

#Projeto 1 - Redes Neurais

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## Mini-projeto: Reconhecimento de Dígitos com MLPs

Para a implementação do reconhecedor de dígitos, utilizamos Tensorflow e Keras, além da biblioteca Numpy para operações matemáticas e Scikit-Learn para funções de métricas de avaliação.

### *O que entregar?*

Taxas de acerto (acurácia por classe e total) com variação de parâmetros (tamanho da rede, taxa de aprendizagem, função de ativação), buscando ganhos de desempenho

### Atribuição dos valores estudados

Escolhemos a seguinte variação de valores a fim de analisar o desempenho do reconhecedor de dígitos

#### MLP

- Tamanho da rede: [1 - 5]
- Taxa de aprendizagem: [0.1 - 0.7]
- Função de ativação: [relu, softmax, tanh, sigmoid]
- Algoritmo de aprendizagem: [adam, rmsprop, sgd]
- Dropout: [0.1 - 0.5] e [0.8]

## Importando bibliotecas e tratando os dados

### Importações

```
import numpy as np
from tensorflow import keras
from keras.datasets import mnist
from tensorflow.keras import layers
from tensorflow.keras.utils import to_categorical
from sklearn.metrics import classification_report, confusion_matrix,
ConfusionMatrixDisplay, accuracy_score
```

### *#Biblioteca de plot*

```
import matplotlib.pyplot as plt
```

### Fazendo download do banco de dados MNIST

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

## Parâmetros e hiperparâmetros

Principais parâmetros que serão utilizados na normalização dos dados e em seu treinamento.

```
input_shape = x_train[0].shape # Formato de entrada a ser aceito pela
primeira camada dos modelos
num_class = 10 # Numero de classes existentes no dataset
batch_size = 32 # Numero de amostras por iteração de treinamento
epochs = 10 # Numero de vezes que o modelo treinara no conjunto
completo de treinamento
val_split = 0.3 # Porcentagem do conjunto de treino a ser usado para a
validacao
verbose = 0 # parametro para modificar os detalhes a serem mostrados
durante o treinamento
```

## Normalização dos dados

- A fim de garantir uma consistência na dimensão dos dados, fazemos uma normalização (dividimos os valores por 255, devido ao intervalo dos valores).

```
x_train = x_train.reshape((x_train.shape[0], 28, 28, 1))/255.
x_test = x_test.reshape((x_test.shape[0], 28, 28, 1))/255.
```

## Categorização das labels

Utilizamos a função `to_categorical`, importada do Keras, a fim de transformar os valores possíveis contidos nas amostras em valorações categóricas contendo 0 ou 1 ao final da rede. Desse modo, devemos ter 10 categorias de output.

```
y_train = to_categorical(y_train, num_class)
y_test = to_categorical(y_test, num_class)
```

## Matriz de confusão e gráficos

```
def historyPlot(model, history_dict, y_test):
    loss_values = history_dict['loss']
    val_loss_values = history_dict['val_loss']
    accuracy = history_dict['accuracy']
    val_accuracy = history_dict['val_accuracy']

    epochs = range(1, len(loss_values) + 1)
    fig, ax = plt.subplots(1, 2, figsize=(14, 6))

    ax[0].plot(epochs, accuracy, 'bo', label='Training accuracy')
    ax[0].plot(epochs, val_accuracy, 'b', label='Validation accuracy')
    ax[0].set_title('Training & Validation Accuracy', fontsize=16)
    ax[0].set_xlabel('Epochs', fontsize=16)
    ax[0].set_ylabel('Accuracy', fontsize=16)
    ax[0].legend()

    ax[1].plot(epochs, loss_values, 'bo', label='Training loss')
    ax[1].plot(epochs, val_loss_values, 'b', label='Validation loss')
```

```

ax[1].set_title('Training & Validation Loss', fontsize=16)
ax[1].set_xlabel('Epochs', fontsize=16)
ax[1].set_ylabel('Loss', fontsize=16)
ax[1].legend()

y_test_argmax = np.argmax(y_test, axis=1)
y_pred = model.predict(x_test)
y_pred_argmax = np.argmax(y_pred, axis=1)
print(classification_report(y_test_argmax, y_pred_argmax))

cm = confusion_matrix(y_test_argmax, y_pred_argmax, labels =
np.unique(y_test_argmax))
cmd = ConfusionMatrixDisplay(cm, display_labels =
np.unique(y_test_argmax))
cmd.plot()
plt.show()

var = cm.diagonal()/cm.sum(axis=1)
print("Accuracy")
_ = [print( "Label " + str(i) + (": {percentage:.2f}"
%).format(percentage=100*var[i])) for i in range(len(var))]

```

## Estudo MLP

### Tamanho da rede

*Valores a serem testados: 1, 2, 3, 4, e 5 camadas*

Primeiramente iremos analisar a influência do tamanho da rede na acurácia e no loss do modelo.

Criamos 5 modelos:

1. Camada densa com 10 unidades (número de classes)
2. Camada densa com 128 unidades + 1 camada densa com 10 unidades (número de classes)
3. Camada densa com 256 unidades + 1 camada densa com 128 unidades + 1 camada densa com 10 unidades (número de classes)
4. Camada densa com 256 unidades + 1 camada densa com 128 unidades + 1 camada densa com 64 unidades + 1 camada densa com 10 unidades (número de classes)
5. Camada densa com 512 unidades + 1 camada densa com 256 unidades + 1 camada densa com 128 unidades + 1 camada densa com 64 unidades + 1 camada densa com 10 unidades (número de classes)

```

model_MLP_1 = keras.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(num_class, activation = 'softmax')
])

```

```

model_MLP_2 = keras.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(128, activation = 'softmax'),
    layers.Dense(num_class, activation = 'softmax')

])

model_MLP_3 = keras.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(256, activation = 'softmax'),
    layers.Dense(128, activation = 'softmax'),
    layers.Dense(num_class, activation = 'softmax')

])

model_MLP_4 = keras.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(256, activation = 'softmax'),
    layers.Dense(128, activation = 'softmax'),
    layers.Dense(64, activation = 'softmax'),
    layers.Dense(num_class, activation = 'softmax')

])

model_MLP_5 = keras.Sequential([
    keras.Input(shape=input_shape),
    layers.Flatten(),
    layers.Dense(512, activation = 'softmax'),
    layers.Dense(256, activation = 'softmax'),
    layers.Dense(128, activation = 'softmax'),
    layers.Dense(64, activation = 'softmax'),
    layers.Dense(num_class, activation = 'softmax')

])

def networkAnalysis(model,x_train = x_train,shape =
input_shape,num_class = num_class, y_train = y_train, x_test = x_test,
y_test = y_test, batch_size = batch_size,epochs = epochs,
validation_split = val_split, verbose = verbose):
    model.compile(optimizer = 'adam', loss = 'categorical_crossentropy',
metrics = 'accuracy')
    history_model = model.fit(x_train, y_train, batch_size = batch_size,
validation_split = val_split, epochs = epochs, verbose = verbose)
    eval = model.evaluate(x_test, y_test)
    print(("Loss: {percentage:.2f}").format(percentage=eval[0]))
    print(("Accuracy: {percentage:.2f}
%").format(percentage=100*(eval[1])))
    historyPlot(model, history_model.history, y_test)

```

```

model_list = [model_MLP_1, model_MLP_2, model_MLP_3, model_MLP_4,
model_MLP_5]
for i in range (5):
    print("MODEL {i}".format(i = i+1))
    networkAnalysis(model_list[i])

```

```

print('-----')
print('-----')

```

MODEL 1

313/313 [=====] - 0s 1ms/step - loss: 0.2693

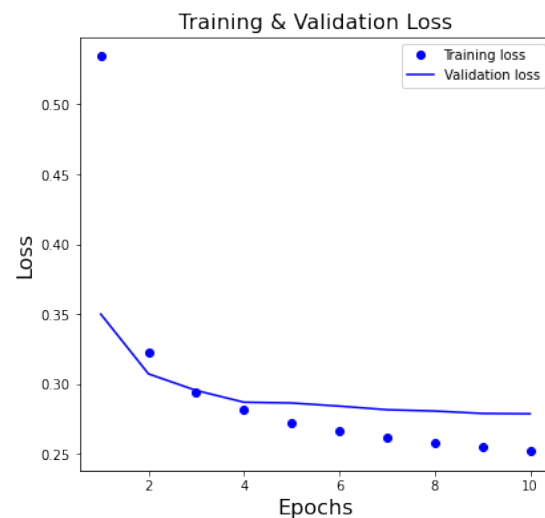
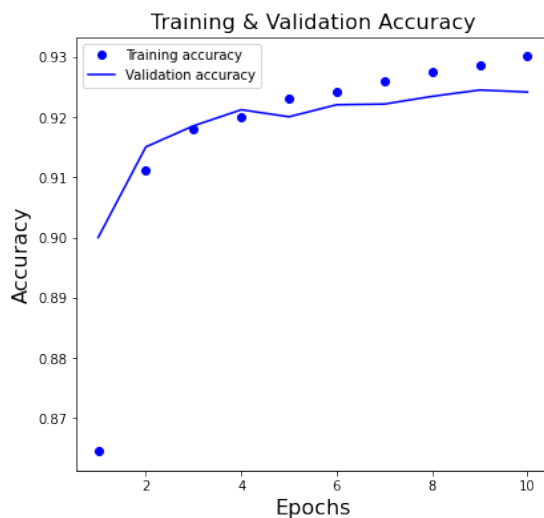
- accuracy: 0.9233

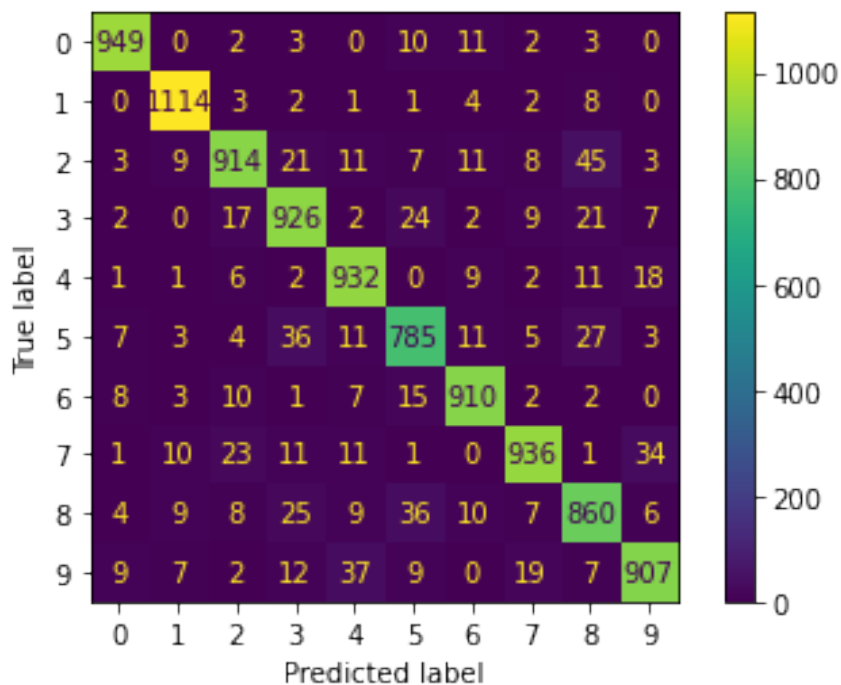
Loss: 0.27

Accuracy: 92.33 %

313/313 [=====] - 0s 1ms/step

	precision	recall	f1-score	support
0	0.96	0.97	0.97	980
1	0.96	0.98	0.97	1135
2	0.92	0.89	0.90	1032
3	0.89	0.92	0.90	1010
4	0.91	0.95	0.93	982
5	0.88	0.88	0.88	892
6	0.94	0.95	0.94	958
7	0.94	0.91	0.93	1028
8	0.87	0.88	0.88	974
9	0.93	0.90	0.91	1009
accuracy			0.92	10000
macro avg	0.92	0.92	0.92	10000
weighted avg	0.92	0.92	0.92	10000





#### Accuracy

Label 0: 96.84 %  
 Label 1: 98.15 %  
 Label 2: 88.57 %  
 Label 3: 91.68 %  
 Label 4: 94.91 %  
 Label 5: 88.00 %  
 Label 6: 94.99 %  
 Label 7: 91.05 %  
 Label 8: 88.30 %  
 Label 9: 89.89 %

#### MODEL 2

313/313 [=====] - 1s 2ms/step - loss: 0.3257

- accuracy: 0.9171

Loss: 0.33

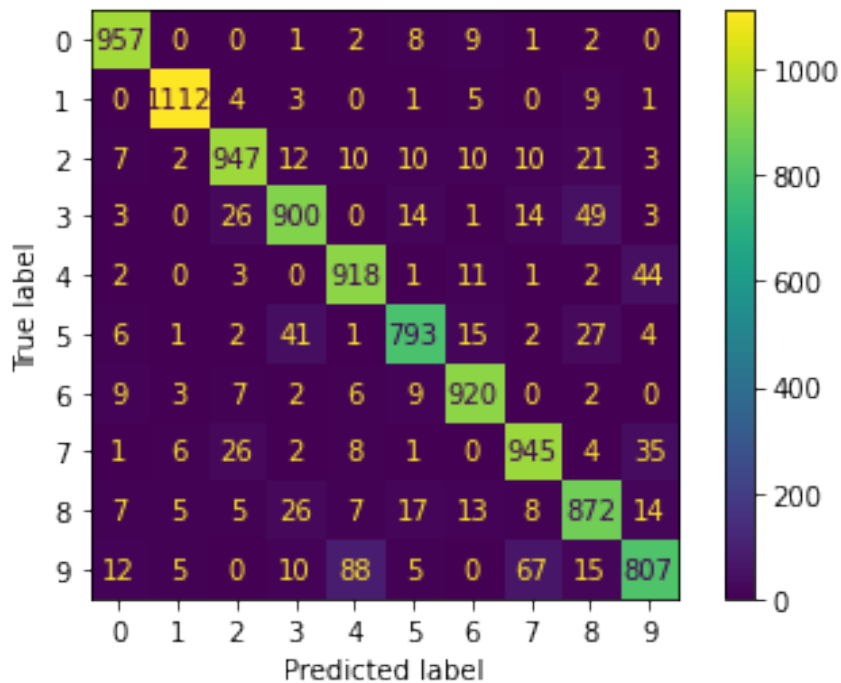
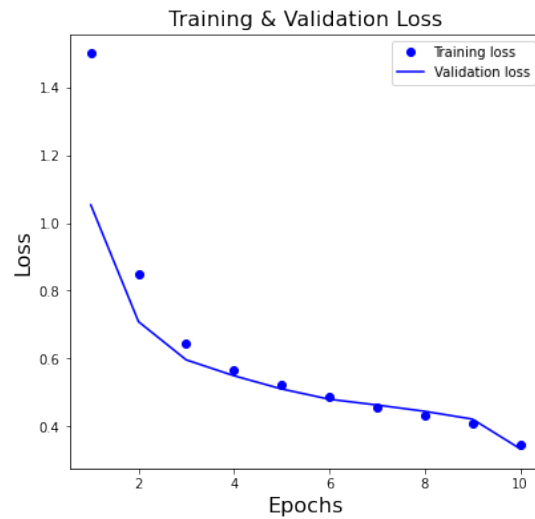
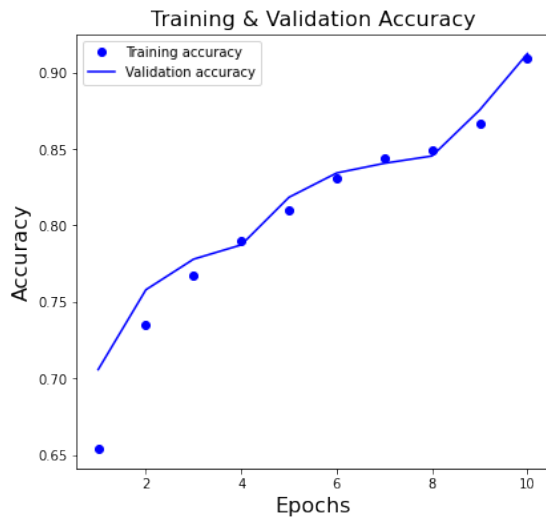
Accuracy: 91.71 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.95	0.98	0.96	980
1	0.98	0.98	0.98	1135
2	0.93	0.92	0.92	1032
3	0.90	0.89	0.90	1010
4	0.88	0.93	0.91	982
5	0.92	0.89	0.91	892
6	0.93	0.96	0.95	958
7	0.90	0.92	0.91	1028
8	0.87	0.90	0.88	974
9	0.89	0.80	0.84	1009

accuracy			0.92	10000
macro avg	0.92	0.92	0.92	10000
weighted avg	0.92	0.92	0.92	10000



Accuracy

Label 0: 97.65 %

Label 1: 97.97 %

Label 2: 91.76 %

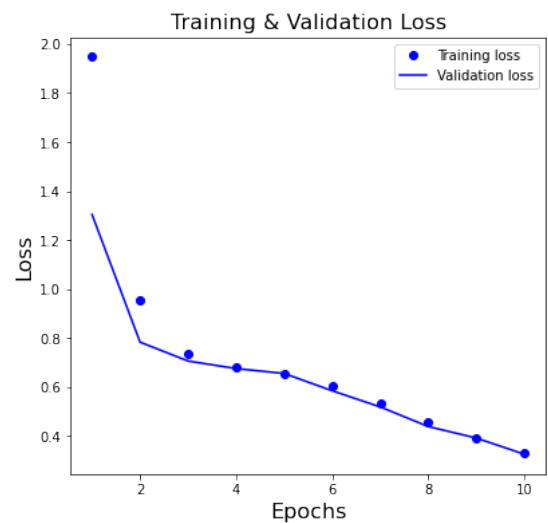
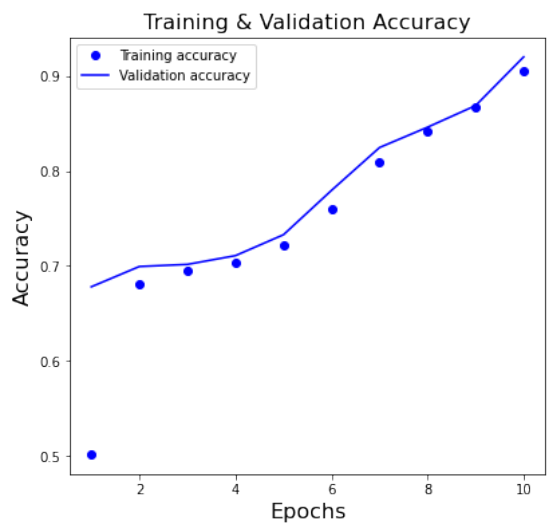
Label 3: 89.11 %

Label 4: 93.48 %

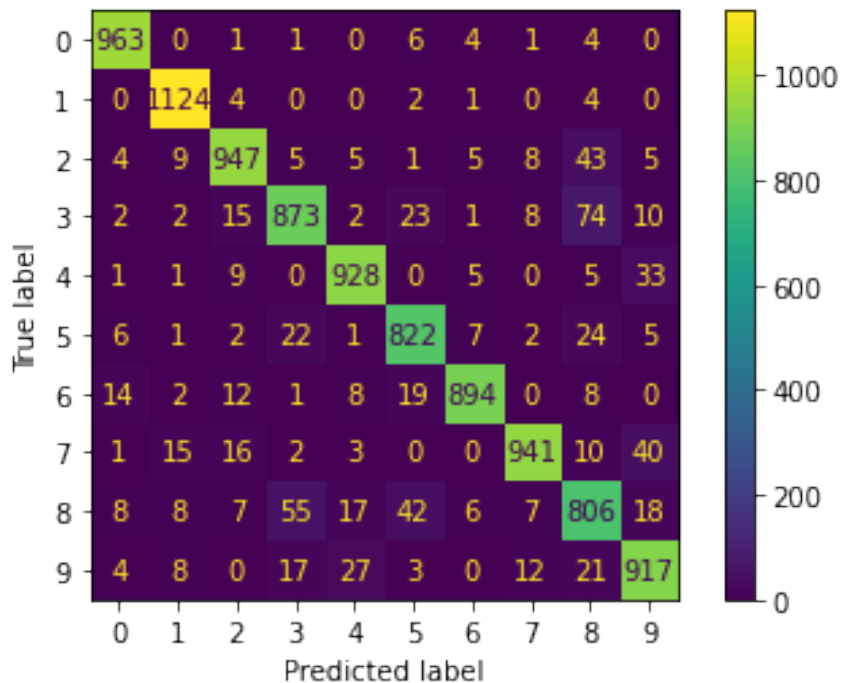
Label 5: 88.90 %

Label 6: 96.03 %  
Label 7: 91.93 %  
Label 8: 89.53 %  
Label 9: 79.98 %  
MODEL 3  
313/313 [=====] - 1s 2ms/step - loss: 0.3219  
- accuracy: 0.9215  
Loss: 0.32  
Accuracy: 92.15 %  
313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
0	0.96	0.98	0.97	980
1	0.96	0.99	0.98	1135
2	0.93	0.92	0.93	1032
3	0.89	0.86	0.88	1010
4	0.94	0.95	0.94	982
5	0.90	0.92	0.91	892
6	0.97	0.93	0.95	958
7	0.96	0.92	0.94	1028
8	0.81	0.83	0.82	974
9	0.89	0.91	0.90	1009
accuracy			0.92	10000
macro avg	0.92	0.92	0.92	10000
weighted avg	0.92	0.92	0.92	10000







Accuracy

Label 0: 98.27 %  
 Label 1: 99.03 %  
 Label 2: 91.76 %  
 Label 3: 86.44 %  
 Label 4: 94.50 %  
 Label 5: 92.15 %  
 Label 6: 93.32 %  
 Label 7: 91.54 %  
 Label 8: 82.75 %  
 Label 9: 90.88 %

MODEL 4

313/313 [=====] - 2s 5ms/step - loss: 0.8484

- accuracy: 0.6079

Loss: 0.85

Accuracy: 60.79 %

313/313 [=====] - 2s 6ms/step

/usr/local/lib/python3.8/dist-packages/sklearn/metrics/\_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))

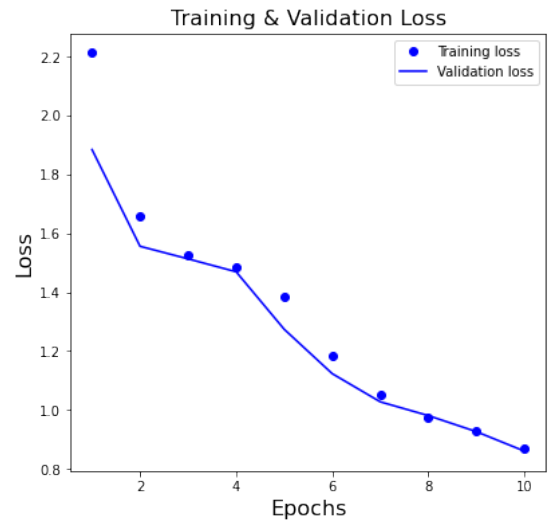
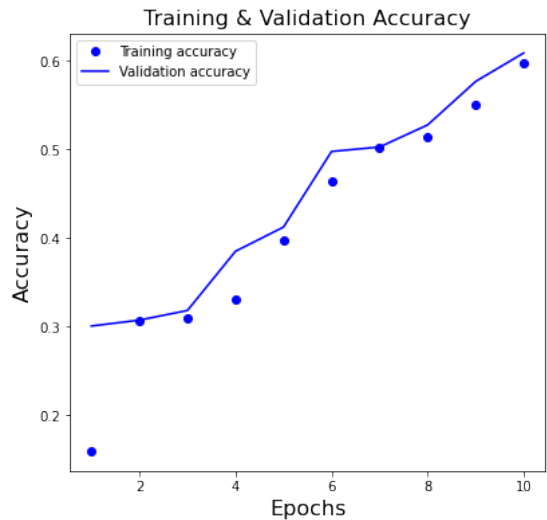
/usr/local/lib/python3.8/dist-packages/sklearn/metrics/\_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

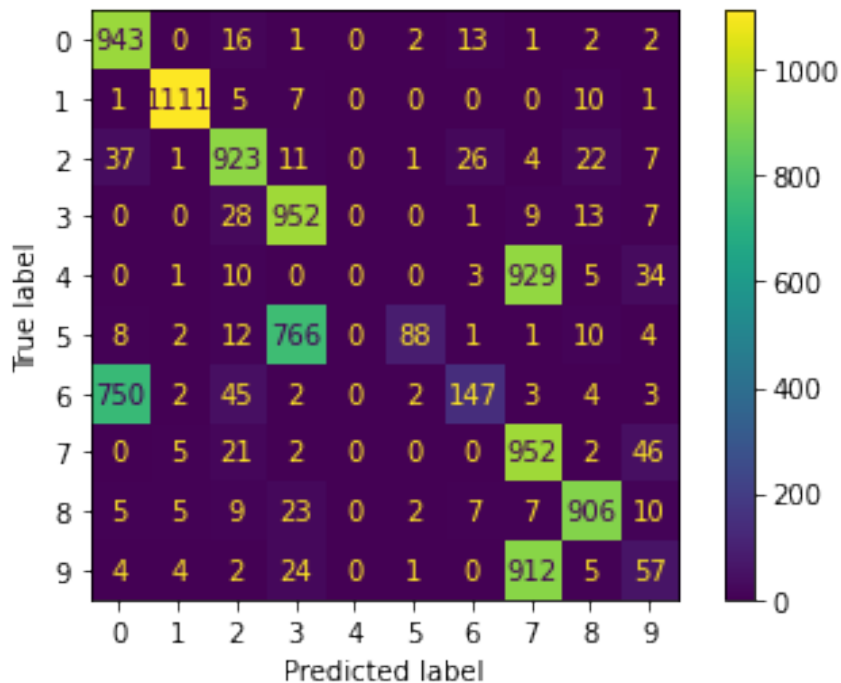
\_warn\_prf(average, modifier, msg\_start, len(result))

/usr/local/lib/python3.8/dist-packages/sklearn/metrics/\_classification

```
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
```

	precision	recall	f1-score	support
0	0.54	0.96	0.69	980
1	0.98	0.98	0.98	1135
2	0.86	0.89	0.88	1032
3	0.53	0.94	0.68	1010
4	0.00	0.00	0.00	982
5	0.92	0.10	0.18	892
6	0.74	0.15	0.25	958
7	0.34	0.93	0.50	1028
8	0.93	0.93	0.93	974
9	0.33	0.06	0.10	1009
accuracy			0.61	10000
macro avg	0.62	0.59	0.52	10000
weighted avg	0.62	0.61	0.53	10000





Accuracy

Label 0: 96.22 %

Label 1: 97.89 %

Label 2: 89.44 %

Label 3: 94.26 %

Label 4: 0.00 %

Label 5: 9.87 %

Label 6: 15.34 %

Label 7: 92.61 %

Label 8: 93.02 %

Label 9: 5.65 %

MODEL 5

313/313 [=====] - 1s 3ms/step - loss: 2.3013

- accuracy: 0.1135

Loss: 2.30

Accuracy: 11.35 %

313/313 [=====] - 1s 3ms/step

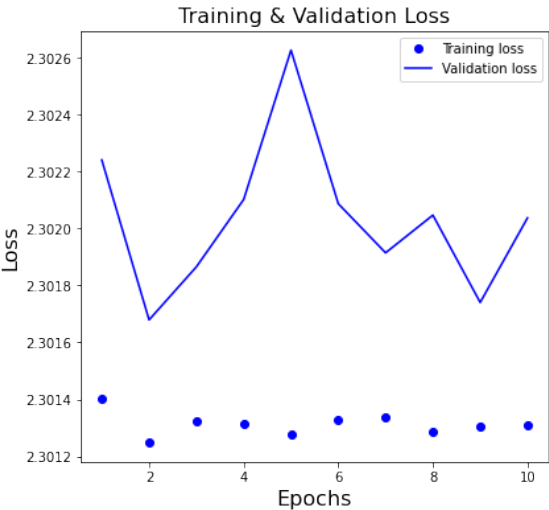
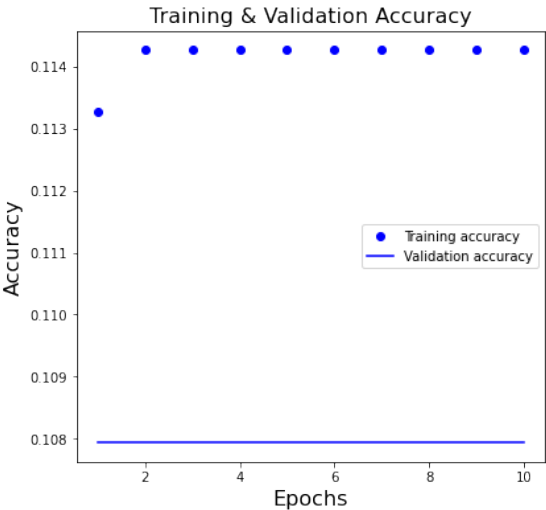
/usr/local/lib/python3.8/dist-packages/sklearn/metrics/\_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

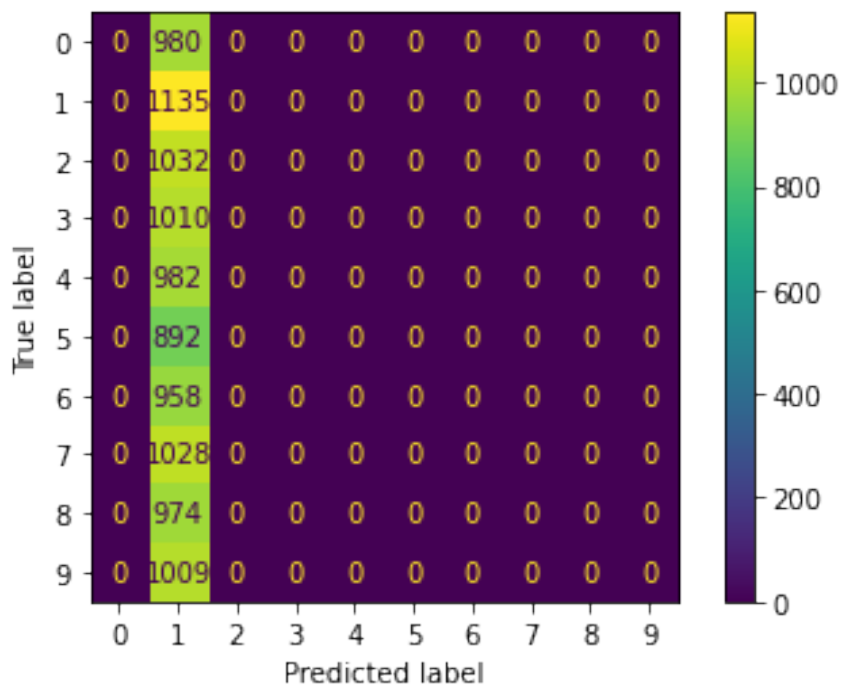
\_warn\_prf(average, modifier, msg\_start, len(result))  
 /usr/local/lib/python3.8/dist-packages/sklearn/metrics/\_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero\_division` parameter to control this behavior.

\_warn\_prf(average, modifier, msg\_start, len(result))  
 /usr/local/lib/python3.8/dist-packages/sklearn/metrics/\_classification

```
.py:1318: UndefinedMetricWarning: Precision and F-score are ill-
defined and being set to 0.0 in labels with no predicted samples. Use
`zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
```

	precision	recall	f1-score	support
0	0.00	0.00	0.00	980
1	0.11	1.00	0.20	1135
2	0.00	0.00	0.00	1032
3	0.00	0.00	0.00	1010
4	0.00	0.00	0.00	982
5	0.00	0.00	0.00	892
6	0.00	0.00	0.00	958
7	0.00	0.00	0.00	1028
8	0.00	0.00	0.00	974
9	0.00	0.00	0.00	1009
accuracy			0.11	10000
macro avg	0.01	0.10	0.02	10000
weighted avg	0.01	0.11	0.02	10000





#### Accuracy

Label 0: 0.00 %  
 Label 1: 100.00 %  
 Label 2: 0.00 %  
 Label 3: 0.00 %  
 Label 4: 0.00 %  
 Label 5: 0.00 %  
 Label 6: 0.00 %  
 Label 7: 0.00 %  
 Label 8: 0.00 %  
 Label 9: 0.00 %

#### ###Análise de resultados

Pode-se observar que, à medida que aumentamos o número de camadas, temos uma menor acurácia do modelo. Esse comportamento pode ser explicado pelo fato de que um número elevado de camadas intermediárias podem causar um overfitting (o valor da Loss Function que aumenta é um indicador de overfitting também).

Para todos os modelos a seguir, fazendo o "tuning" dos parâmetros a fim de otimizar a performance com o otimizador Adam, a métrica acurácia e a função de perda `categorical_crossentropy`, visto que nossa saída é categórica (possuindo 10 classes).

## Taxa de aprendizagem

[0.1, 0.2, 0.05, 0.009, 0.007, 0.005]

Analisaremos agora o impacto da taxa de aprendizagem, para isso compilaremos o 2º modelo básico descrito na seção anterior 6 vezes modificando a taxa de aprendizagem de acordo com os resultados de cada fase do experimento.

- Valores a serem testados: 0.1, 0.2, 0.05, 0.009, 0.007, 0.005

```
def learning_rate_Analysis(model, lr, x_train = x_train, y_train =
y_train, x_test = x_test, y_test = y_test, batch_size =
batch_size, epochs = epochs, validation_split = val_split, verbose =
verbose):
    model.compile(loss = 'categorical_crossentropy', optimizer =
keras.optimizers.Adam(learning_rate = lr), metrics = 'accuracy')
    history_model = model.fit(x_train, y_train, batch_size = batch_size,
epochs = epochs, validation_split = val_split, verbose = verbose)
    eval = model.evaluate(x_test, y_test)
    print("To Learning rate = ", lr, " :")
    print(("Loss: {percentage:.2f}%").format(percentage=eval[0]))
    print(("Accuracy: {percentage:.2f}%").format(percentage=100*(eval[1])))
    historyPlot(model, history_model.history, y_test)

lr_list = [0.1, 0.2, 0.05, 0.009, 0.007, 0.005]
for i in range(6):
    print("Learning Rate: {lr}".format(lr = lr_list[i]))
    learning_rate_Analysis(keras.Sequential([
        keras.Input(shape=input_shape),
        layers.Flatten(),
        layers.Dense(128, activation = 'softmax'),
        layers.Dense(num_class, activation = 'softmax')

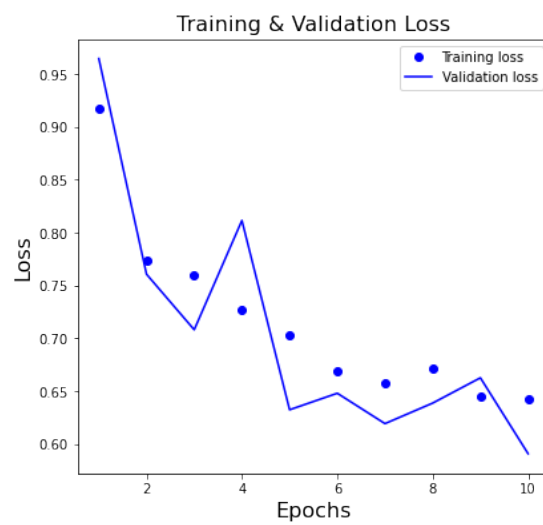
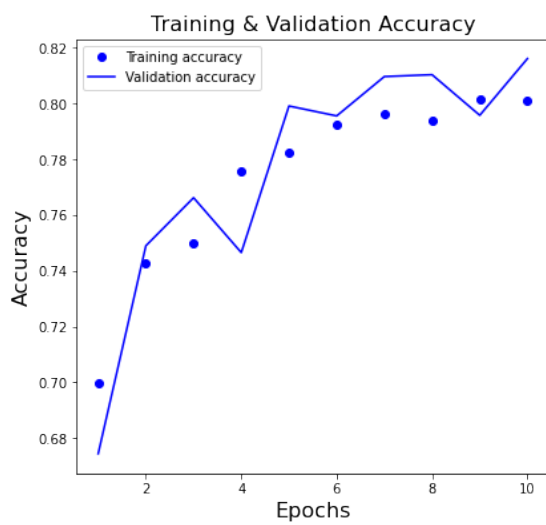
    ]), lr_list[i])

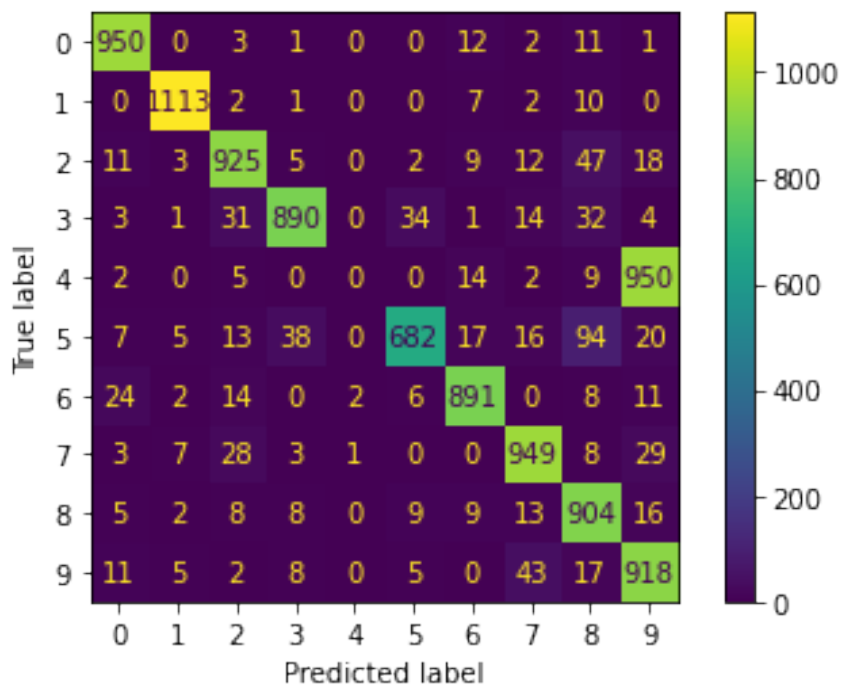
print('-----')
```

```
Learning Rate: 0.1
313/313 [=====] - 1s 2ms/step - loss: 0.5643
- accuracy: 0.8222
To Learning rate = 0.1 :
Loss: 0.56
Accuracy: 82.22 %
313/313 [=====] - 1s 2ms/step
```

	precision	recall	f1-score	support
0	0.94	0.97	0.95	980
1	0.98	0.98	0.98	1135

	2	0.90	0.90	0.90	1032
	3	0.93	0.88	0.91	1010
	4	0.00	0.00	0.00	982
	5	0.92	0.76	0.84	892
	6	0.93	0.93	0.93	958
	7	0.90	0.92	0.91	1028
	8	0.79	0.93	0.86	974
	9	0.47	0.91	0.62	1009
accuracy				0.82	10000
macro avg		0.78	0.82	0.79	10000
weighted avg		0.78	0.82	0.79	10000





#### Accuracy

Label 0: 96.94 %  
 Label 1: 98.06 %  
 Label 2: 89.63 %  
 Label 3: 88.12 %  
 Label 4: 0.00 %  
 Label 5: 76.46 %  
 Label 6: 93.01 %  
 Label 7: 92.32 %  
 Label 8: 92.81 %  
 Label 9: 90.98 %

-----

Learning Rate: 0.2

313/313 [=====] - 1s 2ms/step - loss: 0.7664

- accuracy: 0.7346

To Learning rate = 0.2 :

Loss: 0.77

Accuracy: 73.46 %

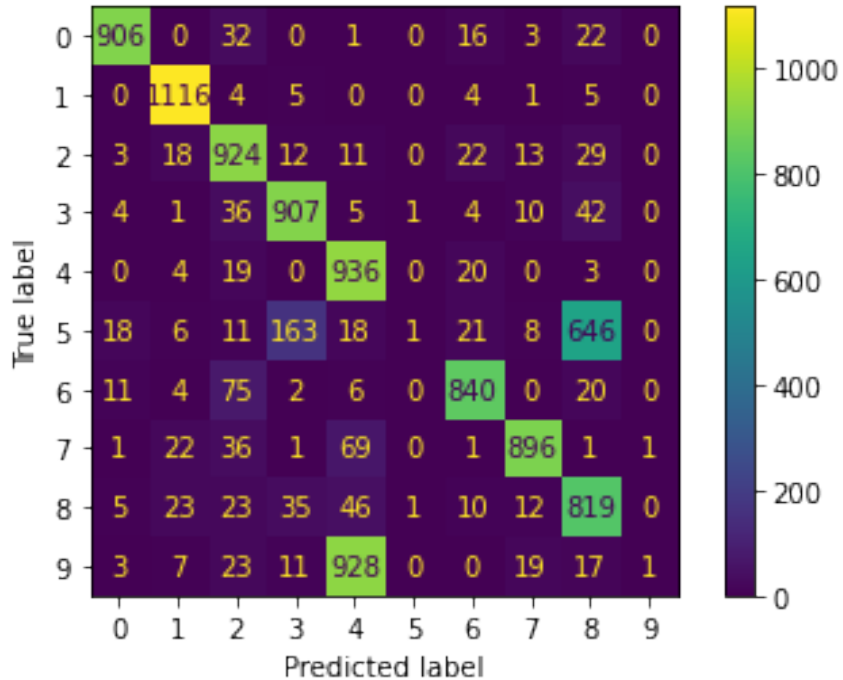
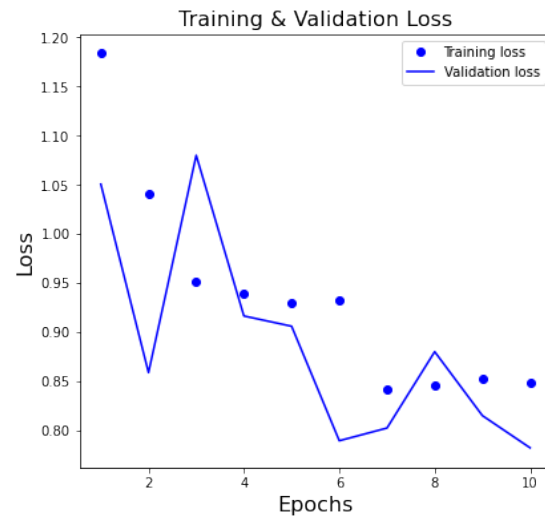
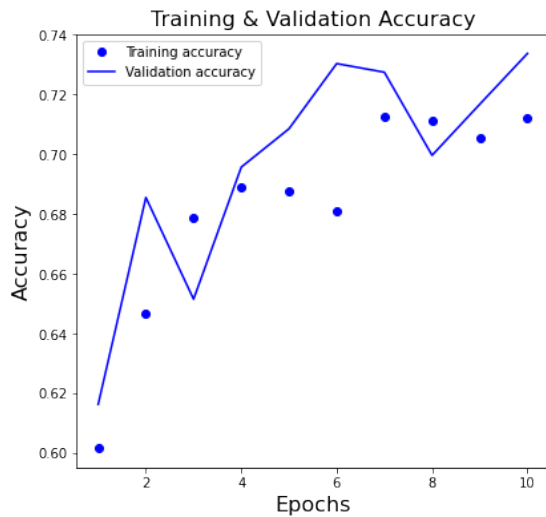
313/313 [=====] - 1s 2ms/step

precision recall f1-score support

0	0.95	0.92	0.94	980
1	0.93	0.98	0.96	1135
2	0.78	0.90	0.83	1032
3	0.80	0.90	0.85	1010
4	0.46	0.95	0.62	982
5	0.33	0.00	0.00	892
6	0.90	0.88	0.89	958



7	0.93	0.87	0.90	1028
8	0.51	0.84	0.64	974
9	0.50	0.00	0.00	1009
accuracy			0.73	10000
macro avg	0.71	0.72	0.66	10000
weighted avg	0.72	0.73	0.67	10000



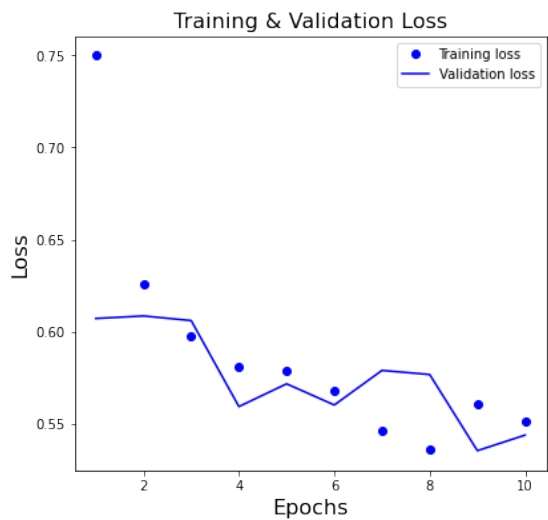
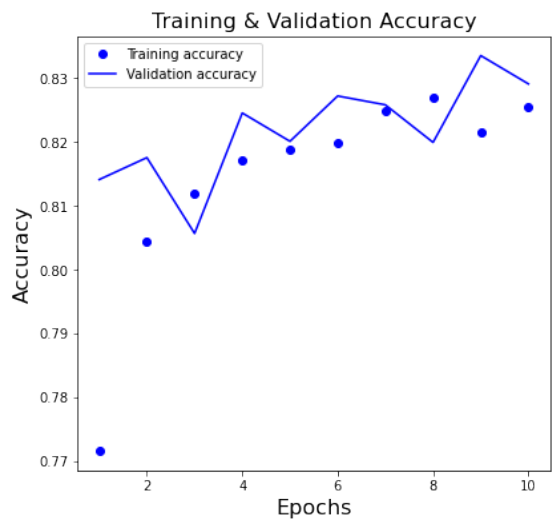
Accuracy  
 Label 0: 92.45 %  
 Label 1: 98.33 %  
 Label 2: 89.53 %

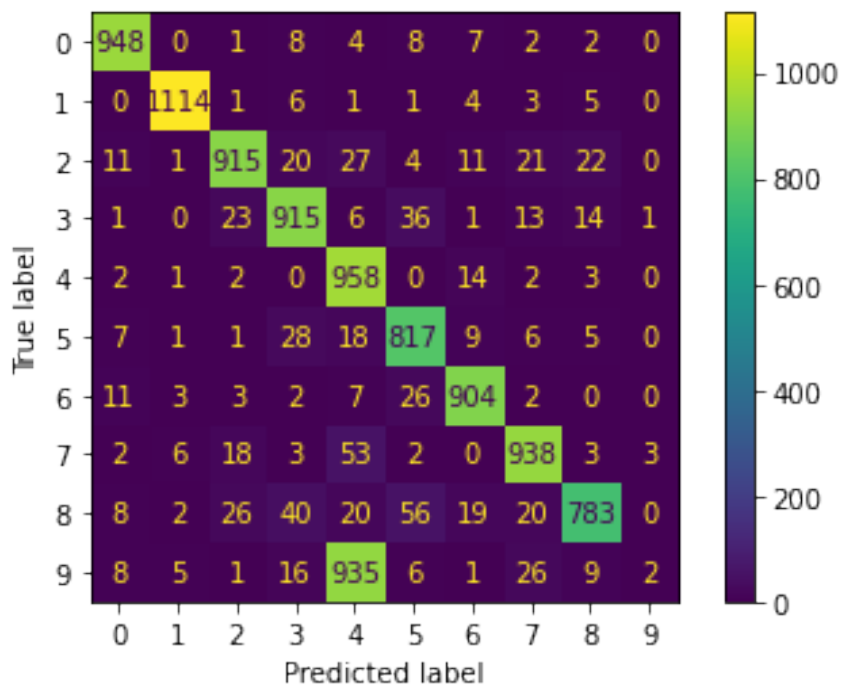
Label 3: 89.80 %  
Label 4: 95.32 %  
Label 5: 0.11 %  
Label 6: 87.68 %  
Label 7: 87.16 %  
Label 8: 84.09 %  
Label 9: 0.10 %

-----  
-----  
Learning Rate: 0.05  
313/313 [=====] - 1s 2ms/step - loss: 0.5322  
- accuracy: 0.8294  
To Learning rate = 0.05 :  
Loss: 0.53  
Accuracy: 82.94 %  
313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

	0	0.95	0.97	0.96	980
	1	0.98	0.98	0.98	1135
	2	0.92	0.89	0.90	1032
	3	0.88	0.91	0.89	1010
	4	0.47	0.98	0.64	982
	5	0.85	0.92	0.88	892
	6	0.93	0.94	0.94	958
	7	0.91	0.91	0.91	1028
	8	0.93	0.80	0.86	974
	9	0.33	0.00	0.00	1009
accuracy				0.83	10000
macro avg		0.82	0.83	0.80	10000
weighted avg		0.82	0.83	0.80	10000





#### Accuracy

Label 0: 96.73 %  
 Label 1: 98.15 %  
 Label 2: 88.66 %  
 Label 3: 90.59 %  
 Label 4: 97.56 %  
 Label 5: 91.59 %  
 Label 6: 94.36 %  
 Label 7: 91.25 %  
 Label 8: 80.39 %  
 Label 9: 0.20 %

-----

Learning Rate: 0.009

313/313 [=====] - 1s 2ms/step - loss: 0.2685

- accuracy: 0.9423

To Learning rate = 0.009 :

Loss: 0.27

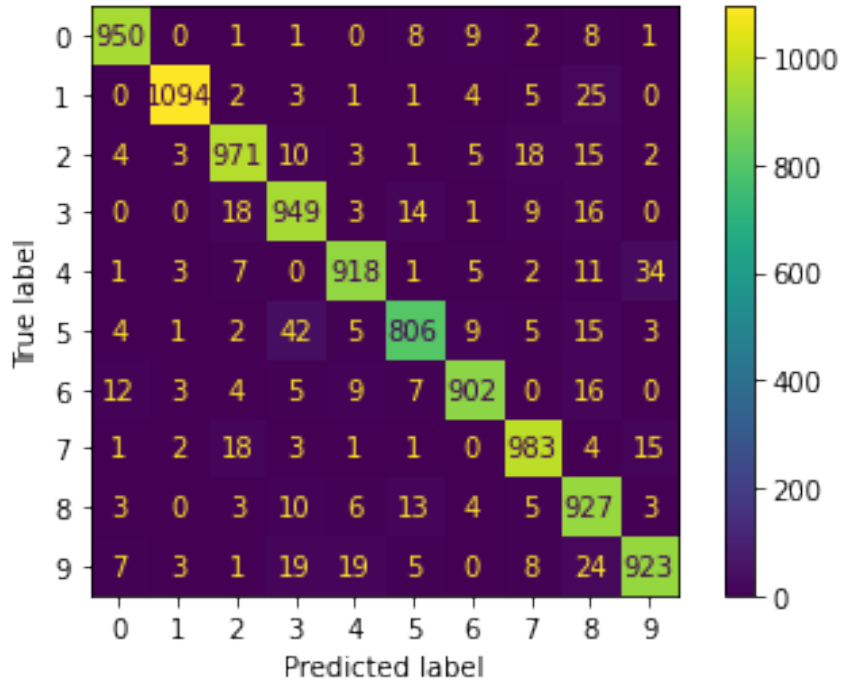
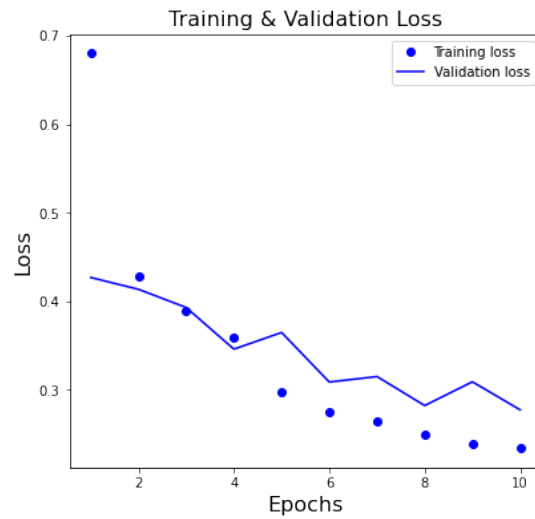
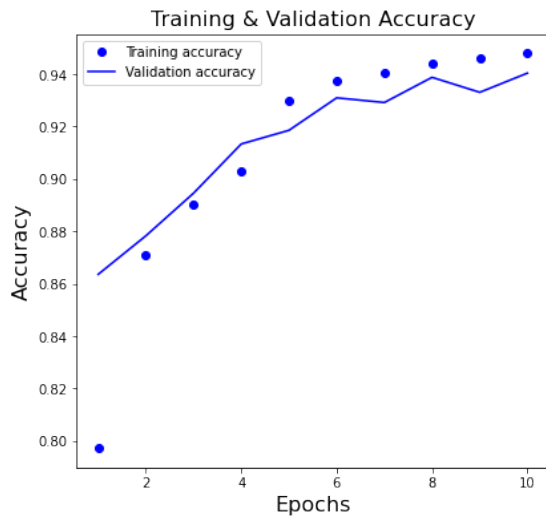
Accuracy: 94.23 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.97	0.97	0.97	980
1	0.99	0.96	0.98	1135
2	0.95	0.94	0.94	1032
3	0.91	0.94	0.92	1010
4	0.95	0.93	0.94	982
5	0.94	0.90	0.92	892
6	0.96	0.94	0.95	958

	7	0.95	0.96	0.95	1028
	8	0.87	0.95	0.91	974
	9	0.94	0.91	0.93	1009
accuracy				0.94	10000
macro avg		0.94	0.94	0.94	10000
weighted avg		0.94	0.94	0.94	10000



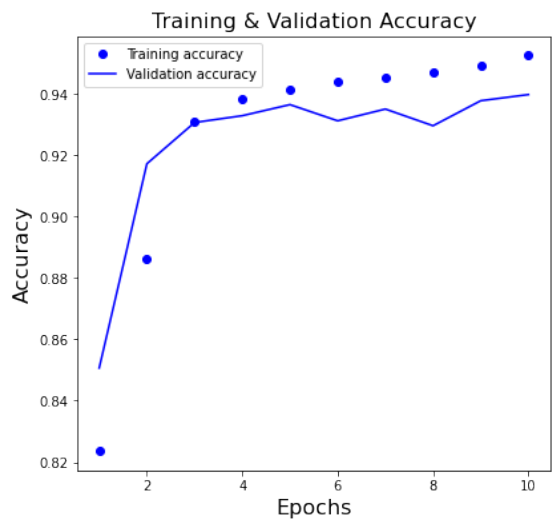
Accuracy  
Label 0: 96.94 %  
Label 1: 96.39 %  
Label 2: 94.09 %

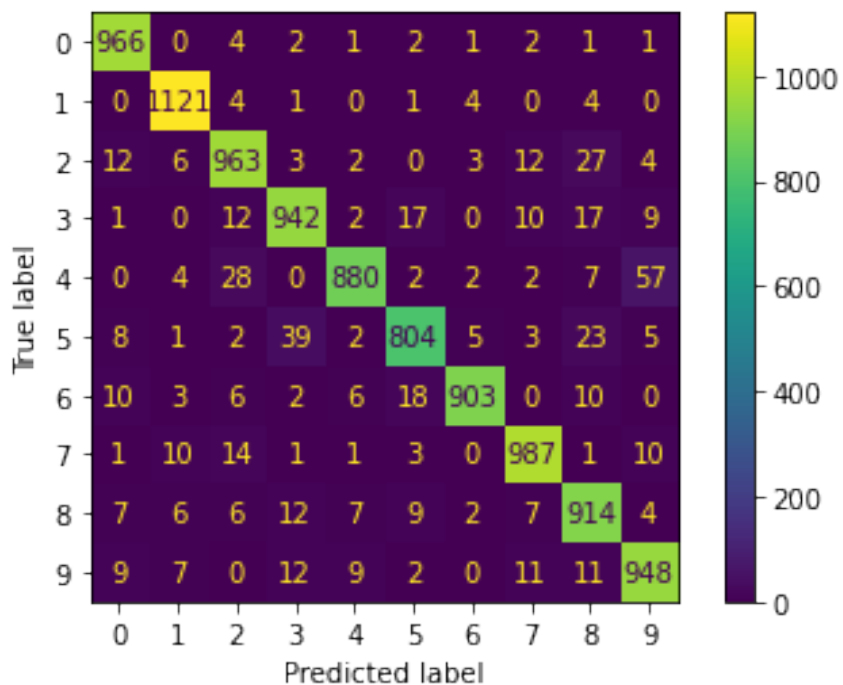
Label 3: 93.96 %  
Label 4: 93.48 %  
Label 5: 90.36 %  
Label 6: 94.15 %  
Label 7: 95.62 %  
Label 8: 95.17 %  
Label 9: 91.48 %

-----  
-----  
Learning Rate: 0.007  
313/313 [=====] - 1s 2ms/step - loss: 0.2659  
- accuracy: 0.9428  
To Learning rate = 0.007 :  
Loss: 0.27  
Accuracy: 94.28 %  
313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

	0	0.95	0.99	0.97	980
	1	0.97	0.99	0.98	1135
	2	0.93	0.93	0.93	1032
	3	0.93	0.93	0.93	1010
	4	0.97	0.90	0.93	982
	5	0.94	0.90	0.92	892
	6	0.98	0.94	0.96	958
	7	0.95	0.96	0.96	1028
	8	0.90	0.94	0.92	974
	9	0.91	0.94	0.93	1009
accuracy				0.94	10000
macro avg		0.94	0.94	0.94	10000
weighted avg		0.94	0.94	0.94	10000





#### Accuracy

Label 0: 98.57 %  
 Label 1: 98.77 %  
 Label 2: 93.31 %  
 Label 3: 93.27 %  
 Label 4: 89.61 %  
 Label 5: 90.13 %  
 Label 6: 94.26 %  
 Label 7: 96.01 %  
 Label 8: 93.84 %  
 Label 9: 93.95 %

Learning Rate: 0.005

313/313 [=====] - 1s 2ms/step - loss: 0.2470  
 - accuracy: 0.9404

To Learning rate = 0.005 :

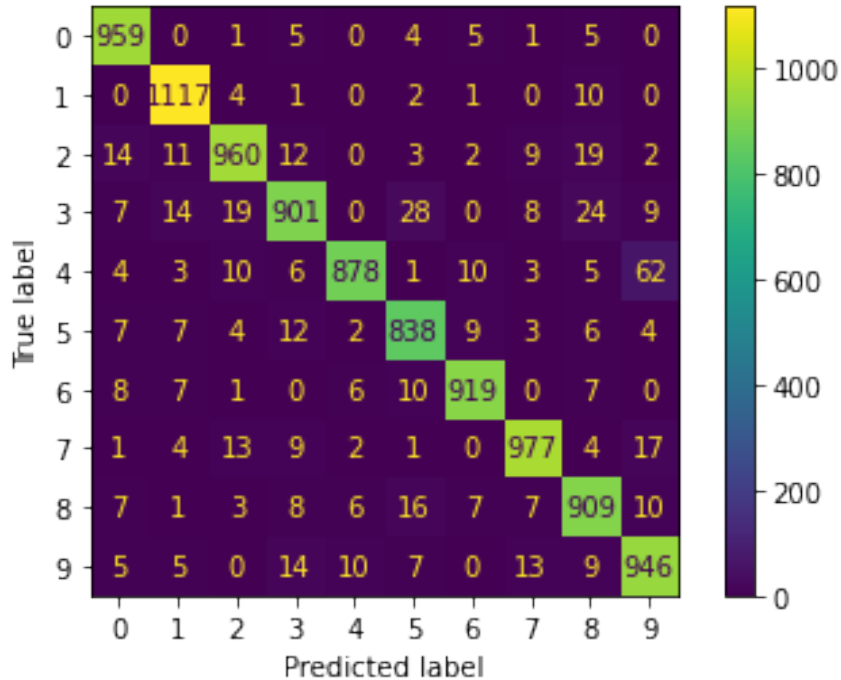
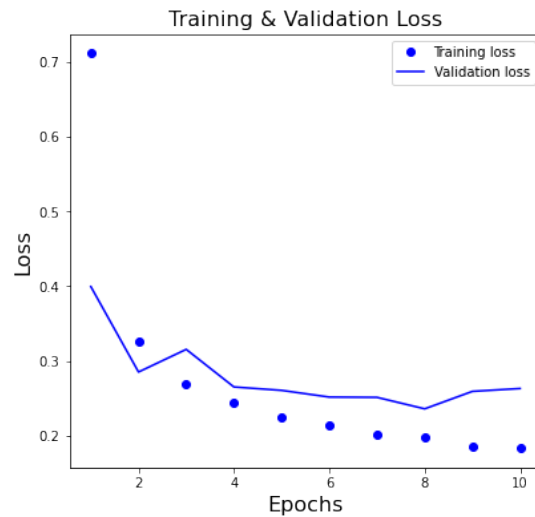
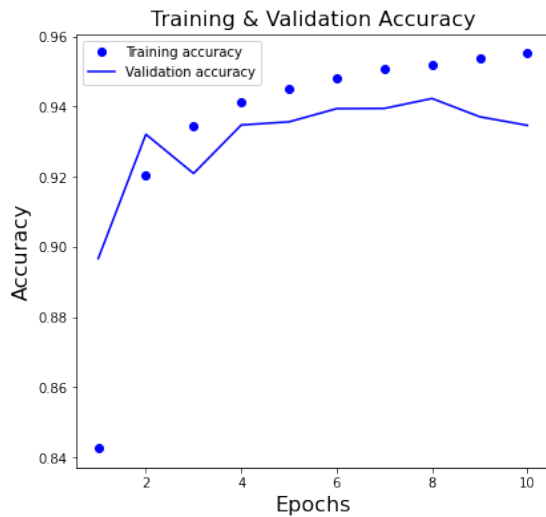
Loss: 0.25

Accuracy: 94.04 %

313/313 [=====] - 1s 2ms/step  
 precision recall f1-score support

0	0.95	0.98	0.96	980
1	0.96	0.98	0.97	1135
2	0.95	0.93	0.94	1032
3	0.93	0.89	0.91	1010
4	0.97	0.89	0.93	982
5	0.92	0.94	0.93	892
6	0.96	0.96	0.96	958

	7	0.96	0.95	0.95	1028
	8	0.91	0.93	0.92	974
	9	0.90	0.94	0.92	1009
accuracy				0.94	10000
macro avg		0.94	0.94	0.94	10000
weighted avg		0.94	0.94	0.94	10000



Accuracy  
Label 0: 97.86 %  
Label 1: 98.41 %  
Label 2: 93.02 %

```

Label 3: 89.21 %
Label 4: 89.41 %
Label 5: 93.95 %
Label 6: 95.93 %
Label 7: 95.04 %
Label 8: 93.33 %
Label 9: 93.76 %

```

```

-----
-----

```

### ###Análise de resultados

Pelos resultados obtidos, pode-se dizer que uma taxa de aprendizado maior (0.1 por exemplo) tende a causar um overshooting, em que a função *Loss* não consegue convergir para um ponto *ótimo*, sempre ultrapassando tal ponto. Nesse quesito, a utilização de uma taxa menor, como 0.007, proveu uma melhor acurácia.

### Função de ativação

*Relu, Sigmoid, Softmax, Tanh*

Nessa sessão, alteramos as funções de ativação na(s) camada(s) intermediária(s) a fim de analisar o modelo e alavancar uma possível melhora em sua performance, não alterando a ativação softmax na camada de saída.

```

def activationFunctionExperiment(activationFunction,x_train =
x_train,shape = input_shape,num_class = num_class, y_train = y_train,
x_test = x_test, y_test = y_test, batch_size = batch_size,epochs =
epochs, validation_split = val_split, verbose = verbose):
    model = keras.Sequential([
        keras.Input(shape=input_shape),
        layers.Flatten(),
        layers.Dense(128, activation = activationFunction),
        layers.Dense(num_class, activation = 'softmax')])
    model.compile(loss = 'categorical_crossentropy', optimizer = 'adam',
metrics = 'accuracy')
    history_model = model.fit(x_train, y_train, batch_size = batch_size,
epochs = epochs, validation_split = val_split, verbose = verbose)
    eval = model.evaluate(x_test, y_test)
    print("To activation fuction = ", activationFunction, " :")
    print(("Loss: {percentage:.2f}").format(percentage=eval[0]))
    print(("Accuracy: {percentage:.2f}
%").format(percentage=100*(eval[1])))
    historyPlot(model, history_model.history, y_test)

activation_list = ['relu', 'sigmoid', 'softmax', 'tanh']
for i in activation_list:
    activationFunctionExperiment(i)

print('-----')
print('-----')

```



313/313 [=====] - 1s 2ms/step - loss: 0.0954

- accuracy: 0.9747

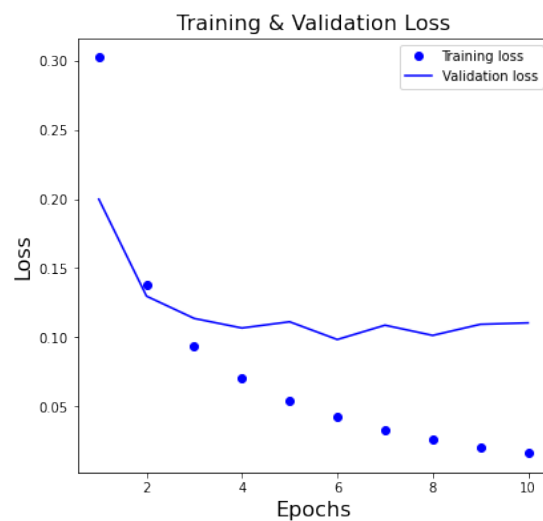
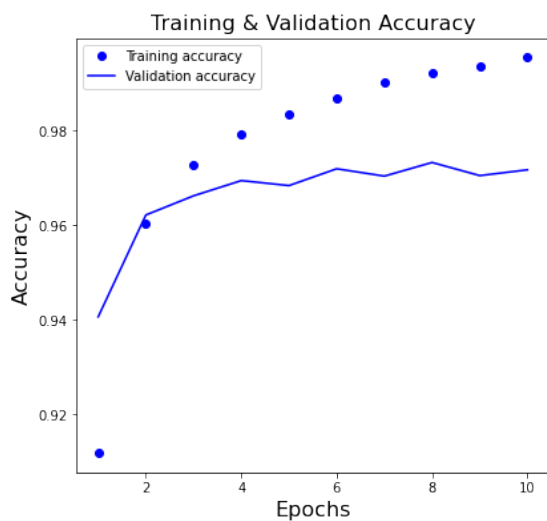
To activation fuction = relu :

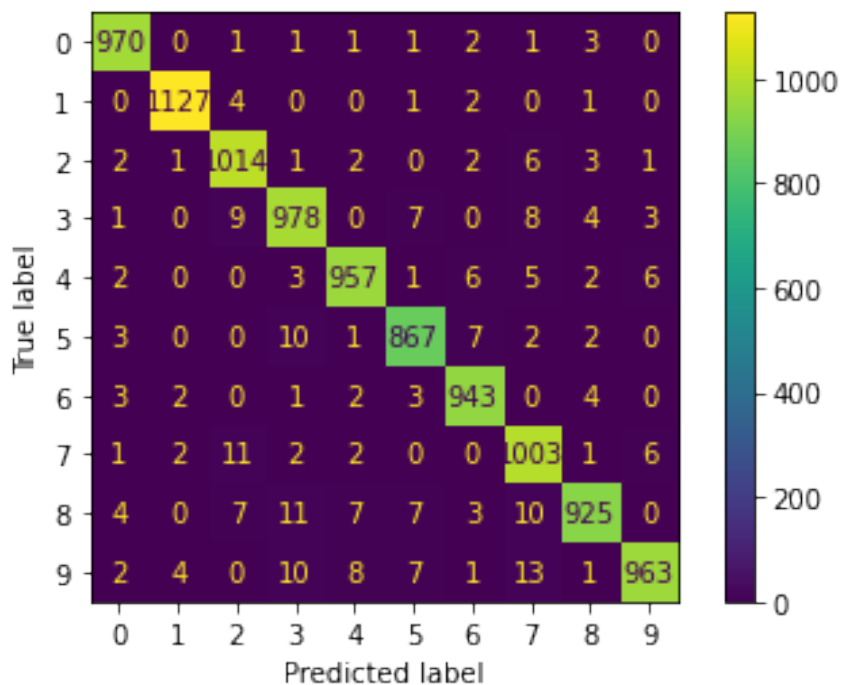
Loss: 0.10

Accuracy: 97.47 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
0	0.98	0.99	0.99	980
1	0.99	0.99	0.99	1135
2	0.97	0.98	0.98	1032
3	0.96	0.97	0.96	1010
4	0.98	0.97	0.98	982
5	0.97	0.97	0.97	892
6	0.98	0.98	0.98	958
7	0.96	0.98	0.97	1028
8	0.98	0.95	0.96	974
9	0.98	0.95	0.97	1009
accuracy			0.97	10000
macro avg	0.97	0.97	0.97	10000
weighted avg	0.97	0.97	0.97	10000





#### Accuracy

Label 0: 98.98 %  
 Label 1: 99.30 %  
 Label 2: 98.26 %  
 Label 3: 96.83 %  
 Label 4: 97.45 %  
 Label 5: 97.20 %  
 Label 6: 98.43 %  
 Label 7: 97.57 %  
 Label 8: 94.97 %  
 Label 9: 95.44 %

-----  
 313/313 [=====] - 1s 2ms/step - loss: 0.0877

- accuracy: 0.9727

To activation fuction = sigmoid :

Loss: 0.09

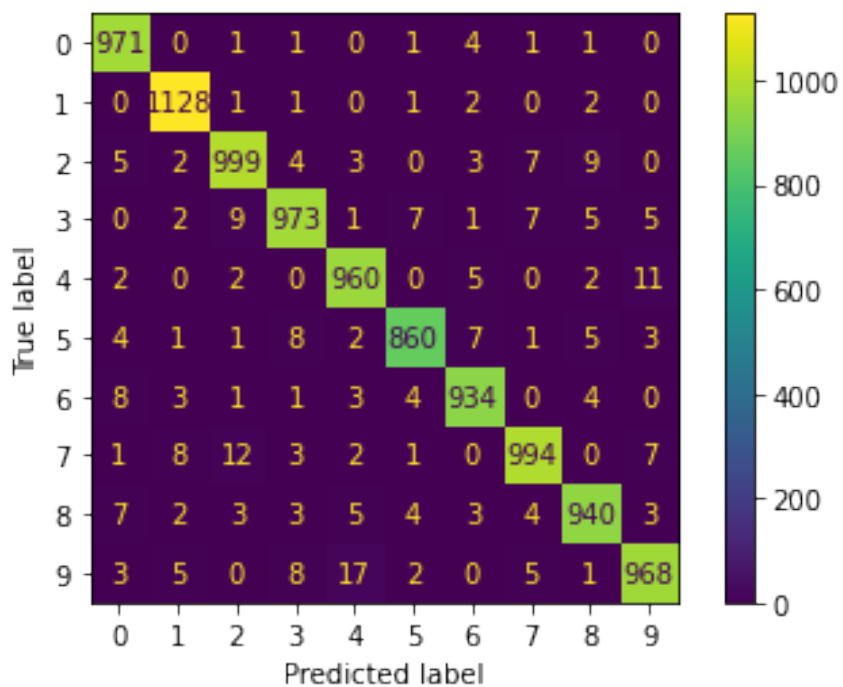
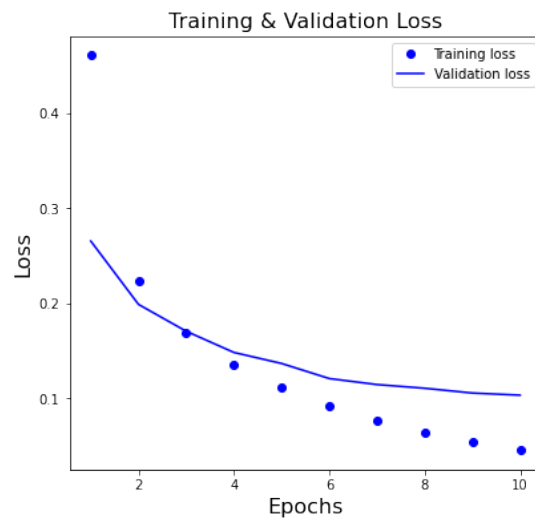
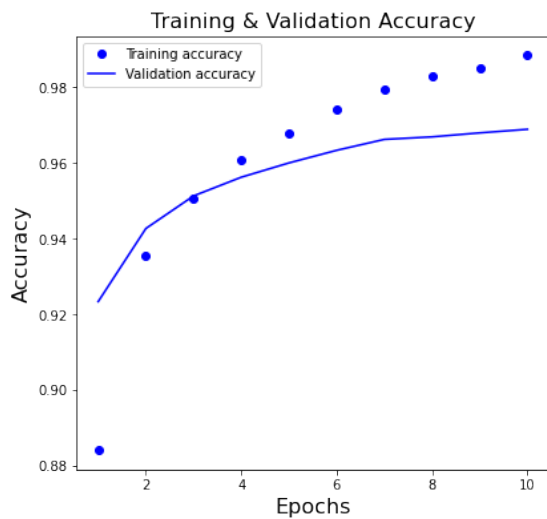
Accuracy: 97.27 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.97	0.99	0.98	980
1	0.98	0.99	0.99	1135
2	0.97	0.97	0.97	1032
3	0.97	0.96	0.97	1010
4	0.97	0.98	0.97	982
5	0.98	0.96	0.97	892
6	0.97	0.97	0.97	958
7	0.98	0.97	0.97	1028

	8	0.97	0.97	0.97	974
	9	0.97	0.96	0.97	1009
accuracy				0.97	10000
macro avg		0.97	0.97	0.97	10000
weighted avg		0.97	0.97	0.97	10000



Accuracy

Label 0: 99.08 %

Label 1: 99.38 %

Label 2: 96.80 %

Label 3: 96.34 %

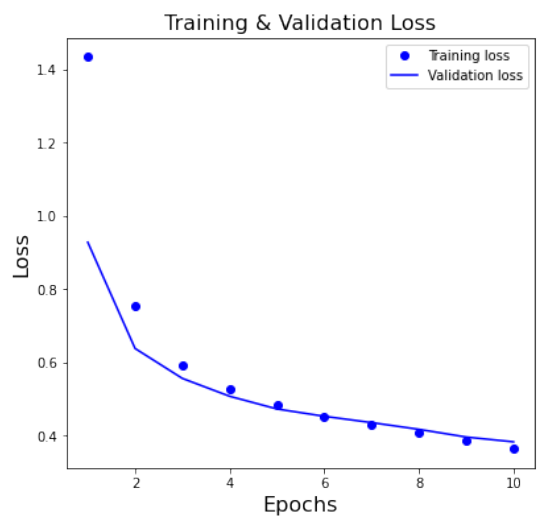
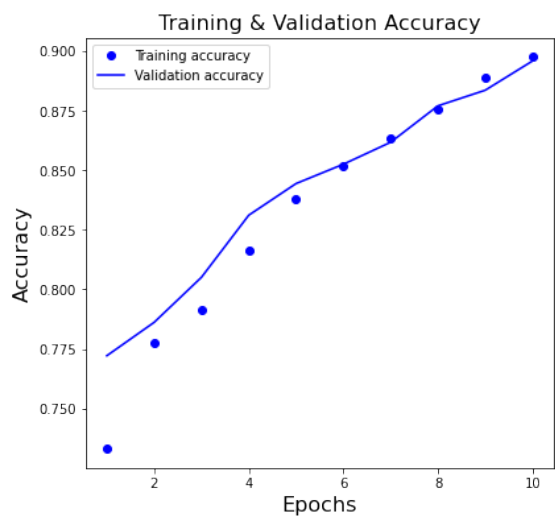
Label 4: 97.76 %  
Label 5: 96.41 %  
Label 6: 97.49 %  
Label 7: 96.69 %  
Label 8: 96.51 %  
Label 9: 95.94 %

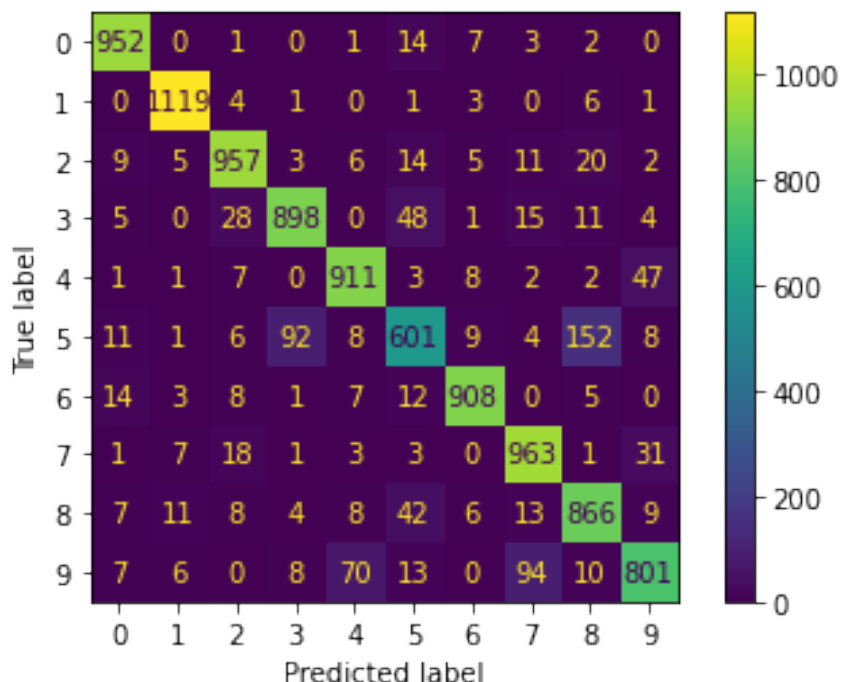
-----  
313/313 [=====] - 1s 2ms/step - loss: 0.3749  
- accuracy: 0.8976

To activation fuction = softmax :  
Loss: 0.37

Accuracy: 89.76 %  
313/313 [=====] - 1s 2ms/step  
precision recall f1-score support

0	0.95	0.97	0.96	980
1	0.97	0.99	0.98	1135
2	0.92	0.93	0.93	1032
3	0.89	0.89	0.89	1010
4	0.90	0.93	0.91	982
5	0.80	0.67	0.73	892
6	0.96	0.95	0.95	958
7	0.87	0.94	0.90	1028
8	0.81	0.89	0.85	974
9	0.89	0.79	0.84	1009
accuracy			0.90	10000
macro avg	0.90	0.89	0.89	10000
weighted avg	0.90	0.90	0.90	10000





#### Accuracy

Label 0: 97.14 %  
 Label 1: 98.59 %  
 Label 2: 92.73 %  
 Label 3: 88.91 %  
 Label 4: 92.77 %  
 Label 5: 67.38 %  
 Label 6: 94.78 %  
 Label 7: 93.68 %  
 Label 8: 88.91 %  
 Label 9: 79.39 %

-----  
 313/313 [=====] - 1s 2ms/step - loss: 0.0857

- accuracy: 0.9723

To activation fuction = tanh :

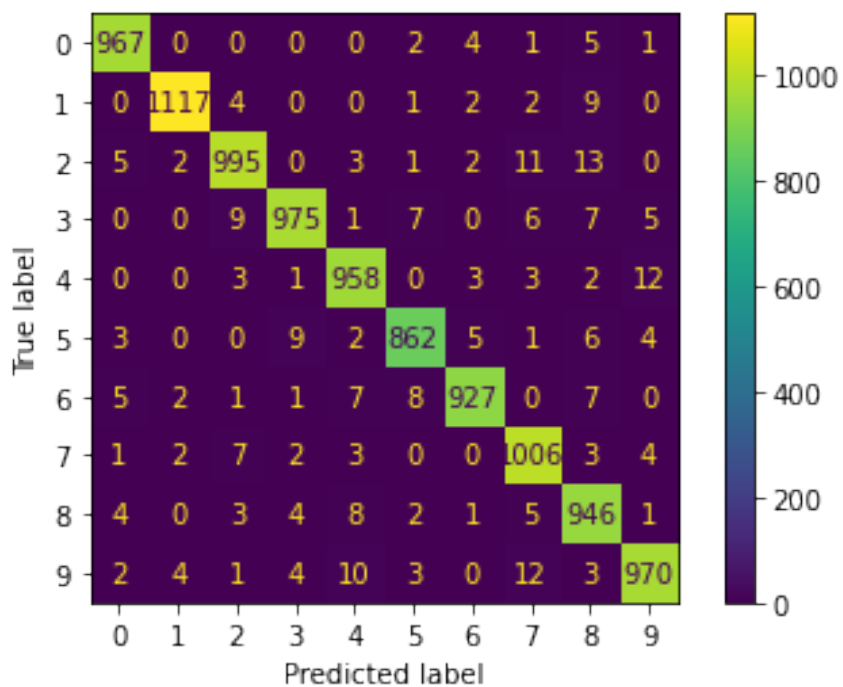
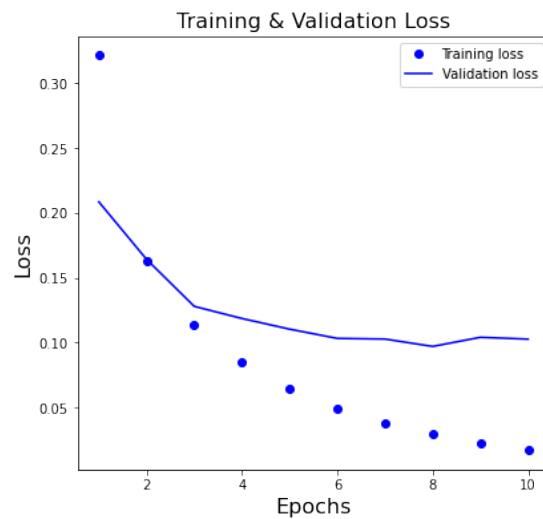
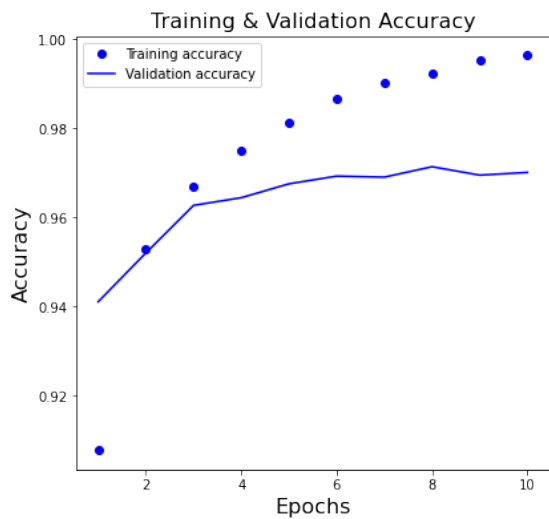
Loss: 0.09

Accuracy: 97.23 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
0	0.98	0.99	0.98	980
1	0.99	0.98	0.99	1135
2	0.97	0.96	0.97	1032
3	0.98	0.97	0.97	1010
4	0.97	0.98	0.97	982
5	0.97	0.97	0.97	892
6	0.98	0.97	0.97	958
7	0.96	0.98	0.97	1028

	8	0.95	0.97	0.96	974
	9	0.97	0.96	0.97	1009
accuracy				0.97	10000
macro avg		0.97	0.97	0.97	10000
weighted avg		0.97	0.97	0.97	10000



Accuracy

Label 0: 98.67 %

Label 1: 98.41 %

Label 2: 96.41 %

Label 3: 96.53 %

```
Label 4: 97.56 %
Label 5: 96.64 %
Label 6: 96.76 %
Label 7: 97.86 %
Label 8: 97.13 %
Label 9: 96.13 %
```

```
-----
-----
```

### ###Análise de resultados

A partir dos resultados obtidos, a função de ativação que performou melhor foi a função *ReLU*, destacando-se por ser linear e favorecendo o cálculo das derivadas parciais.

## Algoritmo de Aprendizagem

### *Adam, RMSProp e SGD*

Gradientes são funções que podem explodir ou esvanecer, na seção anterior, comentamos sobre o "vanishing gradient". que é um dos problemas que podem ocorrer na atualização dos valores dos pesos.

Nesse experimento, iremos variar os algoritmos de atualização na etapa de backpropagation.

Iremos explorar o Adam, RMSProp e Gradiente descendente estocástico(SGD).

```
def optimizerAlgorithmExperiment(model,optimizer,x_train =
x_train,shape = input_shape,num_class = num_class, y_train = y_train,
x_test = x_test, y_test = y_test, batch_size = batch_size,epochs =
epochs, validation_split = val_split, verbose = verbose):
    model.compile(loss = 'categorical_crossentropy', optimizer =
optimizer, metrics = 'accuracy')
    history_model = model.fit(x_train, y_train, batch_size = batch_size,
epochs = epochs, validation_split = val_split, verbose = verbose)
    eval = model.evaluate(x_test, y_test)
    print("To optimizer = ",optimizer," :")
    print(("Loss: {percentage:.2f}").format(percentage=eval[0]))
    print(("Accuracy: {percentage:.2f}
%").format(percentage=100*(eval[1])))
    historyPlot(model, history_model.history, y_test)

optimizer_list = ['sgd', 'rmsprop', 'adam']
for i in optimizer_list:
    optimizerAlgorithmExperiment(keras.Sequential([
        keras.Input(shape=input_shape),
        layers.Flatten(),
        layers.Dense(128, activation = 'relu'),
        layers.Dense(num_class, activation = 'softmax'))), i)
```

```
print('-----
-----')
```

313/313 [=====] - 1s 2ms/step - loss: 0.2036

- accuracy: 0.9408

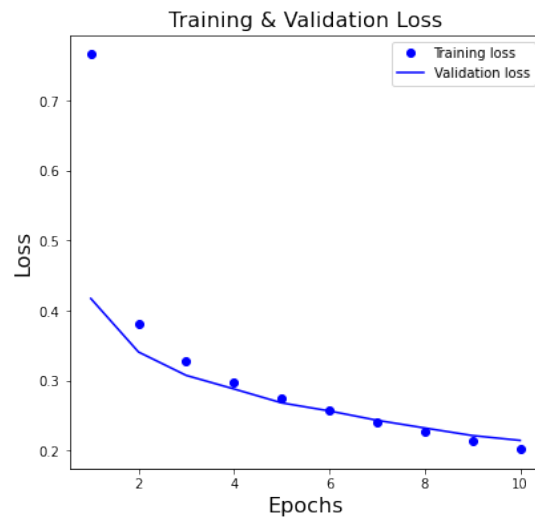
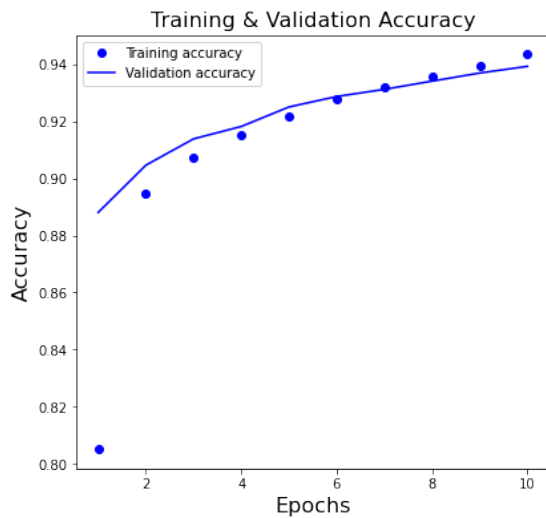
To optimizer = sgd :

Loss: 0.20

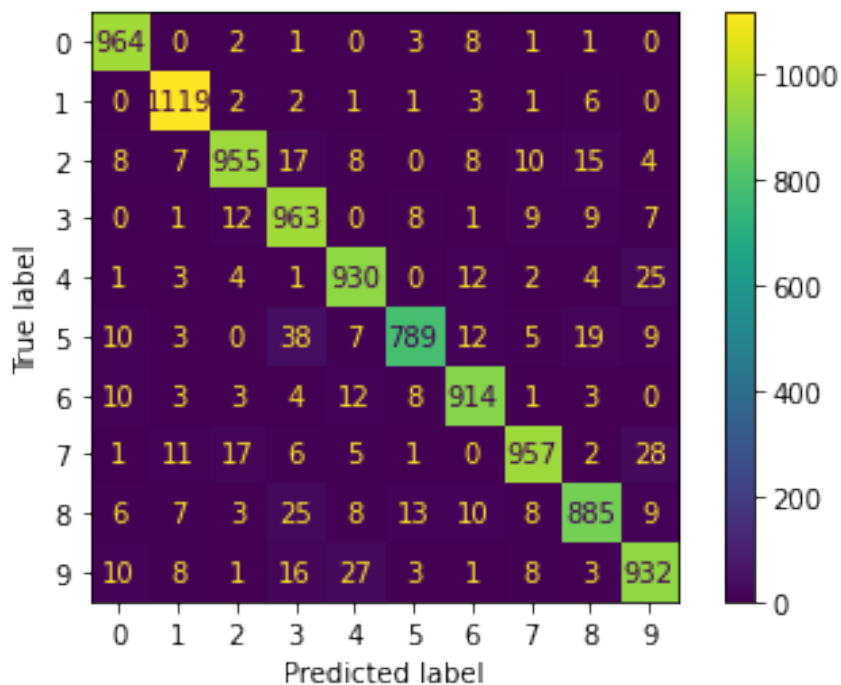
Accuracy: 94.08 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
0	0.95	0.98	0.97	980
1	0.96	0.99	0.97	1135
2	0.96	0.93	0.94	1032
3	0.90	0.95	0.92	1010
4	0.93	0.95	0.94	982
5	0.96	0.88	0.92	892
6	0.94	0.95	0.95	958
7	0.96	0.93	0.94	1028
8	0.93	0.91	0.92	974
9	0.92	0.92	0.92	1009
accuracy			0.94	10000
macro avg	0.94	0.94	0.94	10000
weighted avg	0.94	0.94	0.94	10000







#### Accuracy

Label 0: 98.37 %  
 Label 1: 98.59 %  
 Label 2: 92.54 %  
 Label 3: 95.35 %  
 Label 4: 94.70 %  
 Label 5: 88.45 %  
 Label 6: 95.41 %  
 Label 7: 93.09 %  
 Label 8: 90.86 %  
 Label 9: 92.37 %

-----

313/313 [=====] - 1s 2ms/step - loss: 0.1034

- accuracy: 0.9759

To optimizer = rmsprop :

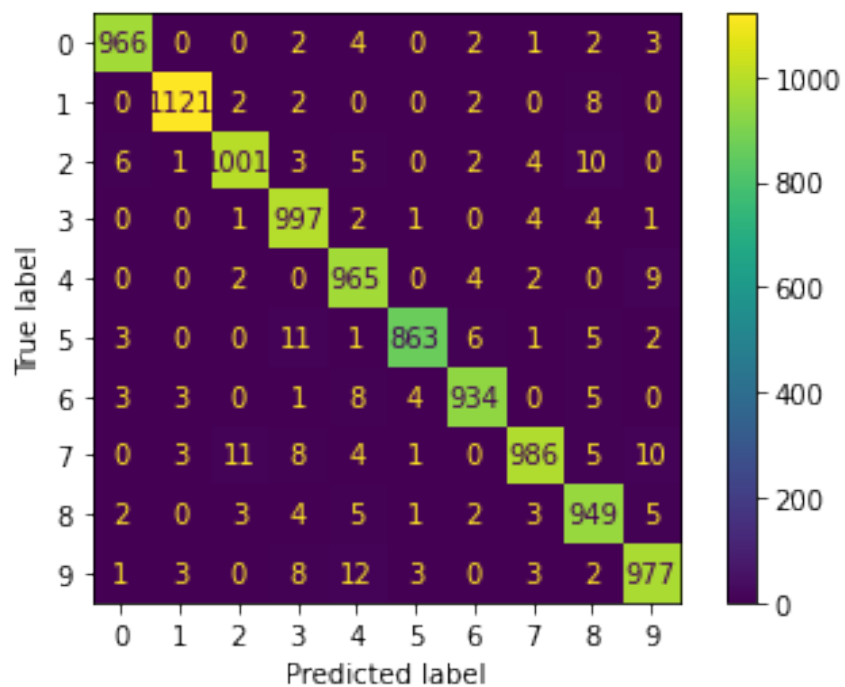
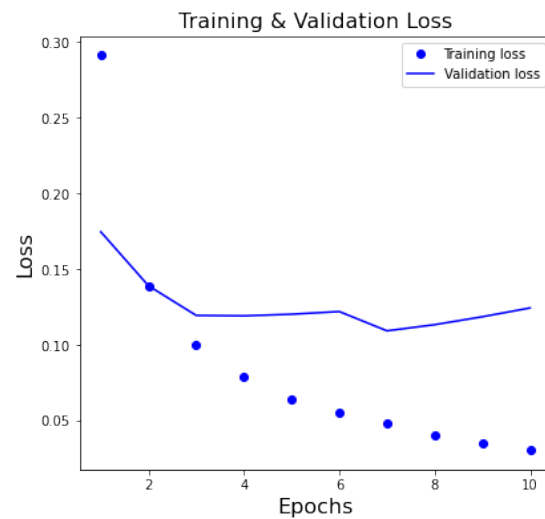
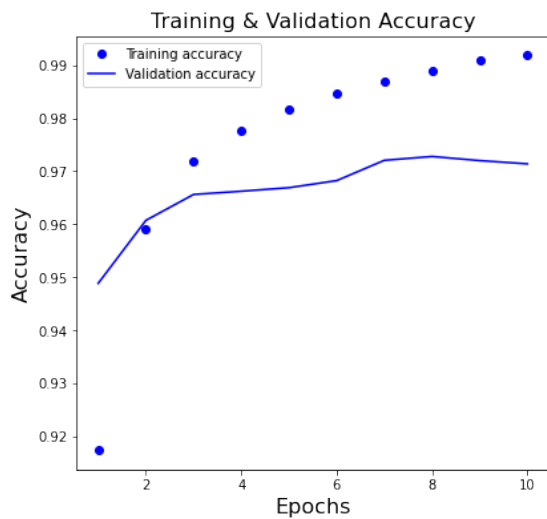
Loss: 0.10

Accuracy: 97.59 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
0	0.98	0.99	0.99	980
1	0.99	0.99	0.99	1135
2	0.98	0.97	0.98	1032
3	0.96	0.99	0.97	1010
4	0.96	0.98	0.97	982
5	0.99	0.97	0.98	892
6	0.98	0.97	0.98	958
7	0.98	0.96	0.97	1028

	8	0.96	0.97	0.97	974
	9	0.97	0.97	0.97	1009
accuracy				0.98	10000
macro avg		0.98	0.98	0.98	10000
weighted avg		0.98	0.98	0.98	10000



Accuracy

Label 0: 98.57 %

Label 1: 98.77 %

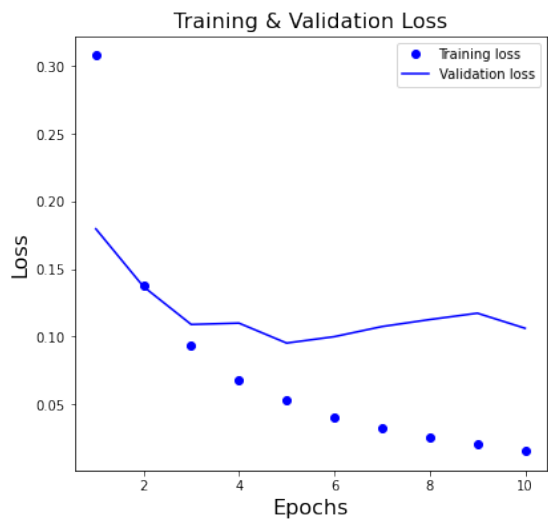
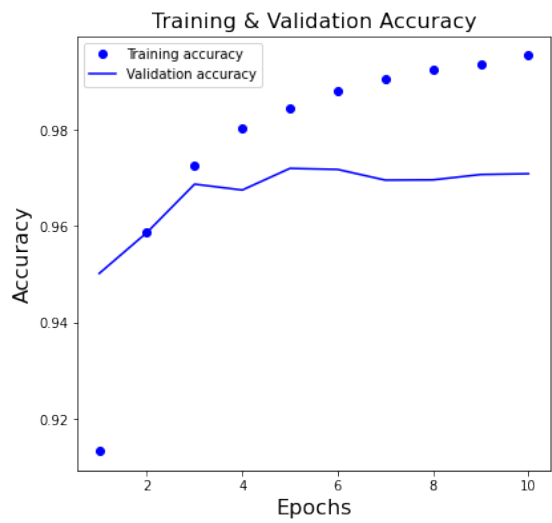
Label 2: 97.00 %

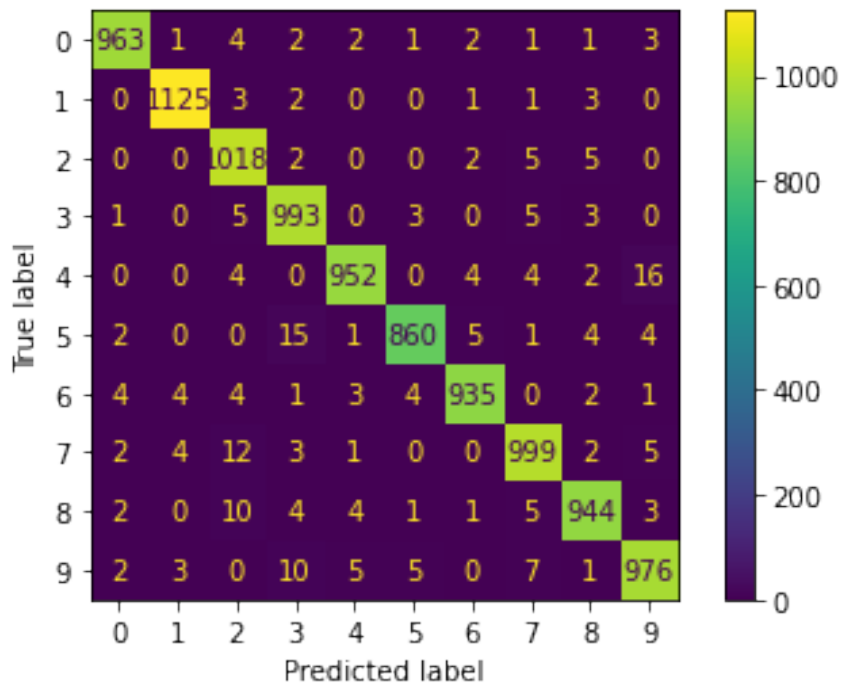
Label 3: 98.71 %

Label 4: 98.27 %  
Label 5: 96.75 %  
Label 6: 97.49 %  
Label 7: 95.91 %  
Label 8: 97.43 %  
Label 9: 96.83 %

-----  
-----  
313/313 [=====] - 1s 3ms/step - loss: 0.0801  
- accuracy: 0.9765  
To optimizer = adam :  
Loss: 0.08  
Accuracy: 97.65 %

	precision	recall	f1-score	support
0	0.99	0.98	0.98	980
1	0.99	0.99	0.99	1135
2	0.96	0.99	0.97	1032
3	0.96	0.98	0.97	1010
4	0.98	0.97	0.98	982
5	0.98	0.96	0.97	892
6	0.98	0.98	0.98	958
7	0.97	0.97	0.97	1028
8	0.98	0.97	0.97	974
9	0.97	0.97	0.97	1009
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000





#### Accuracy

Label 0: 98.27 %  
 Label 1: 99.12 %  
 Label 2: 98.64 %  
 Label 3: 98.32 %  
 Label 4: 96.95 %  
 Label 5: 96.41 %  
 Label 6: 97.60 %  
 Label 7: 97.18 %  
 Label 8: 96.92 %  
 Label 9: 96.73 %

#### ####Análise de resultados

Dos algoritmos de otimização, o Adam se saiu melhor otimizando o modelo. Por ele ser um algoritmo que estende as características do SGD e RMSProp.

#### Dropout

0.1, 0.2, 0.3, 0.4, 0.5 e 0.8

A técnica de dropout consiste no descarte de nós aleatórios entre camadas do modelo. Essa técnica é utilizada para evitar o overfitting dos dados, quando o modelo não é preciso com dados não vistos. Optamos por testar a acurácia e loss para valores entre  $[0.1, 0.5]$  com passo 0.1, e um teste isolado com valoração 0.8.

Aplicamos o dropout entre a camada de input e a camada intermediária.

```

def dropoutExperiment(drop_val,x_train = x_train,shape =
input_shape,num_class = num_class, y_train = y_train, x_test = x_test,
y_test = y_test, batch_size = batch_size,epochs = epochs,
validation_split = val_split, verbose = verbose):
    model = keras.Sequential([
        keras.Input(shape=input_shape),
        layers.Flatten(),
        layers.Dropout(drop_val),
        layers.Dense(128, activation = 'relu'),
        layers.Dense(num_class, activation = 'softmax')

    ])
    model.compile(loss = 'categorical_crossentropy', optimizer = 'adam',
metrics = 'accuracy')
    history_model = model.fit(x_train, y_train, batch_size = batch_size,
epochs = epochs, validation_split = val_split, verbose = verbose)
    eval = model.evaluate(x_test, y_test)
    print(("Loss: {percentage:.2f}").format(percentage=eval[0]))
    print(("Accuracy: {percentage:.2f}
%").format(percentage=100*(eval[1])))
    historyPlot(model, history_model.history, y_test)

```

```

dropout_list = [0.1, 0.2, 0.3, 0.4, 0.5, 0.8]
for i in dropout_list:
    print("Dropout value: ", format(i))
    dropoutExperiment(i)

```

```

print('-----')
print('-----')

```

```

Dropout value: 0.1
313/313 [=====] - 1s 2ms/step - loss: 0.0813
- accuracy: 0.9779
Loss: 0.08
Accuracy: 97.79 %

```

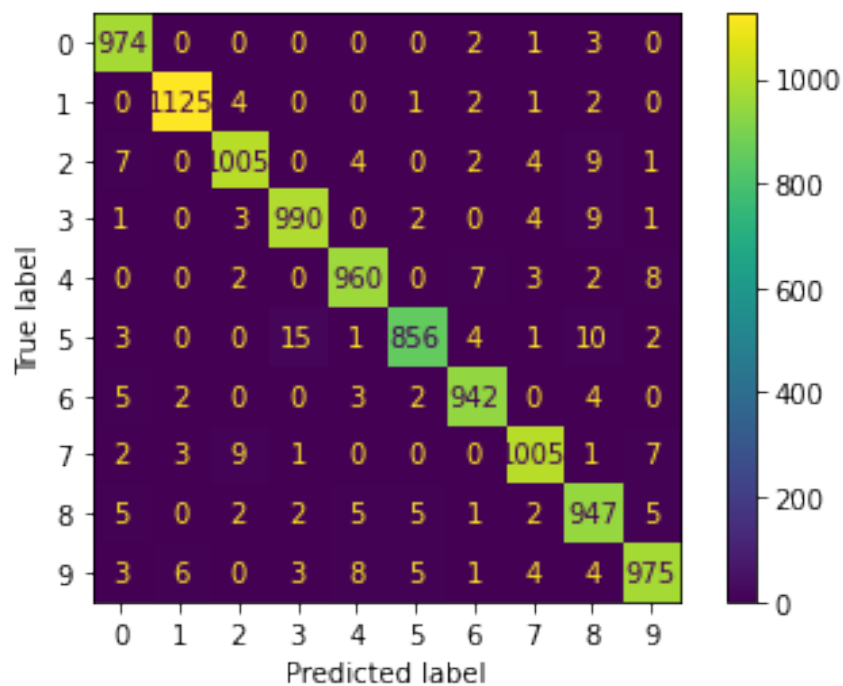
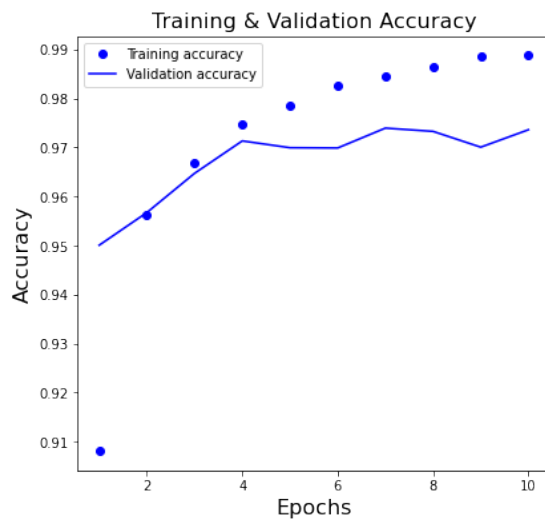
```

313/313 [=====] - 1s 2ms/step
precision recall f1-score support

```

0	0.97	0.99	0.98	980
1	0.99	0.99	0.99	1135
2	0.98	0.97	0.98	1032
3	0.98	0.98	0.98	1010
4	0.98	0.98	0.98	982
5	0.98	0.96	0.97	892
6	0.98	0.98	0.98	958
7	0.98	0.98	0.98	1028
8	0.96	0.97	0.96	974
9	0.98	0.97	0.97	1009

accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000



Accuracy

Label 0: 99.39 %

Label 1: 99.12 %

Label 2: 97.38 %

Label 3: 98.02 %

Label 4: 97.76 %

Label 5: 95.96 %

Label 6: 98.33 %  
Label 7: 97.76 %  
Label 8: 97.23 %  
Label 9: 96.63 %

Dropout value: 0.2

313/313 [=====] - 1s 2ms/step - loss: 0.0730

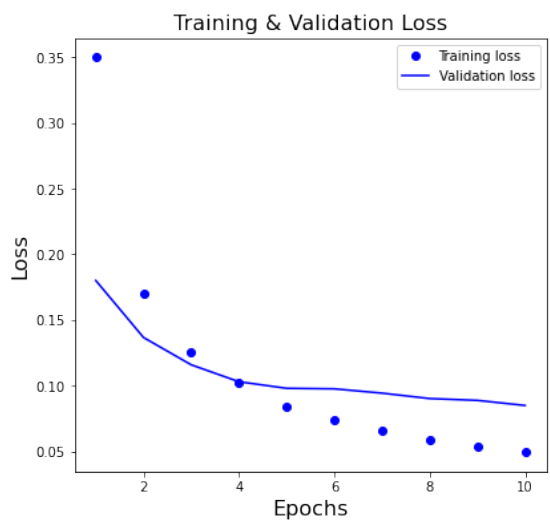
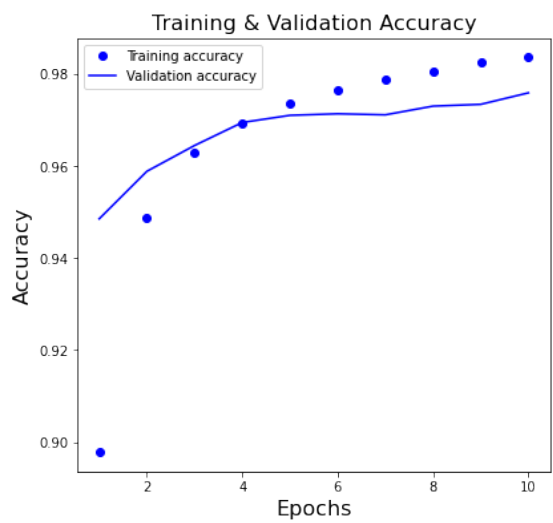
- accuracy: 0.9779

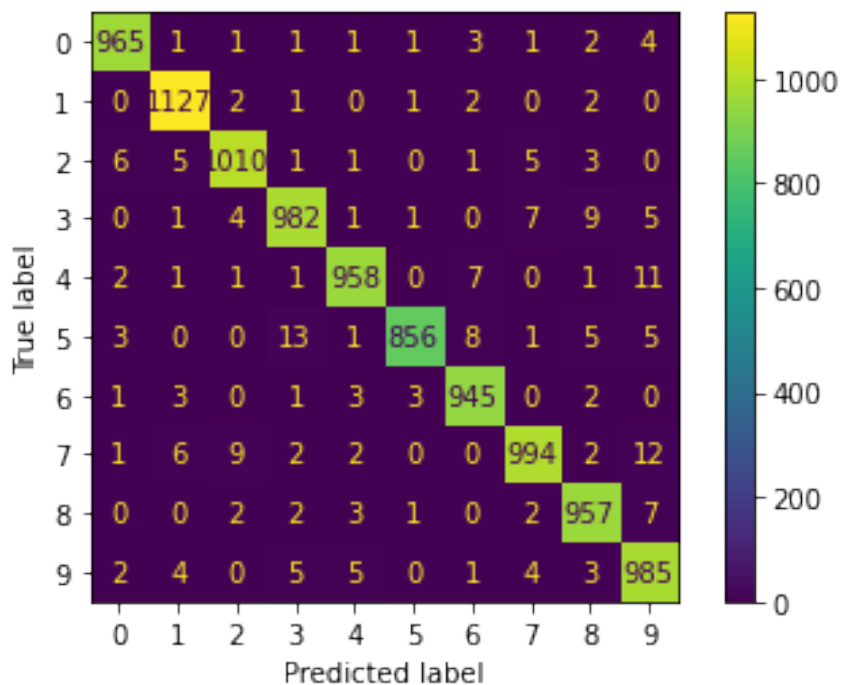
Loss: 0.07

Accuracy: 97.79 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
0	0.98	0.98	0.98	980
1	0.98	0.99	0.99	1135
2	0.98	0.98	0.98	1032
3	0.97	0.97	0.97	1010
4	0.98	0.98	0.98	982
5	0.99	0.96	0.98	892
6	0.98	0.99	0.98	958
7	0.98	0.97	0.97	1028
8	0.97	0.98	0.98	974
9	0.96	0.98	0.97	1009
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000





#### Accuracy

Label 0: 98.47 %  
 Label 1: 99.30 %  
 Label 2: 97.87 %  
 Label 3: 97.23 %  
 Label 4: 97.56 %  
 Label 5: 95.96 %  
 Label 6: 98.64 %  
 Label 7: 96.69 %  
 Label 8: 98.25 %  
 Label 9: 97.62 %

-----

Dropout value: 0.3

313/313 [=====] - 1s 2ms/step - loss: 0.0708

- accuracy: 0.9770

Loss: 0.07

Accuracy: 97.70 %

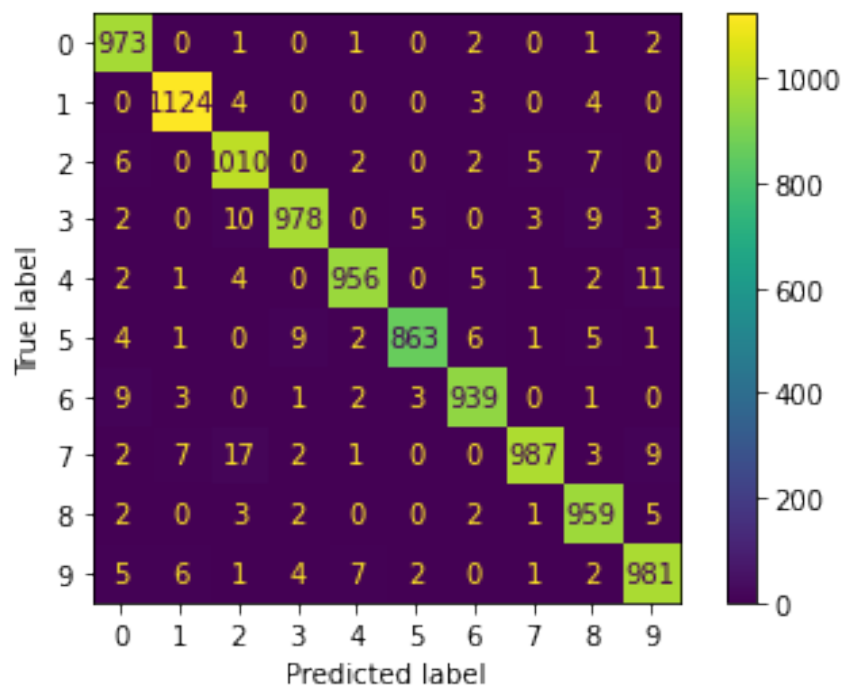
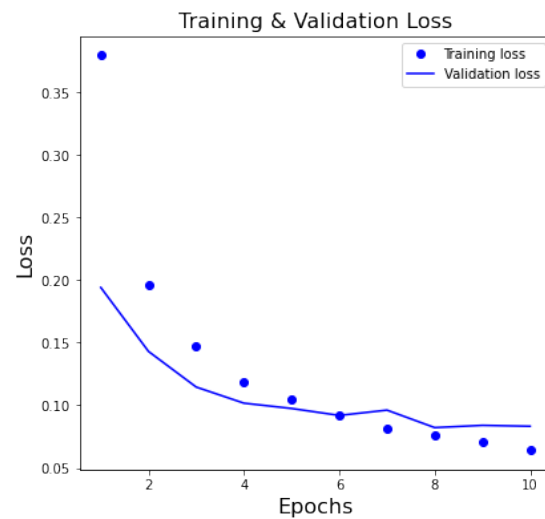
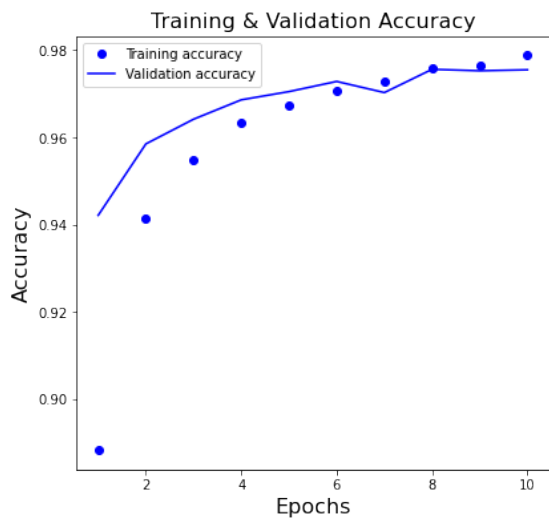
313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.97	0.99	0.98	980
1	0.98	0.99	0.99	1135
2	0.96	0.98	0.97	1032
3	0.98	0.97	0.98	1010
4	0.98	0.97	0.98	982
5	0.99	0.97	0.98	892
6	0.98	0.98	0.98	958
7	0.99	0.96	0.97	1028



	8	0.97	0.98	0.98	974
	9	0.97	0.97	0.97	1009
accuracy				0.98	10000
macro avg		0.98	0.98	0.98	10000
weighted avg		0.98	0.98	0.98	10000



Accuracy

Label 0: 99.29 %

Label 1: 99.03 %

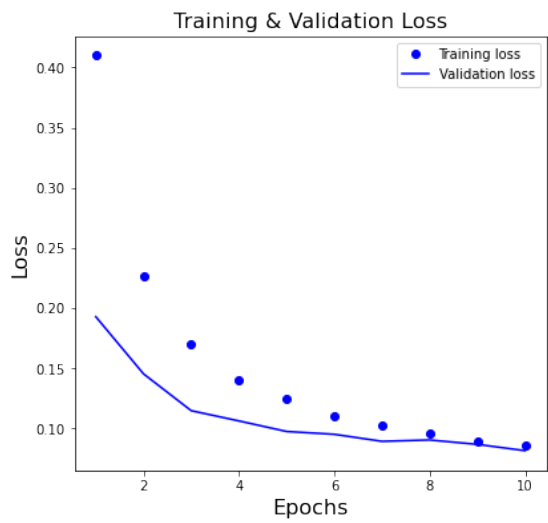
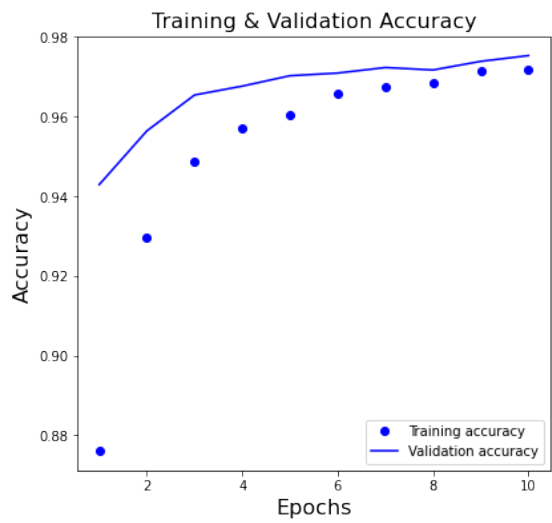
Label 2: 97.87 %

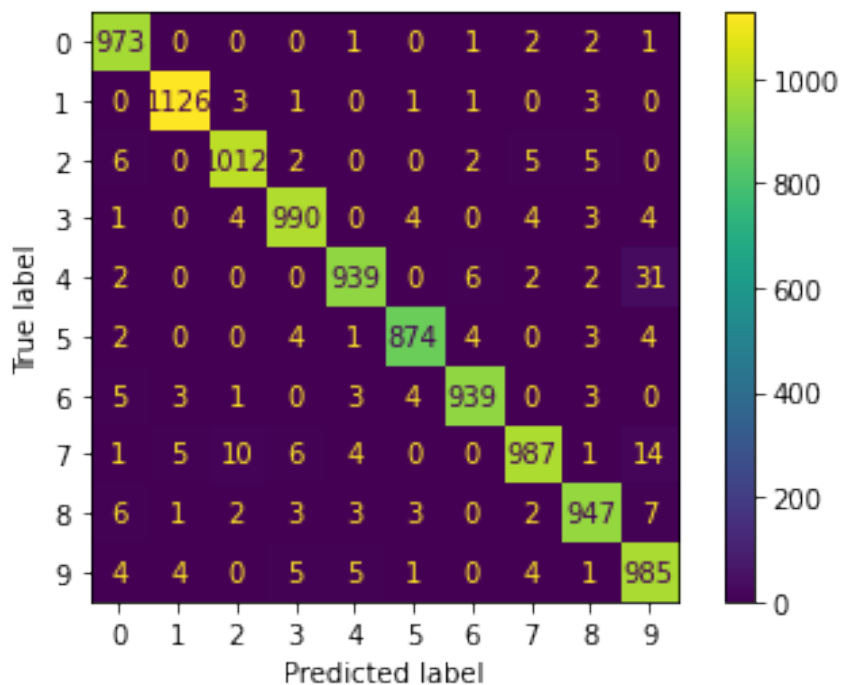
Label 3: 96.83 %

Label 4: 97.35 %  
Label 5: 96.75 %  
Label 6: 98.02 %  
Label 7: 96.01 %  
Label 8: 98.46 %  
Label 9: 97.22 %

-----  
-----  
Dropout value: 0.4  
313/313 [=====] - 1s 2ms/step - loss: 0.0740  
- accuracy: 0.9772  
Loss: 0.07  
Accuracy: 97.72 %

	precision	recall	f1-score	support
0	0.97	0.99	0.98	980
1	0.99	0.99	0.99	1135
2	0.98	0.98	0.98	1032
3	0.98	0.98	0.98	1010
4	0.98	0.96	0.97	982
5	0.99	0.98	0.98	892
6	0.99	0.98	0.98	958
7	0.98	0.96	0.97	1028
8	0.98	0.97	0.97	974
9	0.94	0.98	0.96	1009
accuracy			0.98	10000
macro avg	0.98	0.98	0.98	10000
weighted avg	0.98	0.98	0.98	10000





#### Accuracy

Label 0: 99.29 %  
 Label 1: 99.21 %  
 Label 2: 98.06 %  
 Label 3: 98.02 %  
 Label 4: 95.62 %  
 Label 5: 97.98 %  
 Label 6: 98.02 %  
 Label 7: 96.01 %  
 Label 8: 97.23 %  
 Label 9: 97.62 %

Dropout value: 0.5

313/313 [=====] - 1s 2ms/step - loss: 0.0796

- accuracy: 0.9743

Loss: 0.08

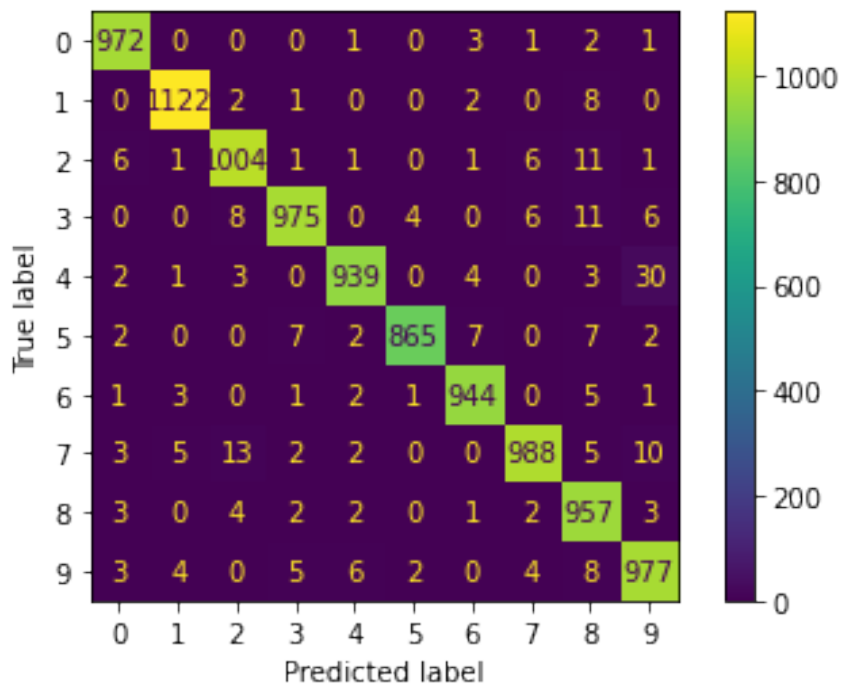
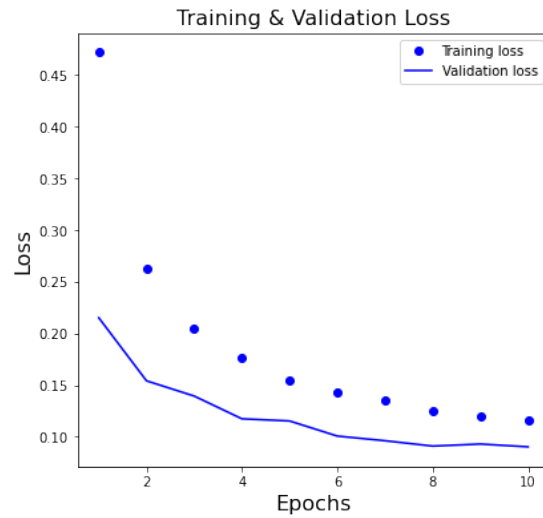
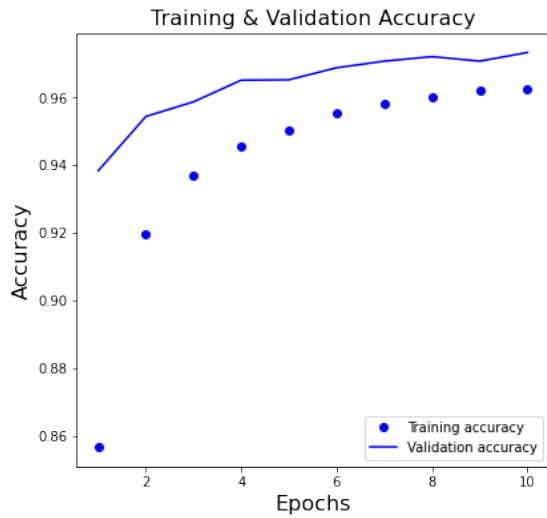
Accuracy: 97.43 %

313/313 [=====] - 1s 2ms/step

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.98	0.99	0.99	980
1	0.99	0.99	0.99	1135
2	0.97	0.97	0.97	1032
3	0.98	0.97	0.97	1010
4	0.98	0.96	0.97	982
5	0.99	0.97	0.98	892
6	0.98	0.99	0.98	958
7	0.98	0.96	0.97	1028

	8	0.94	0.98	0.96	974
	9	0.95	0.97	0.96	1009
accuracy				0.97	10000
macro avg		0.97	0.97	0.97	10000
weighted avg		0.97	0.97	0.97	10000



Accuracy

Label 0: 99.18 %

Label 1: 98.85 %

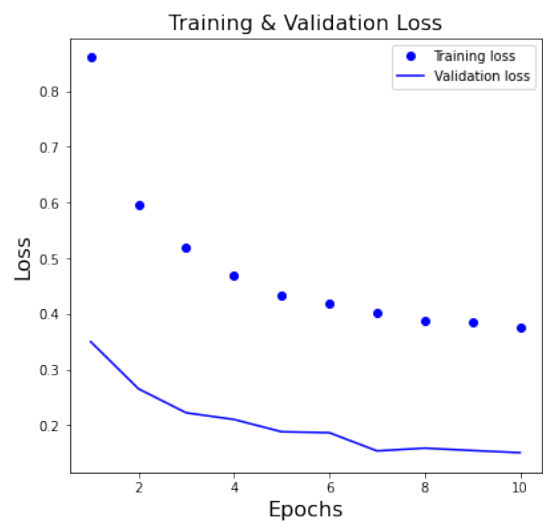
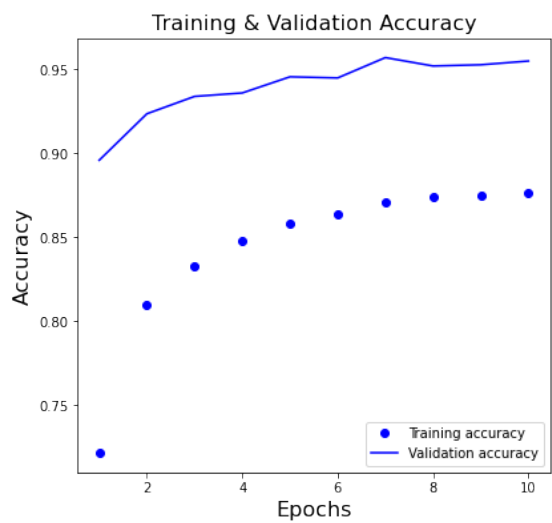
Label 2: 97.29 %

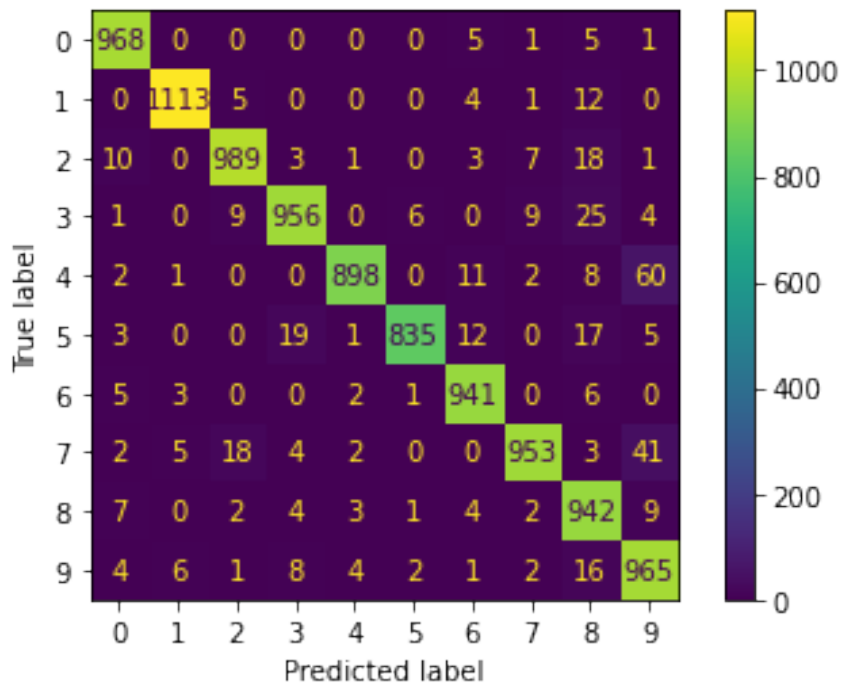
Label 3: 96.53 %

Label 4: 95.62 %  
Label 5: 96.97 %  
Label 6: 98.54 %  
Label 7: 96.11 %  
Label 8: 98.25 %  
Label 9: 96.83 %

-----  
-----  
Dropout value: 0.8  
313/313 [=====] - 1s 2ms/step - loss: 0.1422  
- accuracy: 0.9560  
Loss: 0.14  
Accuracy: 95.60 %

	precision	recall	f1-score	support
0	0.97	0.99	0.98	980
1	0.99	0.98	0.98	1135
2	0.97	0.96	0.96	1032
3	0.96	0.95	0.95	1010
4	0.99	0.91	0.95	982
5	0.99	0.94	0.96	892
6	0.96	0.98	0.97	958
7	0.98	0.93	0.95	1028
8	0.90	0.97	0.93	974
9	0.89	0.96	0.92	1009
accuracy			0.96	10000
macro avg	0.96	0.96	0.96	10000
weighted avg	0.96	0.96	0.96	10000





Accuracy

Label 0: 98.78 %

Label 1: 98.06 %

Label 2: 95.83 %

Label 3: 94.65 %

Label 4: 91.45 %

Label 5: 93.61 %

Label 6: 98.23 %

Label 7: 92.70 %

Label 8: 96.71 %

Label 9: 95.64 %

-----

###Análise de resultado

A partir dos resultados obtidos, percebe-se que um dropout de 80% confere uma pior performance de acurácia no modelo, constituindo uma pior acurácia. Em consonância, valores menores projetam uma maior acurácia, provendo melhor recall e precisão.