

```
#HUMAN ACTIVITY DETECTION ASSIGNMENT
```

```
WE HAVE RAW DATA OF THE ACCELERATION AND GYROSCOPE DATA OF THE 30 PERSONS COLLECTED.
```

```
In [0]: # Code to read csv file into Colaboratory:  
!pip install -U -q PyDrive  
from pydrive.auth import GoogleAuth  
from pydrive.drive import GoogleDrive  
from google.colab import auth  
from oauth2client.client import GoogleCredentials  
# Authenticate and create the PyDrive client.  
auth.authenticate_user()  
gauth = GoogleAuth()  
gauth.credentials = GoogleCredentials.get_application_default()  
drive = GoogleDrive(gauth)
```

```
100% |██████████| 993kB 23.5MB/s ta 0:00:01  
Building wheel for PyDrive (setup.py) ... done
```

```
In [0]: link = 'https://drive.google.com/open?id=1l1adJnTgeHULVuoLdTByqi25-z6shBSL' # The
```

```
In [0]: fluff, id = link.split('=')  
print (id) # Verify that you have everything after '='
```

```
1l1adJnTgeHULVuoLdTByqi25-z6shBSL
```

```
In [0]: import pandas as pd  
downloaded = drive.CreateFile({'id':id})  
downloaded.GetContentFile('uploads')
```

```
In [0]: !mkdir traindata
```

```
In [0]: import os  
os.getcwd()  
os.chdir('/content/traindata')
```

```
In [4]: !pwd
```

```
/content/traindata
```

```
#signals in the raw form provided to us based on the person behavior. the activities he can perform are
```

- walking
- walking upstairs
- walking downstairs
- sitting

- standing
- laying

IN THE ABOVE ACTIVITIES FIRST THREE ACTIVITIES ARE DYNAMIC WHICH INVOLVES THE MOVEMENT OF THE PERSON WHERE AS THE LAST THREE ACTIVITIES ARE STATIC IN WHICH THE PERSON DOES NOT MOVE.

BASED ON THE OBTAINED DATA WE CAN PERFORM THE EXPLORATORY DATA ANALYSIS, DO THE FEATURE EXTRACTION AND WITH THE FEATURE ENGINEERING TECHNIQUES WE CAN OBTAIN THE BEST FEATURES BASED ON THE DATA WE HAVE.

LATER WE CAN EMPLOY INTO THE MODELS AND OBTAIN THE BEST RESULTS BY CHOOSING THE BEST FEATURES AND BEST MODEL

WE CAN USE THE DEEP LEARNING MODELS LIKE LSTM IN WHICH WE CAN USE THE RAW DATA WE OBTAINED AND DIRECTLY EMPLOY INTO THE DEEPMODELS.

WE CAN PERFORM THE HYPERPARAMETER TUNING ON THE MODELS AND OBTAIN THE BEST HYPERPARAMETER TO OBTAIN BEST RESULTS IN TERMS OF HOW ACCURATE OUR MODEL IS.

In [0]:

```
body_acc_x_test.txt  body_gyro_x_train.txt  total_acc_y_test.txt
body_acc_x_train.txt body_gyro_y_test.txt  total_acc_y_train.txt
body_acc_y_test.txt  body_gyro_y_train.txt  total_acc_z_test.txt
body_acc_y_train.txt body_gyro_z_test.txt  total_acc_z_train.txt
body_acc_z_test.txt  body_gyro_z_train.txt  y_test.txt
body_acc_z_train.txt total_acc_x_test.txt  y_train.txt
body_gyro_x_test.txt total_acc_x_train.txt
```

In [0]: import numpy as np

```
signals2=[  
    "body_acc_x_test.txt",  
    "body_acc_y_test.txt",  
    "body_acc_z_test.txt",  
    "body_gyro_x_test.txt",  
    "body_gyro_y_test.txt",  
    "body_gyro_z_test.txt",  
    "total_acc_x_test.txt",  
    "total_acc_y_test.txt",  
    "total_acc_z_test.txt",  
]
```

```
In [0]: SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]
```

```
In [0]: signals1=[

    "body_acc_x_train.txt",
    "body_acc_y_train.txt",
    "body_acc_z_train.txt",
    "body_gyro_x_train.txt",
    "body_gyro_y_train.txt",
    "body_gyro_z_train.txt",
    "total_acc_x_train.txt",
    "total_acc_y_train.txt",
    "total_acc_z_train.txt"
]
```

Type *Markdown* and *LaTeX*: α^2

```
In [0]: def read_csv(filename):
    return pd.read_csv(filename,delim_whitespace=True, header=None)

# Utility function to load the Load
def load_signals(subset):
    signals_data = []

    for signal in signals1:

        signals_data.append(read_csv(signal).as_matrix())


    return np.transpose(signals_data, (1, 2, 0))
def load_signals1(subset):
    signals_data = []

    for signal in signals2:

        signals_data.append(read_csv(signal).as_matrix())


    return np.transpose(signals_data, (1, 2, 0))
```

```
In [0]: ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
    2: 'WALKING_DOWNSTAIRS',
    3: 'SITTING',
    4: 'STANDING',
    5: 'LAYING',
}
```

get_dummies is a type of encoding .we are using to encode the output label for ex; if the label is zero it is represented as 100000 based on the size of the label.

```
In [0]: def load_y(subset):
    y = read_csv("y_train.txt")[0]
    return pd.get_dummies(y).as_matrix()

def load_y1(subset):
    y = read_csv("y_test.txt")[0]
    return pd.get_dummies(y).as_matrix()
```

```
In [0]: def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train,X_test= load_signals('train'),load_signals1('test')
    y_train, y_test = load_y('train'), load_y1('test')

    return X_train, X_test, y_train, y_test
```

```
In [14]: import pandas as pd
X_train, X_test, Y_train, Y_test = load_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:10: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
    # Remove the CWD from sys.path while we load stuff.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:19: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:7: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
    import sys
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:14: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
```

```
In [0]: # Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set_random_seed(42)
```

```
In [0]: # Configuring a session
session_conf = tf.ConfigProto(
    intra_op_parallelism_threads=1,
    inter_op_parallelism_threads=1
)
```

```
In [17]: # Import Keras
from keras import backend as K
sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)
```

Using TensorFlow backend.

we are using the lstm deeplearning model.

```
In [0]: # Importing Libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

```
In [0]: # Initializing parameters
epochs = 30
batch_size = 16
n_hidden = 32
```

```
In [0]: # Utility function to count the number of classes
def _count_classes(y):
    return len(set([tuple(category) for category in y]))
```

```
In [21]: # Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:10: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
    # Remove the CWD from sys.path while we load stuff.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:19: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:7: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
    import sys
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:14: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
```

```
In [22]: timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = _count_classes(Y_train)

print(timesteps)
print(input_dim)
print(len(X_train))
```

```
128
9
7352
```

```
In [0]: def errorplot(x,validationy,testy,ax):
    ax.plot(x,validationy,label='trainloss')
    ax.plot(x,testy,label='validationloss')
    plt.xlabel('number_of_epochs')
    plt.ylabel('categorical_crossentropy')
    plt.legend()
    plt.show()
```

- Defining the Architecture of LSTM

AS THE PART OF MODEL 1 WE ARE USING THE LSTM LAYER WITH THE 32 HIDDEN LAYERS AT FIRST LSTM LAYER. LATER WE ARE USING THE DENSE LAYER WITH THE NUMBER OF OUTPUT ACTIVITIES WE HAVE. WE ARE USING THE DROPOUT INORDER TO REDUCE THE OVERRFITTING OF OUR MODEL.SO THAT IF WE GIVE THE 0.5 AS THE DROPOUT VALUE THEN THE 50 PERCENT OF THE LSTM LAYER WILL BE TURNED OFF.

```
In [23]: # Initializing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_def_library.py:263: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.

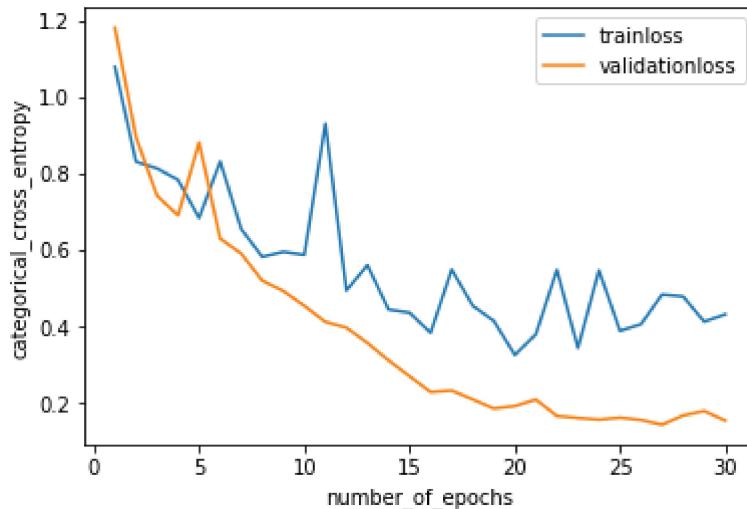
Layer (type)	Output Shape	Param #
<hr/>		
lstm_1 (LSTM)	(None, 32)	5376
<hr/>		
dropout_1 (Dropout)	(None, 32)	0
<hr/>		
dense_1 (Dense)	(None, 6)	198
<hr/>		
Total params: 5,574		
Trainable params: 5,574		
Non-trainable params: 0		

```
In [0]: # Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

```
In [26]: # Training the model
history=model.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_test,
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [=====] - 92s 12ms/step - loss: 1.1821 - ac
c: 0.4849 - val_loss: 1.0799 - val_acc: 0.4812
Epoch 2/30
7352/7352 [=====] - 92s 13ms/step - loss: 0.8964 - ac
c: 0.6049 - val_loss: 0.8318 - val_acc: 0.6328
Epoch 3/30
7352/7352 [=====] - 91s 12ms/step - loss: 0.7430 - ac
c: 0.6514 - val_loss: 0.8144 - val_acc: 0.5904
Epoch 4/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.6915 - ac
c: 0.6616 - val_loss: 0.7841 - val_acc: 0.6179
Epoch 5/30
7352/7352 [=====] - 92s 13ms/step - loss: 0.8822 - ac
c: 0.6315 - val_loss: 0.6848 - val_acc: 0.6301
Epoch 6/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.6310 - ac
c: 0.7087 - val_loss: 0.8325 - val_acc: 0.6926
Epoch 7/30
7352/7352 [=====] - 91s 12ms/step - loss: 0.5917 - ac
c: 0.7489 - val_loss: 0.6560 - val_acc: 0.7296
Epoch 8/30
7352/7352 [=====] - 92s 12ms/step - loss: 0.5208 - ac
c: 0.7729 - val_loss: 0.5831 - val_acc: 0.7513
Epoch 9/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.4937 - ac
c: 0.7826 - val_loss: 0.5962 - val_acc: 0.7251
Epoch 10/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.4549 - ac
c: 0.7996 - val_loss: 0.5883 - val_acc: 0.7014
Epoch 11/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.4131 - ac
c: 0.8211 - val_loss: 0.9308 - val_acc: 0.6919
Epoch 12/30
7352/7352 [=====] - 91s 12ms/step - loss: 0.3980 - ac
c: 0.8395 - val_loss: 0.4951 - val_acc: 0.8303
Epoch 13/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.3580 - ac
c: 0.8719 - val_loss: 0.5613 - val_acc: 0.8276
Epoch 14/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.3124 - ac
c: 0.9021 - val_loss: 0.4453 - val_acc: 0.8690
Epoch 15/30
7352/7352 [=====] - 91s 12ms/step - loss: 0.2706 - ac
c: 0.9176 - val_loss: 0.4370 - val_acc: 0.8711
Epoch 16/30
7352/7352 [=====] - 89s 12ms/step - loss: 0.2295 - ac
c: 0.9266 - val_loss: 0.3845 - val_acc: 0.8887
Epoch 17/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.2333 - ac
c: 0.9253 - val_loss: 0.5497 - val_acc: 0.8541
Epoch 18/30
```

7352/7352 [=====] - 89s 12ms/step - loss: 0.2101 - ac
c: 0.9385 - val_loss: 0.4552 - val_acc: 0.8850
Epoch 19/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.1864 - ac
c: 0.9328 - val_loss: 0.4158 - val_acc: 0.8904
Epoch 20/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.1928 - ac
c: 0.9351 - val_loss: 0.3266 - val_acc: 0.8938
Epoch 21/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.2097 - ac
c: 0.9295 - val_loss: 0.3806 - val_acc: 0.9006
Epoch 22/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.1670 - ac
c: 0.9422 - val_loss: 0.5489 - val_acc: 0.8887
Epoch 23/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.1619 - ac
c: 0.9442 - val_loss: 0.3447 - val_acc: 0.8941
Epoch 24/30
7352/7352 [=====] - 88s 12ms/step - loss: 0.1574 - ac
c: 0.9449 - val_loss: 0.5478 - val_acc: 0.9050
Epoch 25/30
7352/7352 [=====] - 89s 12ms/step - loss: 0.1626 - ac
c: 0.9438 - val_loss: 0.3895 - val_acc: 0.9013
Epoch 26/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.1565 - ac
c: 0.9464 - val_loss: 0.4071 - val_acc: 0.9002
Epoch 27/30
7352/7352 [=====] - 90s 12ms/step - loss: 0.1442 - ac
c: 0.9474 - val_loss: 0.4845 - val_acc: 0.8955
Epoch 28/30
7352/7352 [=====] - 93s 13ms/step - loss: 0.1683 - ac
c: 0.9456 - val_loss: 0.4794 - val_acc: 0.8989
Epoch 29/30
7352/7352 [=====] - 94s 13ms/step - loss: 0.1800 - ac
c: 0.9445 - val_loss: 0.4138 - val_acc: 0.9135
Epoch 30/30
7352/7352 [=====] - 92s 13ms/step - loss: 0.1551 - ac
c: 0.9464 - val_loss: 0.4326 - val_acc: 0.9114

```
In [38]: import matplotlib.pyplot as plt
fig,ax=plt.subplots()
x=list(range(1,31))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



```
In [0]: def confusion_matrix(Y_true, Y_pred):
    Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1)])
    Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])

    return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])
```

```
In [34]: # Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	510	0	0	0	0	0
SITTING	0	347	126	0	0	0
STANDING	0	47	484	1	0	0
WALKING	0	0	0	479	11	11
WALKING_DOWNSTAIRS	0	0	0	0	408	408
WALKING_UPSTAIRS	0	0	2	6	5	5
Pred	WALKING_UPSTAIRS					
True						
LAYING		27				
SITTING		18				
STANDING		0				
WALKING		6				
WALKING_DOWNSTAIRS		12				
WALKING_UPSTAIRS		458				

```
In [35]: score = model.evaluate(X_test, Y_test)
```

2947/2947 [=====] - 6s 2ms/step

```
In [36]: score
```

```
Out[36]: [0.43244978515694077, 0.9114353579911775]
```

##WE HAVE ACHIEVED 90 PERCENT ACCURACY WITH THE SINGLE LSTM LAYER AND 32 CELLS IN LAYER WITH OUT USIG ANY FEATURIASTIONS . WE TRIED TO MINIMISE THE CATEGORICAL CROSS ENTROPY. WE CAN ALO CHANGE AND TUNE THE VARIOUS HYPERPARAMETERS SO THAT WE CAN CONSTRUCT THE BETTER LSTM MODEL.

###model2 we gonna use the 3 lstm layers where the fiirst lstm layer consists of 64 hidden cells and 300 cells in second layer and 200 layers in the third layer.we also use the batch normalisation because we normalise the before entering into the lstm layer but after the data enters into the lstm layers due to performing the activation functions like sigmoid and relu the data may loose the behavior hence we use the batch normalisation so that we can make the data to maintain its behavior we also perform introducing the dropout layer to prevent the overfitting in the data.

```
In [0]: n_hidden = 64
from keras.layers.normalization import BatchNormalization
```

In [49]:

```
model1 = Sequential()
model1.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences=True))
model1.add(BatchNormalization())
model1.add(Dropout(0.6))
model1.add(LSTM(300, return_sequences=True))
model1.add(BatchNormalization())
model1.add(Dropout(0.4))
model1.add(LSTM(200))
model1.add(BatchNormalization())
model1.add(Dropout(0.6))
model1.add(Dense(n_classes, activation='sigmoid'))
model1.summary()
```

Layer (type)	Output Shape	Param #
<hr/>		
lstm_5 (LSTM)	(None, 128, 64)	18944
batch_normalization_4 (Batch Normalization)	(None, 128, 64)	256
dropout_5 (Dropout)	(None, 128, 64)	0
lstm_6 (LSTM)	(None, 128, 300)	438000
batch_normalization_5 (Batch Normalization)	(None, 128, 300)	1200
dropout_6 (Dropout)	(None, 128, 300)	0
lstm_7 (LSTM)	(None, 200)	400800
batch_normalization_6 (Batch Normalization)	(None, 200)	800
dropout_7 (Dropout)	(None, 200)	0
dense_3 (Dense)	(None, 6)	1206
<hr/>		
Total params: 861,206		
Trainable params: 860,078		
Non-trainable params: 1,128		
<hr/>		

In [0]:

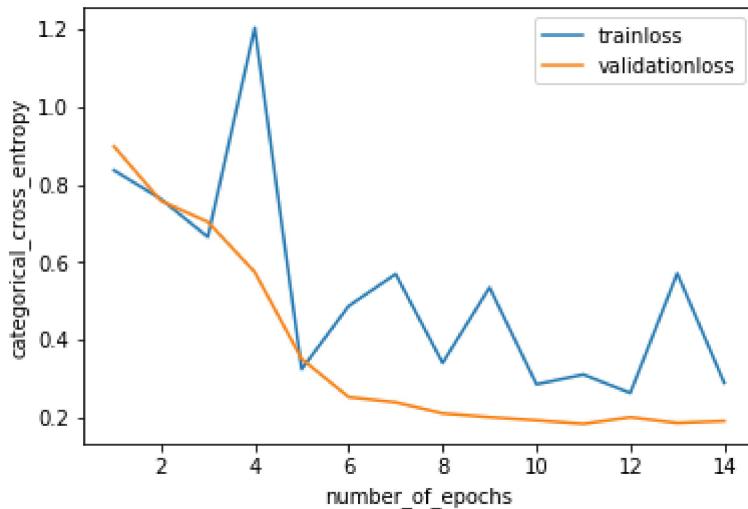
```
# Compiling the model
model1.compile(loss='categorical_crossentropy',
                optimizer='rmsprop',
                metrics=['accuracy'])
```

In [51]: # Training the model

```
history=model1.fit(X_train,  
                    Y_train,  
                    batch_size=batch_size,  
                    validation_data=(X_test, Y_test),  
                    epochs=14)
```

```
Train on 7352 samples, validate on 2947 samples  
Epoch 1/14  
7352/7352 [=====] - 277s 38ms/step - loss: 0.8985 - ac  
c: 0.6249 - val_loss: 0.8367 - val_acc: 0.6210  
Epoch 2/14  
7352/7352 [=====] - 274s 37ms/step - loss: 0.7580 - ac  
c: 0.6483 - val_loss: 0.7627 - val_acc: 0.6084  
Epoch 3/14  
7352/7352 [=====] - 275s 37ms/step - loss: 0.7036 - ac  
c: 0.6677 - val_loss: 0.6646 - val_acc: 0.6956  
Epoch 4/14  
7352/7352 [=====] - 275s 37ms/step - loss: 0.5740 - ac  
c: 0.7578 - val_loss: 1.2045 - val_acc: 0.7258  
Epoch 5/14  
7352/7352 [=====] - 272s 37ms/step - loss: 0.3500 - ac  
c: 0.8886 - val_loss: 0.3237 - val_acc: 0.8941  
Epoch 6/14  
7352/7352 [=====] - 266s 36ms/step - loss: 0.2516 - ac  
c: 0.9163 - val_loss: 0.4864 - val_acc: 0.8901  
Epoch 7/14  
7352/7352 [=====] - 265s 36ms/step - loss: 0.2380 - ac  
c: 0.9218 - val_loss: 0.5689 - val_acc: 0.8717  
Epoch 8/14  
7352/7352 [=====] - 265s 36ms/step - loss: 0.2096 - ac  
c: 0.9283 - val_loss: 0.3397 - val_acc: 0.9087  
Epoch 9/14  
7352/7352 [=====] - 267s 36ms/step - loss: 0.1997 - ac  
c: 0.9276 - val_loss: 0.5344 - val_acc: 0.8999  
Epoch 10/14  
7352/7352 [=====] - 264s 36ms/step - loss: 0.1917 - ac  
c: 0.9357 - val_loss: 0.2845 - val_acc: 0.9087  
Epoch 11/14  
7352/7352 [=====] - 265s 36ms/step - loss: 0.1825 - ac  
c: 0.9357 - val_loss: 0.3097 - val_acc: 0.8697  
Epoch 12/14  
7352/7352 [=====] - 266s 36ms/step - loss: 0.1995 - ac  
c: 0.9249 - val_loss: 0.2621 - val_acc: 0.9175  
Epoch 13/14  
7352/7352 [=====] - 265s 36ms/step - loss: 0.1848 - ac  
c: 0.9316 - val_loss: 0.5709 - val_acc: 0.8785  
Epoch 14/14  
7352/7352 [=====] - 265s 36ms/step - loss: 0.1899 - ac  
c: 0.9335 - val_loss: 0.2883 - val_acc: 0.9063
```

```
In [53]: fig,ax=plt.subplots()
x=list(range(1,15))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



```
In [54]: # Confusion Matrix
print(confusion_matrix(Y_test, model1.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	537	0	0	0		0
SITTING	5	290	194	0		0
STANDING	0	41	490	0		0
WALKING	0	0	0	495		1
WALKING_DOWNSTAIRS	0	0	0	0		420
WALKING_UPSTAIRS	0	0	0	18		14

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	2
STANDING	1
WALKING	0
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	439

```
In [55]: score = model1.evaluate(X_test, Y_test)
```

2947/2947 [=====] - 17s 6ms/step

```
In [56]: score
```

Out[56]: [0.2883422779202473, 0.9063454360366474]

if we observe in the confusion matrix it is very clear that the model is confusing to predict the difference between standing and sitting.

**because both the are static and may giving the similar signals as input.
we have achieved 91 percent accuracy**

###WE ARE RUNNING THE MODEL WITH 2 LSTM LAYERS WITH 32 CELLS IN THE HIDDEN LAYER WE ADD THE OUTPUT DENSE LAYER AND WE TAKE DENSEOUTPUT AT THE WITH SIGMOID AS THE ACTIVATION FUNCTION. WE USE 30 EPOCHS AND OBTAIN THE PERFORMANCE . THIS CASE WE ADDED THE DROPOUT LAYER BWE HAVE NOT DONE THE BATCNORMALISATION. WE TAKE THE DROPOUT RATES OF 50 PERCENT AND ANOTHER DROPOUT LAYER OF 50 PERCENT WHICH MEANS 50 PERCENT OF THE HIDDEN CELLS WILL BE INACTIVE WHILE ADJUSTING THE WEIGHTS.

In [57]:

```
epochs=30
modelx = Sequential()
modelx.add(LSTM(32,return_sequences=True, input_shape=(timesteps, input_dim)))
modelx.add(Dropout(0.5))
modelx.add(LSTM(32))
modelx.add(Dropout(0.5))
modelx.add(Dense(n_classes, activation='sigmoid'))
print(modelx.summary())
modelx.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=[ 'acc'])

history = modelx.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

Layer (type)	Output Shape	Param #
lstm_8 (LSTM)	(None, 128, 32)	5376
dropout_8 (Dropout)	(None, 128, 32)	0
lstm_9 (LSTM)	(None, 32)	8320
dropout_9 (Dropout)	(None, 32)	0
dense_4 (Dense)	(None, 6)	198

Total params: 13,894
Trainable params: 13,894
Non-trainable params: 0

None
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [=====] - 185s 25ms/step - loss: 1.2171 - ac
c: 0.5212 - val_loss: 0.9619 - val_acc: 0.6295
Epoch 2/30
7352/7352 [=====] - 183s 25ms/step - loss: 0.8216 - ac
c: 0.6362 - val_loss: 0.8025 - val_acc: 0.6451
Epoch 3/30
7352/7352 [=====] - 183s 25ms/step - loss: 0.6996 - ac
c: 0.6984 - val_loss: 0.8431 - val_acc: 0.6498
Epoch 4/30
7352/7352 [=====] - 180s 25ms/step - loss: 0.5875 - ac
c: 0.7601 - val_loss: 0.6231 - val_acc: 0.7313
Epoch 5/30
7352/7352 [=====] - 179s 24ms/step - loss: 0.5058 - ac
c: 0.7877 - val_loss: 0.6454 - val_acc: 0.7326
Epoch 6/30
7352/7352 [=====] - 177s 24ms/step - loss: 0.4277 - ac
c: 0.8105 - val_loss: 0.9636 - val_acc: 0.7292
Epoch 7/30
7352/7352 [=====] - 178s 24ms/step - loss: 0.3650 - ac
c: 0.8811 - val_loss: 0.5259 - val_acc: 0.8578
Epoch 8/30
7352/7352 [=====] - 179s 24ms/step - loss: 0.3109 - ac
c: 0.9128 - val_loss: 0.4936 - val_acc: 0.8806
Epoch 9/30

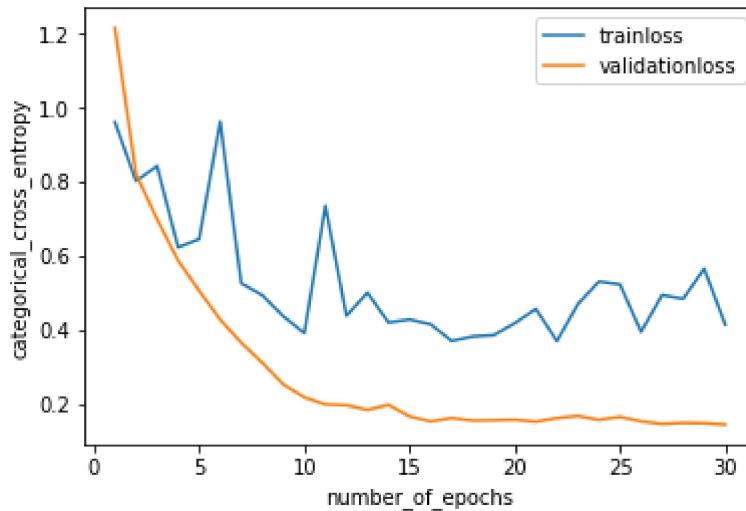
7352/7352 [=====] - 181s 25ms/step - loss: 0.2522 - ac
c: 0.9263 - val_loss: 0.4366 - val_acc: 0.8982
Epoch 10/30
7352/7352 [=====] - 180s 24ms/step - loss: 0.2173 - ac
c: 0.9316 - val_loss: 0.3910 - val_acc: 0.9077
Epoch 11/30
7352/7352 [=====] - 177s 24ms/step - loss: 0.1979 - ac
c: 0.9407 - val_loss: 0.7349 - val_acc: 0.8544
Epoch 12/30
7352/7352 [=====] - 178s 24ms/step - loss: 0.1961 - ac
c: 0.9377 - val_loss: 0.4378 - val_acc: 0.9006
Epoch 13/30
7352/7352 [=====] - 178s 24ms/step - loss: 0.1832 - ac
c: 0.9407 - val_loss: 0.5004 - val_acc: 0.9002
Epoch 14/30
7352/7352 [=====] - 179s 24ms/step - loss: 0.1967 - ac
c: 0.9400 - val_loss: 0.4196 - val_acc: 0.9046
Epoch 15/30
7352/7352 [=====] - 178s 24ms/step - loss: 0.1655 - ac
c: 0.9461 - val_loss: 0.4277 - val_acc: 0.9030
Epoch 16/30
7352/7352 [=====] - 180s 24ms/step - loss: 0.1520 - ac
c: 0.9475 - val_loss: 0.4148 - val_acc: 0.8955
Epoch 17/30
7352/7352 [=====] - 180s 25ms/step - loss: 0.1611 - ac
c: 0.9456 - val_loss: 0.3699 - val_acc: 0.9026
Epoch 18/30
7352/7352 [=====] - 178s 24ms/step - loss: 0.1542 - ac
c: 0.9478 - val_loss: 0.3818 - val_acc: 0.9016
Epoch 19/30
7352/7352 [=====] - 180s 24ms/step - loss: 0.1551 - ac
c: 0.9478 - val_loss: 0.3856 - val_acc: 0.8955
Epoch 20/30
7352/7352 [=====] - 181s 25ms/step - loss: 0.1564 - ac
c: 0.9474 - val_loss: 0.4176 - val_acc: 0.9057
Epoch 21/30
7352/7352 [=====] - 184s 25ms/step - loss: 0.1513 - ac
c: 0.9497 - val_loss: 0.4565 - val_acc: 0.8972
Epoch 22/30
7352/7352 [=====] - 186s 25ms/step - loss: 0.1609 - ac
c: 0.9468 - val_loss: 0.3694 - val_acc: 0.9053
Epoch 23/30
7352/7352 [=====] - 181s 25ms/step - loss: 0.1667 - ac
c: 0.9465 - val_loss: 0.4696 - val_acc: 0.8972
Epoch 24/30
7352/7352 [=====] - 184s 25ms/step - loss: 0.1563 - ac
c: 0.9460 - val_loss: 0.5307 - val_acc: 0.8829
Epoch 25/30
7352/7352 [=====] - 180s 24ms/step - loss: 0.1643 - ac
c: 0.9433 - val_loss: 0.5227 - val_acc: 0.8918
Epoch 26/30
7352/7352 [=====] - 179s 24ms/step - loss: 0.1522 - ac
c: 0.9512 - val_loss: 0.3942 - val_acc: 0.8996
Epoch 27/30
7352/7352 [=====] - 178s 24ms/step - loss: 0.1451 - ac
c: 0.9489 - val_loss: 0.4940 - val_acc: 0.9043
Epoch 28/30

```

7352/7352 [=====] - 178s 24ms/step - loss: 0.1480 - ac
c: 0.9509 - val_loss: 0.4838 - val_acc: 0.8965
Epoch 29/30
7352/7352 [=====] - 179s 24ms/step - loss: 0.1471 - ac
c: 0.9479 - val_loss: 0.5653 - val_acc: 0.8877
Epoch 30/30
7352/7352 [=====] - 177s 24ms/step - loss: 0.1433 - ac
c: 0.9516 - val_loss: 0.4142 - val_acc: 0.9002

```

```
In [58]: fig,ax=plt.subplots()
x=list(range(1,31))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



```
In [59]: print(confusion_matrix(Y_test, modelx.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	510	0	0	0		0
SITTING	1	407	80	0		1
STANDING	0	108	424	0		0
WALKING	0	1	0	474		9
WALKING_DOWNSTAIRS	0	0	0	0		413
WALKING_UPSTAIRS	4	5	4	20		13

Pred	WALKING_UPSTAIRS
True	
LAYING	27
SITTING	2
STANDING	0
WALKING	12
WALKING_DOWNSTAIRS	7
WALKING_UPSTAIRS	425

```
In [60]: score = modelx.evaluate(X_test, Y_test)
```

```
2947/2947 [=====] - 12s 4ms/step
```

```
In [61]: score
```

```
Out[61]: [0.4144287348136521, 0.9002375296912114]
```

##IN THIS MODEL WE HAVE INCREASED THE DROPOUT RATES TO 0.7 BECAUSE THE MODEL IS UNDERGOING OVERFITTING . IF WE OBSERVE THE TRAININGDATA ACCURACY IS NEARLY 0.95 AND 0.9

In [62]:

```
epochs=30
modelx = Sequential()
modelx.add(LSTM(32,return_sequences=True, input_shape=(timesteps, input_dim)))
modelx.add(Dropout(0.6))
modelx.add(LSTM(32))
modelx.add(Dropout(0.6))
modelx.add(Dense(n_classes, activation='sigmoid'))
print(modelx.summary())
modelx.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['acc'])

history = modelx.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

Layer (type)	Output Shape	Param #
lstm_10 (LSTM)	(None, 128, 32)	5376
dropout_10 (Dropout)	(None, 128, 32)	0
lstm_11 (LSTM)	(None, 32)	8320
dropout_11 (Dropout)	(None, 32)	0
dense_5 (Dense)	(None, 6)	198
Total params:	13,894	
Trainable params:	13,894	
Non-trainable params:	0	

None
Train on 7352 samples, validate on 2947 samples
Epoch 1/26
7352/7352 [=====] - 187s 25ms/step - loss: 1.2687 - ac
c: 0.4723 - val_loss: 0.9974 - val_acc: 0.5433
Epoch 2/26
7352/7352 [=====] - 183s 25ms/step - loss: 0.8871 - ac
c: 0.6045 - val_loss: 0.8607 - val_acc: 0.6176
Epoch 3/26
7352/7352 [=====] - 185s 25ms/step - loss: 0.8625 - ac
c: 0.6106 - val_loss: 0.7981 - val_acc: 0.6763
Epoch 4/26
7352/7352 [=====] - 181s 25ms/step - loss: 0.7212 - ac
c: 0.6601 - val_loss: 0.6997 - val_acc: 0.6824
Epoch 5/26
7352/7352 [=====] - 182s 25ms/step - loss: 0.6782 - ac
c: 0.6768 - val_loss: 0.6992 - val_acc: 0.6980
Epoch 6/26
7352/7352 [=====] - 181s 25ms/step - loss: 0.6403 - ac
c: 0.7175 - val_loss: 0.7347 - val_acc: 0.6953
Epoch 7/26
7352/7352 [=====] - 182s 25ms/step - loss: 0.5276 - ac
c: 0.7737 - val_loss: 0.6798 - val_acc: 0.7469
Epoch 8/26
7352/7352 [=====] - 183s 25ms/step - loss: 0.4312 - ac
c: 0.8104 - val_loss: 0.5346 - val_acc: 0.7608
Epoch 9/26

7352/7352 [=====] - 181s 25ms/step - loss: 0.3651 - ac
c: 0.8800 - val_loss: 0.5869 - val_acc: 0.8548
Epoch 10/26
7352/7352 [=====] - 182s 25ms/step - loss: 0.2909 - ac
c: 0.9151 - val_loss: 0.4944 - val_acc: 0.8548
Epoch 11/26
7352/7352 [=====] - 181s 25ms/step - loss: 0.2495 - ac
c: 0.9308 - val_loss: 0.4422 - val_acc: 0.8897
Epoch 12/26
7352/7352 [=====] - 179s 24ms/step - loss: 0.2515 - ac
c: 0.9305 - val_loss: 0.5107 - val_acc: 0.8897
Epoch 13/26
7352/7352 [=====] - 179s 24ms/step - loss: 0.2216 - ac
c: 0.9340 - val_loss: 0.4551 - val_acc: 0.9023
Epoch 14/26
7352/7352 [=====] - 180s 25ms/step - loss: 0.2082 - ac
c: 0.9410 - val_loss: 0.5188 - val_acc: 0.8826
Epoch 15/26
7352/7352 [=====] - 182s 25ms/step - loss: 0.2054 - ac
c: 0.9418 - val_loss: 0.5100 - val_acc: 0.9036
Epoch 16/26
7352/7352 [=====] - 180s 24ms/step - loss: 0.1854 - ac
c: 0.9396 - val_loss: 0.7306 - val_acc: 0.8894
Epoch 17/26
7352/7352 [=====] - 180s 25ms/step - loss: 0.1805 - ac
c: 0.9429 - val_loss: 0.4348 - val_acc: 0.9080
Epoch 18/26
7352/7352 [=====] - 179s 24ms/step - loss: 0.1985 - ac
c: 0.9422 - val_loss: 0.5473 - val_acc: 0.8938
Epoch 19/26
7352/7352 [=====] - 181s 25ms/step - loss: 0.1625 - ac
c: 0.9484 - val_loss: 0.6593 - val_acc: 0.8890
Epoch 20/26
7352/7352 [=====] - 181s 25ms/step - loss: 0.1694 - ac
c: 0.9419 - val_loss: 0.5884 - val_acc: 0.9040
Epoch 21/26
7352/7352 [=====] - 179s 24ms/step - loss: 0.1779 - ac
c: 0.9436 - val_loss: 0.5539 - val_acc: 0.8928
Epoch 22/26
7352/7352 [=====] - 180s 24ms/step - loss: 0.1687 - ac
c: 0.9457 - val_loss: 0.3005 - val_acc: 0.9158
Epoch 23/26
7352/7352 [=====] - 180s 25ms/step - loss: 0.1711 - ac
c: 0.9448 - val_loss: 0.6058 - val_acc: 0.8873
Epoch 24/26
7352/7352 [=====] - 180s 24ms/step - loss: 0.1722 - ac
c: 0.9453 - val_loss: 0.8833 - val_acc: 0.8772
Epoch 25/26
7352/7352 [=====] - 182s 25ms/step - loss: 0.1756 - ac
c: 0.9467 - val_loss: 0.5013 - val_acc: 0.9009
Epoch 26/26
7352/7352 [=====] - 181s 25ms/step - loss: 0.1719 - ac
c: 0.9399 - val_loss: 0.8858 - val_acc: 0.8775

```
In [63]: print(Y_test)
```

```
[[0 0 0 0 1 0]
 [0 0 0 0 1 0]
 [0 0 0 0 1 0]
 ...
 [0 1 0 0 0 0]
 [0 1 0 0 0 0]
 [0 1 0 0 0 0]]
```

```
In [64]: score = modelx.evaluate(X_test, Y_test)
```

```
2947/2947 [=====] - 12s 4ms/step
```

```
In [65]: score
```

```
Out[65]: [0.8857371849105553, 0.8775025449609772]
```

```
In [66]:
```

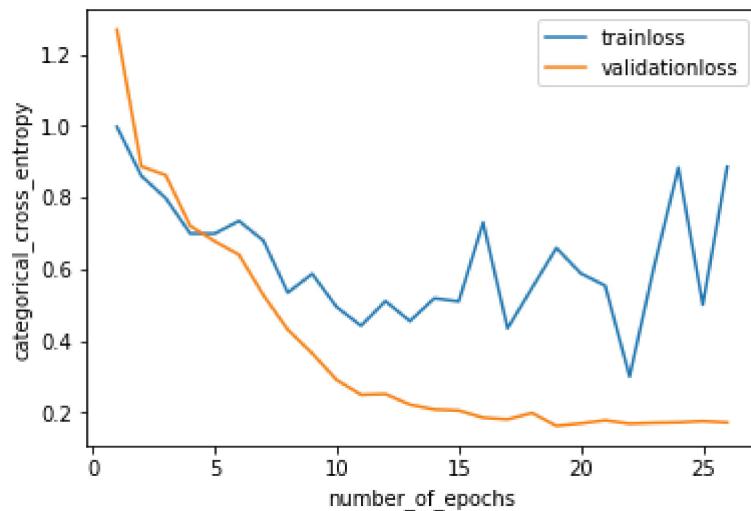
```
print(confusion_matrix(Y_test, modelx.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	537	0	0	0		0
SITTING	5	420	50	0		1
STANDING	0	127	405	0		0
WALKING	0	0	3	422		65
WALKING_DOWNSTAIRS	0	0	0	0		420
WALKING_UPSTAIRS	0	0	0	2		87

Pred	WALKING_UPSTAIRS
------	------------------

True	
LAYING	0
SITTING	15
STANDING	0
WALKING	6
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	382

```
In [68]: fig,ax=plt.subplots()
x=list(range(1,27))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



In [69]:

```
modelnew = Sequential()

modelnew.add(LSTM(64,return_sequences=True, input_shape=(timesteps, input_dim)))
modelnew.add(Dropout(0.7))
modelnew.add(LSTM(64))
modelnew.add(Dropout(0.7))
modelnew.add(Dense(n_classes, activation='sigmoid'))
print(modelnew.summary())
modelnew.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=[ 'a

history= modelnew.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

Layer (type)	Output Shape	Param #
lstm_12 (LSTM)	(None, 128, 64)	18944
dropout_12 (Dropout)	(None, 128, 64)	0
lstm_13 (LSTM)	(None, 64)	33024
dropout_13 (Dropout)	(None, 64)	0
dense_6 (Dense)	(None, 6)	390
<hr/>		
Total params: 52,358		
Trainable params: 52,358		
Non-trainable params: 0		

None
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [=====] - 192s 26ms/step - loss: 1.1373 - ac
c: 0.5105 - val_loss: 0.8658 - val_acc: 0.6210
Epoch 2/20
7352/7352 [=====] - 190s 26ms/step - loss: 0.7867 - ac
c: 0.6147 - val_loss: 0.8071 - val_acc: 0.6043
Epoch 3/20
7352/7352 [=====] - 189s 26ms/step - loss: 0.7100 - ac
c: 0.6568 - val_loss: 0.7686 - val_acc: 0.6186
Epoch 4/20
7352/7352 [=====] - 177s 24ms/step - loss: 0.6425 - ac
c: 0.7016 - val_loss: 0.6528 - val_acc: 0.7285
Epoch 5/20
7352/7352 [=====] - 178s 24ms/step - loss: 0.5010 - ac
c: 0.7841 - val_loss: 0.6199 - val_acc: 0.7832
Epoch 6/20
7352/7352 [=====] - 175s 24ms/step - loss: 0.3937 - ac
c: 0.8475 - val_loss: 0.4984 - val_acc: 0.8568
Epoch 7/20
7352/7352 [=====] - 178s 24ms/step - loss: 0.3220 - ac
c: 0.9038 - val_loss: 0.4374 - val_acc: 0.8778
Epoch 8/20
7352/7352 [=====] - 177s 24ms/step - loss: 0.2444 - ac
c: 0.9263 - val_loss: 0.4876 - val_acc: 0.8792

Epoch 9/20
7352/7352 [=====] - 176s 24ms/step - loss: 0.2079 - ac
c: 0.9342 - val_loss: 0.6881 - val_acc: 0.8643
Epoch 10/20
7352/7352 [=====] - 176s 24ms/step - loss: 0.2132 - ac
c: 0.9353 - val_loss: 0.4767 - val_acc: 0.9040
Epoch 11/20
7352/7352 [=====] - 174s 24ms/step - loss: 0.2299 - ac
c: 0.9346 - val_loss: 0.9965 - val_acc: 0.8235
Epoch 12/20
7352/7352 [=====] - 175s 24ms/step - loss: 0.2027 - ac
c: 0.9374 - val_loss: 0.5993 - val_acc: 0.8972
Epoch 13/20
7352/7352 [=====] - 175s 24ms/step - loss: 0.2300 - ac
c: 0.9317 - val_loss: 0.5145 - val_acc: 0.9019
Epoch 14/20
7352/7352 [=====] - 176s 24ms/step - loss: 0.1850 - ac
c: 0.9384 - val_loss: 0.4399 - val_acc: 0.9067
Epoch 15/20
7352/7352 [=====] - 174s 24ms/step - loss: 0.2105 - ac
c: 0.9406 - val_loss: 0.4615 - val_acc: 0.9101
Epoch 16/20
7352/7352 [=====] - 176s 24ms/step - loss: 0.2250 - ac
c: 0.9340 - val_loss: 0.5820 - val_acc: 0.8941
Epoch 17/20
7352/7352 [=====] - 176s 24ms/step - loss: 0.1939 - ac
c: 0.9396 - val_loss: 0.6567 - val_acc: 0.8833
Epoch 18/20
7352/7352 [=====] - 173s 24ms/step - loss: 0.1955 - ac
c: 0.9406 - val_loss: 0.4993 - val_acc: 0.9057
Epoch 19/20
7352/7352 [=====] - 176s 24ms/step - loss: 0.1722 - ac
c: 0.9442 - val_loss: 0.4915 - val_acc: 0.9070
Epoch 20/20
7352/7352 [=====] - 174s 24ms/step - loss: 0.1724 - ac
c: 0.9467 - val_loss: 0.7762 - val_acc: 0.8795

In [70]:

```
print(confusion_matrix(Y_test, modelnew.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	510	0	27	0		0
SITTING	0	385	104	0		0
STANDING	1	89	442	0		0
WALKING	0	0	0	470		0
WALKING_DOWNSTAIRS	0	0	0	3		412
WALKING_UPSTAIRS	2	1	0	93		2

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	2
STANDING	0
WALKING	26
WALKING_DOWNSTAIRS	5
WALKING_UPSTAIRS	373

In [71]:

```
score = modelnew.evaluate(X_test, Y_test)
```

2947/2947 [=====] - 12s 4ms/step

In [72]:

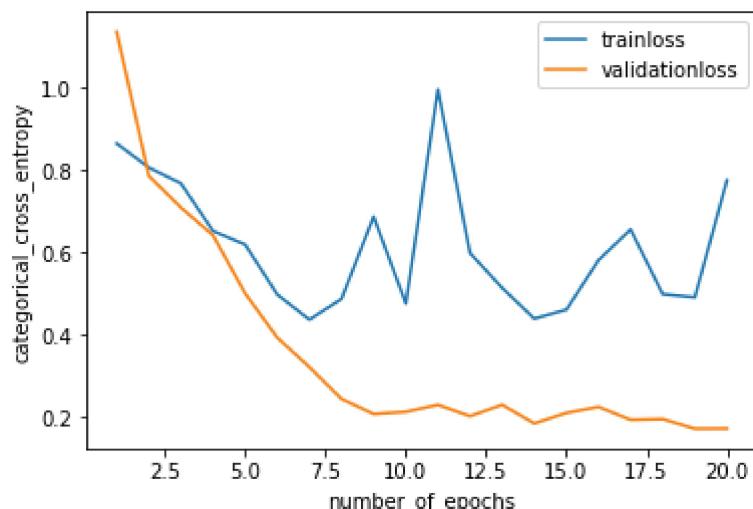
```
score
```

Out[72]:

```
[0.7758174211089318, 0.8795385137427892]
```

In [73]:

```
fig,ax=plt.subplots()
x=list(range(1,21))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



##TRAINING THE MODEL WITH MORE NUMBER OF HIDDEN CELLS IN A LAYER WITH

HIGHER DROPOUTS TO REDUCE THE CHANCES OF OVER FITTING WE HAVE ALSO DONE THE BACHNORMALISATION FOR THE LAYER.

In [74]:

```
modelnew = Sequential()

modelnew.add(LSTM(100,return_sequences=True, input_shape=(timesteps, input_dim)))
modelnew.add(Dropout(0.7))
modelnew.add(LSTM(300))
modelnew.add(Dropout(0.6))
modelnew.add(BatchNormalization())
modelnew.add(Dense(n_classes, activation='sigmoid'))
print(modelnew.summary())
modelnew.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=['a'])

history= modelnew.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

Layer (type)	Output Shape	Param #
lstm_14 (LSTM)	(None, 128, 100)	44000
dropout_14 (Dropout)	(None, 128, 100)	0
lstm_15 (LSTM)	(None, 300)	481200
dropout_15 (Dropout)	(None, 300)	0
batch_normalization_7 (Batch)	(None, 300)	1200
dense_7 (Dense)	(None, 6)	1806
<hr/>		
Total params: 528,206		
Trainable params: 527,606		
Non-trainable params: 600		
<hr/>		

None
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [=====] - 178s 24ms/step - loss: 1.0485 - ac
c: 0.5379 - val_loss: 0.8508 - val_acc: 0.5901
Epoch 2/20
7352/7352 [=====] - 173s 24ms/step - loss: 0.8018 - ac
c: 0.6168 - val_loss: 0.7927 - val_acc: 0.5881
Epoch 3/20
7352/7352 [=====] - 173s 24ms/step - loss: 0.7367 - ac
c: 0.6514 - val_loss: 0.9158 - val_acc: 0.6111
Epoch 4/20
7352/7352 [=====] - 174s 24ms/step - loss: 0.7534 - ac
c: 0.6515 - val_loss: 0.7829 - val_acc: 0.6176
Epoch 5/20
7352/7352 [=====] - 171s 23ms/step - loss: 0.7407 - ac
c: 0.6473 - val_loss: 0.7516 - val_acc: 0.6848
Epoch 6/20
7352/7352 [=====] - 173s 24ms/step - loss: 0.9916 - ac
c: 0.5646 - val_loss: 1.3365 - val_acc: 0.3590
Epoch 7/20
7352/7352 [=====] - 171s 23ms/step - loss: 0.9651 - ac
c: 0.5788 - val_loss: 0.8394 - val_acc: 0.6200

```
Epoch 8/20
7352/7352 [=====] - 173s 23ms/step - loss: 0.7074 - ac
c: 0.6571 - val_loss: 0.8714 - val_acc: 0.6288
Epoch 9/20
7352/7352 [=====] - 172s 23ms/step - loss: 0.6068 - ac
c: 0.7417 - val_loss: 0.7189 - val_acc: 0.7401
Epoch 10/20
7352/7352 [=====] - 173s 23ms/step - loss: 0.7783 - ac
c: 0.7042 - val_loss: 0.6240 - val_acc: 0.8286
Epoch 11/20
7352/7352 [=====] - 171s 23ms/step - loss: 0.3421 - ac
c: 0.8876 - val_loss: 0.3119 - val_acc: 0.9063
Epoch 12/20
7352/7352 [=====] - 172s 23ms/step - loss: 0.2260 - ac
c: 0.9245 - val_loss: 0.4051 - val_acc: 0.8677
Epoch 13/20
7352/7352 [=====] - 173s 24ms/step - loss: 0.2243 - ac
c: 0.9272 - val_loss: 0.3466 - val_acc: 0.8853
Epoch 14/20
7352/7352 [=====] - 171s 23ms/step - loss: 0.2024 - ac
c: 0.9321 - val_loss: 0.4686 - val_acc: 0.9043
Epoch 15/20
7352/7352 [=====] - 172s 23ms/step - loss: 0.2707 - ac
c: 0.9155 - val_loss: 0.4589 - val_acc: 0.9009
Epoch 16/20
7352/7352 [=====] - 170s 23ms/step - loss: 0.1901 - ac
c: 0.9393 - val_loss: 0.5445 - val_acc: 0.8799
Epoch 17/20
7352/7352 [=====] - 173s 23ms/step - loss: 0.1841 - ac
c: 0.9430 - val_loss: 0.5569 - val_acc: 0.8907
Epoch 18/20
7352/7352 [=====] - 170s 23ms/step - loss: 0.1891 - ac
c: 0.9404 - val_loss: 0.3501 - val_acc: 0.9111
Epoch 19/20
7352/7352 [=====] - 171s 23ms/step - loss: 0.1722 - ac
c: 0.9393 - val_loss: 0.3812 - val_acc: 0.9074
Epoch 20/20
7352/7352 [=====] - 170s 23ms/step - loss: 0.1666 - ac
c: 0.9421 - val_loss: 0.5799 - val_acc: 0.8812
```

```
In [75]: score=modelnew.evaluate(X_test, Y_test,verbose=0)
print('test score',score[0])
print('test accuracy',score[1])
```

```
test score 0.5799294071928931
test accuracy 0.8812351543942993
```

In [76]:

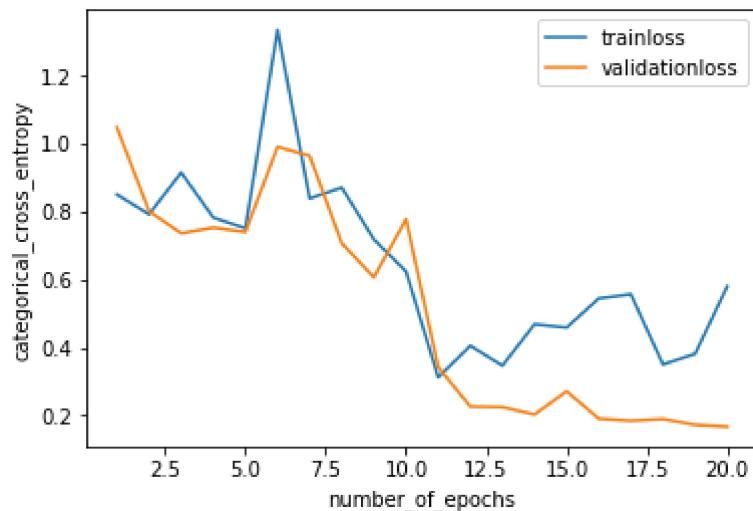
```
print(confusion_matrix(Y_test, modelnew.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	537	0	0	0	0	0
SITTING	4	304	182	0	0	0
STANDING	0	24	508	0	0	0
WALKING	0	0	0	386	68	
WALKING_DOWNSTAIRS	0	0	0	1	419	
WALKING_UPSTAIRS	0	0	0	0	28	

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	1
STANDING	0
WALKING	42
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	443

In [77]:

```
fig,ax=plt.subplots()
x=list(range(1,21))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



CHANGING THE ACTIVATION FUNCTION TO SIGMOID SINCE THE SIGMOID GIVES THE OUTPUT PROBABILITIES THAT BELONGING TO THE PARTICULAR CLASS LABEL. WITH SAME CONIGURATION OF PREVIOUS MODEL WE CHANGE THE ACTIVATION FUNCTION AND CHECK.

In [25]:

```
modelnew = Sequential()

modelnew.add(LSTM(100,return_sequences=True, input_shape=(timesteps, input_dim)))
modelnew.add(Dropout(0.7))
modelnew.add(LSTM(300))
modelnew.add(Dropout(0.6))
modelnew.add(BatchNormalization())

modelnew.add(Dense(n_classes, activation='softmax'))
print(modelnew.summary())
modelnew.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=[ 'a

history= modelnew.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_def_library.py:263: colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3445: calling dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future version.

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 128, 100)	44000
dropout_1 (Dropout)	(None, 128, 100)	0
lstm_2 (LSTM)	(None, 300)	481200
dropout_2 (Dropout)	(None, 300)	0
batch_normalization_1 (Batch	(None, 300)	1200
dense_1 (Dense)	(None, 6)	1806
<hr/>		
Total params: 528,206		
Trainable params: 527,606		
Non-trainable params: 600		

None

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is deprecated and will be removed in a future version.

Instructions for updating:

Use tf.cast instead.

Train on 7352 samples, validate on 2947 samples

Epoch 1/20

7352/7352 [=====] - 159s 22ms/step - loss: 1.0285 - acc: 0.6092 - val_loss: 0.9204 - val_acc: 0.6614

Epoch 2/20

7352/7352 [=====] - 155s 21ms/step - loss: 0.4750 - ac
c: 0.8399 - val_loss: 0.6490 - val_acc: 0.7984
Epoch 3/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.3075 - ac
c: 0.8981 - val_loss: 0.4384 - val_acc: 0.8466
Epoch 4/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.2351 - ac
c: 0.9253 - val_loss: 0.3214 - val_acc: 0.8955
Epoch 5/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.2041 - ac
c: 0.9309 - val_loss: 0.4520 - val_acc: 0.8670
Epoch 6/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.1908 - ac
c: 0.9343 - val_loss: 0.3257 - val_acc: 0.9077
Epoch 7/20
7352/7352 [=====] - 155s 21ms/step - loss: 0.1880 - ac
c: 0.9347 - val_loss: 1.1457 - val_acc: 0.8012
Epoch 8/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.1784 - ac
c: 0.9380 - val_loss: 0.5234 - val_acc: 0.8853
Epoch 9/20
7352/7352 [=====] - 156s 21ms/step - loss: 0.1815 - ac
c: 0.9396 - val_loss: 0.3384 - val_acc: 0.9070
Epoch 10/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.1878 - ac
c: 0.9366 - val_loss: 0.3260 - val_acc: 0.9070
Epoch 11/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.2112 - ac
c: 0.9317 - val_loss: 0.4242 - val_acc: 0.9087
Epoch 12/20
7352/7352 [=====] - 155s 21ms/step - loss: 0.2022 - ac
c: 0.9350 - val_loss: 0.5830 - val_acc: 0.8884
Epoch 13/20
7352/7352 [=====] - 156s 21ms/step - loss: 0.1888 - ac
c: 0.9373 - val_loss: 0.5046 - val_acc: 0.9019
Epoch 14/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.1659 - ac
c: 0.9389 - val_loss: 0.7242 - val_acc: 0.8884
Epoch 15/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.1738 - ac
c: 0.9400 - val_loss: 0.5111 - val_acc: 0.8962
Epoch 16/20
7352/7352 [=====] - 155s 21ms/step - loss: 0.1807 - ac
c: 0.9438 - val_loss: 0.5994 - val_acc: 0.8989
Epoch 17/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.1601 - ac
c: 0.9452 - val_loss: 0.4585 - val_acc: 0.8921
Epoch 18/20
7352/7352 [=====] - 155s 21ms/step - loss: 0.1549 - ac
c: 0.9453 - val_loss: 0.8446 - val_acc: 0.7621
Epoch 19/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.2162 - ac
c: 0.9329 - val_loss: 0.4736 - val_acc: 0.9046
Epoch 20/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.1664 - ac
c: 0.9426 - val_loss: 0.4776 - val_acc: 0.9209

```
In [26]: score=modelnew.evaluate(X_test, Y_test,verbose=0)
print('test score',score[0])
print('test accuracy',score[1])
```

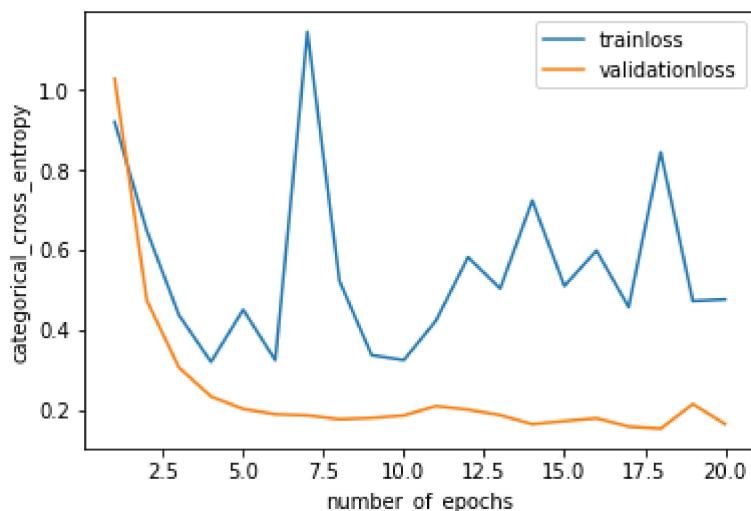
```
test score 0.47755399492043493
test accuracy 0.9209365456396336
```

```
In [29]: print(confusion_matrix(Y_test, modelnew.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	537	0	0	0	0	0
SITTING	3	414	74	0	0	0
STANDING	0	86	446	0	0	0
WALKING	1	1	0	448	44	
WALKING_DOWNSTAIRS	0	0	0	1	419	
WALKING_UPSTAIRS	1	7	2	6	5	

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	0
STANDING	0
WALKING	2
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	450

```
In [31]: import matplotlib.pyplot as plt
fig,ax=plt.subplots()
x=list(range(1,21))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



USING THE SOFTMAX IN CASE OF SIGMOID ACTUALLY THE TEST

**ACCURACY REDUCED WITH SIGMOID WE GOT 0.91 WITH SOFTMAX
WE GOT 0.892. WE WILL TRY WITH RELU ACTIVATION FUNCTION
WITH THE SAME CONFIGURATION.**

In [32]:

```
modela = Sequential()

modela.add(LSTM(100,return_sequences=True, input_shape=(timesteps, input_dim)))
modela.add(Dropout(0.7))
modela.add(LSTM(300))
modela.add(Dropout(0.6))
modela.add(BatchNormalization())
modela.add(Dense(n_classes, activation='relu'))
print(modela.summary())
modela.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=[ 'acc'])

history= modela.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

Layer (type)	Output Shape	Param #
=====		
lstm_3 (LSTM)	(None, 128, 100)	44000
dropout_3 (Dropout)	(None, 128, 100)	0
lstm_4 (LSTM)	(None, 300)	481200
dropout_4 (Dropout)	(None, 300)	0
batch_normalization_2 (Batch)	(None, 300)	1200
dense_2 (Dense)	(None, 6)	1806
=====		
Total params:	528,206	
Trainable params:	527,606	
Non-trainable params:	600	

None
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [=====] - 160s 22ms/step - loss: 2.1252 - acc: 0.4659 - val_loss: 1.2260 - val_acc: 0.6091
Epoch 2/20
7352/7352 [=====] - 156s 21ms/step - loss: 1.3158 - acc: 0.5964 - val_loss: 2.1774 - val_acc: 0.5721
Epoch 3/20
7352/7352 [=====] - 158s 22ms/step - loss: 1.3191 - acc: 0.6215 - val_loss: 1.6510 - val_acc: 0.6121
Epoch 4/20
7352/7352 [=====] - 156s 21ms/step - loss: 1.3987 - acc: 0.6349 - val_loss: 1.3484 - val_acc: 0.6359
Epoch 5/20
7352/7352 [=====] - 159s 22ms/step - loss: 1.2176 - acc: 0.6831 - val_loss: 1.9444 - val_acc: 0.6678
Epoch 6/20
7352/7352 [=====] - 156s 21ms/step - loss: 1.3150 - acc: 0.6912 - val_loss: 2.1620 - val_acc: 0.6620
Epoch 7/20
7352/7352 [=====] - 158s 22ms/step - loss: 1.3720 - acc: 0.7114 - val_loss: 1.9954 - val_acc: 0.7363

```
Epoch 8/20
7352/7352 [=====] - 155s 21ms/step - loss: 1.2773 - ac
c: 0.7431 - val_loss: 1.3247 - val_acc: 0.7282
Epoch 9/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.9720 - ac
c: 0.8067 - val_loss: 1.1600 - val_acc: 0.8286
Epoch 10/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.9090 - ac
c: 0.8874 - val_loss: 1.8553 - val_acc: 0.8436
Epoch 11/20
7352/7352 [=====] - 156s 21ms/step - loss: 1.3277 - ac
c: 0.8677 - val_loss: 1.5042 - val_acc: 0.8700
Epoch 12/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.8304 - ac
c: 0.9006 - val_loss: 1.2530 - val_acc: 0.8622
Epoch 13/20
7352/7352 [=====] - 158s 21ms/step - loss: 0.8321 - ac
c: 0.9042 - val_loss: 1.7096 - val_acc: 0.8585
Epoch 14/20
7352/7352 [=====] - 154s 21ms/step - loss: 0.8371 - ac
c: 0.8938 - val_loss: 2.2182 - val_acc: 0.7299
Epoch 15/20
7352/7352 [=====] - 157s 21ms/step - loss: 0.9504 - ac
c: 0.8962 - val_loss: 2.8795 - val_acc: 0.7645
Epoch 16/20
7352/7352 [=====] - 153s 21ms/step - loss: 0.8878 - ac
c: 0.9023 - val_loss: 1.7750 - val_acc: 0.8042
Epoch 17/20
7352/7352 [=====] - 156s 21ms/step - loss: 1.2889 - ac
c: 0.8713 - val_loss: 2.7426 - val_acc: 0.8117
Epoch 18/20
7352/7352 [=====] - 153s 21ms/step - loss: 2.9924 - ac
c: 0.7046 - val_loss: 6.0092 - val_acc: 0.6132
Epoch 19/20
7352/7352 [=====] - 156s 21ms/step - loss: 3.3477 - ac
c: 0.6115 - val_loss: 5.4340 - val_acc: 0.3363
Epoch 20/20
7352/7352 [=====] - 154s 21ms/step - loss: 2.5352 - ac
c: 0.4474 - val_loss: 3.2740 - val_acc: 0.6121
```

```
In [33]: score=modelnew.evaluate(X_test, Y_test,verbose=0)
print('test score',score[0])
print('test accuracy',score[1])
```

```
test score 0.47755399492043493
test accuracy 0.9209365456396336
```

In [34]:

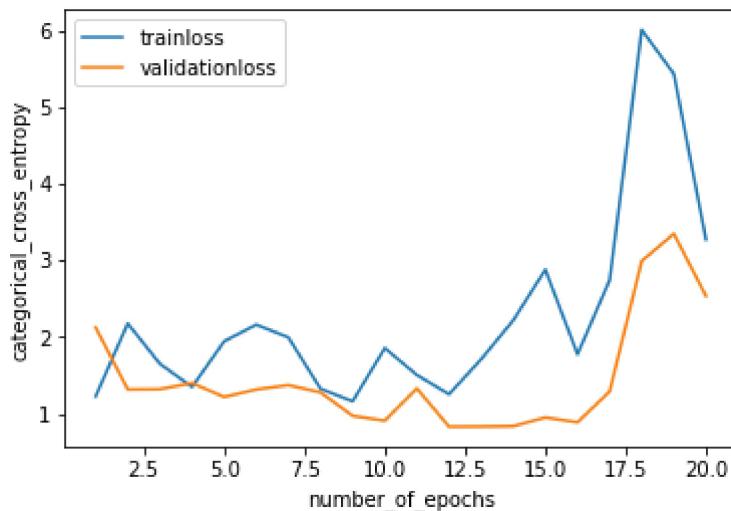
```
print(confusion_matrix(Y_test, modelnew.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	537	0	0	0		0
SITTING	3	414	74	0		0
STANDING	0	86	446	0		0
WALKING	1	1	0	448		44
WALKING_DOWNSTAIRS	0	0	0	1		419
WALKING_UPSTAIRS	1	7	2	6		5

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	0
STANDING	0
WALKING	2
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	450

In [35]:

```
fig,ax=plt.subplots()
x=list(range(1,21))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



WE ACHIEVED 91.6 TEST ACCURACY USING THE RELU AS THE ACTIVATION FUNCTION.

WE GONNA USE THE SINGLE LSTM LAYER SIMPLE MODEL AND ADD DROPOUT AT THE LAYER.

```
In [36]: model3 = Sequential()
# Configuring the parameters
model3.add(LSTM(64, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model3.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model3.add(Dense(n_classes, activation='sigmoid'))
print(model3.summary())

# Compiling the model
model3.compile(loss='categorical_crossentropy',optimizer='rmsprop',metrics=[ 'acc'])

# Training the model
history= model3.fit(X_train,Y_train,batch_size=batch_size,validation_data=(X_te
```

Layer (type)	Output Shape	Param #
lstm_5 (LSTM)	(None, 64)	18944
dropout_5 (Dropout)	(None, 64)	0
dense_3 (Dense)	(None, 6)	390
Total params: 19,334		
Trainable params: 19,334		
Non-trainable params: 0		
<hr/>		
None		
Train on 7352 samples, validate on 2947 samples		
Epoch 1/30		
7352/7352 [=====] - 80s 11ms/step - loss: 1.2424 - acc: 0.4739 - val_loss: 1.0771 - val_acc: 0.5212		
Epoch 2/30		
7352/7352 [=====] - 80s 11ms/step - loss: 0.9438 - acc: 0.5826 - val_loss: 0.8838 - val_acc: 0.6535		
Epoch 3/30		
7352/7352 [=====] - 78s 11ms/step - loss: 0.8002 - acc: 0.6474 - val_loss: 0.8034 - val_acc: 0.6960		
Epoch 4/30		
7352/7352 [=====] - 78s 11ms/step - loss: 0.6630 - acc: 0.7349 - val_loss: 0.7763 - val_acc: 0.7106		
Epoch 5/30		
7352/7352 [=====] - 79s 11ms/step - loss: 0.6058 - acc: 0.7622 - val_loss: 0.6271 - val_acc: 0.7913		
Epoch 6/30		
7352/7352 [=====] - 80s 11ms/step - loss: 0.4932 - acc: 0.8248 - val_loss: 0.5687 - val_acc: 0.8049		
Epoch 7/30		
7352/7352 [=====] - 78s 11ms/step - loss: 0.3686 - acc: 0.8810 - val_loss: 0.4586 - val_acc: 0.8463		
Epoch 8/30		
7352/7352 [=====] - 78s 11ms/step - loss: 0.3234 - acc: 0.8962 - val_loss: 0.6586 - val_acc: 0.8100		
Epoch 9/30		
7352/7352 [=====] - 78s 11ms/step - loss: 0.2582 - acc:		

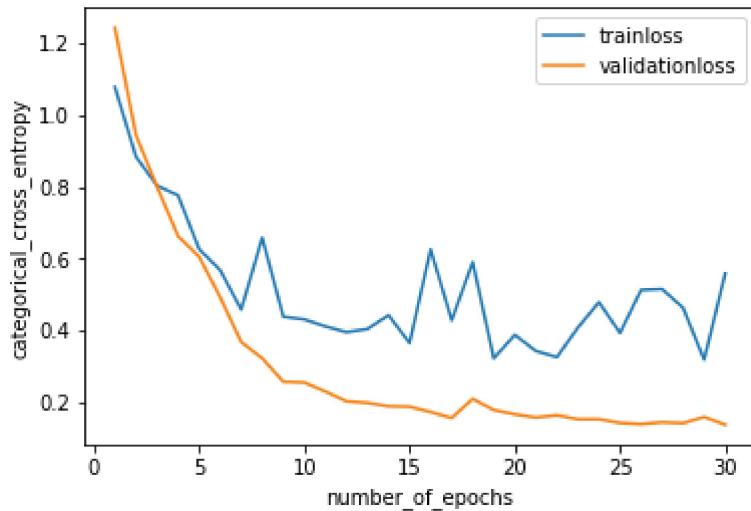
c: 0.9196 - val_loss: 0.4392 - val_acc: 0.8643
Epoch 10/30
7352/7352 [=====] - 79s 11ms/step - loss: 0.2559 - ac
c: 0.9187 - val_loss: 0.4315 - val_acc: 0.8700
Epoch 11/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.2310 - ac
c: 0.9274 - val_loss: 0.4122 - val_acc: 0.8863
Epoch 12/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.2037 - ac
c: 0.9347 - val_loss: 0.3960 - val_acc: 0.8768
Epoch 13/30
7352/7352 [=====] - 79s 11ms/step - loss: 0.1992 - ac
c: 0.9339 - val_loss: 0.4048 - val_acc: 0.8823
Epoch 14/30
7352/7352 [=====] - 80s 11ms/step - loss: 0.1899 - ac
c: 0.9372 - val_loss: 0.4433 - val_acc: 0.8843
Epoch 15/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1885 - ac
c: 0.9319 - val_loss: 0.3658 - val_acc: 0.8935
Epoch 16/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1740 - ac
c: 0.9408 - val_loss: 0.6261 - val_acc: 0.8918
Epoch 17/30
7352/7352 [=====] - 79s 11ms/step - loss: 0.1576 - ac
c: 0.9445 - val_loss: 0.4291 - val_acc: 0.8951
Epoch 18/30
7352/7352 [=====] - 80s 11ms/step - loss: 0.2104 - ac
c: 0.9381 - val_loss: 0.5909 - val_acc: 0.8894
Epoch 19/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1794 - ac
c: 0.9411 - val_loss: 0.3231 - val_acc: 0.8958
Epoch 20/30
7352/7352 [=====] - 79s 11ms/step - loss: 0.1678 - ac
c: 0.9448 - val_loss: 0.3884 - val_acc: 0.8823
Epoch 21/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1588 - ac
c: 0.9478 - val_loss: 0.3436 - val_acc: 0.9036
Epoch 22/30
7352/7352 [=====] - 80s 11ms/step - loss: 0.1651 - ac
c: 0.9430 - val_loss: 0.3266 - val_acc: 0.9101
Epoch 23/30
7352/7352 [=====] - 77s 11ms/step - loss: 0.1540 - ac
c: 0.9476 - val_loss: 0.4088 - val_acc: 0.9023
Epoch 24/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1540 - ac
c: 0.9479 - val_loss: 0.4793 - val_acc: 0.8941
Epoch 25/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1437 - ac
c: 0.9486 - val_loss: 0.3938 - val_acc: 0.9036
Epoch 26/30
7352/7352 [=====] - 79s 11ms/step - loss: 0.1404 - ac
c: 0.9502 - val_loss: 0.5132 - val_acc: 0.8965
Epoch 27/30
7352/7352 [=====] - 77s 11ms/step - loss: 0.1455 - ac
c: 0.9498 - val_loss: 0.5158 - val_acc: 0.9067
Epoch 28/30
7352/7352 [=====] - 78s 11ms/step - loss: 0.1431 - ac

```
c: 0.9509 - val_loss: 0.4635 - val_acc: 0.9023
Epoch 29/30
7352/7352 [=====] - 77s 11ms/step - loss: 0.1601 - ac
c: 0.9491 - val_loss: 0.3193 - val_acc: 0.9019
Epoch 30/30
7352/7352 [=====] - 79s 11ms/step - loss: 0.1388 - ac
c: 0.9509 - val_loss: 0.5589 - val_acc: 0.8894
```

```
In [37]: scores3 = model3.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores3[0]))
print("Test Accuracy: %f%%" % (scores3[1]*100))
```

```
Test Score: 0.559273
Test Accuracy: 88.937903%
```

```
In [39]: fig,ax=plt.subplots()
x=list(range(1,31))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



```
In [40]: # Confusion Matrix  
print(confusion_matrix(Y_test, model3.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	510	0	24	0		0
SITTING	0	388	97	2		0
STANDING	0	101	421	4		0
WALKING	0	0	0	464		19
WALKING_DOWNSTAIRS	0	0	0	22		389
WALKING_UPSTAIRS	0	0	0	19		3

Pred	WALKING_UPSTAIRS
True	
LAYING	3
SITTING	4
STANDING	6
WALKING	13
WALKING_DOWNSTAIRS	9
WALKING_UPSTAIRS	449

###SINGLE LSTM LAYER WITH MORE NUMBER OF CELLS IN EACH HIDDEN LAYER

```
In [41]: model3 = Sequential()
# Configuring the parameters
model3.add(LSTM(300, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model3.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model3.add(Dense(n_classes, activation='softmax'))
print(model3.summary())

# Compiling the model
model3.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Training the model
history3 = model3.fit(X_train, Y_train, batch_size=batch_size, validation_data=(X_val, Y_val))
```

Layer (type)	Output Shape	Param #
lstm_6 (LSTM)	(None, 300)	372000
dropout_6 (Dropout)	(None, 300)	0
dense_4 (Dense)	(None, 6)	1806
Total params:	373,806	
Trainable params:	373,806	
Non-trainable params:	0	

None
 Train on 7352 samples, validate on 2947 samples
 Epoch 1/30
 7352/7352 [=====] - 77s 10ms/step - loss: 1.3546 - acc: 0.4266 - val_loss: 1.4051 - val_acc: 0.3661
 Epoch 2/30
 7352/7352 [=====] - 76s 10ms/step - loss: 1.3603 - acc: 0.3943 - val_loss: 1.2473 - val_acc: 0.4832
 Epoch 3/30
 7352/7352 [=====] - 75s 10ms/step - loss: 1.0384 - acc: 0.5544 - val_loss: 1.2564 - val_acc: 0.4578
 Epoch 4/30
 7352/7352 [=====] - 76s 10ms/step - loss: 0.9501 - acc: 0.5812 - val_loss: 0.8030 - val_acc: 0.6403
 Epoch 5/30
 7352/7352 [=====] - 75s 10ms/step - loss: 0.7200 - acc: 0.6696 - val_loss: 0.7198 - val_acc: 0.6518
 Epoch 6/30
 7352/7352 [=====] - 76s 10ms/step - loss: 0.6276 - acc: 0.7114 - val_loss: 0.8023 - val_acc: 0.6016
 Epoch 7/30
 7352/7352 [=====] - 75s 10ms/step - loss: 0.6397 - acc: 0.7138 - val_loss: 1.4114 - val_acc: 0.4581
 Epoch 8/30
 7352/7352 [=====] - 77s 10ms/step - loss: 0.6261 - acc: 0.7295 - val_loss: 0.5974 - val_acc: 0.7727
 Epoch 9/30
 7352/7352 [=====] - 75s 10ms/step - loss: 0.4491 - acc:

c: 0.8184 - val_loss: 0.5478 - val_acc: 0.8015
Epoch 10/30
7352/7352 [=====] - 76s 10ms/step - loss: 0.4214 - ac
c: 0.8267 - val_loss: 0.4746 - val_acc: 0.8392
Epoch 11/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.3519 - ac
c: 0.8706 - val_loss: 0.4821 - val_acc: 0.8609
Epoch 12/30
7352/7352 [=====] - 77s 10ms/step - loss: 0.2846 - ac
c: 0.8946 - val_loss: 0.4432 - val_acc: 0.8602
Epoch 13/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.2434 - ac
c: 0.9151 - val_loss: 0.3223 - val_acc: 0.8965
Epoch 14/30
7352/7352 [=====] - 74s 10ms/step - loss: 0.2213 - ac
c: 0.9123 - val_loss: 0.3278 - val_acc: 0.9016
Epoch 15/30
7352/7352 [=====] - 74s 10ms/step - loss: 0.1661 - ac
c: 0.9332 - val_loss: 0.3573 - val_acc: 0.8717
Epoch 16/30
7352/7352 [=====] - 77s 10ms/step - loss: 0.1653 - ac
c: 0.9377 - val_loss: 0.3209 - val_acc: 0.8958
Epoch 17/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1550 - ac
c: 0.9415 - val_loss: 0.3320 - val_acc: 0.8979
Epoch 18/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1458 - ac
c: 0.9414 - val_loss: 0.3719 - val_acc: 0.8894
Epoch 19/30
7352/7352 [=====] - 76s 10ms/step - loss: 0.1421 - ac
c: 0.9437 - val_loss: 0.3194 - val_acc: 0.8996
Epoch 20/30
7352/7352 [=====] - 77s 10ms/step - loss: 0.1260 - ac
c: 0.9464 - val_loss: 0.3468 - val_acc: 0.9135
Epoch 21/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1377 - ac
c: 0.9452 - val_loss: 0.3723 - val_acc: 0.8972
Epoch 22/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1458 - ac
c: 0.9456 - val_loss: 0.3059 - val_acc: 0.9084
Epoch 23/30
7352/7352 [=====] - 76s 10ms/step - loss: 0.1386 - ac
c: 0.9438 - val_loss: 0.3887 - val_acc: 0.8941
Epoch 24/30
7352/7352 [=====] - 77s 10ms/step - loss: 0.1660 - ac
c: 0.9353 - val_loss: 0.3356 - val_acc: 0.9097
Epoch 25/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1354 - ac
c: 0.9404 - val_loss: 0.3282 - val_acc: 0.9091
Epoch 26/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1296 - ac
c: 0.9471 - val_loss: 0.3325 - val_acc: 0.9131
Epoch 27/30
7352/7352 [=====] - 75s 10ms/step - loss: 0.1340 - ac
c: 0.9480 - val_loss: 0.3672 - val_acc: 0.9101
Epoch 28/30
7352/7352 [=====] - 74s 10ms/step - loss: 0.1246 - ac

```
c: 0.9495 - val_loss: 0.3432 - val_acc: 0.9206
Epoch 29/30
7352/7352 [=====] - 76s 10ms/step - loss: 0.1309 - ac
c: 0.9461 - val_loss: 0.3198 - val_acc: 0.9016
Epoch 30/30
7352/7352 [=====] - 74s 10ms/step - loss: 0.1248 - ac
c: 0.9463 - val_loss: 0.4055 - val_acc: 0.9009
```

```
In [42]: scores3 = model3.evaluate(X_test, Y_test, verbose=0)
print("Test Score: %f" % (scores3[0]))
print("Test Accuracy: %f%%" % (scores3[1]*100))
```

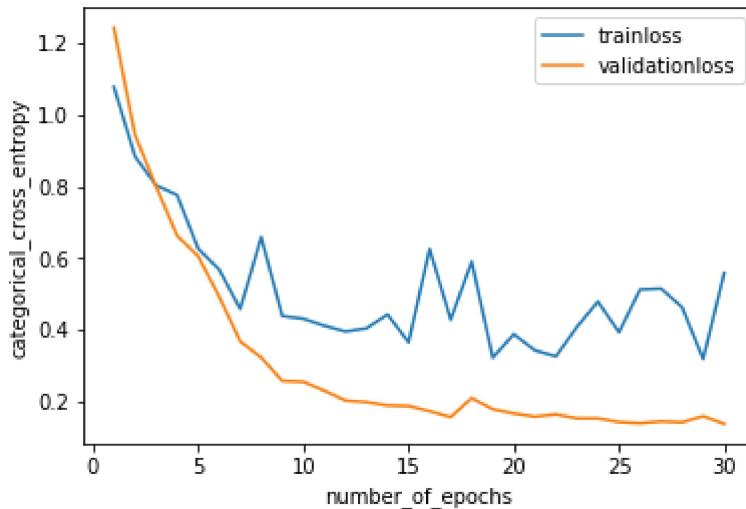
```
Test Score: 0.405478
Test Accuracy: 90.091619%
```

```
In [43]: # Confusion Matrix
print(confusion_matrix(Y_test, model3.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	510	0	1	0		0
SITTING	0	376	111	2		0
STANDING	0	86	444	2		0
WALKING	0	0	0	439		45
WALKING_DOWNSTAIRS	0	0	0	0		420
WALKING_UPSTAIRS	1	0	0	2		2

Pred	WALKING_UPSTAIRS
True	
LAYING	26
SITTING	2
STANDING	0
WALKING	12
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	466

```
In [45]: fig,ax=plt.subplots()
x=list(range(1,31))
validationy=history.history['val_loss']
testy=history.history['loss']
errorplot(x,validationy,testy,ax)
```



```
In [46]: import pandas as pd
data=[[1,(32,6),'YES','YES',0.9,0.3,'SIGMOID'],[3,(64,300,200,6),'YES','YES',0.9,0.3,'TANH'],
pd.DataFrame(data,columns=['NUMBER_OF_LAYERS_OF_LSTM','CONFIGURATION_OF_HIDDEN_CELLS','DROPOUT','BATCHNORMA
```

	NUMBER_OF_LAYERS_OF_LSTM	CONFIGURATION_OF_HIDDEN_CELLS	DROPOUT	BATCHNORMA
0	1	(32, 6)	YES	
1	3	(64, 300, 200, 6)	YES	
2	2	(32, 32, 6)	YES	
3	2	(64, 64, 6)	YES	
4	2	(100, 300, 6)	YES	
5	2	(100, 300, 6)	YES	
6	2	(100, 300, 6)	YES	
7	1	(64, 6)	YES	
8	1	(300, 6)	YES	

CONCLUSION DOCUMENTATION AND KEY TAKEAWAYS

WE ARE PROVIDED WITH THE DATA OF RAW SIGNALS AND THE CLASS LABEL IS MULTILABELLED. THE DATA IS OBTAINED FROM THE ACCELEROMETER AND GYROSCOPE SENSORS IN THE PHONE. GYROSCOPE IS USED TO MEASURE THE ANGULAR

VELOCITY AND ACCELEROMETER USED TO MEASURE THE ACCELERATION WE WILL PREDICT WHAT THE PERSON IS PERFORMING.

THE ACCELEROMETERS ARE TRIAXIAL AND GYROSCOPE IS TRIAXIAL. GIVEN THE TIMESERIES DATA TO PREDICT THE ACTIVITY. WE HAVE BUILD MODELS USING THE LSTM LAYERS AND THE EXTRACTING THE FEATURES FROM THE GIVEN DATA. USING THE FEATURES WE HAVE USED THE MACHINE LEARNING MODELS AND USED MULTICLASS LOGLOSS AS THE METRIC.

USING THE SIMPLE LSTM LAYERS WITH OUT ANY FEATURE EXTACTION AND FEATURE ENGINEERING WE ARE ABLE TO ACHIEVE THE ACCURACY OF 92 PERCENTAGE

In [0]: