Assignment 3: Text Classification With Neural Networks

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The task is to build a text classifier with machine learning models and neural networks.

Dataset: https://www.kaggle.com/datasets/matleonard/nlp-course?select=spam.csv

References:

1. https://towardsdatascience.com/text-classification-on-disaster-tweets-with-lstm-and-word-embedding-df35f039c1db
2. https://fasttext.cc/docs/en/english-vectors.html

In [ ]:
```
!pip install scikit-plot
!pip install fasttext
```

In [1]:
```
# 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
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 keras.preprocessing.sequence import pad_sequences
from keras.layers.core import Activation, Dropout, Dense
from keras.layers import Flatten, LSTM, Bidirectional
from keras.layers import GlobalMaxPooling1D
from keras.layers.embeddings 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


%matplotlib inline
```

In [ ]:
```
# Download nltk packages
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
nltk.download('omw-1.4')
```

In [2]:
```
df = pd.read_csv("spam.csv")
```

In [24]:
```
df.head()
```

Out[24]:

	label	text
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

1. Bag Of Words

Machine Learning Pipeline Class and EDA

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

In [25]:
```
class Pipeline():
  def __init__(self):
    pass
  def toLower(self, x):
    '''Converts string to lowercase'''
    return x.lower()

  def sentenceTokenize(self, x):
    '''Tokenizes document into sentences'''
    sent_tokenizer = nltk.data.load("tokenizers/punkt/english.pickle")
    sentences = sent_tokenizer.tokenize(x)
    return sentences

  def preprocess_sentences(self, text):
    '''Tokenizes sentences into words, removes punctuations, stopwords and
    performs tokenization'''
    word_tokenizer = nltk.RegexpTokenizer(r"\w+")
    special_characters = re.compile("[^A-Za-z0-9 ]")
    # remove punctuation
    s = re.sub(special_characters, " ", text)
    # Word tokenize
    words = word_tokenizer.tokenize(s)
    # Remove Stopwords
    words = self.removeStopwords(words)
    # Perform lemmatization
    words = self.wordnet_lemmatize(words)
    return words


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

  def wordnet_lemmatize(self, sentence):
    '''Lemmatizes tokens in a sentence'''
    lemmatizer = WordNetLemmatizer()
    tokens = [lemmatizer.lemmatize(token, pos='v') for token in sentence]
    return tokens


  def complete_preprocess(self, text):
    '''Performs complete preprocessing on document'''
    #Convert text to lowercase
    text_lower = self.toLower(text)
    #Preprocess all sentences
    preprocessed_sentences = self.preprocess_sentences(text_lower)
    return preprocessed_sentences


  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 create_bow(self, df, col, max_features = 20000):
    df['text_final'] = df[col].apply(lambda x: ' '.join(x))
    X = df['text_final']
    y = df['label']

    le = LabelEncoder()
    y = le.fit_transform(y)
    # Create bag of words using count vectorizer
    cnt_vec = CountVectorizer(analyzer="word", max_features = max_features) #try tuning
    X_bow = cnt_vec.fit_transform(X)

    return(cnt_vec, X_bow, y, le)


  def train_evaluate_model(self, model, X_train, X_test, y_train, y_test):
    '''Train and evaluate specified model, function can be reused with different models'''
    model.fit(X_train, y_train)
    pred_test  = model.predict(X_test)
    pred_train = model.predict(X_train)
    prob_test  = model.predict_proba(X_test)
    prob_train = model.predict_proba(X_train)
    train_acc  = accuracy_score(y_train, pred_train)
    test_acc   = accuracy_score(y_test, pred_test)
    train_auc_score = roc_auc_score(y_train, prob_train[:,1])
    test_auc_score = roc_auc_score(y_test, prob_test[:,1])
    class_report = classification_report(y_test, pred_test)

    print ("Model ROC-AUC score for training sample: %.3f" \
                                      % train_auc_score)
    print ("Model ROC-AUC score for test sample: %.3f" \
                                      % test_auc_score)
    print ("Train Accuracy: ", train_acc)
    print ("Test Accuracy: ", test_acc)
    print ("Classification report: \n", class_report)
    skplt.metrics.plot_confusion_matrix(y_test, pred_test, title="Confusion Matrix",
              text_fontsize='large')
    plt.show()
    return(model)

  def hyperparameter_tuning(self, model, param_grid, X_train, y_train, cv = 5):

        optimal_model = GridSearchCV(
            estimator = model,
            param_grid=param_grid,
            n_jobs = -1,
            cv = cv,
            scoring = 'accuracy',
            verbose=2
        )
        optimal_model.fit(X_train, y_train)
        print(optimal_model.best_score_)
        print(optimal_model.best_params_)
        return(optimal_model.best_estimator_)
```

In [26]:
```
# Instantiate Pipeline
pipeline = Pipeline()
```

We have an imbalanced dataset, with only 13% data as spam. So we need to consider metrics that take these into account, as well as stratified splitting.

In [27]:
```
df['label'].value_counts(normalize = True)
```

Out[27]:
```
ham     0.865937
spam    0.134063
Name: label, dtype: float64
```

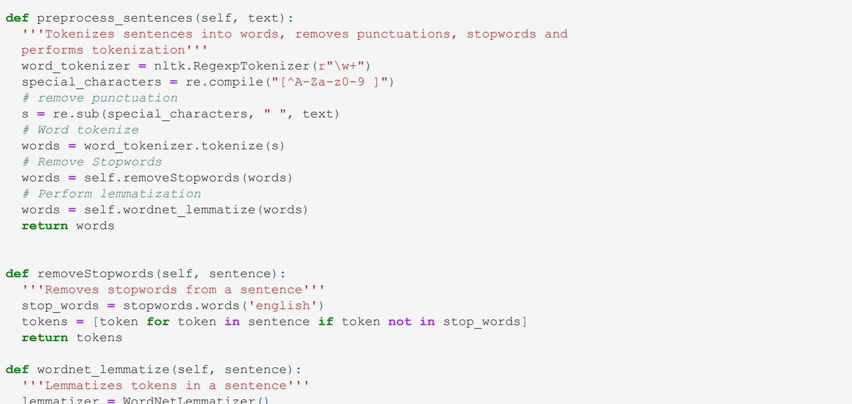
In [28]:
```
df['label'].value_counts()
```

Out[28]:
```
ham     4825
spam     747
Name: label, dtype: int64
```

In [ ]:
```
plt.figure(figsize=(15,8))
sns.countplot(df['label'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2f050df750>
```



In [31]:
```
df["clean_text"] = df['text'].apply(lambda x: pipeline.complete_preprocess(x))
```

In [ ]:
```
df.head()
```

Out[ ]:

	label	text	clean_text
0	ham	Go until jurong point, crazy.. Available only ...	[go, jurong, point, crazy, available, bugis, n...
1	ham	Ok lar... Joking wif u oni...	[ok, lar, joke, wif, u, oni]
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	[free, entry, 2, wkly, comp, win, fa, cup, fin...
3	ham	U dun say so early hor... U c already then say...	[u, dun, say, early, hor, u, c, already, say]
4	ham	Nah I don't think he goes to usf, he lives aro...	[nah, think, go, usf, live, around, though]
...	...	...	...
5567	spam	This is the 2nd time we have tried 2 contact u...	[2nd, time, try, 2, contact, u, u, 750, pound,...
5568	ham	Will Ì_ b going to esplanade fr home?	[b, go, esplanade, fr, home]
5569	ham	Pity, * was in mood for that. So...any other s...	[pity, mood, suggestions]
5570	ham	The guy did some bitching but I acted like i'd...	[guy, bitch, act, like, interest, buy, somethi...
5571	ham	Rofl. Its true to its name	[rofl, true, name]

5572 rows × 3 columns

In [32]:
```
cnt_vec, X_bow, y, le = pipeline.create_bow(df, 'clean_text')
cnt_vec, X_bow.shape
```

Out[32]:
```
(CountVectorizer(max_features=20000), (5572, 7524))
```

In [33]:
```
df.head()
```

Out[33]:

	label	text	clean_text	text_final
0	ham	Go until jurong point, crazy.. Available only ...	[go, jurong, point, crazy, available, bugis, n...	go jurong point crazy available bugis n great ...
1	ham	Ok lar... Joking wif u oni...	[ok, lar, joke, wif, u, oni]	ok lar joke wif u oni
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	[free, entry, 2, wkly, comp, win, fa, cup, fin...	free entry 2 wkly comp win fa cup final tkts 2...
3	ham	U dun say so early hor... U c already then say...	[u, dun, say, early, hor, u, c, already, say]	u dun say early hor u c already say
4	ham	Nah I don't think he goes to usf, he lives aro...	[nah, think, go, usf, live, around, though]	nah think go usf live around though

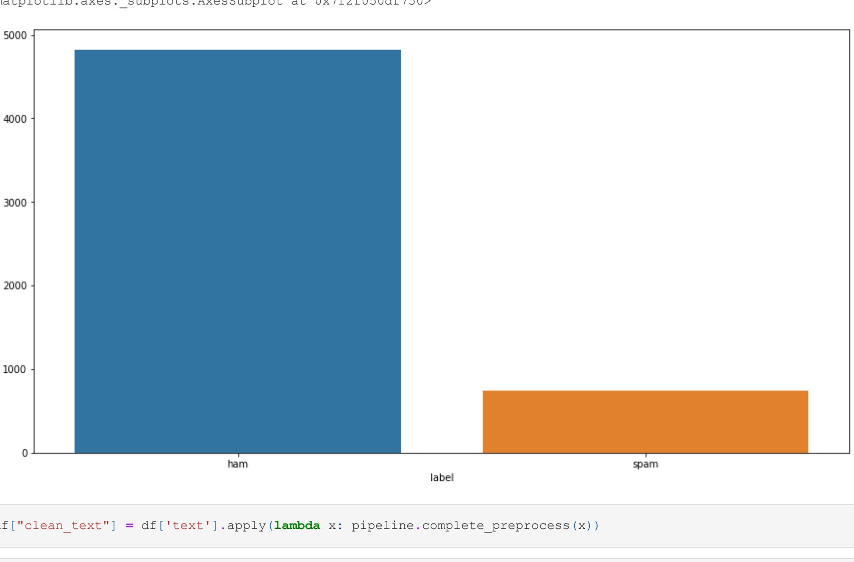
In [ ]:
```
ham_text = ' '.join(df[df['label'] == 'ham']['text_final'])
spam_text = ' '.join(df[df['label'] == 'spam']['text_final'])
```

Wordcloud

Wordclouds indicate most words used for spam are "call, free, mobile, award, cash, text". Whereas for not spam, it has words like "think, tell, come, love, ok" etc

In [ ]:
```
pipeline.generate_wordcloud(ham_text)
```

In [ ]:
```
pipeline.generate_wordcloud(spam_text)
```



In [ ]:
```
le.classes_
```

Out[ ]:
```
array(['ham', 'spam'], dtype=object)
```

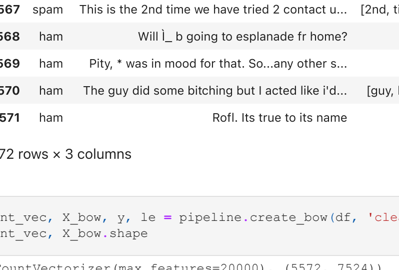
In [ ]:
```
#stratified train test split to maintain ratio of classes
X_train, X_test, y_train, y_test = train_test_split(X_bow.toarray(), y,
                                                    test_size=0.3, random_state=100,
                                                    stratify = y)
print ("Number of spam in training set: " , y_train.sum())
print ("Number of spam in test set: ",y_test.sum())

print ("Ratio of spam in training set: " , round(y_train.sum()/len(y_train),2))
print ("Ratio of spam in testing data set: ", round(y_test.sum()/len(y_test),2))
```

```
Number of spam in training set:  523
Number of spam in test set:  224
Ratio of spam in training set:  0.13
Ratio of spam in testing data set:  0.13
```

Decision Tree Classifier

In [ ]:
```
dt = pipeline.train_evaluate_model(DecisionTreeClassifier(), X_train, X_test, y_train, y_test)
```

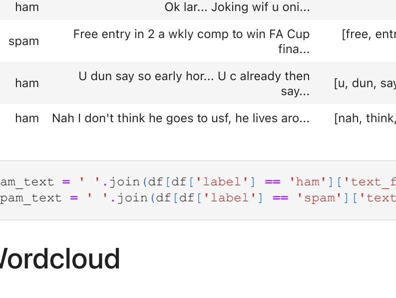
```
Model ROC-AUC score for training sample: 1.000
Model ROC-AUC score for test sample: 0.932
Train Accuracy:  1.0
Test Accuracy:  0.9700956937799043
Classification report:
               precision    recall  f1-score   support

           0       0.98      0.98      0.98      1448
           1       0.90      0.88      0.89       224

    accuracy                           0.97      1672
   macro avg       0.94      0.93      0.94      1672
weighted avg       0.97      0.97      0.97      1672
```



Naive Bayes

In [ ]:
```
nb = pipeline.train_evaluate_model(MultinomialNB(), X_train, X_test, y_train, y_test)
```

```
Model ROC-AUC score for training sample: 0.997
Model ROC-AUC score for test sample: 0.982
Train Accuracy:  0.9930769230769231
Test Accuracy:  0.9808612440191388
Classification report:
               precision    recall  f1-score   support

           0       0.99      0.99      0.99      1448
           1       0.93      0.93      0.93       224

    accuracy                           0.98      1672
   macro avg       0.96      0.96      0.96      1672
weighted avg       0.98      0.98      0.98      1672
```



Logistic Regression

In [ ]:
```
lr = pipeline.train_evaluate_model(LogisticRegression(), X_train, X_test, y_train, y_test)
```

```
Model ROC-AUC score for training sample: 1.000
Model ROC-AUC score for test sample: 0.987
Train Accuracy:  0.9961538461538462
Test Accuracy:  0.9838516746411483
Classification report:
               precision    recall  f1-score   support

           0       0.98      1.00      0.99      1448
           1       0.99      0.88      0.94       224

    accuracy                           0.98      1672
   macro avg       0.99      0.94      0.96      1672
weighted avg       0.98      0.98      0.98      1672
```

Random Forest Classifier

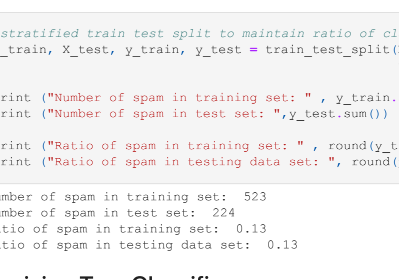
In [ ]:
```
rf = pipeline.train_evaluate_model(RandomForestClassifier(), X_train, X_test, y_train, y_test)
```

```
Model ROC-AUC score for training sample: 1.000
Model ROC-AUC score for test sample: 0.995
Train Accuracy:  1.0
Test Accuracy:  0.9796650717703349
Classification report:
               precision    recall  f1-score   support

           0       0.98      1.00      0.99      1448
           1       1.00      0.85      0.92       224

    accuracy                           0.98      1672
   macro avg       0.99      0.92      0.95      1672
weighted avg       0.98      0.98      0.98      1672
```

Gradient Boosting Classifier

In [ ]:
```
gb = pipeline.train_evaluate_model(GradientBoostingClassifier(), X_train, X_test, y_train, y_test)
```

```
Model ROC-AUC score for training sample: 0.999
Model ROC-AUC score for test sample: 0.979
Train Accuracy:  0.9797435897435898
Test Accuracy:  0.9694976076555024
Classification report:
               precision    recall  f1-score   support

           0       0.97      1.00      0.98      1448
           1       0.96      0.80      0.88       224

    accuracy                           0.97      1672
   macro avg       0.97      0.90      0.93      1672
weighted avg       0.97      0.97      0.97      1672
```



Logistic Regression performs the best as it has overall good accuracy, and misclassifies less not spam as spam, which is the desired behavior because we do not want to label an important message as spam.

2. Deep Learning Models

Following neural network models have been trained with different embeddings:

- GloVe Embeddings
  - Vanilla Neural Network
  - LSTM
  - BiLSTM
  - BiLSTM with Attention
- FastText Embeddings
  - Vanilla Neural Network
  - LSTM
  - BiLSTM
  - BiLSTM with Attention
- Word2Vec Embeddings
  - Vanilla Neural Network
  - LSTM
  - BiLSTM
  - BiLSTM with Attention

In [6]:
```
# Mount data
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

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 [3]:
```
# 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 [4]:
```
class DLPipeline():
  def __init__(self):
    pass
  def preprocess(self, text):
    '''Preprocesses text, removes punctuation and extra spaces'''
    special_characters = re.compile("[^A-Za-z0-9 ]")
    # remove punctuation
    s = re.sub(special_characters, " ", text)
    s = re.sub(r"\s+[a-zA-Z]\s+", ' ', s)
    s = re.sub(r'\s+', ' ', s)
    return s

  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['acc'])
    plt.plot(history.history['val_acc'])
    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_simple_nn_model(self, embedding_matrix, vocab_size, maxlen, embedding_dim):
    '''Create a vanilla neural network model'''
    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 flatten layer
    model.add(Flatten())
    # Add the final Dense layer for classification
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
    return model

  def create_globalavg_nn_model(self, embedding_matrix, vocab_size, maxlen, embedding_dim):
    '''Create a vanilla neural network model with Global average pooling instead of Flatten'''
    model = Sequential()
    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 flatten layer
    model.add(GlobalAveragePooling1D())
    # Add the final Dense layer for classification
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
    return model

  def create_LSTM_nn_model(self, embedding_matrix, vocab_size, maxlen, embedding_dim, trainable = False):
    '''Creates an LSTM 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=trainable)
    model.add(embedding_layer)
    # Add a LSTM layer
    model.add(LSTM(128))
    # Add the final Dense layer for classification
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
    return model

  def create_BiLSTM_nn_model(self, embedding_matrix, vocab_size, maxlen, embedding_dim):
    '''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
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
    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
    outputs=Dense(1, trainable=True, activation='sigmoid')(attention_layer)
    model = Model(x,outputs)
    model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['acc'])
    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: ", 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 = [1 * (x[0]>=0.5) for x in y_pred]
    test_auc_score = roc_auc_score(y_test, y_pred)
    print(classification_report(y_test, y_pred_bool))
    print("Model ROC-AUC score for test sample: %.3f" \
                                      % test_auc_score)
    skplt.metrics.plot_confusion_matrix(y_test, y_pred_bool, title="Confusion Matrix",
              text_fontsize='large')
    plt.show()
```

In [5]:

```
# Instantiate DL Pipeline
dl_pipeline = DLPipeline()
```

Data Preprocessing

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

In [6]:

```
X = list(df['text'].apply(lambda x: dl_pipeline.preprocess(x)))
# Encode the y variable
le = LabelEncoder()
y = le.fit_transform(df['label'])
y
```

Out[6]:

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

In [7]:

```
len(X), y.shape
```

Out[7]:

```
(5572, (5572,))
```

Train Test Split

I have created a stratified train test split of 80-20 % to take care of class imbalance.

In [8]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=42, stratify = y)
```

Tokenize Data

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

In [9]:

```
X_train, X_test, tokenizer, vocab_size = dl_pipeline.tokenize(X_train, X_test)
len(X_train), len(tokenizer.word_index)
```

Out[9]:

```
(4457, 7688)
```

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 [10]:

```
max_len = 100
X_train, X_test = dl_pipeline.create_padding(X_train, X_test, max_len)
X_train.shape, X_test.shape
```

Out[10]:

```
((4457, 100), (1115, 100))
```

Neural Networks with Glove Embeddings

I have trained 4 models with pre trained Glove Embeddings:

- Simple Neural Network
- LSTM
- BiLSTM
- BiLSTM with Attention

Loading Glove Vectors

Let us load the pretrained Glove embeddings in a dictionary.

In [55]:

```
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 [56]:

```
embedding_dim = 100
embedding_matrix = dl_pipeline.create_glove_embedding_matrix(tokenizer, glove_embeddings_dict, vocab_size, embe

embedding_matrix.shape
```

Out[56]:

```
(7689, 100)
```

Neural Network

Let us create a simple neural network model with only embedding layer and flatten layer, with the embeddings from Glove.

In [57]:

```
nn_model = dl_pipeline.create_simple_nn_model(embedding_matrix, vocab_size, max_len,embedding_dim)
```

In [58]:

```
nn_model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_7 (Embedding)     (None, 100, 100)          768900

 flatten_1 (Flatten)         (None, 10000)             0

 dense_7 (Dense)             (None, 1)                 10001

=================================================================
Total params: 778,901
Trainable params: 10,001
Non-trainable params: 768,900
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size

In [59]:

```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(nn_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 1s 17ms/step - loss: 0.3649 - acc: 0.8766 - val_loss: 0.2586 - val_ac
c: 0.9070
Epoch 2/20
28/28 [==============================] - 0s 6ms/step - loss: 0.1958 - acc: 0.9397 - val_loss: 0.1941 - val_acc:
0.9361
Epoch 3/20
28/28 [==============================] - 0s 6ms/step - loss: 0.1493 - acc: 0.9619 - val_loss: 0.1672 - val_acc:
0.9484
Epoch 4/20
28/28 [==============================] - 0s 6ms/step - loss: 0.1249 - acc: 0.9691 - val_loss: 0.1503 - val_acc:
0.9574
Epoch 5/20
28/28 [==============================] - 0s 8ms/step - loss: 0.1091 - acc: 0.9739 - val_loss: 0.1398 - val_acc:
0.9574
Epoch 6/20
28/28 [==============================] - 0s 7ms/step - loss: 0.0974 - acc: 0.9767 - val_loss: 0.1297 - val_acc:
0.9641
Epoch 7/20
28/28 [==============================] - 0s 8ms/step - loss: 0.0882 - acc: 0.9781 - val_loss: 0.1211 - val_acc:
0.9686
Epoch 8/20
28/28 [==============================] - 0s 5ms/step - loss: 0.0802 - acc: 0.9812 - val_loss: 0.1208 - val_acc:
0.9664
Epoch 9/20
28/28 [==============================] - 0s 8ms/step - loss: 0.0737 - acc: 0.9829 - val_loss: 0.1113 - val_acc:
0.9697
Epoch 10/20
28/28 [==============================] - 0s 7ms/step - loss: 0.0682 - acc: 0.9857 - val_loss: 0.1097 - val_acc:
0.9697
Epoch 11/20
28/28 [==============================] - 0s 6ms/step - loss: 0.0635 - acc: 0.9863 - val_loss: 0.1062 - val_acc:
0.9709
Epoch 12/20
28/28 [==============================] - 0s 5ms/step - loss: 0.0594 - acc: 0.9879 - val_loss: 0.1033 - val_acc:
0.9675
Epoch 13/20
28/28 [==============================] - 0s 7ms/step - loss: 0.0557 - acc: 0.9885 - val_loss: 0.1033 - val_acc:
0.9697
Epoch 14/20
28/28 [==============================] - 0s 9ms/step - loss: 0.0525 - acc: 0.9893 - val_loss: 0.1021 - val_acc:
0.9697
Epoch 15/20
28/28 [==============================] - 0s 6ms/step - loss: 0.0493 - acc: 0.9902 - val_loss: 0.0987 - val_acc:
0.9697
Epoch 16/20
28/28 [==============================] - 0s 5ms/step - loss: 0.0467 - acc: 0.9905 - val_loss: 0.0982 - val_acc:
0.9697
Epoch 17/20
28/28 [==============================] - 0s 6ms/step - loss: 0.0441 - acc: 0.9910 - val_loss: 0.0966 - val_acc:
0.9697
Epoch 18/20
28/28 [==============================] - 0s 5ms/step - loss: 0.0421 - acc: 0.9924 - val_loss: 0.1001 - val_acc:
0.9709
Epoch 19/20
28/28 [==============================] - 0s 7ms/step - loss: 0.0401 - acc: 0.9927 - val_loss: 0.0956 - val_acc:
0.9686
Epoch 20/20
28/28 [==============================] - 0s 6ms/step - loss: 0.0379 - acc: 0.9930 - val_loss: 0.0957 - val_acc:
0.9686
35/35 [==============================] - 0s 3ms/step - loss: 0.0907 - acc: 0.9731
Test loss, Test Accuracy:  [0.09068842232227325, 0.9730941653251648]
```

Evaluate Model

Evaluate model with different metrics:

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

In [60]:

```
dl_pipeline.evaluate_model(nn_model, X_test, y_test)
```

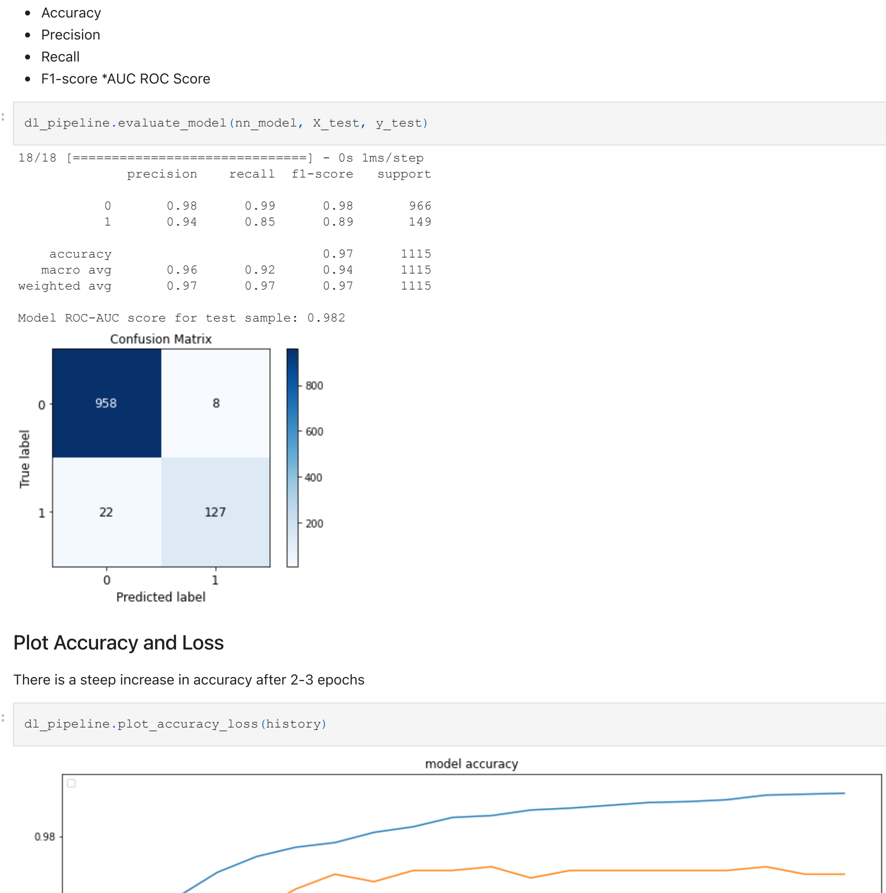
```
18/18 [==============================] - 0s 1ms/step
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       966
           1       0.94      0.85      0.89       149

    accuracy                           0.97      1115
   macro avg       0.96      0.92      0.94      1115
weighted avg       0.97      0.97      0.97      1115

Model ROC-AUC score for test sample: 0.982
```

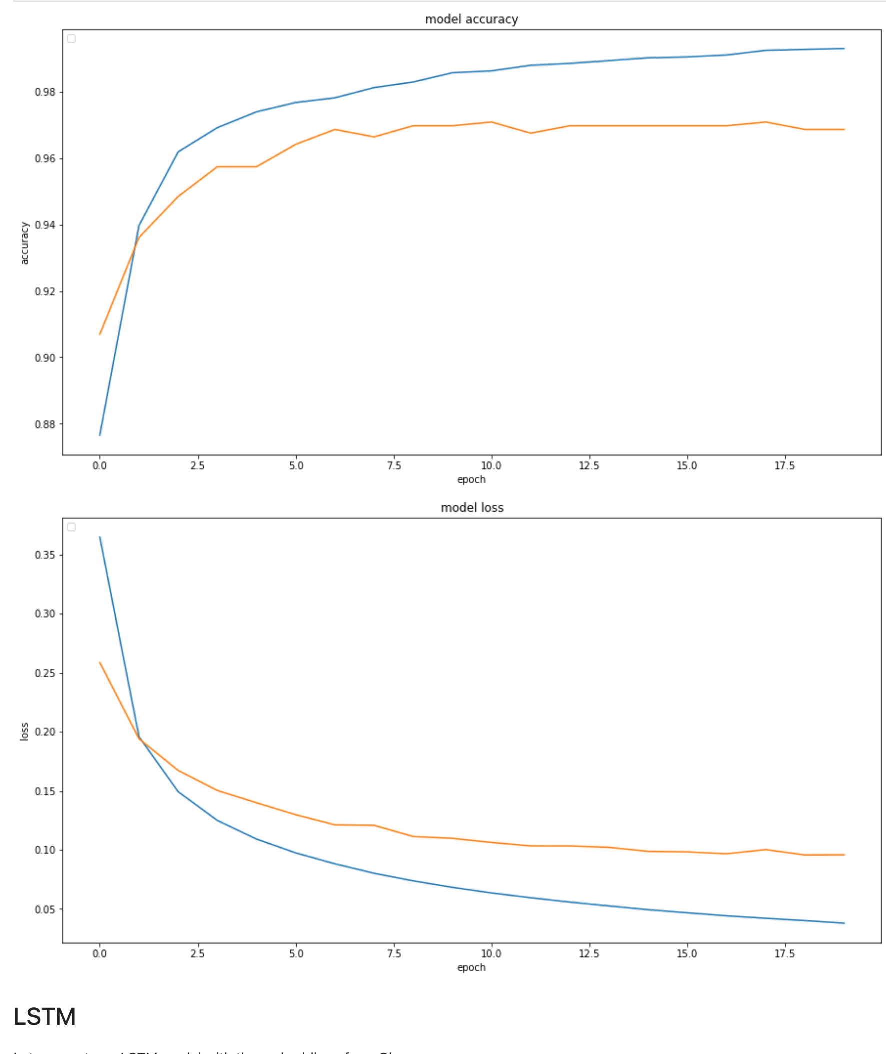
Plot Accuracy and Loss

There is a steep increase in accuracy after 2-3 epochs

In [61]:

```
dl_pipeline.plot_accuracy_loss(history)
```





LSTM

Let us create an LSTM model with the embeddings from Glove.

In [67]:

```
lstm_model = dl_pipeline.create_LSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [68]:

```
lstm_model.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_9 (Embedding)     (None, 100, 100)          768900

 lstm_7 (LSTM)               (None, 128)               117248

 dense_9 (Dense)             (None, 1)                 129

=================================================================
Total params: 886,277
Trainable params: 117,377
Non-trainable params: 768,900
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [69]:

```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(lstm_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 2s 31ms/step - loss: 0.4714 - acc: 0.8738 - val_loss: 0.2459 - val_ac
c: 0.9070
Epoch 2/20
28/28 [==============================] - 0s 12ms/step - loss: 0.2251 - acc: 0.9408 - val_loss: 0.1954 - val_ac
c: 0.9529
Epoch 3/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1391 - acc: 0.9599 - val_loss: 0.1691 - val_ac
c: 0.9406
Epoch 4/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1431 - acc: 0.9560 - val_loss: 0.1485 - val_ac
c: 0.9608
Epoch 5/20
28/28 [==============================] - 0s 11ms/step - loss: 0.1314 - acc: 0.9649 - val_loss: 0.1358 - val_ac
c: 0.9720
Epoch 6/20
28/28 [==============================] - 0s 11ms/step - loss: 0.1080 - acc: 0.9731 - val_loss: 0.1492 - val_ac
c: 0.9552
Epoch 7/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1069 - acc: 0.9717 - val_loss: 0.2304 - val_ac
c: 0.9496
Epoch 8/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1738 - acc: 0.9509 - val_loss: 0.1340 - val_ac
c: 0.9641
Epoch 9/20
28/28 [==============================] - 0s 11ms/step - loss: 0.1118 - acc: 0.9677 - val_loss: 0.1394 - val_ac
c: 0.9664
Epoch 10/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0920 - acc: 0.9770 - val_loss: 0.1020 - val_ac
c: 0.9720
Epoch 11/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0752 - acc: 0.9792 - val_loss: 0.0927 - val_ac
c: 0.9742
Epoch 12/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0779 - acc: 0.9773 - val_loss: 0.1058 - val_ac
c: 0.9697
Epoch 13/20
28/28 [==============================] - 0s 10ms/step - loss: 0.0702 - acc: 0.9798 - val_loss: 0.0926 - val_ac
c: 0.9787
Epoch 14/20
28/28 [==============================] - 0s 10ms/step - loss: 0.0676 - acc: 0.9840 - val_loss: 0.0807 - val_ac
c: 0.9765
Epoch 15/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0565 - acc: 0.9865 - val_loss: 0.1214 - val_ac
c: 0.9765
Epoch 16/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0605 - acc: 0.9843 - val_loss: 0.0977 - val_ac
c: 0.9652
Epoch 17/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0581 - acc: 0.9823 - val_loss: 0.0996 - val_ac
c: 0.9753
Epoch 18/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0627 - acc: 0.9820 - val_loss: 0.0977 - val_ac
c: 0.9742
Epoch 19/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0899 - acc: 0.9784 - val_loss: 0.1055 - val_ac
c: 0.9675
Epoch 20/20
28/28 [==============================] - 0s 11ms/step - loss: 0.0541 - acc: 0.9851 - val_loss: 0.0998 - val_ac
c: 0.9731
35/35 [==============================] - 0s 5ms/step - loss: 0.0831 - acc: 0.9803
Test loss, Test Accuracy:  [0.08305352926254272, 0.9802690744400024]
```

Evaluate Model

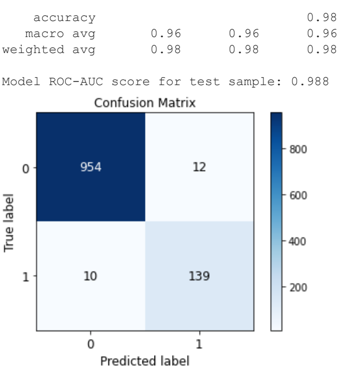
Evaluate model with different metrics:

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

In [70]:

```
dl_pipeline.evaluate_model(lstm_model, X_test, y_test)
```

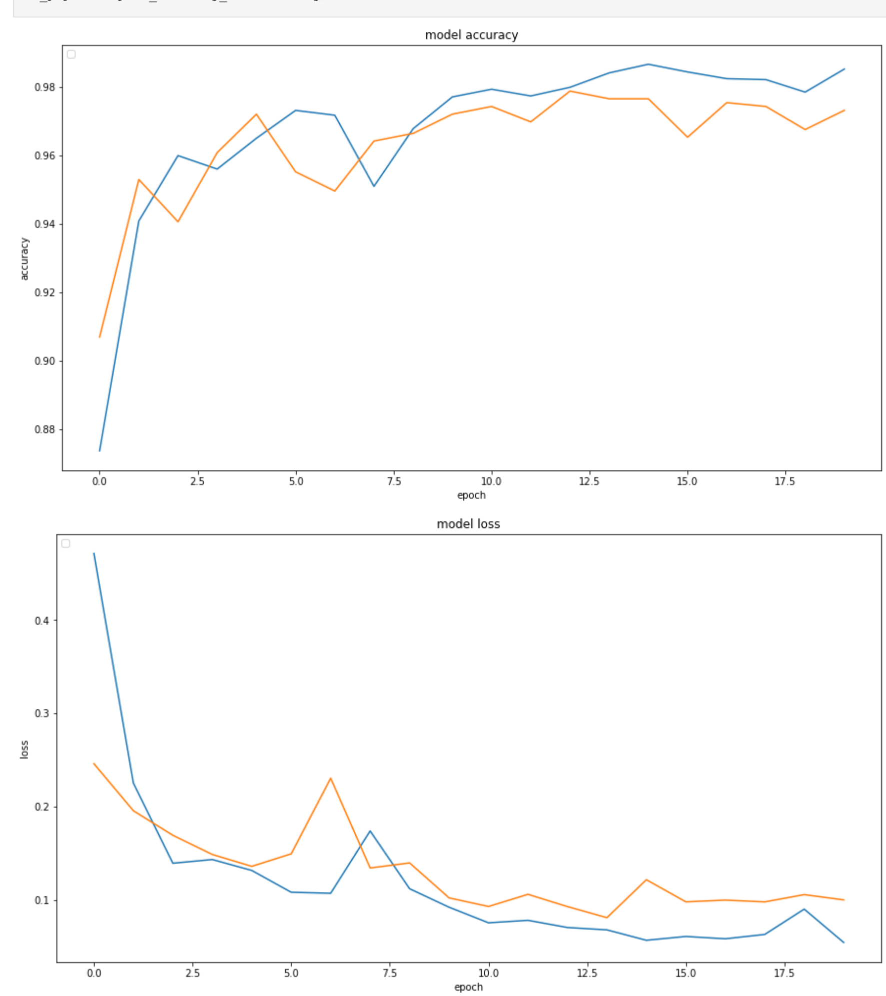
```
18/18 [==============================] - 0s 5ms/step
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       966
           1       0.92      0.93      0.93       149

    accuracy                           0.98      1115
   macro avg       0.96      0.96      0.96      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.988
```

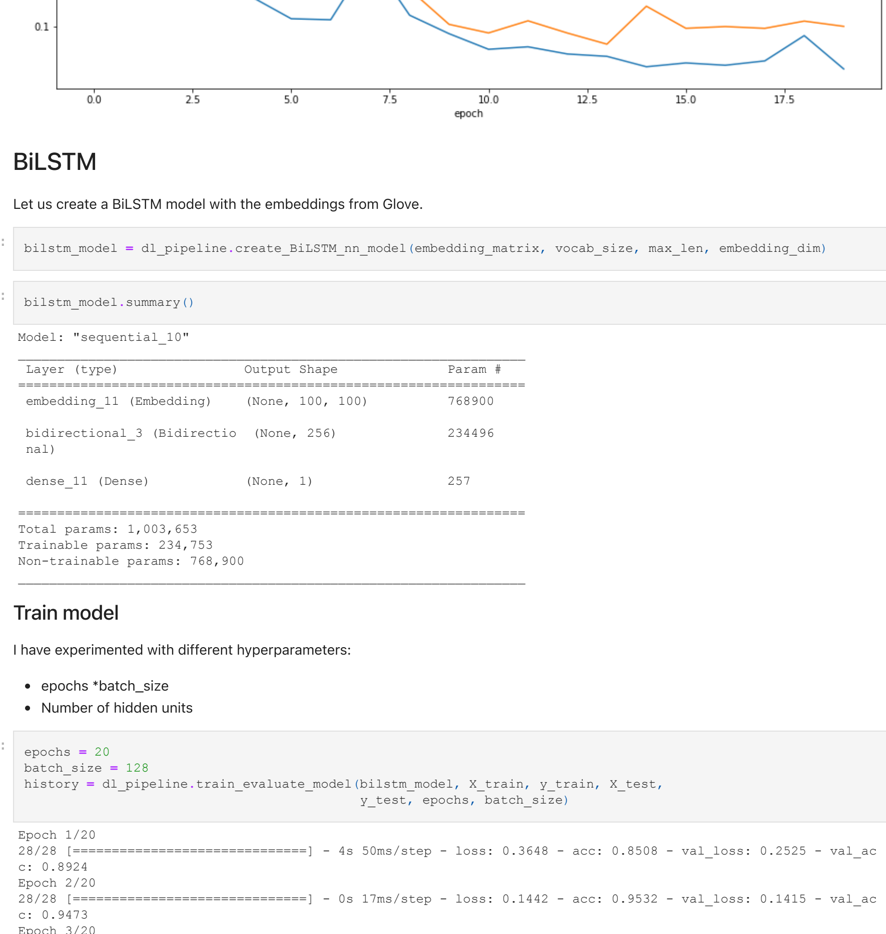


Plot Accuracy and Loss

In [71]:

```
dl_pipeline.plot_accuracy_loss(history)
```





BiLSTM

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

In [79]:

```
bilstm_model = dl_pipeline.create_BiLSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [80]:

```
bilstm_model.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_11 (Embedding)    (None, 100, 100)          768900

 bidirectional_3 (Bidirectio  (None, 256)              234496
 nal)

 dense_11 (Dense)            (None, 1)                 257

=================================================================
Total params: 1,003,653
Trainable params: 234,753
Non-trainable params: 768,900
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [81]:

```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(bilstm_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 4s 50ms/step - loss: 0.3648 - acc: 0.8508 - val_loss: 0.2525 - val_ac
c: 0.8924
Epoch 2/20
28/28 [==============================] - 0s 17ms/step - loss: 0.1442 - acc: 0.9532 - val_loss: 0.1415 - val_ac
c: 0.9473
Epoch 3/20
28/28 [==============================] - 0s 18ms/step - loss: 0.0954 - acc: 0.9728 - val_loss: 0.0934 - val_ac
c: 0.9709
Epoch 4/20
28/28 [==============================] - 0s 18ms/step - loss: 0.0755 - acc: 0.9773 - val_loss: 0.0854 - val_ac
c: 0.9720
Epoch 5/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0631 - acc: 0.9818 - val_loss: 0.0726 - val_ac
c: 0.9753
Epoch 6/20
28/28 [==============================] - 1s 24ms/step - loss: 0.0589 - acc: 0.9829 - val_loss: 0.0848 - val_ac
c: 0.9686
Epoch 7/20
28/28 [==============================] - 1s 24ms/step - loss: 0.0478 - acc: 0.9857 - val_loss: 0.0734 - val_ac
c: 0.9765
Epoch 8/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0524 - acc: 0.9849 - val_loss: 0.0731 - val_ac
c: 0.9776
Epoch 9/20
28/28 [==============================] - 1s 25ms/step - loss: 0.0392 - acc: 0.9893 - val_loss: 0.0761 - val_ac
c: 0.9742
Epoch 10/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0326 - acc: 0.9919 - val_loss: 0.0702 - val_ac
c: 0.9798
Epoch 11/20
28/28 [==============================] - 0s 17ms/step - loss: 0.0329 - acc: 0.9910 - val_loss: 0.0633 - val_ac
c: 0.9809
Epoch 12/20
28/28 [==============================] - 0s 18ms/step - loss: 0.0317 - acc: 0.9910 - val_loss: 0.0614 - val_ac
c: 0.9821
Epoch 13/20
28/28 [==============================] - 1s 18ms/step - loss: 0.0241 - acc: 0.9927 - val_loss: 0.0731 - val_ac
c: 0.9798
Epoch 14/20
28/28 [==============================] - 1s 20ms/step - loss: 0.0170 - acc: 0.9961 - val_loss: 0.0611 - val_ac
c: 0.9809
Epoch 15/20
28/28 [==============================] - 1s 18ms/step - loss: 0.0149 - acc: 0.9964 - val_loss: 0.0835 - val_ac
c: 0.9787
Epoch 16/20
28/28 [==============================] - 0s 18ms/step - loss: 0.0135 - acc: 0.9966 - val_loss: 0.0912 - val_ac
c: 0.9787
Epoch 17/20
28/28 [==============================] - 0s 17ms/step - loss: 0.0397 - acc: 0.9882 - val_loss: 0.0632 - val_ac
c: 0.9809
Epoch 18/20
28/28 [==============================] - 1s 18ms/step - loss: 0.0263 - acc: 0.9919 - val_loss: 0.0965 - val_ac
c: 0.9742
Epoch 19/20
28/28 [==============================] - 0s 17ms/step - loss: 0.0191 - acc: 0.9952 - val_loss: 0.0656 - val_ac
c: 0.9809
Epoch 20/20
28/28 [==============================] - 0s 18ms/step - loss: 0.0117 - acc: 0.9972 - val_loss: 0.0571 - val_ac
c: 0.9809
35/35 [==============================] - 0s 7ms/step - loss: 0.0577 - acc: 0.9839
Test loss, Test Accuracy:  [0.05771006643772125, 0.9838564991950989]
```

Evaluate Model

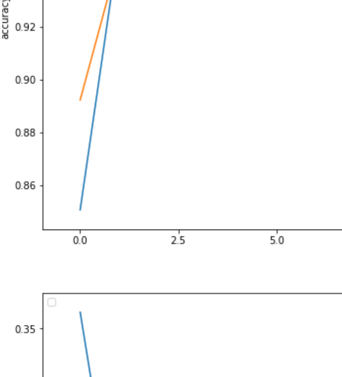
Evaluate model with different metrics:

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

In [82]:

```
dl_pipeline.evaluate_model(bilstm_model, X_test, y_test)
```

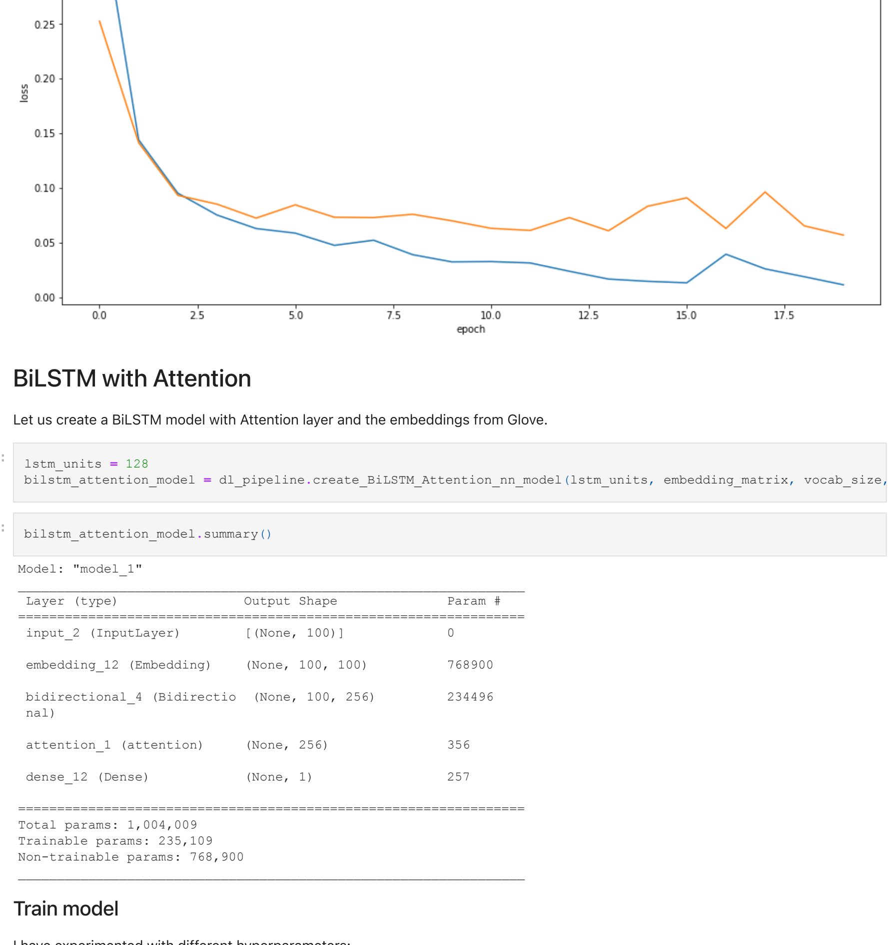
```
18/18 [==============================] - 1s 8ms/step
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       966
           1       0.95      0.93      0.94       149

    accuracy                           0.98      1115
   macro avg       0.97      0.96      0.96      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.992
```

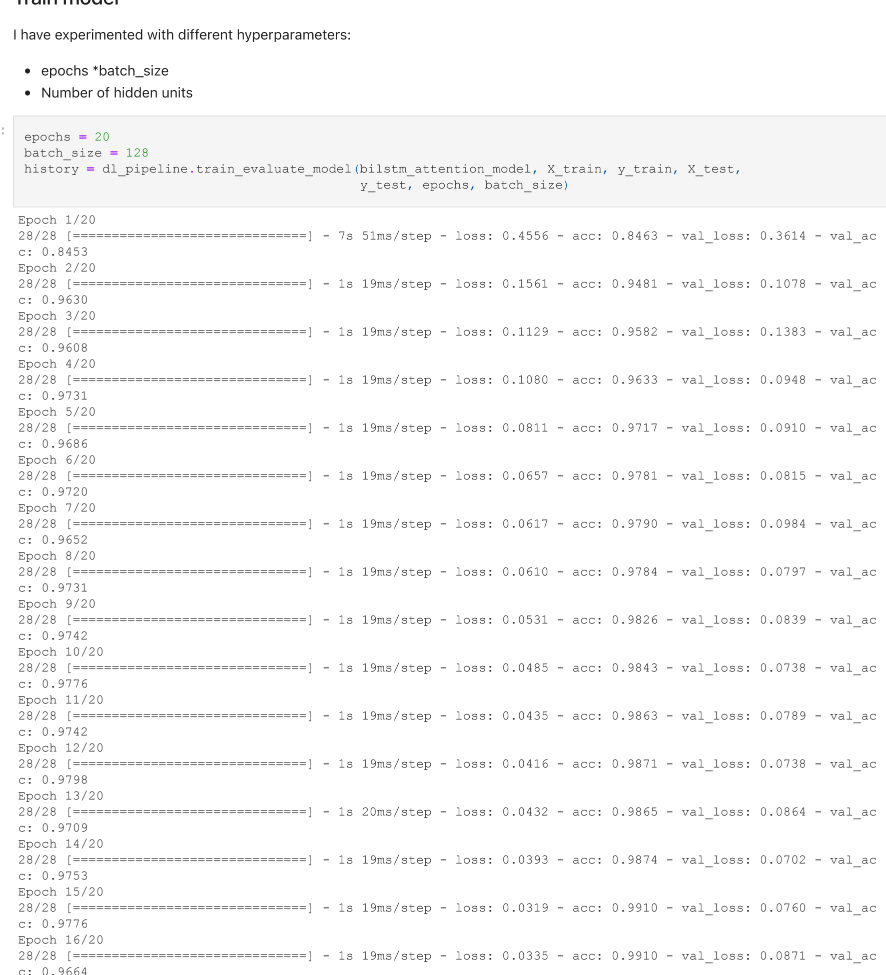


Plot Accuracy and Loss

In [84]:

```
dl_pipeline.plot_accuracy_loss(history)
```





BiLSTM with Attention

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

In [85]:

```
lstm_units = 128
bilstm_attention_model = dl_pipeline.create_BiLSTM_Attention_nn_model(lstm_units, embedding_matrix, vocab_size,
```

In [86]:

```
bilstm_attention_model.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 100)]             0

 embedding_12 (Embedding)    (None, 100, 100)          768900

 bidirectional_4 (Bidirectio  (None, 100, 256)         234496
 nal)

 attention_1 (attention)     (None, 256)               356

 dense_12 (Dense)            (None, 1)                 257

=================================================================
Total params: 1,004,009
Trainable params: 235,109
Non-trainable params: 768,900
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [87]:

```
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
28/28 [==============================] - 7s 51ms/step - loss: 0.4556 - acc: 0.8463 - val_loss: 0.3614 - val_ac
c: 0.8453
Epoch 2/20
28/28 [==============================] - 1s 19ms/step - loss: 0.1561 - acc: 0.9481 - val_loss: 0.1078 - val_ac
c: 0.9630
Epoch 3/20
28/28 [==============================] - 1s 19ms/step - loss: 0.1129 - acc: 0.9582 - val_loss: 0.1383 - val_ac
c: 0.9608
Epoch 4/20
28/28 [==============================] - 1s 19ms/step - loss: 0.1080 - acc: 0.9633 - val_loss: 0.0948 - val_ac
c: 0.9731
Epoch 5/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0811 - acc: 0.9717 - val_loss: 0.0910 - val_ac
c: 0.9686
Epoch 6/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0657 - acc: 0.9781 - val_loss: 0.0815 - val_ac
c: 0.9720
Epoch 7/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0617 - acc: 0.9790 - val_loss: 0.0984 - val_ac
c: 0.9652
Epoch 8/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0610 - acc: 0.9784 - val_loss: 0.0797 - val_ac
c: 0.9731
Epoch 9/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0531 - acc: 0.9826 - val_loss: 0.0839 - val_ac
c: 0.9742
Epoch 10/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0485 - acc: 0.9843 - val_loss: 0.0738 - val_ac
c: 0.9776
Epoch 11/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0435 - acc: 0.9863 - val_loss: 0.0789 - val_ac
c: 0.9742
Epoch 12/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0416 - acc: 0.9871 - val_loss: 0.0738 - val_ac
c: 0.9798
Epoch 13/20
28/28 [==============================] - 1s 20ms/step - loss: 0.0432 - acc: 0.9865 - val_loss: 0.0864 - val_ac
c: 0.9709
Epoch 14/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0393 - acc: 0.9874 - val_loss: 0.0702 - val_ac
c: 0.9753
Epoch 15/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0319 - acc: 0.9910 - val_loss: 0.0760 - val_ac
c: 0.9776
Epoch 16/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0335 - acc: 0.9910 - val_loss: 0.0871 - val_ac
c: 0.9664
Epoch 17/20
28/28 [==============================] - 1s 20ms/step - loss: 0.0415 - acc: 0.9865 - val_loss: 0.0966 - val_ac
c: 0.9731
Epoch 18/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0426 - acc: 0.9868 - val_loss: 0.0963 - val_ac
c: 0.9720
Epoch 19/20
28/28 [==============================] - 1s 19ms/step - loss: 0.0379 - acc: 0.9896 - val_loss: 0.1001 - val_ac
c: 0.9709
Epoch 20/20
28/28 [==============================] - 1s 20ms/step - loss: 0.0338 - acc: 0.9899 - val_loss: 0.0940 - val_ac
c: 0.9731
35/35 [==============================] - 0s 8ms/step - loss: 0.0716 - acc: 0.9830
Test loss, Test Accuracy:  [0.07156720757484436, 0.9829596281051636]
```

Evaluate Model

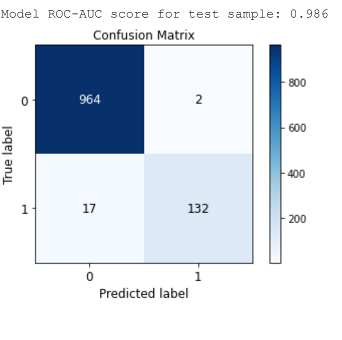
Evaluate model with different metrics:

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

In [88]:

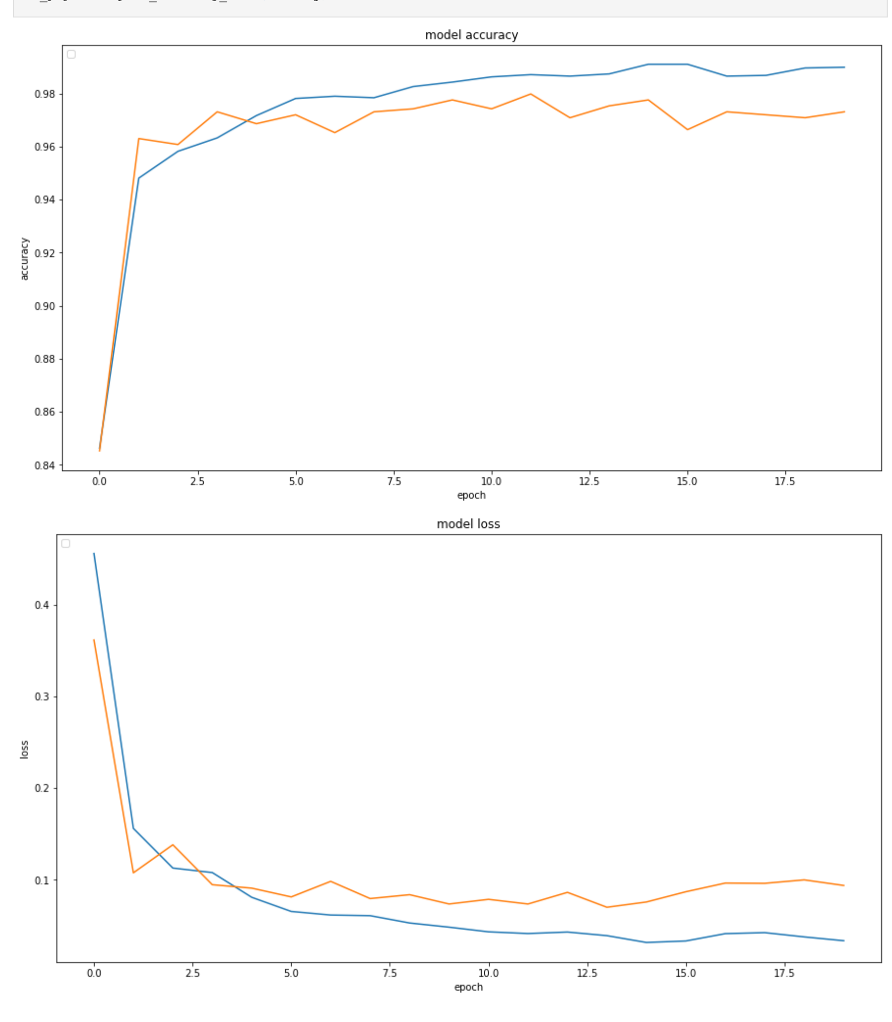
```
dl_pipeline.evaluate_model(bilstm_attention_model, X_test, y_test)
```

```
18/18 [==============================] - 1s 9ms/step
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       966
           1       0.99      0.89      0.93       149

    accuracy                           0.98      1115
   macro avg       0.98      0.94      0.96      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.986
```



Plot Accuracy and Loss

In [89]:
```
dl_pipeline.plot_accuracy_loss(history)
```



Simple Neural Network with FastText

Loading FastText Vectors

Let us load the pretrained FastText embeddings in a dictionary.

In [13]:
```
root = "/content/drive/MyDrive/"
fasttext_file_name = 'cc.en.300.bin'

fasttext_embedding_dict = dl_pipeline.load_fasttext_embedding_dictionary(root, fasttext_file_name)
```

```
Warning : `load_model` does not return WordVectorModel or SupervisedModel any more, but a `FastText` object whi
ch is very similar.
```

Creating Embedding Matrix

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

In [14]:
```
embedding_dim = 300
embedding_matrix = dl_pipeline.create_embedding_matrix(tokenizer, fasttext_embedding_dict, vocab_size, embeddir
```

Neural Network

Let us create a simple neural network model with the embeddings from Fasttext.

In [15]:
```
embedding_dim = 300
lstm_units = 128
fasttext_nn_model = dl_pipeline.create_simple_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [16]:
```
fasttext_nn_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 100, 300)          2306700

 flatten (Flatten)           (None, 30000)             0

 dense (Dense)               (None, 1)                 30001

=================================================================
Total params: 2,336,701
Trainable params: 30,001
Non-trainable params: 2,306,700
_________________________________________________________________
```

In [17]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(fasttext_nn_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 3s 9ms/step - loss: 0.4587 - acc: 0.8637 - val_loss: 0.3524 - val_acc:
0.8666
Epoch 2/20
28/28 [==============================] - 0s 4ms/step - loss: 0.2642 - acc: 0.9234 - val_loss: 0.2492 - val_acc:
0.9193
Epoch 3/20
28/28 [==============================] - 0s 4ms/step - loss: 0.1962 - acc: 0.9526 - val_loss: 0.2070 - val_acc:
0.9361
Epoch 4/20
28/28 [==============================] - 0s 4ms/step - loss: 0.1603 - acc: 0.9593 - val_loss: 0.1783 - val_acc:
0.9484
Epoch 5/20
28/28 [==============================] - 0s 4ms/step - loss: 0.1366 - acc: 0.9666 - val_loss: 0.1587 - val_acc:
0.9540
Epoch 6/20
28/28 [==============================] - 0s 5ms/step - loss: 0.1194 - acc: 0.9722 - val_loss: 0.1457 - val_acc:
0.9574
Epoch 7/20
28/28 [==============================] - 0s 4ms/step - loss: 0.1064 - acc: 0.9770 - val_loss: 0.1337 - val_acc:
0.9664
Epoch 8/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0960 - acc: 0.9806 - val_loss: 0.1252 - val_acc:
0.9664
Epoch 9/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0877 - acc: 0.9820 - val_loss: 0.1184 - val_acc:
0.9675
Epoch 10/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0806 - acc: 0.9820 - val_loss: 0.1128 - val_acc:
0.9686
Epoch 11/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0746 - acc: 0.9851 - val_loss: 0.1077 - val_acc:
0.9709
Epoch 12/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0694 - acc: 0.9863 - val_loss: 0.1038 - val_acc:
0.9720
Epoch 13/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0649 - acc: 0.9868 - val_loss: 0.0998 - val_acc:
0.9720
Epoch 14/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0609 - acc: 0.9874 - val_loss: 0.0973 - val_acc:
0.9731
Epoch 15/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0573 - acc: 0.9874 - val_loss: 0.0946 - val_acc:
0.9731
Epoch 16/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0541 - acc: 0.9882 - val_loss: 0.0921 - val_acc:
0.9731
Epoch 17/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0512 - acc: 0.9888 - val_loss: 0.0904 - val_acc:
0.9753
Epoch 18/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0486 - acc: 0.9899 - val_loss: 0.0886 - val_acc:
0.9753
Epoch 19/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0463 - acc: 0.9905 - val_loss: 0.0867 - val_acc:
0.9753
Epoch 20/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0441 - acc: 0.9916 - val_loss: 0.0855 - val_acc:
0.9753
35/35 [==============================] - 0s 2ms/step - loss: 0.0982 - acc: 0.9758
Test loss, Test Accuracy:  [0.09824149310588837, 0.9757847785949707]
```

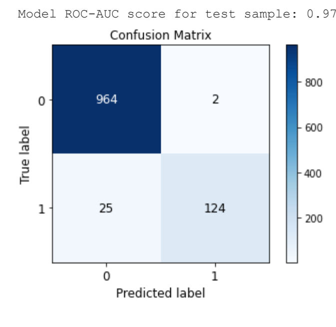
Evaluate Model

Evaluate model with different metrics:

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

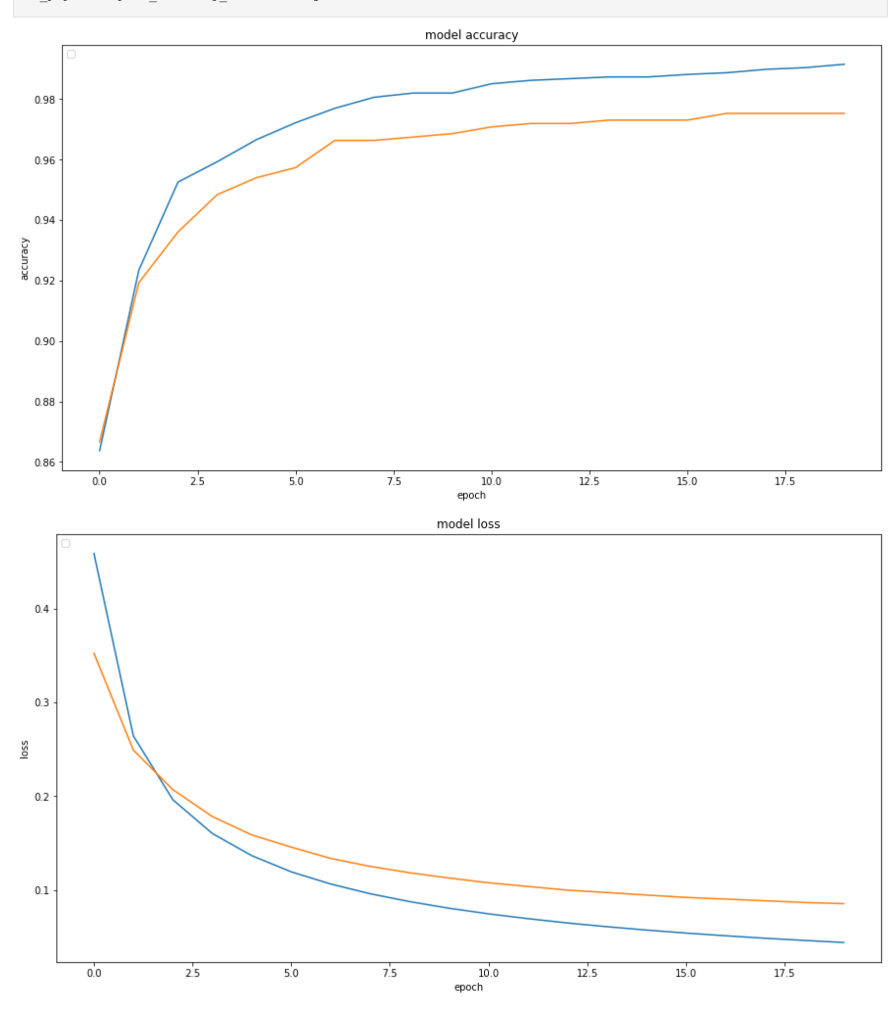
In [18]:
```
dl_pipeline.evaluate_model(fasttext_nn_model, X_test, y_test)
```

```
18/18 [==============================] - 0s 2ms/step
              precision    recall  f1-score   support

           0       0.97      1.00      0.99       966
           1       0.98      0.83      0.90       149

    accuracy                           0.98      1115
   macro avg       0.98      0.92      0.94      1115
weighted avg       0.98      0.98      0.97      1115

Model ROC-AUC score for test sample: 0.977
```



Plot Accuracy and Loss

In [19]:
```
dl_pipeline.plot_accuracy_loss(history)
```



LSTM

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

In [20]:
```
embedding_dim = 300
lstm_units = 128
fasttext_lstm_model = dl_pipeline.create_LSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [21]:
```
fasttext_lstm_model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_1 (Embedding)     (None, 100, 300)          2306700

 lstm (LSTM)                 (None, 128)               219648

 dense_1 (Dense)             (None, 1)                 129

=================================================================
Total params: 2,526,477
Trainable params: 219,777
Non-trainable params: 2,306,700
_________________________________________________________________
```

In [22]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(fasttext_lstm_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 5s 33ms/step - loss: 0.4754 - acc: 0.8687 - val_loss: 0.4345 - val_ac
c: 0.8430
Epoch 2/20
28/28 [==============================] - 0s 12ms/step - loss: 0.3433 - acc: 0.8712 - val_loss: 0.3102 - val_ac
c: 0.8430
Epoch 3/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1919 - acc: 0.9077 - val_loss: 0.1861 - val_ac
c: 0.9686
Epoch 4/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1524 - acc: 0.9644 - val_loss: 0.1555 - val_ac
c: 0.9630
Epoch 5/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1408 - acc: 0.9624 - val_loss: 0.1566 - val_ac
c: 0.9619
Epoch 6/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1727 - acc: 0.9557 - val_loss: 0.4075 - val_ac
c: 0.8834
Epoch 7/20
28/28 [==============================] - 0s 13ms/step - loss: 0.3726 - acc: 0.8816 - val_loss: 0.4183 - val_ac
c: 0.8576
Epoch 8/20
28/28 [==============================] - 0s 12ms/step - loss: 0.3622 - acc: 0.8822 - val_loss: 0.4095 - val_ac
c: 0.8576
Epoch 9/20
28/28 [==============================] - 0s 13ms/step - loss: 0.3386 - acc: 0.8954 - val_loss: 0.2247 - val_ac
c: 0.8430
Epoch 10/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1507 - acc: 0.9523 - val_loss: 0.1556 - val_ac
c: 0.9529
Epoch 11/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0944 - acc: 0.9728 - val_loss: 0.1138 - val_ac
c: 0.9664
Epoch 12/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0824 - acc: 0.9781 - val_loss: 0.1052 - val_ac
c: 0.9697
Epoch 13/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0695 - acc: 0.9792 - val_loss: 0.1089 - val_ac
c: 0.9596
Epoch 14/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0744 - acc: 0.9773 - val_loss: 0.1080 - val_ac
c: 0.9709
Epoch 15/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0670 - acc: 0.9818 - val_loss: 0.0979 - val_ac
c: 0.9709
Epoch 16/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0674 - acc: 0.9815 - val_loss: 0.1094 - val_ac
c: 0.9720
Epoch 17/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0662 - acc: 0.9778 - val_loss: 0.1030 - val_ac
c: 0.9765
Epoch 18/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0614 - acc: 0.9849 - val_loss: 0.1218 - val_ac
c: 0.9742
Epoch 19/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0665 - acc: 0.9801 - val_loss: 0.1038 - val_ac
c: 0.9765
Epoch 20/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0628 - acc: 0.9840 - val_loss: 0.1012 - val_ac
c: 0.9697
35/35 [==============================] - 0s 4ms/step - loss: 0.1009 - acc: 0.9740
Test loss, Test Accuracy:  [0.10091537982225418, 0.9739910364151001]
```

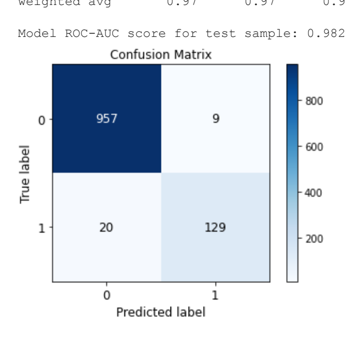
Evaluate Model

Evaluate model with different metrics:

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

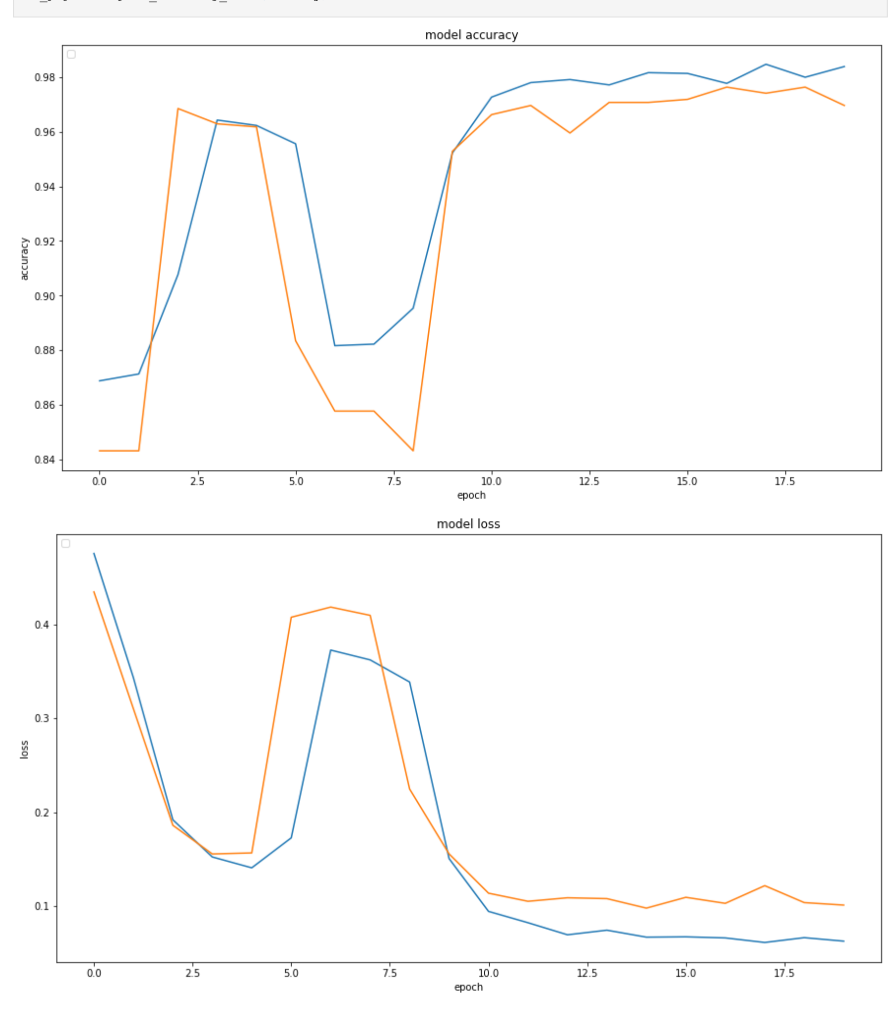
In [23]:
```
dl_pipeline.evaluate_model(fasttext_lstm_model, X_test, y_test)
```

```
18/18 [==============================] - 0s 4ms/step
              precision    recall  f1-score   support

           0       0.98      0.99      0.99       966
           1       0.93      0.87      0.90       149

    accuracy                           0.97      1115
   macro avg       0.96      0.93      0.94      1115
weighted avg       0.97      0.97      0.97      1115

Model ROC-AUC score for test sample: 0.982
```



Plot Accuracy and Loss

In [24]:
```
dl_pipeline.plot_accuracy_loss(history)
```



BiLSTM

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

In [25]:
```
embedding_dim = 300
lstm_units = 128
fasttext_bilstm_model = dl_pipeline.create_BiLSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim
```

In [26]:
```
fasttext_bilstm_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 100, 300)          2306700

 bidirectional (Bidirectiona  (None, 256)              439296
 l)

 dense_2 (Dense)             (None, 1)                 257

=================================================================
Total params: 2,746,253
Trainable params: 439,553
Non-trainable params: 2,306,700
_________________________________________________________________
```

In [27]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(fasttext_bilstm_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 4s 54ms/step - loss: 0.3630 - acc: 0.8547 - val_loss: 0.2082 - val_ac
c: 0.9271
Epoch 2/20
28/28 [==============================] - 1s 21ms/step - loss: 0.1033 - acc: 0.9652 - val_loss: 0.1110 - val_ac
c: 0.9675
Epoch 3/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0801 - acc: 0.9770 - val_loss: 0.0993 - val_ac
c: 0.9753
Epoch 4/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0554 - acc: 0.9829 - val_loss: 0.0788 - val_ac
c: 0.9709
Epoch 5/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0491 - acc: 0.9840 - val_loss: 0.0764 - val_ac
c: 0.9753
Epoch 6/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0492 - acc: 0.9840 - val_loss: 0.0648 - val_ac
c: 0.9832
Epoch 7/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0478 - acc: 0.9857 - val_loss: 0.0672 - val_ac
c: 0.9854
Epoch 8/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0369 - acc: 0.9896 - val_loss: 0.0661 - val_ac
c: 0.9832
Epoch 9/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0302 - acc: 0.9907 - val_loss: 0.0571 - val_ac
c: 0.9854
Epoch 10/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0245 - acc: 0.9933 - val_loss: 0.0721 - val_ac
c: 0.9832
Epoch 11/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0237 - acc: 0.9938 - val_loss: 0.1001 - val_ac
c: 0.9753
Epoch 12/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0291 - acc: 0.9907 - val_loss: 0.0577 - val_ac
c: 0.9888
Epoch 13/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0186 - acc: 0.9958 - val_loss: 0.0594 - val_ac
c: 0.9877
Epoch 14/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0158 - acc: 0.9969 - val_loss: 0.0629 - val_ac
c: 0.9877
Epoch 15/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0150 - acc: 0.9964 - val_loss: 0.0573 - val_ac
c: 0.9854
Epoch 16/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0134 - acc: 0.9966 - val_loss: 0.0583 - val_ac
c: 0.9877
Epoch 17/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0130 - acc: 0.9969 - val_loss: 0.0552 - val_ac
c: 0.9865
Epoch 18/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0116 - acc: 0.9975 - val_loss: 0.0624 - val_ac
c: 0.9877
Epoch 19/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0106 - acc: 0.9975 - val_loss: 0.0593 - val_ac
c: 0.9877
Epoch 20/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0240 - acc: 0.9935 - val_loss: 0.0523 - val_ac
c: 0.9888
35/35 [==============================] - 0s 7ms/step - loss: 0.0614 - acc: 0.9883
Test loss, Test Accuracy:  [0.06143366917967796, 0.9883407950401306]
```

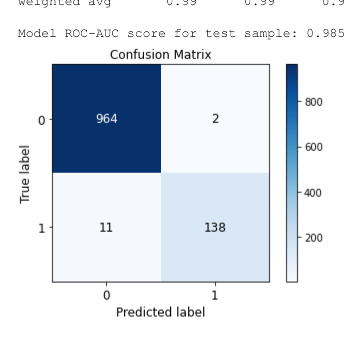
Evaluate Model

Evaluate model with different metrics:

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

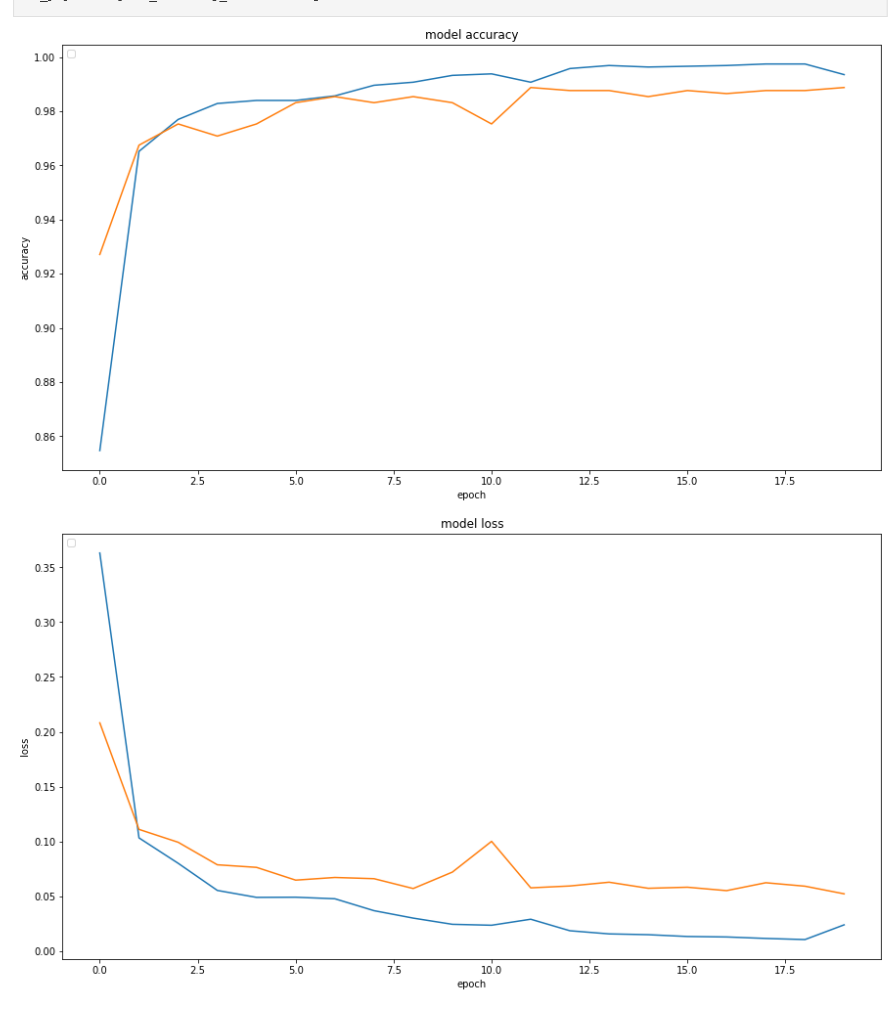
In [28]:
```
dl_pipeline.evaluate_model(fasttext_bilstm_model, X_test, y_test)
```

```
18/18 [==============================] - 1s 7ms/step
              precision    recall  f1-score   support

           0       0.99      1.00      0.99       966
           1       0.99      0.93      0.96       149

    accuracy                           0.99      1115
   macro avg       0.99      0.96      0.97      1115
weighted avg       0.99      0.99      0.99      1115

Model ROC-AUC score for test sample: 0.985
```



Plot Accuracy and Loss

In [29]:
```
dl_pipeline.plot_accuracy_loss(history)
```



BiLSTM with Attention

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

In [30]:
```
lstm_units = 128
fasttext_bilstm_attention_model = dl_pipeline.create_BiLSTM_Attention_nn_model(lstm_units, embedding_matrix, vo
```

In [31]:
```
fasttext_bilstm_attention_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 100)]             0

 embedding_3 (Embedding)     (None, 100, 300)          2306700

 bidirectional_1 (Bidirectio  (None, 100, 256)         439296
 nal)

 attention (attention)       (None, 256)               356

 dense_3 (Dense)             (None, 1)                 257

=================================================================
Total params: 2,746,609
Trainable params: 439,909
Non-trainable params: 2,306,700
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [32]:
```
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(fasttext_bilstm_attention_model, X_train, y_train, X_test,
                                           y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 5s 59ms/step - loss: 0.4369 - acc: 0.8589 - val_loss: 0.2514 - val_ac
c: 0.9238
Epoch 2/20
28/28 [==============================] - 1s 23ms/step - loss: 0.1937 - acc: 0.9330 - val_loss: 0.1303 - val_ac
c: 0.9574
Epoch 3/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0921 - acc: 0.9652 - val_loss: 0.1072 - val_ac
c: 0.9675
Epoch 4/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0618 - acc: 0.9792 - val_loss: 0.0796 - val_ac
c: 0.9686
Epoch 5/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0556 - acc: 0.9820 - val_loss: 0.0821 - val_ac
c: 0.9709
Epoch 6/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0439 - acc: 0.9877 - val_loss: 0.0700 - val_ac
c: 0.9765
Epoch 7/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0408 - acc: 0.9857 - val_loss: 0.0992 - val_ac
c: 0.9652
Epoch 8/20
28/28 [==============================] - 1s 22ms/step - loss: 0.0459 - acc: 0.9846 - val_loss: 0.0761 - val_ac
c: 0.9731
Epoch 9/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0469 - acc: 0.9846 - val_loss: 0.0970 - val_ac
c: 0.9742
Epoch 10/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0462 - acc: 0.9851 - val_loss: 0.0742 - val_ac
c: 0.9720
Epoch 11/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0435 - acc: 0.9832 - val_loss: 0.0648 - val_ac
c: 0.9753
Epoch 12/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0331 - acc: 0.9863 - val_loss: 0.0623 - val_ac
c: 0.9821
Epoch 13/20
28/28 [==============================] - 1s 24ms/step - loss: 0.0317 - acc: 0.9863 - val_loss: 0.0627 - val_ac
c: 0.9854
Epoch 14/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0283 - acc: 0.9910 - val_loss: 0.0620 - val_ac
c: 0.9776
Epoch 15/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0228 - acc: 0.9930 - val_loss: 0.0653 - val_ac
c: 0.9809
Epoch 16/20
28/28 [==============================] - 1s 24ms/step - loss: 0.0204 - acc: 0.9933 - val_loss: 0.0608 - val_ac
c: 0.9821
Epoch 17/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0173 - acc: 0.9947 - val_loss: 0.0584 - val_ac
c: 0.9843
Epoch 18/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0168 - acc: 0.9950 - val_loss: 0.0683 - val_ac
c: 0.9798
Epoch 19/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0201 - acc: 0.9919 - val_loss: 0.0660 - val_ac
c: 0.9832
Epoch 20/20
28/28 [==============================] - 1s 36ms/step - loss: 0.0192 - acc: 0.9924 - val_loss: 0.0969 - val_ac
c: 0.9753
35/35 [==============================] - 1s 13ms/step - loss: 0.0870 - acc: 0.9776
Test loss, Test Accuracy:  [0.08700524270534515, 0.9775784611701965]
```

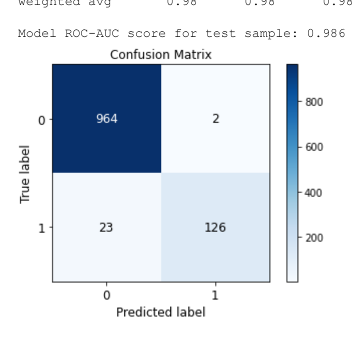
Evaluate Model

Evaluate model with different metrics:

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

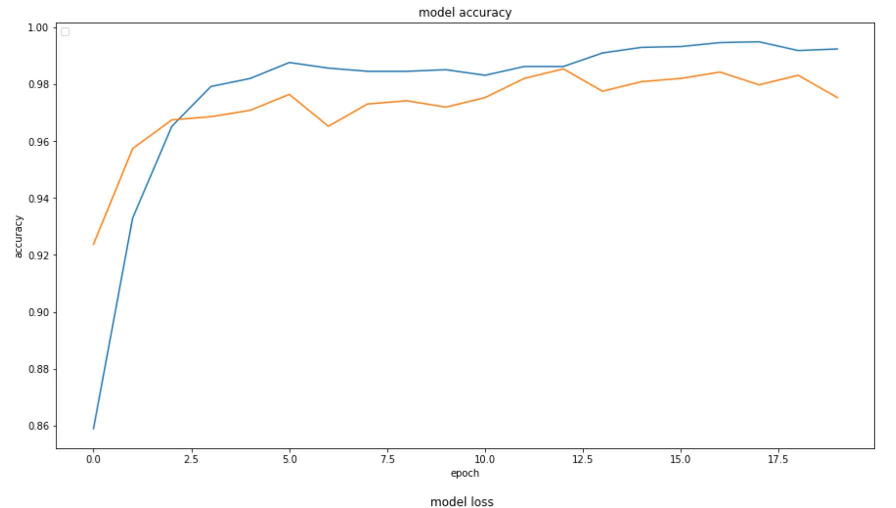
In [33]:
```
dl_pipeline.evaluate_model(fasttext_bilstm_attention_model, X_test, y_test)
```

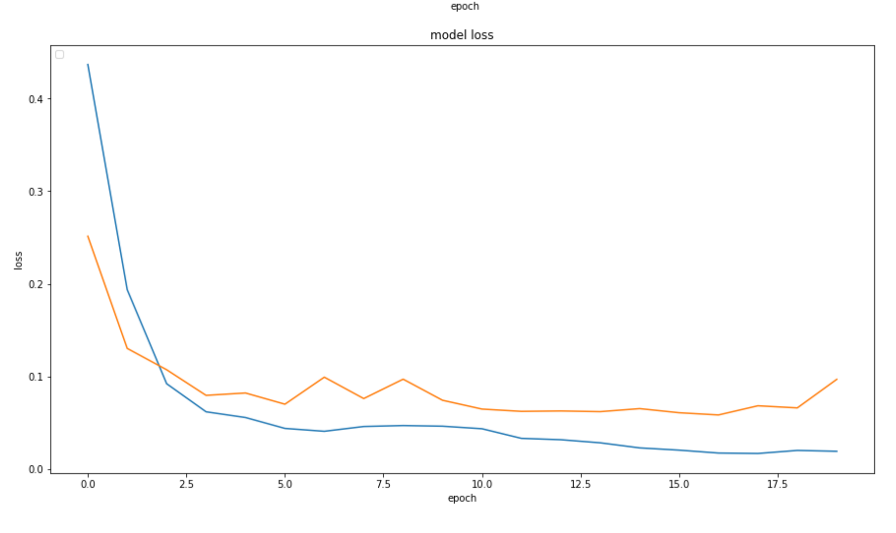
```
18/18 [==============================] - 1s 9ms/step
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       966
           1       0.98      0.85      0.91       149

    accuracy                           0.98      1115
   macro avg       0.98      0.92      0.95      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.986
```



Plot Accuracy and Loss

In [34]:
```
dl_pipeline.plot_accuracy_loss(history)
```





Simple Neural Network with Word2Vec

Loading Word2Vec Vectors

Let us load the pretrained Word2Vec embeddings in a dictionary.

In [11]:
```python
root = "/content/drive/MyDrive/"
w2vec_file_name = 'GoogleNews-vectors-negative300.bin'

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

```
2022-06-24 23:15:05,623 : INFO : loading projection weights from /content/drive/MyDrive/GoogleNews-vectors-nega
tive300.bin
Loading word2vec model
2022-06-24 23:16:00,144 : INFO : loaded (3000000, 300) matrix from /content/drive/MyDrive/GoogleNews-vectors-ne
gative300.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 [12]:
```python
embedding_dim = 300
embedding_matrix = dl_pipeline.create_embedding_matrix(tokenizer, w2vec_embedding_dict, vocab_size, embedding_c
```

Neural Network

Let us create a simple neural network model with the embeddings from Word2Vec.

In [17]:
```python
embedding_dim = 300
lstm_units = 128
w2vec_nn_model = dl_pipeline.create_simple_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [21]:
```python
w2vec_nn_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 100, 300)          2306700

 flatten (Flatten)           (None, 30000)             0

 dense (Dense)               (None, 1)                 30001

=================================================================
Total params: 2,336,701
Trainable params: 30,001
Non-trainable params: 2,306,700
_________________________________________________________________
```

In [18]:
```python
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(w2vec_nn_model, X_train, y_train, X_test,
                                            y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 4s 14ms/step - loss: 0.4310 - acc: 0.8637 - val_loss: 0.3226 - val_ac
c: 0.8576
Epoch 2/20
28/28 [==============================] - 0s 5ms/step - loss: 0.2274 - acc: 0.9374 - val_loss: 0.2175 - val_acc:
0.9339
Epoch 3/20
28/28 [==============================] - 0s 4ms/step - loss: 0.1634 - acc: 0.9590 - val_loss: 0.1802 - val_acc:
0.9428
Epoch 4/20
28/28 [==============================] - 0s 5ms/step - loss: 0.1311 - acc: 0.9697 - val_loss: 0.1566 - val_acc:
0.9529
Epoch 5/20
28/28 [==============================] - 0s 4ms/step - loss: 0.1107 - acc: 0.9759 - val_loss: 0.1424 - val_acc:
0.9585
Epoch 6/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0965 - acc: 0.9776 - val_loss: 0.1320 - val_acc:
0.9630
Epoch 7/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0856 - acc: 0.9801 - val_loss: 0.1232 - val_acc:
0.9641
Epoch 8/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0769 - acc: 0.9826 - val_loss: 0.1171 - val_acc:
0.9652
Epoch 9/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0698 - acc: 0.9840 - val_loss: 0.1123 - val_acc:
0.9664
Epoch 10/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0639 - acc: 0.9851 - val_loss: 0.1078 - val_acc:
0.9675
Epoch 11/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0588 - acc: 0.9863 - val_loss: 0.1042 - val_acc:
0.9686
Epoch 12/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0543 - acc: 0.9871 - val_loss: 0.1014 - val_acc:
0.9697
Epoch 13/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0504 - acc: 0.9885 - val_loss: 0.0988 - val_acc:
0.9697
Epoch 14/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0470 - acc: 0.9888 - val_loss: 0.0966 - val_acc:
0.9709
Epoch 15/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0439 - acc: 0.9902 - val_loss: 0.0956 - val_acc:
0.9709
Epoch 16/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0412 - acc: 0.9919 - val_loss: 0.0932 - val_acc:
0.9709
Epoch 17/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0387 - acc: 0.9924 - val_loss: 0.0918 - val_acc:
0.9709
Epoch 18/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0364 - acc: 0.9927 - val_loss: 0.0911 - val_acc:
0.9709
Epoch 19/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0344 - acc: 0.9933 - val_loss: 0.0901 - val_acc:
0.9709
Epoch 20/20
28/28 [==============================] - 0s 4ms/step - loss: 0.0326 - acc: 0.9935 - val_loss: 0.0897 - val_acc:
0.9709
35/35 [==============================] - 0s 2ms/step - loss: 0.0888 - acc: 0.9704
Test loss, Test Accuracy:  [0.08876458555459976, 0.9704036116600037]
```

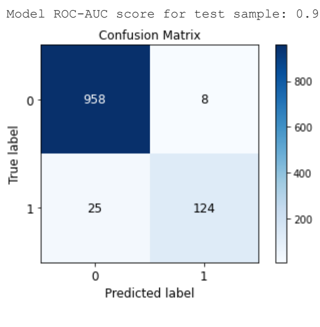
Evaluate Model

Evaluate model with different metrics:

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

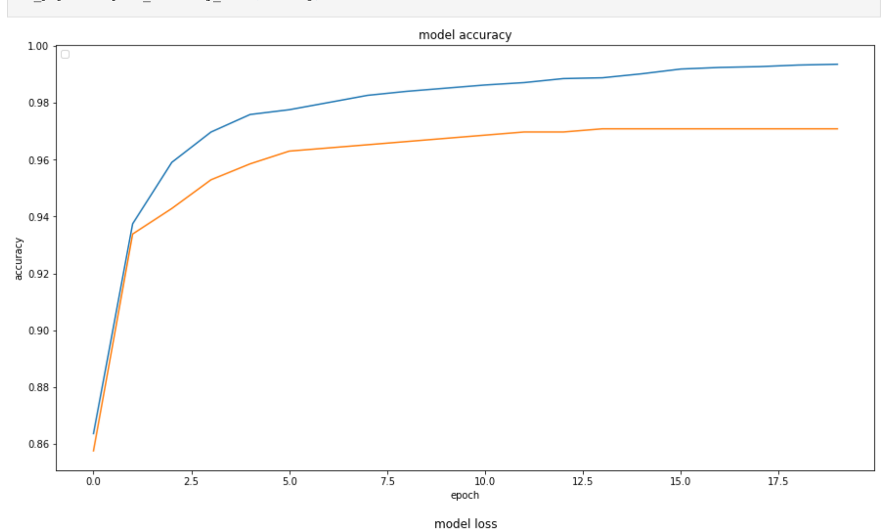
In [19]:
```python
dl_pipeline.evaluate_model(w2vec_nn_model, X_test, y_test)
```

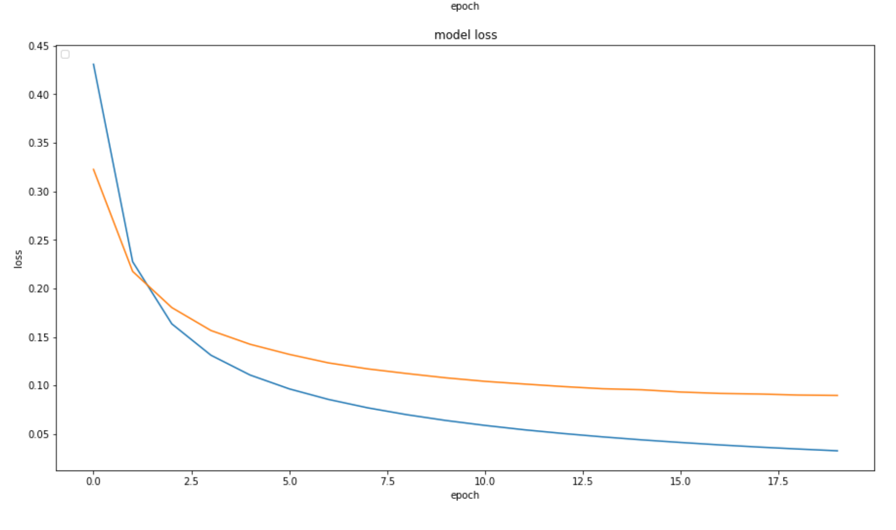
```
18/18 [==============================] - 0s 1ms/step
              precision    recall  f1-score   support

           0       0.97      0.99      0.98       966
           1       0.94      0.83      0.88       149

    accuracy                           0.97      1115
   macro avg       0.96      0.91      0.93      1115
weighted avg       0.97      0.97      0.97      1115

Model ROC-AUC score for test sample: 0.985
```



Plot Accuracy and Loss

In [20]:
```python
dl_pipeline.plot_accuracy_loss(history)
```





LSTM

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

In [20]:
```python
embedding_dim = 300
lstm_units = 128
w2vec_lstm_model = dl_pipeline.create_LSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [14]:
```python
w2vec_lstm_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 100, 300)          2306700

 lstm (LSTM)                 (None, 128)               219648

 dense (Dense)               (None, 1)                 129

=================================================================
Total params: 2,526,477
Trainable params: 219,777
Non-trainable params: 2,306,700
_________________________________________________________________
```

In [21]:
```python
epochs = 20
batch_size = 128
history = dl_pipeline.train_evaluate_model(w2vec_lstm_model, X_train, y_train, X_test,
                                            y_test, epochs, batch_size)
```

```
Epoch 1/20
28/28 [==============================] - 3s 33ms/step - loss: 0.4184 - acc: 0.8760 - val_loss: 0.1624 - val_ac
c: 0.9529
Epoch 2/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1622 - acc: 0.9582 - val_loss: 0.1660 - val_ac
c: 0.9608
Epoch 3/20
28/28 [==============================] - 0s 14ms/step - loss: 0.1303 - acc: 0.9568 - val_loss: 0.1378 - val_ac
c: 0.9417
Epoch 4/20
28/28 [==============================] - 0s 12ms/step - loss: 0.1008 - acc: 0.9697 - val_loss: 0.0999 - val_ac
c: 0.9787
Epoch 5/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0994 - acc: 0.9745 - val_loss: 0.1321 - val_ac
c: 0.9731
Epoch 6/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0856 - acc: 0.9792 - val_loss: 0.0764 - val_ac
c: 0.9776
Epoch 7/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0674 - acc: 0.9832 - val_loss: 0.0940 - val_ac
c: 0.9798
Epoch 8/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0547 - acc: 0.9871 - val_loss: 0.0715 - val_ac
c: 0.9787
Epoch 9/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0503 - acc: 0.9860 - val_loss: 0.0600 - val_ac
c: 0.9832
Epoch 10/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0597 - acc: 0.9820 - val_loss: 0.0558 - val_ac
c: 0.9865
Epoch 11/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0504 - acc: 0.9877 - val_loss: 0.0774 - val_ac
c: 0.9765
Epoch 12/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0684 - acc: 0.9837 - val_loss: 0.0987 - val_ac
c: 0.9686
Epoch 13/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0729 - acc: 0.9806 - val_loss: 0.0584 - val_ac
c: 0.9877
Epoch 14/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0526 - acc: 0.9891 - val_loss: 0.0595 - val_ac
c: 0.9877
Epoch 15/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0421 - acc: 0.9910 - val_loss: 0.0894 - val_ac
c: 0.9776
Epoch 16/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0469 - acc: 0.9882 - val_loss: 0.0460 - val_ac
c: 0.9854
Epoch 17/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0372 - acc: 0.9930 - val_loss: 0.0562 - val_ac
c: 0.9899
Epoch 18/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0436 - acc: 0.9891 - val_loss: 0.0591 - val_ac
c: 0.9832
Epoch 19/20
28/28 [==============================] - 0s 13ms/step - loss: 0.0369 - acc: 0.9930 - val_loss: 0.0514 - val_ac
c: 0.9899
Epoch 20/20
28/28 [==============================] - 0s 12ms/step - loss: 0.0345 - acc: 0.9930 - val_loss: 0.1154 - val_ac
c: 0.9675
35/35 [==============================] - 0s 6ms/step - loss: 0.1009 - acc: 0.9767
Test loss, Test Accuracy:  [0.10087353736162186, 0.9766815900802612]
```

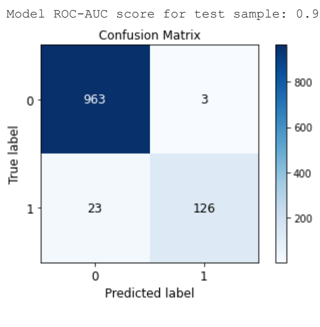
Evaluate Model

Evaluate model with different metrics:

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

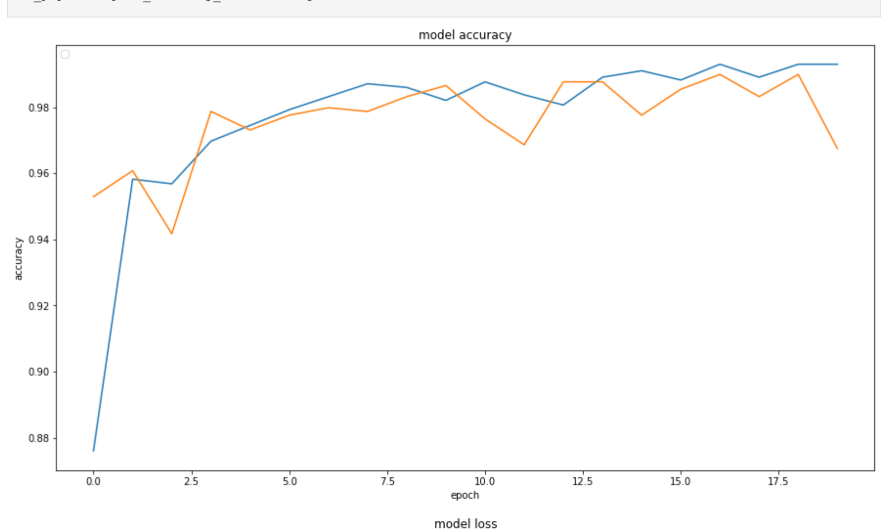
In [22]:
```python
dl_pipeline.evaluate_model(w2vec_lstm_model, X_test, y_test)
```

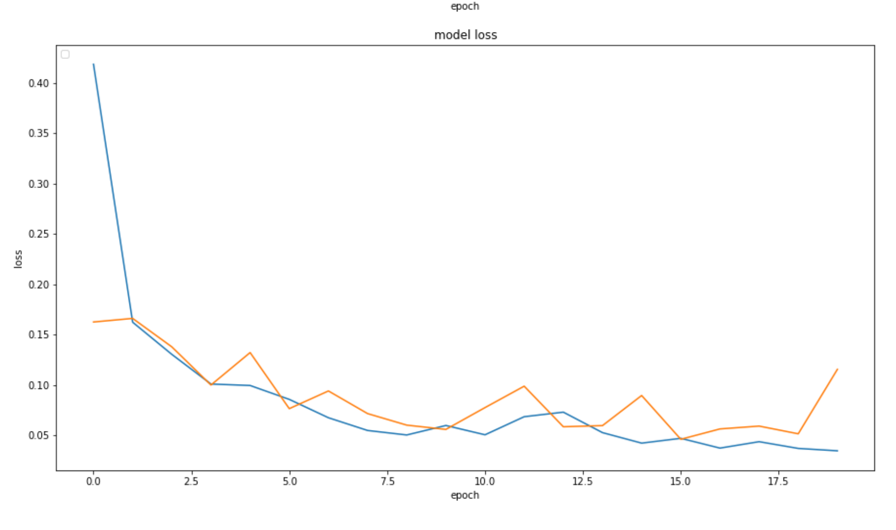
```
18/18 [==============================] - 1s 6ms/step
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       966
           1       0.98      0.85      0.91       149

    accuracy                           0.98      1115
   macro avg       0.98      0.92      0.95      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.988
```



Plot Accuracy and Loss

In [23]:
```python
dl_pipeline.plot_accuracy_loss(history)
```





BiLSTM

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

In [26]:
```python
embedding_dim = 300
lstm_units = 128
w2vec_bilstm_model = dl_pipeline.create_BiLSTM_nn_model(embedding_matrix, vocab_size, max_len, embedding_dim)
```

In [27]:
```python
w2vec_bilstm_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_2 (Embedding)     (None, 100, 300)          2306700

 bidirectional (Bidirectiona  (None, 256)              439296
 l)

 dense_2 (Dense)             (None, 1)                 257

=================================================================
Total params: 2,746,253
Trainable params: 439,553
Non-trainable params: 2,306,700
_________________________________________________________________
```

In [28]:
```python
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
28/28 [==============================] - 4s 53ms/step - loss: 0.3693 - acc: 0.8575 - val_loss: 0.1878 - val_ac
c: 0.9316
Epoch 2/20
28/28 [==============================] - 1s 21ms/step - loss: 0.1675 - acc: 0.9475 - val_loss: 0.1935 - val_ac
c: 0.9428
Epoch 3/20
28/28 [==============================] - 1s 21ms/step - loss: 0.1054 - acc: 0.9666 - val_loss: 0.1391 - val_ac
c: 0.9596
Epoch 4/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0750 - acc: 0.9762 - val_loss: 0.0991 - val_ac
c: 0.9664
Epoch 5/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0646 - acc: 0.9787 - val_loss: 0.1052 - val_ac
c: 0.9675
Epoch 6/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0567 - acc: 0.9826 - val_loss: 0.0856 - val_ac
c: 0.9720
Epoch 7/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0527 - acc: 0.9843 - val_loss: 0.0810 - val_ac
c: 0.9720
Epoch 8/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0482 - acc: 0.9854 - val_loss: 0.0911 - val_ac
c: 0.9742
Epoch 9/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0419 - acc: 0.9885 - val_loss: 0.0737 - val_ac
c: 0.9753
Epoch 10/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0367 - acc: 0.9896 - val_loss: 0.0808 - val_ac
c: 0.9776
Epoch 11/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0342 - acc: 0.9905 - val_loss: 0.0665 - val_ac
c: 0.9753
Epoch 12/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0308 - acc: 0.9924 - val_loss: 0.0666 - val_ac
c: 0.9787
Epoch 13/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0268 - acc: 0.9930 - val_loss: 0.0639 - val_ac
c: 0.9776
Epoch 14/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0247 - acc: 0.9938 - val_loss: 0.0908 - val_ac
c: 0.9675
Epoch 15/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0326 - acc: 0.9905 - val_loss: 0.0712 - val_ac
c: 0.9787
Epoch 16/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0249 - acc: 0.9927 - val_loss: 0.0632 - val_ac
c: 0.9787
Epoch 17/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0223 - acc: 0.9938 - val_loss: 0.0583 - val_ac
c: 0.9821
Epoch 18/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0169 - acc: 0.9955 - val_loss: 0.0567 - val_ac
c: 0.9832
Epoch 19/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0163 - acc: 0.9952 - val_loss: 0.0573 - val_ac
c: 0.9843
Epoch 20/20
28/28 [==============================] - 1s 21ms/step - loss: 0.0143 - acc: 0.9961 - val_loss: 0.0609 - val_ac
c: 0.9832
35/35 [==============================] - 0s 9ms/step - loss: 0.0709 - acc: 0.9848
Test loss, Test Accuracy:  [0.0708785429596901, 0.9847533702850342]
```

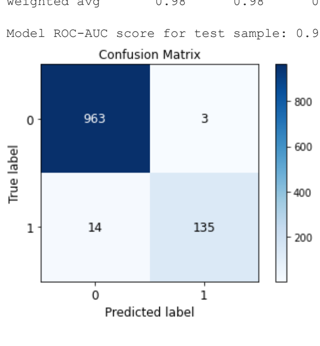
Evaluate Model

Evaluate model with different metrics:

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

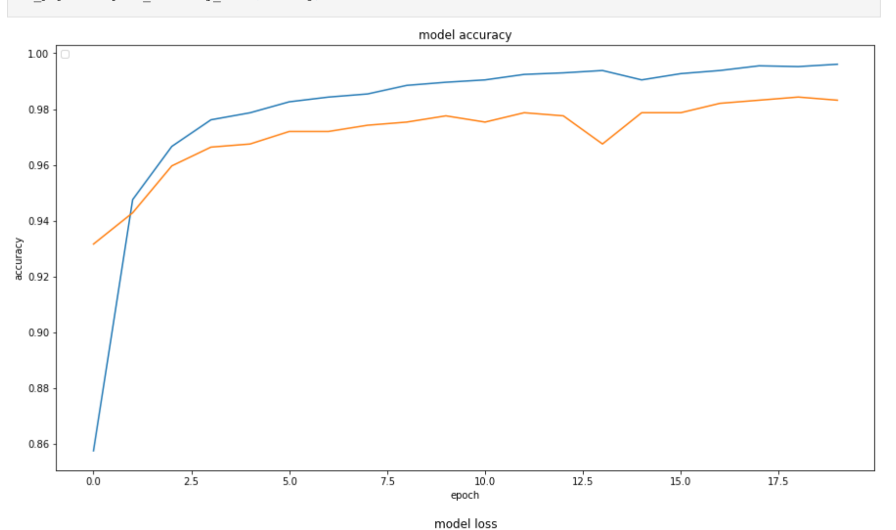
In [29]:
```python
dl_pipeline.evaluate_model(w2vec_bilstm_model, X_test, y_test)
```

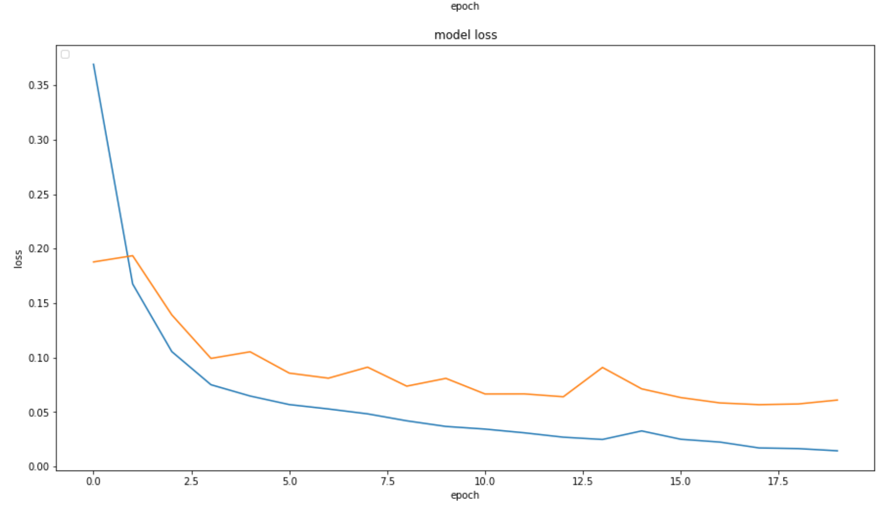
```
18/18 [==============================] - 1s 7ms/step
              precision    recall  f1-score   support

           0       0.99      1.00      0.99       966
           1       0.98      0.91      0.94       149

    accuracy                           0.98      1115
   macro avg       0.98      0.95      0.97      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.989
```



Plot Accuracy and Loss

In [30]:
```python
dl_pipeline.plot_accuracy_loss(history)
```





BiLSTM with Attention

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

In [31]:
```python
lstm_units = 128
w2vec_bilstm_attention_model = dl_pipeline.create_BiLSTM_Attention_nn_model(lstm_units, embedding_matrix, vocab
```

In [32]:
```python
w2vec_bilstm_attention_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 100)]             0

 embedding_3 (Embedding)     (None, 100, 300)          2306700

 bidirectional_1 (Bidirectio  (None, 100, 256)         439296
 nal)

 attention (attention)       (None, 256)               356

 dense_3 (Dense)             (None, 1)                 257

=================================================================
Total params: 2,746,609
Trainable params: 439,909
Non-trainable params: 2,306,700
_________________________________________________________________
```

Train model

I have experimented with different hyperparameters:

- epochs *batch_size
- Number of hidden units

In [33]:
```python
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)
```

```
Epoch 1/20
28/28 [==============================] - 5s 56ms/step - loss: 0.4460 - acc: 0.8676 - val_loss: 0.3703 - val_ac
c: 0.8430
Epoch 2/20
28/28 [==============================] - 1s 23ms/step - loss: 0.2031 - acc: 0.9304 - val_loss: 0.1800 - val_ac
c: 0.9361
Epoch 3/20
28/28 [==============================] - 1s 23ms/step - loss: 0.1072 - acc: 0.9610 - val_loss: 0.0959 - val_ac
c: 0.9664
Epoch 4/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0698 - acc: 0.9770 - val_loss: 0.0895 - val_ac
c: 0.9652
Epoch 5/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0783 - acc: 0.9748 - val_loss: 0.0758 - val_ac
c: 0.9731
Epoch 6/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0661 - acc: 0.9790 - val_loss: 0.0623 - val_ac
c: 0.9809
Epoch 7/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0476 - acc: 0.9857 - val_loss: 0.0681 - val_ac
c: 0.9765
Epoch 8/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0397 - acc: 0.9877 - val_loss: 0.0605 - val_ac
c: 0.9832
Epoch 9/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0339 - acc: 0.9905 - val_loss: 0.0607 - val_ac
c: 0.9832
Epoch 10/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0322 - acc: 0.9896 - val_loss: 0.0551 - val_ac
c: 0.9821
Epoch 11/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0341 - acc: 0.9899 - val_loss: 0.0518 - val_ac
c: 0.9877
Epoch 12/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0279 - acc: 0.9913 - val_loss: 0.0629 - val_ac
c: 0.9776
Epoch 13/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0249 - acc: 0.9916 - val_loss: 0.0735 - val_ac
c: 0.9787
Epoch 14/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0235 - acc: 0.9930 - val_loss: 0.0791 - val_ac
c: 0.9765
Epoch 15/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0191 - acc: 0.9935 - val_loss: 0.0626 - val_ac
c: 0.9787
Epoch 16/20
28/28 [==============================] - 1s 22ms/step - loss: 0.0189 - acc: 0.9938 - val_loss: 0.1067 - val_ac
c: 0.9731
Epoch 17/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0664 - acc: 0.9781 - val_loss: 0.1002 - val_ac
c: 0.9686
Epoch 18/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0535 - acc: 0.9846 - val_loss: 0.0877 - val_ac
c: 0.9753
Epoch 19/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0400 - acc: 0.9891 - val_loss: 0.0855 - val_ac
c: 0.9765
Epoch 20/20
28/28 [==============================] - 1s 23ms/step - loss: 0.0417 - acc: 0.9899 - val_loss: 0.1079 - val_ac
c: 0.9709
35/35 [==============================] - 0s 9ms/step - loss: 0.0892 - acc: 0.9803
Test loss, Test Accuracy:  [0.08921894431114197, 0.9802690744400024]
```

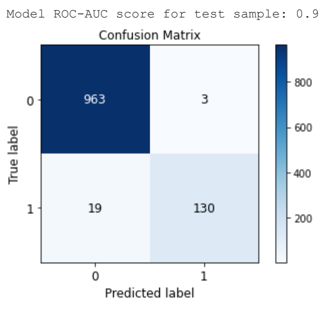
Evaluate Model

Evaluate model with different metrics:

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

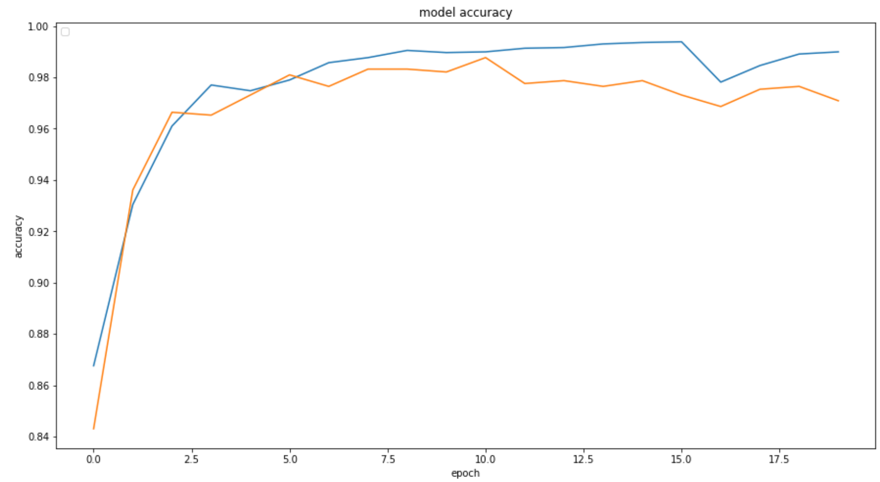
In [34]:
```python
dl_pipeline.evaluate_model(w2vec_bilstm_attention_model, X_test, y_test)
```

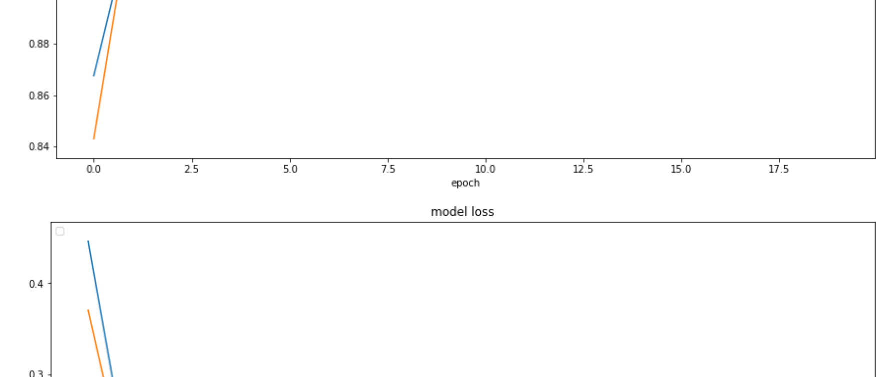
```
18/18 [==============================] - 1s 8ms/step
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       966
           1       0.98      0.87      0.92       149

    accuracy                           0.98      1115
   macro avg       0.98      0.93      0.96      1115
weighted avg       0.98      0.98      0.98      1115

Model ROC-AUC score for test sample: 0.981
```



Plot Accuracy and Loss

In [35]:
```python
dl_pipeline.plot_accuracy_loss(history)
```





Model 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, AUC ROC etc, apart from accuracy.

GloVe Embeddings:

	Accuracy	Weighted Avg Precision	Weighted Avg Recall	Weighted Avg F1-Score	AUC ROC Score
Neural Network	0.97	0.97	0.97	0.97	0.982
LSTM	0.98	0.98	0.98	0.98	0.988
BiLSTM	0.98	0.98	0.98	0.98	0.992
BiLSTM with Attention	0.98	0.98	0.98	0.98	0.986

FastText Embeddings:

	Accuracy	Weighted Avg Precision	Weighted Avg Recall	Weighted Avg F1-Score	AUC ROC Score
Neural Network	0.98	0.98	0.98	0.97	0.977
LSTM	0.97	0.97	0.97	0.97	0.982
BiLSTM	0.99	0.99	0.99	0.99	0.985
BiLSTM with Attention	0.98	0.98	0.98	0.98	0.986

Word2Vec Embeddings:

	Accuracy	Weighted Avg Precision	Weighted Avg Recall	Weighted Avg F1-Score	AUC ROC Score
Neural Network	0.97	0.97	0.97	0.97	0.985
LSTM	0.98	0.98	0.98	0.98	0.988
BiLSTM	0.98	0.98	0.98	0.98	0.989
BiLSTM with Attention	0.98	0.98	0.98	0.98	0.981

- For almost all models, the metrics improve as we go from NN > LSTM > BiLSTM > BiLSTM with Attention
- All Embedding methods perform quite well, with Glove embeddings giving best performance with BiLSTM
- FastText + BiLSTM has accuracy 0.99 and 0.985 AUC ROC, 0.9 F1 score
- Glove + BiLSTM has similar competitive performance, but it misclassifies more Not Spam as Spam than Fasttext, which is not desired, so Fasttext + BiLSTM is better.

Productionising Model

The Classification model that we have trained for detecting spam and not spam can be implemented as a **microservice**.

The trained model will be saved, along with the weights and loaded when the microservice is started.

The model will be deployed on a server, and since it is a spam detection model, it will be **invoked automatically** everytime a new text/email is received in the inbox of users.

The microservice will also be responsible to **preprocess the new input** in the format required by the model, eg tokenization etc

Model input: Text to be classified as Spam/Not Spam

The microservice API can be implemented using:

- *Flask*
- *Connexion* (Flask +Swagger)

To test the deployed model, *Postman* can be used with different text inputs.

Another way to productionize the model could be to build a small web app. This can be done using *Streamlit* or other web app libraries.

Finally, to make sure the service is portable and independent of OS and other dependencies, it can be converted to a **Docker** container. Having a Docker container will make it easier to maintain and refresh our models, if we make some training technique changes, architecture changes and want to deploy a retrained model.

To make sure that our API can handle large number of requests, we can consider Cloud solutions like **AWS** and **Kubernetes**.

```
In [ ]:
```