Authentication of wireless devices using radio frequency fingerprints by Neural Network

تایید هویت دستگاه های بیسیم بااستفاده از اثر انگشت فرکانس رادیویی

در این پروژه سعی گردیده تا روشی کارا مبتنی بر هوش مصنوعی جهت تعیین ، تغییر هویت دستگاه‌های مجاز از دستگاه‌های غیرمجاز که تلاش در تغییر هویت خود جهت ورود به شبکه ی محلی را دارند شناسایی کرده و از ورود دستگاه‌های غیر مجاز به این شبکه امن جلوگیری شود.امروزه روش‌های احراز هویت متعددی مانند احراز هویت مبتنی بر رمز عبور، احراز هویت مبتنی بر گواهی و .. وجود دارد. روش ارائه شده ، احراز هویت بر اساس اثرانگشت فرکانس رادیویی دستگاه های بیسیم و مدل بندی آنها با الگوریتم های یادگیری ماشین می باشد . در این مطالعه تجربی ، از پایگاه داده با 12000 داده که دارای 103 ویژگی می باشند و توسط دستگاه گیرنده رادیویی Hack RF One در مرکز شهید باقری سازمان جهاد خودکفایی سپاه انجام پذیرفته، استفاده گردیده

Double-click (or enter) to edit

Import Package

```
#Enter the required package
import pandas as pd
import numpy as np
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score,precision_score,f1_score,balanced_accuracy_
from sklearn import metrics
import time
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
```

Import Data

```
#import Data
!gdown --id 1W7v3NevY_SgZoCnh78rEwUVyvk3X91Qv
```

```
/usr/local/lib/python3.10/dist-packages/gdown/__main__.py:140: FutureWarning: Option `--id` was deprecated in version 4
  warnings.warn(
Downloading...
From: https://drive.google.com/uc?id=1W7v3NevY_SgZoCnh78rEwUVyvk3X91Qv
To: /content/Test1to5.csv
100% 9.19M/9.19M [00:00<00:00, 34.5MB/s]
```

```
#read csv file
data = pd.read_csv('/content/Test1to5.csv')
```

```
data.head()
```

	Phi_n1	F_n1	Mean1	STD1	SKW1	KUR1	Phi_n2	F_n2	Mean2	STD2	...	STD16	!
0	0.999141	0.000000	-0.015057	0.099842	0.001906	2.779727	0.999188	0.00000	-0.018842	0.099018	...	0.098440	0.0
1	0.999313	0.000027	0.000350	0.243067	-0.523430	11.148045	0.999000	-0.00007	-0.013981	0.099325	...	0.099466	-0.0
2	0.999250	-0.000010	-0.014142	0.100139	-0.001865	2.779996	0.999375	0.00001	-0.016759	0.097628	...	0.102085	-0.0(
3	0.999105	-0.000023	-0.015235	0.153331	-0.319403	24.730970	0.998938	0.00004	-0.013445	0.099671	...	0.100696	-0.0
4	0.999309	0.000032	-0.015633	0.150284	1.360318	22.540028	0.999812	0.00008	-0.074362	0.456864	...	0.098123	0.0

5 rows × 103 columns

```
#مشخص کردن ستون ها
data.columns
```

```
Index(['Phi_n1', 'F_n1', 'Mean1', 'STD1', 'SKW1', 'KUR1', 'Phi_n2', 'F_n2',
       'Mean2', 'STD2',
       ...
       'STD16', 'SKW16', 'KUR16', 'Phi_n17', 'F_n17', 'Mean17', 'STD17',
       'SKW17', 'KUR17', 'Label'],
      dtype='object', length=103)
```

```
data.describe()
```

	Phi_n1	F_n1	Mean1	STD1	SKW1	KUR1	Phi_n2	F_n2	Mear
count	8000.000000	8.000000e+03	8000.000000	8000.000000	8000.000000	8000.000000	8000.000000	8.000000e+03	8000.00000
mean	0.999002	7.907750e-09	-0.013134	0.140551	0.044696	7.915667	0.998999	8.467672e-07	-0.01212
std	0.000192	2.373898e-05	0.009456	0.066359	0.595578	6.833200	0.000361	6.257780e-05	0.05393
min	0.998445	-8.700000e-05	-0.066114	0.076449	-4.292039	2.644673	0.997625	-3.580990e-04	-0.80899
25%	0.998867	-1.680000e-05	-0.014115	0.086361	-0.004183	2.824920	0.998750	-3.980000e-05	-0.01398
50%	0.998980	0.000000e+00	-0.013424	0.106767	0.003242	2.869999	0.999000	0.000000e+00	-0.01345
75%	0.999156	1.680000e-05	-0.012431	0.198011	0.014663	12.821652	0.999250	3.980000e-05	-0.01292
max	0.999480	9.450000e-05	0.034575	0.338543	3.410070	38.420326	1.000000	2.785210e-04	0.79440

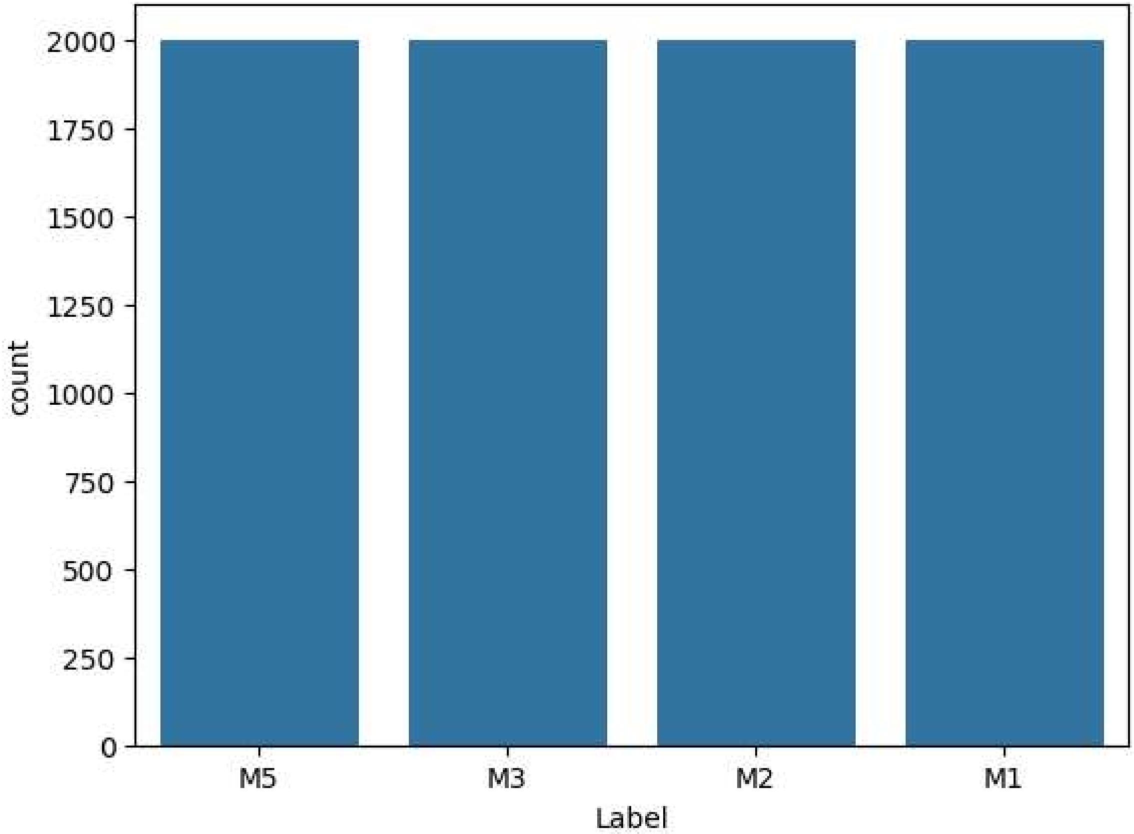
8 rows × 102 columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8000 entries, 0 to 7999
Columns: 103 entries, Phi_n1 to Label
dtypes: float64(102), object(1)
memory usage: 6.3+ MB
```

```
import seaborn as sns
sns.countplot(data=data,x='Label')
```

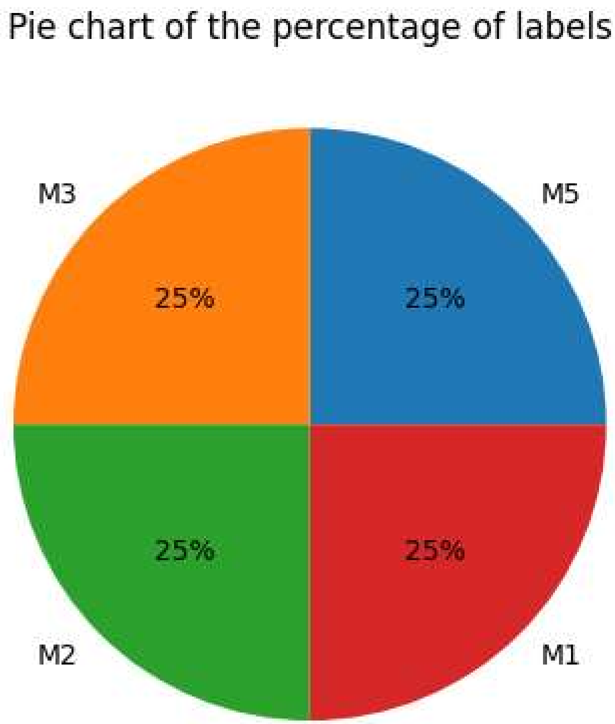
```
<Axes: xlabel='Label', ylabel='count'>
```




```
#تعیین درصد لیبل ها
import matplotlib.pyplot as plt
```

```
count_Class=pd.value_counts(data["Label"], sort= True)
count_Class.plot(kind = 'pie',  autopct='%1.0f%%')
plt.title('Pie chart of the percentage of labels')
plt.ylabel('')
plt.show()
```

```
<ipython-input-9-4ff03f9c9bca>:3: FutureWarning: pandas.value_counts is deprecated and will be removed in a future vers
  count_Class=pd.value_counts(data["Label"], sort= True)
```




```
X=data.drop(['Label'], axis = 1)
y=data.Label.values
print(f"Shape Data:",X.shape)
```

```
print(f"Shape Label:",y.shape)
print(f"Format and element of Label is:",set(y))
```

```
Shape Data: (8000, 102)
Shape Label: (8000,)
Format and element of Label is: {'M5', 'M1', 'M2', 'M3'}
```

```
# Step 2 - Convert Label to number
from sklearn.preprocessing import LabelEncoder
labelEncoder_Label =  LabelEncoder() #from sklearn
y = labelEncoder_Label.fit_transform(y)
print(f"Format and element of Label is:",set(y))
```

```
Format and element of Label is: {0, 1, 2, 3}
```

ANN

```
#Import the libraries for neural networks
from time import perf_counter
import tensorflow as tf
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, Activation
from tensorflow.keras.optimizers import Adam, Adagrad
```

```
# Hold-out validation

# first one
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.1,random_state = 1)
```

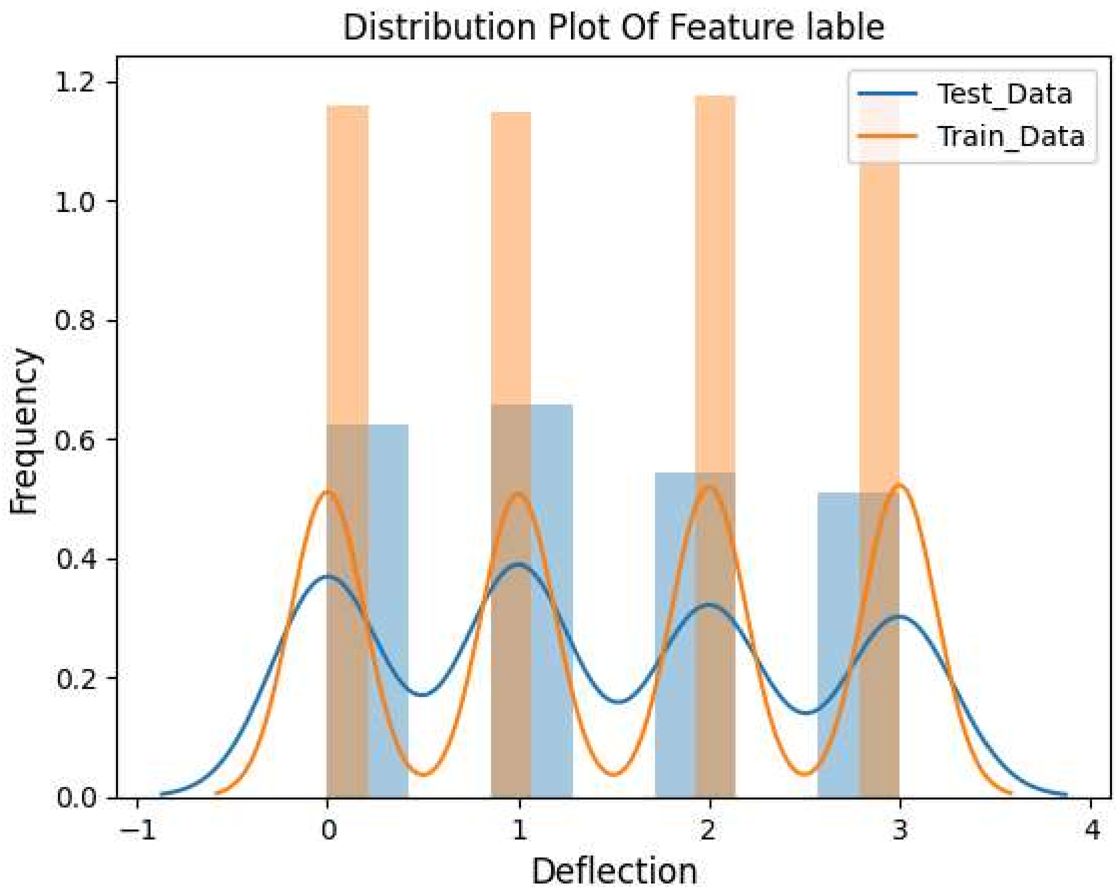
```
# Second one
X_train, X_valid, y_train, y_valid = train_test_split(X_train, y_train, train_size = 0
#stratify=y_trainدر اینجا چون نسبتلیبل ها نا متقارن است از طبقه بندی داده ها استفاده کردیم
print("shape of X_train is : ",X_train.shape)
print("shape of X_test is : ",X_test.shape)
print("shape of X_valid is : ",X_valid.shape)

print("shape of y_train is : ",y_train.shape)
print("shape of y_test is : ",y_test.shape)
print("shape of y_valid is : ",y_valid.shape)
```

```
shape of X_train is :  (6480, 102)
shape of X_test is :  (800, 102)
shape of X_valid is :  (720, 102)
shape of y_train is :  (6480,)
shape of y_test is :  (800,)
shape of y_valid is :  (720,)
```

```
#نمودار توزیع داده چگالی وارده برای تست و ترین
import numpy as np
import seaborn as sn
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
data1 =y_test
data2 =y_train
res = sn.distplot(data1)
res2 = sn.distplot(data2)
plt.xlabel('Deflection',fontsize=12)
plt.ylabel('Frequency',fontsize=12)
plt.title('Distribution Plot Of Feature lable')
```

```
plt.legend(['Test_Data', 'Train_Data'])
plt.show()
plt.savefig('Distribution Plot of Feature lable.eps',format='eps')
plt.savefig('Distribution Plot of Feature lable.svg',format='svg')
```




```
<Figure size 640x480 with 0 Axes>
```

```
n_classes = len(set(y_train))#تعداد کلاس ها با توجه به تنوع لیبل ها
n_samples, n_features = X_train.shape#تعداد سطر و تعداد ستون های ماتریس ترین
```

```
#Definition of swish activation function with Beta parameter
def swish_beta(x, beta=1.328):
    return x * (1 / (1 + tf.exp(-beta * x)))


# Building the neural network (Functional API)
##define input layer
input_layer = Input(shape=(n_features,), name='input_layer')

##Defining 2 hidden layers
Layer_1 = Dense(20, activation=None, name='Layer_1')(input_layer)
S1=tf.keras.layers.Lambda(swish_beta)(Layer_1)
Layer_2 = Dense(40, activation=None, name='Layer_2')(S1)
S2=tf.keras.layers.Lambda(swish_beta)(Layer_2)
Layer_3 = Dense(20, activation=None, name='Layer_3')(S2)
S3=tf.keras.layers.Lambda(swish_beta)(Layer_3)
##Defining  output layer y1
output = Dense(n_classes, activation="softmax", name='output')(S3)

##Defining the model by specifying the input and output layers
fc_model = Model(inputs=input_layer, outputs=output)


fc_model.summary()
```

Model: "functional_2"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 102)	0
Layer_1 (Dense)	(None, 20)	2,060
lambda_4 (Lambda)	(None, 20)	0
Layer_2 (Dense)	(None, 40)	840
lambda_5 (Lambda)	(None, 40)	0
Layer_3 (Dense)	(None, 20)	820
lambda_6 (Lambda)	(None, 20)	0
output (Dense)	(None, 4)	84

Total params: 3,804 (14.86 KB)
Trainable params: 3,804 (14.86 KB)
Non-trainable params: 0 (0.00 B)

```
#model compile
#metric = tf.keras.metrics.SparseCategoricalAccuracy()
#metric=tf.keras.metrics.SparseCategoricalAccuracy(
 #   name="sparse_categorical_accuracy", dtype=None)

opt = tf.keras.optimizers.Adam(learning_rate=0.0001,beta_1=0.97,
    beta_2=0.998,
    epsilon=1e-07)
loss = tf.keras.losses.SparseCategoricalCrossentropy()
fc_model.compile(loss=loss,optimizer=opt,metrics=[tf.keras.metrics.SparseCategoricalAc

#model fit and prdict
```

```
start_tra = perf_counter()

history = fc_model.fit(X_train, y_train, epochs=3000, verbose=True,
          batch_size=2000, validation_data=(X_valid, y_valid))


end_tra = perf_counter()
print(f'train phase time with ANN: ', round((end_tra-start_tra), 1))
```

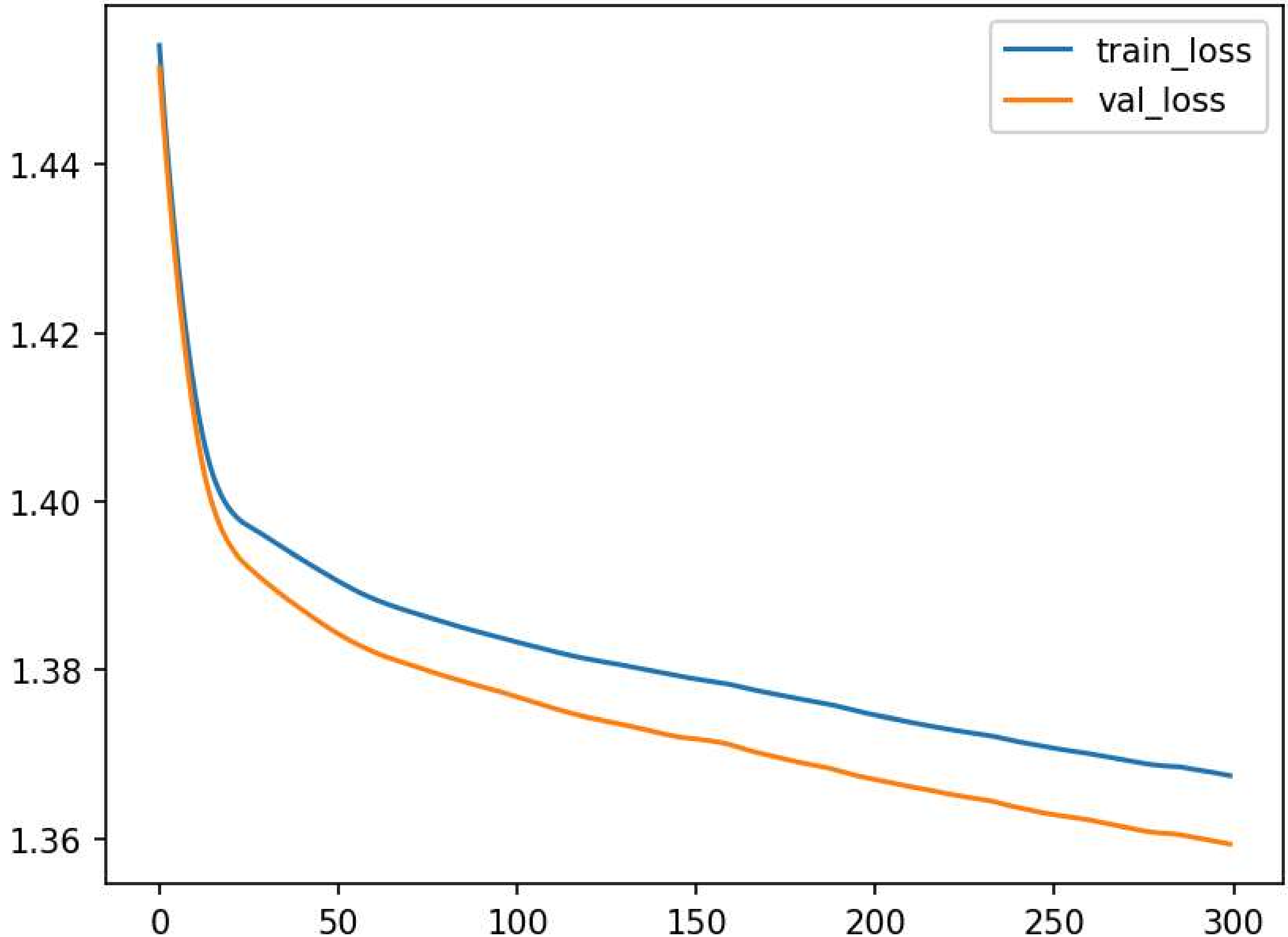
```
Streaming output truncated to the last 5000 lines.
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1275 - sparse_categorical_accuracy: 0.6861 - val_los
Epoch 502/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1272 - sparse_categorical_accuracy: 0.6885 - val_los
Epoch 503/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1252 - sparse_categorical_accuracy: 0.6835 - val_los
Epoch 504/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 1.1244 - sparse_categorical_accuracy: 0.6676 - val_los
Epoch 505/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1268 - sparse_categorical_accuracy: 0.6666 - val_los
Epoch 506/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 15ms/step - loss: 1.1214 - sparse_categorical_accuracy: 0.6804 - val_los
Epoch 507/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1222 - sparse_categorical_accuracy: 0.6802 - val_los
Epoch 508/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1206 - sparse_categorical_accuracy: 0.6730 - val_los
Epoch 509/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1233 - sparse_categorical_accuracy: 0.6614 - val_los
Epoch 510/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1250 - sparse_categorical_accuracy: 0.6699 - val_los
Epoch 511/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1221 - sparse_categorical_accuracy: 0.6770 - val_los
Epoch 512/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1219 - sparse_categorical_accuracy: 0.6895 - val_los
Epoch 513/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 1.1174 - sparse_categorical_accuracy: 0.6974 - val_los
Epoch 514/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1223 - sparse_categorical_accuracy: 0.6923 - val_los
Epoch 515/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 14ms/step - loss: 1.1196 - sparse_categorical_accuracy: 0.6833 - val_los
```

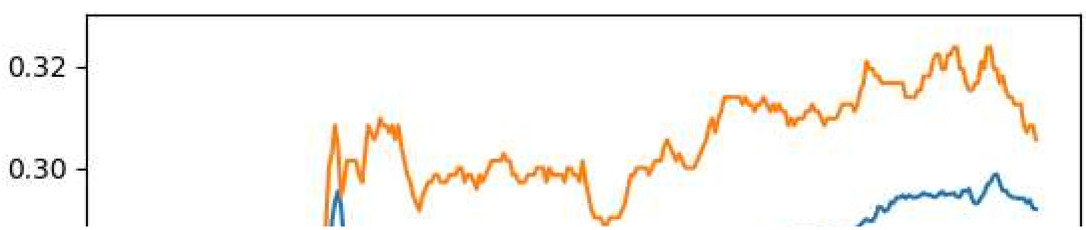
```
Epoch 516/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1161 - sparse_categorical_accuracy: 0.6814 - val_los
Epoch 517/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1139 - sparse_categorical_accuracy: 0.6825 - val_los
Epoch 518/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1110 - sparse_categorical_accuracy: 0.6888 - val_los
Epoch 519/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1156 - sparse_categorical_accuracy: 0.6987 - val_los
Epoch 520/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1097 - sparse_categorical_accuracy: 0.6922 - val_los
Epoch 521/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1094 - sparse_categorical_accuracy: 0.6861 - val_los
Epoch 522/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1125 - sparse_categorical_accuracy: 0.6802 - val_los
Epoch 523/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1089 - sparse_categorical_accuracy: 0.6891 - val_los
Epoch 524/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 13ms/step - loss: 1.1103 - sparse_categorical_accuracy: 0.6860 - val_los
Epoch 525/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1095 - sparse_categorical_accuracy: 0.6872 - val_los
Epoch 526/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1084 - sparse_categorical_accuracy: 0.6818 - val_los
Epoch 527/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 11ms/step - loss: 1.1119 - sparse_categorical_accuracy: 0.6679 - val_los
Epoch 528/3000
4/4 ━━━━━━━━━━━━━━━━━━━━ 0s 12ms/step - loss: 1.1076 - sparse_categorical_accuracy: 0.6660 - val_los
Epoch 529/3000
```

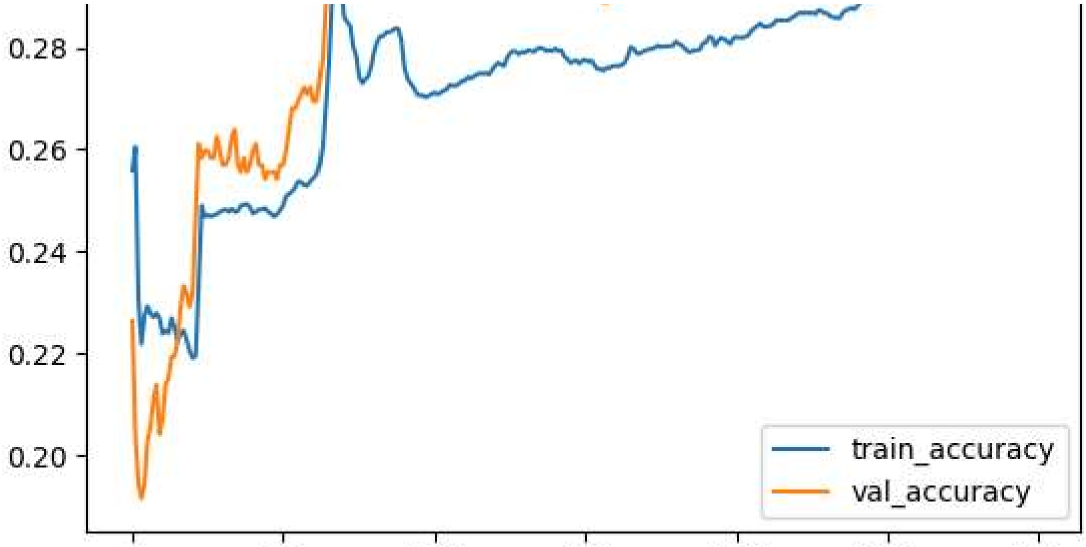
```
import matplotlib.pyplot as plt

plt.figure(dpi=150)
# plt.grid()
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.legend(['train_loss', 'val_loss'])
plt.show()
plt.savefig('Train loss vs Validation loss.png', format='png')  # save plot to png
```

```
plt.plot(history.history['sparse_categorical_accuracy'])
plt.plot(history.history['val_sparse_categorical_accuracy'])
plt.legend(['train_accuracy', 'val_accuracy'])
plt.savefig('Train acc vs Validation accuracy.png', format='png')  # save plot to png
```


train_loss
val_loss
1.44
1.42
1.40
1.38
1.36
0
50
100
150
200
250
300


0.32
0.30




```
# validate the network
score=fc_model.evaluate(X_valid,y_valid)
val_loss=score[0]
val_acc=score[1]
print('validation of loss is :',val_loss)
print('validation of  accuracy is :',val_acc)
```

```
23/23 ━━━━━━━━━━━━━━━━━━━━ 2s 35ms/step - loss: 1.3609 - sparse_categorical_accuracy: 0.2926
validation of loss is : 1.35934579372406
validation of  accuracy is : 0.3055555522441864
```

```
fc_model.evaluate(X_test, y_test)
```

```
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.3552 - sparse_categorical_accuracy: 0.3053
[1.3606407642364502, 0.2849999964237213]
```

```
y_pred = fc_model.predict(X_test)
```

```
y_pred_labels = [np.argmax(i) for i in y_pred]
```

```
cm = tf.math.confusion_matrix(labels= y_test, predictions= y_pred_labels, num_classes=
print(cm)
```

```
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 1ms/step
tf.Tensor(
[[ 42  16  23 133]
 [ 58  36  21 110]
 [ 21  11  40 114]
 [ 39  15  11 110]], shape=(4, 4), dtype=int32)
```

```
y_pred = np.argmax(fc_model.predict(X_test), axis=1)

# Calculate the precision
precision = precision_score(y_test, y_pred, labels=np.unique(y_test), average='micro')
f1_score_value =f1_score(y_test, y_pred, labels=np.unique(y_test), average='micro')
recall_score_value =recall_score(y_test, y_pred, labels=np.unique(y_test), average='mi
accuracy_score_value = accuracy_score(y_test, y_pred)
print('Precision:', precision)
print('f1_score_value:', f1_score_value)
print('recall_score_value:', recall_score_value)
print('Accuracy_score_value:', accuracy_score_value)



#classification_report

from sklearn.metrics import classification_report
precision = precision_score(y_test, y_pred, labels=np.unique(y_test), average=None)
f1_score_value =f1_score(y_test, y_pred, labels=np.unique(y_test), average=None)
recall_score_value =recall_score(y_test, y_pred, labels=np.unique(y_test), average=Non
accuracy_score_value = accuracy_score(y_test, y_pred)
```

```
target_names = ['M1', 'M2', 'M3','M5']
print(classification_report(y_test, y_pred, target_names=target_names))

# Create a DataFrame with the metrics
metrics = {
    'Metrics': ['M1', 'M2', 'M3', 'M5', 'Average'],
    'Precision': [precision[0], precision[1], precision[2], precision[3], np.m
    'Recall': [recall_score_value[0], recall_score_value[1], recall_score_valu
    'F1-score': [f1_score_value[0], f1_score_value[1], f1_score_value[2], f1_s
    'Accuracy': ['', '', '', '', accuracy_score_value]
}

df = pd.DataFrame(metrics)

# Print the DataFrame
print(df)
```

```
   Metrics  Precision    Recall  F1-score Accuracy
0       M1   0.772512  0.761682  0.767059
1       M2   0.822335  0.720000  0.767773
2       M3   0.824121  0.881720  0.851948
3       M5   0.761658  0.840000  0.798913
4  Average   0.795156  0.800851  0.796423    0.795
```

```
# Create a DataFrame with the metrics
metrics = {
    'Metrics': ['M1', 'M2', 'M3', 'M5',  'Average'],
    'Precision': [precision[0], precision[1], precision[2], precision[3],  np.mean(pr
    'Recall': [recall_score_value[0], recall_score_value[1], recall_score_value[2], r
```

```
    'F1-score': [f1_score_value[0], f1_score_value[1], f1_score_value[2], f1_score_va
    'Accuracy': ['', '', '', '',  accuracy_score_value]
}

df = pd.DataFrame(metrics)
print(df)
```

```
   Metrics  Precision    Recall  F1-score Accuracy
0       M1   0.772512  0.761682  0.767059
1       M2   0.822335  0.720000  0.767773
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4  Average   0.795156  0.800851  0.796423    0.795
```

```
plt.figure(dpi=200)
sns.heatmap(cm, annot=True, fmt='d')
plt.xlabel("Predicted")
plt.ylabel("Actual")
```

```
Text(101.44444444444443, 0.5, 'Actual')
```