Machine learning methods

Preprocessing

In [41]:

```
#Function written to plot confusion matrix
import itertools
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)
    ax = plt.gca()
    ax.set_ylim(-.5, 5.5)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [42]:

```
#Function generated to run any model
from datetime import datetime
def perform_model(model, X_train, y_train, X_test, y_test, class_labels, cm_normalize=True,
                 print_cm=True, cm_cmap=plt.cm.Reds):


    # to store results at various phases
    results = dict()

    # time at which model starts training
    train_start_time = datetime.now()
    print('training the model..')
    model.fit(X_train, y_train)
    print('Done \n \n')
    train_end_time = datetime.now()
    results['training_time'] =  train_end_time - train_start_time
    print('training_time(HH:MM:SS.ms) - {}\n\n'.format(results['training_time']))


    # predict test data
    print('Predicting test data')
    test_start_time = datetime.now()
    y_pred = model.predict(X_test)
    test_end_time = datetime.now()
    print('Done \n \n')
    results['testing_time'] = test_end_time - test_start_time
    print('testing time(HH:MM:SS:ms) - {}\n\n'.format(results['testing_time']))
    results['predicted'] = y_pred


    # calculate overall accuracty of the model
    accuracy = metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
    # store accuracy in results
    results['accuracy'] = accuracy
    print('|Accuracy|')

    print('\n    {}\n\n'.format(accuracy))


    # confusion matrix
    cm = metrics.confusion_matrix(y_test, y_pred)
    results['confusion_matrix'] = cm
    if print_cm:
        print('|Confusion Matrix|')
        print('\n {}'.format(cm))

    # plot confusin matrix
    plt.figure(figsize=(8,8))
    plt.grid(b=False)
    plot_confusion_matrix(cm, classes=class_labels, normalize=True, title='Normalized confu
    ax = plt.gca()
    ax.set_ylim(-.5,5.5)
    plt.show()
    # get classification report
    print('|Classification Report|')
    classification_report = metrics.classification_report(y_test, y_pred)
    # store report in results
    results['classification_report'] = classification_report
    print(classification_report)
```

```
    # add the trained  model to the results
    results['model'] = model

    return results
```

In [43]:

```
#Method to print attributes for gridSearch
def print_grid_search_attributes(model):
    # Estimator that gave highest score among all the estimators formed in GridSearch
    print('|      Best Estimator     |')
    print('\n\t{}\n'.format(model.best_estimator_))
    # parameters that gave best results while performing grid search
    print('|Best parameters|')

    print('\tParameters of best estimator : \n\n\t{}\n'.format(model.best_params_))


    #  number of cross validation splits
    print('|   No of CrossValidation sets   |')
    print('\n\tTotal numbre of cross validation sets: {}\n'.format(model.n_splits_))


    # Average cross validated score of the best estimator, from the Grid Search
    print('|        Best Score       |')
    print('\n\tAverage Cross Validate scores of best estimator : \n\n\t{}\n'.format(model.b
```

In [44]:

```
#Importing libraries
from sklearn import linear_model
from sklearn import metrics

from sklearn.model_selection import GridSearchCV
```

Machine learning methods for Hand to mouth movements

In [45]:

```
#Reading in hand to mouth gestures
import numpy as np
import pandas as pd
htm= pd.read_csv('htmallgesturesfinal.csv')
htm.head()
#print(htm.shape)
```

Out[45]:

	aX	aY	aZ	gX	gY	gZ	gesture
0	0.272	-1.297	0.457	69.519	-38.818	12.390	1
1	0.257	-1.252	0.480	65.063	-39.307	18.494	1
2	0.266	-1.249	0.483	62.073	-38.452	25.940	1
3	0.298	-1.223	0.468	51.880	-34.729	41.260	1
4	0.299	-1.164	0.462	47.791	-32.959	48.157	1

In [46]:

```
#Splitting gesture data and gesture classification
X = htm.drop(['gesture'], axis=1)
y = htm.gesture
print(X.shape, y.shape)
```

```
(12019, 6) (12019,)
```

In [47]:

```
# splitting X and y into training and testing sets for hand to mouth gestures
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=1)
print('X_train and y_train : ({},{})'.format(X_train.shape, y_train.shape))
print('X_test  and y_test  : ({},{})'.format(X_test.shape, y_test.shape))
```

```
X_train and y_train : ((9014, 6),(9014,))
X_test  and y_test  : ((3005, 6),(3005,))
```

In [48]:

```
#Generating labels for hand to mouth gestures
labelshtm = ["Drinking", "Eating Apple", "Spoon to Mouth", "Fork to Mouth", "Eating Sweets"
```

In [49]:

```
# logistic regression for hand to mouth movements
parameters = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1']}
log_reg = linear_model.LogisticRegression()
log_reg_grid = GridSearchCV(log_reg, param_grid=parameters, cv=3, verbose=1, n_jobs=-1)
log_reg_grid_results =  perform_model(log_reg_grid, X_train, y_train, X_test, y_test, class
```

```
Done


training_time(HH:MM:SS.ms) - 0:00:07.375994


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.004000
```

In [50]:

```
#KNN for hand to mouth movements
from sklearn.neighbors import KNeighborsClassifier

#knn
# start Grid search
parameters = {'n_neighbors': [1, 10, 11, 20, 30]}
log_knn = KNeighborsClassifier(n_neighbors=19)

log_knn_grid = GridSearchCV(log_knn, param_grid=parameters, cv=3, verbose=1, n_jobs=-1)
log_knn_grid_results =  perform_model(log_knn_grid, X_train, y_train, X_test, y_test, class
```

```
training the model..
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Done


training_time(HH:MM:SS.ms) - 0:00:00.911999


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.163003


|Accuracy|

    0.5344425956738769
```

In [51]:

```
#Decision Tree for hand to mouth movements
from sklearn.tree import DecisionTreeClassifier
parameters = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=parameters, n_jobs=-1)
dt_grid_results = perform_model(dt_grid, X_train, y_train, X_test, y_test, class_labels=lab
print_grid_search_attributes(dt_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:00.358000


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.003001


|Accuracy|

    0.7304492512479202
```

In [52]:

```
#Random Forest Classifier for hand to mouth movements
from sklearn.ensemble import RandomForestClassifier
params = {'n_estimators': np.arange(10,201,20), 'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=params, n_jobs=-1)
rfc_grid_results = perform_model(rfc_grid, X_train, y_train, X_test, y_test, class_labels=l
print_grid_search_attributes(rfc_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:01:06.383998


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.007002


|Accuracy|

    0.7078202995008319
```

In [53]:

```
import numpy as np
import tensorflow as tf
SEED = 1337
np.random.seed(SEED)
tf.random.set_seed(SEED)
GESTURES = [
    "htmallgesturesfinal"

]

SAMPLES_PER_GESTURE = 119
NUM_GESTURES = len(GESTURES)

ONE_HOT_ENCODED_GESTURES = np.eye(NUM_GESTURES)
inputs = []
outputs = []

for gesture_index in range(NUM_GESTURES):
  gesture = GESTURES[gesture_index]
  print(f"Processing index {gesture_index} for gesture '{gesture}'.")

  output = ONE_HOT_ENCODED_GESTURES[gesture_index]

  df = pd.read_csv(gesture + ".csv", low_memory=False)

  num_recordings = int(df.shape[0] / SAMPLES_PER_GESTURE)

  print(f"\tThere are {num_recordings} recordings of the {gesture} gesture.")

  for i in range(num_recordings):
    tensor = []
    for j in range(SAMPLES_PER_GESTURE):
      index = i * SAMPLES_PER_GESTURE + j

      tensor += [
          (df['aX'][index] + 4) / 8,
          (df['aY'][index] + 4) / 8,
          (df['aZ'][index] + 4) / 8,
          (df['gX'][index] + 2000) / 4000,
          (df['gY'][index] + 2000) / 4000,
          (df['gZ'][index] + 2000) / 4000
      ]

    inputs.append(tensor)
    outputs.append(output)

inputs = np.array(inputs)
outputs = np.array(outputs)
```

```
Processing index 0 for gesture 'htmallgesturesfinal'.
	There are 101 recordings of the htmallgesturesfinal gesture.
```

In [54]:

```
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(20, activation='relu'))
model.add(tf.keras.layers.Dense(15, activation='relu'))
model.add(tf.keras.layers.Dense(NUM_GESTURES, activation='softmax'))
model.compile(optimizer='rmsprop', loss='mse', metrics=['mae','accuracy'])
history = model.fit(X_train, y_train, epochs=600, batch_size=1, validation_data=(X_test, y_
```

```
Epoch 1/600
9014/9014 [==============================] - 16s 2ms/step - loss: 6.1023
- mae: 2.0357 - accuracy: 0.1954 - val_loss: 5.8945 - val_mae: 1.9864 - v
al_accuracy: 0.2060
Epoch 2/600
9014/9014 [==============================] - 14s 2ms/step - loss: 6.1023
- mae: 2.0357 - accuracy: 0.1954 - val_loss: 5.8945 - val_mae: 1.9864 - v
al_accuracy: 0.2060
Epoch 3/600
9014/9014 [==============================] - 14s 2ms/step - loss: 6.1023
- mae: 2.0357 - accuracy: 0.1954 - val_loss: 5.8945 - val_mae: 1.9864 - v
al_accuracy: 0.2060
Epoch 4/600
9014/9014 [==============================] - 14s 2ms/step - loss: 6.1023
- mae: 2.0357 - accuracy: 0.1954 - val_loss: 5.8945 - val_mae: 1.9864 - v
al_accuracy: 0.2060
Epoch 5/600
9014/9014 [==============================] - 14s 2ms/step - loss: 6.1023
- mae: 2.0357 - accuracy: 0.1954 - val_loss: 5.8945 - val_mae: 1.9864 - v
```

Non-hand to mouth

In [55]:

```
#Reading in  non-hand to mouth gestures
nonhtm = pd.read_csv('nonhtmallgesturesfinal.csv')
nonhtm.head()
#print( nonhtm.shape)
```

Out[55]:

	aX	aY	aZ	gX	gY	gZ	gesture
0	0.099	1.658	0.412	94.116	-36.255	-26.062	1
1	0.078	1.196	0.562	127.319	-26.978	-42.603	1
2	0.155	0.714	0.749	139.648	-13.000	-47.668	1
3	0.217	0.500	0.919	141.418	-4.578	-50.903	1
4	0.232	0.435	0.878	136.108	-1.587	-59.875	1

In [56]:

```
#Splitting gesture data and gesture classification
X1 = nonhtm.drop(['gesture'], axis=1)
y1 = nonhtm.gesture
print(X1.shape, y1.shape)
```

```
(12138, 6) (12138,)
```

In [57]:

```
#splitting X and y into training and testing sets for non-hand to mouth gestures
from sklearn.model_selection import train_test_split
X_train1, X_test1, y_train1, y_test1 = train_test_split(X1, y1, test_size=0.25, random_stat
print('X_train1 and y_train1 : ({},{})'.format(X_train1.shape, y_train1.shape))
print('X_test1  and y_test1  : ({},{})'.format(X_test1.shape, y_test1.shape))
```

```
X_train1 and y_train1 : ((9103, 6),(9103,))
X_test1  and y_test1  : ((3035, 6),(3035,))
```

In [58]:

```
#Generating labels for non-hand to mouth gesture
labelsnonhtm = ["Head Scratch", "Using phone", "Reaching", "Typing", "Writing" ]
```

In [59]:

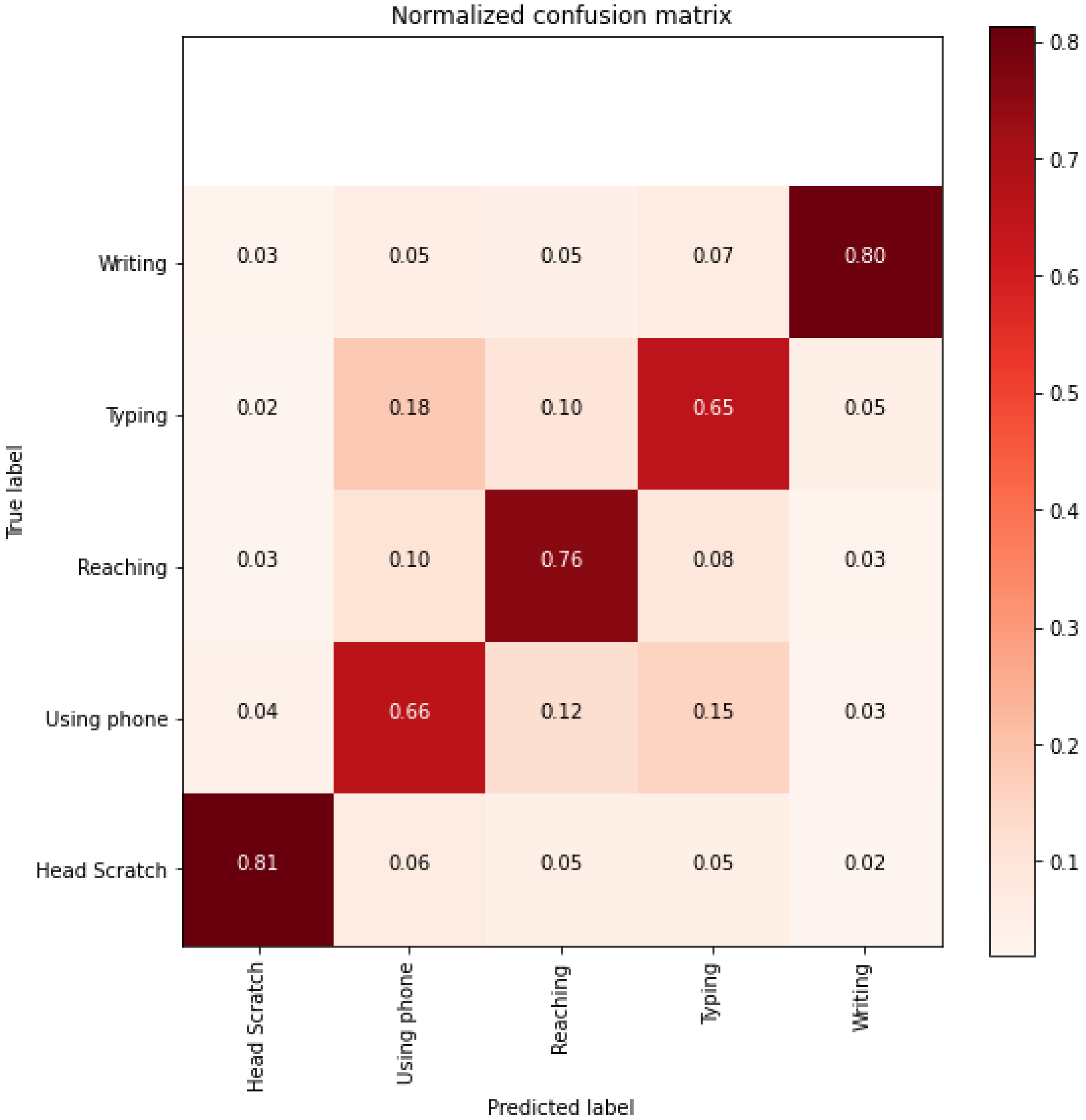
```
# Grid search for non-hand to mouth movements
parameters = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1']}
log_reg = linear_model.LogisticRegression()
log_reg_grid = GridSearchCV(log_reg, param_grid=parameters, cv=3, verbose=1, n_jobs=-1)
log_reg_grid_results =  perform_model(log_reg_grid, X_train1, y_train1, X_test1, y_test1, c
```

```
|Accuracy|

    0.7762767710049423


|Confusion Matrix|

 [[630   7  10  12  20]
 [  7 136  82 381   2]
 [ 16  53 440  34   9]
 [  2  23   5 564   3]
 [  1   0  12   0 586]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matpl
otlibDeprecationWarning: The 'b' parameter of grid() has been renamed 'vi
sible' since Matplotlib 3.5; support for the old name will be dropped two
minor releases later.
  plt.grid(b=False)
```

In [60]:

```
#KNN for non-hand to mouth movements
from sklearn.neighbors import KNeighborsClassifier

#knn
# start Grid search
parameters = {'n_neighbors': [1, 10, 11, 20, 30]}
log_knn = KNeighborsClassifier(n_neighbors=19)

log_knn_grid = GridSearchCV(log_knn, param_grid=parameters, cv=3, verbose=1, n_jobs=-1)
log_knn_grid_results =  perform_model(log_knn_grid, X_train1, y_train1, X_test1, y_test1, c
```

```
training the model..
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Done


training_time(HH:MM:SS.ms) - 0:00:00.857934


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.072859


|Accuracy|

    0.7373970345963756


|Confusion Matrix|

 [[552  43  35  35  14]
 [ 25 399  74  93  17]
 [ 14  57 419  44  18]
 [ 14 107  58 389  29]
 [ 19  31  28  42 479]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```

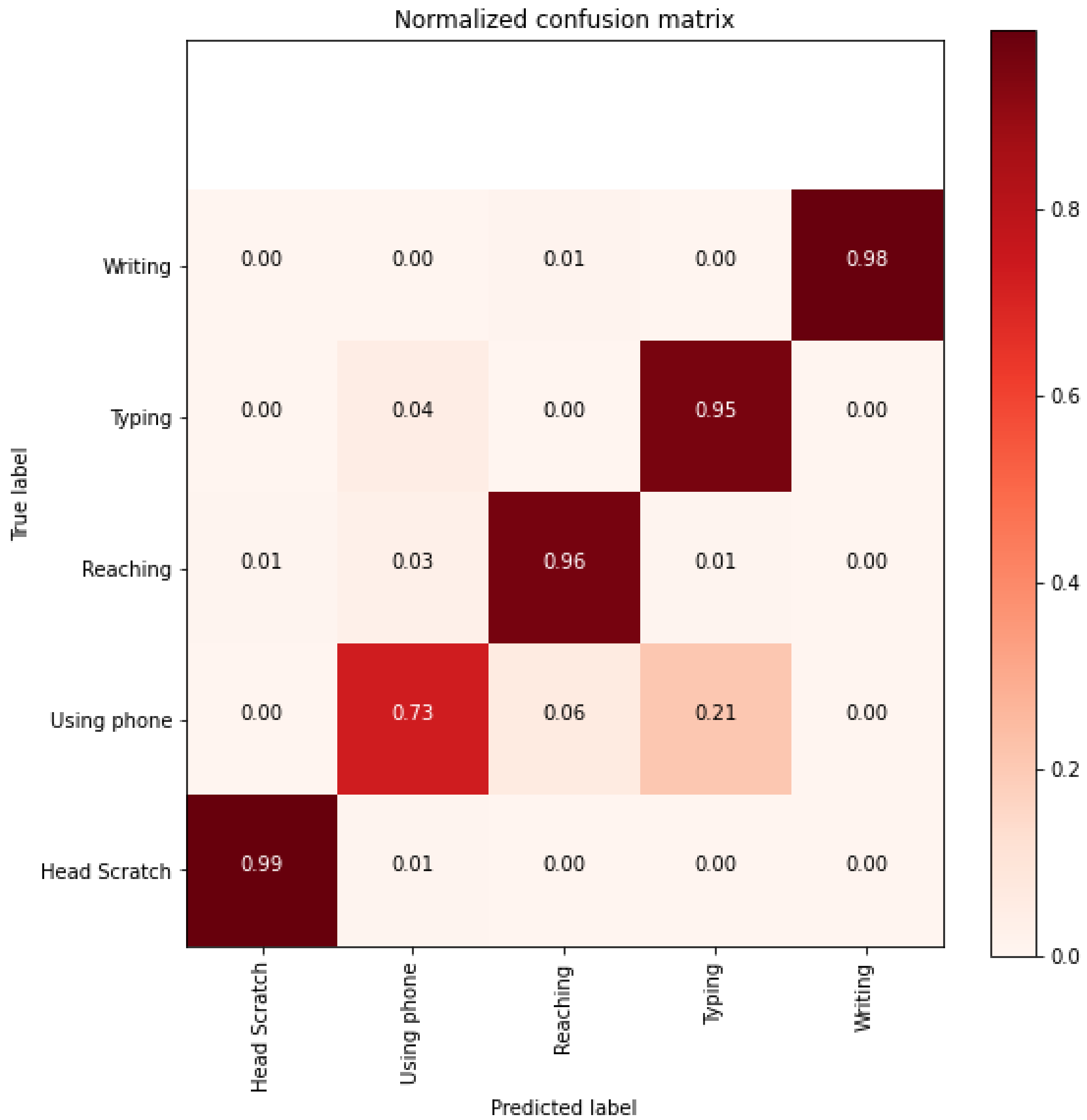



```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.88      0.81      0.85       679
           2       0.63      0.66      0.64       608
           3       0.68      0.76      0.72       552
           4       0.65      0.65      0.65       597
           5       0.86      0.80      0.83       599

    accuracy                           0.74      3035
   macro avg       0.74      0.74      0.74      3035
weighted avg       0.74      0.74      0.74      3035
```

In [61]:

```
#Decision Tree for hand to mouth movements
from sklearn.tree import DecisionTreeClassifier
parameters = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=parameters, n_jobs=-1)
dt_grid_results = perform_model(dt_grid, X_train1, y_train1, X_test1, y_test1, class_labels
print_grid_search_attributes(dt_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:00.333638


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.002001


|Accuracy|

    0.9238879736408566


|Confusion Matrix|

 [[673   4   1   1   0]
 [  1 442  36 127   2]
 [  3  16 530   3   0]
 [  0  26   2 569   0]
 [  1   2   5   1 590]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```



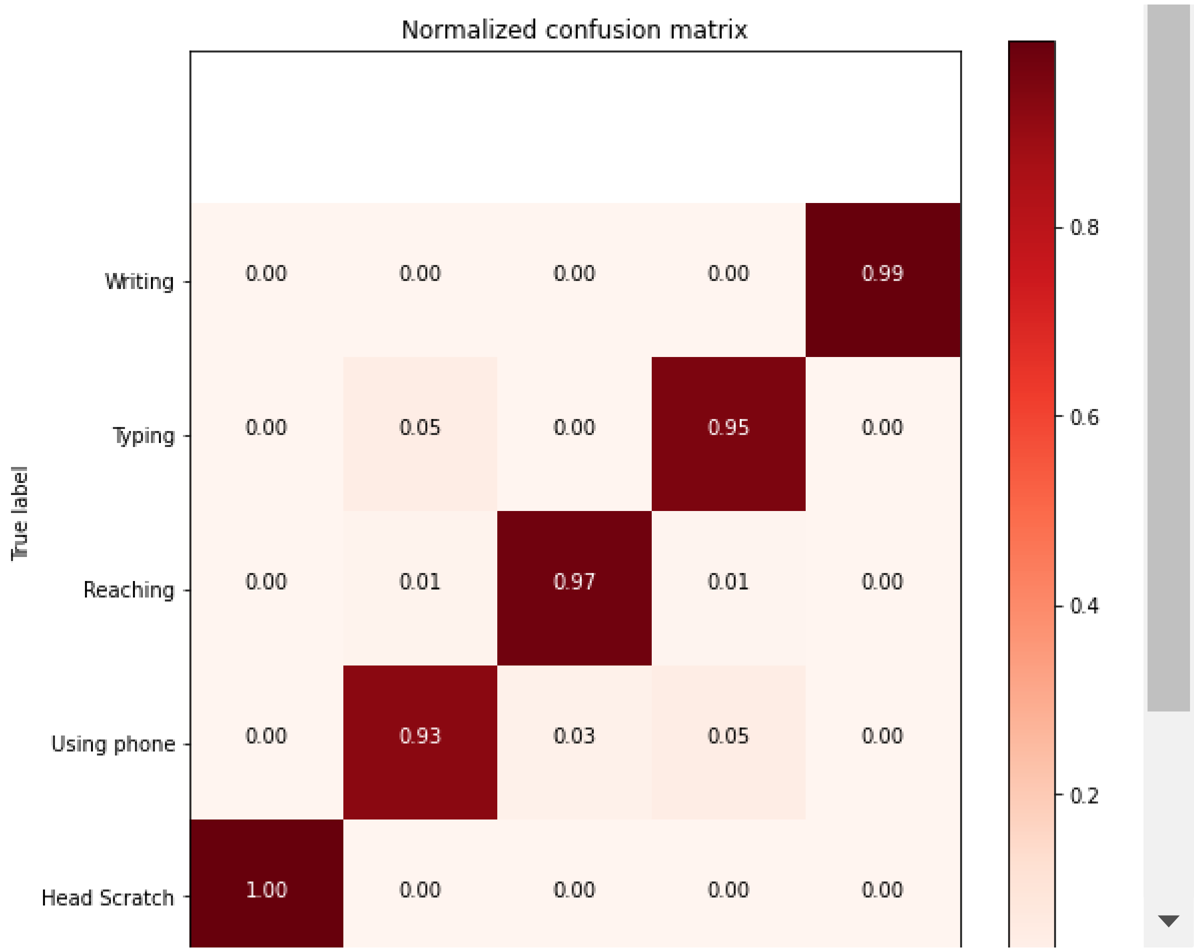

```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.99      0.99      0.99       679
           2       0.90      0.73      0.81       608
           3       0.92      0.96      0.94       552
           4       0.81      0.95      0.88       597
           5       1.00      0.98      0.99       599

    accuracy                           0.92      3035
   macro avg       0.93      0.92      0.92      3035
weighted avg       0.93      0.92      0.92      3035

|      Best Estimator     |

        DecisionTreeClassifier(max_depth=9)

|Best parameters|
        Parameters of best estimator :

        {'max_depth': 9}

|   No of CrossValidation sets   |

        Total numbre of cross validation sets: 5
```

```
|        Best Score       |

Average Cross Validate scores of best estimator :

0.9170605451659817
```

In [62]:

```
#Random Forest Classifier for non-hand to mouth movements
from sklearn.ensemble import RandomForestClassifier
params = {'n_estimators': np.arange(10,201,20), 'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=params, n_jobs=-1)
rfc_grid_results = perform_model(rfc_grid, X_train1, y_train1, X_test1, y_test1, class_labe
print_grid_search_attributes(rfc_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:49.992522


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.080999


|Accuracy|

    0.9693574958813839


|Confusion Matrix|

 [[677   2   0   0   0]
 [  1 563  16  28   0]
 [  2   8 538   3   1]
 [  0  27   1 569   0]
 [  1   1   1   1 595]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```




```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.99      1.00      1.00       679
           2       0.94      0.93      0.93       608
           3       0.97      0.97      0.97       552
           4       0.95      0.95      0.95       597
           5       1.00      0.99      1.00       599

    accuracy                           0.97      3035
   macro avg       0.97      0.97      0.97      3035
weighted avg       0.97      0.97      0.97      3035

|      Best Estimator     |

        RandomForestClassifier(max_depth=13, n_estimators=190)

|Best parameters|
        Parameters of best estimator :

        {'max_depth': 13, 'n_estimators': 190}

|   No of CrossValidation sets   |

        Total numbre of cross validation sets: 5

|       Best Score        |

        Average Cross Validate scores of best estimator :

        0.9660548183282944
```

In [63]:

```
#Neural Network for non hand to mouth gestures
import numpy as np
SEED = 1337
np.random.seed(SEED)
tf.random.set_seed(SEED)
NONHTMGESTURES = [
    "nonhtmallgesturesfinal"

]

SAMPLES_PER_NONHTMGESTURE = 119
NUM_NONHTMGESTURES = len(GESTURES)

ONE_HOT_ENCODED_NONHTMGESTURES = np.eye(NUM_NONHTMGESTURES)
inputsnonhtm = []
outputsnonhtm = []

for nonhtmgesture_index in range(NUM_NONHTMGESTURES):
  nonhtmgesture = NONHTMGESTURES[nonhtmgesture_index]
  print(f"Processing index {nonhtmgesture_index} for nonhtmgesture '{nonhtmgesture}'.")

  output = ONE_HOT_ENCODED_NONHTMGESTURES[nonhtmgesture_index]

  df = pd.read_csv(nonhtmgesture + ".csv", low_memory=False)

  num_recordings = int(df.shape[0] / SAMPLES_PER_NONHTMGESTURE)

  print(f"\tThere are {num_recordings} recordings of the {nonhtmgesture} gesture.")

  for i in range(num_recordings):
    tensor = []
    for j in range(SAMPLES_PER_NONHTMGESTURE):
      index = i * SAMPLES_PER_NONHTMGESTURE + j

      tensor += [
          (df['aX'][index] + 4) / 8,
          (df['aY'][index] + 4) / 8,
          (df['aZ'][index] + 4) / 8,
          (df['gX'][index] + 2000) / 4000,
          (df['gY'][index] + 2000) / 4000,
          (df['gZ'][index] + 2000) / 4000
      ]

    inputsnonhtm.append(tensor)
    outputsnonhtm.append(output)

inputsnonhtm = np.array(inputsnonhtm)
outputsnonhtm= np.array(outputsnonhtm)
```

```
Processing index 0 for nonhtmgesture 'nonhtmallgesturesfinal'.
        There are 102 recordings of the nonhtmallgesturesfinal gesture.
```

In [64]:

```
num_inputsnonhtm = len(inputsnonhtm)
randomizenonhtm = np.arange(num_inputsnonhtm)
np.random.shuffle(randomizenonhtm)

inputsnonhtm = inputsnonhtm[randomizenonhtm]
outputsnonhtm = outputsnonhtm[randomizenonhtm]

TRAIN_SPLITNONHTM = int(0.6 * num_inputsnonhtm)
TEST_SPLITNONHTM = int(0.2 * num_inputsnonhtm + TRAIN_SPLITNONHTM)

inputs_train_nonhtm, inputs_test_nonhtm, inputs_validate_nnhtm = np.split(inputsnonhtm, [TR
outputs_train_nonhtm, outputs_test_nonhtm, outputs_validate_nonhtm = np.split(outputsnonhtm
```

In [65]:

```
from tensorflow import keras
from tensorflow.keras import layers
```

In [66]:

```
model_non = tf.keras.Sequential()
model_non.add(tf.keras.layers.Dense(20, activation='relu'))
model_non.add(tf.keras.layers.Dense(15, activation='relu'))
model_non.add(tf.keras.layers.Dense(NUM_GESTURES, activation='softmax'))
model_non.compile(optimizer='rmsprop', loss='mse', metrics=['accuracy'])
history_non = model.fit(X_train1, y_train1, epochs=600, batch_size=1, validation_data=(X_te
```

```
9103/9103 [==============================] - 9s 999us/step - loss: 5.8911
- mae: 1.9665 - accuracy: 0.2130 - val_loss: 5.8560 - val_mae: 1.9437 - v
al_accuracy: 0.2237
Epoch 597/600
9103/9103 [==============================] - 9s 992us/step - loss: 5.8911
- mae: 1.9665 - accuracy: 0.2130 - val_loss: 5.8560 - val_mae: 1.9437 - v
al_accuracy: 0.2237
Epoch 598/600
9103/9103 [==============================] - 9s 984us/step - loss: 5.8911
- mae: 1.9665 - accuracy: 0.2130 - val_loss: 5.8560 - val_mae: 1.9437 - v
al_accuracy: 0.2237
Epoch 599/600
9103/9103 [==============================] - 9s 984us/step - loss: 5.8911
- mae: 1.9665 - accuracy: 0.2130 - val_loss: 5.8560 - val_mae: 1.9437 - v
al_accuracy: 0.2237
Epoch 600/600
9103/9103 [==============================] - 9s 985us/step - loss: 5.8911
- mae: 1.9665 - accuracy: 0.2130 - val_loss: 5.8560 - val_mae: 1.9437 - v
al_accuracy: 0.2237
```

Both Hand to mouth and non-hand to mouth

In [67]:

```
#Reading in  non-hand to mouth gestures
allgestures = pd.read_csv('allgestures.csv')
allgestures.head()
#print( allgestures.shape)
```

Out[67]:

	aX	aY	aZ	gX	gY	gZ	gesture
0	0.272	-1.297	0.457	69.519	-38.818	12.390	1
1	0.257	-1.252	0.480	65.063	-39.307	18.494	1
2	0.266	-1.249	0.483	62.073	-38.452	25.940	1
3	0.298	-1.223	0.468	51.880	-34.729	41.260	1
4	0.299	-1.164	0.462	47.791	-32.959	48.157	1

In [68]:

```
#Splitting gesture data and gesture classification
X2 = allgestures.drop(['gesture'], axis=1)
y2 = allgestures.gesture
print(X2.shape, y2.shape)
```

```
(24157, 6) (24157,)
```

In [69]:

```
#splitting X and y into training and testing sets for non-hand to mouth gestures
from sklearn.model_selection import train_test_split
X_train2, X_test2, y_train2, y_test2 = train_test_split(X2, y2, test_size=0.25, random_stat
print('X_train2 and y_train2 : ({},{})'.format(X_train2.shape, y_train2.shape))
print('X_test2  and y_test2  : ({},{})'.format(X_test2.shape, y_test2.shape))
```

```
X_train2 and y_train2 : ((18117, 6),(18117,))
X_test2  and y_test2  : ((6040, 6),(6040,))
```

In [70]:

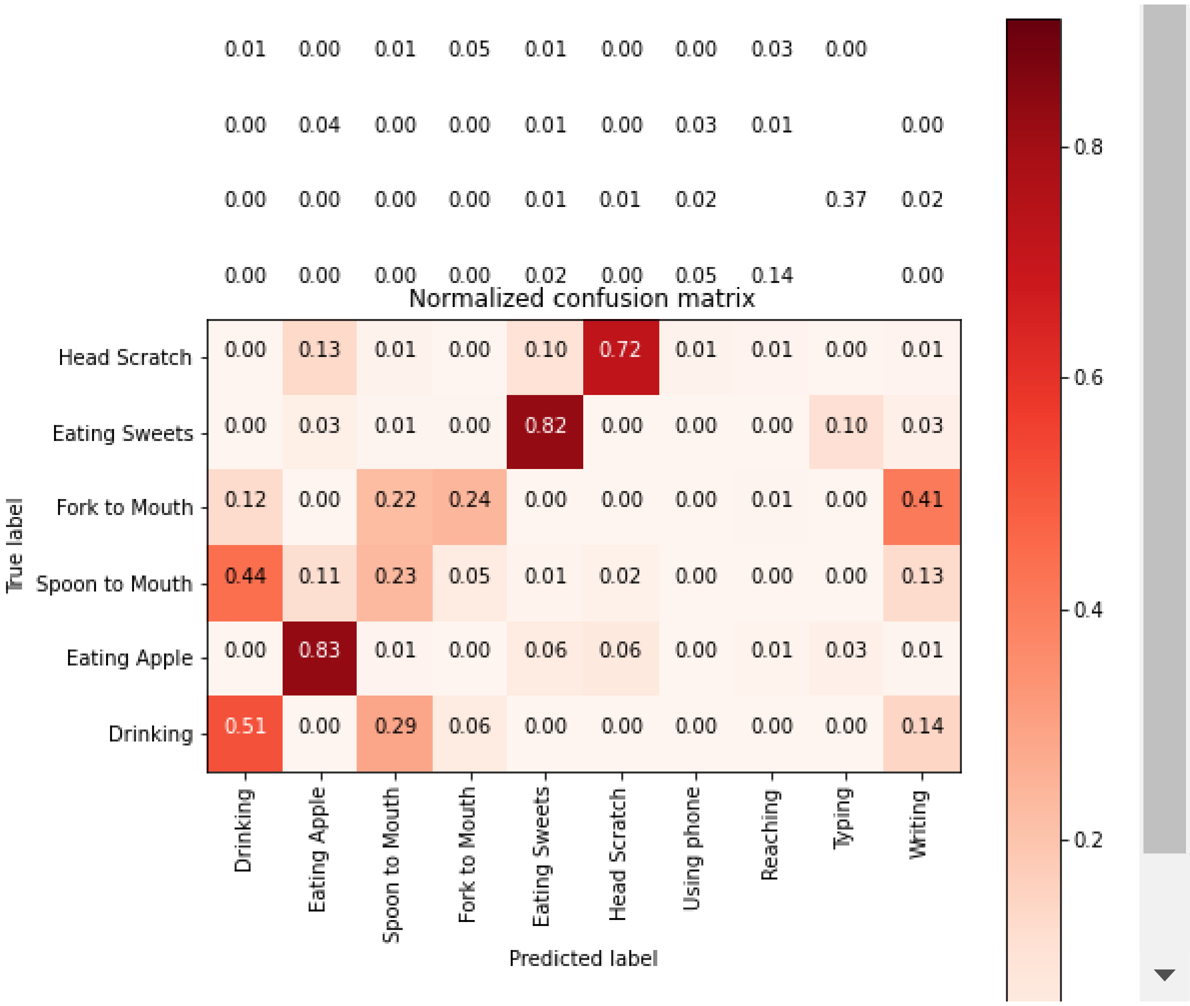
```
#Generating labels for non-hand to mouth gesture
all_labels = [ "Drinking", "Eating Apple", "Spoon to Mouth", "Fork to Mouth", "Eating Sweet
```

In [71]:

```
# Grid search for non-hand to mouth movements
parameters = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1']}
log_reg = linear_model.LogisticRegression()
log_reg_grid = GridSearchCV(log_reg, param_grid=parameters, cv=3, verbose=1, n_jobs=-1)
log_reg_grid_results =  perform_model(log_reg_grid, X_train2, y_train2, X_test2, y_test2, c
```

```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits

c:\Users\ronan\AppData\Local\Programs\Python\Python310\lib\site-packages\skl
earn\model_selection\_validation.py:372: FitFailedWarning:
18 fits failed out of a total of 36.
The score on these train-test partitions for these parameters will be set to
nan.
If these failures are not expected, you can try to debug them by setting err
or_score='raise'.

Below are more details about the failures:
----------------------------------------------------------------------------
----
18 fits failed with the following error:
Traceback (most recent call last):
  File "c:\Users\ronan\AppData\Local\Programs\Python\Python310\lib\site-pack
ages\sklearn\model_selection\_validation.py", line 680, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "c:\Users\ronan\AppData\Local\Programs\Python\Python310\lib\site-pack
ages\sklearn\linear_model\_logistic.py", line 1461, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "c:\Users\ronan\AppData\Local\Programs\Python\Python310\lib\site-pack
ages\sklearn\linear_model\_logistic.py", line 447, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 pena
lty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
c:\Users\ronan\AppData\Local\Programs\Python\Python310\lib\site-packages\skl
earn\model_selection\_search.py:969: UserWarning: One or more of the test sc
ores are non-finite: [0.48672518        nan 0.5427499         nan 0.55489319
nan
 0.54837997        nan 0.57001711        nan 0.56256555        nan]
  warnings.warn(
c:\Users\ronan\AppData\Local\Programs\Python\Python310\lib\site-packages\skl
earn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to conv
erge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  n_iter_i = _check_optimize_result(
C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```

```
Done


training_time(HH:MM:SS.ms) - 0:00:08.459100


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.002000


|Accuracy|

    0.5602649006622517


|Confusion Matrix|

 [[326   0 181  36   0   0   0   0   0  92]
 [  0 437   4   0  30  34   0   6  14   3]
 [317  83 168  36   8  17   0   0   2  91]
 [ 76   0 136 146   0   0   0   4   0 248]
 [  1  18   3   2 456   0   0   0  58  17]
 [  0  90  10   0  67 491  10   5   2   7]
 [  0   2   0   0  13   1  30  81 463   2]
 [  0   0   0   1   6   6  15 351 227  14]
 [  0  23   0   0   8   0  15   3 495   0]
 [  5   0   8  29   7   0   0  18   1 484]]
```

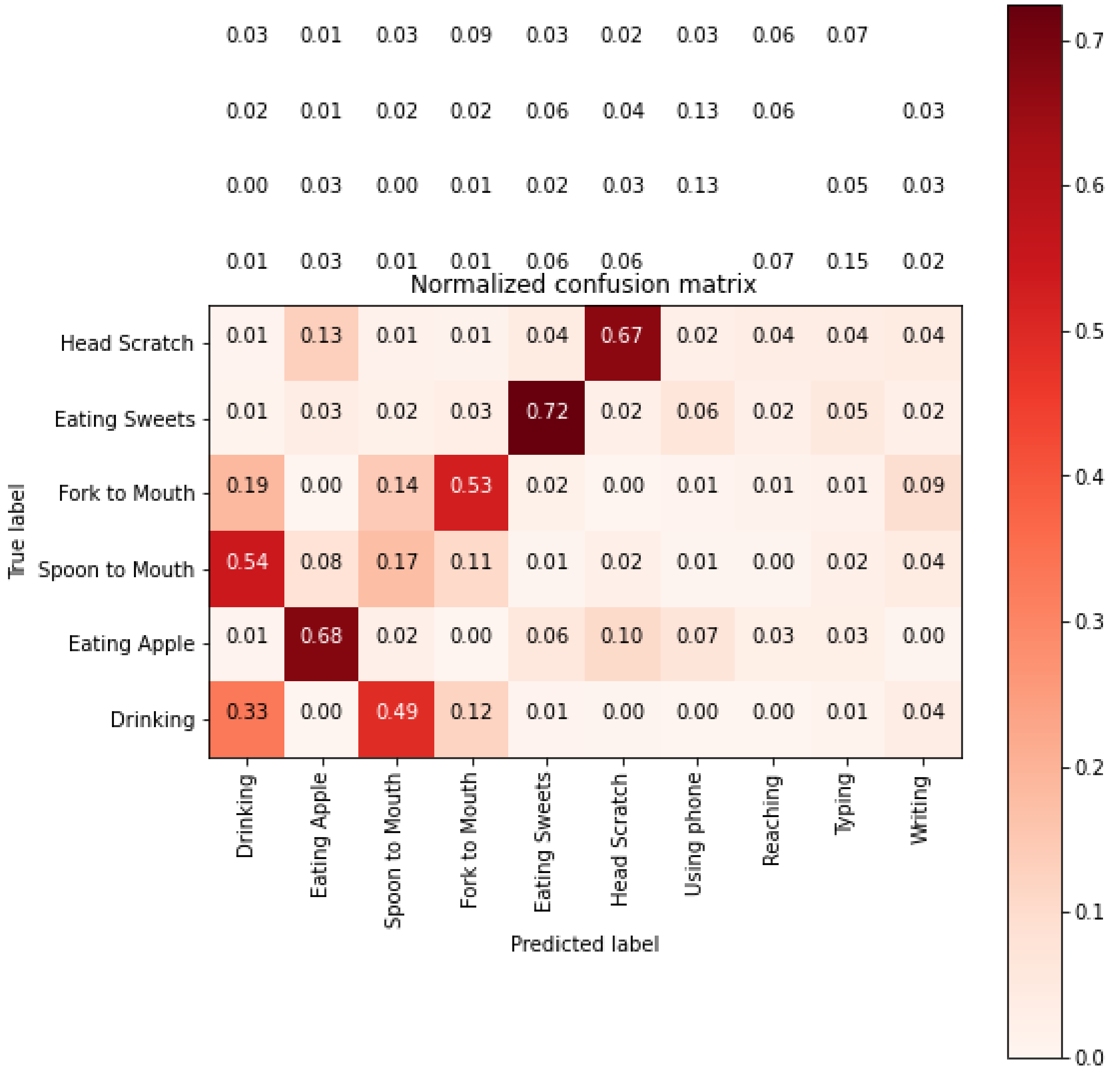



```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.45      0.51      0.48       635
           2       0.67      0.83      0.74       528
           3       0.33      0.23      0.27       722
           4       0.58      0.24      0.34       610
           5       0.77      0.82      0.79       555
           6       0.89      0.72      0.80       682
           7       0.43      0.05      0.09       592
           8       0.75      0.57      0.65       620
           9       0.39      0.91      0.55       544
          10       0.51      0.88      0.64       552

    accuracy                           0.56      6040
   macro avg       0.58      0.58      0.53      6040
weighted avg       0.58      0.56      0.53      6040
```

In [72]:

```
#KNN for non-hand to mouth movements
from sklearn.neighbors import KNeighborsClassifier

#knn
# start Grid search
parameters = {'n_neighbors': [1, 10, 11, 20, 30]}
log_knn = KNeighborsClassifier(n_neighbors=19)

log_knn_grid = GridSearchCV(log_knn, param_grid=parameters, cv=3, verbose=1, n_jobs=-1)
log_knn_grid_results =  perform_model(log_knn_grid, X_train2, y_train2, X_test2, y_test2, c
```

```
training the model..
Fitting 3 folds for each of 5 candidates, totalling 15 fits
Done


training_time(HH:MM:SS.ms) - 0:00:00.868000


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.161999


|Accuracy|

    0.5493377483443709


|Confusion Matrix|

 [[210   0 311  77   4   2   0   1   7  23]
 [  3 360  13   0  32  55  35  14  14   2]
 [392  56 125  77   4  18   4   3  16  27]
 [113   0  88 321  11   1   4   7   9  56]
 [  5  19  10  17 402  12  36  12  29  13]
 [  4  88  10   8  26 456  16  24  24  26]
 [  4  20   4   5  35  37 345  42  87  13]
 [  3  21   3   9  11  18  79 424  33  19]
 [ 13   7  10   9  34  23  70  30 331  17]
 [ 17   3  19  49  17  13  17  34  39 344]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```

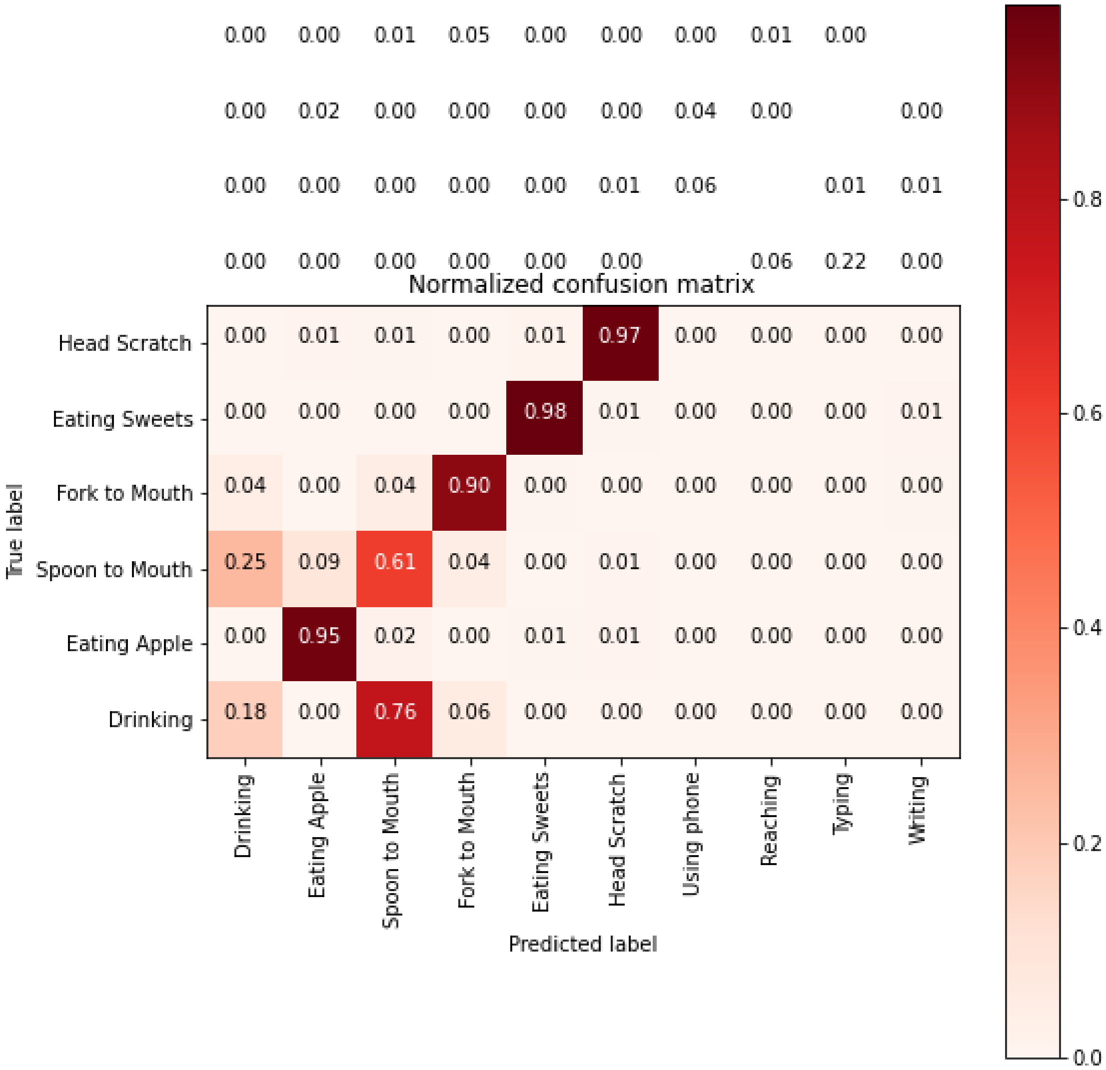



```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.27      0.33      0.30       635
           2       0.63      0.68      0.65       528
           3       0.21      0.17      0.19       722
           4       0.56      0.53      0.54       610
           5       0.70      0.72      0.71       555
           6       0.72      0.67      0.69       682
           7       0.57      0.58      0.58       592
           8       0.72      0.68      0.70       620
           9       0.56      0.61      0.58       544
          10       0.64      0.62      0.63       552

    accuracy                           0.55      6040
   macro avg       0.56      0.56      0.56      6040
weighted avg       0.55      0.55      0.55      6040
```

In [73]:

```
#Decision Tree for hand to mouth movements
from sklearn.tree import DecisionTreeClassifier
parameters = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=parameters, n_jobs=-1)
dt_grid_results = perform_model(dt_grid, X_train2, y_train2, X_test2, y_test2, class_labels
print_grid_search_attributes(dt_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:00.354396


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.001961


|Accuracy|

    0.7978476821192053


|Confusion Matrix|

 [[114   0 484  37   0   0   0   0   0   0]
 [  0 504  12   0   3   5   2   1   1   0]
 [182  63 437  31   0   8   0   0   0   1]
 [ 25   0  27 551   3   0   0   1   0   3]
 [  0   2   0   1 544   3   0   0   0   5]
 [  0   7   5   0   8 659   1   0   0   2]
 [  0   1   0   0   0   0 424  35 131   1]
 [  0   0   0   0   0   4  36 567   8   5]
 [  0   9   0   0   2   0  21   1 510   1]
 [  0   1   3  28   2   0   2   7   0 509]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```



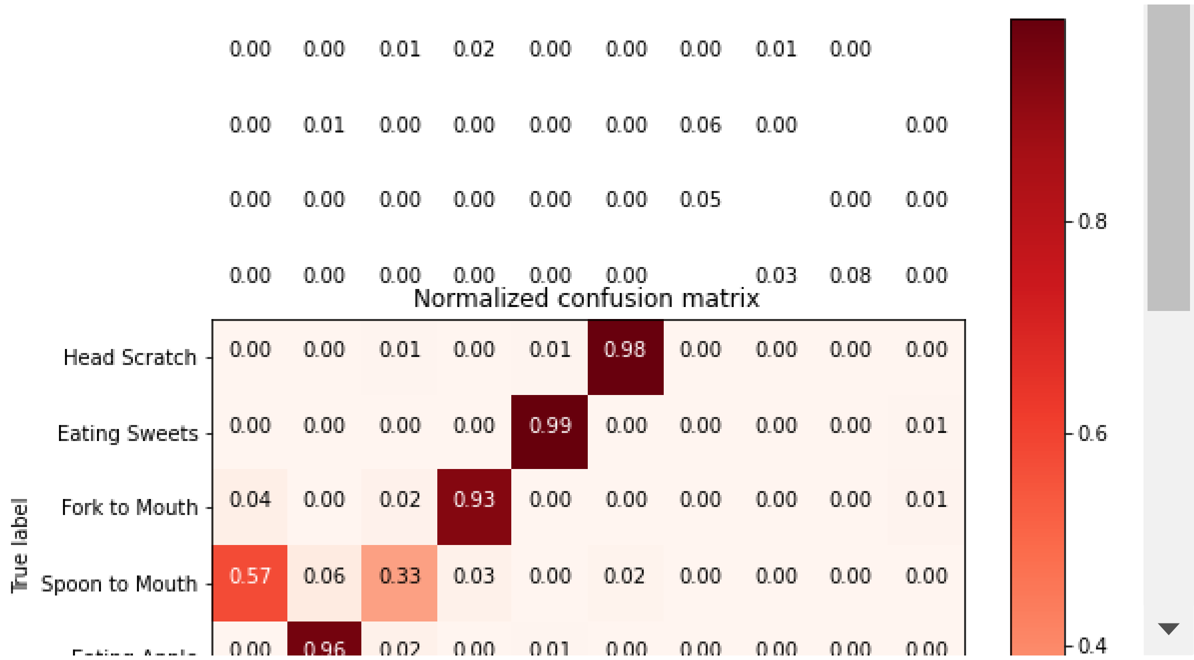

```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.36      0.18      0.24       635
           2       0.86      0.95      0.90       528
           3       0.45      0.61      0.52       722
           4       0.85      0.90      0.88       610
           5       0.97      0.98      0.97       555
           6       0.97      0.97      0.97       682
           7       0.87      0.72      0.79       592
           8       0.93      0.91      0.92       620
           9       0.78      0.94      0.85       544
          10       0.97      0.92      0.94       552

    accuracy                           0.80      6040
   macro avg       0.80      0.81      0.80      6040
weighted avg       0.79      0.80      0.79      6040

|      Best Estimator      |

        DecisionTreeClassifier(max_depth=9)

|Best parameters|
        Parameters of best estimator :

        {'max_depth': 9}

|   No of CrossValidation sets   |
```

```
Total numbre of cross validation sets: 5

|        Best Score       |

Average Cross Validate scores of best estimator :

0.8067006596925822
```

In [74]:

```
#Random Forest Classifier for non-hand to mouth movements
from sklearn.ensemble import RandomForestClassifier
params = {'n_estimators': np.arange(10,201,20), 'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=params, n_jobs=-1)
rfc_grid_results = perform_model(rfc_grid, X_train2, y_train2, X_test2, y_test2, class_labe
print_grid_search_attributes(rfc_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:01:54.323775


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.012990


|Accuracy|

    0.8069536423841059


|Confusion Matrix|

 [[187   0 426  22   0   0   0   0   0   0]
 [  0 506  13   0   4   2   1   0   1   1]
 [414  42 236  19   0  11   0   0   0   0]
 [ 22   0  13 568   0   0   0   0   0   7]
 [  0   0   1   1 549   0   0   0   0   4]
 [  0   1   4   1   4 670   1   0   0   1]
 [  0   0   0   0   0   1 530  16  45   0]
 [  0   0   0   0   0   2  29 587   1   1]
 [  0   5   0   0   0   1  30   0 508   0]
 [  1   0   3  10   1   0   0   4   0 533]]

C:\Users\ronan\AppData\Local\Temp\ipykernel_19964\3379774174.py:49: Matplotl
ibDeprecationWarning: The 'b' parameter of grid() has been renamed 'visible'
since Matplotlib 3.5; support for the old name will be dropped two minor rel
eases later.
  plt.grid(b=False)
```




```
|Classifiction Report|
              precision    recall  f1-score   support

           1       0.30      0.29      0.30       635
           2       0.91      0.96      0.94       528
           3       0.34      0.33      0.33       722
           4       0.91      0.93      0.92       610
           5       0.98      0.99      0.99       555
           6       0.98      0.98      0.98       682
           7       0.90      0.90      0.90       592
           8       0.97      0.95      0.96       620
           9       0.92      0.93      0.92       544
          10       0.97      0.97      0.97       552

    accuracy                           0.81      6040
   macro avg       0.82      0.82      0.82      6040
weighted avg       0.80      0.81      0.81      6040

|      Best Estimator     |

        RandomForestClassifier(max_depth=11, n_estimators=10)

|Best parameters|
        Parameters of best estimator :

        {'max_depth': 11, 'n_estimators': 10}

|   No of CrossValidation sets   |

        Total numbre of cross validation sets: 5

|        Best Score        |

        Average Cross Validate scores of best estimator :

        0.8179604458637147
```

In [75]:

```
import numpy as np
SEED = 1337
np.random.seed(SEED)
tf.random.set_seed(SEED)
ALLGESTURES = [
    "allgestures"
]

SAMPLES_PER_ALLGESTURES = 119
NUM_ALLGESTURES = len(ALLGESTURES)

ONE_HOT_ENCODED_ALLGESTURES = np.eye(NUM_ALLGESTURES)
inputsall = []
outputsall = []

for allgestures_index in range(NUM_ALLGESTURES):
  allgestures = ALLGESTURES[allgestures_index]
  print(f"Processing index {allgestures_index} for gesture '{allgestures}'.")

  output = ONE_HOT_ENCODED_ALLGESTURES[allgestures_index]

  df = pd.read_csv(allgestures + ".csv", low_memory=False)

  num_recordings = int(df.shape[0] / SAMPLES_PER_ALLGESTURES)

  print(f"\tThere are {num_recordings} recordings of the {allgestures} gestures.")

  for i in range(num_recordings):
    tensor = []
    for j in range(SAMPLES_PER_ALLGESTURES):
      index = i * SAMPLES_PER_ALLGESTURES + j

      tensor += [
          (df['aX'][index] + 4) / 8,
          (df['aY'][index] + 4) / 8,
          (df['aZ'][index] + 4) / 8,
          (df['gX'][index] + 2000) / 4000,
          (df['gY'][index] + 2000) / 4000,
          (df['gZ'][index] + 2000) / 4000
      ]

    inputsall.append(tensor)
    outputsall.append(output)

inputsall = np.array(inputsall)
outputsall = np.array(outputsall)
```

```
Processing index 0 for gesture 'allgestures'.
        There are 203 recordings of the allgestures gestures.
```

In [76]:

```
num_inputsall = len(inputsall)
randomizeall = np.arange(num_inputsall)
np.random.shuffle(randomizeall)

inputsall = inputsall[randomizeall]
outputsall = outputsall[randomizeall]

TRAIN_SPLITALL = int(0.6 * num_inputsall)
TEST_SPLITALL = int(0.2 * num_inputsall + TRAIN_SPLITALL)

inputs_train_all, inputs_test_all, inputs_validate_all = np.split(inputsall, [TRAIN_SPLITAL
outputs_train_all, outputs_test_all, outputs_validate_all = np.split(outputsall, [TRAIN_SPL
```

In [77]:

```
from tensorflow import keras
from tensorflow.keras import layers
```

In [78]:

```
model_all = tf.keras.Sequential()
model_all.add(tf.keras.layers.Dense(20, activation='relu'))
model_all.add(tf.keras.layers.Dense(15, activation='relu'))
model_all.add(tf.keras.layers.Dense(NUM_GESTURES, activation='softmax'))
model_all.compile(optimizer='rmsprop', loss='mse', metrics=['accuracy'])
history_all = model.fit(X_train2, y_train2, epochs=600, batch_size=1, validation_data=(X_te
```

```
Epoch 1/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 2/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 3/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 4/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 5/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 6/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 7/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 8/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 9/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 10/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 11/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 12/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 13/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
```

```
- val_accuracy: 0.1051
Epoch 14/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 15/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 16/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 17/600
18117/18117 [==============================] - 25s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 18/600
18117/18117 [==============================] - 26s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 19/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 20/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 21/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 22/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 23/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 24/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 25/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 26/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 27/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 28/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
```

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Epoch 29/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 30/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 31/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 32/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 33/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 34/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 35/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 36/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 37/600
18117/18117 [==============================] - 26s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 38/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 39/600
18117/18117 [==============================] - 18s 999us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 40/600
18117/18117 [==============================] - 18s 987us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 41/600
18117/18117 [==============================] - 18s 982us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 42/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 43/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 44/600
```

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18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 45/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 46/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 47/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 48/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 49/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 50/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 51/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 52/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 53/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 54/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 55/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 56/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 57/600
18117/18117 [==============================] - 18s 983us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 58/600
18117/18117 [==============================] - 17s 961us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 59/600
18117/18117 [==============================] - 17s 960us/step - loss: 28.
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6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 60/600
18117/18117 [==============================] - 17s 962us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 61/600
18117/18117 [==============================] - 17s 958us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 62/600
18117/18117 [==============================] - 17s 963us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 63/600
18117/18117 [==============================] - 17s 955us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 64/600
18117/18117 [==============================] - 18s 976us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 65/600
18117/18117 [==============================] - 17s 959us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 66/600
18117/18117 [==============================] - 17s 957us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 67/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 68/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 69/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 70/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 71/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 72/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 73/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 74/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
```

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- val_accuracy: 0.1051
Epoch 75/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 76/600
18117/18117 [==============================] - 18s 994us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 77/600
18117/18117 [==============================] - 17s 961us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 78/600
18117/18117 [==============================] - 17s 930us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 79/600
18117/18117 [==============================] - 17s 958us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 80/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 81/600
18117/18117 [==============================] - 17s 958us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 82/600
18117/18117 [==============================] - 18s 978us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 83/600
18117/18117 [==============================] - 18s 985us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 84/600
18117/18117 [==============================] - 17s 954us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 85/600
18117/18117 [==============================] - 17s 933us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 86/600
18117/18117 [==============================] - 17s 924us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 87/600
18117/18117 [==============================] - 17s 965us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 88/600
18117/18117 [==============================] - 17s 952us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 89/600
18117/18117 [==============================] - 17s 959us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
```

```
Epoch 90/600
18117/18117 [==============================] - 18s 994us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 91/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 92/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 93/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 94/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 95/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 96/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 97/600
18117/18117 [==============================] - 17s 936us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 98/600
18117/18117 [==============================] - 17s 932us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 99/600
18117/18117 [==============================] - 17s 943us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 100/600
18117/18117 [==============================] - 18s 989us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 101/600
18117/18117 [==============================] - 18s 976us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 102/600
18117/18117 [==============================] - 18s 978us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 103/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 104/600
18117/18117 [==============================] - 18s 981us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 105/600
```

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18117/18117 [==============================] - 17s 959us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 106/600
18117/18117 [==============================] - 17s 930us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 107/600
18117/18117 [==============================] - 18s 995us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 108/600
18117/18117 [==============================] - 17s 947us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 109/600
18117/18117 [==============================] - 18s 969us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 110/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 111/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 112/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 113/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 114/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 115/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 116/600
18117/18117 [==============================] - 18s 991us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 117/600
18117/18117 [==============================] - 17s 950us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 118/600
18117/18117 [==============================] - 17s 924us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 119/600
18117/18117 [==============================] - 18s 975us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 120/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
```

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54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 121/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 122/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 123/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 124/600
18117/18117 [==============================] - 18s 970us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 125/600
18117/18117 [==============================] - 18s 967us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 126/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 127/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 128/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 129/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 130/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 131/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 132/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 133/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 134/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 135/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
```

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- val_accuracy: 0.1051
Epoch 136/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 137/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 138/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 139/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 140/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 141/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 142/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 143/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 144/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 145/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 146/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 147/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 148/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 149/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 150/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
```

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Epoch 151/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 152/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 153/600
18117/18117 [==============================] - 30s 2ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 154/600
18117/18117 [==============================] - 68s 4ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 155/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 156/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 157/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 158/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 159/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 160/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 161/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 162/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 163/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 164/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 165/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 166/600
```

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18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 167/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 168/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 169/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 170/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 171/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 172/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 173/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 174/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 175/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 176/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 177/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 178/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 179/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 180/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 181/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
```

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54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 182/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 183/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 184/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 185/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 186/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 187/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 188/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 189/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 190/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 191/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 192/600
18117/18117 [==============================] - 26s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 193/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 194/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 195/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 196/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
```

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- val_accuracy: 0.1051
Epoch 197/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 198/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 199/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 200/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 201/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 202/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 203/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 204/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 205/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 206/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 207/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 208/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 209/600
18117/18117 [==============================] - 18s 973us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 210/600
18117/18117 [==============================] - 18s 997us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 211/600
18117/18117 [==============================] - 18s 990us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
```

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Epoch 212/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 213/600
18117/18117 [==============================] - 18s 994us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 214/600
18117/18117 [==============================] - 18s 991us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 215/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 216/600
18117/18117 [==============================] - 18s 995us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 217/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 218/600
18117/18117 [==============================] - 18s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 219/600
18117/18117 [==============================] - 18s 992us/step - loss: 28.
6754 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.41
13 - val_accuracy: 0.1051
Epoch 220/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 221/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 222/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 223/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 224/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 225/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 226/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 227/600
```

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18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 228/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 229/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 230/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 231/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 232/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 233/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 234/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 235/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 236/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 237/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 238/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 239/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 240/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 241/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 242/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
```

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54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 243/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 244/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 245/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 246/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 247/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 248/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 249/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 250/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 251/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 252/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 253/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 254/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 255/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 256/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 257/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
```

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- val_accuracy: 0.1051
Epoch 258/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 259/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 260/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 261/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 262/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 263/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 264/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 265/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 266/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 267/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 268/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 269/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 270/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 271/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 272/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
```

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Epoch 273/600
18117/18117 [==============================] - 38s 2ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 274/600
18117/18117 [==============================] - 48s 3ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 275/600
18117/18117 [==============================] - 53s 3ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 276/600
18117/18117 [==============================] - 34s 2ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 277/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 278/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 279/600
18117/18117 [==============================] - 19s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 280/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 281/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 282/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 283/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 284/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 285/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 286/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 287/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 288/600
```

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18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 289/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 290/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 291/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 292/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 293/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 294/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 295/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 296/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 297/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 298/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 299/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 300/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 301/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 302/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 303/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
```

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54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 304/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 305/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 306/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 307/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 308/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 309/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 310/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 311/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 312/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 313/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 314/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 315/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 316/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 317/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 318/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
```

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- val_accuracy: 0.1051
Epoch 319/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 320/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 321/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 322/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 323/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 324/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 325/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 326/600
18117/18117 [==============================] - 28s 2ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 327/600
18117/18117 [==============================] - 49s 3ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 328/600
18117/18117 [==============================] - 36s 2ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 329/600
18117/18117 [==============================] - 27s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 330/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 331/600
18117/18117 [==============================] - 26s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 332/600
18117/18117 [==============================] - 26s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 333/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
```

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Epoch 334/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 335/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 336/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 337/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 338/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 339/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 340/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 341/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 342/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 343/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 344/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 345/600
18117/18117 [==============================] - 21s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 346/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 347/600
18117/18117 [==============================] - 23s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 348/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 349/600
```

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18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 350/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 351/600
18117/18117 [==============================] - 25s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 352/600
18117/18117 [==============================] - 25s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 353/600
18117/18117 [==============================] - 24s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 354/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 355/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 356/600
18117/18117 [==============================] - 20s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 357/600
18117/18117 [==============================] - 22s 1ms/step - loss: 28.67
54 - mae: 4.5352 - accuracy: 0.0963 - val_loss: 27.4927 - val_mae: 4.4113
- val_accuracy: 0.1051
Epoch 358/600
18087/18117 [============================>.] - ETA: 0s - loss: 28.6842 -
 mae: 4.5360 - accuracy: 0.0963
```