

Project07_PLN_Deep

May 13, 2020

1 Projeto 07 - Medicina Personalizada - Redefinindo o Tratamento de Câncer

<https://www.kaggle.com/c/msk-redefining-cancer-treatment/>

Conforme desafio do Kaggle, criei um modelo para classificar automaticamente variações genéticas. Utilizei Deep Learning como técnica de modelagem preditiva. Nesse notebook não utilizei as bases completas por se tratar de um estudo de caso.

```
[1]: # Importação de bibliotecas
import pandas as pd # Manipulação com dataframes
import numpy as np # Manipulação e tratamento de dados
import matplotlib.pyplot as plt # data viz
import seaborn as sns # data viz
sns.set(style="ticks")
import string # Aplicações com strings
import re # Regex
from nltk.corpus import stopwords # stopwords para PLN
from nltk.stem import LancasterStemmer # Stemming para PLN
from nltk.tokenize import RegexpTokenizer # Tokenizar por expressões regulares
from sklearn.feature_extraction.text import TfidfVectorizer # term frequency-
inverse document frequency
from keras.models import Sequential # modelo deep learning
from keras.layers import Dense # modelo ''
from keras.optimizers import SGD # modelo ''
import warnings
warnings.filterwarnings("ignore")
```

Using TensorFlow backend.

```
[2]: # Carregando os datasets
train_text = pd.read_csv("data_files/training_text", sep = "\\|\\|")
train_variants = pd.read_csv("data_files/training_variants")

test_text = pd.read_csv("data_files/test_text", sep = "\\|\\|")
test_variants = pd.read_csv("data_files/test_variants")
```

```
[3]: # Visualizando os dados de treino train_text
train_text.head()
```

```
[3]:   ID                                     Text
0    0  Cyclin-dependent kinases (CDKs) regulate a var...
1    1  Abstract Background  Non-small cell lung canc...
2    2  Abstract Background  Non-small cell lung canc...
3    3  Recent evidence has demonstrated that acquired...
4    4  Oncogenic mutations in the monomeric Casitas B...
```

```
[4]: # Visualizando os dados de treino train_variants
train_variants.head()
```

```
[4]:   ID   Gene      Variation  Class
0    0  FAM58A  Truncating Mutations    1
1    1    CBL           W802*         2
2    2    CBL           Q249E         2
3    3    CBL           N454D         3
4    4    CBL           L399V         4
```

```
[5]: # Juntando as duas tabelas
df_train = pd.merge(train_text, train_variants, how='left', on='ID')
df_test = pd.merge(test_text, test_variants, how='left', on='ID')
df_train.head()
```

```
[5]:   ID                                     Text   Gene \
0    0  Cyclin-dependent kinases (CDKs) regulate a var...  FAM58A
1    1  Abstract Background  Non-small cell lung canc...    CBL
2    2  Abstract Background  Non-small cell lung canc...    CBL
3    3  Recent evidence has demonstrated that acquired...    CBL
4    4  Oncogenic mutations in the monomeric Casitas B...    CBL

      Variation  Class
0  Truncating Mutations    1
1           W802*         2
2           Q249E         2
3           N454D         3
4           L399V         4
```

```
[6]: # Transformando colunas numéricas em categóricas
df_train[['ID', 'Class']] = df_train[['ID', 'Class']].astype(str)

# Dimensão do dataframe e o tipo das colunas
print("Linhas e colunas: " + str(df_train.shape) + '\n')
print("Data types: \n" + str(df_train.dtypes))
```

Linhas e colunas: (139, 5)

Data types:

```
ID          object
Text        object
Gene        object
Variation   object
Class       object
dtype: object
```

```
[7]: # Sumário dos dados
df_train.describe()
```

```
[7]:
```

	ID	Text	Gene	Variation	\
count	139	139	139	139	
unique	139	87	23	120	
top	38	Oncogenic mutations in the monomeric Casitas B...	CBL	Deletion	
freq	1	8	25	9	

	Class
count	139
unique	9
top	4
freq	53

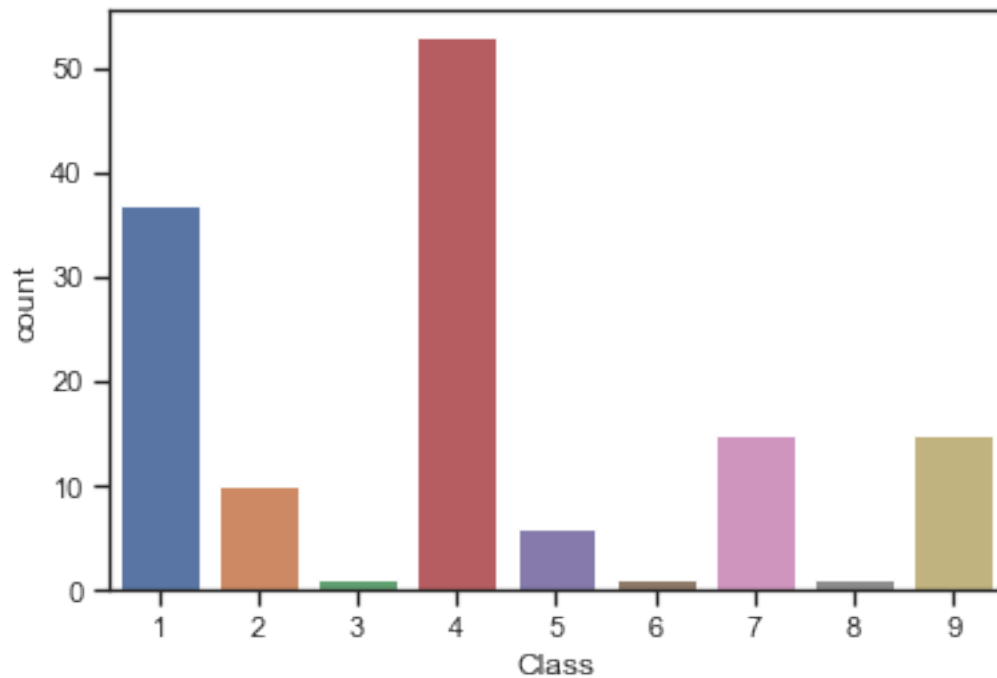
```
[8]: # Checando se há valores missing
df_train.isna().sum()
```

```
[8]: ID          0
Text          0
Gene          0
Variation     0
Class         0
dtype: int64
```

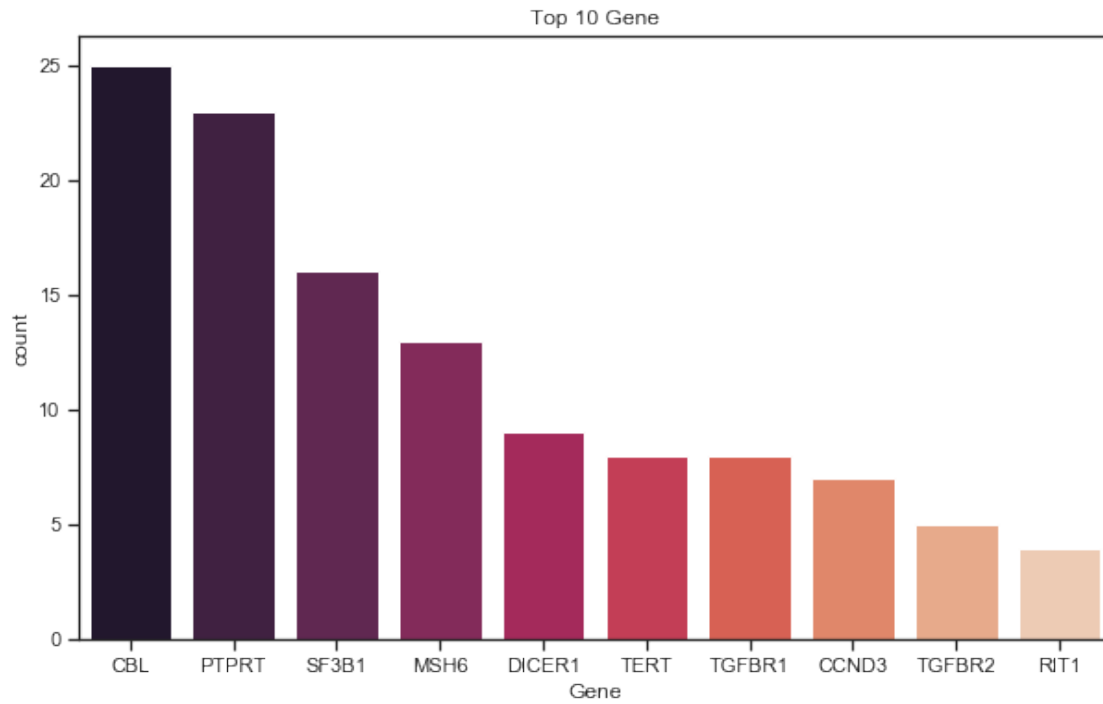
Análise exploratória:

```
[9]: # Analisando variável target
sns.countplot(x="Class", data=df_train)
```

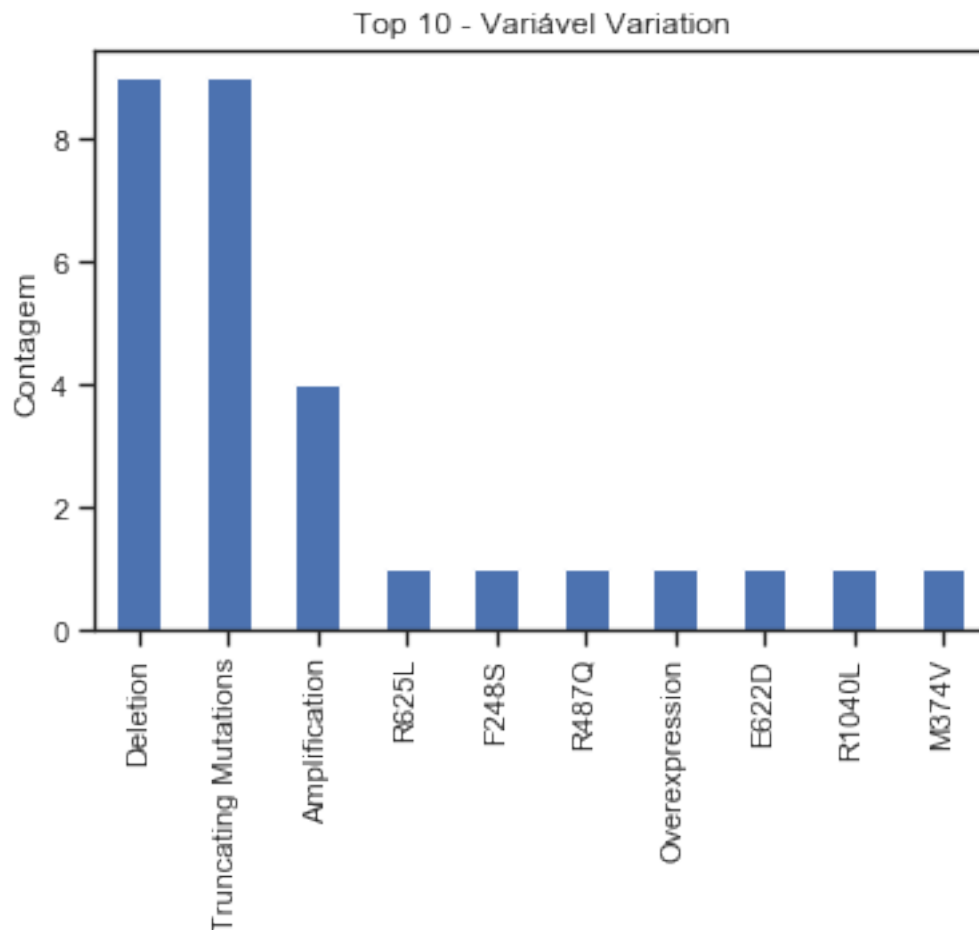
```
[9]: <matplotlib.axes._subplots.AxesSubplot at 0x24c4fe79c88>
```



```
[29]: # Contagem Top 10 Gene
plt.figure(figsize=(10,6))
ax = sns.countplot(x="Gene", data=df_train, order=df_train['Gene'].
    ↳value_counts().iloc[:10].index, palette="rocket")
ax.set_title('Top 10 Gene')
plt.show()
```



```
[30]: # Variation (the aminoacid change for this mutations)
ax = df_train['Variation'].value_counts().iloc[:10].plot(kind="bar")
ax.set_ylabel("Contagem")
ax.set_title("Top 10 - Variável Variation")
plt.show()
```



Algumas conclusões dos dados de treino

- Classes: É possível visualizar que as maiores proporções das classes estão entre 4 e 1.
- Gene: Cerca de 60% dos Genes estão concentrados em: CBL, PTPRT, SF3B1, MSH6.
- Variation: As categorias desse atributo são praticamente únicas. Podemos estudar as particularidades das 3 primeiras categorias, mas provavelmente essa variável não será usada para previsões.

Na próxima vou explorar a variável 'Text' que precisa tratamento de texto para análise.

Análise exploratória e pré-processamento - Variável 'Text'

[12]: *## Pré-processamento dos dados / Feature engineering*

```
# criar coluna Class p/ df teste  
df_test.insert(4,column= 'Class', value= -1)  
  
# Juntar dataframes de treino e teste
```

```

df_final = df_train.append(df_test, ignore_index=True) #ignore_index para não
↳ termos index duplicados

# criando coluna com contagem de palavras
df_final['count_words'] = df_final.Text.apply(lambda x: len(x.split(' '))) #
↳ criando coluna com contagem de palavras

# criando coluna de label treino/teste
df_final['data'] = df_final.Class.apply(lambda x: 'Teste' if x == -1 else
↳ 'Treino')

df_final.head()

```

```

[12]: ID          Text      Gene \
0  0  Cyclin-dependent kinases (CDKs) regulate a var...  FAM58A
1  1  Abstract Background  Non-small cell lung canc...   CBL
2  2  Abstract Background  Non-small cell lung canc...   CBL
3  3  Recent evidence has demonstrated that acquired...   CBL
4  4  Oncogenic mutations in the monomeric Casitas B...   CBL

      Variation Class  count_words  data
0  Truncating Mutations      1      6105  Treino
1                W802*      2      5783  Treino
2                Q249E      2      5783  Treino
3                N454D      3      5625  Treino
4                L399V      4      6248  Treino

```

```

[13]: ## Análise do texto

# Sumarização de alguns dados do atributo 'Text'
print("Total de palavras treino/teste: \n" + str(df_final.groupby("data").
↳ count_words.sum()))
print("\n Média de palavras: " + str(int(df_final.count_words.mean())))
print(" Menor nr de palavras: " + str(df_final.count_words.min()))

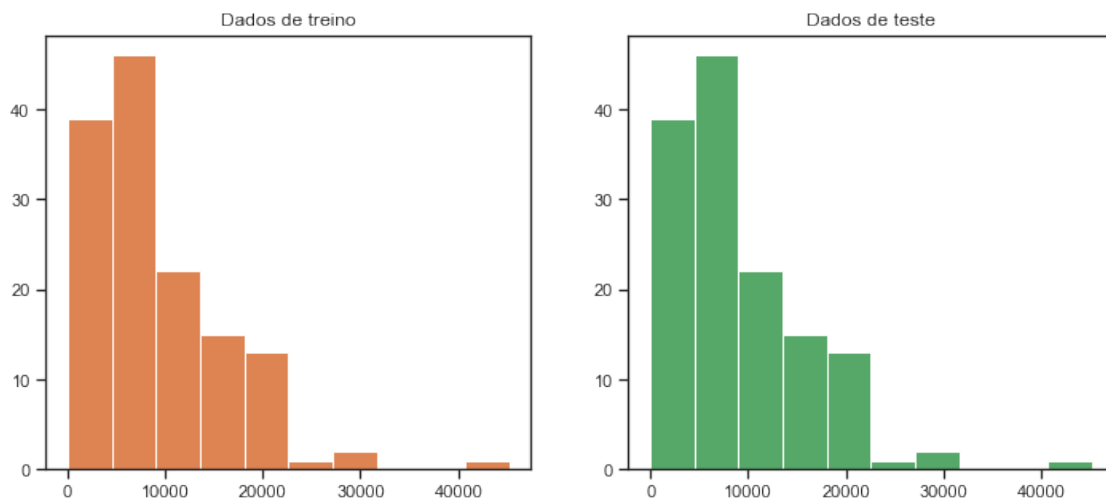
# Coletando as count_words de treino e teste
x1 = df_final.loc[df_final.data=='Treino', 'count_words']
x2 = df_final.loc[df_final.data=='Teste', 'count_words']

# Plotando os gráficos
fig, axs = plt.subplots(1, 2, figsize=(12,5))
axs[0].hist(x1, color='C1')
axs[1].hist(x2, color = 'C2')
axs[0].set_title('Dados de treino')
axs[1].set_title('Dados de teste')
plt.show()

```

```
Total de palavras treino/teste:
data
Teste      1272023
Treino     1272023
Name: count_words, dtype: int64
```

```
Média de palavras: 9151
Menor nr de palavras: 1
```



Nota-se que a quantidade de palavras tanto para conjunto de treino quanto de teste é a mesma, assim como sua distribuição.

Um fato importante é que o dataset possui pelo menos um texto com apenas 1 palavra. Será necessário remover esse registro pois aparentemente é um erro.

```
[14]: # Contagem de casos com 10 palavras ou menos
print("Casos <= 10 palavras: " + str((df_final.count_words <= 10).sum()))

# Removendo casos com texto com menos de 10 palavras.
df_final = df_final[df_final.count_words > 10]

# Após remoção
print("Novo mínimo nr de palavras após tratamento: " + str(df_final.count_words.
    ↪min()))
```

```
Casos <= 10 palavras: 2
Novo mínimo nr de palavras após tratamento: 1153
```

```
[15]: ## Processamento de texto

# Criando função para tratamento do texto
```



```

english_stops = set(stopwords.words('english'))
lanc_stemmer = LancasterStemmer()

def text_transform(text):

    text = text.translate(str.maketrans('', '', string.punctuation)).lower()
    ↪ #Punctuation / lowercase
    text = [word for word in text.split() if word not in english_stops] #
    ↪ separando as palavras e removendo stopwords
    text = [lanc_stemmer.stem(word) for word in text] # Stemming
    text = [word for word in text if not word.isnumeric()] # removendo apenas
    ↪ números
    new_text = ' '.join(text) # juntando o texto novamente

    return new_text

# Aplicando a função de transformação dos dados
X = df_final.Text.apply(text_transform)
print(X)

```

```

0      cyclindepend kinas cdks reg vary funda cellul ...
1      abstract background nonsmal cel lung cant nscl...
2      abstract background nonsmal cel lung cant nscl...
3      rec evid demonst acquir unip disom aupd novel ...
4      oncog mut monom casita blin lymphom cbl gen fo...

...

272     rna mat import complex biolog process requir s...
273     splicing fact sf3b1 common mut gen myelodyspla...
274     mut gen encod protein involv rna splicing foun...
275     precurs mrna splicing catalys spliceosome macr...
276     malign mesotheliom mm aggress neoplasm assoc y ...
Name: Text, Length: 276, dtype: object

```

```

[16]: # Criando a tf-idf
tfidf = TfidfVectorizer().fit_transform(X) # criando tfidf matrix
tfidf= tfidf.toarray() # transformando para array
tfidf.shape # dimensões

```

[16]: (276, 27703)

```

[17]: # OneHot encoding - Variável Gene
X_Gene = pd.get_dummies(df_final.Gene)
X_Gene

```

```

[17]:
      ABCA1  ABCA12  ABCA4  ABCD1  ACADS  ACOX1  ACSL4  AGXT  ARSA  ATM  ...  \
0         0         0         0         0         0         0         0         0         0         0  ...
1         0         0         0         0         0         0         0         0         0         0  ...

```

2	0	0	0	0	0	0	0	0	0	0	...
3	0	0	0	0	0	0	0	0	0	0	...
4	0	0	0	0	0	0	0	0	0	0	...
..
272	0	0	0	0	0	0	0	0	0	0	...
273	0	0	0	0	0	0	0	0	0	0	...
274	0	0	0	0	0	0	0	0	0	0	...
275	0	0	0	0	0	0	0	0	0	0	...
276	0	0	0	0	0	0	0	0	0	0	...

	TSC1	TSHR	TYR	UBE3A	UMOD	UROS	VCP	VHL	VWF	ZFPM2
0	0	0	0	0	0	0	0	0	0	0
1	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0
..
272	0	0	0	0	0	0	1	0	0	0
273	0	0	0	0	0	0	0	0	0	0
274	0	0	0	0	0	0	0	0	0	0
275	0	0	0	0	0	0	0	0	0	0
276	0	0	0	0	0	0	0	0	0	0

[276 rows x 142 columns]

```
[18]: # Concatena tf-idf e X_Gene criados com variáveis 'data' e 'Class' em uma matriz
X = np.column_stack(list([tfidf, X_Gene, df_final['data'], df_final['Class']]))
    ↳ # junta por nível de coluna

# Preparação de X e Y (features e target)
train = X[df_final['data'] == 'Treino'] # Separa dados de treino
X_train = train[:, :-2] # prepara as variáveis de entrada, removendo as duas
    ↳ últimas colunas
Y_train = train[:, -1] # pegando a última coluna onde estão as classes
Y_train_encoded = pd.get_dummies(Y_train) # onehot encoding para classes
    ↳ (necessário para meu modelo)

# Agora para teste
test = X[df_final['data'] == 'Teste'] # Separa dados de teste
X_test = test[:, :-2] # prepara as variáveis de entrada, removendo as duas
    ↳ últimas colunas

print("Dimensões dos dados de entrada: " + str(X_train.shape))
print("Dimensões : " + str(Y_train_encoded.shape))
```

Dimensões dos dados de entrada: (138, 27845)

Dimensões : (138, 9)

Criação do modelo de Deep Learning

```
[19]: # Cria o modelo
model = Sequential()
model.add(Dense(12, input_dim = 27845, kernel_initializer = 'uniform',
    ↪activation = 'relu'))
model.add(Dense(8, kernel_initializer = 'uniform', activation = 'relu'))
model.add(Dense(9, activation = 'sigmoid', kernel_initializer = 'uniform'))

# Compila o modelo - com otimizador Stochastic Gradient Descent
model.compile(loss = 'categorical_crossentropy',
              optimizer = SGD(lr = 0.01, momentum = 0.9, nesterov = True),
              metrics = ['accuracy'])

model.summary()
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 12)	334152
dense_2 (Dense)	(None, 8)	104
dense_3 (Dense)	(None, 9)	81

Total params: 334,337
Trainable params: 334,337
Non-trainable params: 0

```
[20]: # Executa o modelo e valida nos mesmos dados em que foi criado (treino)
model.fit(X_train, Y_train_encoded, epochs = 300, batch_size = 10)
```

```
Epoch 1/300
138/138 [=====] - 0s 2ms/step - loss: 2.1881 -
accuracy: 0.3551
Epoch 2/300
138/138 [=====] - 0s 1ms/step - loss: 2.1541 -
accuracy: 0.3841
Epoch 3/300
138/138 [=====] - 0s 1ms/step - loss: 2.1177 -
accuracy: 0.3841
Epoch 4/300
138/138 [=====] - 0s 1ms/step - loss: 2.0835 -
accuracy: 0.3841
Epoch 5/300
```

138/138 [=====] - 0s 1ms/step - loss: 2.0544 -
accuracy: 0.3841
Epoch 6/300
138/138 [=====] - 0s 1ms/step - loss: 2.0276 -
accuracy: 0.3841
Epoch 7/300
138/138 [=====] - 0s 1ms/step - loss: 2.0035 -
accuracy: 0.3841
Epoch 8/300
138/138 [=====] - 0s 1ms/step - loss: 1.9813 -
accuracy: 0.3841
Epoch 9/300
138/138 [=====] - 0s 1ms/step - loss: 1.9622 -
accuracy: 0.3841
Epoch 10/300
138/138 [=====] - 0s 1ms/step - loss: 1.9428 -
accuracy: 0.3841
Epoch 11/300
138/138 [=====] - 0s 1ms/step - loss: 1.9250 -
accuracy: 0.3841
Epoch 12/300
138/138 [=====] - 0s 1ms/step - loss: 1.9088 -
accuracy: 0.3841
Epoch 13/300
138/138 [=====] - 0s 1ms/step - loss: 1.8933 -
accuracy: 0.3841
Epoch 14/300
138/138 [=====] - 0s 1ms/step - loss: 1.8784 -
accuracy: 0.3841
Epoch 15/300
138/138 [=====] - 0s 1ms/step - loss: 1.8643 -
accuracy: 0.3841
Epoch 16/300
138/138 [=====] - 0s 1ms/step - loss: 1.8500 -
accuracy: 0.3841
Epoch 17/300
138/138 [=====] - 0s 2ms/step - loss: 1.8374 -
accuracy: 0.3841
Epoch 18/300
138/138 [=====] - 0s 1ms/step - loss: 1.8245 -
accuracy: 0.3841
Epoch 19/300
138/138 [=====] - 0s 1ms/step - loss: 1.8119 -
accuracy: 0.3841
Epoch 20/300
138/138 [=====] - 0s 1ms/step - loss: 1.7996 -
accuracy: 0.3841
Epoch 21/300

138/138 [=====] - 0s 1ms/step - loss: 1.7879 -
accuracy: 0.3841
Epoch 22/300
138/138 [=====] - 0s 1ms/step - loss: 1.7755 -
accuracy: 0.3841
Epoch 23/300
138/138 [=====] - 0s 1ms/step - loss: 1.7646 -
accuracy: 0.3841
Epoch 24/300
138/138 [=====] - 0s 1ms/step - loss: 1.7528 -
accuracy: 0.3841
Epoch 25/300
138/138 [=====] - 0s 1ms/step - loss: 1.7422 -
accuracy: 0.3841
Epoch 26/300
138/138 [=====] - 0s 1ms/step - loss: 1.7317 -
accuracy: 0.3841
Epoch 27/300
138/138 [=====] - 0s 1ms/step - loss: 1.7207 -
accuracy: 0.3841
Epoch 28/300
138/138 [=====] - 0s 1ms/step - loss: 1.7109 -
accuracy: 0.3841
Epoch 29/300
138/138 [=====] - 0s 1ms/step - loss: 1.7020 -
accuracy: 0.3841
Epoch 30/300
138/138 [=====] - 0s 1ms/step - loss: 1.6924 -
accuracy: 0.3841
Epoch 31/300
138/138 [=====] - 0s 1ms/step - loss: 1.6846 -
accuracy: 0.3841
Epoch 32/300
138/138 [=====] - 0s 1ms/step - loss: 1.6766 -
accuracy: 0.3841
Epoch 33/300
138/138 [=====] - 0s 1ms/step - loss: 1.6703 -
accuracy: 0.3841
Epoch 34/300
138/138 [=====] - 0s 1ms/step - loss: 1.6642 -
accuracy: 0.3841
Epoch 35/300
138/138 [=====] - 0s 2ms/step - loss: 1.6591 -
accuracy: 0.3841
Epoch 36/300
138/138 [=====] - 0s 1ms/step - loss: 1.6546 -
accuracy: 0.3841
Epoch 37/300

138/138 [=====] - 0s 1ms/step - loss: 1.6510 -
accuracy: 0.3841
Epoch 38/300
138/138 [=====] - 0s 1ms/step - loss: 1.6480 -
accuracy: 0.3841
Epoch 39/300
138/138 [=====] - 0s 1ms/step - loss: 1.6440 -
accuracy: 0.3841
Epoch 40/300
138/138 [=====] - 0s 1ms/step - loss: 1.6420 -
accuracy: 0.3841
Epoch 41/300
138/138 [=====] - 0s 1ms/step - loss: 1.6421 -
accuracy: 0.3841
Epoch 42/300
138/138 [=====] - 0s 1ms/step - loss: 1.6384 -
accuracy: 0.3841
Epoch 43/300
138/138 [=====] - 0s 1ms/step - loss: 1.6375 -
accuracy: 0.3841
Epoch 44/300
138/138 [=====] - 0s 1ms/step - loss: 1.6348 -
accuracy: 0.3841
Epoch 45/300
138/138 [=====] - 0s 1ms/step - loss: 1.6349 -
accuracy: 0.3841
Epoch 46/300
138/138 [=====] - 0s 1ms/step - loss: 1.6325 -
accuracy: 0.3841
Epoch 47/300
138/138 [=====] - 0s 1ms/step - loss: 1.6317 -
accuracy: 0.3841
Epoch 48/300
138/138 [=====] - 0s 1ms/step - loss: 1.6300 -
accuracy: 0.3841
Epoch 49/300
138/138 [=====] - 0s 1ms/step - loss: 1.6297 -
accuracy: 0.3841
Epoch 50/300
138/138 [=====] - 0s 1ms/step - loss: 1.6292 -
accuracy: 0.3841
Epoch 51/300
138/138 [=====] - 0s 1ms/step - loss: 1.6285 -
accuracy: 0.3841
Epoch 52/300
138/138 [=====] - 0s 1ms/step - loss: 1.6268 -
accuracy: 0.3841
Epoch 53/300

138/138 [=====] - 0s 1ms/step - loss: 1.6259 -
accuracy: 0.3841
Epoch 54/300
138/138 [=====] - ETA: 0s - loss: 1.6274 - accuracy:
0.38 - 0s 1ms/step - loss: 1.6243 - accuracy: 0.3841
Epoch 55/300
138/138 [=====] - 0s 1ms/step - loss: 1.6230 -
accuracy: 0.3841
Epoch 56/300
138/138 [=====] - 0s 1ms/step - loss: 1.6226 -
accuracy: 0.3841
Epoch 57/300
138/138 [=====] - 0s 1ms/step - loss: 1.6205 -
accuracy: 0.3841
Epoch 58/300
138/138 [=====] - 0s 1ms/step - loss: 1.6187 -
accuracy: 0.3841
Epoch 59/300
138/138 [=====] - 0s 1ms/step - loss: 1.6173 -
accuracy: 0.3841
Epoch 60/300
138/138 [=====] - 0s 1ms/step - loss: 1.6159 -
accuracy: 0.3841
Epoch 61/300
138/138 [=====] - 0s 1ms/step - loss: 1.6135 -
accuracy: 0.3841
Epoch 62/300
138/138 [=====] - 0s 1ms/step - loss: 1.6111 -
accuracy: 0.3841
Epoch 63/300
138/138 [=====] - 0s 1ms/step - loss: 1.6083 -
accuracy: 0.3841
Epoch 64/300
138/138 [=====] - 0s 1ms/step - loss: 1.6053 -
accuracy: 0.3841
Epoch 65/300
138/138 [=====] - 0s 1ms/step - loss: 1.6031 -
accuracy: 0.3841
Epoch 66/300
138/138 [=====] - 0s 1ms/step - loss: 1.5996 -
accuracy: 0.3841
Epoch 67/300
138/138 [=====] - 0s 1ms/step - loss: 1.5957 -
accuracy: 0.3841
Epoch 68/300
138/138 [=====] - 0s 1ms/step - loss: 1.5907 -
accuracy: 0.3841
Epoch 69/300

138/138 [=====] - 0s 1ms/step - loss: 1.5858 -
accuracy: 0.3841
Epoch 70/300
138/138 [=====] - 0s 1ms/step - loss: 1.5791 -
accuracy: 0.3841
Epoch 71/300
138/138 [=====] - 0s 1ms/step - loss: 1.5732 -
accuracy: 0.3841
Epoch 72/300
138/138 [=====] - 0s 1ms/step - loss: 1.5660 -
accuracy: 0.3841
Epoch 73/300
138/138 [=====] - 0s 1ms/step - loss: 1.5580 -
accuracy: 0.3841
Epoch 74/300
138/138 [=====] - 0s 1ms/step - loss: 1.5479 -
accuracy: 0.3841
Epoch 75/300
138/138 [=====] - 0s 1ms/step - loss: 1.5381 -
accuracy: 0.3841
Epoch 76/300
138/138 [=====] - 0s 1ms/step - loss: 1.5263 -
accuracy: 0.3841
Epoch 77/300
138/138 [=====] - 0s 1ms/step - loss: 1.5120 -
accuracy: 0.3841
Epoch 78/300
138/138 [=====] - 0s 1ms/step - loss: 1.4981 -
accuracy: 0.3841
Epoch 79/300
138/138 [=====] - 0s 1ms/step - loss: 1.4832 -
accuracy: 0.3841
Epoch 80/300
138/138 [=====] - 0s 1ms/step - loss: 1.4671 -
accuracy: 0.3841
Epoch 81/300
138/138 [=====] - 0s 1ms/step - loss: 1.4500 -
accuracy: 0.3841
Epoch 82/300
138/138 [=====] - 0s 1ms/step - loss: 1.4321 -
accuracy: 0.3841
Epoch 83/300
138/138 [=====] - 0s 1ms/step - loss: 1.4140 -
accuracy: 0.3841
Epoch 84/300
138/138 [=====] - 0s 1ms/step - loss: 1.4004 -
accuracy: 0.3841
Epoch 85/300

138/138 [=====] - 0s 1ms/step - loss: 1.3903 -
accuracy: 0.3841
Epoch 86/300
138/138 [=====] - 0s 1ms/step - loss: 1.3795 -
accuracy: 0.3841
Epoch 87/300
138/138 [=====] - 0s 1ms/step - loss: 1.3692 -
accuracy: 0.3841
Epoch 88/300
138/138 [=====] - 0s 1ms/step - loss: 1.3580 -
accuracy: 0.3841
Epoch 89/300
138/138 [=====] - 0s 1ms/step - loss: 1.3476 -
accuracy: 0.3841
Epoch 90/300
138/138 [=====] - 0s 1ms/step - loss: 1.3376 -
accuracy: 0.3841
Epoch 91/300
138/138 [=====] - 0s 1ms/step - loss: 1.3265 -
accuracy: 0.3841
Epoch 92/300
138/138 [=====] - 0s 1ms/step - loss: 1.3170 -
accuracy: 0.3841
Epoch 93/300
138/138 [=====] - 0s 1ms/step - loss: 1.3043 -
accuracy: 0.3841
Epoch 94/300
138/138 [=====] - 0s 1ms/step - loss: 1.2949 -
accuracy: 0.3841
Epoch 95/300
138/138 [=====] - 0s 1ms/step - loss: 1.2846 -
accuracy: 0.3841
Epoch 96/300
138/138 [=====] - 0s 1ms/step - loss: 1.2748 -
accuracy: 0.3841
Epoch 97/300
138/138 [=====] - 0s 1ms/step - loss: 1.2645 -
accuracy: 0.3841
Epoch 98/300
138/138 [=====] - 0s 1ms/step - loss: 1.2544 -
accuracy: 0.3841
Epoch 99/300
138/138 [=====] - 0s 1ms/step - loss: 1.2435 -
accuracy: 0.3841
Epoch 100/300
138/138 [=====] - 0s 1ms/step - loss: 1.2342 -
accuracy: 0.3841
Epoch 101/300

```

138/138 [=====] - 0s 1ms/step - loss: 1.2238 -
accuracy: 0.3841
Epoch 102/300
138/138 [=====] - 0s 1ms/step - loss: 1.2145 -
accuracy: 0.3841
Epoch 103/300
138/138 [=====] - 0s 1ms/step - loss: 1.2036 -
accuracy: 0.3841
Epoch 104/300
138/138 [=====] - 0s 1ms/step - loss: 1.1936 -
accuracy: 0.3841
Epoch 105/300
138/138 [=====] - 0s 1ms/step - loss: 1.1845 -
accuracy: 0.3841
Epoch 106/300
138/138 [=====] - 0s 1ms/step - loss: 1.1742 -
accuracy: 0.3841
Epoch 107/300
138/138 [=====] - 0s 1ms/step - loss: 1.1651 -
accuracy: 0.3841
Epoch 108/300
138/138 [=====] - 0s 1ms/step - loss: 1.1548 -
accuracy: 0.3841
Epoch 109/300
138/138 [=====] - 0s 1ms/step - loss: 1.1482 -
accuracy: 0.3841
Epoch 110/300
138/138 [=====] - 0s 1ms/step - loss: 1.1383 -
accuracy: 0.3913
Epoch 111/300
138/138 [=====] - 0s 1ms/step - loss: 1.1302 -
accuracy: 0.4855
Epoch 112/300
138/138 [=====] - 0s 1ms/step - loss: 1.1225 -
accuracy: 0.4928
Epoch 113/300
138/138 [=====] - 0s 1ms/step - loss: 1.1116 -
accuracy: 0.4928
Epoch 114/300
138/138 [=====] - 0s 1ms/step - loss: 1.1032 -
accuracy: 0.4928
Epoch 115/300
138/138 [=====] - 0s 1ms/step - loss: 1.0912 -
accuracy: 0.4928
Epoch 116/300
138/138 [=====] - 0s 1ms/step - loss: 1.0844 -
accuracy: 0.4928
Epoch 117/300

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138/138 [=====] - 0s 1ms/step - loss: 1.0710 -
accuracy: 0.4928
Epoch 118/300
138/138 [=====] - 0s 1ms/step - loss: 1.0561 -
accuracy: 0.4928
Epoch 119/300
138/138 [=====] - 0s 1ms/step - loss: 1.0420 -
accuracy: 0.4928
Epoch 120/300
138/138 [=====] - 0s 1ms/step - loss: 1.0279 -
accuracy: 0.4928
Epoch 121/300
138/138 [=====] - 0s 1ms/step - loss: 1.0106 -
accuracy: 0.4928
Epoch 122/300
138/138 [=====] - 0s 1ms/step - loss: 0.9959 -
accuracy: 0.4928
Epoch 123/300
138/138 [=====] - 0s 1ms/step - loss: 0.9825 -
accuracy: 0.5362
Epoch 124/300
138/138 [=====] - 0s 1ms/step - loss: 0.9716 -
accuracy: 0.5870
Epoch 125/300
138/138 [=====] - 0s 1ms/step - loss: 0.9595 -
accuracy: 0.5652
Epoch 126/300
138/138 [=====] - 0s 1ms/step - loss: 0.9495 -
accuracy: 0.5507
Epoch 127/300
138/138 [=====] - 0s 1ms/step - loss: 0.9401 -
accuracy: 0.5725
Epoch 128/300
138/138 [=====] - 0s 1ms/step - loss: 0.9316 -
accuracy: 0.5217
Epoch 129/300
138/138 [=====] - 0s 1ms/step - loss: 0.9139 -
accuracy: 0.5435
Epoch 130/300
138/138 [=====] - 0s 1ms/step - loss: 0.9043 -
accuracy: 0.5217
Epoch 131/300
138/138 [=====] - 0s 1ms/step - loss: 0.8884 -
accuracy: 0.5435
Epoch 132/300
138/138 [=====] - 0s 1ms/step - loss: 0.8658 -
accuracy: 0.5942
Epoch 133/300

138/138 [=====] - 0s 1ms/step - loss: 0.8280 -
accuracy: 0.6014
Epoch 134/300
138/138 [=====] - 0s 1ms/step - loss: 0.8142 -
accuracy: 0.6232
Epoch 135/300
138/138 [=====] - 0s 1ms/step - loss: 0.7631 -
accuracy: 0.6667
Epoch 136/300
138/138 [=====] - 0s 2ms/step - loss: 0.7441 -
accuracy: 0.6594
Epoch 137/300
138/138 [=====] - 0s 1ms/step - loss: 0.7133 -
accuracy: 0.7029
Epoch 138/300
138/138 [=====] - 0s 1ms/step - loss: 0.6792 -
accuracy: 0.7101
Epoch 139/300
138/138 [=====] - 0s 2ms/step - loss: 0.6930 -
accuracy: 0.6957
Epoch 140/300
138/138 [=====] - 0s 1ms/step - loss: 0.6592 -
accuracy: 0.7101
Epoch 141/300
138/138 [=====] - 0s 1ms/step - loss: 0.6551 -
accuracy: 0.7319
Epoch 142/300
138/138 [=====] - 0s 1ms/step - loss: 0.6255 -
accuracy: 0.7246
Epoch 143/300
138/138 [=====] - 0s 1ms/step - loss: 0.6123 -
accuracy: 0.7536
Epoch 144/300
138/138 [=====] - 0s 1ms/step - loss: 0.6173 -
accuracy: 0.7101
Epoch 145/300
138/138 [=====] - 0s 1ms/step - loss: 0.5981 -
accuracy: 0.7681
Epoch 146/300
138/138 [=====] - 0s 1ms/step - loss: 0.5877 -
accuracy: 0.7464
Epoch 147/300
138/138 [=====] - 0s 1ms/step - loss: 0.5936 -
accuracy: 0.7464
Epoch 148/300
138/138 [=====] - 0s 1ms/step - loss: 0.5804 -
accuracy: 0.7464
Epoch 149/300

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138/138 [=====] - 0s 1ms/step - loss: 0.5599 -
accuracy: 0.7319
Epoch 150/300
138/138 [=====] - 0s 1ms/step - loss: 0.5496 -
accuracy: 0.7681
Epoch 151/300
138/138 [=====] - 0s 1ms/step - loss: 0.5422 -
accuracy: 0.7464
Epoch 152/300
138/138 [=====] - 0s 1ms/step - loss: 0.5386 -
accuracy: 0.7536
Epoch 153/300
138/138 [=====] - 0s 1ms/step - loss: 0.5649 -
accuracy: 0.7391
Epoch 154/300
138/138 [=====] - 0s 2ms/step - loss: 0.5425 -
accuracy: 0.7681
Epoch 155/300
138/138 [=====] - 0s 2ms/step - loss: 0.5515 -
accuracy: 0.7609
Epoch 156/300
138/138 [=====] - 0s 1ms/step - loss: 0.5174 -
accuracy: 0.7609
Epoch 157/300
138/138 [=====] - 0s 1ms/step - loss: 0.5093 -
accuracy: 0.7826
Epoch 158/300
138/138 [=====] - 0s 1ms/step - loss: 0.5141 -
accuracy: 0.7826
Epoch 159/300
138/138 [=====] - 0s 1ms/step - loss: 0.4926 -
accuracy: 0.7899
Epoch 160/300
138/138 [=====] - 0s 1ms/step - loss: 0.4934 -
accuracy: 0.7609
Epoch 161/300
138/138 [=====] - 0s 1ms/step - loss: 0.4906 -
accuracy: 0.7754
Epoch 162/300
138/138 [=====] - 0s 1ms/step - loss: 0.4865 -
accuracy: 0.7899
Epoch 163/300
138/138 [=====] - 0s 1ms/step - loss: 0.4774 -
accuracy: 0.7681
Epoch 164/300
138/138 [=====] - 0s 1ms/step - loss: 0.4851 -
accuracy: 0.7754
Epoch 165/300

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138/138 [=====] - 0s 1ms/step - loss: 0.4812 -
accuracy: 0.7681
Epoch 166/300
138/138 [=====] - 0s 1ms/step - loss: 0.4454 -
accuracy: 0.7609
Epoch 167/300
138/138 [=====] - 0s 1ms/step - loss: 0.4475 -
accuracy: 0.7971
Epoch 168/300
138/138 [=====] - 0s 1ms/step - loss: 0.4535 -
accuracy: 0.7754
Epoch 169/300
138/138 [=====] - 0s 1ms/step - loss: 0.4347 -
accuracy: 0.7826
Epoch 170/300
138/138 [=====] - 0s 1ms/step - loss: 0.4652 -
accuracy: 0.7754
Epoch 171/300
138/138 [=====] - 0s 1ms/step - loss: 0.4905 -
accuracy: 0.7609
Epoch 172/300
138/138 [=====] - 0s 2ms/step - loss: 0.4438 -
accuracy: 0.7826
Epoch 173/300
138/138 [=====] - 0s 2ms/step - loss: 0.4465 -
accuracy: 0.7681
Epoch 174/300
138/138 [=====] - 0s 2ms/step - loss: 0.4823 -
accuracy: 0.7681
Epoch 175/300
138/138 [=====] - 0s 1ms/step - loss: 0.4460 -
accuracy: 0.7754
Epoch 176/300
138/138 [=====] - 0s 1ms/step - loss: 0.4343 -
accuracy: 0.7609
Epoch 177/300
138/138 [=====] - 0s 1ms/step - loss: 0.4213 -
accuracy: 0.7971
Epoch 178/300
138/138 [=====] - 0s 1ms/step - loss: 0.4328 -
accuracy: 0.7899
Epoch 179/300
138/138 [=====] - 0s 1ms/step - loss: 0.4695 -
accuracy: 0.7681
Epoch 180/300
138/138 [=====] - 0s 1ms/step - loss: 0.4863 -
accuracy: 0.7609
Epoch 181/300

138/138 [=====] - 0s 1ms/step - loss: 0.4103 -
accuracy: 0.7899
Epoch 182/300
138/138 [=====] - 0s 1ms/step - loss: 0.4686 -
accuracy: 0.7681
Epoch 183/300
138/138 [=====] - 0s 1ms/step - loss: 0.4382 -
accuracy: 0.7536
Epoch 184/300
138/138 [=====] - 0s 1ms/step - loss: 0.4257 -
accuracy: 0.7681
Epoch 185/300
138/138 [=====] - 0s 1ms/step - loss: 0.4097 -
accuracy: 0.7754
Epoch 186/300
138/138 [=====] - 0s 1ms/step - loss: 0.4116 -
accuracy: 0.7754
Epoch 187/300
138/138 [=====] - 0s 1ms/step - loss: 0.4979 -
accuracy: 0.7464
Epoch 188/300
138/138 [=====] - 0s 1ms/step - loss: 0.4045 -
accuracy: 0.7826
Epoch 189/300
138/138 [=====] - 0s 1ms/step - loss: 0.4803 -
accuracy: 0.7826
Epoch 190/300
138/138 [=====] - 0s 1ms/step - loss: 0.4463 -
accuracy: 0.7754
Epoch 191/300
138/138 [=====] - 0s 1ms/step - loss: 0.4218 -
accuracy: 0.7681
Epoch 192/300
138/138 [=====] - 0s 1ms/step - loss: 0.4829 -
accuracy: 0.7464
Epoch 193/300
138/138 [=====] - 0s 1ms/step - loss: 0.4250 -
accuracy: 0.7754
Epoch 194/300
138/138 [=====] - 0s 1ms/step - loss: 0.4173 -
accuracy: 0.7754
Epoch 195/300
138/138 [=====] - 0s 1ms/step - loss: 0.3823 -
accuracy: 0.7754
Epoch 196/300
138/138 [=====] - 0s 1ms/step - loss: 0.4189 -
accuracy: 0.7826
Epoch 197/300

138/138 [=====] - 0s 1ms/step - loss: 0.3845 -
accuracy: 0.7754
Epoch 198/300
138/138 [=====] - 0s 1ms/step - loss: 0.4393 -
accuracy: 0.7681
Epoch 199/300
138/138 [=====] - 0s 1ms/step - loss: 0.4225 -
accuracy: 0.7826
Epoch 200/300
138/138 [=====] - 0s 1ms/step - loss: 0.4323 -
accuracy: 0.7536
Epoch 201/300
138/138 [=====] - 0s 1ms/step - loss: 0.3714 -
accuracy: 0.8043
Epoch 202/300
138/138 [=====] - 0s 1ms/step - loss: 0.4209 -
accuracy: 0.7754
Epoch 203/300
138/138 [=====] - 0s 1ms/step - loss: 0.3741 -
accuracy: 0.7681
Epoch 204/300
138/138 [=====] - 0s 1ms/step - loss: 0.4125 -
accuracy: 0.7826
Epoch 205/300
138/138 [=====] - 0s 1ms/step - loss: 0.4189 -
accuracy: 0.7826
Epoch 206/300
138/138 [=====] - 0s 1ms/step - loss: 0.4081 -
accuracy: 0.7536
Epoch 207/300
138/138 [=====] - 0s 1ms/step - loss: 0.4070 -
accuracy: 0.7899
Epoch 208/300
138/138 [=====] - 0s 1ms/step - loss: 0.4206 -
accuracy: 0.7536
Epoch 209/300
138/138 [=====] - 0s 1ms/step - loss: 0.4491 -
accuracy: 0.7681
Epoch 210/300
138/138 [=====] - 0s 1ms/step - loss: 0.4216 -
accuracy: 0.7899
Epoch 211/300
138/138 [=====] - 0s 1ms/step - loss: 0.3905 -
accuracy: 0.7826
Epoch 212/300
138/138 [=====] - 0s 1ms/step - loss: 0.4066 -
accuracy: 0.7826
Epoch 213/300

138/138 [=====] - 0s 1ms/step - loss: 0.3876 -
accuracy: 0.7971
Epoch 214/300
138/138 [=====] - 0s 1ms/step - loss: 0.3919 -
accuracy: 0.7754
Epoch 215/300
138/138 [=====] - 0s 1ms/step - loss: 0.3998 -
accuracy: 0.7609
Epoch 216/300
138/138 [=====] - 0s 1ms/step - loss: 0.4238 -
accuracy: 0.7826
Epoch 217/300
138/138 [=====] - 0s 1ms/step - loss: 0.4067 -
accuracy: 0.7826
Epoch 218/300
138/138 [=====] - 0s 1ms/step - loss: 0.3907 -
accuracy: 0.7826
Epoch 219/300
138/138 [=====] - 0s 2ms/step - loss: 0.3689 -
accuracy: 0.7899
Epoch 220/300
138/138 [=====] - 0s 2ms/step - loss: 0.4083 -
accuracy: 0.7754
Epoch 221/300
138/138 [=====] - 0s 1ms/step - loss: 0.3729 -
accuracy: 0.7826
Epoch 222/300
138/138 [=====] - 0s 2ms/step - loss: 0.3587 -
accuracy: 0.7826
Epoch 223/300
138/138 [=====] - 0s 1ms/step - loss: 0.4035 -
accuracy: 0.7536
Epoch 224/300
138/138 [=====] - 0s 1ms/step - loss: 0.3543 -
accuracy: 0.7971
Epoch 225/300
138/138 [=====] - 0s 1ms/step - loss: 0.3763 -
accuracy: 0.7681
Epoch 226/300
138/138 [=====] - 0s 1ms/step - loss: 0.3632 -
accuracy: 0.7826
Epoch 227/300
138/138 [=====] - 0s 1ms/step - loss: 0.3582 -
accuracy: 0.7899
Epoch 228/300
138/138 [=====] - 0s 1ms/step - loss: 0.3854 -
accuracy: 0.7826
Epoch 229/300

138/138 [=====] - 0s 1ms/step - loss: 0.3330 -
 accuracy: 0.7899: 0s - loss: 0.2989 - accuracy: 0.
 Epoch 230/300
 138/138 [=====] - 0s 2ms/step - loss: 0.3642 -
 accuracy: 0.7681
 Epoch 231/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3986 -
 accuracy: 0.7754
 Epoch 232/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3420 -
 accuracy: 0.8043
 Epoch 233/300
 138/138 [=====] - 0s 1ms/step - loss: 0.4165 -
 accuracy: 0.7609
 Epoch 234/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3438 -
 accuracy: 0.7899
 Epoch 235/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3308 -
 accuracy: 0.7971
 Epoch 236/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3519 -
 accuracy: 0.8043
 Epoch 237/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3739 -
 accuracy: 0.8043
 Epoch 238/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3642 -
 accuracy: 0.7826
 Epoch 239/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3474 -
 accuracy: 0.7826
 Epoch 240/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3771 -
 accuracy: 0.7899
 Epoch 241/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3686 -
 accuracy: 0.7754
 Epoch 242/300
 138/138 [=====] - 0s 1ms/step - loss: 0.4119 -
 accuracy: 0.7899
 Epoch 243/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3567 -
 accuracy: 0.7826
 Epoch 244/300
 138/138 [=====] - 0s 1ms/step - loss: 0.3631 -
 accuracy: 0.7899
 Epoch 245/300

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138/138 [=====] - 0s 1ms/step - loss: 0.3200 -
accuracy: 0.7826
Epoch 246/300
138/138 [=====] - 0s 1ms/step - loss: 0.3037 -
accuracy: 0.8043
Epoch 247/300
138/138 [=====] - 0s 1ms/step - loss: 0.3383 -
accuracy: 0.7754
Epoch 248/300
138/138 [=====] - 0s 1ms/step - loss: 0.3465 -
accuracy: 0.7971
Epoch 249/300
138/138 [=====] - 0s 1ms/step - loss: 0.3308 -
accuracy: 0.7899
Epoch 250/300
138/138 [=====] - 0s 1ms/step - loss: 0.3613 -
accuracy: 0.8188
Epoch 251/300
138/138 [=====] - 0s 1ms/step - loss: 0.3359 -
accuracy: 0.8188
Epoch 252/300
138/138 [=====] - 0s 1ms/step - loss: 0.3184 -
accuracy: 0.7971
Epoch 253/300
138/138 [=====] - 0s 1ms/step - loss: 0.3594 -
accuracy: 0.7826
Epoch 254/300
138/138 [=====] - 0s 1ms/step - loss: 0.3432 -
accuracy: 0.7754
Epoch 255/300
138/138 [=====] - 0s 1ms/step - loss: 0.3547 -
accuracy: 0.7826
Epoch 256/300
138/138 [=====] - 0s 1ms/step - loss: 0.3606 -
accuracy: 0.8116
Epoch 257/300
138/138 [=====] - 0s 1ms/step - loss: 0.3841 -
accuracy: 0.7899
Epoch 258/300
138/138 [=====] - 0s 1ms/step - loss: 0.3125 -
accuracy: 0.7971
Epoch 259/300
138/138 [=====] - 0s 1ms/step - loss: 0.3731 -
accuracy: 0.8043
Epoch 260/300
138/138 [=====] - 0s 1ms/step - loss: 0.3504 -
accuracy: 0.7971
Epoch 261/300

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138/138 [=====] - 0s 1ms/step - loss: 0.3095 -
accuracy: 0.7971
Epoch 262/300
138/138 [=====] - 0s 1ms/step - loss: 0.3413 -
accuracy: 0.7899
Epoch 263/300
138/138 [=====] - 0s 1ms/step - loss: 0.3376 -
accuracy: 0.7826
Epoch 264/300
138/138 [=====] - 0s 1ms/step - loss: 0.3418 -
accuracy: 0.8116
Epoch 265/300
138/138 [=====] - 0s 1ms/step - loss: 0.3366 -
accuracy: 0.8043
Epoch 266/300
138/138 [=====] - 0s 1ms/step - loss: 0.3763 -
accuracy: 0.7899
Epoch 267/300
138/138 [=====] - 0s 1ms/step - loss: 0.3516 -
accuracy: 0.7899
Epoch 268/300
138/138 [=====] - 0s 1ms/step - loss: 0.3676 -
accuracy: 0.7899
Epoch 269/300
138/138 [=====] - 0s 1ms/step - loss: 0.3127 -
accuracy: 0.8043
Epoch 270/300
138/138 [=====] - 0s 1ms/step - loss: 0.3210 -
accuracy: 0.8116
Epoch 271/300
138/138 [=====] - 0s 1ms/step - loss: 0.3098 -
accuracy: 0.7899
Epoch 272/300
138/138 [=====] - 0s 1ms/step - loss: 0.3646 -
accuracy: 0.7754
Epoch 273/300
138/138 [=====] - 0s 1ms/step - loss: 0.3636 -
accuracy: 0.7971
Epoch 274/300
138/138 [=====] - 0s 1ms/step - loss: 0.3070 -
accuracy: 0.7971
Epoch 275/300
138/138 [=====] - 0s 1ms/step - loss: 0.3150 -
accuracy: 0.7754
Epoch 276/300
138/138 [=====] - 0s 1ms/step - loss: 0.3461 -
accuracy: 0.7971
Epoch 277/300

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138/138 [=====] - 0s 1ms/step - loss: 0.3633 -
accuracy: 0.7971
Epoch 278/300
138/138 [=====] - 0s 1ms/step - loss: 0.3606 -
accuracy: 0.7899
Epoch 279/300
138/138 [=====] - 0s 1ms/step - loss: 0.2754 -
accuracy: 0.8043
Epoch 280/300
138/138 [=====] - 0s 1ms/step - loss: 0.3107 -
accuracy: 0.8116
Epoch 281/300
138/138 [=====] - 0s 1ms/step - loss: 0.3152 -
accuracy: 0.7681
Epoch 282/300
138/138 [=====] - 0s 1ms/step - loss: 0.3616 -
accuracy: 0.7971
Epoch 283/300
138/138 [=====] - 0s 1ms/step - loss: 0.3225 -
accuracy: 0.7899
Epoch 284/300
138/138 [=====] - 0s 1ms/step - loss: 0.3056 -
accuracy: 0.8116
Epoch 285/300
138/138 [=====] - 0s 1ms/step - loss: 0.3100 -
accuracy: 0.7899
Epoch 286/300
138/138 [=====] - 0s 1ms/step - loss: 0.3610 -
accuracy: 0.7826
Epoch 287/300
138/138 [=====] - 0s 1ms/step - loss: 0.3223 -
accuracy: 0.7899
Epoch 288/300
138/138 [=====] - 0s 1ms/step - loss: 0.3269 -
accuracy: 0.7971
Epoch 289/300
138/138 [=====] - 0s 1ms/step - loss: 0.3204 -
accuracy: 0.7971
Epoch 290/300
138/138 [=====] - 0s 1ms/step - loss: 0.2970 -
accuracy: 0.7971
Epoch 291/300
138/138 [=====] - 0s 1ms/step - loss: 0.3000 -
accuracy: 0.8043
Epoch 292/300
138/138 [=====] - 0s 1ms/step - loss: 0.3109 -
accuracy: 0.7971
Epoch 293/300

```

```

138/138 [=====] - 0s 1ms/step - loss: 0.3423 -
accuracy: 0.7971
Epoch 294/300
138/138 [=====] - 0s 1ms/step - loss: 0.2971 -
accuracy: 0.7971
Epoch 295/300
138/138 [=====] - 0s 1ms/step - loss: 0.3390 -
accuracy: 0.7826
Epoch 296/300
138/138 [=====] - 0s 1ms/step - loss: 0.3101 -
accuracy: 0.7971
Epoch 297/300
138/138 [=====] - 0s 1ms/step - loss: 0.3020 -
accuracy: 0.7826
Epoch 298/300
138/138 [=====] - 0s 1ms/step - loss: 0.3012 -
accuracy: 0.8116
Epoch 299/300
138/138 [=====] - 0s 1ms/step - loss: 0.3093 -
accuracy: 0.7826
Epoch 300/300
138/138 [=====] - 0s 1ms/step - loss: 0.2775 -
accuracy: 0.7826

```

[20]: <keras.callbacks.callbacks.History at 0x24c535efcc8>

```

[21]: # Avalia os resultados do modelo
scores = model.evaluate(X_train, Y_train_encoded)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))

```

```

138/138 [=====] - 0s 905us/step
accuracy: 78.99%

```

```

[22]: # Compila o modelo com outro otimizador: Adam Gradient Descent algorithm
model.compile(loss = 'categorical_crossentropy',
              optimizer = 'adam',
              metrics = ['accuracy'])

# Executa o modelo e valida nos mesmos dados em que foi criado (treino)
model.fit(X_train, Y_train_encoded, epochs = 200, batch_size = 5)

```

```

Epoch 1/200
138/138 [=====] - 0s 3ms/step - loss: 0.2525 -
accuracy: 0.8043
Epoch 2/200
138/138 [=====] - ETA: 0s - loss: 0.2417 - accuracy:
0.81 - 0s 2ms/step - loss: 0.2409 - accuracy: 0.8188
Epoch 3/200

```

138/138 [=====] - 0s 2ms/step - loss: 0.2452 -
 accuracy: 0.7971
 Epoch 4/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2374 -
 accuracy: 0.8043
 Epoch 5/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2424 -
 accuracy: 0.7899
 Epoch 6/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2303 -
 accuracy: 0.7971
 Epoch 7/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2378 -
 accuracy: 0.8188
 Epoch 8/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2308 -
 accuracy: 0.8043
 Epoch 9/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2337 -
 accuracy: 0.7971
 Epoch 10/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2331 -
 accuracy: 0.8116
 Epoch 11/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2312 -
 accuracy: 0.8116
 Epoch 12/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2405 -
 accuracy: 0.7899
 Epoch 13/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2448 -
 accuracy: 0.8043
 Epoch 14/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2384 -
 accuracy: 0.8043
 Epoch 15/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2486 -
 accuracy: 0.8116
 Epoch 16/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2258 -
 accuracy: 0.8116
 Epoch 17/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2336 -
 accuracy: 0.8043
 Epoch 18/200
 138/138 [=====] - 0s 2ms/step - loss: 0.2330 -
 accuracy: 0.8116
 Epoch 19/200

138/138 [=====] - 0s 2ms/step - loss: 0.2387 -
accuracy: 0.7971
Epoch 20/200
138/138 [=====] - 0s 2ms/step - loss: 0.2281 -
accuracy: 0.8043
Epoch 21/200
138/138 [=====] - 0s 2ms/step - loss: 0.2239 -
accuracy: 0.8188
Epoch 22/200
138/138 [=====] - 0s 2ms/step - loss: 0.2253 -
accuracy: 0.8043
Epoch 23/200
138/138 [=====] - 0s 2ms/step - loss: 0.2237 -
accuracy: 0.7971
Epoch 24/200
138/138 [=====] - 0s 2ms/step - loss: 0.2245 -
accuracy: 0.8116
Epoch 25/200
138/138 [=====] - 0s 2ms/step - loss: 0.2225 -
accuracy: 0.8043
Epoch 26/200
138/138 [=====] - 0s 2ms/step - loss: 0.2255 -
accuracy: 0.8188
Epoch 27/200
138/138 [=====] - 0s 2ms/step - loss: 0.2198 -
accuracy: 0.8116
Epoch 28/200
138/138 [=====] - 0s 2ms/step - loss: 0.2209 -
accuracy: 0.8116
Epoch 29/200
138/138 [=====] - 0s 2ms/step - loss: 0.2219 -
accuracy: 0.8116
Epoch 30/200
138/138 [=====] - 0s 2ms/step - loss: 0.2210 -
accuracy: 0.8043
Epoch 31/200
138/138 [=====] - 0s 2ms/step - loss: 0.2249 -
accuracy: 0.7971
Epoch 32/200
138/138 [=====] - 0s 2ms/step - loss: 0.2237 -
accuracy: 0.8043
Epoch 33/200
138/138 [=====] - 0s 2ms/step - loss: 0.2183 -
accuracy: 0.7971
Epoch 34/200
138/138 [=====] - 0s 2ms/step - loss: 0.2213 -
accuracy: 0.8116
Epoch 35/200


```

138/138 [=====] - 0s 2ms/step - loss: 0.2248 -
accuracy: 0.7899
Epoch 36/200
138/138 [=====] - 0s 2ms/step - loss: 0.2188 -
accuracy: 0.8043
Epoch 37/200
138/138 [=====] - 0s 2ms/step - loss: 0.2244 -
accuracy: 0.8116
Epoch 38/200
138/138 [=====] - 0s 2ms/step - loss: 0.2210 -
accuracy: 0.8043
Epoch 39/200
138/138 [=====] - 0s 2ms/step - loss: 0.2264 -
accuracy: 0.8116
Epoch 40/200
138/138 [=====] - 0s 2ms/step - loss: 0.2216 -
accuracy: 0.7681
Epoch 41/200
138/138 [=====] - 0s 2ms/step - loss: 0.2241 -
accuracy: 0.8116
Epoch 42/200
138/138 [=====] - 0s 2ms/step - loss: 0.2169 -
accuracy: 0.8116
Epoch 43/200
138/138 [=====] - 0s 2ms/step - loss: 0.2173 -
accuracy: 0.8043
Epoch 44/200
138/138 [=====] - 0s 2ms/step - loss: 0.2170 -
accuracy: 0.7899
Epoch 45/200
138/138 [=====] - 0s 2ms/step - loss: 0.2204 -
accuracy: 0.7899
Epoch 46/200
138/138 [=====] - 0s 2ms/step - loss: 0.2162 -
accuracy: 0.8043
Epoch 47/200
138/138 [=====] - 0s 2ms/step - loss: 0.2160 -
accuracy: 0.7971
Epoch 48/200
138/138 [=====] - 0s 2ms/step - loss: 0.2175 -
accuracy: 0.8043
Epoch 49/200
138/138 [=====] - 0s 2ms/step - loss: 0.2220 -
accuracy: 0.8116
Epoch 50/200
138/138 [=====] - 0s 2ms/step - loss: 0.2112 -
accuracy: 0.8116
Epoch 51/200

```

```

138/138 [=====] - 0s 2ms/step - loss: 0.2220 -
accuracy: 0.7754
Epoch 52/200
138/138 [=====] - 0s 2ms/step - loss: 0.2104 -
accuracy: 0.8116
Epoch 53/200
138/138 [=====] - 0s 2ms/step - loss: 0.2145 -
accuracy: 0.8188
Epoch 54/200
138/138 [=====] - 0s 2ms/step - loss: 0.2133 -
accuracy: 0.8043
Epoch 55/200
138/138 [=====] - 0s 2ms/step - loss: 0.2220 -
accuracy: 0.8116
Epoch 56/200
138/138 [=====] - ETA: 0s - loss: 0.1987 - accuracy:
0.7923 ETA: 0s - loss: 0.2533 - accuracy - 0s 2ms/step - loss: 0.2102 -
accuracy: 0.7826
Epoch 57/200
138/138 [=====] - 0s 2ms/step - loss: 0.2209 -
accuracy: 0.7826
Epoch 58/200
138/138 [=====] - 0s 2ms/step - loss: 0.2089 -
accuracy: 0.8116
Epoch 59/200
138/138 [=====] - 0s 2ms/step - loss: 0.2105 -
accuracy: 0.8116
Epoch 60/200
138/138 [=====] - 0s 2ms/step - loss: 0.2133 -
accuracy: 0.8188
Epoch 61/200
138/138 [=====] - 0s 2ms/step - loss: 0.2317 -
accuracy: 0.7899
Epoch 62/200
138/138 [=====] - 0s 2ms/step - loss: 0.2237 -
accuracy: 0.8116
Epoch 63/200
138/138 [=====] - 0s 2ms/step - loss: 0.2192 -
accuracy: 0.7899
Epoch 64/200
138/138 [=====] - 0s 2ms/step - loss: 0.2220 -
accuracy: 0.7826
Epoch 65/200
138/138 [=====] - 0s 2ms/step - loss: 0.2157 -
accuracy: 0.8188
Epoch 66/200
138/138 [=====] - 0s 2ms/step - loss: 0.2103 -
accuracy: 0.8116

```

Epoch 67/200
138/138 [=====] - 0s 2ms/step - loss: 0.2099 -
accuracy: 0.8188

Epoch 68/200
138/138 [=====] - 0s 2ms/step - loss: 0.2149 -
accuracy: 0.8333

Epoch 69/200
138/138 [=====] - 0s 2ms/step - loss: 0.2168 -
accuracy: 0.8913

Epoch 70/200
138/138 [=====] - 0s 2ms/step - loss: 0.2289 -
accuracy: 0.8913

Epoch 71/200
138/138 [=====] - 0s 2ms/step - loss: 0.2156 -
accuracy: 0.8986

Epoch 72/200
138/138 [=====] - 0s 2ms/step - loss: 0.2116 -
accuracy: 0.8913

Epoch 73/200
138/138 [=====] - 0s 2ms/step - loss: 0.2263 -
accuracy: 0.9203

Epoch 74/200
138/138 [=====] - 0s 2ms/step - loss: 0.2072 -
accuracy: 0.9203

Epoch 75/200
138/138 [=====] - 0s 2ms/step - loss: 0.1472 -
accuracy: 0.9058

Epoch 76/200
138/138 [=====] - 0s 2ms/step - loss: 0.1415 -
accuracy: 0.9275

Epoch 77/200
138/138 [=====] - 0s 2ms/step - loss: 0.1413 -
accuracy: 0.9275

Epoch 78/200
138/138 [=====] - 0s 2ms/step - loss: 0.1406 -
accuracy: 0.9130

Epoch 79/200
138/138 [=====] - 0s 2ms/step - loss: 0.1428 -
accuracy: 0.9130

Epoch 80/200
138/138 [=====] - 0s 2ms/step - loss: 0.1422 -
accuracy: 0.9275

Epoch 81/200
138/138 [=====] - 0s 2ms/step - loss: 0.1344 -
accuracy: 0.9203

Epoch 82/200
138/138 [=====] - 0s 2ms/step - loss: 0.1357 -
accuracy: 0.8986

Epoch 83/200
138/138 [=====] - 0s 2ms/step - loss: 0.1312 -
accuracy: 0.9203
Epoch 84/200
138/138 [=====] - 0s 2ms/step - loss: 0.1350 -
accuracy: 0.9203
Epoch 85/200
138/138 [=====] - 0s 2ms/step - loss: 0.1365 -
accuracy: 0.9203
Epoch 86/200
138/138 [=====] - 0s 2ms/step - loss: 0.1312 -
accuracy: 0.9130
Epoch 87/200
138/138 [=====] - 0s 2ms/step - loss: 0.1341 -
accuracy: 0.9203
Epoch 88/200
138/138 [=====] - 0s 2ms/step - loss: 0.1385 -
accuracy: 0.9058
Epoch 89/200
138/138 [=====] - 0s 2ms/step - loss: 0.1271 -
accuracy: 0.9275
Epoch 90/200
138/138 [=====] - 0s 2ms/step - loss: 0.1458 -
accuracy: 0.9203
Epoch 91/200
138/138 [=====] - 0s 2ms/step - loss: 0.1327 -
accuracy: 0.9348
Epoch 92/200
138/138 [=====] - 0s 2ms/step - loss: 0.1378 -
accuracy: 0.9058
Epoch 93/200
138/138 [=====] - 0s 2ms/step - loss: 0.1326 -
accuracy: 0.9203
Epoch 94/200
138/138 [=====] - 0s 2ms/step - loss: 0.1415 -
accuracy: 0.9130
Epoch 95/200
138/138 [=====] - 0s 2ms/step - loss: 0.1301 -
accuracy: 0.9130
Epoch 96/200
138/138 [=====] - 0s 2ms/step - loss: 0.1414 -
accuracy: 0.9275
Epoch 97/200
138/138 [=====] - 0s 2ms/step - loss: 0.1406 -
accuracy: 0.8986
Epoch 98/200
138/138 [=====] - 0s 2ms/step - loss: 0.1407 -
accuracy: 0.9275

Epoch 99/200
138/138 [=====] - 0s 2ms/step - loss: 0.1336 -
accuracy: 0.9058
Epoch 100/200
138/138 [=====] - 0s 2ms/step - loss: 0.1377 -
accuracy: 0.9058
Epoch 101/200
138/138 [=====] - 0s 2ms/step - loss: 0.1366 -
accuracy: 0.9058
Epoch 102/200
138/138 [=====] - 0s 2ms/step - loss: 0.1264 -
accuracy: 0.9203
Epoch 103/200
138/138 [=====] - 0s 2ms/step - loss: 0.1295 -
accuracy: 0.9130
Epoch 104/200
138/138 [=====] - 0s 2ms/step - loss: 0.1403 -
accuracy: 0.8841
Epoch 105/200
138/138 [=====] - 0s 2ms/step - loss: 0.1362 -
accuracy: 0.9130
Epoch 106/200
138/138 [=====] - 0s 2ms/step - loss: 0.1356 -
accuracy: 0.9130
Epoch 107/200
138/138 [=====] - 0s 2ms/step - loss: 0.1279 -
accuracy: 0.9275
Epoch 108/200
138/138 [=====] - 0s 2ms/step - loss: 0.1370 -
accuracy: 0.9130
Epoch 109/200
138/138 [=====] - 0s 2ms/step - loss: 0.1333 -
accuracy: 0.9130
Epoch 110/200
138/138 [=====] - 0s 2ms/step - loss: 0.1339 -
accuracy: 0.9203
Epoch 111/200
138/138 [=====] - 0s 2ms/step - loss: 0.1376 -
accuracy: 0.9130
Epoch 112/200
138/138 [=====] - 0s 2ms/step - loss: 0.1370 -
accuracy: 0.9275
Epoch 113/200
138/138 [=====] - 0s 2ms/step - loss: 0.1360 -
accuracy: 0.8986
Epoch 114/200
138/138 [=====] - 0s 2ms/step - loss: 0.1344 -
accuracy: 0.9058

Epoch 115/200
138/138 [=====] - 0s 2ms/step - loss: 0.1485 -
accuracy: 0.9275
Epoch 116/200
138/138 [=====] - 0s 2ms/step - loss: 0.1510 -
accuracy: 0.9203
Epoch 117/200
138/138 [=====] - 0s 2ms/step - loss: 0.1296 -
accuracy: 0.9203
Epoch 118/200
138/138 [=====] - 0s 2ms/step - loss: 0.1327 -
accuracy: 0.9275
Epoch 119/200
138/138 [=====] - 0s 2ms/step - loss: 0.1346 -
accuracy: 0.9130
Epoch 120/200
138/138 [=====] - 0s 2ms/step - loss: 0.1346 -
accuracy: 0.9130
Epoch 121/200
138/138 [=====] - 0s 2ms/step - loss: 0.1399 -
accuracy: 0.9203
Epoch 122/200
138/138 [=====] - 0s 2ms/step - loss: 0.1338 -
accuracy: 0.9130
Epoch 123/200
138/138 [=====] - 0s 3ms/step - loss: 0.1339 -
accuracy: 0.9058
Epoch 124/200
138/138 [=====] - 0s 2ms/step - loss: 0.1378 -
accuracy: 0.9203
Epoch 125/200
138/138 [=====] - 0s 2ms/step - loss: 0.1403 -
accuracy: 0.8986
Epoch 126/200
138/138 [=====] - 0s 2ms/step - loss: 0.1516 -
accuracy: 0.8986
Epoch 127/200
138/138 [=====] - 0s 2ms/step - loss: 0.1337 -
accuracy: 0.9130
Epoch 128/200
138/138 [=====] - 0s 2ms/step - loss: 0.1340 -
accuracy: 0.9203
Epoch 129/200
138/138 [=====] - 0s 2ms/step - loss: 0.1404 -
accuracy: 0.8986
Epoch 130/200
138/138 [=====] - 0s 2ms/step - loss: 0.1327 -
accuracy: 0.9275

Epoch 131/200
138/138 [=====] - 0s 2ms/step - loss: 0.1301 -
accuracy: 0.9130
Epoch 132/200
138/138 [=====] - 0s 2ms/step - loss: 0.1263 -
accuracy: 0.9348
Epoch 133/200
138/138 [=====] - 0s 2ms/step - loss: 0.1426 -
accuracy: 0.9203
Epoch 134/200
138/138 [=====] - 0s 2ms/step - loss: 0.1368 -
accuracy: 0.8986
Epoch 135/200
138/138 [=====] - 0s 2ms/step - loss: 0.1367 -
accuracy: 0.9203
Epoch 136/200
138/138 [=====] - 0s 2ms/step - loss: 0.1315 -
accuracy: 0.9130
Epoch 137/200
138/138 [=====] - 0s 2ms/step - loss: 0.1357 -
accuracy: 0.9130
Epoch 138/200
138/138 [=====] - 0s 2ms/step - loss: 0.1358 -
accuracy: 0.9275
Epoch 139/200
138/138 [=====] - 0s 2ms/step - loss: 0.1316 -
accuracy: 0.9130
Epoch 140/200
138/138 [=====] - 0s 2ms/step - loss: 0.1330 -
accuracy: 0.8986
Epoch 141/200
138/138 [=====] - 0s 2ms/step - loss: 0.1295 -
accuracy: 0.9130
Epoch 142/200
138/138 [=====] - 0s 2ms/step - loss: 0.1340 -
accuracy: 0.9058
Epoch 143/200
138/138 [=====] - 0s 2ms/step - loss: 0.1466 -
accuracy: 0.8841
Epoch 144/200
138/138 [=====] - 0s 2ms/step - loss: 0.1509 -
accuracy: 0.9203
Epoch 145/200
138/138 [=====] - 0s 2ms/step - loss: 0.1363 -
accuracy: 0.8986
Epoch 146/200
138/138 [=====] - 0s 2ms/step - loss: 0.1339 -
accuracy: 0.8986

Epoch 147/200
138/138 [=====] - 0s 2ms/step - loss: 0.1289 -
accuracy: 0.9203
Epoch 148/200
138/138 [=====] - 0s 2ms/step - loss: 0.1355 -
accuracy: 0.8986
Epoch 149/200
138/138 [=====] - 0s 2ms/step - loss: 0.1249 -
accuracy: 0.9203
Epoch 150/200
138/138 [=====] - 0s 2ms/step - loss: 0.1368 -
accuracy: 0.9203
Epoch 151/200
138/138 [=====] - 0s 2ms/step - loss: 0.1326 -
accuracy: 0.9130
Epoch 152/200
138/138 [=====] - 0s 2ms/step - loss: 0.1329 -
accuracy: 0.9203
Epoch 153/200
138/138 [=====] - 0s 2ms/step - loss: 0.1294 -
accuracy: 0.9203
Epoch 154/200
138/138 [=====] - 0s 2ms/step - loss: 0.1315 -
accuracy: 0.9058
Epoch 155/200
138/138 [=====] - 0s 2ms/step - loss: 0.1315 -
accuracy: 0.9203
Epoch 156/200
138/138 [=====] - 0s 2ms/step - loss: 0.1289 -
accuracy: 0.9130
Epoch 157/200
138/138 [=====] - 0s 2ms/step - loss: 0.1350 -
accuracy: 0.9130
Epoch 158/200
138/138 [=====] - 0s 2ms/step - loss: 0.1394 -
accuracy: 0.8913
Epoch 159/200
138/138 [=====] - 0s 2ms/step - loss: 0.1320 -
accuracy: 0.9130
Epoch 160/200
138/138 [=====] - 0s 2ms/step - loss: 0.1378 -
accuracy: 0.9203
Epoch 161/200
138/138 [=====] - 0s 2ms/step - loss: 0.1310 -
accuracy: 0.9275
Epoch 162/200
138/138 [=====] - 0s 2ms/step - loss: 0.1314 -
accuracy: 0.9203

Epoch 163/200
138/138 [=====] - 0s 2ms/step - loss: 0.1468 -
accuracy: 0.8768
Epoch 164/200
138/138 [=====] - 0s 2ms/step - loss: 0.1362 -
accuracy: 0.9058
Epoch 165/200
138/138 [=====] - 0s 2ms/step - loss: 0.1345 -
accuracy: 0.9058
Epoch 166/200
138/138 [=====] - 0s 2ms/step - loss: 0.1473 -
accuracy: 0.9203
Epoch 167/200
138/138 [=====] - 0s 2ms/step - loss: 0.1366 -
accuracy: 0.8986
Epoch 168/200
138/138 [=====] - 0s 2ms/step - loss: 0.1310 -
accuracy: 0.9130
Epoch 169/200
138/138 [=====] - 0s 2ms/step - loss: 0.1360 -
accuracy: 0.9275
Epoch 170/200
138/138 [=====] - 0s 2ms/step - loss: 0.1336 -
accuracy: 0.9203
Epoch 171/200
138/138 [=====] - 0s 2ms/step - loss: 0.1344 -
accuracy: 0.9058
Epoch 172/200
138/138 [=====] - 0s 2ms/step - loss: 0.1395 -
accuracy: 0.8986
Epoch 173/200
138/138 [=====] - 0s 2ms/step - loss: 0.1368 -
accuracy: 0.9130
Epoch 174/200
138/138 [=====] - 0s 2ms/step - loss: 0.1388 -
accuracy: 0.9130
Epoch 175/200
138/138 [=====] - 0s 2ms/step - loss: 0.1368 -
accuracy: 0.9275
Epoch 176/200
138/138 [=====] - 0s 2ms/step - loss: 0.1425 -
accuracy: 0.8841
Epoch 177/200
138/138 [=====] - 0s 2ms/step - loss: 0.1321 -
accuracy: 0.9130
Epoch 178/200
138/138 [=====] - 0s 2ms/step - loss: 0.1277 -
accuracy: 0.9058

Epoch 179/200
138/138 [=====] - 0s 2ms/step - loss: 0.1369 -
accuracy: 0.9130

Epoch 180/200
138/138 [=====] - 0s 2ms/step - loss: 0.1318 -
accuracy: 0.9130

Epoch 181/200
138/138 [=====] - 0s 2ms/step - loss: 0.1336 -
accuracy: 0.9275

Epoch 182/200
138/138 [=====] - 0s 2ms/step - loss: 0.1356 -
accuracy: 0.9203

Epoch 183/200
138/138 [=====] - 0s 2ms/step - loss: 0.1360 -
accuracy: 0.9275

Epoch 184/200
138/138 [=====] - 0s 2ms/step - loss: 0.1303 -
accuracy: 0.9130

Epoch 185/200
138/138 [=====] - 0s 2ms/step - loss: 0.1374 -
accuracy: 0.9058

Epoch 186/200
138/138 [=====] - 0s 2ms/step - loss: 0.1464 -
accuracy: 0.9203

Epoch 187/200
138/138 [=====] - 0s 2ms/step - loss: 0.1266 -
accuracy: 0.8986

Epoch 188/200
138/138 [=====] - 0s 2ms/step - loss: 0.1362 -
accuracy: 0.9058

Epoch 189/200
138/138 [=====] - 0s 2ms/step - loss: 0.1273 -
accuracy: 0.9275

Epoch 190/200
138/138 [=====] - 0s 2ms/step - loss: 0.1334 -
accuracy: 0.9275

Epoch 191/200
138/138 [=====] - 0s 2ms/step - loss: 0.1292 -
accuracy: 0.9058

Epoch 192/200
138/138 [=====] - 0s 2ms/step - loss: 0.1437 -
accuracy: 0.8986

Epoch 193/200
138/138 [=====] - 0s 2ms/step - loss: 0.1410 -
accuracy: 0.9130

Epoch 194/200
138/138 [=====] - 0s 2ms/step - loss: 0.1421 -
accuracy: 0.9058

```

Epoch 195/200
138/138 [=====] - 0s 2ms/step - loss: 0.1383 -
accuracy: 0.9203
Epoch 196/200
138/138 [=====] - 0s 2ms/step - loss: 0.1293 -
accuracy: 0.9275
Epoch 197/200
138/138 [=====] - 0s 2ms/step - loss: 0.1290 -
accuracy: 0.9203
Epoch 198/200
138/138 [=====] - 0s 2ms/step - loss: 0.1312 -
accuracy: 0.9130
Epoch 199/200
138/138 [=====] - 0s 2ms/step - loss: 0.1337 -
accuracy: 0.9058
Epoch 200/200
138/138 [=====] - 0s 2ms/step - loss: 0.1300 -
accuracy: 0.9275

```

[22]: <keras.callbacks.callbacks.History at 0x24c6e62c848>

```

[23]: # Avalia os resultados do modelo
scores = model.evaluate(X_train, Y_train_encoded)
print("%s: %.2f%" % (model.metrics_names[1], scores[1]*100))

```

```

138/138 [=====] - 0s 932us/step
accuracy: 92.75%

```

```

[24]: # Prevendo as classes dos dados de teste
pred_class = model.predict_classes(X_test)
classes = np.array(range(1, 10))
preds = classes[pred_class]
preds

```

```

[24]: array([4, 2, 2, 4, 4, 4, 4, 1, 4, 4, 4, 4, 4, 4, 4, 1, 4, 4, 4, 6, 4,
          5, 4, 4, 4, 4, 4, 7, 4, 4, 7, 4, 2, 7, 4, 4, 4, 4, 4, 1, 4, 1,
          4, 1, 4, 1, 4, 4, 1, 1, 4, 1, 1, 1, 4, 1, 1, 4, 1, 4, 4, 4, 1, 1,
          4, 7, 7, 7, 1, 2, 1, 4, 1, 2, 2, 2, 2, 2, 2, 2, 7, 7, 4, 7, 7, 7,
          4, 4, 1, 4, 4, 4, 1, 4, 4, 2, 4, 4, 1, 1, 4, 1, 4, 1, 5, 1, 1, 5,
          1, 5, 4, 4, 4, 1, 1, 4, 1, 1, 4, 9, 6, 6, 6, 6, 6, 6, 6, 6, 6, 6,
          6, 6, 6, 6, 6, 4])

```

```

[25]: ## Formatando no arquivo de submission

# Onehot encoding classes
preds_onehot = pd.get_dummies(preds)

# Criando df final de entrega

```

```
df_submission = pd.concat([df_test['ID'][:-1], preds_onehot], axis = 1).
    ↳astype(int)
df_submission
```

```
[25]:
```

	ID	1	2	4	5	6	7	9
0	0	0	0	1	0	0	0	0
1	1	0	1	0	0	0	0	0
2	2	0	1	0	0	0	0	0
3	3	0	0	1	0	0	0	0
4	4	0	0	1	0	0	0	0
...
133	133	0	0	0	0	1	0	0
134	134	0	0	0	0	1	0	0
135	135	0	0	0	0	1	0	0
136	136	0	0	0	0	1	0	0
137	137	0	0	1	0	0	0	0

[138 rows x 8 columns]

```
[26]: # Salvando arquivo de submissão
df_submission.to_csv('submission.csv', index=False)
```