In [2]:
```python
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
```

In [3]:
```python
hea = pd.read_csv("C:\\Users\Ritik\OneDrive - Indian Institute of Technology (BHU)
hea.head(5)
```

Out[3]:

	Alloy ID	Alloy	Al	Co	Cr	Fe	Ni	Cu	Mn	Ti	...	Annealing_Temp	Anı
0	Alloy 0000	Al0.5NbTaTiV	0.111111	0.0	0.0	0.0	0.0	0.0	0.0	0.222222	...	NaN	
1	Alloy 0001	Al0.75MoNbTiV	0.157895	0.0	0.0	0.0	0.0	0.0	0.0	0.210526	...	NaN	
2	Alloy 0002	Al0.25MoNbTiV	0.058824	0.0	0.0	0.0	0.0	0.0	0.0	0.235294	...	NaN	
3	Alloy 0003	Al0.25NbTaTiV	0.058824	0.0	0.0	0.0	0.0	0.0	0.0	0.235294	...	NaN	
4	Alloy 0004	Al0.2MoTaTiV	0.047619	0.0	0.0	0.0	0.0	0.0	0.0	0.238095	...	NaN	

5 rows × 51 columns

In [4]:
```python
hea.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1360 entries, 0 to 1359
Data columns (total 51 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   Alloy ID               1360 non-null   object 
 1   Alloy                  1360 non-null   object 
 2   Al                     1360 non-null   float64
 3   Co                     1360 non-null   float64
 4   Cr                     1360 non-null   float64
 5   Fe                     1360 non-null   float64
 6   Ni                     1360 non-null   float64
 7   Cu                     1360 non-null   float64
 8   Mn                     1360 non-null   float64
 9   Ti                     1360 non-null   float64
 10  V                      1360 non-null   float64
 11  Nb                     1360 non-null   float64
 12  Mo                     1360 non-null   float64
 13  Zr                     1360 non-null   float64
 14  Hf                     1360 non-null   float64
 15  Ta                     1360 non-null   float64
 16  W                      1360 non-null   float64
 17  C                      1360 non-null   float64
 18  Mg                     1360 non-null   float64
 19  Zn                     1360 non-null   float64
 20  Si                     1360 non-null   float64
 21  Re                     1360 non-null   float64
 22  N                      1360 non-null   float64
 23  Sc                     1360 non-null   int64  
 24  Li                     1360 non-null   float64
 25  Sn                     1360 non-null   float64
 26  Be                     1360 non-null   int64  
 27  Num_of_Elem            1360 non-null   int64  
 28  Density_calc           1355 non-null   float64
 29  dHmix                  1360 non-null   float64
 30  dSmix                  1360 non-null   float64
 31  dGmix                  1360 non-null   float64
 32  Tm                     1360 non-null   float64
 33  n.Para                 1359 non-null   float64
 34  Atom.Size.Diff         1360 non-null   float64
 35  Elect.Diff             1360 non-null   float64
 36  VEC                    1360 non-null   float64
 37  Sythesis_Route         1360 non-null   object 
 38  Hot-Cold_Working       444 non-null    object 
 39  Homogenization_Temp    571 non-null    float64
 40  Homogenization_Time    561 non-null    float64
 41  Annealing_Temp         603 non-null    object 
 42  Annealing_Time_(min)   594 non-null    float64
 43  Quenching              269 non-null    object 
 44  HPR                    56 non-null     object 
 45  Microstructure_        1360 non-null   object 
 46  Multiphase             1355 non-null   object 
 47  IM_Structure           432 non-null    object 
 48  Microstructure         1360 non-null   object 
 49  Phases                 1360 non-null   object 
 50  References             1360 non-null   object 
dtypes: float64(35), int64(3), object(13)
memory usage: 542.0+ KB
```

In [5]:
```python
hea.drop(["Hot-Cold_Working", "Homogenization_Temp", "Homogenization_Time", "Anneal
```

In [6]:
```python
hea.corr()
```

Out[6]:

	Al	Co	Cr	Fe	Ni	Cu	Mn	
Al	1.000000	-0.106613	-0.075731	-0.003295	0.001423	0.153287	-0.103176	-0.12290
Co	-0.106613	1.000000	0.671023	0.340902	0.639405	-0.001393	-0.007302	-0.59271
Cr	-0.075731	0.671023	1.000000	0.333622	0.551724	0.063945	0.020042	-0.56581
Fe	-0.003295	0.340902	0.333622	1.000000	0.454811	0.073410	0.499551	-0.63865
Ni	0.001423	0.639405	0.551724	0.454811	1.000000	0.132956	0.132578	-0.62675
Cu	0.153287	-0.001393	0.063945	0.073410	0.132956	1.000000	-0.066844	-0.12310
Mn	-0.103176	-0.007302	0.020042	0.499551	0.132578	-0.066844	1.000000	-0.34614
Ti	-0.122905	-0.592717	-0.565814	-0.638655	-0.626758	-0.123103	-0.346147	1.00000
V	-0.023904	-0.295680	-0.234436	-0.229267	-0.337782	-0.119738	-0.164174	0.25237
Nb	-0.180460	-0.614753	-0.555781	-0.672615	-0.719121	-0.214188	-0.336851	0.67671
Mo	-0.185502	-0.305761	-0.292122	-0.357632	-0.381125	-0.133263	-0.203447	0.14781
Zr	-0.222381	-0.546496	-0.553202	-0.569906	-0.596499	-0.163159	-0.283754	0.77871
Hf	-0.220642	-0.415681	-0.466434	-0.432047	-0.455074	-0.124312	-0.215672	0.49600
Ta	-0.201105	-0.430069	-0.467288	-0.438006	-0.474045	-0.144231	-0.220244	0.32214
W	-0.123663	-0.178559	-0.145675	-0.182975	-0.214086	-0.067145	-0.102531	-0.07999
C	0.013720	0.038243	0.022169	0.046254	-0.004096	-0.032855	0.062405	-0.06463
Mg	0.415349	-0.088405	-0.100301	-0.088625	-0.096775	0.057653	-0.023163	-0.06987
Zn	0.375716	-0.086148	-0.097110	-0.085353	-0.094957	0.043804	-0.029536	-0.06808
Si	0.165690	-0.068039	-0.107736	-0.062490	-0.084836	0.004064	-0.062409	0.01541
Re	-0.031602	-0.050720	-0.058455	-0.052303	-0.055906	-0.017010	-0.025974	0.09543
N	-0.052708	0.344500	0.169282	-0.042019	-0.093245	-0.028370	-0.042609	-0.06686
Sc	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
Li	0.108265	-0.035838	-0.041303	-0.036956	-0.039502	-0.005579	-0.018353	-0.02832
Sn	0.070426	-0.030725	-0.035410	-0.031684	-0.033866	-0.010304	-0.015734	-0.02428
Be	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
Num_of_Elem	0.162035	-0.016855	0.018389	0.106226	0.004995	0.208335	-0.089553	-0.07477
Density_calc	-0.660639	-0.052177	-0.134119	-0.196460	-0.170223	-0.141393	-0.076704	-0.00703
dHmix	-0.394763	-0.109673	-0.078287	-0.086898	-0.242074	0.009566	0.063935	0.09261
dSmix	-0.120716	-0.142931	0.021219	-0.047423	-0.028377	0.220454	-0.134256	0.08588
dGmix	-0.512600	-0.363551	-0.326586	-0.581383	-0.544188	-0.245331	-0.351174	0.45750
Tm	-0.510353	-0.368474	-0.327436	-0.581854	-0.545462	-0.239465	-0.353351	0.45870
n.Para	-0.172708	-0.208215	-0.204755	-0.176140	-0.234820	-0.018734	-0.059201	0.24814
Atom.Size.Diff	0.233805	-0.389222	-0.329589	-0.229042	-0.326863	0.020308	-0.144174	0.36786
Elect.Diff	-0.090902	-0.143713	-0.144202	-0.141632	-0.161087	-0.042298	-0.028063	0.08038
VEC	-0.137902	0.761811	0.672652	0.709095	0.848656	0.237102	0.346421	-0.79795

35 rows × 35 columns

In [7]:
```
hea.drop(["Be", "Sc"] , axis = 1 , inplace = True)
```

In [8]:
```
hea.columns
```

Out[8]:
```
Index(['Alloy ID', 'Alloy ', 'Al', 'Co', 'Cr', 'Fe', 'Ni', 'Cu', 'Mn', 'Ti',
       'V', 'Nb', 'Mo', 'Zr', 'Hf', 'Ta', 'W', 'C', 'Mg', 'Zn', 'Si', 'Re',
       'N', 'Li', 'Sn', 'Num_of_Elem', 'Density_calc', 'dHmix', 'dSmix',
       'dGmix', 'Tm', 'n.Para', 'Atom.Size.Diff', 'Elect.Diff', 'VEC',
       'Sythesis_Route', 'IM_Structure', 'Microstructure', 'Phases'],
      dtype='object')
```

In [9]:
```
hea.drop(["Sythesis_Route", "IM_Structure"] , axis = 1 , inplace = True)
```

In [10]:
```
hea["Microstructure"].describe()
```

Out[10]:
```
count     1360
unique       7
top        BCC
freq       441
Name: Microstructure, dtype: object
```

In [11]:
```
hea["Microstructure"].value_counts()
```

Out[11]:
```
BCC                441
FCC                354
FCC + Im           231
BCC + Im           179
FCC + BCC          102
FCC + BCC + Im      47
Im                   6
Name: Microstructure, dtype: int64
```

In [12]:
```
labels = hea["Microstructure"]
```

In [13]:
```
labels.describe()
```

Out[13]:
```
count     1360
unique       7
top        BCC
freq       441
Name: Microstructure, dtype: object
```

In [14]:
```
hea.drop(["Microstructure"], axis = 1, inplace = True)
```

In [15]:
```
hea.drop(["Alloy ID", "Alloy "], axis = 1 , inplace = True)
```

In [16]:
```
hea.shape
```

Out[16]:
```
(1360, 34)
```

In [17]:
```
para_median = hea['n.Para'].median()
hea["n.Para"].fillna(para_median ,inplace = True)
```

In [18]:
```
dens_med = hea["Density_calc"].median()
hea["Density_calc"].fillna(dens_med , inplace = True)
```

In [19]:
```
hea.drop(["Phases"], axis = 1 , inplace = True)
```

In [20]:
```
hea.drop(['Al', 'Co', 'Cr', 'Fe', 'Ni', 'Cu', 'Mn', 'Ti', 'V', 'Nb', 'Mo', 'Zr',
       'Hf', 'Ta', 'W', 'C', 'Mg', 'Zn', 'Si', 'Re', 'N', 'Li', 'Sn',
```

```
        'Num_of_Elem', 'Density_calc','dGmix','n.Para'], axis = 1 , inplace = True)
```

In [21]:
```
hea.columns
```

Out[21]:
```
Index(['dHmix', 'dSmix', 'Tm', 'Atom.Size.Diff', 'Elect.Diff', 'VEC'], dtype='obje
ct')
```

In [22]:
```
hea.columns
```

Out[22]:
```
Index(['dHmix', 'dSmix', 'Tm', 'Atom.Size.Diff', 'Elect.Diff', 'VEC'], dtype='obje
ct')
```

In [23]:
```
from sklearn.model_selection import train_test_split
train_hea, test_hea , train_labels , test_labels = train_test_split(hea , labels,
```

In [24]:
```
train_hea.shape
```

Out[24]:
```
(1020, 6)
```

In [25]:
```
from sklearn.model_selection import train_test_split
train_hea, test_hea , train_labels , test_labels = train_test_split(hea , labels,
```

In [26]:
```
def prepare_targets(train_labels, test_labels):
    from sklearn import preprocessing
    le = preprocessing.LabelEncoder()
    le.fit(train_labels)
    train_labels_enc = le.transform(train_labels)
    test_labels_enc = le.transform(test_labels)
    return train_labels_enc, test_labels_enc
train_labels_enc, test_labels_enc = prepare_targets(train_labels, test_labels)
```

In [ ]:
```
input_shape = train_hea.shape[1:]
num_classes = len(np.unique(train_labels_enc))


model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(32, activation='relu', input_shape=input_shape),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(20, activation='leaky_relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(63, activation='leaky_relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(20, activation='relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(47, activation='relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(20, activation='leaky_relu'),
    tf.keras.layers.Dropout(0.3),
    tf.keras.layers.Dense(89, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(20, activation='leaky_relu'),
    tf.keras.layers.Dropout(0.7),
    tf.keras.layers.Dense(20, activation='relu'),
    tf.keras.layers.Dropout(0.7),
    tf.keras.layers.Dense(20, activation='relu'),
    tf.keras.layers.Dropout(0.7),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

```
model.fit(train_hea, train_labels_enc, epochs=200, validation_split=0.3)
test_loss, test_acc = model.evaluate(test_hea, test_labels_enc)
print('Test accuracy:', test_acc)
```

```
Epoch 1/200
23/23 [==============================] - 6s 34ms/step - loss: 177.4395 - accuracy:
0.1457 - val_loss: 2.4451 - val_accuracy: 0.0261
Epoch 2/200
23/23 [==============================] - 0s 8ms/step - loss: 70.1704 - accuracy:
0.1709 - val_loss: 2.2181 - val_accuracy: 0.0261
Epoch 3/200
23/23 [==============================] - 0s 7ms/step - loss: 41.5678 - accuracy:
0.1751 - val_loss: 1.9203 - val_accuracy: 0.0556
Epoch 4/200
23/23 [==============================] - 0s 8ms/step - loss: 29.1053 - accuracy:
0.1583 - val_loss: 1.8686 - val_accuracy: 0.3105
Epoch 5/200
23/23 [==============================] - 0s 7ms/step - loss: 21.9484 - accuracy:
0.1541 - val_loss: 1.8541 - val_accuracy: 0.3105
Epoch 6/200
23/23 [==============================] - 0s 7ms/step - loss: 16.2423 - accuracy:
0.1989 - val_loss: 1.8710 - val_accuracy: 0.4346
Epoch 7/200
23/23 [==============================] - 0s 8ms/step - loss: 13.3950 - accuracy:
0.1709 - val_loss: 1.8706 - val_accuracy: 0.2778
Epoch 8/200
23/23 [==============================] - 0s 7ms/step - loss: 11.4833 - accuracy:
0.1793 - val_loss: 1.8639 - val_accuracy: 0.2614
Epoch 9/200
23/23 [==============================] - 0s 7ms/step - loss: 9.6259 - accuracy: 0.
1891 - val_loss: 1.8532 - val_accuracy: 0.2614
Epoch 10/200
23/23 [==============================] - 0s 7ms/step - loss: 8.3002 - accuracy: 0.
1723 - val_loss: 1.8451 - val_accuracy: 0.2614
Epoch 11/200
23/23 [==============================] - 0s 9ms/step - loss: 7.8509 - accuracy: 0.
1793 - val_loss: 1.8371 - val_accuracy: 0.2614
Epoch 12/200
23/23 [==============================] - 0s 9ms/step - loss: 6.9151 - accuracy: 0.
2101 - val_loss: 1.8295 - val_accuracy: 0.2614
Epoch 13/200
23/23 [==============================] - 0s 8ms/step - loss: 6.0711 - accuracy: 0.
2101 - val_loss: 1.8223 - val_accuracy: 0.2614
Epoch 14/200
23/23 [==============================] - 0s 8ms/step - loss: 5.2935 - accuracy: 0.
1849 - val_loss: 1.8153 - val_accuracy: 0.2614
Epoch 15/200
23/23 [==============================] - 0s 9ms/step - loss: 4.1468 - accuracy: 0.
2115 - val_loss: 1.8095 - val_accuracy: 0.2614
Epoch 16/200
23/23 [==============================] - 0s 8ms/step - loss: 4.2136 - accuracy: 0.
2017 - val_loss: 1.8031 - val_accuracy: 0.2614
Epoch 17/200
23/23 [==============================] - 0s 9ms/step - loss: 3.7778 - accuracy: 0.
1989 - val_loss: 1.7968 - val_accuracy: 0.2614
Epoch 18/200
23/23 [==============================] - 0s 9ms/step - loss: 3.4719 - accuracy: 0.
2353 - val_loss: 1.7903 - val_accuracy: 0.2614
Epoch 19/200
23/23 [==============================] - 0s 9ms/step - loss: 3.8178 - accuracy: 0.
2283 - val_loss: 1.7846 - val_accuracy: 0.2614
Epoch 20/200
23/23 [==============================] - 0s 9ms/step - loss: 3.7663 - accuracy: 0.
2269 - val_loss: 1.7792 - val_accuracy: 0.2614
Epoch 21/200
23/23 [==============================] - 0s 9ms/step - loss: 3.5243 - accuracy: 0.
2213 - val_loss: 1.7737 - val_accuracy: 0.2614
Epoch 22/200
```

```
23/23 [==============================] - 0s 9ms/step - loss: 3.0189 - accuracy: 0.
2563 - val_loss: 1.7686 - val_accuracy: 0.2614
Epoch 23/200
23/23 [==============================] - 0s 9ms/step - loss: 3.1078 - accuracy: 0.
2493 - val_loss: 1.7636 - val_accuracy: 0.2614
Epoch 24/200
23/23 [==============================] - 0s 10ms/step - loss: 2.8596 - accuracy:
0.2563 - val_loss: 1.7585 - val_accuracy: 0.2614
Epoch 25/200
23/23 [==============================] - 0s 9ms/step - loss: 2.9722 - accuracy: 0.
2465 - val_loss: 1.7537 - val_accuracy: 0.2614
Epoch 26/200
23/23 [==============================] - 0s 8ms/step - loss: 2.7988 - accuracy: 0.
2731 - val_loss: 1.7492 - val_accuracy: 0.3105
Epoch 27/200
23/23 [==============================] - 0s 8ms/step - loss: 2.6815 - accuracy: 0.
2689 - val_loss: 1.7447 - val_accuracy: 0.3105
Epoch 28/200
23/23 [==============================] - 0s 8ms/step - loss: 2.4466 - accuracy: 0.
2871 - val_loss: 1.7409 - val_accuracy: 0.3105
Epoch 29/200
23/23 [==============================] - 0s 7ms/step - loss: 2.4903 - accuracy: 0.
2675 - val_loss: 1.7371 - val_accuracy: 0.3105
Epoch 30/200
23/23 [==============================] - 0s 8ms/step - loss: 2.2123 - accuracy: 0.
2969 - val_loss: 1.7334 - val_accuracy: 0.3105
Epoch 31/200
23/23 [==============================] - 0s 8ms/step - loss: 2.3156 - accuracy: 0.
2857 - val_loss: 1.7298 - val_accuracy: 0.3105
Epoch 32/200
23/23 [==============================] - 0s 8ms/step - loss: 2.3765 - accuracy: 0.
2647 - val_loss: 1.7263 - val_accuracy: 0.3105
Epoch 33/200
23/23 [==============================] - 0s 8ms/step - loss: 2.2808 - accuracy: 0.
2969 - val_loss: 1.7231 - val_accuracy: 0.3105
Epoch 34/200
23/23 [==============================] - 0s 8ms/step - loss: 2.1862 - accuracy: 0.
3053 - val_loss: 1.7199 - val_accuracy: 0.3105
Epoch 35/200
23/23 [==============================] - 0s 9ms/step - loss: 2.2302 - accuracy: 0.
2829 - val_loss: 1.7167 - val_accuracy: 0.3105
Epoch 36/200
23/23 [==============================] - 0s 8ms/step - loss: 2.0767 - accuracy: 0.
2927 - val_loss: 1.7139 - val_accuracy: 0.3105
Epoch 37/200
23/23 [==============================] - 0s 7ms/step - loss: 2.0849 - accuracy: 0.
2815 - val_loss: 1.7111 - val_accuracy: 0.3105
Epoch 38/200
23/23 [==============================] - 0s 8ms/step - loss: 1.9851 - accuracy: 0.
3095 - val_loss: 1.7082 - val_accuracy: 0.3105
Epoch 39/200
23/23 [==============================] - 0s 8ms/step - loss: 1.9280 - accuracy: 0.
2815 - val_loss: 1.7055 - val_accuracy: 0.3105
Epoch 40/200
23/23 [==============================] - 0s 7ms/step - loss: 1.9069 - accuracy: 0.
2871 - val_loss: 1.7029 - val_accuracy: 0.3105
Epoch 41/200
23/23 [==============================] - 0s 9ms/step - loss: 1.9287 - accuracy: 0.
3011 - val_loss: 1.7002 - val_accuracy: 0.3105
Epoch 42/200
23/23 [==============================] - 0s 8ms/step - loss: 2.0504 - accuracy: 0.
3053 - val_loss: 1.6978 - val_accuracy: 0.3105
Epoch 43/200
23/23 [==============================] - 0s 8ms/step - loss: 2.0003 - accuracy: 0.
```

```
3039 - val_loss: 1.6956 - val_accuracy: 0.3105
Epoch 44/200
23/23 [==============================] - 0s 8ms/step - loss: 1.9672 - accuracy: 0.
2955 - val_loss: 1.6937 - val_accuracy: 0.3105
Epoch 45/200
23/23 [==============================] - 0s 8ms/step - loss: 1.8795 - accuracy: 0.
3025 - val_loss: 1.6915 - val_accuracy: 0.3105
Epoch 46/200
23/23 [==============================] - 0s 8ms/step - loss: 1.8639 - accuracy: 0.
3221 - val_loss: 1.6896 - val_accuracy: 0.3105
Epoch 47/200
23/23 [==============================] - 0s 8ms/step - loss: 1.9650 - accuracy: 0.
3221 - val_loss: 1.6877 - val_accuracy: 0.3105
Epoch 48/200
23/23 [==============================] - 0s 8ms/step - loss: 2.0184 - accuracy: 0.
3095 - val_loss: 1.6858 - val_accuracy: 0.3105
Epoch 49/200
23/23 [==============================] - 0s 8ms/step - loss: 1.9230 - accuracy: 0.
3165 - val_loss: 1.6842 - val_accuracy: 0.3105
Epoch 50/200
23/23 [==============================] - 0s 8ms/step - loss: 1.7842 - accuracy: 0.
3263 - val_loss: 1.6824 - val_accuracy: 0.3105
Epoch 51/200
23/23 [==============================] - 0s 9ms/step - loss: 1.8645 - accuracy: 0.
3179 - val_loss: 1.6809 - val_accuracy: 0.3105
Epoch 52/200
23/23 [==============================] - 0s 8ms/step - loss: 1.8227 - accuracy: 0.
3067 - val_loss: 1.6793 - val_accuracy: 0.3105
Epoch 53/200
23/23 [==============================] - 0s 8ms/step - loss: 1.8059 - accuracy: 0.
3109 - val_loss: 1.6778 - val_accuracy: 0.3105
Epoch 54/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7915 - accuracy: 0.
3221 - val_loss: 1.6766 - val_accuracy: 0.3105
Epoch 55/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7985 - accuracy: 0.
3067 - val_loss: 1.6752 - val_accuracy: 0.3105
Epoch 56/200
23/23 [==============================] - 0s 7ms/step - loss: 1.8027 - accuracy: 0.
3137 - val_loss: 1.6738 - val_accuracy: 0.3105
Epoch 57/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7412 - accuracy: 0.
3081 - val_loss: 1.6727 - val_accuracy: 0.3105
Epoch 58/200
23/23 [==============================] - 0s 8ms/step - loss: 1.7549 - accuracy: 0.
3263 - val_loss: 1.6716 - val_accuracy: 0.3105
Epoch 59/200
23/23 [==============================] - 0s 8ms/step - loss: 1.7869 - accuracy: 0.
3109 - val_loss: 1.6704 - val_accuracy: 0.3105
Epoch 60/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7564 - accuracy: 0.
3193 - val_loss: 1.6693 - val_accuracy: 0.3105
Epoch 61/200
23/23 [==============================] - 0s 8ms/step - loss: 1.7835 - accuracy: 0.
3179 - val_loss: 1.6681 - val_accuracy: 0.3105
Epoch 62/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7365 - accuracy: 0.
3151 - val_loss: 1.6673 - val_accuracy: 0.3105
Epoch 63/200
23/23 [==============================] - 0s 8ms/step - loss: 1.6908 - accuracy: 0.
3165 - val_loss: 1.6663 - val_accuracy: 0.3105
Epoch 64/200
23/23 [==============================] - 0s 8ms/step - loss: 1.7257 - accuracy: 0.
3193 - val_loss: 1.6653 - val_accuracy: 0.3105
```

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Epoch 65/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7259 - accuracy: 0.
3207 - val_loss: 1.6645 - val_accuracy: 0.3105
Epoch 66/200
23/23 [==============================] - 0s 7ms/step - loss: 1.7284 - accuracy: 0.
3193 - val_loss: 1.6636 - val_accuracy: 0.3105
Epoch 67/200
23/23 [==============================] - 0s 8ms/step - loss: 1.7345 - accuracy: 0.
3179 - val_loss: 1.6628 - val_accuracy: 0.3105
Epoch 68/200
 1/23 [>.............................] - ETA: 0s - loss: 1.6801 - accuracy: 0.3125
```