Text Mercato Assignment Submission

- Name - Suryansh Singh Rawat
- Email - suryanshsinghrawat@gmail.com
- Phone - +917722035623

Note

- The model will predict the Material, Pattern and Neckline attribute for the same image URL input.
- We are free to take your assumptions and solve the problem.
- We are assuming that the input images in the model will be downloaded already.
- The model gives a decent overall accuracy (~95%) and the performance on unseen images is also decent.

Requirements

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import nltk
import re
import string
import pickle
import cv2
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
import tensorflow as tf
from tensorflow.keras.applications import ResNet50, imagenet_utils
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Conv2D, Dropout, MaxPooling2D, Flatten, Dense, BatchNormalization, Input, \
                                    LSTM, Embedding, Input, TimeDistributed, Bidirectional, Activation, RepeatVector, Concatenate
```

In [ ]:

```
from google.colab import drive
drive.mount('/content/drive')
```

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

In [ ]:

```
cd /content/drive/MyDrive/TM Assignment
```

```
/content/drive/MyDrive/TM Assignment
```

In [ ]:

```
df = pd.read_excel('dataset 1.xlsx')
df.head()
```

Out[ ]:

	Title	Description	Material	Pattern	Neckline	Image_Path
0	Peach Poly Crepe jumpsuit	This stylish foil print kurta from janasya is ...	Crepe	Printed	Round Neck	/images/pic_0.jpg
1	Light Brown Bias Yoke Checks Top	This check pattern top by Work Label is crafte...	Cotton	Checks	Round Neck	/images/pic_1.jpg
2	Off White Geometric Straight Cotton Dobby Top ...	Featuring elegant printed details, this off wh...	Viscose	Checks	Round Neck	/images/pic_2.jpg
3	Blue Me Away Cape Top	Add an extra dose of style to your casual ward...	Polyester	Solid/Plain	V-Neck	/images/pic_3.jpg
4	Yellow On A High Gown	Yellow polyester georgette maxi dress. Polyest...	Polyester	Solid/Plain	V-Neck	/images/pic_4.jpg

In [ ]:

```
#Adding a '.' before the image path to access it
df['Image_Path'] = '.'+df['Image_Path']
imgpath = df['Image_Path']
material = df['Material']
pattern = df['Pattern']
neckline = df['Neckline']
```

In [ ]:

```
#Adding a '_' in place of spaces so that tokenizer considers them as a single word
for i in range(len(neckline)):
  neckline[i] = neckline[i].replace(' ','_')
for i in range(len(pattern)):
  pattern[i] = pattern[i].replace(' ','_')
for i in range(len(material)):
  material[i] = material[i].replace(' ','_')
```

In [ ]:

```
#dataset with above changes
```

```
df.head()
```

Out[ ]:

	Title	Description	Material	Pattern	Neckline	Image_Path
0	Peach Poly Crepe jumpsuit	This stylish foil print kurta from janasya is ...	Crepe	Printed	Round_Neck	./images/pic_0.jpg
1	Light Brown Bias Yoke Checks Top	This check pattern top by Work Label is crafte...	Cotton	Checks	Round_Neck	./images/pic_1.jpg
2	Off White Geometric Straight Cotton Dobby Top ...	Featuring elegant printed details, this off wh...	Viscose	Checks	Round_Neck	./images/pic_2.jpg
3	Blue Me Away Cape Top	Add an extra dose of style to your casual ward...	Polyester	Solid/Plain	V-Neck	./images/pic_3.jpg
4	Yellow On A High Gown	Yellow polyester georgette maxi dress. Polyest...	Polyester	Solid/Plain	V-Neck	./images/pic_4.jpg

In [ ]:

```
k = 4 #random number from 0-499
img = cv2.imread(imgpath[k])
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
plt.imshow(img)
plt.xlabel((material[k],pattern[k],neckline[k]));
```

In [ ]:

```
#importing and downloading the pretrained weights from ResNet50
ResNet = ResNet50(include_top=True)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kern
els.h5
102973440/102967424 [==============================] - 1s 0us/step
```

In [ ]:

```
ResNet_model = ResNet50(weights='imagenet')
ResNet_model = Model(inputs=ResNet_model.inputs, outputs=ResNet_model.layers[-2].output)
ResNet_model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to                     
==================================================================================================
input_2 (InputLayer)            [(None, 224, 224, 3) 0                                            
__________________________________________________________________________________________________
conv1_pad (ZeroPadding2D)       (None, 230, 230, 3)  0           input_2[0][0]                    
__________________________________________________________________________________________________
conv1_conv (Conv2D)             (None, 112, 112, 64) 9472        conv1_pad[0][0]                  
__________________________________________________________________________________________________
conv1_bn (BatchNormalization)   (None, 112, 112, 64) 256         conv1_conv[0][0]                 
__________________________________________________________________________________________________
conv1_relu (Activation)         (None, 112, 112, 64) 0           conv1_bn[0][0]                   
__________________________________________________________________________________________________
pool1_pad (ZeroPadding2D)       (None, 114, 114, 64) 0           conv1_relu[0][0]                 
__________________________________________________________________________________________________
pool1_pool (MaxPooling2D)       (None, 56, 56, 64)   0           pool1_pad[0][0]                  
__________________________________________________________________________________________________
conv2_block1_1_conv (Conv2D)    (None, 56, 56, 64)   4160        pool1_pool[0][0]                 
__________________________________________________________________________________________________
conv2_block1_1_bn (BatchNormali (None, 56, 56, 64)   256         conv2_block1_1_conv[0][0]        
__________________________________________________________________________________________________
conv2_block1_1_relu (Activation (None, 56, 56, 64)   0           conv2_block1_1_bn[0][0]          
__________________________________________________________________________________________________
conv2_block1_2_conv (Conv2D)    (None, 56, 56, 64)   36928       conv2_block1_1_relu[0][0]        
__________________________________________________________________________________________________
conv2_block1_2_bn (BatchNormali (None, 56, 56, 64)   256         conv2_block1_2_conv[0][0]        
__________________________________________________________________________________________________
conv2_block1_2_relu (Activation (None, 56, 56, 64)   0           conv2_block1_2_bn[0][0]          
__________________________________________________________________________________________________
conv2_block1_0_conv (Conv2D)    (None, 56, 56, 256)  16640       pool1_pool[0][0]                 
__________________________________________________________________________________________________
conv2_block1_3_conv (Conv2D)    (None, 56, 56, 256)  16640       conv2_block1_2_relu[0][0]        
__________________________________________________________________________________________________
conv2_block1_0_bn (BatchNormali (None, 56, 56, 256)  1024        conv2_block1_0_conv[0][0]        
__________________________________________________________________________________________________
conv2_block1_3_bn (BatchNormali (None, 56, 56, 256)  1024        conv2_block1_3_conv[0][0]        
__________________________________________________________________________________________________
conv2_block1_add (Add)          (None, 56, 56, 256)  0           conv2_block1_0_bn[0][0]          
                                                                 conv2_block1_3_bn[0][0]          
__________________________________________________________________________________________________
conv2_block1_out (Activation)   (None, 56, 56, 256)  0           conv2_block1_add[0][0]           
__________________________________________________________________________________________________
conv2_block2_1_conv (Conv2D)    (None, 56, 56, 64)   16448       conv2_block1_out[0][0]           
__________________________________________________________________________________________________
conv2_block2_1_bn (BatchNormali (None, 56, 56, 64)   256         conv2_block2_1_conv[0][0]        
__________________________________________________________________________________________________
```

conv2_block2_1_relu (Activation	(None, 56, 56, 64)	0	conv2_block2_1_bn[0][0]
conv2_block2_2_conv (Conv2D)	(None, 56, 56, 64)	36928	conv2_block2_1_relu[0][0]
conv2_block2_2_bn (BatchNormali	(None, 56, 56, 64)	256	conv2_block2_2_conv[0][0]
conv2_block2_2_relu (Activation	(None, 56, 56, 64)	0	conv2_block2_2_bn[0][0]
conv2_block2_3_conv (Conv2D)	(None, 56, 56, 256)	16640	conv2_block2_2_relu[0][0]
conv2_block2_3_bn (BatchNormali	(None, 56, 56, 256)	1024	conv2_block2_3_conv[0][0]
conv2_block2_add (Add)	(None, 56, 56, 256)	0	conv2_block1_out[0][0] conv2_block2_3_bn[0][0]
conv2_block2_out (Activation)	(None, 56, 56, 256)	0	conv2_block2_add[0][0]
conv2_block3_1_conv (Conv2D)	(None, 56, 56, 64)	16448	conv2_block2_out[0][0]
conv2_block3_1_bn (BatchNormali	(None, 56, 56, 64)	256	conv2_block3_1_conv[0][0]
conv2_block3_1_relu (Activation	(None, 56, 56, 64)	0	conv2_block3_1_bn[0][0]
conv2_block3_2_conv (Conv2D)	(None, 56, 56, 64)	36928	conv2_block3_1_relu[0][0]
conv2_block3_2_bn (BatchNormali	(None, 56, 56, 64)	256	conv2_block3_2_conv[0][0]
conv2_block3_2_relu (Activation	(None, 56, 56, 64)	0	conv2_block3_2_bn[0][0]
conv2_block3_3_conv (Conv2D)	(None, 56, 56, 256)	16640	conv2_block3_2_relu[0][0]
conv2_block3_3_bn (BatchNormali	(None, 56, 56, 256)	1024	conv2_block3_3_conv[0][0]
conv2_block3_add (Add)	(None, 56, 56, 256)	0	conv2_block2_out[0][0] conv2_block3_3_bn[0][0]
conv2_block3_out (Activation)	(None, 56, 56, 256)	0	conv2_block3_add[0][0]
conv3_block1_1_conv (Conv2D)	(None, 28, 28, 128)	32896	conv2_block3_out[0][0]
conv3_block1_1_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block1_1_conv[0][0]
conv3_block1_1_relu (Activation	(None, 28, 28, 128)	0	conv3_block1_1_bn[0][0]
conv3_block1_2_conv (Conv2D)	(None, 28, 28, 128)	147584	conv3_block1_1_relu[0][0]
conv3_block1_2_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block1_2_conv[0][0]
conv3_block1_2_relu (Activation	(None, 28, 28, 128)	0	conv3_block1_2_bn[0][0]
conv3_block1_0_conv (Conv2D)	(None, 28, 28, 512)	131584	conv2_block3_out[0][0]
conv3_block1_3_conv (Conv2D)	(None, 28, 28, 512)	66048	conv3_block1_2_relu[0][0]
conv3_block1_0_bn (BatchNormali	(None, 28, 28, 512)	2048	conv3_block1_0_conv[0][0]
conv3_block1_3_bn (BatchNormali	(None, 28, 28, 512)	2048	conv3_block1_3_conv[0][0]
conv3_block1_add (Add)	(None, 28, 28, 512)	0	conv3_block1_0_bn[0][0] conv3_block1_3_bn[0][0]
conv3_block1_out (Activation)	(None, 28, 28, 512)	0	conv3_block1_add[0][0]
conv3_block2_1_conv (Conv2D)	(None, 28, 28, 128)	65664	conv3_block1_out[0][0]
conv3_block2_1_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block2_1_conv[0][0]
conv3_block2_1_relu (Activation	(None, 28, 28, 128)	0	conv3_block2_1_bn[0][0]
conv3_block2_2_conv (Conv2D)	(None, 28, 28, 128)	147584	conv3_block2_1_relu[0][0]
conv3_block2_2_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block2_2_conv[0][0]
conv3_block2_2_relu (Activation	(None, 28, 28, 128)	0	conv3_block2_2_bn[0][0]
conv3_block2_3_conv (Conv2D)	(None, 28, 28, 512)	66048	conv3_block2_2_relu[0][0]
conv3_block2_3_bn (BatchNormali	(None, 28, 28, 512)	2048	conv3_block2_3_conv[0][0]
conv3_block2_add (Add)	(None, 28, 28, 512)	0	conv3_block1_out[0][0] conv3_block2_3_bn[0][0]
conv3_block2_out (Activation)	(None, 28, 28, 512)	0	conv3_block2_add[0][0]
conv3_block3_1_conv (Conv2D)	(None, 28, 28, 128)	65664	conv3_block2_out[0][0]
conv3_block3_1_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block3_1_conv[0][0]
conv3_block3_1_relu (Activation	(None, 28, 28, 128)	0	conv3_block3_1_bn[0][0]
conv3_block3_2_conv (Conv2D)	(None, 28, 28, 128)	147584	conv3_block3_1_relu[0][0]
conv3_block3_2_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block3_2_conv[0][0]
conv3_block3_2_relu (Activation	(None, 28, 28, 128)	0	conv3_block3_2_bn[0][0]
conv3_block3_3_conv (Conv2D)	(None, 28, 28, 512)	66048	conv3_block3_2_relu[0][0]
conv3_block3_3_bn (BatchNormali	(None, 28, 28, 512)	2048	conv3_block3_3_conv[0][0]
conv3_block3_add (Add)	(None, 28, 28, 512)	0	conv3_block2_out[0][0] conv3_block3_3_bn[0][0]

conv3_block3_out (Activation)	(None, 28, 28, 512)	0	conv3_block3_add[0][0]
conv3_block4_1_conv (Conv2D)	(None, 28, 28, 128)	65664	conv3_block3_out[0][0]
conv3_block4_1_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block4_1_conv[0][0]
conv3_block4_1_relu (Activation	(None, 28, 28, 128)	0	conv3_block4_1_bn[0][0]
conv3_block4_2_conv (Conv2D)	(None, 28, 28, 128)	147584	conv3_block4_1_relu[0][0]
conv3_block4_2_bn (BatchNormali	(None, 28, 28, 128)	512	conv3_block4_2_conv[0][0]
conv3_block4_2_relu (Activation	(None, 28, 28, 128)	0	conv3_block4_2_bn[0][0]
conv3_block4_3_conv (Conv2D)	(None, 28, 28, 512)	66048	conv3_block4_2_relu[0][0]
conv3_block4_3_bn (BatchNormali	(None, 28, 28, 512)	2048	conv3_block4_3_conv[0][0]
conv3_block4_add (Add)	(None, 28, 28, 512)	0	conv3_block3_out[0][0] conv3_block4_3_bn[0][0]
conv3_block4_out (Activation)	(None, 28, 28, 512)	0	conv3_block4_add[0][0]
conv4_block1_1_conv (Conv2D)	(None, 14, 14, 256)	131328	conv3_block4_out[0][0]
conv4_block1_1_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block1_1_conv[0][0]
conv4_block1_1_relu (Activation	(None, 14, 14, 256)	0	conv4_block1_1_bn[0][0]
conv4_block1_2_conv (Conv2D)	(None, 14, 14, 256)	590080	conv4_block1_1_relu[0][0]
conv4_block1_2_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block1_2_conv[0][0]
conv4_block1_2_relu (Activation	(None, 14, 14, 256)	0	conv4_block1_2_bn[0][0]
conv4_block1_0_conv (Conv2D)	(None, 14, 14, 1024)	525312	conv3_block4_out[0][0]
conv4_block1_3_conv (Conv2D)	(None, 14, 14, 1024)	263168	conv4_block1_2_relu[0][0]
conv4_block1_0_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block1_0_conv[0][0]
conv4_block1_3_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block1_3_conv[0][0]
conv4_block1_add (Add)	(None, 14, 14, 1024)	0	conv4_block1_0_bn[0][0] conv4_block1_3_bn[0][0]
conv4_block1_out (Activation)	(None, 14, 14, 1024)	0	conv4_block1_add[0][0]
conv4_block2_1_conv (Conv2D)	(None, 14, 14, 256)	262400	conv4_block1_out[0][0]
conv4_block2_1_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block2_1_conv[0][0]
conv4_block2_1_relu (Activation	(None, 14, 14, 256)	0	conv4_block2_1_bn[0][0]
conv4_block2_2_conv (Conv2D)	(None, 14, 14, 256)	590080	conv4_block2_1_relu[0][0]
conv4_block2_2_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block2_2_conv[0][0]
conv4_block2_2_relu (Activation	(None, 14, 14, 256)	0	conv4_block2_2_bn[0][0]
conv4_block2_3_conv (Conv2D)	(None, 14, 14, 1024)	263168	conv4_block2_2_relu[0][0]
conv4_block2_3_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block2_3_conv[0][0]
conv4_block2_add (Add)	(None, 14, 14, 1024)	0	conv4_block1_out[0][0] conv4_block2_3_bn[0][0]
conv4_block2_out (Activation)	(None, 14, 14, 1024)	0	conv4_block2_add[0][0]
conv4_block3_1_conv (Conv2D)	(None, 14, 14, 256)	262400	conv4_block2_out[0][0]
conv4_block3_1_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block3_1_conv[0][0]
conv4_block3_1_relu (Activation	(None, 14, 14, 256)	0	conv4_block3_1_bn[0][0]
conv4_block3_2_conv (Conv2D)	(None, 14, 14, 256)	590080	conv4_block3_1_relu[0][0]
conv4_block3_2_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block3_2_conv[0][0]
conv4_block3_2_relu (Activation	(None, 14, 14, 256)	0	conv4_block3_2_bn[0][0]
conv4_block3_3_conv (Conv2D)	(None, 14, 14, 1024)	263168	conv4_block3_2_relu[0][0]
conv4_block3_3_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block3_3_conv[0][0]
conv4_block3_add (Add)	(None, 14, 14, 1024)	0	conv4_block2_out[0][0] conv4_block3_3_bn[0][0]
conv4_block3_out (Activation)	(None, 14, 14, 1024)	0	conv4_block3_add[0][0]
conv4_block4_1_conv (Conv2D)	(None, 14, 14, 256)	262400	conv4_block3_out[0][0]
conv4_block4_1_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block4_1_conv[0][0]
conv4_block4_1_relu (Activation	(None, 14, 14, 256)	0	conv4_block4_1_bn[0][0]
conv4_block4_2_conv (Conv2D)	(None, 14, 14, 256)	590080	conv4_block4_1_relu[0][0]
conv4_block4_2_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block4_2_conv[0][0]
conv4_block4_2_relu (Activation	(None, 14, 14, 256)	0	conv4_block4_2_bn[0][0]

conv4_block4_3_conv (Conv2D)	(None, 14, 14, 1024)	263168	conv4_block4_2_relu[0][0]
conv4_block4_3_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block4_3_conv[0][0]
conv4_block4_add (Add)	(None, 14, 14, 1024)	0	conv4_block3_out[0][0] conv4_block4_3_bn[0][0]
conv4_block4_out (Activation)	(None, 14, 14, 1024)	0	conv4_block4_add[0][0]
conv4_block5_1_conv (Conv2D)	(None, 14, 14, 256)	262400	conv4_block4_out[0][0]
conv4_block5_1_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block5_1_conv[0][0]
conv4_block5_1_relu (Activation	(None, 14, 14, 256)	0	conv4_block5_1_bn[0][0]
conv4_block5_2_conv (Conv2D)	(None, 14, 14, 256)	590080	conv4_block5_1_relu[0][0]
conv4_block5_2_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block5_2_conv[0][0]
conv4_block5_2_relu (Activation	(None, 14, 14, 256)	0	conv4_block5_2_bn[0][0]
conv4_block5_3_conv (Conv2D)	(None, 14, 14, 1024)	263168	conv4_block5_2_relu[0][0]
conv4_block5_3_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block5_3_conv[0][0]
conv4_block5_add (Add)	(None, 14, 14, 1024)	0	conv4_block4_out[0][0] conv4_block5_3_bn[0][0]
conv4_block5_out (Activation)	(None, 14, 14, 1024)	0	conv4_block5_add[0][0]
conv4_block6_1_conv (Conv2D)	(None, 14, 14, 256)	262400	conv4_block5_out[0][0]
conv4_block6_1_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block6_1_conv[0][0]
conv4_block6_1_relu (Activation	(None, 14, 14, 256)	0	conv4_block6_1_bn[0][0]
conv4_block6_2_conv (Conv2D)	(None, 14, 14, 256)	590080	conv4_block6_1_relu[0][0]
conv4_block6_2_bn (BatchNormali	(None, 14, 14, 256)	1024	conv4_block6_2_conv[0][0]
conv4_block6_2_relu (Activation	(None, 14, 14, 256)	0	conv4_block6_2_bn[0][0]
conv4_block6_3_conv (Conv2D)	(None, 14, 14, 1024)	263168	conv4_block6_2_relu[0][0]
conv4_block6_3_bn (BatchNormali	(None, 14, 14, 1024)	4096	conv4_block6_3_conv[0][0]
conv4_block6_add (Add)	(None, 14, 14, 1024)	0	conv4_block5_out[0][0] conv4_block6_3_bn[0][0]
conv4_block6_out (Activation)	(None, 14, 14, 1024)	0	conv4_block6_add[0][0]
conv5_block1_1_conv (Conv2D)	(None, 7, 7, 512)	524800	conv4_block6_out[0][0]
conv5_block1_1_bn (BatchNormali	(None, 7, 7, 512)	2048	conv5_block1_1_conv[0][0]
conv5_block1_1_relu (Activation	(None, 7, 7, 512)	0	conv5_block1_1_bn[0][0]
conv5_block1_2_conv (Conv2D)	(None, 7, 7, 512)	2359808	conv5_block1_1_relu[0][0]
conv5_block1_2_bn (BatchNormali	(None, 7, 7, 512)	2048	conv5_block1_2_conv[0][0]
conv5_block1_2_relu (Activation	(None, 7, 7, 512)	0	conv5_block1_2_bn[0][0]
conv5_block1_0_conv (Conv2D)	(None, 7, 7, 2048)	2099200	conv4_block6_out[0][0]
conv5_block1_3_conv (Conv2D)	(None, 7, 7, 2048)	1050624	conv5_block1_2_relu[0][0]
conv5_block1_0_bn (BatchNormali	(None, 7, 7, 2048)	8192	conv5_block1_0_conv[0][0]
conv5_block1_3_bn (BatchNormali	(None, 7, 7, 2048)	8192	conv5_block1_3_conv[0][0]
conv5_block1_add (Add)	(None, 7, 7, 2048)	0	conv5_block1_0_bn[0][0] conv5_block1_3_bn[0][0]
conv5_block1_out (Activation)	(None, 7, 7, 2048)	0	conv5_block1_add[0][0]
conv5_block2_1_conv (Conv2D)	(None, 7, 7, 512)	1049088	conv5_block1_out[0][0]
conv5_block2_1_bn (BatchNormali	(None, 7, 7, 512)	2048	conv5_block2_1_conv[0][0]
conv5_block2_1_relu (Activation	(None, 7, 7, 512)	0	conv5_block2_1_bn[0][0]
conv5_block2_2_conv (Conv2D)	(None, 7, 7, 512)	2359808	conv5_block2_1_relu[0][0]
conv5_block2_2_bn (BatchNormali	(None, 7, 7, 512)	2048	conv5_block2_2_conv[0][0]
conv5_block2_2_relu (Activation	(None, 7, 7, 512)	0	conv5_block2_2_bn[0][0]
conv5_block2_3_conv (Conv2D)	(None, 7, 7, 2048)	1050624	conv5_block2_2_relu[0][0]
conv5_block2_3_bn (BatchNormali	(None, 7, 7, 2048)	8192	conv5_block2_3_conv[0][0]
conv5_block2_add (Add)	(None, 7, 7, 2048)	0	conv5_block1_out[0][0] conv5_block2_3_bn[0][0]
conv5_block2_out (Activation)	(None, 7, 7, 2048)	0	conv5_block2_add[0][0]
conv5_block3_1_conv (Conv2D)	(None, 7, 7, 512)	1049088	conv5_block2_out[0][0]
conv5_block3_1_bn (BatchNormali	(None, 7, 7, 512)	2048	conv5_block3_1_conv[0][0]
conv5_block3_1_relu (Activation	(None, 7, 7, 512)	0	conv5_block3_1_bn[0][0]

```
conv5_block3_2_conv (Conv2D)     (None, 7, 7, 512)    2359808     conv5_block3_1_relu[0][0]
__________________________________________________________________________________________________
conv5_block3_2_bn (BatchNormali (None, 7, 7, 512)    2048        conv5_block3_2_conv[0][0]
__________________________________________________________________________________________________
conv5_block3_2_relu (Activation (None, 7, 7, 512)    0           conv5_block3_2_bn[0][0]
__________________________________________________________________________________________________
conv5_block3_3_conv (Conv2D)     (None, 7, 7, 2048)   1050624     conv5_block3_2_relu[0][0]
__________________________________________________________________________________________________
conv5_block3_3_bn (BatchNormali (None, 7, 7, 2048)   8192        conv5_block3_3_conv[0][0]
__________________________________________________________________________________________________
conv5_block3_add (Add)           (None, 7, 7, 2048)   0           conv5_block2_out[0][0]
                                                                  conv5_block3_3_bn[0][0]
__________________________________________________________________________________________________
conv5_block3_out (Activation)    (None, 7, 7, 2048)   0           conv5_block3_add[0][0]
__________________________________________________________________________________________________
avg_pool (GlobalAveragePooling2 (None, 2048)         0           conv5_block3_out[0][0]
==================================================================================================
Total params: 23,587,712
Trainable params: 23,534,592
Non-trainable params: 53,120
__________________________________________________________________________________________________
```

In [ ]:

```
imgfeatures = {}
count = 0
for i in range(len(imgpath)):
  img = cv2.imread(imgpath[i])
  img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
  img = cv2.resize(img,(224,224))
  img = img.reshape(1,224,224,3)
  imgfeatures[imgpath[i]] = ResNet_model.predict(img)[0]
  count+=1
  if count%50 == 0:
    print(count,'image features predicted')
```

```
50 image features predicted
100 image features predicted
150 image features predicted
200 image features predicted
250 image features predicted
300 image features predicted
350 image features predicted
400 image features predicted
450 image features predicted
500 image features predicted
```

In [12]:

```
#Creating dictionaries of eack attribute (material,pattern,neckline)
material_catalouge = {}
for i in range(len(imgpath)):
  material_catalouge[imgpath[i]] = material[i]
pattern_catalouge = {}
for i in range(len(imgpath)):
  pattern_catalouge[imgpath[i]] = pattern[i]
neckline_catalouge = {}
for i in range(len(imgpath)):
  neckline_catalouge[imgpath[i]] = neckline[i]
```

In [13]:

```
#Tokenizer for material attribute
tokenizer1 = Tokenizer(filters='!')
data1 = []
for i in range(len(imgpath)):
  data1.append(material_catalouge[imgpath[i]])
tokenizer1.fit_on_texts(data1)
total_words1 = int(len(tokenizer1.word_index))+1
print(total_words1)
print(tokenizer1.word_index)
print(tokenizer1.word_counts)
```

```
31
{'polyester': 1, 'cotton': 2, 'viscose': 3, 'crepe': 4, 'rayon': 5, 'georgette': 6, 'satin': 7, 'linen': 8, 'knitted': 9, 'denim': 10, 'nylon': 11, 'velvet': 12, 'silk': 13, 'chiffon': 14, 'organza': 15, 'net': 16, 'crinkled': 17, 'khadi': 18, 'polycotton': 19, 'leather': 20, 'organic': 21, 'polyamide': 22, 'lyocell': 23, 'lace': 24, 'suede': 25, 'wool': 26, 'modal': 27, 'poplin': 28, 'sequin': 29, 'blended_fabric': 30}
OrderedDict([('crepe', 40), ('cotton', 129), ('viscose', 57), ('polyester', 147), ('denim', 6), ('rayon', 33), ('crinkled', 2), ('georgette', 14), ('satin', 12), ('khadi', 2), ('knitted', 7), ('velvet', 5), ('linen', 12), ('silk', 5), ('chiffon', 4), ('leather', 1), ('organic', 1), ('organza', 3), ('nylon', 6), ('polyamide', 1), ('polycotton', 2), ('lyocell', 1), ('lace', 1), ('suede', 1), ('wool', 1), ('net', 3), ('modal', 1), ('poplin', 1), ('sequin', 1), ('blended_fabric', 1)])
```

In [14]:

```
#Tokenizer for pattern attribute
tokenizer2 = Tokenizer(filters='!')
data2 = []
for i in range(len(imgpath)):
  data2.append(pattern_catalouge[imgpath[i]])
tokenizer2.fit_on_texts(data2)
total_words2 = int(len(tokenizer2.word_index))+1
print(total_words2)
print(tokenizer2.word_index)
print(tokenizer2.word_counts)
```

```
19
{'solid/plain': 1, 'printed': 2, 'floral': 3, 'stripes': 4, 'embellished/sequined': 5, 'polka_dots': 6, 'checks': 7, 'embroidered': 8, 'patterned': 9, 'detailing': 10, 'ruffled': 11, 'pleated': 12, 'geometric': 13, 'mirror_work': 14, 'animal_print': 15, 'ombre': 16, 'plaid': 17, 'tie_&_dye': 18}
OrderedDict([('printed', 81), ('checks', 15), ('solid/plain', 204), ('floral', 62), ('mirror_work', 1), ('stripes', 36), ('pattern
```

ed', 12), ('detailing', 9), ('ruffled', 8), ('geometric', 5), ('polka_dots', 19), ('embellished/sequined', 23), ('embroidered', 13
), ('pleated', 8), ('animal_print', 1), ('ombre', 1), ('plaid', 1), ('tie_&_dye', 1)])

In [15]:

```
#Tokenizer for neckline attribute
tokenizer3 = Tokenizer(filters='!')
data3 = []
for i in range(len(imgpath)):
  data3.append(neckline_catalouge[imgpath[i]])
tokenizer3.fit_on_texts(data3)
total_words3 = int(len(tokenizer3.word_index))+1
print(total_words3)
print(tokenizer3.word_index)
print(tokenizer3.word_counts)
```

```
23
{'v-neck': 1, 'round_neck': 2, 'collar_neck': 3, 'shoulder_straps': 4, 'high_neck': 5, 'boat_neck': 6, 'mandarin_neck': 7, 'off_sho
ulder': 8, 'square_neck': 9, 'halter_neck': 10, 'keyhole_neck': 11, 'crew_neck': 12, 'one_shoulder': 13, 'sweetheart': 14, 'plungin
g_neck': 15, 'strapless/tube': 16, 'hooded': 17, 'ruffled_neck': 18, 'scoop_neck': 19, 'cowl_neck': 20, 'queen_anne': 21, 'cold_sho
ulder': 22}
OrderedDict([('round_neck', 103), ('v-neck', 113), ('off_shoulder', 18), ('collar_neck', 56), ('high_neck', 32), ('keyhole_neck',
10), ('ruffled_neck', 2), ('shoulder_straps', 47), ('sweetheart', 6), ('crew_neck', 10), ('square_neck', 17), ('halter_neck', 11),
('mandarin_neck', 23), ('boat_neck', 25), ('plunging_neck', 6), ('one_shoulder', 10), ('strapless/tube', 4), ('hooded', 3), ('scoo
p_neck', 1), ('cowl_neck', 1), ('queen_anne', 1), ('cold_shoulder', 1)])
```

In [16]:

```
#Creating input sequence for material attribute
input_sequence1 = []
image_input1 = []
for j in range(len(data1)):
  token_list = tokenizer1.texts_to_sequences([data1[j]])[0][0]
  input_sequence1.append(token_list)
  image_input1.append(imgfeatures[imgpath[j]])
print(len(input_sequence1))
print(len(image_input1))
```

```
500
500
```

In [17]:

```
#input and output for predicting material attribute
x1 = image_input1
y1 = tf.keras.utils.to_categorical(input_sequence1, num_classes=total_words1)

x1 = np.array(x1)
y1 = np.array(y1)
x1.shape,y1.shape
```

Out[17]:

```
((500, 2048), (500, 31))
```

In [19]:

```
#Creating input sequence for pattern attribute
input_sequence2 = []
image_input2 = []
for j in range(len(data2)):
  token_list = tokenizer2.texts_to_sequences([data2[j]])[0][0]
  input_sequence2.append(token_list)
  image_input2.append(imgfeatures[imgpath[j]])
print(len(input_sequence2))
print(len(image_input2))
```

```
500
500
```

In [20]:

```
#input and output for predicting pattern attribute
x2 = image_input2
y2 = tf.keras.utils.to_categorical(input_sequence2, num_classes=total_words2)

x2 = np.array(x2)
y2 = np.array(y2)
x2.shape,y2.shape
```

Out[20]:

```
((500, 2048), (500, 19))
```

In [21]:

```
#Creating input sequence for neckline attribute
input_sequence3 = []
image_input3 = []
for j in range(len(data3)):
  token_list = tokenizer3.texts_to_sequences([data3[j]])[0][0]
  input_sequence3.append(token_list)
  image_input3.append(imgfeatures[imgpath[j]])
print(len(input_sequence3))
print(len(image_input3))
```

```
500
500
```

In [22]:

```
#input and output for predicting neckline attribute
```

```
x3 = image_input3
y3 = tf.keras.utils.to_categorical(input_sequence3, num_classes=total_words3)

x3 = np.array(x3)
y3 = np.array(y3)
x3.shape,y3.shape
```

Out[22]:

```
((500, 2048), (500, 23))
```

Model Training for Material

In [26]:

```
model1 = Sequential()
model1.add(Dense(100, input_dim=2048, activation='relu'))
model1.add(Dense(units=256))
model1.add(Dropout(0.5))
model1.add(Dense(units=256))
model1.add(Dropout(0.5))
model1.add(Dense(units=128))
model1.add(Dropout(0.2))
model1.add(Dense(total_words1, activation='softmax'))
model1.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model1.summary()
history1 = model1.fit(x1, y1, epochs=300, batch_size=32, verbose=2)
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_15 (Dense)             (None, 100)               204900    
_________________________________________________________________
dense_16 (Dense)             (None, 256)               25856     
_________________________________________________________________
dropout_9 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_17 (Dense)             (None, 256)               65792     
_________________________________________________________________
dropout_10 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_18 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_11 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_19 (Dense)             (None, 31)                3999      
=================================================================
Total params: 333,443
Trainable params: 333,443
Non-trainable params: 0
_________________________________________________________________
Epoch 1/300
16/16 - 0s - loss: 3.0929 - accuracy: 0.2100
Epoch 2/300
16/16 - 0s - loss: 2.3455 - accuracy: 0.3240
Epoch 3/300
16/16 - 0s - loss: 2.1490 - accuracy: 0.3900
Epoch 4/300
16/16 - 0s - loss: 1.9675 - accuracy: 0.4360
Epoch 5/300
16/16 - 0s - loss: 1.8420 - accuracy: 0.4540
Epoch 6/300
16/16 - 0s - loss: 1.7010 - accuracy: 0.4860
Epoch 7/300
16/16 - 0s - loss: 1.5746 - accuracy: 0.5080
Epoch 8/300
16/16 - 0s - loss: 1.4749 - accuracy: 0.5560
Epoch 9/300
16/16 - 0s - loss: 1.3644 - accuracy: 0.5780
Epoch 10/300
16/16 - 0s - loss: 1.3141 - accuracy: 0.5820
Epoch 11/300
16/16 - 0s - loss: 1.1237 - accuracy: 0.6460
Epoch 12/300
16/16 - 0s - loss: 1.1838 - accuracy: 0.6320
Epoch 13/300
16/16 - 0s - loss: 1.0267 - accuracy: 0.6900
Epoch 14/300
16/16 - 0s - loss: 1.0224 - accuracy: 0.7040
Epoch 15/300
16/16 - 0s - loss: 0.9165 - accuracy: 0.7120
Epoch 16/300
16/16 - 0s - loss: 0.7623 - accuracy: 0.7460
Epoch 17/300
16/16 - 0s - loss: 0.7192 - accuracy: 0.7720
Epoch 18/300
16/16 - 0s - loss: 0.7478 - accuracy: 0.7560
Epoch 19/300
16/16 - 0s - loss: 0.6345 - accuracy: 0.7980
Epoch 20/300
16/16 - 0s - loss: 0.5721 - accuracy: 0.8100
Epoch 21/300
16/16 - 0s - loss: 0.5252 - accuracy: 0.8500
Epoch 22/300
16/16 - 0s - loss: 0.5361 - accuracy: 0.8200
Epoch 23/300
16/16 - 0s - loss: 0.5457 - accuracy: 0.8220
Epoch 24/300
16/16 - 0s - loss: 0.4936 - accuracy: 0.8440
Epoch 25/300
16/16 - 0s - loss: 0.4998 - accuracy: 0.8440
```

```
Epoch 26/300
16/16 - 0s - loss: 0.5170 - accuracy: 0.8440
Epoch 27/300
16/16 - 0s - loss: 0.5404 - accuracy: 0.8520
Epoch 28/300
16/16 - 0s - loss: 0.5226 - accuracy: 0.8300
Epoch 29/300
16/16 - 0s - loss: 0.5240 - accuracy: 0.8260
Epoch 30/300
16/16 - 0s - loss: 0.4997 - accuracy: 0.8540
Epoch 31/300
16/16 - 0s - loss: 0.4612 - accuracy: 0.8400
Epoch 32/300
16/16 - 0s - loss: 0.4481 - accuracy: 0.8620
Epoch 33/300
16/16 - 0s - loss: 0.4134 - accuracy: 0.8760
Epoch 34/300
16/16 - 0s - loss: 0.5285 - accuracy: 0.8200
Epoch 35/300
16/16 - 0s - loss: 0.5143 - accuracy: 0.8420
Epoch 36/300
16/16 - 0s - loss: 0.3896 - accuracy: 0.8760
Epoch 37/300
16/16 - 0s - loss: 0.3726 - accuracy: 0.8900
Epoch 38/300
16/16 - 0s - loss: 0.4470 - accuracy: 0.8600
Epoch 39/300
16/16 - 0s - loss: 0.4391 - accuracy: 0.8620
Epoch 40/300
16/16 - 0s - loss: 0.3847 - accuracy: 0.8640
Epoch 41/300
16/16 - 0s - loss: 0.4102 - accuracy: 0.8640
Epoch 42/300
16/16 - 0s - loss: 0.3536 - accuracy: 0.8820
Epoch 43/300
16/16 - 0s - loss: 0.3464 - accuracy: 0.9000
Epoch 44/300
16/16 - 0s - loss: 0.3083 - accuracy: 0.9060
Epoch 45/300
16/16 - 0s - loss: 0.2986 - accuracy: 0.8980
Epoch 46/300
16/16 - 0s - loss: 0.3135 - accuracy: 0.9100
Epoch 47/300
16/16 - 0s - loss: 0.2848 - accuracy: 0.9100
Epoch 48/300
16/16 - 0s - loss: 0.2710 - accuracy: 0.9080
Epoch 49/300
16/16 - 0s - loss: 0.3259 - accuracy: 0.8760
Epoch 50/300
16/16 - 0s - loss: 0.3270 - accuracy: 0.8840
Epoch 51/300
16/16 - 0s - loss: 0.4217 - accuracy: 0.8820
Epoch 52/300
16/16 - 0s - loss: 0.3453 - accuracy: 0.8820
Epoch 53/300
16/16 - 0s - loss: 0.2786 - accuracy: 0.9120
Epoch 54/300
16/16 - 0s - loss: 0.5507 - accuracy: 0.8340
Epoch 55/300
16/16 - 0s - loss: 0.4503 - accuracy: 0.8640
Epoch 56/300
16/16 - 0s - loss: 0.3187 - accuracy: 0.8960
Epoch 57/300
16/16 - 0s - loss: 0.3474 - accuracy: 0.8960
Epoch 58/300
16/16 - 0s - loss: 0.5341 - accuracy: 0.8500
Epoch 59/300
16/16 - 0s - loss: 0.3238 - accuracy: 0.8960
Epoch 60/300
16/16 - 0s - loss: 0.3466 - accuracy: 0.9040
Epoch 61/300
16/16 - 0s - loss: 0.2986 - accuracy: 0.8980
Epoch 62/300
16/16 - 0s - loss: 0.2303 - accuracy: 0.9260
Epoch 63/300
16/16 - 0s - loss: 0.2476 - accuracy: 0.9200
Epoch 64/300
16/16 - 0s - loss: 0.2402 - accuracy: 0.9200
Epoch 65/300
16/16 - 0s - loss: 0.2518 - accuracy: 0.9160
Epoch 66/300
16/16 - 0s - loss: 0.3096 - accuracy: 0.9040
Epoch 67/300
16/16 - 0s - loss: 0.3202 - accuracy: 0.8960
Epoch 68/300
16/16 - 0s - loss: 0.2601 - accuracy: 0.9160
Epoch 69/300
16/16 - 0s - loss: 0.2287 - accuracy: 0.9260
Epoch 70/300
16/16 - 0s - loss: 0.2142 - accuracy: 0.9340
Epoch 71/300
16/16 - 0s - loss: 0.2378 - accuracy: 0.9220
Epoch 72/300
16/16 - 0s - loss: 0.2214 - accuracy: 0.9160
Epoch 73/300
16/16 - 0s - loss: 0.2409 - accuracy: 0.9200
Epoch 74/300
16/16 - 0s - loss: 0.3269 - accuracy: 0.9040
Epoch 75/300
16/16 - 0s - loss: 0.2381 - accuracy: 0.9140
Epoch 76/300
16/16 - 0s - loss: 0.2521 - accuracy: 0.9180
Epoch 77/300
```

```
Epoch 77/300
16/16 - 0s - loss: 0.2374 - accuracy: 0.9200
Epoch 78/300
16/16 - 0s - loss: 0.2353 - accuracy: 0.9160
Epoch 79/300
16/16 - 0s - loss: 0.1739 - accuracy: 0.9380
Epoch 80/300
16/16 - 0s - loss: 0.2070 - accuracy: 0.9280
Epoch 81/300
16/16 - 0s - loss: 0.1920 - accuracy: 0.9360
Epoch 82/300
16/16 - 0s - loss: 0.2556 - accuracy: 0.9140
Epoch 83/300
16/16 - 0s - loss: 0.2513 - accuracy: 0.9160
Epoch 84/300
16/16 - 0s - loss: 0.2274 - accuracy: 0.9380
Epoch 85/300
16/16 - 0s - loss: 0.2718 - accuracy: 0.9060
Epoch 86/300
16/16 - 0s - loss: 0.2880 - accuracy: 0.9140
Epoch 87/300
16/16 - 0s - loss: 0.2443 - accuracy: 0.9280
Epoch 88/300
16/16 - 0s - loss: 0.2222 - accuracy: 0.9180
Epoch 89/300
16/16 - 0s - loss: 0.2273 - accuracy: 0.9160
Epoch 90/300
16/16 - 0s - loss: 0.1733 - accuracy: 0.9360
Epoch 91/300
16/16 - 0s - loss: 0.1807 - accuracy: 0.9440
Epoch 92/300
16/16 - 0s - loss: 0.1794 - accuracy: 0.9400
Epoch 93/300
16/16 - 0s - loss: 0.1966 - accuracy: 0.9340
Epoch 94/300
16/16 - 0s - loss: 0.1845 - accuracy: 0.9360
Epoch 95/300
16/16 - 0s - loss: 0.2200 - accuracy: 0.9360
Epoch 96/300
16/16 - 0s - loss: 0.2261 - accuracy: 0.9180
Epoch 97/300
16/16 - 0s - loss: 0.2131 - accuracy: 0.9240
Epoch 98/300
16/16 - 0s - loss: 0.2249 - accuracy: 0.9320
Epoch 99/300
16/16 - 0s - loss: 0.2374 - accuracy: 0.9220
Epoch 100/300
16/16 - 0s - loss: 0.2608 - accuracy: 0.9240
Epoch 101/300
16/16 - 0s - loss: 0.3688 - accuracy: 0.9080
Epoch 102/300
16/16 - 0s - loss: 0.4740 - accuracy: 0.8780
Epoch 103/300
16/16 - 0s - loss: 0.3890 - accuracy: 0.8860
Epoch 104/300
16/16 - 0s - loss: 0.3807 - accuracy: 0.8900
Epoch 105/300
16/16 - 0s - loss: 0.2126 - accuracy: 0.9300
Epoch 106/300
16/16 - 0s - loss: 0.2173 - accuracy: 0.9300
Epoch 107/300
16/16 - 0s - loss: 0.2399 - accuracy: 0.9360
Epoch 108/300
16/16 - 0s - loss: 0.2603 - accuracy: 0.9240
Epoch 109/300
16/16 - 0s - loss: 0.2421 - accuracy: 0.9280
Epoch 110/300
16/16 - 0s - loss: 0.1957 - accuracy: 0.9380
Epoch 111/300
16/16 - 0s - loss: 0.1774 - accuracy: 0.9280
Epoch 112/300
16/16 - 0s - loss: 0.1658 - accuracy: 0.9520
Epoch 113/300
16/16 - 0s - loss: 0.1337 - accuracy: 0.9500
Epoch 114/300
16/16 - 0s - loss: 0.2984 - accuracy: 0.9220
Epoch 115/300
16/16 - 0s - loss: 0.2672 - accuracy: 0.9180
Epoch 116/300
16/16 - 0s - loss: 0.1549 - accuracy: 0.9520
Epoch 117/300
16/16 - 0s - loss: 0.2014 - accuracy: 0.9360
Epoch 118/300
16/16 - 0s - loss: 0.1512 - accuracy: 0.9500
Epoch 119/300
16/16 - 0s - loss: 0.1204 - accuracy: 0.9540
Epoch 120/300
16/16 - 0s - loss: 0.1232 - accuracy: 0.9580
Epoch 121/300
16/16 - 0s - loss: 0.0910 - accuracy: 0.9680
Epoch 122/300
16/16 - 0s - loss: 0.1053 - accuracy: 0.9660
Epoch 123/300
16/16 - 0s - loss: 0.0670 - accuracy: 0.9700
Epoch 124/300
16/16 - 0s - loss: 0.0780 - accuracy: 0.9760
Epoch 125/300
16/16 - 0s - loss: 0.1359 - accuracy: 0.9560
Epoch 126/300
16/16 - 0s - loss: 0.1267 - accuracy: 0.9620
Epoch 127/300
16/16 - 0s - loss: 0.1683 - accuracy: 0.9520
Epoch 128/300
```

```
16/16 - 0s - loss: 0.1395 - accuracy: 0.9600
Epoch 129/300
16/16 - 0s - loss: 0.1402 - accuracy: 0.9540
Epoch 130/300
16/16 - 0s - loss: 0.2592 - accuracy: 0.9220
Epoch 131/300
16/16 - 0s - loss: 0.2358 - accuracy: 0.9320
Epoch 132/300
16/16 - 0s - loss: 0.2560 - accuracy: 0.9260
Epoch 133/300
16/16 - 0s - loss: 0.2176 - accuracy: 0.9400
Epoch 134/300
16/16 - 0s - loss: 0.2195 - accuracy: 0.9360
Epoch 135/300
16/16 - 0s - loss: 0.2253 - accuracy: 0.9440
Epoch 136/300
16/16 - 0s - loss: 0.1922 - accuracy: 0.9360
Epoch 137/300
16/16 - 0s - loss: 0.2545 - accuracy: 0.9360
Epoch 138/300
16/16 - 0s - loss: 0.4631 - accuracy: 0.8960
Epoch 139/300
16/16 - 0s - loss: 0.2905 - accuracy: 0.9040
Epoch 140/300
16/16 - 0s - loss: 0.3796 - accuracy: 0.9060
Epoch 141/300
16/16 - 0s - loss: 0.3665 - accuracy: 0.8860
Epoch 142/300
16/16 - 0s - loss: 0.2550 - accuracy: 0.9280
Epoch 143/300
16/16 - 0s - loss: 0.2778 - accuracy: 0.9260
Epoch 144/300
16/16 - 0s - loss: 0.2359 - accuracy: 0.9280
Epoch 145/300
16/16 - 0s - loss: 0.2008 - accuracy: 0.9460
Epoch 146/300
16/16 - 0s - loss: 0.1300 - accuracy: 0.9580
Epoch 147/300
16/16 - 0s - loss: 0.1517 - accuracy: 0.9600
Epoch 148/300
16/16 - 0s - loss: 0.0993 - accuracy: 0.9720
Epoch 149/300
16/16 - 0s - loss: 0.1276 - accuracy: 0.9660
Epoch 150/300
16/16 - 0s - loss: 0.1076 - accuracy: 0.9600
Epoch 151/300
16/16 - 0s - loss: 0.1317 - accuracy: 0.9580
Epoch 152/300
16/16 - 0s - loss: 0.0961 - accuracy: 0.9640
Epoch 153/300
16/16 - 0s - loss: 0.1110 - accuracy: 0.9620
Epoch 154/300
16/16 - 0s - loss: 0.1407 - accuracy: 0.9660
Epoch 155/300
16/16 - 0s - loss: 0.0832 - accuracy: 0.9700
Epoch 156/300
16/16 - 0s - loss: 0.0817 - accuracy: 0.9640
Epoch 157/300
16/16 - 0s - loss: 0.1026 - accuracy: 0.9660
Epoch 158/300
16/16 - 0s - loss: 0.1431 - accuracy: 0.9600
Epoch 159/300
16/16 - 0s - loss: 0.0675 - accuracy: 0.9700
Epoch 160/300
16/16 - 0s - loss: 0.1034 - accuracy: 0.9640
Epoch 161/300
16/16 - 0s - loss: 0.1227 - accuracy: 0.9700
Epoch 162/300
16/16 - 0s - loss: 0.2557 - accuracy: 0.9340
Epoch 163/300
16/16 - 0s - loss: 0.3293 - accuracy: 0.9220
Epoch 164/300
16/16 - 0s - loss: 0.4145 - accuracy: 0.8980
Epoch 165/300
16/16 - 0s - loss: 0.2369 - accuracy: 0.9200
Epoch 166/300
16/16 - 0s - loss: 0.1991 - accuracy: 0.9360
Epoch 167/300
16/16 - 0s - loss: 0.2479 - accuracy: 0.9280
Epoch 168/300
16/16 - 0s - loss: 0.2038 - accuracy: 0.9460
Epoch 169/300
16/16 - 0s - loss: 0.1874 - accuracy: 0.9440
Epoch 170/300
16/16 - 0s - loss: 0.1634 - accuracy: 0.9640
Epoch 171/300
16/16 - 0s - loss: 0.1230 - accuracy: 0.9620
Epoch 172/300
16/16 - 0s - loss: 0.1173 - accuracy: 0.9620
Epoch 173/300
16/16 - 0s - loss: 0.1104 - accuracy: 0.9660
Epoch 174/300
16/16 - 0s - loss: 0.1209 - accuracy: 0.9560
Epoch 175/300
16/16 - 0s - loss: 0.1472 - accuracy: 0.9600
Epoch 176/300
16/16 - 0s - loss: 0.1647 - accuracy: 0.9540
Epoch 177/300
16/16 - 0s - loss: 0.1773 - accuracy: 0.9660
Epoch 178/300
16/16 - 0s - loss: 0.2100 - accuracy: 0.9500
Epoch 179/300
```

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16/16 - 0s - loss: 0.1433 - accuracy: 0.9560
Epoch 180/300
16/16 - 0s - loss: 0.1023 - accuracy: 0.9720
Epoch 181/300
16/16 - 0s - loss: 0.0641 - accuracy: 0.9720
Epoch 182/300
16/16 - 0s - loss: 0.0632 - accuracy: 0.9780
Epoch 183/300
16/16 - 0s - loss: 0.0640 - accuracy: 0.9800
Epoch 184/300
16/16 - 0s - loss: 0.0660 - accuracy: 0.9820
Epoch 185/300
16/16 - 0s - loss: 0.0680 - accuracy: 0.9800
Epoch 186/300
16/16 - 0s - loss: 0.0924 - accuracy: 0.9640
Epoch 187/300
16/16 - 0s - loss: 0.1318 - accuracy: 0.9720
Epoch 188/300
16/16 - 0s - loss: 0.1084 - accuracy: 0.9660
Epoch 189/300
16/16 - 0s - loss: 0.1643 - accuracy: 0.9540
Epoch 190/300
16/16 - 0s - loss: 0.1477 - accuracy: 0.9520
Epoch 191/300
16/16 - 0s - loss: 0.2304 - accuracy: 0.9400
Epoch 192/300
16/16 - 0s - loss: 0.5002 - accuracy: 0.8940
Epoch 193/300
16/16 - 0s - loss: 0.2864 - accuracy: 0.9260
Epoch 194/300
16/16 - 0s - loss: 0.5307 - accuracy: 0.8660
Epoch 195/300
16/16 - 0s - loss: 0.3661 - accuracy: 0.9240
Epoch 196/300
16/16 - 0s - loss: 0.1536 - accuracy: 0.9480
Epoch 197/300
16/16 - 0s - loss: 0.1404 - accuracy: 0.9600
Epoch 198/300
16/16 - 0s - loss: 0.1892 - accuracy: 0.9520
Epoch 199/300
16/16 - 0s - loss: 0.1690 - accuracy: 0.9560
Epoch 200/300
16/16 - 0s - loss: 0.0725 - accuracy: 0.9740
Epoch 201/300
16/16 - 0s - loss: 0.2288 - accuracy: 0.9360
Epoch 202/300
16/16 - 0s - loss: 0.2135 - accuracy: 0.9520
Epoch 203/300
16/16 - 0s - loss: 0.1655 - accuracy: 0.9540
Epoch 204/300
16/16 - 0s - loss: 0.1551 - accuracy: 0.9480
Epoch 205/300
16/16 - 0s - loss: 0.1130 - accuracy: 0.9600
Epoch 206/300
16/16 - 0s - loss: 0.0854 - accuracy: 0.9780
Epoch 207/300
16/16 - 0s - loss: 0.0898 - accuracy: 0.9620
Epoch 208/300
16/16 - 0s - loss: 0.0956 - accuracy: 0.9720
Epoch 209/300
16/16 - 0s - loss: 0.0931 - accuracy: 0.9740
Epoch 210/300
16/16 - 0s - loss: 0.2425 - accuracy: 0.9600
Epoch 211/300
16/16 - 0s - loss: 0.1246 - accuracy: 0.9600
Epoch 212/300
16/16 - 0s - loss: 0.0930 - accuracy: 0.9720
Epoch 213/300
16/16 - 0s - loss: 0.0872 - accuracy: 0.9640
Epoch 214/300
16/16 - 0s - loss: 0.0866 - accuracy: 0.9760
Epoch 215/300
16/16 - 0s - loss: 0.1453 - accuracy: 0.9600
Epoch 216/300
16/16 - 0s - loss: 0.2483 - accuracy: 0.9360
Epoch 217/300
16/16 - 0s - loss: 0.2341 - accuracy: 0.9300
Epoch 218/300
16/16 - 0s - loss: 0.1684 - accuracy: 0.9600
Epoch 219/300
16/16 - 0s - loss: 0.1187 - accuracy: 0.9640
Epoch 220/300
16/16 - 0s - loss: 0.1592 - accuracy: 0.9540
Epoch 221/300
16/16 - 0s - loss: 0.1280 - accuracy: 0.9700
Epoch 222/300
16/16 - 0s - loss: 0.1792 - accuracy: 0.9520
Epoch 223/300
16/16 - 0s - loss: 0.2328 - accuracy: 0.9380
Epoch 224/300
16/16 - 0s - loss: 0.1148 - accuracy: 0.9660
Epoch 225/300
16/16 - 0s - loss: 0.1687 - accuracy: 0.9560
Epoch 226/300
16/16 - 0s - loss: 0.1110 - accuracy: 0.9740
Epoch 227/300
16/16 - 0s - loss: 0.1249 - accuracy: 0.9640
Epoch 228/300
16/16 - 0s - loss: 0.0873 - accuracy: 0.9780
Epoch 229/300
16/16 - 0s - loss: 0.0992 - accuracy: 0.9740
Epoch 230/300
16/16 - 0s - loss: 0.0719 - accuracy: 0.9680
```

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16/16 - 0s - loss: 0.0719 - accuracy: 0.9680
Epoch 231/300
16/16 - 0s - loss: 0.0808 - accuracy: 0.9740
Epoch 232/300
16/16 - 0s - loss: 0.0506 - accuracy: 0.9860
Epoch 233/300
16/16 - 0s - loss: 0.1002 - accuracy: 0.9660
Epoch 234/300
16/16 - 0s - loss: 0.0860 - accuracy: 0.9720
Epoch 235/300
16/16 - 0s - loss: 0.1088 - accuracy: 0.9680
Epoch 236/300
16/16 - 0s - loss: 0.0910 - accuracy: 0.9680
Epoch 237/300
16/16 - 0s - loss: 0.0972 - accuracy: 0.9680
Epoch 238/300
16/16 - 0s - loss: 0.1781 - accuracy: 0.9540
Epoch 239/300
16/16 - 0s - loss: 0.3423 - accuracy: 0.9320
Epoch 240/300
16/16 - 0s - loss: 0.4065 - accuracy: 0.9060
Epoch 241/300
16/16 - 0s - loss: 0.2405 - accuracy: 0.9240
Epoch 242/300
16/16 - 0s - loss: 0.2264 - accuracy: 0.9400
Epoch 243/300
16/16 - 0s - loss: 0.1827 - accuracy: 0.9560
Epoch 244/300
16/16 - 0s - loss: 0.1072 - accuracy: 0.9560
Epoch 245/300
16/16 - 0s - loss: 0.1030 - accuracy: 0.9640
Epoch 246/300
16/16 - 0s - loss: 0.0959 - accuracy: 0.9660
Epoch 247/300
16/16 - 0s - loss: 0.1247 - accuracy: 0.9600
Epoch 248/300
16/16 - 0s - loss: 0.0705 - accuracy: 0.9780
Epoch 249/300
16/16 - 0s - loss: 0.0619 - accuracy: 0.9800
Epoch 250/300
16/16 - 0s - loss: 0.0541 - accuracy: 0.9780
Epoch 251/300
16/16 - 0s - loss: 0.0453 - accuracy: 0.9860
Epoch 252/300
16/16 - 0s - loss: 0.0272 - accuracy: 0.9920
Epoch 253/300
16/16 - 0s - loss: 0.0436 - accuracy: 0.9860
Epoch 254/300
16/16 - 0s - loss: 0.0683 - accuracy: 0.9840
Epoch 255/300
16/16 - 0s - loss: 0.0987 - accuracy: 0.9780
Epoch 256/300
16/16 - 0s - loss: 0.0449 - accuracy: 0.9860
Epoch 257/300
16/16 - 0s - loss: 0.0613 - accuracy: 0.9780
Epoch 258/300
16/16 - 0s - loss: 0.0653 - accuracy: 0.9780
Epoch 259/300
16/16 - 0s - loss: 0.0693 - accuracy: 0.9760
Epoch 260/300
16/16 - 0s - loss: 0.0720 - accuracy: 0.9760
Epoch 261/300
16/16 - 0s - loss: 0.0938 - accuracy: 0.9640
Epoch 262/300
16/16 - 0s - loss: 0.0969 - accuracy: 0.9660
Epoch 263/300
16/16 - 0s - loss: 0.1370 - accuracy: 0.9540
Epoch 264/300
16/16 - 0s - loss: 0.0855 - accuracy: 0.9760
Epoch 265/300
16/16 - 0s - loss: 0.2581 - accuracy: 0.9480
Epoch 266/300
16/16 - 0s - loss: 0.2690 - accuracy: 0.9480
Epoch 267/300
16/16 - 0s - loss: 0.1181 - accuracy: 0.9680
Epoch 268/300
16/16 - 0s - loss: 0.1375 - accuracy: 0.9720
Epoch 269/300
16/16 - 0s - loss: 0.1316 - accuracy: 0.9620
Epoch 270/300
16/16 - 0s - loss: 0.0853 - accuracy: 0.9720
Epoch 271/300
16/16 - 0s - loss: 0.1039 - accuracy: 0.9620
Epoch 272/300
16/16 - 0s - loss: 0.0609 - accuracy: 0.9820
Epoch 273/300
16/16 - 0s - loss: 0.1062 - accuracy: 0.9700
Epoch 274/300
16/16 - 0s - loss: 0.1118 - accuracy: 0.9620
Epoch 275/300
16/16 - 0s - loss: 0.1981 - accuracy: 0.9480
Epoch 276/300
16/16 - 0s - loss: 0.2543 - accuracy: 0.9480
Epoch 277/300
16/16 - 0s - loss: 0.1850 - accuracy: 0.9460
Epoch 278/300
16/16 - 0s - loss: 0.2033 - accuracy: 0.9520
Epoch 279/300
16/16 - 0s - loss: 0.4777 - accuracy: 0.9140
Epoch 280/300
16/16 - 0s - loss: 0.2996 - accuracy: 0.9280
Epoch 281/300
16/16 - 0s - loss: 0.2094 - accuracy: 0.9520
```

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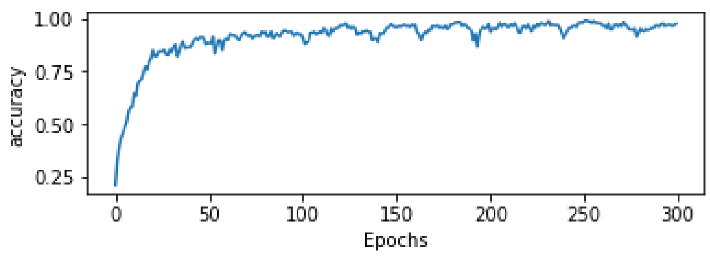
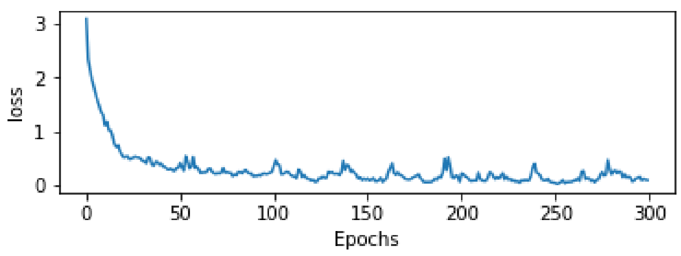
Epoch 282/300
16/16 - 0s - loss: 0.2684 - accuracy: 0.9420
Epoch 283/300
16/16 - 0s - loss: 0.2797 - accuracy: 0.9380
Epoch 284/300
16/16 - 0s - loss: 0.2281 - accuracy: 0.9500
Epoch 285/300
16/16 - 0s - loss: 0.2626 - accuracy: 0.9440
Epoch 286/300
16/16 - 0s - loss: 0.2508 - accuracy: 0.9480
Epoch 287/300
16/16 - 0s - loss: 0.1530 - accuracy: 0.9540
Epoch 288/300
16/16 - 0s - loss: 0.2114 - accuracy: 0.9560
Epoch 289/300
16/16 - 0s - loss: 0.1468 - accuracy: 0.9660
Epoch 290/300
16/16 - 0s - loss: 0.1669 - accuracy: 0.9660
Epoch 291/300
16/16 - 0s - loss: 0.1499 - accuracy: 0.9620
Epoch 292/300
16/16 - 0s - loss: 0.0774 - accuracy: 0.9720
Epoch 293/300
16/16 - 0s - loss: 0.0931 - accuracy: 0.9760
Epoch 294/300
16/16 - 0s - loss: 0.1329 - accuracy: 0.9640
Epoch 295/300
16/16 - 0s - loss: 0.1380 - accuracy: 0.9680
Epoch 296/300
16/16 - 0s - loss: 0.1632 - accuracy: 0.9700
Epoch 297/300
16/16 - 0s - loss: 0.0977 - accuracy: 0.9700
Epoch 298/300
16/16 - 0s - loss: 0.1250 - accuracy: 0.9640
Epoch 299/300
16/16 - 0s - loss: 0.1111 - accuracy: 0.9680
Epoch 300/300
16/16 - 0s - loss: 0.1016 - accuracy: 0.9740
```

In [33]:

```
def plot_graphs(history, string):
  plt.plot(history.history[string])
  plt.xlabel("Epochs")
  plt.ylabel(string)
  plt.show()
plt.subplot(2,1,1)
plot_graphs(history1, 'accuracy')
plt.subplot(2,1,2)
plot_graphs(history1, 'loss')
```





Model Training for Patterns

In [36]:

```
model2 = Sequential()
model2.add(Dense(100, input_dim=2048, activation='relu'))
model2.add(Dense(units=256))
model2.add(Dropout(0.5))
model2.add(Dense(units=256))
model2.add(Dropout(0.5))
model2.add(Dense(units=128))
model2.add(Dropout(0.2))
model2.add(Dense(total_words2, activation='softmax'))
model2.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model2.summary()
history2 = model2.fit(x2, y2, epochs=300, batch_size=32, verbose=2)
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_25 (Dense)             (None, 100)               204900
_________________________________________________________________
dense_26 (Dense)             (None, 256)               25856
_________________________________________________________________
dropout_15 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_27 (Dense)             (None, 256)               65792
_________________________________________________________________
dropout_16 (Dropout)         (None, 256)               0
_________________________________________________________________
dense_28 (Dense)             (None, 128)               32896
```

```
_________________________________________________________________
dropout_17 (Dropout)         (None, 128)               0
_________________________________________________________________
dense_29 (Dense)             (None, 19)                2451
=================================================================
Total params: 331,895
Trainable params: 331,895
Non-trainable params: 0
_________________________________________________________________
Epoch 1/300
16/16 - 0s - loss: 2.7978 - accuracy: 0.2840
Epoch 2/300
16/16 - 0s - loss: 1.7233 - accuracy: 0.5220
Epoch 3/300
16/16 - 0s - loss: 1.5331 - accuracy: 0.5560
Epoch 4/300
16/16 - 0s - loss: 1.4002 - accuracy: 0.6000
Epoch 5/300
16/16 - 0s - loss: 1.1983 - accuracy: 0.6320
Epoch 6/300
16/16 - 0s - loss: 1.0382 - accuracy: 0.6740
Epoch 7/300
16/16 - 0s - loss: 0.9289 - accuracy: 0.7120
Epoch 8/300
16/16 - 0s - loss: 0.8333 - accuracy: 0.7420
Epoch 9/300
16/16 - 0s - loss: 0.7069 - accuracy: 0.7680
Epoch 10/300
16/16 - 0s - loss: 0.6320 - accuracy: 0.8020
Epoch 11/300
16/16 - 0s - loss: 0.6581 - accuracy: 0.7980
Epoch 12/300
16/16 - 0s - loss: 0.5456 - accuracy: 0.8380
Epoch 13/300
16/16 - 0s - loss: 0.5179 - accuracy: 0.8320
Epoch 14/300
16/16 - 0s - loss: 0.4104 - accuracy: 0.8680
Epoch 15/300
16/16 - 0s - loss: 0.4376 - accuracy: 0.8620
Epoch 16/300
16/16 - 0s - loss: 0.4264 - accuracy: 0.8480
Epoch 17/300
16/16 - 0s - loss: 0.3525 - accuracy: 0.8880
Epoch 18/300
16/16 - 0s - loss: 0.2948 - accuracy: 0.9000
Epoch 19/300
16/16 - 0s - loss: 0.2842 - accuracy: 0.9120
Epoch 20/300
16/16 - 0s - loss: 0.2819 - accuracy: 0.8940
Epoch 21/300
16/16 - 0s - loss: 0.3217 - accuracy: 0.8980
Epoch 22/300
16/16 - 0s - loss: 0.2833 - accuracy: 0.8940
Epoch 23/300
16/16 - 0s - loss: 0.2772 - accuracy: 0.9040
Epoch 24/300
16/16 - 0s - loss: 0.2403 - accuracy: 0.9240
Epoch 25/300
16/16 - 0s - loss: 0.1866 - accuracy: 0.9320
Epoch 26/300
16/16 - 0s - loss: 0.2383 - accuracy: 0.9240
Epoch 27/300
16/16 - 0s - loss: 0.2702 - accuracy: 0.9120
Epoch 28/300
16/16 - 0s - loss: 0.3363 - accuracy: 0.8980
Epoch 29/300
16/16 - 0s - loss: 0.3415 - accuracy: 0.8880
Epoch 30/300
16/16 - 0s - loss: 0.3017 - accuracy: 0.8980
Epoch 31/300
16/16 - 0s - loss: 0.1859 - accuracy: 0.9400
Epoch 32/300
16/16 - 0s - loss: 0.1954 - accuracy: 0.9440
Epoch 33/300
16/16 - 0s - loss: 0.1493 - accuracy: 0.9500
Epoch 34/300
16/16 - 0s - loss: 0.1586 - accuracy: 0.9480
Epoch 35/300
16/16 - 0s - loss: 0.1160 - accuracy: 0.9540
Epoch 36/300
16/16 - 0s - loss: 0.1157 - accuracy: 0.9620
Epoch 37/300
16/16 - 0s - loss: 0.1156 - accuracy: 0.9620
Epoch 38/300
16/16 - 0s - loss: 0.1071 - accuracy: 0.9680
Epoch 39/300
16/16 - 0s - loss: 0.0724 - accuracy: 0.9740
Epoch 40/300
16/16 - 0s - loss: 0.0718 - accuracy: 0.9740
Epoch 41/300
16/16 - 0s - loss: 0.0953 - accuracy: 0.9660
Epoch 42/300
16/16 - 0s - loss: 0.0970 - accuracy: 0.9740
Epoch 43/300
16/16 - 0s - loss: 0.0698 - accuracy: 0.9760
Epoch 44/300
16/16 - 0s - loss: 0.0978 - accuracy: 0.9720
Epoch 45/300
16/16 - 0s - loss: 0.0965 - accuracy: 0.9720
Epoch 46/300
16/16 - 0s - loss: 0.1285 - accuracy: 0.9580
Epoch 47/300
```

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16/16 - 0s - loss: 0.2808 - accuracy: 0.9280
Epoch 48/300
16/16 - 0s - loss: 0.1502 - accuracy: 0.9560
Epoch 49/300
16/16 - 0s - loss: 0.1472 - accuracy: 0.9560
Epoch 50/300
16/16 - 0s - loss: 0.2458 - accuracy: 0.9380
Epoch 51/300
16/16 - 0s - loss: 0.3549 - accuracy: 0.8820
Epoch 52/300
16/16 - 0s - loss: 0.2608 - accuracy: 0.9080
Epoch 53/300
16/16 - 0s - loss: 0.2544 - accuracy: 0.9280
Epoch 54/300
16/16 - 0s - loss: 0.2808 - accuracy: 0.9120
Epoch 55/300
16/16 - 0s - loss: 0.2351 - accuracy: 0.9380
Epoch 56/300
16/16 - 0s - loss: 0.2903 - accuracy: 0.9080
Epoch 57/300
16/16 - 0s - loss: 0.3152 - accuracy: 0.9080
Epoch 58/300
16/16 - 0s - loss: 0.3995 - accuracy: 0.8880
Epoch 59/300
16/16 - 0s - loss: 0.2171 - accuracy: 0.9260
Epoch 60/300
16/16 - 0s - loss: 0.2255 - accuracy: 0.9380
Epoch 61/300
16/16 - 0s - loss: 0.1867 - accuracy: 0.9420
Epoch 62/300
16/16 - 0s - loss: 0.2232 - accuracy: 0.9300
Epoch 63/300
16/16 - 0s - loss: 0.1931 - accuracy: 0.9440
Epoch 64/300
16/16 - 0s - loss: 0.1606 - accuracy: 0.9420
Epoch 65/300
16/16 - 0s - loss: 0.1338 - accuracy: 0.9540
Epoch 66/300
16/16 - 0s - loss: 0.1236 - accuracy: 0.9640
Epoch 67/300
16/16 - 0s - loss: 0.0818 - accuracy: 0.9760
Epoch 68/300
16/16 - 0s - loss: 0.0924 - accuracy: 0.9660
Epoch 69/300
16/16 - 0s - loss: 0.0596 - accuracy: 0.9800
Epoch 70/300
16/16 - 0s - loss: 0.0937 - accuracy: 0.9780
Epoch 71/300
16/16 - 0s - loss: 0.1188 - accuracy: 0.9700
Epoch 72/300
16/16 - 0s - loss: 0.1503 - accuracy: 0.9580
Epoch 73/300
16/16 - 0s - loss: 0.1507 - accuracy: 0.9580
Epoch 74/300
16/16 - 0s - loss: 0.2650 - accuracy: 0.9200
Epoch 75/300
16/16 - 0s - loss: 0.1761 - accuracy: 0.9460
Epoch 76/300
16/16 - 0s - loss: 0.1156 - accuracy: 0.9620
Epoch 77/300
16/16 - 0s - loss: 0.1261 - accuracy: 0.9580
Epoch 78/300
16/16 - 0s - loss: 0.1327 - accuracy: 0.9600
Epoch 79/300
16/16 - 0s - loss: 0.1327 - accuracy: 0.9620
Epoch 80/300
16/16 - 0s - loss: 0.1128 - accuracy: 0.9680
Epoch 81/300
16/16 - 0s - loss: 0.1497 - accuracy: 0.9580
Epoch 82/300
16/16 - 0s - loss: 0.1488 - accuracy: 0.9560
Epoch 83/300
16/16 - 0s - loss: 0.1150 - accuracy: 0.9640
Epoch 84/300
16/16 - 0s - loss: 0.0655 - accuracy: 0.9740
Epoch 85/300
16/16 - 0s - loss: 0.0504 - accuracy: 0.9780
Epoch 86/300
16/16 - 0s - loss: 0.0622 - accuracy: 0.9780
Epoch 87/300
16/16 - 0s - loss: 0.0632 - accuracy: 0.9780
Epoch 88/300
16/16 - 0s - loss: 0.0554 - accuracy: 0.9780
Epoch 89/300
16/16 - 0s - loss: 0.1270 - accuracy: 0.9720
Epoch 90/300
16/16 - 0s - loss: 0.1383 - accuracy: 0.9580
Epoch 91/300
16/16 - 0s - loss: 0.1649 - accuracy: 0.9560
Epoch 92/300
16/16 - 0s - loss: 0.1664 - accuracy: 0.9460
Epoch 93/300
16/16 - 0s - loss: 0.2111 - accuracy: 0.9480
Epoch 94/300
16/16 - 0s - loss: 0.1844 - accuracy: 0.9480
Epoch 95/300
16/16 - 0s - loss: 0.1819 - accuracy: 0.9480
Epoch 96/300
16/16 - 0s - loss: 0.2293 - accuracy: 0.9480
Epoch 97/300
16/16 - 0s - loss: 0.1362 - accuracy: 0.9540
Epoch 98/300
16/16 - 0s - loss: 0.1800 - accuracy: 0.9520
```

```
16/16 - 0s - loss: 0.1800 - accuracy: 0.9520
Epoch 99/300
16/16 - 0s - loss: 0.1483 - accuracy: 0.9620
Epoch 100/300
16/16 - 0s - loss: 0.0795 - accuracy: 0.9700
Epoch 101/300
16/16 - 0s - loss: 0.2326 - accuracy: 0.9460
Epoch 102/300
16/16 - 0s - loss: 0.2158 - accuracy: 0.9480
Epoch 103/300
16/16 - 0s - loss: 0.1245 - accuracy: 0.9600
Epoch 104/300
16/16 - 0s - loss: 0.1458 - accuracy: 0.9620
Epoch 105/300
16/16 - 0s - loss: 0.1635 - accuracy: 0.9540
Epoch 106/300
16/16 - 0s - loss: 0.1234 - accuracy: 0.9700
Epoch 107/300
16/16 - 0s - loss: 0.1215 - accuracy: 0.9520
Epoch 108/300
16/16 - 0s - loss: 0.1260 - accuracy: 0.9740
Epoch 109/300
16/16 - 0s - loss: 0.1195 - accuracy: 0.9600
Epoch 110/300
16/16 - 0s - loss: 0.0798 - accuracy: 0.9800
Epoch 111/300
16/16 - 0s - loss: 0.0527 - accuracy: 0.9840
Epoch 112/300
16/16 - 0s - loss: 0.0666 - accuracy: 0.9800
Epoch 113/300
16/16 - 0s - loss: 0.0522 - accuracy: 0.9840
Epoch 114/300
16/16 - 0s - loss: 0.0721 - accuracy: 0.9780
Epoch 115/300
16/16 - 0s - loss: 0.1350 - accuracy: 0.9640
Epoch 116/300
16/16 - 0s - loss: 0.1094 - accuracy: 0.9700
Epoch 117/300
16/16 - 0s - loss: 0.0957 - accuracy: 0.9740
Epoch 118/300
16/16 - 0s - loss: 0.2323 - accuracy: 0.9440
Epoch 119/300
16/16 - 0s - loss: 0.1425 - accuracy: 0.9640
Epoch 120/300
16/16 - 0s - loss: 0.0800 - accuracy: 0.9760
Epoch 121/300
16/16 - 0s - loss: 0.0794 - accuracy: 0.9820
Epoch 122/300
16/16 - 0s - loss: 0.1153 - accuracy: 0.9700
Epoch 123/300
16/16 - 0s - loss: 0.0599 - accuracy: 0.9840
Epoch 124/300
16/16 - 0s - loss: 0.1045 - accuracy: 0.9700
Epoch 125/300
16/16 - 0s - loss: 0.0594 - accuracy: 0.9820
Epoch 126/300
16/16 - 0s - loss: 0.1090 - accuracy: 0.9700
Epoch 127/300
16/16 - 0s - loss: 0.0598 - accuracy: 0.9840
Epoch 128/300
16/16 - 0s - loss: 0.0299 - accuracy: 0.9880
Epoch 129/300
16/16 - 0s - loss: 0.0448 - accuracy: 0.9820
Epoch 130/300
16/16 - 0s - loss: 0.0366 - accuracy: 0.9860
Epoch 131/300
16/16 - 0s - loss: 0.0446 - accuracy: 0.9820
Epoch 132/300
16/16 - 0s - loss: 0.0320 - accuracy: 0.9920
Epoch 133/300
16/16 - 0s - loss: 0.0559 - accuracy: 0.9880
Epoch 134/300
16/16 - 0s - loss: 0.0616 - accuracy: 0.9840
Epoch 135/300
16/16 - 0s - loss: 0.0570 - accuracy: 0.9800
Epoch 136/300
16/16 - 0s - loss: 0.0366 - accuracy: 0.9860
Epoch 137/300
16/16 - 0s - loss: 0.0516 - accuracy: 0.9800
Epoch 138/300
16/16 - 0s - loss: 0.1750 - accuracy: 0.9620
Epoch 139/300
16/16 - 0s - loss: 0.3272 - accuracy: 0.9520
Epoch 140/300
16/16 - 0s - loss: 0.3724 - accuracy: 0.9280
Epoch 141/300
16/16 - 0s - loss: 0.4507 - accuracy: 0.9060
Epoch 142/300
16/16 - 0s - loss: 0.2545 - accuracy: 0.9280
Epoch 143/300
16/16 - 0s - loss: 0.2306 - accuracy: 0.9480
Epoch 144/300
16/16 - 0s - loss: 0.3514 - accuracy: 0.9400
Epoch 145/300
16/16 - 0s - loss: 0.2158 - accuracy: 0.9260
Epoch 146/300
16/16 - 0s - loss: 0.2605 - accuracy: 0.9500
Epoch 147/300
16/16 - 0s - loss: 0.1332 - accuracy: 0.9660
Epoch 148/300
16/16 - 0s - loss: 0.0869 - accuracy: 0.9720
Epoch 149/300
16/16 - 0s - loss: 0.0556 - accuracy: 0.9800
```

```
Epoch 150/300
16/16 - 0s - loss: 0.0662 - accuracy: 0.9760
Epoch 151/300
16/16 - 0s - loss: 0.0737 - accuracy: 0.9740
Epoch 152/300
16/16 - 0s - loss: 0.1115 - accuracy: 0.9660
Epoch 153/300
16/16 - 0s - loss: 0.1240 - accuracy: 0.9600
Epoch 154/300
16/16 - 0s - loss: 0.1020 - accuracy: 0.9740
Epoch 155/300
16/16 - 0s - loss: 0.0775 - accuracy: 0.9800
Epoch 156/300
16/16 - 0s - loss: 0.0869 - accuracy: 0.9780
Epoch 157/300
16/16 - 0s - loss: 0.0896 - accuracy: 0.9740
Epoch 158/300
16/16 - 0s - loss: 0.0838 - accuracy: 0.9720
Epoch 159/300
16/16 - 0s - loss: 0.0763 - accuracy: 0.9780
Epoch 160/300
16/16 - 0s - loss: 0.1331 - accuracy: 0.9680
Epoch 161/300
16/16 - 0s - loss: 0.0756 - accuracy: 0.9820
Epoch 162/300
16/16 - 0s - loss: 0.0616 - accuracy: 0.9780
Epoch 163/300
16/16 - 0s - loss: 0.0998 - accuracy: 0.9700
Epoch 164/300
16/16 - 0s - loss: 0.1901 - accuracy: 0.9560
Epoch 165/300
16/16 - 0s - loss: 0.0932 - accuracy: 0.9700
Epoch 166/300
16/16 - 0s - loss: 0.0571 - accuracy: 0.9800
Epoch 167/300
16/16 - 0s - loss: 0.0882 - accuracy: 0.9760
Epoch 168/300
16/16 - 0s - loss: 0.0950 - accuracy: 0.9680
Epoch 169/300
16/16 - 0s - loss: 0.0530 - accuracy: 0.9820
Epoch 170/300
16/16 - 0s - loss: 0.0539 - accuracy: 0.9840
Epoch 171/300
16/16 - 0s - loss: 0.0427 - accuracy: 0.9860
Epoch 172/300
16/16 - 0s - loss: 0.0497 - accuracy: 0.9880
Epoch 173/300
16/16 - 0s - loss: 0.0528 - accuracy: 0.9840
Epoch 174/300
16/16 - 0s - loss: 0.0603 - accuracy: 0.9800
Epoch 175/300
16/16 - 0s - loss: 0.0377 - accuracy: 0.9900
Epoch 176/300
16/16 - 0s - loss: 0.1296 - accuracy: 0.9740
Epoch 177/300
16/16 - 0s - loss: 0.1234 - accuracy: 0.9800
Epoch 178/300
16/16 - 0s - loss: 0.1842 - accuracy: 0.9640
Epoch 179/300
16/16 - 0s - loss: 0.1282 - accuracy: 0.9780
Epoch 180/300
16/16 - 0s - loss: 0.1127 - accuracy: 0.9660
Epoch 181/300
16/16 - 0s - loss: 0.1775 - accuracy: 0.9540
Epoch 182/300
16/16 - 0s - loss: 0.2062 - accuracy: 0.9620
Epoch 183/300
16/16 - 0s - loss: 0.2146 - accuracy: 0.9560
Epoch 184/300
16/16 - 0s - loss: 0.2134 - accuracy: 0.9520
Epoch 185/300
16/16 - 0s - loss: 0.1064 - accuracy: 0.9700
Epoch 186/300
16/16 - 0s - loss: 0.2510 - accuracy: 0.9480
Epoch 187/300
16/16 - 0s - loss: 0.1448 - accuracy: 0.9620
Epoch 188/300
16/16 - 0s - loss: 0.1551 - accuracy: 0.9600
Epoch 189/300
16/16 - 0s - loss: 0.0676 - accuracy: 0.9820
Epoch 190/300
16/16 - 0s - loss: 0.0824 - accuracy: 0.9760
Epoch 191/300
16/16 - 0s - loss: 0.0983 - accuracy: 0.9680
Epoch 192/300
16/16 - 0s - loss: 0.2191 - accuracy: 0.9580
Epoch 193/300
16/16 - 0s - loss: 0.1546 - accuracy: 0.9660
Epoch 194/300
16/16 - 0s - loss: 0.1816 - accuracy: 0.9580
Epoch 195/300
16/16 - 0s - loss: 0.1930 - accuracy: 0.9760
Epoch 196/300
16/16 - 0s - loss: 0.1278 - accuracy: 0.9720
Epoch 197/300
16/16 - 0s - loss: 0.1219 - accuracy: 0.9720
Epoch 198/300
16/16 - 0s - loss: 0.0596 - accuracy: 0.9840
Epoch 199/300
16/16 - 0s - loss: 0.0601 - accuracy: 0.9760
Epoch 200/300
16/16 - 0s - loss: 0.0478 - accuracy: 0.9860
```

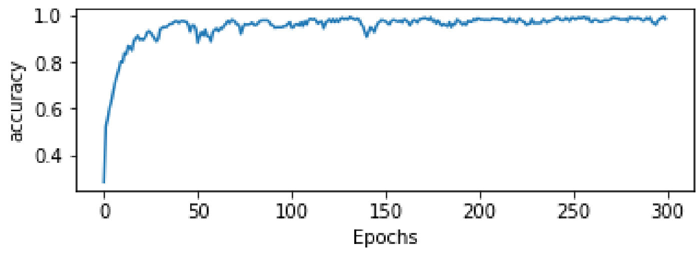
```
Epoch 201/300
16/16 - 0s - loss: 0.0904 - accuracy: 0.9840
Epoch 202/300
16/16 - 0s - loss: 0.0735 - accuracy: 0.9800
Epoch 203/300
16/16 - 0s - loss: 0.0708 - accuracy: 0.9820
Epoch 204/300
16/16 - 0s - loss: 0.0905 - accuracy: 0.9780
Epoch 205/300
16/16 - 0s - loss: 0.0530 - accuracy: 0.9820
Epoch 206/300
16/16 - 0s - loss: 0.0897 - accuracy: 0.9780
Epoch 207/300
16/16 - 0s - loss: 0.0788 - accuracy: 0.9800
Epoch 208/300
16/16 - 0s - loss: 0.0439 - accuracy: 0.9860
Epoch 209/300
16/16 - 0s - loss: 0.0640 - accuracy: 0.9840
Epoch 210/300
16/16 - 0s - loss: 0.1081 - accuracy: 0.9840
Epoch 211/300
16/16 - 0s - loss: 0.0646 - accuracy: 0.9840
Epoch 212/300
16/16 - 0s - loss: 0.1032 - accuracy: 0.9800
Epoch 213/300
16/16 - 0s - loss: 0.0632 - accuracy: 0.9840
Epoch 214/300
16/16 - 0s - loss: 0.0901 - accuracy: 0.9740
Epoch 215/300
16/16 - 0s - loss: 0.1276 - accuracy: 0.9700
Epoch 216/300
16/16 - 0s - loss: 0.1131 - accuracy: 0.9720
Epoch 217/300
16/16 - 0s - loss: 0.0632 - accuracy: 0.9880
Epoch 218/300
16/16 - 0s - loss: 0.1136 - accuracy: 0.9740
Epoch 219/300
16/16 - 0s - loss: 0.0732 - accuracy: 0.9820
Epoch 220/300
16/16 - 0s - loss: 0.1728 - accuracy: 0.9700
Epoch 221/300
16/16 - 0s - loss: 0.1515 - accuracy: 0.9680
Epoch 222/300
16/16 - 0s - loss: 0.0742 - accuracy: 0.9860
Epoch 223/300
16/16 - 0s - loss: 0.0977 - accuracy: 0.9800
Epoch 224/300
16/16 - 0s - loss: 0.1186 - accuracy: 0.9740
Epoch 225/300
16/16 - 0s - loss: 0.1295 - accuracy: 0.9700
Epoch 226/300
16/16 - 0s - loss: 0.2069 - accuracy: 0.9580
Epoch 227/300
16/16 - 0s - loss: 0.1790 - accuracy: 0.9620
Epoch 228/300
16/16 - 0s - loss: 0.2194 - accuracy: 0.9640
Epoch 229/300
16/16 - 0s - loss: 0.0664 - accuracy: 0.9840
Epoch 230/300
16/16 - 0s - loss: 0.2477 - accuracy: 0.9660
Epoch 231/300
16/16 - 0s - loss: 0.2841 - accuracy: 0.9660
Epoch 232/300
16/16 - 0s - loss: 0.1499 - accuracy: 0.9660
Epoch 233/300
16/16 - 0s - loss: 0.2140 - accuracy: 0.9660
Epoch 234/300
16/16 - 0s - loss: 0.1523 - accuracy: 0.9680
Epoch 235/300
16/16 - 0s - loss: 0.0721 - accuracy: 0.9820
Epoch 236/300
16/16 - 0s - loss: 0.0873 - accuracy: 0.9780
Epoch 237/300
16/16 - 0s - loss: 0.1714 - accuracy: 0.9680
Epoch 238/300
16/16 - 0s - loss: 0.0717 - accuracy: 0.9760
Epoch 239/300
16/16 - 0s - loss: 0.0742 - accuracy: 0.9760
Epoch 240/300
16/16 - 0s - loss: 0.0635 - accuracy: 0.9800
Epoch 241/300
16/16 - 0s - loss: 0.0568 - accuracy: 0.9820
Epoch 242/300
16/16 - 0s - loss: 0.0305 - accuracy: 0.9900
Epoch 243/300
16/16 - 0s - loss: 0.0362 - accuracy: 0.9900
Epoch 244/300
16/16 - 0s - loss: 0.1063 - accuracy: 0.9800
Epoch 245/300
16/16 - 0s - loss: 0.1059 - accuracy: 0.9780
Epoch 246/300
16/16 - 0s - loss: 0.1005 - accuracy: 0.9780
Epoch 247/300
16/16 - 0s - loss: 0.0428 - accuracy: 0.9880
Epoch 248/300
16/16 - 0s - loss: 0.0524 - accuracy: 0.9840
Epoch 249/300
16/16 - 0s - loss: 0.0884 - accuracy: 0.9740
Epoch 250/300
16/16 - 0s - loss: 0.0529 - accuracy: 0.9880
Epoch 251/300
16/16 - 0s - loss: 0.0446 - accuracy: 0.9880
Epoch 252/300
```

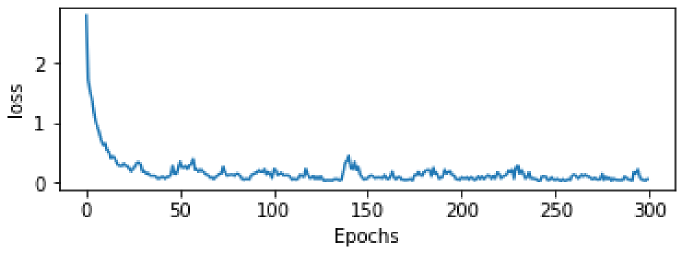
```
Epoch 252/300
16/16 - 0s - loss: 0.0645 - accuracy: 0.9820
Epoch 253/300
16/16 - 0s - loss: 0.0442 - accuracy: 0.9860
Epoch 254/300
16/16 - 0s - loss: 0.0299 - accuracy: 0.9900
Epoch 255/300
16/16 - 0s - loss: 0.0582 - accuracy: 0.9860
Epoch 256/300
16/16 - 0s - loss: 0.0336 - accuracy: 0.9900
Epoch 257/300
16/16 - 0s - loss: 0.0388 - accuracy: 0.9920
Epoch 258/300
16/16 - 0s - loss: 0.0595 - accuracy: 0.9820
Epoch 259/300
16/16 - 0s - loss: 0.0466 - accuracy: 0.9900
Epoch 260/300
16/16 - 0s - loss: 0.1189 - accuracy: 0.9740
Epoch 261/300
16/16 - 0s - loss: 0.1341 - accuracy: 0.9700
Epoch 262/300
16/16 - 0s - loss: 0.1171 - accuracy: 0.9800
Epoch 263/300
16/16 - 0s - loss: 0.0750 - accuracy: 0.9800
Epoch 264/300
16/16 - 0s - loss: 0.0903 - accuracy: 0.9780
Epoch 265/300
16/16 - 0s - loss: 0.1353 - accuracy: 0.9720
Epoch 266/300
16/16 - 0s - loss: 0.1060 - accuracy: 0.9720
Epoch 267/300
16/16 - 0s - loss: 0.1354 - accuracy: 0.9760
Epoch 268/300
16/16 - 0s - loss: 0.1104 - accuracy: 0.9800
Epoch 269/300
16/16 - 0s - loss: 0.0984 - accuracy: 0.9760
Epoch 270/300
16/16 - 0s - loss: 0.0736 - accuracy: 0.9800
Epoch 271/300
16/16 - 0s - loss: 0.0583 - accuracy: 0.9820
Epoch 272/300
16/16 - 0s - loss: 0.0802 - accuracy: 0.9900
Epoch 273/300
16/16 - 0s - loss: 0.0595 - accuracy: 0.9880
Epoch 274/300
16/16 - 0s - loss: 0.0556 - accuracy: 0.9860
Epoch 275/300
16/16 - 0s - loss: 0.0610 - accuracy: 0.9860
Epoch 276/300
16/16 - 0s - loss: 0.1504 - accuracy: 0.9800
Epoch 277/300
16/16 - 0s - loss: 0.0474 - accuracy: 0.9820
Epoch 278/300
16/16 - 0s - loss: 0.1004 - accuracy: 0.9800
Epoch 279/300
16/16 - 0s - loss: 0.0625 - accuracy: 0.9840
Epoch 280/300
16/16 - 0s - loss: 0.0834 - accuracy: 0.9740
Epoch 281/300
16/16 - 0s - loss: 0.0334 - accuracy: 0.9900
Epoch 282/300
16/16 - 0s - loss: 0.0691 - accuracy: 0.9880
Epoch 283/300
16/16 - 0s - loss: 0.0529 - accuracy: 0.9860
Epoch 284/300
16/16 - 0s - loss: 0.0455 - accuracy: 0.9840
Epoch 285/300
16/16 - 0s - loss: 0.0441 - accuracy: 0.9880
Epoch 286/300
16/16 - 0s - loss: 0.0423 - accuracy: 0.9860
Epoch 287/300
16/16 - 0s - loss: 0.0478 - accuracy: 0.9840
Epoch 288/300
16/16 - 0s - loss: 0.1039 - accuracy: 0.9760
Epoch 289/300
16/16 - 0s - loss: 0.0801 - accuracy: 0.9780
Epoch 290/300
16/16 - 0s - loss: 0.0538 - accuracy: 0.9880
Epoch 291/300
16/16 - 0s - loss: 0.0490 - accuracy: 0.9820
Epoch 292/300
16/16 - 0s - loss: 0.0338 - accuracy: 0.9900
Epoch 293/300
16/16 - 0s - loss: 0.1794 - accuracy: 0.9700
Epoch 294/300
16/16 - 0s - loss: 0.1621 - accuracy: 0.9660
Epoch 295/300
16/16 - 0s - loss: 0.2261 - accuracy: 0.9580
Epoch 296/300
16/16 - 0s - loss: 0.0987 - accuracy: 0.9740
Epoch 297/300
16/16 - 0s - loss: 0.0544 - accuracy: 0.9840
Epoch 298/300
16/16 - 0s - loss: 0.0427 - accuracy: 0.9880
Epoch 299/300
16/16 - 0s - loss: 0.0353 - accuracy: 0.9940
Epoch 300/300
16/16 - 0s - loss: 0.0598 - accuracy: 0.9840
```

In [38]:

```
plt.subplot(2,1,1)
```

```
plot_graphs(history2, 'accuracy')
plt.subplot(2,1,2)
plot_graphs(history2, 'loss')
```





Model Training for Neckline

In [41]:

```
model3 = Sequential()
model3.add(Dense(100, input_dim=2048, activation='relu'))
model3.add(Dense(units=256))
model3.add(Dropout(0.5))
model3.add(Dense(units=256))
model3.add(Dropout(0.5))
model3.add(Dense(units=128))
model3.add(Dropout(0.2))
model3.add(Dense(total_words3, activation='softmax'))
model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
model3.summary()
history3 = model3.fit(x3, y3, epochs=300, batch_size=32, verbose=2)
```

```
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_35 (Dense)             (None, 100)               204900    
_________________________________________________________________
dense_36 (Dense)             (None, 256)               25856     
_________________________________________________________________
dropout_21 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_37 (Dense)             (None, 256)               65792     
_________________________________________________________________
dropout_22 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_38 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_23 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_39 (Dense)             (None, 23)                2967      
=================================================================
Total params: 332,411
Trainable params: 332,411
Non-trainable params: 0
_________________________________________________________________
Epoch 1/300
16/16 - 0s - loss: 3.2002 - accuracy: 0.1520
Epoch 2/300
16/16 - 0s - loss: 2.6779 - accuracy: 0.2040
Epoch 3/300
16/16 - 0s - loss: 2.4799 - accuracy: 0.2460
Epoch 4/300
16/16 - 0s - loss: 2.3746 - accuracy: 0.2760
Epoch 5/300
16/16 - 0s - loss: 2.2931 - accuracy: 0.2900
Epoch 6/300
16/16 - 0s - loss: 2.1555 - accuracy: 0.3340
Epoch 7/300
16/16 - 0s - loss: 2.1466 - accuracy: 0.3240
Epoch 8/300
16/16 - 0s - loss: 2.0065 - accuracy: 0.3860
Epoch 9/300
16/16 - 0s - loss: 1.9023 - accuracy: 0.4320
Epoch 10/300
16/16 - 0s - loss: 1.8621 - accuracy: 0.4040
Epoch 11/300
16/16 - 0s - loss: 1.6747 - accuracy: 0.4820
Epoch 12/300
16/16 - 0s - loss: 1.5787 - accuracy: 0.5140
Epoch 13/300
16/16 - 0s - loss: 1.5429 - accuracy: 0.5340
Epoch 14/300
16/16 - 0s - loss: 1.4973 - accuracy: 0.5260
Epoch 15/300
16/16 - 0s - loss: 1.3967 - accuracy: 0.5700
Epoch 16/300
16/16 - 0s - loss: 1.2631 - accuracy: 0.5920
Epoch 17/300
16/16 - 0s - loss: 1.2711 - accuracy: 0.5960
Epoch 18/300
16/16 - 0s - loss: 1.1642 - accuracy: 0.6360
Epoch 19/300
16/16 - 0s - loss: 1.0760 - accuracy: 0.6420
```

```
Epoch 20/300
16/16 - 0s - loss: 1.0863 - accuracy: 0.6460
Epoch 21/300
16/16 - 0s - loss: 0.9746 - accuracy: 0.6960
Epoch 22/300
16/16 - 0s - loss: 0.9865 - accuracy: 0.6820
Epoch 23/300
16/16 - 0s - loss: 0.9670 - accuracy: 0.6840
Epoch 24/300
16/16 - 0s - loss: 0.8072 - accuracy: 0.7460
Epoch 25/300
16/16 - 0s - loss: 0.8241 - accuracy: 0.7540
Epoch 26/300
16/16 - 0s - loss: 0.8013 - accuracy: 0.7360
Epoch 27/300
16/16 - 0s - loss: 0.8487 - accuracy: 0.7520
Epoch 28/300
16/16 - 0s - loss: 0.8703 - accuracy: 0.7060
Epoch 29/300
16/16 - 0s - loss: 0.9247 - accuracy: 0.6760
Epoch 30/300
16/16 - 0s - loss: 0.8691 - accuracy: 0.7160
Epoch 31/300
16/16 - 0s - loss: 0.8722 - accuracy: 0.7260
Epoch 32/300
16/16 - 0s - loss: 0.7389 - accuracy: 0.7680
Epoch 33/300
16/16 - 0s - loss: 0.7204 - accuracy: 0.7640
Epoch 34/300
16/16 - 0s - loss: 0.7116 - accuracy: 0.7700
Epoch 35/300
16/16 - 0s - loss: 0.6878 - accuracy: 0.7740
Epoch 36/300
16/16 - 0s - loss: 0.6047 - accuracy: 0.7940
Epoch 37/300
16/16 - 0s - loss: 0.6149 - accuracy: 0.8080
Epoch 38/300
16/16 - 0s - loss: 0.5889 - accuracy: 0.8160
Epoch 39/300
16/16 - 0s - loss: 0.6663 - accuracy: 0.7840
Epoch 40/300
16/16 - 0s - loss: 0.6246 - accuracy: 0.7980
Epoch 41/300
16/16 - 0s - loss: 0.6096 - accuracy: 0.8000
Epoch 42/300
16/16 - 0s - loss: 0.5084 - accuracy: 0.8160
Epoch 43/300
16/16 - 0s - loss: 0.4585 - accuracy: 0.8500
Epoch 44/300
16/16 - 0s - loss: 0.6307 - accuracy: 0.7920
Epoch 45/300
16/16 - 0s - loss: 0.5734 - accuracy: 0.8260
Epoch 46/300
16/16 - 0s - loss: 0.5101 - accuracy: 0.8340
Epoch 47/300
16/16 - 0s - loss: 0.4554 - accuracy: 0.8540
Epoch 48/300
16/16 - 0s - loss: 0.5467 - accuracy: 0.8140
Epoch 49/300
16/16 - 0s - loss: 0.7615 - accuracy: 0.7860
Epoch 50/300
16/16 - 0s - loss: 0.7992 - accuracy: 0.7500
Epoch 51/300
16/16 - 0s - loss: 0.6706 - accuracy: 0.7860
Epoch 52/300
16/16 - 0s - loss: 0.5685 - accuracy: 0.8140
Epoch 53/300
16/16 - 0s - loss: 0.4878 - accuracy: 0.8500
Epoch 54/300
16/16 - 0s - loss: 0.5258 - accuracy: 0.8460
Epoch 55/300
16/16 - 0s - loss: 0.4708 - accuracy: 0.8500
Epoch 56/300
16/16 - 0s - loss: 0.4855 - accuracy: 0.8440
Epoch 57/300
16/16 - 0s - loss: 0.4870 - accuracy: 0.8460
Epoch 58/300
16/16 - 0s - loss: 0.4678 - accuracy: 0.8680
Epoch 59/300
16/16 - 0s - loss: 0.4040 - accuracy: 0.8680
Epoch 60/300
16/16 - 0s - loss: 0.3773 - accuracy: 0.8720
Epoch 61/300
16/16 - 0s - loss: 0.4176 - accuracy: 0.8740
Epoch 62/300
16/16 - 0s - loss: 0.3813 - accuracy: 0.8700
Epoch 63/300
16/16 - 0s - loss: 0.3588 - accuracy: 0.8760
Epoch 64/300
16/16 - 0s - loss: 0.3404 - accuracy: 0.8880
Epoch 65/300
16/16 - 0s - loss: 0.4243 - accuracy: 0.8620
Epoch 66/300
16/16 - 0s - loss: 1.0596 - accuracy: 0.7220
Epoch 67/300
16/16 - 0s - loss: 0.7779 - accuracy: 0.7840
Epoch 68/300
16/16 - 0s - loss: 0.5991 - accuracy: 0.8060
Epoch 69/300
16/16 - 0s - loss: 0.5608 - accuracy: 0.8200
Epoch 70/300
16/16 - 0s - loss: 0.4620 - accuracy: 0.8440
Epoch 71/300
```

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Epoch 71/300
16/16 - 0s - loss: 0.4174 - accuracy: 0.8560
Epoch 72/300
16/16 - 0s - loss: 0.4372 - accuracy: 0.8620
Epoch 73/300
16/16 - 0s - loss: 0.3582 - accuracy: 0.8880
Epoch 74/300
16/16 - 0s - loss: 0.2759 - accuracy: 0.9240
Epoch 75/300
16/16 - 0s - loss: 0.2874 - accuracy: 0.9020
Epoch 76/300
16/16 - 0s - loss: 0.3394 - accuracy: 0.8920
Epoch 77/300
16/16 - 0s - loss: 0.3592 - accuracy: 0.9060
Epoch 78/300
16/16 - 0s - loss: 0.3111 - accuracy: 0.9100
Epoch 79/300
16/16 - 0s - loss: 0.3280 - accuracy: 0.9100
Epoch 80/300
16/16 - 0s - loss: 0.2610 - accuracy: 0.9060
Epoch 81/300
16/16 - 0s - loss: 0.3364 - accuracy: 0.9000
Epoch 82/300
16/16 - 0s - loss: 0.2813 - accuracy: 0.9060
Epoch 83/300
16/16 - 0s - loss: 0.3154 - accuracy: 0.8840
Epoch 84/300
16/16 - 0s - loss: 0.3332 - accuracy: 0.8940
Epoch 85/300
16/16 - 0s - loss: 0.3125 - accuracy: 0.9180
Epoch 86/300
16/16 - 0s - loss: 0.3244 - accuracy: 0.9020
Epoch 87/300
16/16 - 0s - loss: 0.2972 - accuracy: 0.9060
Epoch 88/300
16/16 - 0s - loss: 0.3101 - accuracy: 0.9020
Epoch 89/300
16/16 - 0s - loss: 0.2585 - accuracy: 0.9240
Epoch 90/300
16/16 - 0s - loss: 0.2616 - accuracy: 0.9420
Epoch 91/300
16/16 - 0s - loss: 0.2200 - accuracy: 0.9340
Epoch 92/300
16/16 - 0s - loss: 0.2835 - accuracy: 0.9100
Epoch 93/300
16/16 - 0s - loss: 0.2315 - accuracy: 0.9140
Epoch 94/300
16/16 - 0s - loss: 0.2861 - accuracy: 0.9000
Epoch 95/300
16/16 - 0s - loss: 0.4503 - accuracy: 0.8740
Epoch 96/300
16/16 - 0s - loss: 0.3254 - accuracy: 0.8820
Epoch 97/300
16/16 - 0s - loss: 0.3768 - accuracy: 0.8840
Epoch 98/300
16/16 - 0s - loss: 0.3656 - accuracy: 0.9000
Epoch 99/300
16/16 - 0s - loss: 0.3834 - accuracy: 0.8700
Epoch 100/300
16/16 - 0s - loss: 0.3272 - accuracy: 0.9000
Epoch 101/300
16/16 - 0s - loss: 0.4253 - accuracy: 0.8840
Epoch 102/300
16/16 - 0s - loss: 0.3820 - accuracy: 0.8800
Epoch 103/300
16/16 - 0s - loss: 0.3162 - accuracy: 0.9080
Epoch 104/300
16/16 - 0s - loss: 0.2531 - accuracy: 0.9220
Epoch 105/300
16/16 - 0s - loss: 0.2533 - accuracy: 0.9120
Epoch 106/300
16/16 - 0s - loss: 0.2919 - accuracy: 0.9020
Epoch 107/300
16/16 - 0s - loss: 0.2839 - accuracy: 0.9100
Epoch 108/300
16/16 - 0s - loss: 0.2929 - accuracy: 0.8940
Epoch 109/300
16/16 - 0s - loss: 0.2156 - accuracy: 0.9320
Epoch 110/300
16/16 - 0s - loss: 0.2143 - accuracy: 0.9320
Epoch 111/300
16/16 - 0s - loss: 0.2562 - accuracy: 0.9180
Epoch 112/300
16/16 - 0s - loss: 0.2972 - accuracy: 0.9020
Epoch 113/300
16/16 - 0s - loss: 0.2401 - accuracy: 0.9100
Epoch 114/300
16/16 - 0s - loss: 0.2643 - accuracy: 0.9300
Epoch 115/300
16/16 - 0s - loss: 0.3799 - accuracy: 0.8840
Epoch 116/300
16/16 - 0s - loss: 0.2464 - accuracy: 0.9200
Epoch 117/300
16/16 - 0s - loss: 0.3386 - accuracy: 0.9100
Epoch 118/300
16/16 - 0s - loss: 0.3017 - accuracy: 0.8860
Epoch 119/300
16/16 - 0s - loss: 0.3065 - accuracy: 0.9100
Epoch 120/300
16/16 - 0s - loss: 0.1880 - accuracy: 0.9440
Epoch 121/300
16/16 - 0s - loss: 0.2498 - accuracy: 0.9280
Epoch 122/300
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16/16 - 0s - loss: 0.3954 - accuracy: 0.8760
Epoch 123/300
16/16 - 0s - loss: 0.3736 - accuracy: 0.8940
Epoch 124/300
16/16 - 0s - loss: 0.2995 - accuracy: 0.9120
Epoch 125/300
16/16 - 0s - loss: 0.4020 - accuracy: 0.8740
Epoch 126/300
16/16 - 0s - loss: 0.3958 - accuracy: 0.8840
Epoch 127/300
16/16 - 0s - loss: 0.2587 - accuracy: 0.9160
Epoch 128/300
16/16 - 0s - loss: 0.2138 - accuracy: 0.9340
Epoch 129/300
16/16 - 0s - loss: 0.1700 - accuracy: 0.9440
Epoch 130/300
16/16 - 0s - loss: 0.1894 - accuracy: 0.9360
Epoch 131/300
16/16 - 0s - loss: 0.1897 - accuracy: 0.9300
Epoch 132/300
16/16 - 0s - loss: 0.2429 - accuracy: 0.9160
Epoch 133/300
16/16 - 0s - loss: 0.3643 - accuracy: 0.8960
Epoch 134/300
16/16 - 0s - loss: 0.3173 - accuracy: 0.8980
Epoch 135/300
16/16 - 0s - loss: 0.2053 - accuracy: 0.9380
Epoch 136/300
16/16 - 0s - loss: 0.2314 - accuracy: 0.9260
Epoch 137/300
16/16 - 0s - loss: 0.2079 - accuracy: 0.9360
Epoch 138/300
16/16 - 0s - loss: 0.2584 - accuracy: 0.9120
Epoch 139/300
16/16 - 0s - loss: 0.1640 - accuracy: 0.9500
Epoch 140/300
16/16 - 0s - loss: 0.2115 - accuracy: 0.9500
Epoch 141/300
16/16 - 0s - loss: 0.2418 - accuracy: 0.9300
Epoch 142/300
16/16 - 0s - loss: 0.2250 - accuracy: 0.9260
Epoch 143/300
16/16 - 0s - loss: 0.1822 - accuracy: 0.9400
Epoch 144/300
16/16 - 0s - loss: 0.1751 - accuracy: 0.9420
Epoch 145/300
16/16 - 0s - loss: 0.2119 - accuracy: 0.9420
Epoch 146/300
16/16 - 0s - loss: 0.2557 - accuracy: 0.9280
Epoch 147/300
16/16 - 0s - loss: 0.2541 - accuracy: 0.9180
Epoch 148/300
16/16 - 0s - loss: 0.2740 - accuracy: 0.9140
Epoch 149/300
16/16 - 0s - loss: 0.2380 - accuracy: 0.9360
Epoch 150/300
16/16 - 0s - loss: 0.1901 - accuracy: 0.9420
Epoch 151/300
16/16 - 0s - loss: 0.1606 - accuracy: 0.9420
Epoch 152/300
16/16 - 0s - loss: 0.2233 - accuracy: 0.9380
Epoch 153/300
16/16 - 0s - loss: 0.1627 - accuracy: 0.9400
Epoch 154/300
16/16 - 0s - loss: 0.1384 - accuracy: 0.9600
Epoch 155/300
16/16 - 0s - loss: 0.1586 - accuracy: 0.9480
Epoch 156/300
16/16 - 0s - loss: 0.2348 - accuracy: 0.9180
Epoch 157/300
16/16 - 0s - loss: 0.2550 - accuracy: 0.9260
Epoch 158/300
16/16 - 0s - loss: 0.3101 - accuracy: 0.8920
Epoch 159/300
16/16 - 0s - loss: 0.2287 - accuracy: 0.9260
Epoch 160/300
16/16 - 0s - loss: 0.4745 - accuracy: 0.8600
Epoch 161/300
16/16 - 0s - loss: 0.5899 - accuracy: 0.8300
Epoch 162/300
16/16 - 0s - loss: 0.4653 - accuracy: 0.8840
Epoch 163/300
16/16 - 0s - loss: 0.3406 - accuracy: 0.8860
Epoch 164/300
16/16 - 0s - loss: 0.2663 - accuracy: 0.9240
Epoch 165/300
16/16 - 0s - loss: 0.1793 - accuracy: 0.9440
Epoch 166/300
16/16 - 0s - loss: 0.1494 - accuracy: 0.9540
Epoch 167/300
16/16 - 0s - loss: 0.1510 - accuracy: 0.9440
Epoch 168/300
16/16 - 0s - loss: 0.1941 - accuracy: 0.9360
Epoch 169/300
16/16 - 0s - loss: 0.1719 - accuracy: 0.9460
Epoch 170/300
16/16 - 0s - loss: 0.1799 - accuracy: 0.9540
Epoch 171/300
16/16 - 0s - loss: 0.1727 - accuracy: 0.9440
Epoch 172/300
16/16 - 0s - loss: 0.1957 - accuracy: 0.9320
Epoch 173/300
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16/16 - 0s - loss: 0.1821 - accuracy: 0.9420
Epoch 174/300
16/16 - 0s - loss: 0.1880 - accuracy: 0.9480
Epoch 175/300
16/16 - 0s - loss: 0.2227 - accuracy: 0.9480
Epoch 176/300
16/16 - 0s - loss: 0.2100 - accuracy: 0.9300
Epoch 177/300
16/16 - 0s - loss: 0.1535 - accuracy: 0.9480
Epoch 178/300
16/16 - 0s - loss: 0.1161 - accuracy: 0.9660
Epoch 179/300
16/16 - 0s - loss: 0.1401 - accuracy: 0.9620
Epoch 180/300
16/16 - 0s - loss: 0.1350 - accuracy: 0.9620
Epoch 181/300
16/16 - 0s - loss: 0.1751 - accuracy: 0.9460
Epoch 182/300
16/16 - 0s - loss: 0.1904 - accuracy: 0.9360
Epoch 183/300
16/16 - 0s - loss: 0.2353 - accuracy: 0.9400
Epoch 184/300
16/16 - 0s - loss: 0.2158 - accuracy: 0.9340
Epoch 185/300
16/16 - 0s - loss: 0.2814 - accuracy: 0.9340
Epoch 186/300
16/16 - 0s - loss: 0.2673 - accuracy: 0.9280
Epoch 187/300
16/16 - 0s - loss: 0.1039 - accuracy: 0.9660
Epoch 188/300
16/16 - 0s - loss: 0.2116 - accuracy: 0.9360
Epoch 189/300
16/16 - 0s - loss: 0.2568 - accuracy: 0.9140
Epoch 190/300
16/16 - 0s - loss: 0.2121 - accuracy: 0.9260
Epoch 191/300
16/16 - 0s - loss: 0.1669 - accuracy: 0.9580
Epoch 192/300
16/16 - 0s - loss: 0.1343 - accuracy: 0.9560
Epoch 193/300
16/16 - 0s - loss: 0.1387 - accuracy: 0.9560
Epoch 194/300
16/16 - 0s - loss: 0.1364 - accuracy: 0.9500
Epoch 195/300
16/16 - 0s - loss: 0.2710 - accuracy: 0.9100
Epoch 196/300
16/16 - 0s - loss: 0.2745 - accuracy: 0.9140
Epoch 197/300
16/16 - 0s - loss: 0.1655 - accuracy: 0.9520
Epoch 198/300
16/16 - 0s - loss: 0.2221 - accuracy: 0.9440
Epoch 199/300
16/16 - 0s - loss: 0.1603 - accuracy: 0.9440
Epoch 200/300
16/16 - 0s - loss: 0.1963 - accuracy: 0.9320
Epoch 201/300
16/16 - 0s - loss: 0.2100 - accuracy: 0.9440
Epoch 202/300
16/16 - 0s - loss: 0.2005 - accuracy: 0.9320
Epoch 203/300
16/16 - 0s - loss: 0.2097 - accuracy: 0.9300
Epoch 204/300
16/16 - 0s - loss: 0.1529 - accuracy: 0.9440
Epoch 205/300
16/16 - 0s - loss: 0.2243 - accuracy: 0.9500
Epoch 206/300
16/16 - 0s - loss: 0.1583 - accuracy: 0.9480
Epoch 207/300
16/16 - 0s - loss: 0.1451 - accuracy: 0.9640
Epoch 208/300
16/16 - 0s - loss: 0.1523 - accuracy: 0.9560
Epoch 209/300
16/16 - 0s - loss: 0.2243 - accuracy: 0.9300
Epoch 210/300
16/16 - 0s - loss: 0.1571 - accuracy: 0.9580
Epoch 211/300
16/16 - 0s - loss: 0.2013 - accuracy: 0.9420
Epoch 212/300
16/16 - 0s - loss: 0.3567 - accuracy: 0.9000
Epoch 213/300
16/16 - 0s - loss: 0.2147 - accuracy: 0.9440
Epoch 214/300
16/16 - 0s - loss: 0.1987 - accuracy: 0.9260
Epoch 215/300
16/16 - 0s - loss: 0.2024 - accuracy: 0.9360
Epoch 216/300
16/16 - 0s - loss: 0.1022 - accuracy: 0.9600
Epoch 217/300
16/16 - 0s - loss: 0.1458 - accuracy: 0.9560
Epoch 218/300
16/16 - 0s - loss: 0.1171 - accuracy: 0.9660
Epoch 219/300
16/16 - 0s - loss: 0.1419 - accuracy: 0.9560
Epoch 220/300
16/16 - 0s - loss: 0.1610 - accuracy: 0.9540
Epoch 221/300
16/16 - 0s - loss: 0.1624 - accuracy: 0.9400
Epoch 222/300
16/16 - 0s - loss: 0.1287 - accuracy: 0.9600
Epoch 223/300
16/16 - 0s - loss: 0.1458 - accuracy: 0.9540
Epoch 224/300
16/16 - 0s - loss: 0.1341 - accuracy: 0.9660
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16/16 - 0s - loss: 0.1341 - accuracy: 0.9660
Epoch 225/300
16/16 - 0s - loss: 0.2196 - accuracy: 0.9360
Epoch 226/300
16/16 - 0s - loss: 0.2852 - accuracy: 0.9360
Epoch 227/300
16/16 - 0s - loss: 0.2932 - accuracy: 0.9260
Epoch 228/300
16/16 - 0s - loss: 0.2797 - accuracy: 0.9160
Epoch 229/300
16/16 - 0s - loss: 0.1932 - accuracy: 0.9420
Epoch 230/300
16/16 - 0s - loss: 0.1517 - accuracy: 0.9640
Epoch 231/300
16/16 - 0s - loss: 0.1153 - accuracy: 0.9540
Epoch 232/300
16/16 - 0s - loss: 0.1123 - accuracy: 0.9600
Epoch 233/300
16/16 - 0s - loss: 0.0985 - accuracy: 0.9640
Epoch 234/300
16/16 - 0s - loss: 0.0722 - accuracy: 0.9700
Epoch 235/300
16/16 - 0s - loss: 0.0908 - accuracy: 0.9640
Epoch 236/300
16/16 - 0s - loss: 0.1360 - accuracy: 0.9480
Epoch 237/300
16/16 - 0s - loss: 0.1409 - accuracy: 0.9500
Epoch 238/300
16/16 - 0s - loss: 0.1335 - accuracy: 0.9640
Epoch 239/300
16/16 - 0s - loss: 0.2693 - accuracy: 0.9440
Epoch 240/300
16/16 - 0s - loss: 0.1471 - accuracy: 0.9460
Epoch 241/300
16/16 - 0s - loss: 0.1191 - accuracy: 0.9500
Epoch 242/300
16/16 - 0s - loss: 0.1867 - accuracy: 0.9500
Epoch 243/300
16/16 - 0s - loss: 0.1520 - accuracy: 0.9500
Epoch 244/300
16/16 - 0s - loss: 0.2098 - accuracy: 0.9480
Epoch 245/300
16/16 - 0s - loss: 0.1530 - accuracy: 0.9520
Epoch 246/300
16/16 - 0s - loss: 0.1858 - accuracy: 0.9520
Epoch 247/300
16/16 - 0s - loss: 0.1175 - accuracy: 0.9600
Epoch 248/300
16/16 - 0s - loss: 0.1085 - accuracy: 0.9540
Epoch 249/300
16/16 - 0s - loss: 0.1251 - accuracy: 0.9600
Epoch 250/300
16/16 - 0s - loss: 0.0971 - accuracy: 0.9720
Epoch 251/300
16/16 - 0s - loss: 0.1062 - accuracy: 0.9660
Epoch 252/300
16/16 - 0s - loss: 0.0820 - accuracy: 0.9640
Epoch 253/300
16/16 - 0s - loss: 0.0966 - accuracy: 0.9640
Epoch 254/300
16/16 - 0s - loss: 0.1383 - accuracy: 0.9560
Epoch 255/300
16/16 - 0s - loss: 0.1308 - accuracy: 0.9560
Epoch 256/300
16/16 - 0s - loss: 0.1152 - accuracy: 0.9720
Epoch 257/300
16/16 - 0s - loss: 0.1117 - accuracy: 0.9600
Epoch 258/300
16/16 - 0s - loss: 0.1199 - accuracy: 0.9480
Epoch 259/300
16/16 - 0s - loss: 0.1554 - accuracy: 0.9620
Epoch 260/300
16/16 - 0s - loss: 0.1441 - accuracy: 0.9500
Epoch 261/300
16/16 - 0s - loss: 0.2241 - accuracy: 0.9460
Epoch 262/300
16/16 - 0s - loss: 0.2572 - accuracy: 0.9320
Epoch 263/300
16/16 - 0s - loss: 0.1475 - accuracy: 0.9600
Epoch 264/300
16/16 - 0s - loss: 0.1768 - accuracy: 0.9360
Epoch 265/300
16/16 - 0s - loss: 0.1324 - accuracy: 0.9580
Epoch 266/300
16/16 - 0s - loss: 0.2121 - accuracy: 0.9480
Epoch 267/300
16/16 - 0s - loss: 0.1676 - accuracy: 0.9340
Epoch 268/300
16/16 - 0s - loss: 0.1344 - accuracy: 0.9560
Epoch 269/300
16/16 - 0s - loss: 0.0942 - accuracy: 0.9700
Epoch 270/300
16/16 - 0s - loss: 0.1082 - accuracy: 0.9680
Epoch 271/300
16/16 - 0s - loss: 0.1351 - accuracy: 0.9640
Epoch 272/300
16/16 - 0s - loss: 0.1027 - accuracy: 0.9760
Epoch 273/300
16/16 - 0s - loss: 0.1166 - accuracy: 0.9560
Epoch 274/300
16/16 - 0s - loss: 0.1397 - accuracy: 0.9540
Epoch 275/300
16/16 - 0s - loss: 0.2340 - accuracy: 0.9380
```

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Epoch 276/300
16/16 - 0s - loss: 0.4359 - accuracy: 0.8860
Epoch 277/300
16/16 - 0s - loss: 0.5402 - accuracy: 0.8780
Epoch 278/300
16/16 - 0s - loss: 0.4663 - accuracy: 0.8960
Epoch 279/300
16/16 - 0s - loss: 0.2758 - accuracy: 0.9180
Epoch 280/300
16/16 - 0s - loss: 0.2934 - accuracy: 0.9180
Epoch 281/300
16/16 - 0s - loss: 0.3066 - accuracy: 0.9160
Epoch 282/300
16/16 - 0s - loss: 0.2788 - accuracy: 0.9080
Epoch 283/300
16/16 - 0s - loss: 0.5001 - accuracy: 0.8820
Epoch 284/300
16/16 - 0s - loss: 0.4202 - accuracy: 0.9060
Epoch 285/300
16/16 - 0s - loss: 0.3554 - accuracy: 0.9160
Epoch 286/300
16/16 - 0s - loss: 0.1807 - accuracy: 0.9400
Epoch 287/300
16/16 - 0s - loss: 0.1384 - accuracy: 0.9440
Epoch 288/300
16/16 - 0s - loss: 0.1030 - accuracy: 0.9660
Epoch 289/300
16/16 - 0s - loss: 0.0680 - accuracy: 0.9740
Epoch 290/300
16/16 - 0s - loss: 0.0805 - accuracy: 0.9660
Epoch 291/300
16/16 - 0s - loss: 0.1211 - accuracy: 0.9620
Epoch 292/300
16/16 - 0s - loss: 0.1360 - accuracy: 0.9520
Epoch 293/300
16/16 - 0s - loss: 0.1242 - accuracy: 0.9560
Epoch 294/300
16/16 - 0s - loss: 0.1985 - accuracy: 0.9360
Epoch 295/300
16/16 - 0s - loss: 0.1255 - accuracy: 0.9640
Epoch 296/300
16/16 - 0s - loss: 0.0714 - accuracy: 0.9760
Epoch 297/300
16/16 - 0s - loss: 0.1320 - accuracy: 0.9580
Epoch 298/300
16/16 - 0s - loss: 0.1259 - accuracy: 0.9580
Epoch 299/300
16/16 - 0s - loss: 0.1023 - accuracy: 0.9580
Epoch 300/300
16/16 - 0s - loss: 0.1095 - accuracy: 0.9760
```
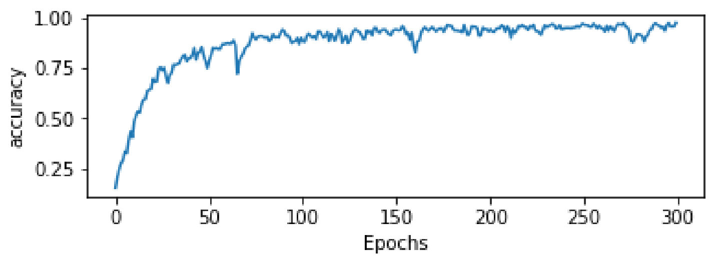
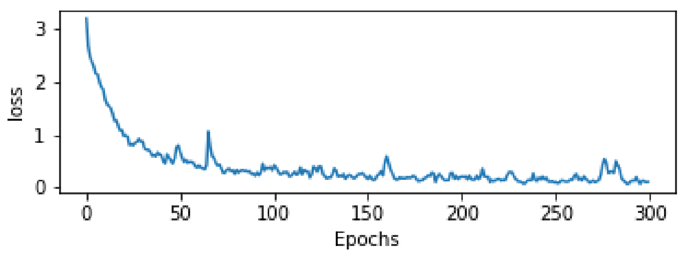

In [42]:

```
plt.subplot(2,1,1)
plot_graphs(history3, 'accuracy')
plt.subplot(2,1,2)
plot_graphs(history3, 'loss')
```





Function for predicting the Clothing attributes

In [51]:

```
def predict_img_attributes(path):
  img = cv2.imread(path)
  img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
  img1 = cv2.resize(img,(224,224))
  img2 = img1.reshape(1,224,224,3)
  img_inp = np.array(ResNet_model.predict(img2)[0]).reshape(1,2048)
  output_material = ""
  output_pattern = ""
  output_neckline = ""
  predicted_material = np.argmax(model1.predict(img_inp))
  predicted_pattern = np.argmax(model2.predict(img_inp))
  predicted_neckline = np.argmax(model3.predict(img_inp))
  for word, index in tokenizer1.word_index.items():
    if index == predicted_material:
      output_material = word
  for word, index in tokenizer2.word_index.items():
    if index == predicted_pattern:
      output_pattern = word
  for word, index in tokenizer3.word_index.items():
    if index == predicted_neckline:
```

```
        output_neckline = word
    plt.imshow(img)
    print('predicted material class is ('+output_material+')\n'+
          'predicted pattern class is ('+output_pattern+')\n'+
          'predicted neckline class is ('+output_neckline+')\n')
    #plt.xlabel(('Actual attributes=',material_catalouge[path],pattern_catalouge[path],neckline_catalouge[path]));
```

Trying our model on unseen data

In [63]:

```
predict_img_attributes('./imgnew9.jpg')
```

```
predicted material class is (polyester)
predicted pattern class is (solid/plain)
predicted neckline class is (round_neck)
```

In [65]:

```
predict_img_attributes('./imgnew1.jpg')
```

```
predicted material class is (cotton)
predicted pattern class is (printed)
predicted neckline class is (keyhole_neck)
```

In [69]:

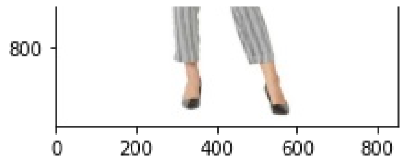
```
predict_img_attributes('./imgnew7.jpg')
```

```
predicted material class is (cotton)
predicted pattern class is (solid/plain)
predicted neckline class is (boat_neck)
```

In [70]:

```
predict_img_attributes('./imgnew13.jpg')
```

```
predicted material class is (cotton)
predicted pattern class is (stripes)
predicted neckline class is (v-neck)
```



In [ ]: