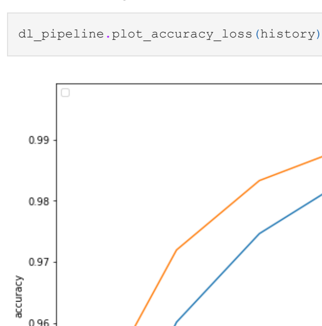
Evaluate Model

Evaluate model with different metrics:

- Accuracy
- Precision
- Recall
- F1-score

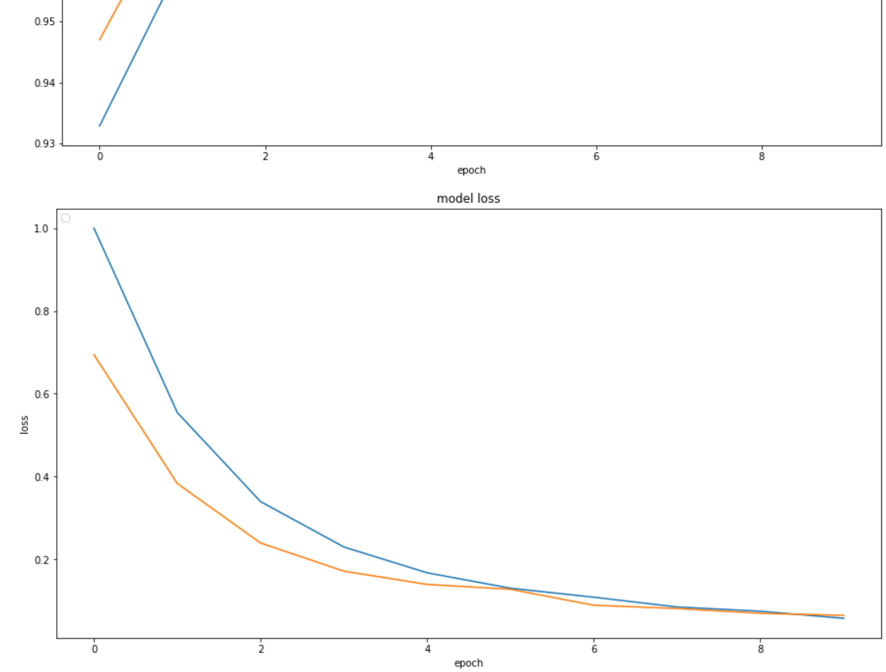
In [73]:
```
dl_pipeline.evaluate_model(bilstm_model, X_test, y_test)
```

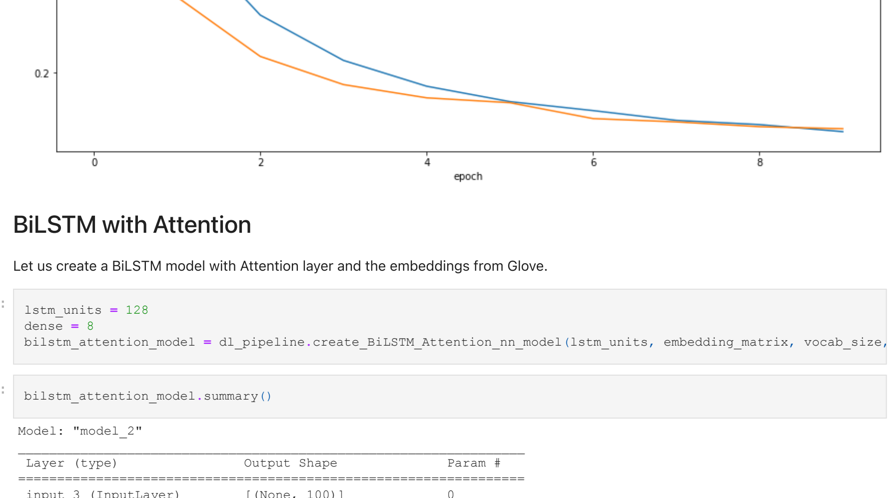
```
13/13 [==============================] - 7s 311ms/step
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        33
           1       1.00      1.00      1.00         9
           2       1.00      0.94      0.97        48
           3       1.00      0.92      0.96        38
           4       0.99      0.99      0.99       632
           5       1.00      1.00      1.00         1
           6       1.00      1.00      1.00        36
           7       0.43      1.00      0.60         3

    accuracy                           0.99       800
   macro avg       0.93      0.98      0.94       800
weighted avg       0.99      0.99      0.99       800
```



Plot Accuracy and Loss

In [74]:
```
dl_pipeline.plot_accuracy_loss(history)
```





BiLSTM with Attention

Let us create a BiLSTM model with Attention layer and the embeddings from Glove.

In [75]:
```
lstm_units = 128
dense = 8
bilstm_attention_model = dl_pipeline.create_BiLSTM_Attention_nn_model(lstm_units, embedding_matrix, vocab_size,
```

In [76]:
```
bilstm_attention_model.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 100)]             0

 embedding_5 (Embedding)     (None, 100, 100)          76400

 bidirectional_5 (Bidirectio  (None, 100, 256)         234496
 nal)

 attention_2 (attention)     (None, 256)               356

 dense_5 (Dense)             (None, 8)                 2056

=================================================================
Total params: 313,308
Trainable params: 236,908
Non-trainable params: 76,400
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [77]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(bilstm_attention_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
31/31 [==============================] - 26s 695ms/step - loss: 1.2477 - accuracy: 0.9188 - precision: 0.7507 - recall: 0.5250 - val_loss: 0.9030 - val_accuracy: 0.9374 - val_precision: 0.7497 - val_recall: 0.7497
Epoch 2/20
31/31 [==============================] - 20s 653ms/step - loss: 0.8210 - accuracy: 0.9445 - precision: 0.7895 - recall: 0.7585 - val_loss: 0.6943 - val_accuracy: 0.9489 - val_precision: 0.8349 - val_recall: 0.7373
Epoch 3/20
31/31 [==============================] - 20s 654ms/step - loss: 0.5880 - accuracy: 0.9588 - precision: 0.8855 - recall: 0.7701 - val_loss: 0.4694 - val_accuracy: 0.9696 - val_precision: 0.9656 - val_recall: 0.7849
Epoch 4/20
31/31 [==============================] - 22s 717ms/step - loss: 0.3695 - accuracy: 0.9750 - precision: 0.9466 - recall: 0.8482 - val_loss: 0.2439 - val_accuracy: 0.9841 - val_precision: 0.9597 - val_recall: 0.9111
Epoch 5/20
31/31 [==============================] - 20s 661ms/step - loss: 0.2506 - accuracy: 0.9843 - precision: 0.9625 - recall: 0.9095 - val_loss: 0.2026 - val_accuracy: 0.9862 - val_precision: 0.9526 - val_recall: 0.9359
Epoch 6/20
31/31 [==============================] - 20s 656ms/step - loss: 0.2119 - accuracy: 0.9863 - precision: 0.9636 - recall: 0.9253 - val_loss: 0.1697 - val_accuracy: 0.9907 - val_precision: 0.9735 - val_recall: 0.9514
Epoch 7/20
31/31 [==============================] - 22s 700ms/step - loss: 0.1860 - accuracy: 0.9885 - precision: 0.9640 - recall: 0.9428 - val_loss: 0.1558 - val_accuracy: 0.9911 - val_precision: 0.9706 - val_recall: 0.9576
Epoch 8/20
31/31 [==============================] - 20s 658ms/step - loss: 0.1723 - accuracy: 0.9894 - precision: 0.9670 - recall: 0.9472 - val_loss: 0.1870 - val_accuracy: 0.9875 - val_precision: 0.9598 - val_recall: 0.9390
Epoch 9/20
31/31 [==============================] - 22s 725ms/step - loss: 0.1458 - accuracy: 0.9907 - precision: 0.9718 - recall: 0.9535 - val_loss: 0.2177 - val_accuracy: 0.9840 - val_precision: 0.9752 - val_recall: 0.8945
Epoch 10/20
31/31 [==============================] - 20s 657ms/step - loss: 0.1443 - accuracy: 0.9908 - precision: 0.9711 - recall: 0.9545 - val_loss: 0.1068 - val_accuracy: 0.9926 - val_precision: 0.9800 - val_recall: 0.9607
Epoch 11/20
31/31 [==============================] - 20s 659ms/step - loss: 0.0988 - accuracy: 0.9933 - precision: 0.9781 - recall: 0.9685 - val_loss: 0.0974 - val_accuracy: 0.9931 - val_precision: 0.9760 - val_recall: 0.9690
Epoch 12/20
31/31 [==============================] - 22s 724ms/step - loss: 0.0933 - accuracy: 0.9936 - precision: 0.9776 - recall: 0.9708 - val_loss: 0.1058 - val_accuracy: 0.9925 - val_precision: 0.9739 - val_recall: 0.9659
Epoch 13/20
31/31 [==============================] - 20s 656ms/step - loss: 0.1005 - accuracy: 0.9926 - precision: 0.9744 - recall: 0.9664 - val_loss: 0.1127 - val_accuracy: 0.9919 - val_precision: 0.9718 - val_recall: 0.9628
Epoch 14/20
31/31 [==============================] - 20s 660ms/step - loss: 0.0891 - accuracy: 0.9935 - precision: 0.9786 - recall: 0.9690 - val_loss: 0.1002 - val_accuracy: 0.9930 - val_precision: 0.9750 - val_recall: 0.9690
Epoch 15/20
31/31 [==============================] - 21s 665ms/step - loss: 0.0698 - accuracy: 0.9950 - precision: 0.9831 - recall: 0.9767 - val_loss: 0.0788 - val_accuracy: 0.9944 - val_precision: 0.9793 - val_recall: 0.9762
Epoch 16/20
31/31 [==============================] - 21s 663ms/step - loss: 0.0541 - accuracy: 0.9958 - precision: 0.9857 - recall: 0.9809 - val_loss: 0.0802 - val_accuracy: 0.9955 - val_precision: 0.9844 - val_recall: 0.9793
Epoch 17/20
31/31 [==============================] - 20s 658ms/step - loss: 0.0589 - accuracy: 0.9963 - precision: 0.9870 - recall: 0.9829 - val_loss: 0.1071 - val_accuracy: 0.9925 - val_precision: 0.9729 - val_recall: 0.9669
Epoch 18/20
31/31 [==============================] - 22s 725ms/step - loss: 0.0472 - accuracy: 0.9968 - precision: 0.9883 - recall: 0.9858 - val_loss: 0.0726 - val_accuracy: 0.9963 - val_precision: 0.9865 - val_recall: 0.9835
Epoch 19/20
31/31 [==============================] - 23s 732ms/step - loss: 0.0441 - accuracy: 0.9972 - precision: 0.9904 - recall: 0.9871 - val_loss: 0.1026 - val_accuracy: 0.9944 - val_precision: 0.9793 - val_recall: 0.9762
Epoch 20/20
31/31 [==============================] - 23s 734ms/step - loss: 0.0622 - accuracy: 0.9959 - precision: 0.9857 - recall: 0.9814 - val_loss: 0.0860 - val_accuracy: 0.9956 - val_precision: 0.9844 - val_recall: 0.9804
25/25 [==============================] - 3s 107ms/step - loss: 0.0707 - accuracy: 0.9978 - precision: 0.9912 - recall: 0.9912
Test loss, Test Accuracy, Test Precision, Test Recall:  [0.07072429358959198, 0.9978125095367432, 0.9912499785423279, 0.9912499785423279]
```

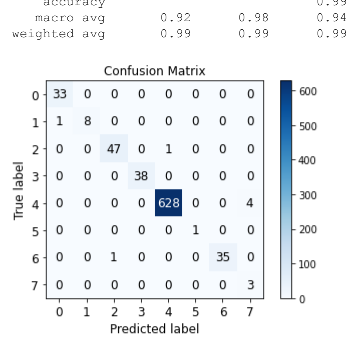
Evaluate Model

Evaluate model with different metrics:

- Accuracy
- Precision
- Recall
- F1-score

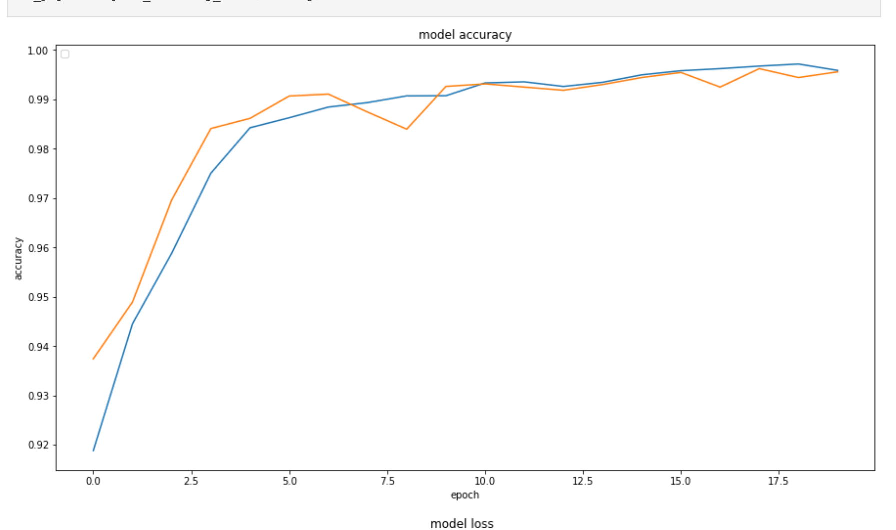
In [78]:
```
dl_pipeline.evaluate_model(bilstm_attention_model, X_test, y_test)
```

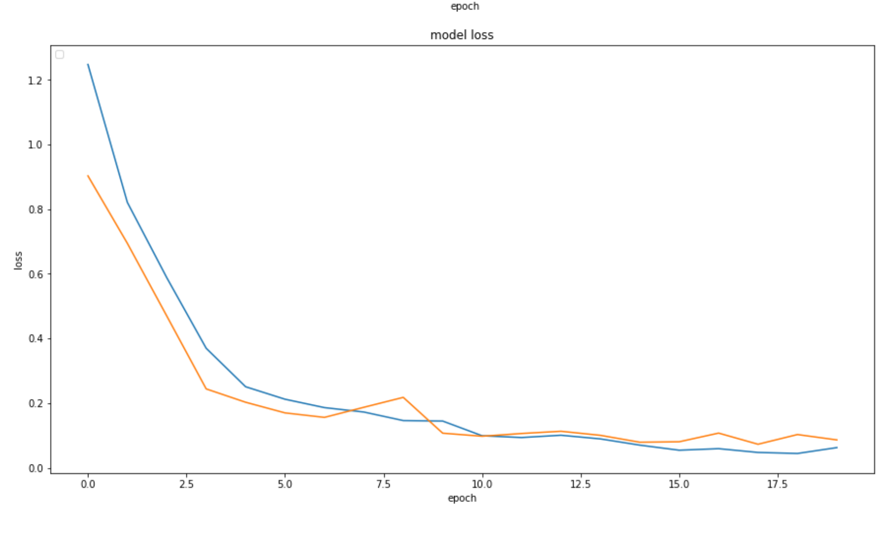
```
13/13 [==============================] - 5s 266ms/step
              precision    recall  f1-score   support

           0       0.97      1.00      0.99        33
           1       1.00      0.89      0.94         9
           2       0.98      0.98      0.98        48
           3       1.00      1.00      1.00        38
           4       1.00      0.99      1.00       632
           5       1.00      1.00      1.00         1
           6       1.00      0.97      0.99        36
           7       0.43      1.00      0.60         3

    accuracy                           0.99       800
   macro avg       0.92      0.98      0.94       800
weighted avg       0.99      0.99      0.99       800
```



Plot Accuracy and Loss

In [79]:
```
dl_pipeline.plot_accuracy_loss(history)
```





Neural Networks with Word2Vec

Loading Word2Vec Vectors

Let us load the pretrained Word2Vec embeddings in a dictionary.

In [17]:
```
root = "/content/drive/MyDrive/"
w2vec_file_name = 'GoogleNews-vectors-negative300.bin'

w2vec_embedding_dict = dl_pipeline.load_w2vec_embedding_dictionary(root, w2vec_file_name)
```

```
2022-07-09 20:10:52,177 : INFO : loading projection weights from /content/drive/MyDrive/GoogleNews-vectors-negative300.bin
Loading word2vec model
2022-07-09 20:11:56,569 : INFO : loaded (3000000, 300) matrix from /content/drive/MyDrive/GoogleNews-vectors-negative300.bin
```

Creating Embedding Matrix

We will create an embedding matrix from the Word2Vec vectors that will be used as weights in the embedding layer of our neural networks.

In [18]:
```
embedding_dim = 300
embedding_matrix = dl_pipeline.create_embedding_matrix(tokenizer, w2vec_embedding_dict, vocab_size, embedding_d
```

BiLSTM

Let us create an BiLSTM model with the embeddings from Fasttext.

In [82]:
```
embedding_dim = 300
lstm_units = 128
dense = 8
w2vec_bilstm_model = dl_pipeline.create_BiLSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim, d
```

In [83]:
```
w2vec_bilstm_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_6 (Embedding)     (None, 100, 300)          229200    
                                                                 
 bidirectional_6 (Bidirectio  (None, 256)              439296    
 nal)                                                            
                                                                 
 dense_6 (Dense)             (None, 8)                 2056      
                                                                 
=================================================================
Total params: 670,552
Trainable params: 441,352
Non-trainable params: 229,200
_________________________________________________________________
```

In [ ]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(w2vec_bilstm_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
31/31 [==============================] - 34s 914ms/step - loss: 1.0152 - accuracy: 0.9310 - precision: 0.8196 - recall: 0.5743 - val_loss: 0.6508 - val_accuracy: 0.9484 - val_precision: 0.8287 - val_recall: 0.7404
Epoch 2/20
31/31 [==============================] - 32s 1s/step - loss: 0.5153 - accuracy: 0.9646 - precision: 0.9060 - recall: 0.8001 - val_loss: 0.3357 - val_accuracy: 0.9761 - val_precision: 0.9463 - val_recall: 0.8573
Epoch 3/20
31/31 [==============================] - 30s 977ms/step - loss: 0.3086 - accuracy: 0.9785 - precision: 0.9464 - recall: 0.8774 - val_loss: 0.2085 - val_accuracy: 0.9851 - val_precision: 0.9692 - val_recall: 0.9100
Epoch 4/20
31/31 [==============================] - 29s 951ms/step - loss: 0.2083 - accuracy: 0.9845 - precision: 0.9603 - recall: 0.9141 - val_loss: 0.1475 - val_accuracy: 0.9886 - val_precision: 0.9661 - val_recall: 0.9421
Epoch 5/20
31/31 [==============================] - 28s 906ms/step - loss: 0.1449 - accuracy: 0.9895 - precision: 0.9683 - recall: 0.9467 - val_loss: 0.1127 - val_accuracy: 0.9926 - val_precision: 0.9789 - val_recall: 0.9617
Epoch 6/20
31/31 [==============================] - 28s 908ms/step - loss: 0.1037 - accuracy: 0.9931 - precision: 0.9778 - recall: 0.9666 - val_loss: 0.0848 - val_accuracy: 0.9934 - val_precision: 0.9781 - val_recall: 0.9690
Epoch 7/20
31/31 [==============================] - 30s 967ms/step - loss: 0.0762 - accuracy: 0.9951 - precision: 0.9836 - recall: 0.9772 - val_loss: 0.0752 - val_accuracy: 0.9950 - val_precision: 0.9833 - val_recall: 0.9762
Epoch 8/20
31/31 [==============================] - 27s 882ms/step - loss: 0.0571 - accuracy: 0.9964 - precision: 0.9875 - recall: 0.9834 - val_loss: 0.0661 - val_accuracy: 0.9953 - val_precision: 0.9844 - val_recall: 0.9783
Epoch 9/20
31/31 [==============================] - 28s 910ms/step - loss: 0.0503 - accuracy: 0.9969 - precision: 0.9889 - recall: 0.9866 - val_loss: 0.0621 - val_accuracy: 0.9957 - val_precision: 0.9844 - val_recall: 0.9814
Epoch 10/20
31/31 [==============================] - 27s 889ms/step - loss: 0.0383 - accuracy: 0.9977 - precision: 0.9920 - recall: 0.9899 - val_loss: 0.0535 - val_accuracy: 0.9964 - val_precision: 0.9886 - val_recall: 0.9824
Epoch 11/20
31/31 [==============================] - 27s 876ms/step - loss: 0.0336 - accuracy: 0.9981 - precision: 0.9930 - recall: 0.9915 - val_loss: 0.0535 - val_accuracy: 0.9960 - val_precision: 0.9865 - val_recall: 0.9814
Epoch 12/20
31/31 [==============================] - 28s 916ms/step - loss: 0.0283 - accuracy: 0.9982 - precision: 0.9933 - recall: 0.9922 - val_loss: 0.0481 - val_accuracy: 0.9963 - val_precision: 0.9875 - val_recall: 0.9824
Epoch 13/20
31/31 [==============================] - 28s 904ms/step - loss: 0.0241 - accuracy: 0.9986 - precision: 0.9946 - recall: 0.9943 - val_loss: 0.0487 - val_accuracy: 0.9966 - val_precision: 0.9876 - val_recall: 0.9855
Epoch 14/20
31/31 [==============================] - 29s 949ms/step - loss: 0.0206 - accuracy: 0.9989 - precision: 0.9956 - recall: 0.9953 - val_loss: 0.0512 - val_accuracy: 0.9959 - val_precision: 0.9845 - val_recall: 0.9824
Epoch 15/20
31/31 [==============================] - 28s 918ms/step - loss: 0.0169 - accuracy: 0.9991 - precision: 0.9966 - recall: 0.9961 - val_loss: 0.0481 - val_accuracy: 0.9966 - val_precision: 0.9876 - val_recall: 0.9855
Epoch 16/20
31/31 [==============================] - 27s 879ms/step - loss: 0.0146 - accuracy: 0.9995 - precision: 0.9984 - recall: 0.9974 - val_loss: 0.0443 - val_accuracy: 0.9966 - val_precision: 0.9886 - val_recall: 0.9845
Epoch 17/20
24/31 [======================>.......] - ETA: 5s - loss: 0.0134 - accuracy: 0.9995 - precision: 0.9980 - recall: 0.9977
```

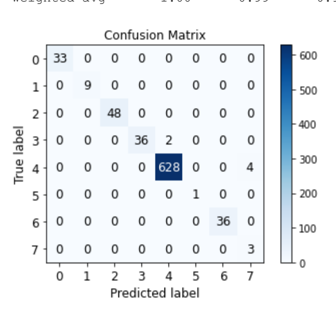
Evaluate Model

Evaluate model with different metrics:

- Accuracy
- Precision
- Recall
- F1-score

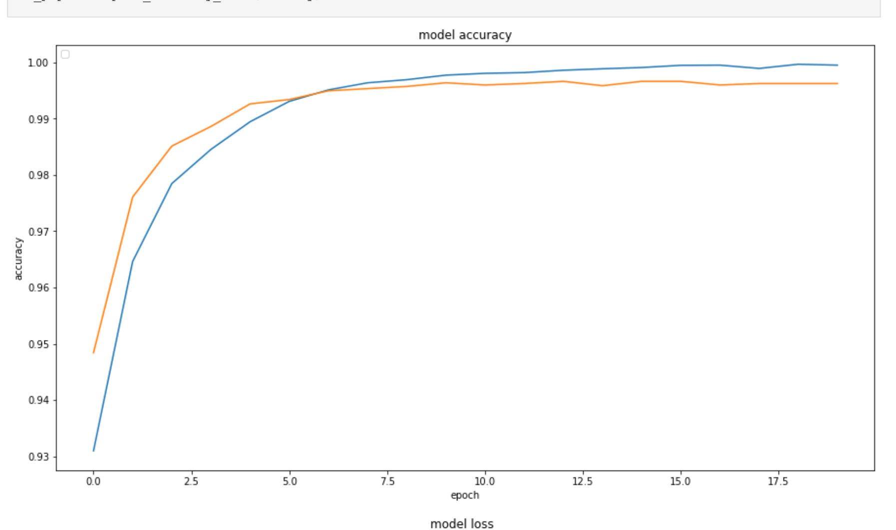
In [85]:
```
dl_pipeline.evaluate_model(w2vec_bilstm_model, X_test, y_test)
```

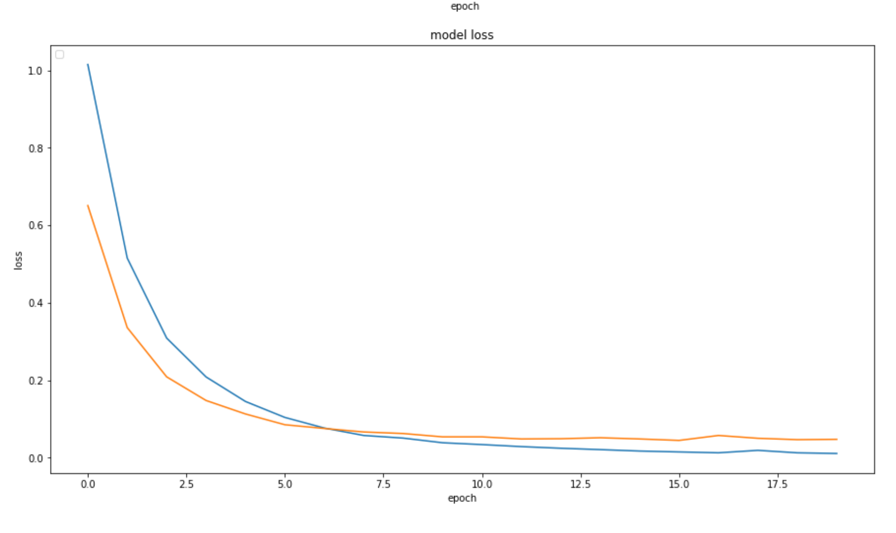
```
13/13 [==============================] - 8s 390ms/step
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        33
           1       1.00      1.00      1.00         9
           2       1.00      1.00      1.00        48
           3       1.00      0.95      0.97        38
           4       1.00      0.99      1.00       632
           5       1.00      1.00      1.00         1
           6       1.00      1.00      1.00        36
           7       0.43      1.00      0.60         3

    accuracy                           0.99       800
   macro avg       0.93      0.99      0.95       800
weighted avg       1.00      0.99      0.99       800
```



Plot Accuracy and Loss

In [86]:
```
dl_pipeline.plot_accuracy_loss(history)
```





BiLSTM with Attention

Let us create a BiLSTM model with Attention layer and the embeddings from Fasttext.

In [19]:
```
lstm_units = 128
dense = 8
w2vec_bilstm_attention_model = dl_pipeline.create_BiLSTM_Attention_nn_model(lstm_units, embedding_matrix, vocab
```

In [20]:
```
w2vec_bilstm_attention_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 input_1 (InputLayer)        [(None, 100)]             0         
                                                                 
 embedding (Embedding)       (None, 100, 300)          229200    
                                                                 
 bidirectional (Bidirectiona  (None, 100, 256)         439296    
 l)                                                              
                                                                 
 attention (attention)       (None, 256)               356       
                                                                 
 dense (Dense)               (None, 8)                 2056      
                                                                 
=================================================================
Total params: 670,908
Trainable params: 441,708
Non-trainable params: 229,200
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [ ]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(w2vec_bilstm_attention_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

Evaluate Model

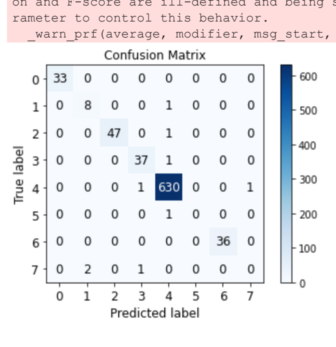
Evaluate model with different metrics:

- Accuracy
- Precision
- Recall
- F1-score *AUC ROC Score

In [92]:
```
dl_pipeline.evaluate_model(w2vec_bilstm_attention_model, X_test, y_test)
```

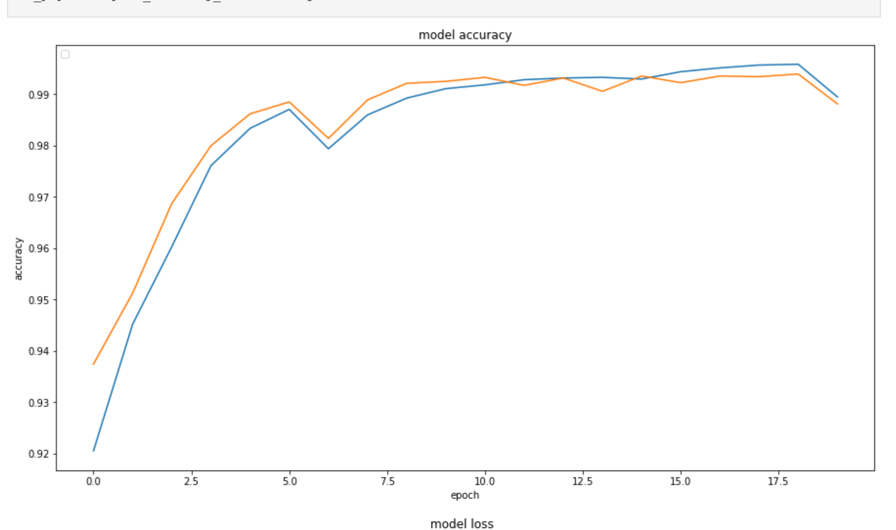
```
13/13 [==============================] - 4s 294ms/step
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        33
           1       0.80      0.89      0.84         9
           2       1.00      0.98      0.99        48
           3       0.95      0.97      0.96        38
           4       0.99      1.00      1.00       632
           5       0.00      0.00      0.00         1
           6       1.00      1.00      1.00        36
           7       0.00      0.00      0.00         3

    accuracy                           0.99       800
   macro avg       0.72      0.73      0.72       800
weighted avg       0.99      0.99      0.99       800
```

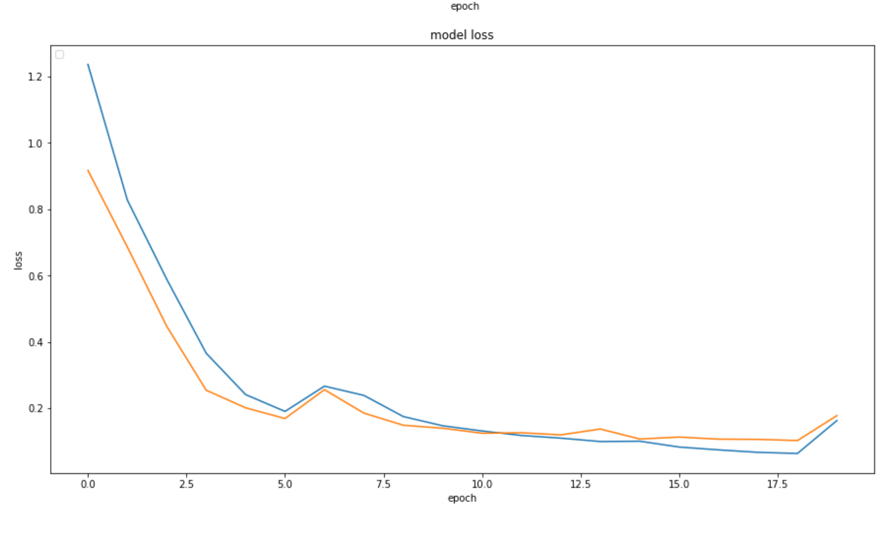
```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



Plot Accuracy and Loss

In [94]:
```
dl_pipeline.plot_accuracy_loss(history)
```





BERT Model

Let us create a model with pretrained BERT embeddings. I will use the model provided by Tensorflow with KerasLayer wrapper. Let us define the preprocess and embedding layers.

In [22]:
```
bert_preprocess = hub.KerasLayer("https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3")
bert_encoder = hub.KerasLayer("https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/4")
```

```
2022-07-09 20:21:14,318 : INFO : Using /tmp/tfhub_modules to cache modules.
2022-07-09 20:21:14,327 : INFO : Downloading TF-Hub Module 'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3'.
2022-07-09 20:21:15,642 : INFO : Downloaded https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3, Total size: 1.96MB
2022-07-09 20:21:15,648 : INFO : Downloaded TF-Hub Module 'https://tfhub.dev/tensorflow/bert_en_uncased_preprocess/3'.
2022-07-09 20:21:19,093 : INFO : Downloading TF-Hub Module 'https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/4'.
2022-07-09 20:21:35,954 : INFO : Downloaded https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/4, Total size: 429.66MB
2022-07-09 20:21:35,957 : INFO : Downloaded TF-Hub Module 'https://tfhub.dev/tensorflow/bert_en_uncased_L-12_H-768_A-12/4'.
```

In [23]:
```
dense = 8
bert_model = dl_pipeline.create_bert_model(bert_preprocess, bert_encoder, dense)
```

In [24]:
```
bert_model.summary()
```

```
Model: "model_1"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to                     
==================================================================================================
 text (InputLayer)              [(None,)]            0           []                               
                                                                                                  
 keras_layer (KerasLayer)       {'input_mask': (Non  0           ['text[0][0]']                   
                                e, 128),                                                          
                                 'input_type_ids':                                                
                                (None, 128),                                                      
                                 'input_word_ids':                                                
                                (None, 128)}                                                      
                                                                                                  
 keras_layer_1 (KerasLayer)     {'default': (None,   109482241   ['keras_layer[0][0]',            
                                768),                             'keras_layer[0][1]',            
                                 'encoder_outputs':               'keras_layer[0][2]']            
                                 [(None, 128, 768),                                               
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768)],                                               
                                 'pooled_output': (                                               
                                None, 768),                                                       
                                 'sequence_output':                                               
                                 (None, 128, 768)}                                                
                                                                                                  
 dropout (Dropout)              (None, 768)          0           ['keras_layer_1[0][13]']         
                                                                                                  
 output (Dense)                 (None, 8)            6152        ['dropout[0][0]']                
                                                                                                  
==================================================================================================
Total params: 109,488,393
Trainable params: 6,152
Non-trainable params: 109,482,241
__________________________________________________________________________________________________
```

In [25]:
```
# X train and test for BERT model
X_train = np.array(train_df['text'])
X_test = np.array(test_df['text'])
```

Train model

I have experimented with different hyperparameters:

- epochs
- batch_size
- Number of hidden units

In [26]:
```
epochs = 20
batch_size = 8
history = dl_pipeline.train_evaluate_model(bert_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
484/484 [==============================] - 63s 108ms/step - loss: 0.8799 - accuracy: 0.9427 - precision: 0.7942 - recall: 0.7305 - val_loss: 0.8141 - val_accuracy: 0.9462 - val_precision: 0.8356 - val_recall: 0.7094
Epoch 2/20
484/484 [==============================] - 51s 105ms/step - loss: 0.7216 - accuracy: 0.9501 - precision: 0.8343 - recall: 0.7499 - val_loss: 0.7751 - val_accuracy: 0.9501 - val_precision: 0.8827 - val_recall: 0.6929
Epoch 3/20
484/484 [==============================] - 50s 104ms/step - loss: 0.6520 - accuracy: 0.9543 - precision: 0.8546 - recall: 0.7647 - val_loss: 0.5797 - val_accuracy: 0.9558 - val_precision: 0.8507 - val_recall: 0.7839
Epoch 4/20
484/484 [==============================] - 51s 105ms/step - loss: 0.6087 - accuracy: 0.9569 - precision: 0.8620 - recall: 0.7799 - val_loss: 0.5333 - val_accuracy: 0.9582 - val_precision: 0.8570 - val_recall: 0.7994
Epoch 5/20
484/484 [==============================] - 50s 104ms/step - loss: 0.5625 - accuracy: 0.9589 - precision: 0.8677 - recall: 0.7921 - val_loss: 0.5256 - val_accuracy: 0.9666 - val_precision: 0.9079 - val_recall: 0.8159
Epoch 6/20
484/484 [==============================] - 51s 105ms/step - loss: 0.5413 - accuracy: 0.9613 - precision: 0.8780 - recall: 0.8022 - val_loss: 0.5252 - val_accuracy: 0.9554 - val_precision: 0.8330 - val_recall: 0.8046
Epoch 7/20
484/484 [==============================] - 51s 106ms/step - loss: 0.5207 - accuracy: 0.9617 - precision: 0.8750 - recall: 0.8092 - val_loss: 0.5130 - val_accuracy: 0.9581 - val_precision: 0.8529 - val_recall: 0.8035
Epoch 8/20
484/484 [==============================] - 51s 105ms/step - loss: 0.4961 - accuracy: 0.9628 - precision: 0.8789 - recall: 0.8143 - val_loss: 0.4816 - val_accuracy: 0.9617 - val_precision: 0.8683 - val_recall: 0.8180
Epoch 9/20
484/484 [==============================] - 51s 104ms/step - loss: 0.4820 - accuracy: 0.9647 - precision: 0.8872 - recall: 0.8221 - val_loss: 0.4249 - val_accuracy: 0.9664 - val_precision: 0.8838 - val_recall: 0.8418
Epoch 10/20
484/484 [==============================] - 51s 105ms/step - loss: 0.4695 - accuracy: 0.9649 - precision: 0.8866 - recall: 0.8249 - val_loss: 0.4258 - val_accuracy: 0.9652 - val_precision: 0.8769 - val_recall: 0.8397
Epoch 11/20
484/484 [==============================] - 51s 105ms/step - loss: 0.4515 - accuracy: 0.9674 - precision: 0.8933 - recall: 0.8397 - val_loss: 0.4431 - val_accuracy: 0.9713 - val_precision: 0.9181 - val_recall: 0.8459
Epoch 12/20
484/484 [==============================] - 51s 105ms/step - loss: 0.4386 - accuracy: 0.9681 - precision: 0.8959 - recall: 0.8430 - val_loss: 0.4111 - val_accuracy: 0.9666 - val_precision: 0.8866 - val_recall: 0.8407
Epoch 13/20
484/484 [==============================] - 50s 104ms/step - loss: 0.4472 - accuracy: 0.9666 - precision: 0.8921 - recall: 0.8340 - val_loss: 0.4055 - val_accuracy: 0.9699 - val_precision: 0.8980 - val_recall: 0.8563
Epoch 14/20
484/484 [==============================] - 51s 105ms/step - loss: 0.4324 - accuracy: 0.9676 - precision: 0.8936 - recall: 0.8407 - val_loss: 0.4058 - val_accuracy: 0.9729 - val_precision: 0.9267 - val_recall: 0.8501
Epoch 15/20
484/484 [==============================] - 50s 104ms/step - loss: 0.4299 - accuracy: 0.9674 - precision: 0.8907 - recall: 0.8430 - val_loss: 0.4042 - val_accuracy: 0.9692 - val_precision: 0.8932 - val_recall: 0.8563
Epoch 16/20
484/484 [==============================] - 50s 104ms/step - loss: 0.4127 - accuracy: 0.9698 - precision: 0.8997 - recall: 0.8534 - val_loss: 0.3900 - val_accuracy: 0.9695 - val_precision: 0.8892 - val_recall: 0.8635
Epoch 17/20
484/484 [==============================] - 50s 104ms/step - loss: 0.4021 - accuracy: 0.9702 - precision: 0.9015 - recall: 0.8547 - val_loss: 0.3732 - val_accuracy: 0.9696 - val_precision: 0.8944 - val_recall: 0.8583
Epoch 18/20
484/484 [==============================] - 50s 104ms/step - loss: 0.4069 - accuracy: 0.9697 - precision: 0.9007 - recall: 0.8513 - val_loss: 0.4002 - val_accuracy: 0.9691 - val_precision: 0.8897 - val_recall: 0.8594
Epoch 19/20
484/484 [==============================] - 51s 105ms/step - loss: 0.3941 - accuracy: 0.9701 - precision: 0.8997 - recall: 0.8560 - val_loss: 0.3831 - val_accuracy: 0.9718 - val_precision: 0.8988 - val_recall: 0.8728
Epoch 20/20
484/484 [==============================] - 50s 104ms/step - loss: 0.3860 - accuracy: 0.9712 - precision: 0.9037 - recall: 0.8611 - val_loss: 0.3492 - val_accuracy: 0.9736 - val_precision: 0.9098 - val_recall: 0.8759
25/25 [==============================] - 8s 335ms/step - loss: 0.2870 - accuracy: 0.9803 - precision: 0.9365 - recall: 0.9038
Test loss, Test Accuracy, Test Precision, Test Recall:  [0.2869974672794342, 0.9803125262260437, 0.9365285038948059, 0.9037500023841858]
```

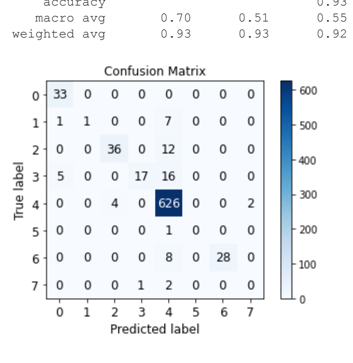
Evaluate Model

Evaluate model with different metrics:

- Accuracy
- Precision
- Recall
- F1-score

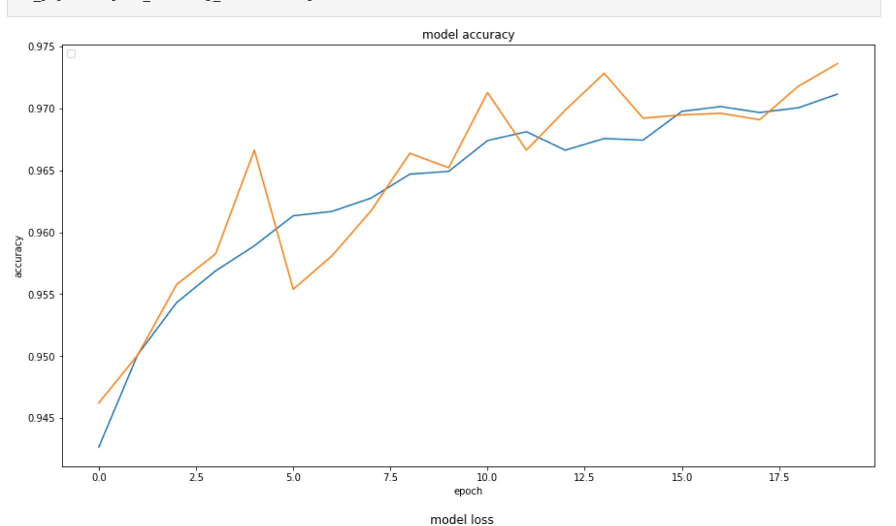
In [27]:
```
dl_pipeline.evaluate_model(bert_model, X_test, y_test)
```

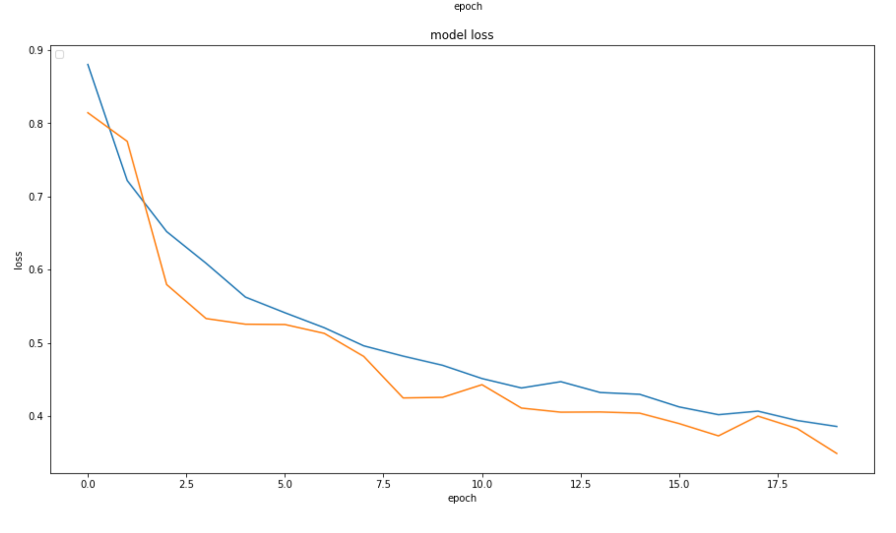
```
13/13 [==============================] - 9s 689ms/step
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
              precision    recall  f1-score   support

           0       0.85      1.00      0.92        33
           1       1.00      0.11      0.20         9
           2       0.90      0.75      0.82        48
           3       0.94      0.45      0.61        38
           4       0.93      0.99      0.96       632
           5       0.00      0.00      0.00         1
           6       1.00      0.78      0.88        36
           7       0.00      0.00      0.00         3

    accuracy                           0.93       800
   macro avg       0.70      0.51      0.55       800
weighted avg       0.93      0.93      0.92       800
```



Plot Accuracy and Loss

In [28]:
```
dl_pipeline.plot_accuracy_loss(history)
```





Model Performance Comparison

These are the model performance metrics for different models with different embedding vectors. As the classification problem is imbalanced, we should also look at metrics like Precision, Recall etc, apart from accuracy.

	Accuracy	Weighted Avg Precision	Weighted Avg Recall	Weighted Avg F1-Score
BiLSTM (Glove)	0.99	0.99	0.99	0.99
BiLSTM with Attention (Glove)	0.99	0.99	0.99	0.99
BiLSTM (Word2Vec)	0.99	1.0	0.99	0.99
BiLSTM with Attention (Word2Vec)	0.99	0.99	0.99	0.99
BERT	0.93	0.93	0.93	0.92

- All models perform almost similarly across different metrics
- BiLSTM with Word2Vec has the best performance, 1.0 weighted average precision
- It correctly classifies majority of instances from classes with low support as well
- BERT is computationally expensive, and requires a GPU for faster processing. It also has a lower performance

Improving model performance with data:

Model performance can be improved by increasing the amount of data. Deep learning models are known to perform better with a large amount of data, and it will also prevent overfitting.

The dataset has class imbalance, with 3 classes having 1% data. To improve performance, it will be beneficial to collect more data from these classes and create a balanced distribution across classes.

Model performance also depends on quality of the data, so it is important to collect data that is as diverse and varied as possible.

Data augmentation techniques to increase data can also be used. Some data augmentation techniques include

- Back Translation - Translating to another language and back, which gives a newer sentence with similar context.
- Random word insertion - Replace random words with synonyms.
- Random Deletion - Randomly delete some word from sentence.

These techniques can be used if it is difficult to obtain more data, the augmented data will be new for the model, but easier to generate and will help in generalisation.