

In [1]:

```
## Import all important libraries
from tensorflow.keras.applications.imagenet_utils import preprocess_input
from tensorflow.keras.applications import ResNet50, imagenet_utils
from tensorflow.keras.preprocessing.image import img_to_array, load_img, ImageDataGenerator
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.utils import to_categorical
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Conv2D, Dropout, MaxPooling2D, Flatten, Dense, Batch
Normalization, Input, \
                                LSTM, Embedding, Input, TimeDistributed, Bidirection
al, Activation, RepeatVector, Concatenate
from keras.preprocessing.sequence import pad_sequences

import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
from glob import glob
import cv2
import os
```

In [2]:

```
## Link a colab with google drive
from google.colab import drive
drive.mount('/content/drive')
```

Mounted at /content/drive

In [3]:

```
cd /content/drive/MyDrive/assignment
```

```
/content/drive/MyDrive/catalogue assignment
```

In [4]:

```
pwd
```

Out[4]:

```
'/content/drive/MyDrive/catalogue assignment'
```

In [5]:

```
## Read the file
df = pd.read_excel('dataset.xlsx')
df.head()
```

Out[5]:

	Title	Description	Material	Pattern	Neckline	Image_Path	Image_Path.1	Unnamed: 7
0	Peach Poly Crepe jumpsuit	This stylish foil print kurta from janasya is ...	Crepe	Printed	Round Neck	/images/pic_0.jpg	/images/pic_0.jpg	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	/images/pic_1.jpg	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	/images/pic_2.jpg	NaN

3	Blue Me Army Cape Top	Add an extra dose of style to your casual ward...	Material	Pattern	Neckline	Image_Path	Image_Path_1	Unnamed: NaN
4	Yellow On A High Gown	Yellow polyester georgette maxi dress. Polyest...	Polyester	Solid/Plain	V-Neck	/images/pic_4.jpg	/images/pic_4.jpg	NaN

In [6]:

```
## Store the image path and description in list
path = list(df['Image_Path'])
Image_Description = list(df["Description"])
```

## Image Preprocessing

In [7]:

```
## Edit the image path
imagePath = []
for i in path:
    ip = "." + i
    imagePath.append(ip)
```

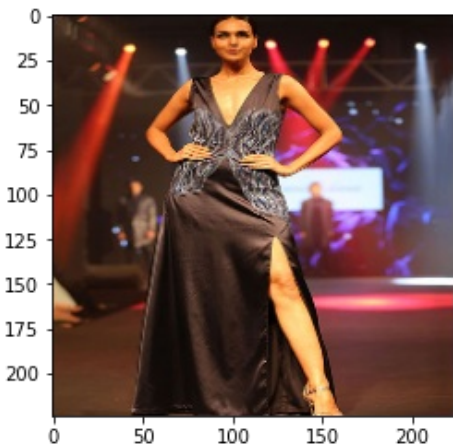
In [11]:

In [8]:

```
img = cv2.imread('./images/pic_82.jpg')
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
img = cv2.resize(img, (224,224))
plt.imshow(img)
```

Out[8]:

<matplotlib.image.AxesImage at 0x7ff1b78db0b8>



In [9]:

```
## Call ResNet model
ResNet = ResNet50(include_top=True)
```

Downloading data from [https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50\\_weights\\_tf\\_dim\\_ordering\\_tf\\_kernels.h5](https://storage.googleapis.com/tensorflow/keras-applications/resnet/resnet50_weights_tf_dim_ordering_tf_kernels.h5)  
102973440/102967424 [=====] - 4s 0us/step

In [10]:

```
## Apply ResNet model on all images
last = ResNet.layers[-2].output
modell = Model(inputs = ResNet.input, outputs = last)
modell.summary()
```

Model: "model"

Layer (type)	Output Shape	Param #	Connected to
=====			
input_1 (InputLayer)	[(None, 224, 224, 3)]	0	
=====			
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_1[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 (BatchNormalization)	(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 (BatchNormalization)	(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 (BatchNormalization)	(None, 56, 56, 256)	1024	conv2_block1_0_conv[0][0]
=====			
conv2_block1_3_bn (BatchNormalization)	(None, 56, 56, 256)	1024	conv2_block1_3_conv[0][0]

]			
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conv2_block1_add (Add)	(None, 56, 56, 256)	0	conv2_block1_0_bn[0][0]
			conv2_block1_3_bn[0][0]
]			
<hr/>			
conv2_block1_out (Activation)	(None, 56, 56, 256)	0	conv2_block1_add[0][0]
<hr/>			
conv2_block2_1_conv (Conv2D)	(None, 56, 56, 64)	16448	conv2_block1_out[0][0]
<hr/>			
conv2_block2_1_bn (BatchNormali	(None, 56, 56, 64)	256	conv2_block2_1_conv[0][0]
]			
<hr/>			
conv2_block2_1_relu (Activation	(None, 56, 56, 64)	0	conv2_block2_1_bn[0][0]
<hr/>			
conv2_block2_2_conv (Conv2D)	(None, 56, 56, 64)	36928	conv2_block2_1_relu[0][0]
]			
<hr/>			
conv2_block2_2_bn (BatchNormali	(None, 56, 56, 64)	256	conv2_block2_2_conv[0][0]
]			
<hr/>			
conv2_block2_2_relu (Activation	(None, 56, 56, 64)	0	conv2_block2_2_bn[0][0]
<hr/>			
conv2_block2_3_conv (Conv2D)	(None, 56, 56, 256)	16640	conv2_block2_2_relu[0][0]
]			
<hr/>			
conv2_block2_3_bn (BatchNormali	(None, 56, 56, 256)	1024	conv2_block2_3_conv[0][0]
]			
<hr/>			
conv2_block2_add (Add)	(None, 56, 56, 256)	0	conv2_block1_out[0][0]
			conv2_block2_3_bn[0][0]
]			
<hr/>			
conv2_block2_out (Activation)	(None, 56, 56, 256)	0	conv2_block2_add[0][0]
<hr/>			
conv2_block3_1_conv (Conv2D)	(None, 56, 56, 64)	16448	conv2_block2_out[0][0]
<hr/>			
conv2_block3_1_bn (BatchNormali	(None, 56, 56, 64)	256	conv2_block3_1_conv[0][0]
]			
<hr/>			
conv2_block3_1_relu (Activation	(None, 56, 56, 64)	0	conv2_block3_1_bn[0][0]
<hr/>			
conv2_block3_2_conv (Conv2D)	(None, 56, 56, 64)	36928	conv2_block3_1_relu[0][0]
]			
<hr/>			
conv2_block32_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_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_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_out	(Activation)	(None, 14, 14, 1024)	0	conv4_block3_3_bn[0][0]
conv4_block4_1_conv	(Conv2D)	(None, 14, 14, 256)	262400	conv4_block3_add[0][0]
conv4_block4_1_bn	(BatchNormali	(None, 14, 14, 256)	1024	conv4_block3_out[0][0]
conv4_block4_1_relu	(Activation)	(None, 14, 14, 256)	0	conv4_block4_1_conv[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]
<hr/>				
conv5_block3_3_bn	(BatchNormali	(None, 7, 7, 2048)	8192	conv5_block3_3_conv[0][0]
<hr/>				
conv5_block3_add	(Add)	(None, 7, 7, 2048)	0	conv5_block2_out[0][0]
				conv5_block3_3_bn[0][0]
<hr/>				
conv5_block3_out	(Activation)	(None, 7, 7, 2048)	0	conv5_block3_add[0][0]
<hr/>				
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 [11]:

```
## Lets predict using ResNet model and add it in a dictionary
images_features = {}
count = 0
for i in imagePath:
    img = cv2.imread(i)
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    img = cv2.resize(img, (224,224))

    img = img.reshape(1,224,224,3)
    pred = model.predict(img).reshape(2048,)

    # img_name = i.split('/')[ -1]

    images_features[i] = pred

    count += 1

    if count > 1499:
        break

elif count % 50 == 0:
    print(count)
```

50  
100  
150  
200  
250  
300  
350  
400  
450  
500

In [36]:

```
## Values stored in image features dictionary
images_features['./images/pic 82.jpg']
```

Out[36]:

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278 279 280 281 282 283 284 285 286 287 288 289 290 291 292 293 294 295 296 297 298 299 300 301 302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324 325 326 327 328 329 330 331 332 333 334 335 336 337 338 339 340 341 342 343 344 345 346 347 348 349 350 351 352 353 354 355 356 357 358 359 360 361 362 363 364 365 366 367 368 369 370 371 372 373 374 375 376 377 378 379 380 381 382 383 384 385 386 387 388 389 390 391 392 393 394 395 396 397 398 399 400 401 402 403 404 405 406 407 408 409 410 411 412 413 414 415 416 417 418 419 420 421 422 423 424 425 426 427 428 429 430 431 432 433 434 435 436 437 438 439 440 441 442 443 444 445 446 447 448 449 450 451 452 453 454 455 456 457 458 459 460 461 462 463 464 465 466 467 468 469 470 471 472 473 474 475 476 477 478 479 480 481 482 483 484 485 486 487 488 489 490 491 492 493 494 495 496 497 498 499 500 501 502 503 504 505 506 507 508 509 510 511 512 513 514 515 516 517 518 519 520 521 522 523 524 525 526 527 528 529 530 531 532 533 534 535 536 537 538 539 540 541 542 543 544 545 546 547 548 549 550 551 552 553 554 555 556 557 558 559 560 561 562 563 564 565 566 567 568 569 570 571 572 573 574 575 576 577 578 579 580 581 582 583 584 585 586 587 588 589 590 591 592 593 594 595 596 597 598 599 600 601 602 603 604 605 606 607 608 609 610 611 612 613 614 615 616 617 618 619 620 621 622 623 624 625 626 627 628 629 630 631 632 633 634 635 636 637 638 639 640 641 642 643 644 645 646 647 648 649 650 651 652 653 654 655 656 657 658 659 660 661 662 663 664 665 666 667 668 669 670 671 672 673 674 675 676 677 678 679 680 681 682 683 684 685 686 687 688 689 690 691 692 693 694 695 696 697 698 699 700 701 702 703 704 705 706 707 708 709 710 711 712 713 714 715 716 717 718 719 720 721 722 723 724 725 726 727 728 729 730 731 732 733 734 735 736 737 738 739 740 741 742 743 744 745 746 747 748 749 750 751 752 753 754 755 756 757 758 759 760 761 762 763 764 765 766 767 768 769 770 771 772 773 774 775 776 777 778 779 780 781 782 783 784 785 786 787 788 789 790 791 792 793 794 795 796 797 798 799 800 801 802 803 804 805 806 807 808 809 810 811 812 813 814 815 816 817 818 819 820 821 822 823 824 825 826 827 828 829 830 831 832 833 834 835 836 837 838 839 840 841 842 843 844 845 846 847 848 849 850 851 852 853 854 855 856 857 858 859 860 861 862 863 864 865 866 867 868 869 870 871 872 873 874 875 876 877 878 879 880 881 882 883 884 885 886 887 888 889 890 891 892 893 894 895 896 897 898 899 900 901 902 903 904 905 906 907 908 909 910 911 912 913 914 915 916 917 918 919 920 921 922 923 924 925 926 927 928 929 930 931 932 933 934 935 936 937 938 939 940 941 942 943 944 945 946 947 948 949 950 951 952 953 954 955 956 957 958 959 960 961 962 963 964 965 966 967 968 969 970 971 972 973 974 975 976 977 978 979 980 981 982 983 984 985 986 987 988 989 990 991 992 993 994 995 996 997 998 999 1000 1001 1002 1003 1004 1005 1006 1007 1008 1009 1010 1011 1012 1013 1014 1015 1016 1017 1018 1019 1020 1021 1022 1023 1024 1025 1026 1027 1028 1029 1030 1031 1032 1033 1034 1035 1036 1037 1038 1039 1040 1

```
array([1.6811163 , 2.175395 , 0.06980729, ..., 0.03872671, 1.4715201 ,
       0.19152299], dtype=float32)
```

In [ ]:

## Text Preprocessing

In [12]:

```
# Add Imagepath and Description in one dictionary i.e., Key as Image path and values as d
escription
dataa = {}
for i, j in zip(imagePath, Iamge_Description):
    dataa[i] = j
```

In [211]:

```
for i in range(5):
    plt.figure()
    img_name = imagePath[i]

    img = cv2.imread(img_name)

    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.xlabel(dataa[img_name])
    plt.imshow(img)
```



This stylish foil print kurta from janasya is made of poly crepe and comes in an attractive peach color. It features 3/4 sleeve,round neck,a-line and it is calf length kurta that is suitable for casual occasions. Team it with matching leggings for a chic look.



This check pattern top by Work Label is crafted in cotton. Featuring a bias check at the yoke and straight check pattern in bottom half, a smart round Neckline, 3/4th sleeves, this mid hip length top offers a stylish & comfortable fit. Style this top with a trouser/skirt and medium high heels for chic look at work. This top can also be styled with a pair of stud earrings and a pair your regular sneakers to attain a casual look.



Featuring elegant printed details, this off white top and skirt set from Jaipur Kurti makes a statement addition to your casual wardrobe. Style this set with a pair of high heels and statement accessories to complete the look.



Add an extra dose of style to your casual wardrobe with this elegant blue cape top from Twenty Dresses. Style With: A pair of black denims, colour block heels and statement earrings will complete this look!



Yellow polyester georgette maxi dress. Polyester knit lining inside for comfort. Overlapping v neckline with gathers at bust. Flared sleeves with attached belt at the waist. Concealed zipper on the left.

In [ ]:

In [13]:

```
## Preprocess the description
def preprocessed(txt):
    modified = txt.lower()
    ## Add start and end element in description
    modified = 'startofseq ' + modified + ' endofseq'
    return modified
```

In [14]:

```
## Apply the preprocessing on our dict
for k,v in dataa.items():
    dataa[k] = preprocessed(v)
```

In [15]:

```
## After preprocessing
dataa['./images/pic_199.jpg']
```

Out[15]:

'startofseq olive polyester crepe dress. wrap style v neckline with three fourth sleeves. button detail on the left thigh. elasticated waist with an attached tie up belt. ruching on the sleeve sides with tie up detailing. fit and flare silhouette. endofseq'

In [ ]:

## Create Vocabulary

In [16]:

```
## Create a Vocabulary or Vocabulary of dictionary
count_words = {}
for k,v in dataa.items():

    for word in v.split():
        if word not in count_words:

            count_words[word] = 0

        else:
            count_words[word] += 1
```

In [17]:

```
## total number of style word present in our description
count_words['style']
```

Out[17]:

231

In [38]:

```
## Total words present  
len(count_words)
```

Out[38]:

1939

In [ ]:

In [18]:

```
## concert a caption dict in the interger words i.e., machine understandable form  
## Key as imagePath and description converted to integers  
for k, v in dataa.items():  
  
    encoded = []  
    for word in v.split():  
        encoded.append(count_words[word])  
  
    dataa[k] = encoded
```

In [129]:

```
### decription in integer format  
dataa['./images/pic_199.jpg']
```

Out[129]:

```
[499,  
 5,  
 119,  
 45,  
 46,  
 23,  
 231,  
 40,  
 59,  
 713,  
 14,  
 12,  
 34,  
 44,  
 19,  
 136,  
 472,  
 14,  
 0,  
 24,  
 56,  
 713,  
 80,  
 8,  
 26,  
 48,  
 4,  
 6,  
 136,  
 472,  
 15,  
 5,  
 713,  
 26,  
 48,  
 9,  
 54,  
 921,  
 ...]
```



```
34,  
40,  
499]
```

In [ ]:

## Built Generator Function

Splitting each word and setting next word to repredicted as our output.

In [19]:

```
max_len = 0  
for k, v in dataa.items():  
  
    if len(v) > max_len:  
        max_len = len(v)  
    print(v)
```

```
[499, 562, 18, 2, 28, 7, 166, 1, 238, 25, 200, 1, 45, 921, 18, 226, 80, 1, 7, 2, 175, 128,  
2, 0, 0, 921, 175, 238, 0, 14, 7, 45, 238, 1, 308, 61, 5, 35, 175, 713, 6, 4, 308, 876, 32  
, 167, 499]  
[499, 562, 7, 6, 197, 114, 13, 5, 238, 126, 226, 0, 40, 876, 1, 7, 137, 472, 12, 921, 29,  
7, 6, 226, 14, 0, 876, 7, 46, 12, 29, 56, 562, 1, 3, 14, 197, 0, 876, 18, 44, 13, 66, 231,  
562, 197, 713, 876, 0, 921, 0, 80, 151, 308, 32, 37, 137, 0, 562, 197, 21, 4, 39, 4, 713,  
876, 183, 200, 4, 29, 921, 876, 183, 126, 77, 19, 326, 3, 876, 61, 167, 499]  
[499, 66, 64, 76, 5, 46, 26, 48, 59, 19, 713, 876, 11, 3, 30, 10, 137, 472, 69, 12, 921,  
44, 13, 69, 63, 308, 51, 921, 53, 5, 1, 137, 472, 11, 308, 45, 64, 23, 10, 20, 69, 713, 87  
6, 5, 2, 308, 472, 5, 126, 2, 23, 238, 3, 226, 308, 876, 3, 19, 45, 238, 876, 3, 200, 9,  
16, 44, 45, 10, 36, 28, 151, 876, 12, 24, 921, 7, 16, 57, 9, 49, 7, 7, 226, 2, 1, 499]  
[499, 562, 66, 64, 76, 214, 114, 2, 238, 126, 226, 45, 921, 128, 876, 22, 66, 0, 59, 12,  
52, 0, 118, 166, 472, 12, 876, 69, 11, 51, 19, 921, 876, 77, 66, 231, 562, 214, 713, 876,  
183, 200, 80, 151, 921, 68, 55, 326, 152, 472, 167, 50, 562, 214, 17, 7, 7, 562, 19, 238,  
8, 713, 13, 921, 7, 114, 8, 7, 921, 7, 8, 7, 200, 14, 921, 18, 10, 7, 166, 7, 9, 7, 308, 8  
76, 10, 7, 7, 499]
```

In [21]:

```
## Maximum length array  
max_len
```

Out[21]:

88

In [20]:

```
## Generate a X, y_in and y_out taking photo dict(i.e., contain ResNet prediction) and ca  
ption dict(i.e., contain description in integer)  
VOCAB_SIZE = len(count_words)  
  
def generator(photo, caption):  
  
    X = []  
    y_in = []  
    y_out = []  
  
    for k, v in caption.items():  
  
        for i in range(1, len(v)):  
            X.append(photo[k])          ## Appending image features to X var  
  
            in_seq= [v[:i]]              ## splitting the description in a sequence i.e., 0-1, 0  
-1-2, 0-1-2-3, .....  
            out_seq = v[i]               ## Next word  
  
            ## use pad sequence to convert the variable length to max_len i.e., 88  
            in_seq= pad_sequences(in_seq, maxlen=max_len, padding='post', truncating='post')[
```

```
0]
    out_seq = to_categorical([out_seq], num_classes=VOCAB_SIZE)[0]

    y_in.append(in_seq)
    y_out.append(out_seq)

    return X, y_in, y_out
```

In [22]:

```
## run the generator func and add values in Variables
X, y_in, y_out = generator(images_features, dataa)
```

In [23]:

```
## length of all variables
len(X), len(y_in), len(y_out)
```

Out[23]:

```
(18526, 18526, 18526)
```

In [24]:

```
## convert them in array
X = np.array(X)
y_in = np.array(y_in, dtype='float64')
y_out = np.array(y_out, dtype='float64')
```

In [25]:

```
## shapes
X.shape, y_in.shape, y_out.shape
```

Out[25]:

```
((18526, 2048), (18526, 88), (18526, 1939))
```

In [ ]:

In [26]:

```
## Built a model
embedding_size = 128
max_len = max_len
vocab_size = len(count_words)

image_model = Sequential()

image_model.add(Dense(embedding_size, input_shape=(2048,), activation='relu'))
image_model.add(RepeatVector(max_len))

image_model.summary()

language_model = Sequential()

language_model.add(Embedding(input_dim=vocab_size, output_dim=embedding_size, input_length=max_len))
language_model.add(LSTM(256, return_sequences=True))
language_model.add(TimeDistributed(Dense(embedding_size)))

language_model.summary()

conca = Concatenate()([image_model.output, language_model.output])
x = LSTM(128, return_sequences=True)(conca)
x = LSTM(512, return_sequences=False)(x)
x = Dense(vocab_size)(x)
out = Activation('softmax')(x)
model = Model(inputs=[image_model.input, language_model.input], outputs = out)
```

```
# model.load_weights("../input/model_weights.h5")
model.compile(loss='categorical_crossentropy', optimizer='RMSprop', metrics=['accuracy'])
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 128)	262272
repeat_vector (RepeatVector)	(None, 88, 128)	0
Total params: 262,272		
Trainable params: 262,272		
Non-trainable params: 0		

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 88, 128)	248192
lstm (LSTM)	(None, 88, 256)	394240
time_distributed (TimeDistri	(None, 88, 128)	32896
Total params: 675,328		
Trainable params: 675,328		
Non-trainable params: 0		

Model: "model\_1"

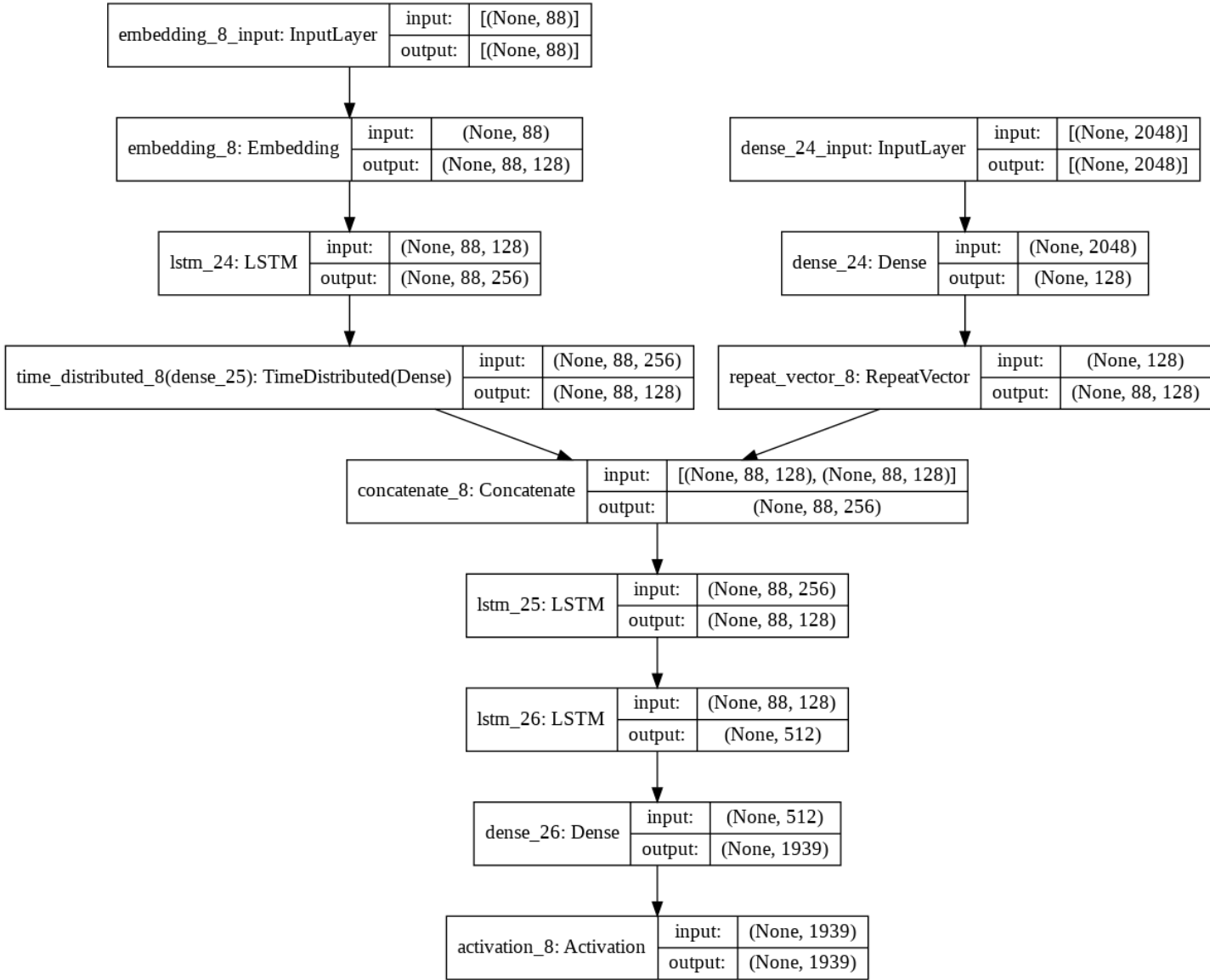
Layer (type)	Output Shape	Param #	Connected to
embedding_input (InputLayer)	[(None, 88)]	0	
dense_input (InputLayer)	[(None, 2048)]	0	
embedding (Embedding)	(None, 88, 128)	248192	embedding_input[0][0]
dense (Dense)	(None, 128)	262272	dense_input[0][0]
lstm (LSTM)	(None, 88, 256)	394240	embedding[0][0]
repeat_vector (RepeatVector)	(None, 88, 128)	0	dense[0][0]
time_distributed (TimeDistribut	(None, 88, 128)	32896	lstm[0][0]
concatenate (Concatenate)	(None, 88, 256)	0	repeat_vector[0][0] time_distributed[0][0]

lstm_1 (LSTM)	(None, 88, 128)	197120	concatenate[0][0]
lstm_2 (LSTM)	(None, 512)	1312768	lstm_1[0][0]
dense_2 (Dense)	(None, 1939)	994707	lstm_2[0][0]
activation (Activation)	(None, 1939)	0	dense_2[0][0]
=====			
=====			
Total params: 3,442,195			
Trainable params: 3,442,195			
Non-trainable params: 0			

In [231]:

```
## plot the model
from keras.utils import plot_model
plot_model(model, show_shapes=True)
```

Out[231]:



In [39]:

```
## fit the model
```

```
model.fit([X, y_in], y_out, batch_size=512, epochs=100)
```

```
Epoch 1/100
37/37 [=====] - 5s 122ms/step - loss: 1.4714 - accuracy: 0.4606
Epoch 2/100
37/37 [=====] - 5s 122ms/step - loss: 1.4515 - accuracy: 0.4631
Epoch 3/100
37/37 [=====] - 5s 122ms/step - loss: 1.4225 - accuracy: 0.4693
Epoch 4/100
37/37 [=====] - 5s 122ms/step - loss: 1.4209 - accuracy: 0.4718
Epoch 5/100
37/37 [=====] - 5s 122ms/step - loss: 1.3986 - accuracy: 0.4790
Epoch 6/100
37/37 [=====] - 5s 122ms/step - loss: 1.4113 - accuracy: 0.4777
Epoch 7/100
37/37 [=====] - 5s 122ms/step - loss: 1.3611 - accuracy: 0.4937
Epoch 8/100
37/37 [=====] - 5s 122ms/step - loss: 1.3763 - accuracy: 0.4870
Epoch 9/100
37/37 [=====] - 5s 122ms/step - loss: 1.3655 - accuracy: 0.4924
Epoch 10/100
37/37 [=====] - 5s 122ms/step - loss: 1.3272 - accuracy: 0.5000
Epoch 11/100
37/37 [=====] - 5s 122ms/step - loss: 1.3415 - accuracy: 0.4927
Epoch 12/100
37/37 [=====] - 5s 122ms/step - loss: 1.3139 - accuracy: 0.5032
Epoch 13/100
37/37 [=====] - 5s 122ms/step - loss: 1.2895 - accuracy: 0.5129
Epoch 14/100
37/37 [=====] - 5s 122ms/step - loss: 1.2911 - accuracy: 0.5095
Epoch 15/100
37/37 [=====] - 5s 122ms/step - loss: 1.2813 - accuracy: 0.5110
Epoch 16/100
37/37 [=====] - 5s 122ms/step - loss: 1.2531 - accuracy: 0.5260
Epoch 17/100
37/37 [=====] - 5s 122ms/step - loss: 1.2794 - accuracy: 0.5088
Epoch 18/100
37/37 [=====] - 5s 123ms/step - loss: 1.2497 - accuracy: 0.5239
Epoch 19/100
37/37 [=====] - 5s 122ms/step - loss: 1.2194 - accuracy: 0.5336
Epoch 20/100
37/37 [=====] - 5s 122ms/step - loss: 1.1858 - accuracy: 0.5460
Epoch 21/100
37/37 [=====] - 5s 122ms/step - loss: 1.2254 - accuracy: 0.5234
Epoch 22/100
37/37 [=====] - 5s 122ms/step - loss: 1.1997 - accuracy: 0.5367
Epoch 23/100
37/37 [=====] - 5s 122ms/step - loss: 1.1962 - accuracy: 0.5363
Epoch 24/100
37/37 [=====] - 5s 122ms/step - loss: 1.1838 - accuracy: 0.5397
Epoch 25/100
37/37 [=====] - 5s 122ms/step - loss: 1.1940 - accuracy: 0.5369
Epoch 26/100
37/37 [=====] - 5s 122ms/step - loss: 1.1538 - accuracy: 0.5476
Epoch 27/100
37/37 [=====] - 5s 122ms/step - loss: 1.1542 - accuracy: 0.5473
Epoch 28/100
37/37 [=====] - 5s 122ms/step - loss: 1.1371 - accuracy: 0.5533
Epoch 29/100
37/37 [=====] - 5s 122ms/step - loss: 1.1375 - accuracy: 0.5547
Epoch 30/100
37/37 [=====] - 5s 122ms/step - loss: 1.1251 - accuracy: 0.5603
Epoch 31/100
37/37 [=====] - 5s 123ms/step - loss: 1.1008 - accuracy: 0.5701
Epoch 32/100
37/37 [=====] - 5s 122ms/step - loss: 1.1123 - accuracy: 0.5619
Epoch 33/100
37/37 [=====] - 5s 122ms/step - loss: 1.0945 - accuracy: 0.5764
Epoch 34/100
37/37 [=====] - 5s 122ms/step - loss: 1.1006 - accuracy: 0.5672
Epoch 35/100
37/37 [=====] - 5s 122ms/step - loss: 1.0747 - accuracy: 0.5790
```

```
Epoch 36/100
37/37 [=====] - 4s 121ms/step - loss: 1.0785 - accuracy: 0.5794
Epoch 37/100
37/37 [=====] - 4s 121ms/step - loss: 1.0668 - accuracy: 0.5803
Epoch 38/100
37/37 [=====] - 5s 122ms/step - loss: 1.0536 - accuracy: 0.5852
Epoch 39/100
37/37 [=====] - 4s 121ms/step - loss: 1.0509 - accuracy: 0.5840
Epoch 40/100
37/37 [=====] - 4s 121ms/step - loss: 1.0445 - accuracy: 0.5878
Epoch 41/100
37/37 [=====] - 4s 121ms/step - loss: 1.0306 - accuracy: 0.5897
Epoch 42/100
37/37 [=====] - 5s 122ms/step - loss: 1.0072 - accuracy: 0.6037
Epoch 43/100
37/37 [=====] - 5s 122ms/step - loss: 1.0295 - accuracy: 0.5896
Epoch 44/100
37/37 [=====] - 4s 121ms/step - loss: 1.0032 - accuracy: 0.6005
Epoch 45/100
37/37 [=====] - 4s 121ms/step - loss: 0.9969 - accuracy: 0.6082
Epoch 46/100
37/37 [=====] - 5s 122ms/step - loss: 0.9912 - accuracy: 0.6013
Epoch 47/100
37/37 [=====] - 5s 122ms/step - loss: 0.9955 - accuracy: 0.6054
Epoch 48/100
37/37 [=====] - 4s 121ms/step - loss: 0.9620 - accuracy: 0.6213
Epoch 49/100
37/37 [=====] - 5s 122ms/step - loss: 0.9702 - accuracy: 0.6109
Epoch 50/100
37/37 [=====] - 4s 122ms/step - loss: 0.9627 - accuracy: 0.6186
Epoch 51/100
37/37 [=====] - 4s 122ms/step - loss: 0.9370 - accuracy: 0.6305
Epoch 52/100
37/37 [=====] - 4s 121ms/step - loss: 0.9604 - accuracy: 0.6214
Epoch 53/100
37/37 [=====] - 4s 121ms/step - loss: 0.9364 - accuracy: 0.6233
Epoch 54/100
37/37 [=====] - 5s 122ms/step - loss: 0.9293 - accuracy: 0.6257
Epoch 55/100
37/37 [=====] - 5s 122ms/step - loss: 0.9374 - accuracy: 0.6290
Epoch 56/100
37/37 [=====] - 4s 121ms/step - loss: 0.8935 - accuracy: 0.6423
Epoch 57/100
37/37 [=====] - 5s 122ms/step - loss: 0.9190 - accuracy: 0.6292
Epoch 58/100
37/37 [=====] - 5s 122ms/step - loss: 0.9076 - accuracy: 0.6348
Epoch 59/100
37/37 [=====] - 5s 122ms/step - loss: 0.9192 - accuracy: 0.6288
Epoch 60/100
37/37 [=====] - 5s 122ms/step - loss: 0.8836 - accuracy: 0.6448
Epoch 61/100
37/37 [=====] - 4s 121ms/step - loss: 0.9071 - accuracy: 0.6333
Epoch 62/100
37/37 [=====] - 4s 121ms/step - loss: 0.8794 - accuracy: 0.6436
Epoch 63/100
37/37 [=====] - 5s 122ms/step - loss: 0.8736 - accuracy: 0.6460
Epoch 64/100
37/37 [=====] - 5s 122ms/step - loss: 0.8650 - accuracy: 0.6546
Epoch 65/100
37/37 [=====] - 4s 121ms/step - loss: 0.8506 - accuracy: 0.6574
Epoch 66/100
37/37 [=====] - 5s 122ms/step - loss: 0.8570 - accuracy: 0.6542
Epoch 67/100
37/37 [=====] - 5s 122ms/step - loss: 0.8744 - accuracy: 0.6498
Epoch 68/100
37/37 [=====] - 5s 122ms/step - loss: 0.8098 - accuracy: 0.6746
Epoch 69/100
37/37 [=====] - 5s 122ms/step - loss: 0.8531 - accuracy: 0.6551
Epoch 70/100
37/37 [=====] - 4s 121ms/step - loss: 0.8211 - accuracy: 0.6654
Epoch 71/100
37/37 [=====] - 4s 122ms/step - loss: 0.8292 - accuracy: 0.6617
```

```
Epoch 72/100
37/37 [=====] - 4s 121ms/step - loss: 0.8033 - accuracy: 0.6729
Epoch 73/100
37/37 [=====] - 5s 122ms/step - loss: 0.8163 - accuracy: 0.6654
Epoch 74/100
37/37 [=====] - 4s 121ms/step - loss: 0.8328 - accuracy: 0.6651
Epoch 75/100
37/37 [=====] - 4s 121ms/step - loss: 0.8084 - accuracy: 0.6743
Epoch 76/100
37/37 [=====] - 4s 122ms/step - loss: 0.7946 - accuracy: 0.6769
Epoch 77/100
37/37 [=====] - 4s 121ms/step - loss: 0.8199 - accuracy: 0.6652
Epoch 78/100
37/37 [=====] - 5s 122ms/step - loss: 0.7744 - accuracy: 0.6887
Epoch 79/100
37/37 [=====] - 5s 122ms/step - loss: 0.7978 - accuracy: 0.6704
Epoch 80/100
37/37 [=====] - 4s 121ms/step - loss: 0.7784 - accuracy: 0.6856
Epoch 81/100
37/37 [=====] - 5s 122ms/step - loss: 0.7526 - accuracy: 0.6946
Epoch 82/100
37/37 [=====] - 5s 122ms/step - loss: 0.7907 - accuracy: 0.6760
Epoch 83/100
37/37 [=====] - 4s 121ms/step - loss: 0.7506 - accuracy: 0.6970
Epoch 84/100
37/37 [=====] - 5s 122ms/step - loss: 0.7514 - accuracy: 0.6943
Epoch 85/100
37/37 [=====] - 4s 121ms/step - loss: 0.7391 - accuracy: 0.6976
Epoch 86/100
37/37 [=====] - 4s 121ms/step - loss: 0.7358 - accuracy: 0.7040
Epoch 87/100
37/37 [=====] - 4s 121ms/step - loss: 0.7416 - accuracy: 0.6930
Epoch 88/100
37/37 [=====] - 4s 121ms/step - loss: 0.7407 - accuracy: 0.6992
Epoch 89/100
37/37 [=====] - 4s 121ms/step - loss: 0.7381 - accuracy: 0.6982
Epoch 90/100
37/37 [=====] - 5s 122ms/step - loss: 0.7355 - accuracy: 0.6971
Epoch 91/100
37/37 [=====] - 4s 121ms/step - loss: 0.7219 - accuracy: 0.7032
Epoch 92/100
37/37 [=====] - 4s 121ms/step - loss: 0.7267 - accuracy: 0.7031
Epoch 93/100
37/37 [=====] - 4s 121ms/step - loss: 0.7046 - accuracy: 0.7103
Epoch 94/100
37/37 [=====] - 4s 121ms/step - loss: 0.7373 - accuracy: 0.7016
Epoch 95/100
37/37 [=====] - 4s 121ms/step - loss: 0.7072 - accuracy: 0.7162
Epoch 96/100
37/37 [=====] - 4s 121ms/step - loss: 0.7127 - accuracy: 0.7124
Epoch 97/100
37/37 [=====] - 4s 121ms/step - loss: 0.6965 - accuracy: 0.7169
Epoch 98/100
37/37 [=====] - 4s 121ms/step - loss: 0.6849 - accuracy: 0.7186
Epoch 99/100
37/37 [=====] - 4s 121ms/step - loss: 0.6938 - accuracy: 0.7154
Epoch 100/100
37/37 [=====] - 4s 121ms/step - loss: 0.6948 - accuracy: 0.7156
```

Out[39]:

```
<tensorflow.python.keras.callbacks.History at 0x7fef61ddcac8>
```

In [40]:

```
## Inverse the dictionary
inv_dict = {v:k for k, v in count_words.items() }
```

In [45]:

```
## save the model
model.save('image_desc.h5')
```

In [ ]:

## Predictions

In [69]:

```
## function to convert the image in machine readable format
def getImage(x):

    # test_img_path = imagePath[x]

    test_img = cv2.imread(x)
    test_img = cv2.cvtColor(test_img, cv2.COLOR_BGR2RGB)

    test_img = cv2.resize(test_img, (224,224))

    test_img = np.reshape(test_img, (1,224,224,3))

    return test_img
```

In [70]:

```
test_feature = model1.predict(getImage('newimg2.jpg')).reshape(1,2048)
```

In [71]:

```
text_inp = ['startofseq']

count = 0
desc = ''
while count < 25:
    count += 1

    encoded = []
    for i in text_inp:
        encoded.append(count_words[i])

    encoded = [encoded]

    encoded = pad_sequences(encoded, padding='post', truncating='post', maxlen=max_len)

    prediction = np.argmax(model.predict([test_feature, encoded]))          ## Returns
    a highest prob word

    sampled_word = inv_dict[prediction]

    desc = desc + ' ' + sampled_word

    if sampled_word == 'endofseq':
        break

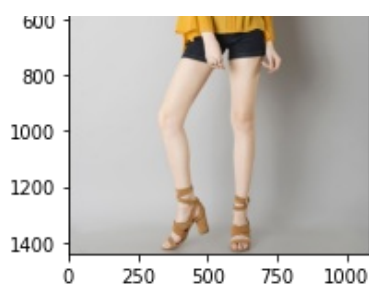
    text_inp.append(sampled_word)
```

In [73]:

```
imag = cv2.imread('newimg2.jpg')
imag = cv2.cvtColor(imag, cv2.COLOR_BGR2RGB)
plt.imshow(imag)
plt.xlabel(desc);
```







this strappy tie-up top by is is your in left and a box neck, rib-knit fabric, fabric, rayon and and the the sling left left

## Predict the decription of dataset images

In [ ]:

In [ ]:

```
## function to convert the image in machine readable format
def getImage(x):

    test_img_path = imagePath[x]

    test_img = cv2.imread(test_img_path)
    test_img = cv2.cvtColor(test_img, cv2.COLOR_BGR2RGB)

    test_img = cv2.resize(test_img, (224,224))

    test_img = np.reshape(test_img, (1,224,224,3))

    return test_img
```

In [44]:

```
for i in range(5):

    no = np.random.randint(100,500,(1,1))[0,0]
    test_feature = model1.predict(getImage(no)).reshape(1,2048)

    test_img_path = imagePath[no]
    test_img = cv2.imread(test_img_path)
    test_img = cv2.cvtColor(test_img, cv2.COLOR_BGR2RGB)

    text_inp = ['startofseq']

    count = 0
    desc = ''
    while count < 25:
        count += 1

        encoded = []
        for i in text_inp:
            encoded.append(count_words[i])

        encoded = [encoded]

        encoded = pad_sequences(encoded, padding='post', truncating='post', maxlen=max_len)

        prediction = np.argmax(model.predict([test_feature, encoded]))

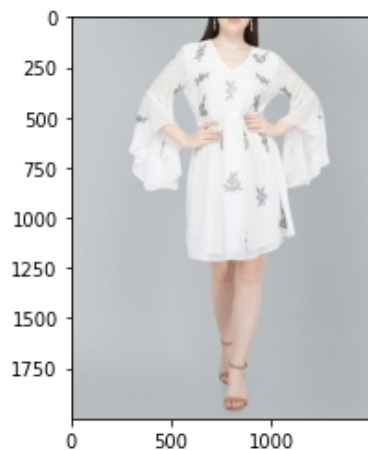
        sampled_word = inv_dict[prediction]

        desc = desc + ' ' + sampled_word

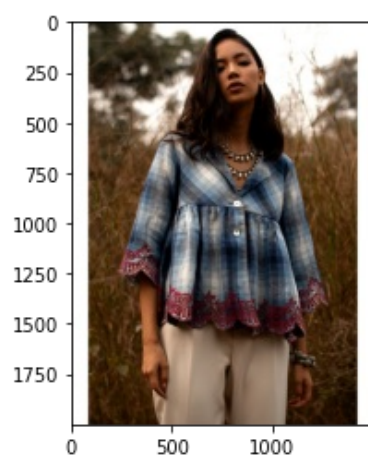
    if sampled_word == 'endofseq':
        break
```

```
text_inp.append(sampled_word)
```

```
plt.figure()  
plt.imshow(test_img)  
plt.xlabel(desc)
```



this white dress by platform platform is your in polyester and features a side neck, long half sleeves and kazo denims fun fun buy this



this neck, fun left from half rib-knit will be a buttoned tie to your placket you collection. side a half and rayon waist pair this



this black jumpsuit by fun is your in cotton and features a half rayon waist a fine style style tie-up and neck, neck, a a



cuffs half printed polyester fabric, style. only. sleeveless box tie with button fabric, the kazo front front front and and cuffs. pants neck waist a



this black placket jumpsuit from kazo will be a you tie to your placket you collection. side a tie neck and short waist pair this