MNIST

Dropout como Regularização

Aplicação da técnica Dropout em uma Rede Neural Artificial para classificação de números

Aluno:

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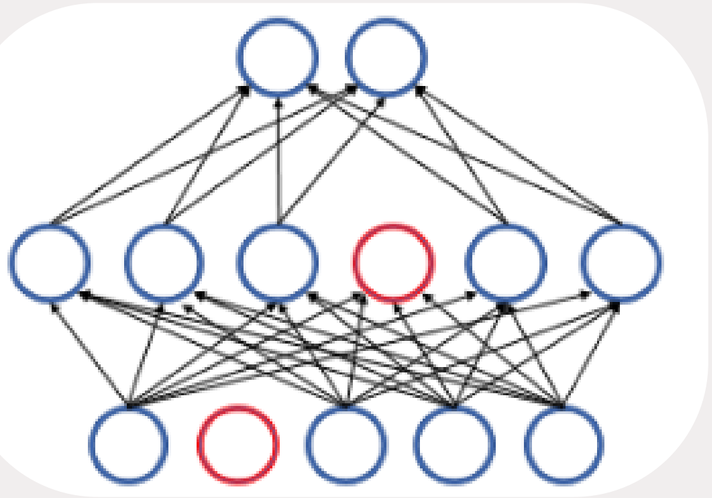


O que é MNIST?

- MNIST - Modified National Institute of Standards and Technology
- Repositório de imagens manuscritas em tom de cinza;
- 60.000 (Treino) x 10.000 (Teste);
- 28x28 pixels; 0 a 255; uint8;
- Imagem → Rótulo
- As redes neurais têm se mostrado eficazes em reconhecimento de padrões em aplicações como OCR (reconhecimento óptico de caracteres) e automação industrial

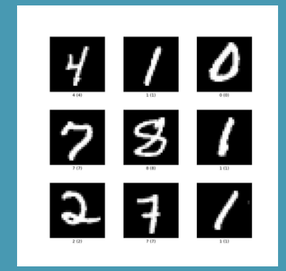
OBJETIVO GERAL

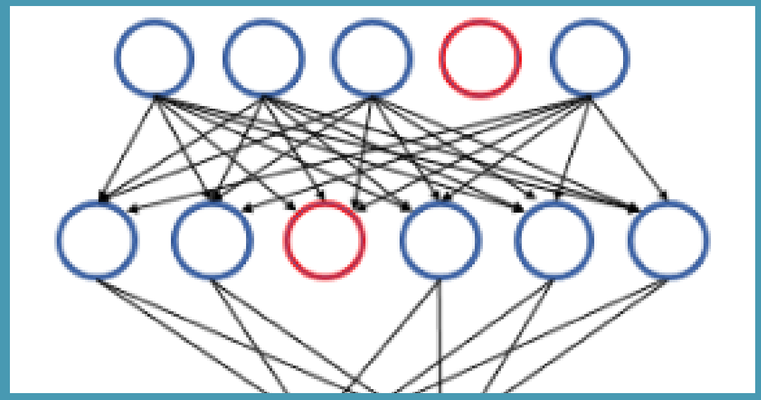
Aprendizado: Treinar a rede para identificar corretamente os dígitos manuscritos.

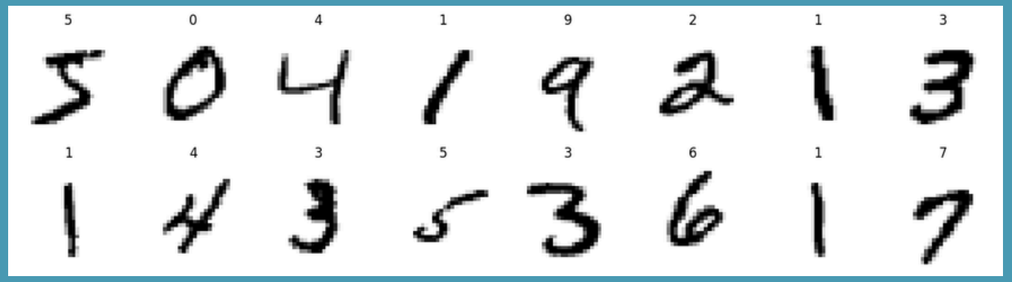
Generalização: Garantir bom desempenho com dados novos (não vistos).

Dropout: Reduzir overfitting desativando aleatoriamente neurônios durante o treino.

MNIST: Base de dados com 70 mil imagens de dígitos (0–9).



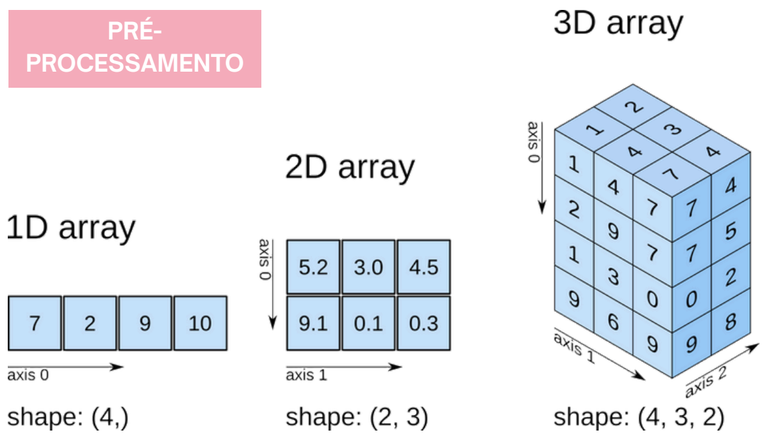


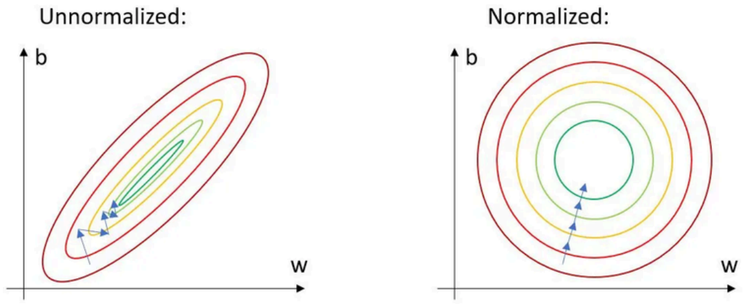


METODOLOGIA

MNIST → PRÉ-PROCESSAMENTO → RNA COM DROPOUT → TREINAMENTO (ADAM) → AVALIAÇÃO

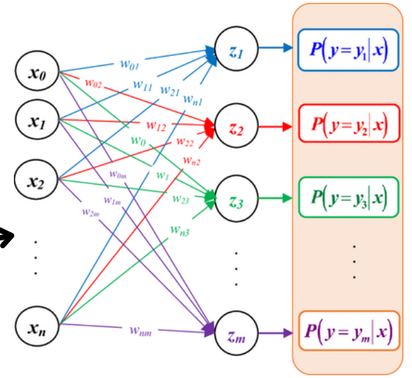
PRÉ-PROCESSAMENTO



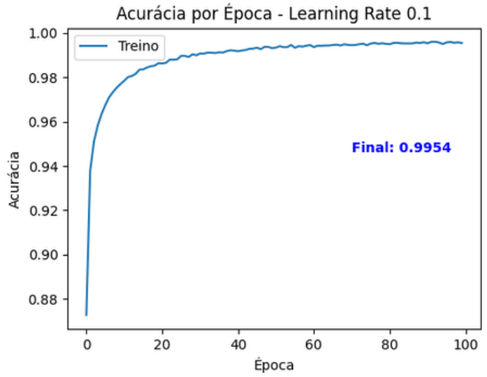


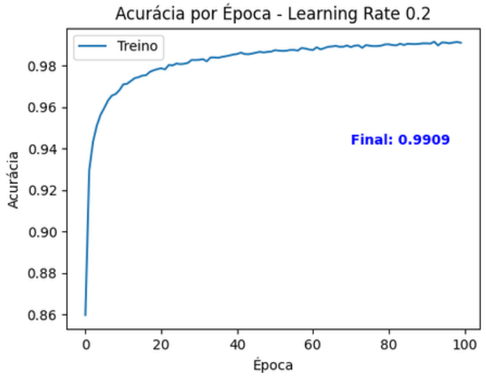
RNA COM DROPOUT

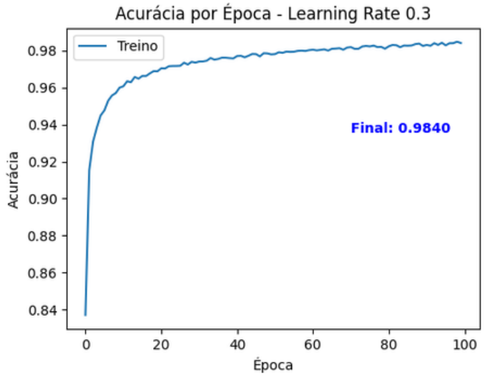
- INPUT - shape=784,1
- HIDEN LAYER - 64 neurônios - relu
- DROPOUT LAYER - rate variado
- OUTPUT LAYER - 10 neurônios - softmax

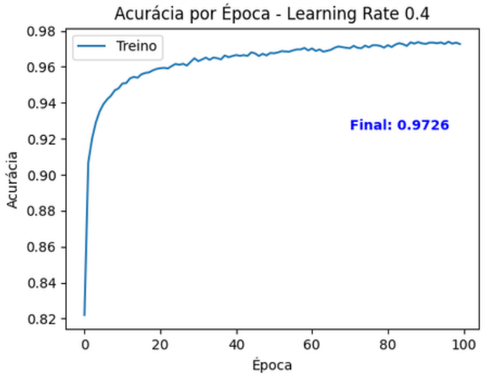


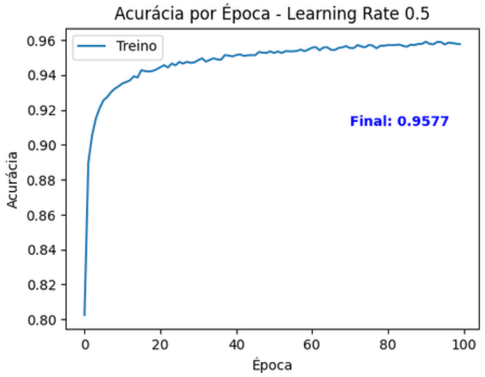
RESULTADOS

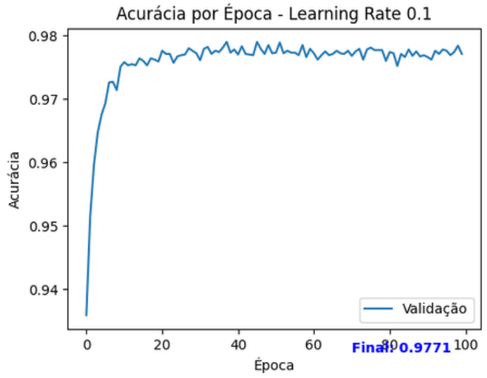

Acurácia por Época - Learning Rate 0.1
Treino
Final: 0.9954
Acurácia
Época

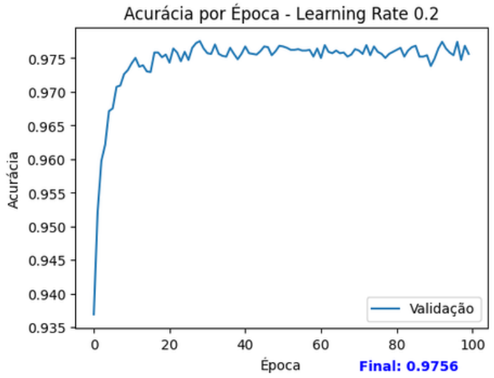

Acurácia por Época - Learning Rate 0.2
Treino
Final: 0.9909
Acurácia
Época

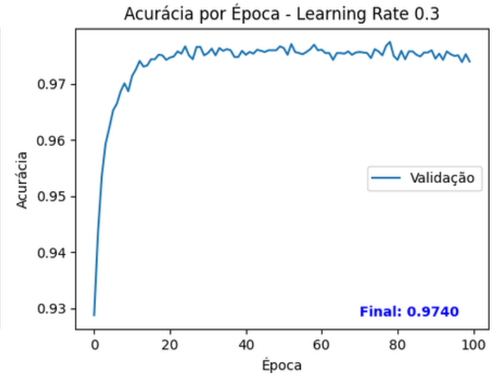

Acurácia por Época - Learning Rate 0.3
Treino
Final: 0.9840
Acurácia
Época

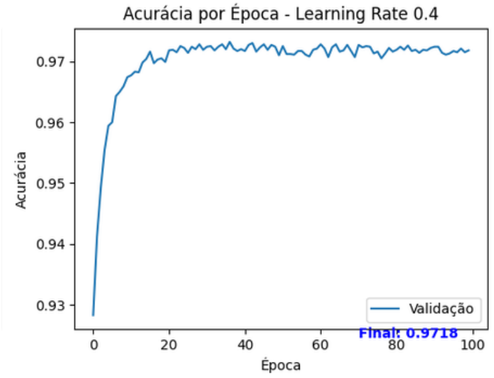

Acurácia por Época - Learning Rate 0.4
Treino
Final: 0.9726
Acurácia
Época

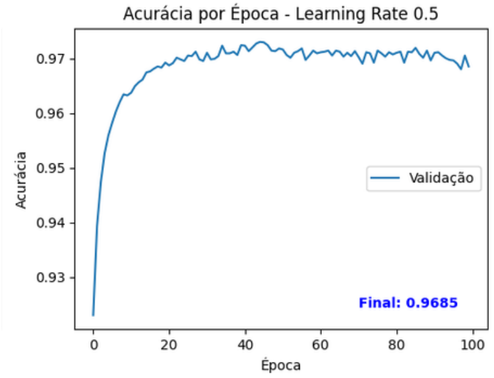

Acurácia por Época - Learning Rate 0.5
Treino
Final: 0.9577
Acurácia
Época


Acurácia por Época - Learning Rate 0.1
Validação
Final: 0.9771
Acurácia
Época

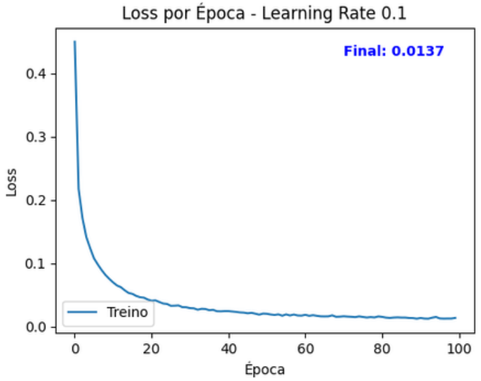

Acurácia por Época - Learning Rate 0.2
Validação
Final: 0.9756
Acurácia
Época

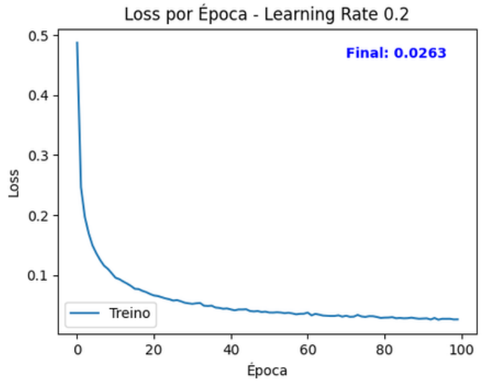

Acurácia por Época - Learning Rate 0.3
Validação
Final: 0.9740
Acurácia
Época

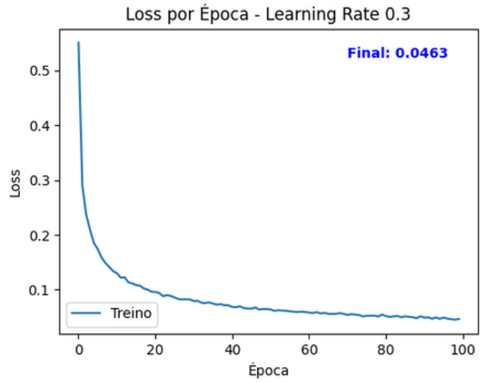

Acurácia por Época - Learning Rate 0.4
Validação
Final: 0.9718
Acurácia
Época

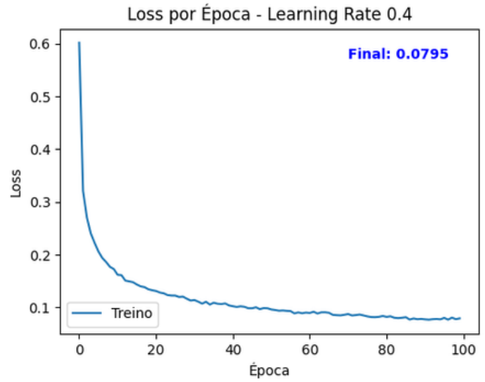

Acurácia por Época - Learning Rate 0.5
Validação
Final: 0.9685
Acurácia
Época

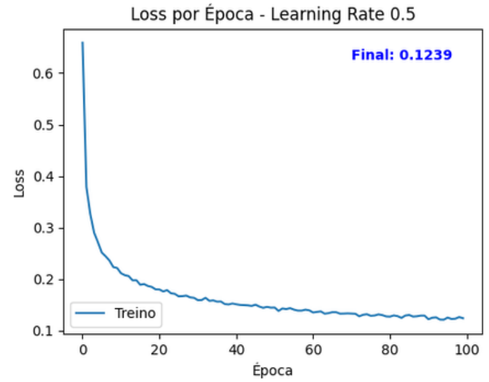
RESULTADOS

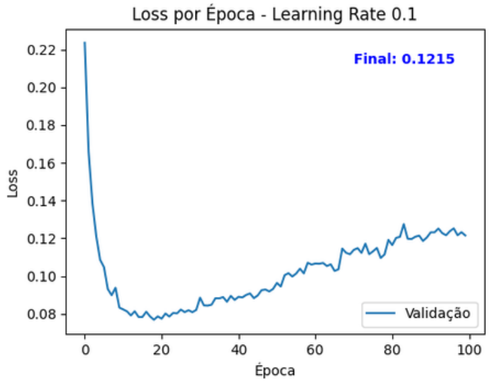

Loss por Época - Learning Rate 0.1
Final: 0.0137
Treino
Loss
Época

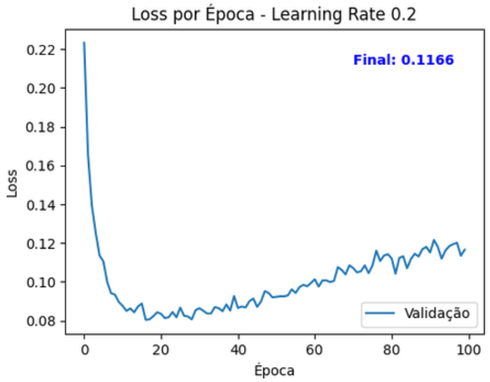

Loss por Época - Learning Rate 0.2
Final: 0.0263
Treino
Loss
Época

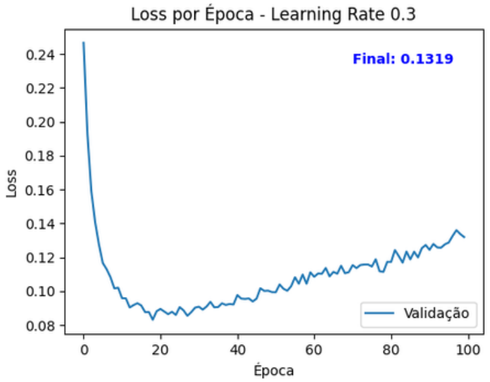

Loss por Época - Learning Rate 0.3
Final: 0.0463
Treino
Loss
Época

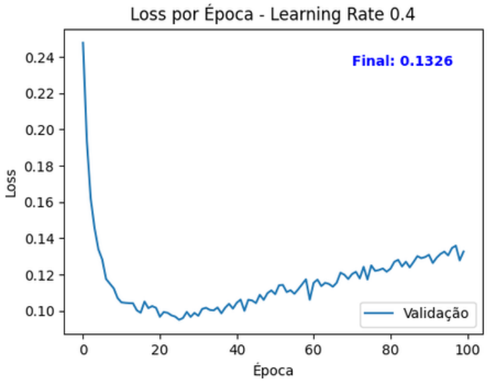

Loss por Época - Learning Rate 0.4
Final: 0.0795
Treino
Loss
Época

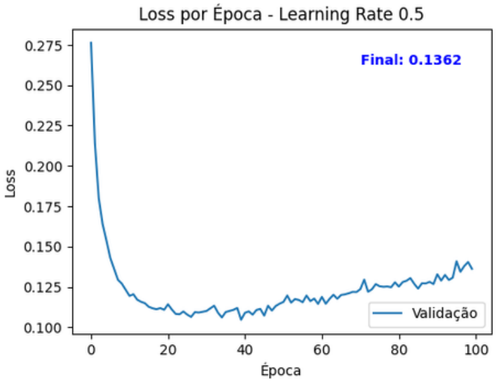

Loss por Época - Learning Rate 0.5
Final: 0.1239
Treino
Loss
Época


Loss por Época - Learning Rate 0.1
Final: 0.1215
Validação
Loss
Época

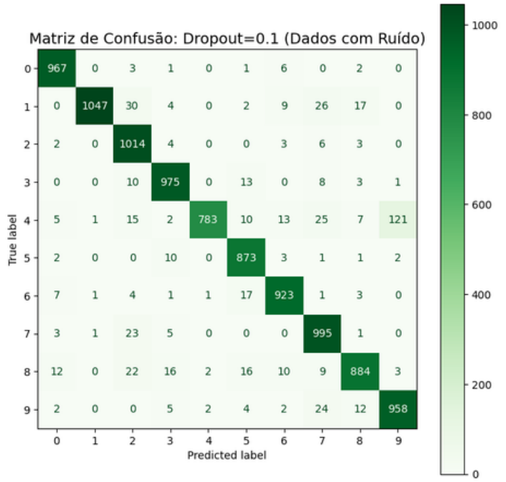

Loss por Época - Learning Rate 0.2
Final: 0.1166
Validação
Loss
Época

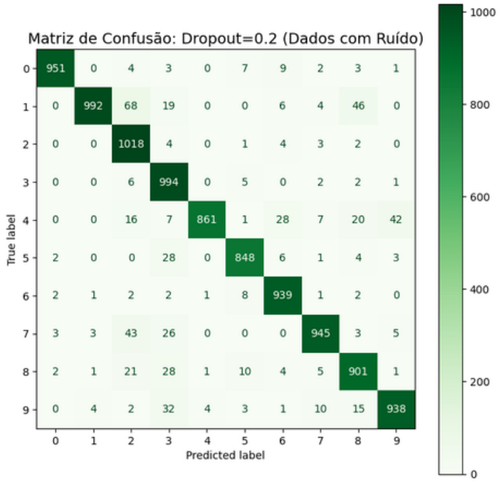

Loss por Época - Learning Rate 0.3
Final: 0.1319
Validação
Loss
Época

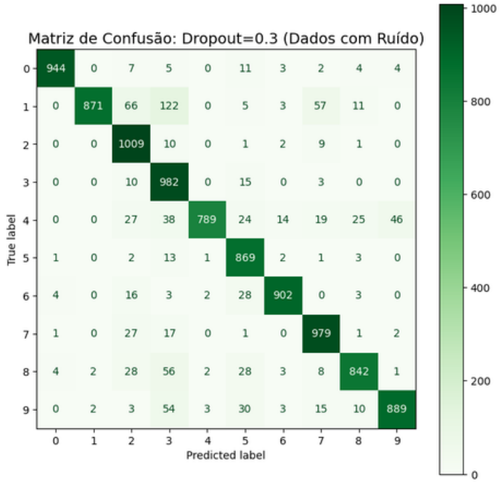

Loss por Época - Learning Rate 0.4
Final: 0.1326
Validação
Loss
Época

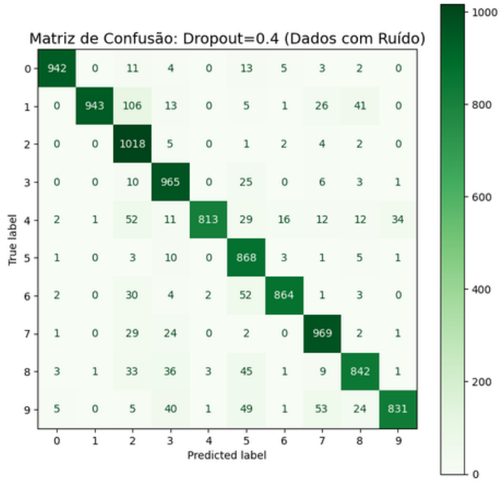

Loss por Época - Learning Rate 0.5
Final: 0.1362
Validação
Loss
Época

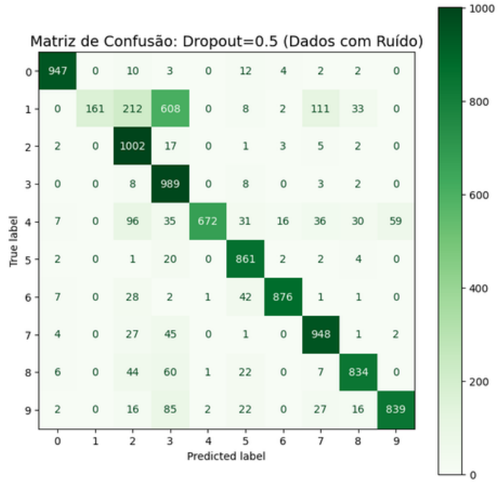
RESULTADOS











	precision	recall	f1-score	support
0	0.97	0.99	0.98	980
1	1.00	0.92	0.96	1135
2	0.90	0.98	0.94	1032
3	0.95	0.97	0.96	1010
4	0.99	0.80	0.88	982
5	0.93	0.98	0.96	892
6	0.95	0.96	0.96	958
7	0.91	0.97	0.94	1028
8	0.95	0.91	0.93	974
9	0.88	0.95	0.91	1009
accuracy			0.94	10000
macro avg	0.94	0.94	0.94	10000
weighted avg	0.94	0.94	0.94	10000

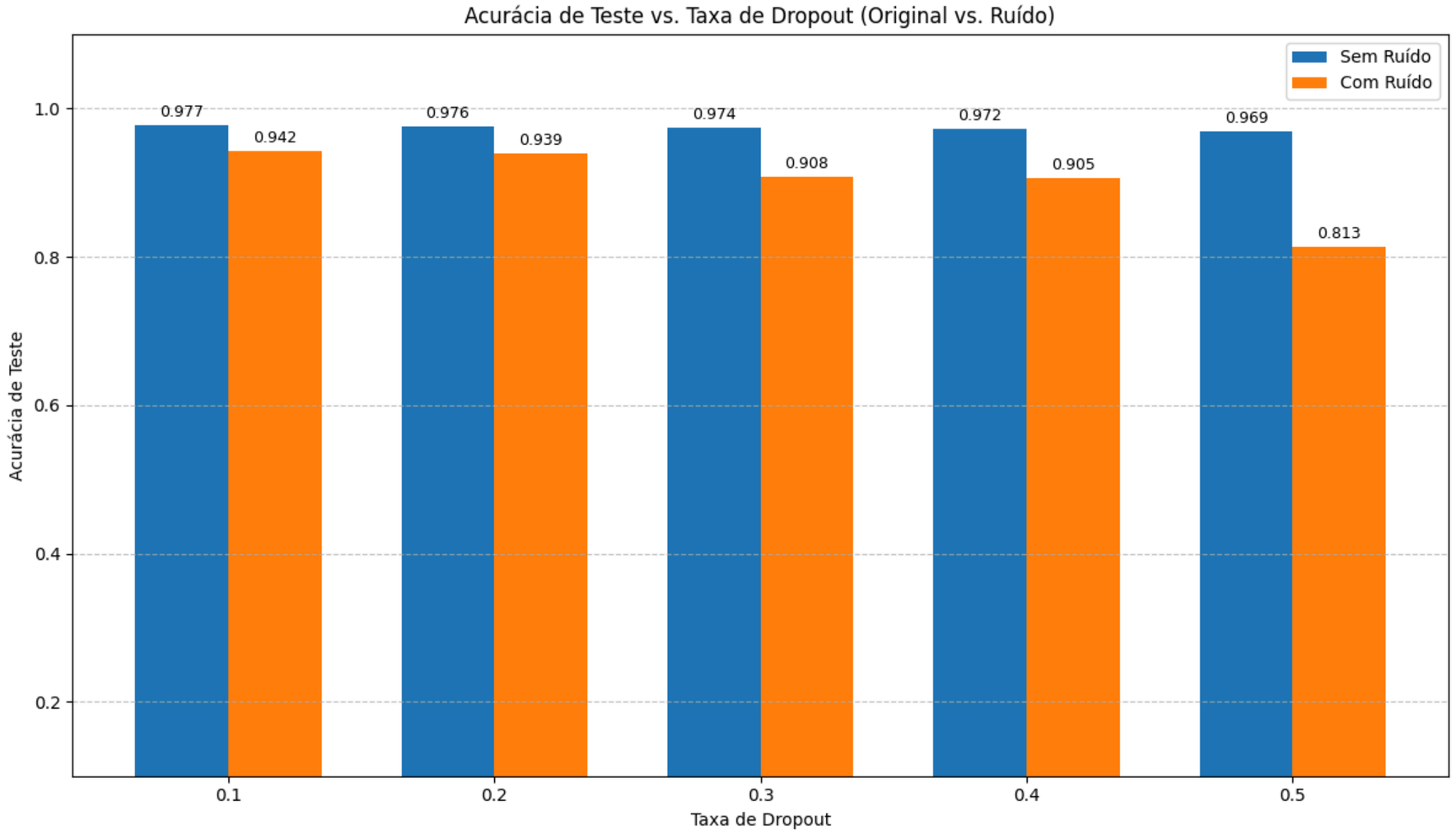
	precision	recall	f1-score	support
0	0.99	0.97	0.98	980
1	0.99	0.87	0.93	1135
2	0.86	0.99	0.92	1032
3	0.87	0.98	0.92	1010
4	0.99	0.88	0.93	982
5	0.96	0.95	0.96	892
6	0.94	0.98	0.96	958
7	0.96	0.92	0.94	1028
8	0.90	0.93	0.91	974
9	0.95	0.93	0.94	1009
accuracy			0.94	10000
macro avg	0.94	0.94	0.94	10000
weighted avg	0.94	0.94	0.94	10000

	precision	recall	f1-score	support
0	0.99	0.96	0.98	980
1	1.00	0.77	0.87	1135
2	0.84	0.98	0.91	1032
3	0.76	0.97	0.85	1010
4	0.99	0.80	0.89	982
5	0.86	0.97	0.91	892
6	0.97	0.94	0.95	958
7	0.90	0.95	0.92	1028
8	0.94	0.86	0.90	974
9	0.94	0.88	0.91	1009
accuracy			0.91	10000
macro avg	0.92	0.91	0.91	10000
weighted avg	0.92	0.91	0.91	10000

	precision	recall	f1-score	support
0	0.99	0.96	0.97	980
1	1.00	0.83	0.91	1135
2	0.78	0.99	0.87	1032
3	0.87	0.96	0.91	1010
4	0.99	0.83	0.90	982
5	0.80	0.97	0.88	892
6	0.97	0.90	0.93	958
7	0.89	0.94	0.92	1028
8	0.90	0.86	0.88	974
9	0.96	0.82	0.88	1009
accuracy			0.91	10000
macro avg	0.91	0.91	0.91	10000
weighted avg	0.92	0.91	0.91	10000

	precision	recall	f1-score	support
0	0.97	0.97	0.97	980
1	1.00	0.14	0.25	1135
2	0.69	0.97	0.81	1032
3	0.53	0.98	0.69	1010
4	0.99	0.68	0.81	982
5	0.85	0.97	0.91	892
6	0.97	0.91	0.94	958
7	0.83	0.92	0.87	1028
8	0.90	0.86	0.88	974
9	0.93	0.83	0.88	1009
accuracy			0.81	10000
macro avg	0.87	0.82	0.80	10000
weighted avg	0.87	0.81	0.79	10000

RESULTADOS


Acurácia de Teste vs. Taxa de Dropout (Original vs. Ruído)
Sem Ruído
Com Ruído
Acurácia de Teste
Taxa de Dropout
1.0
0.8
0.6
0.4
0.2
0.1
0.2
0.3
0.4
0.5
0.977
0.942
0.976
0.939
0.974
0.908
0.972
0.905
0.969
0.813

CONCLUSÃO

- Para o cenário Sem Ruído, o Dropout de 0.1 e 0.2 entregam a melhor acurácia de teste (97.7% e 97.6%);
- Dropouts de 0.3 a 0.5 são mais eficazes em prevenir o overfitting;
- O Dropout de 0.5 sofreu uma queda drástica de 15.3%;
- O Dropout de 0.1 e 0.2 apresentaram a menor perda percentual e as maiores acurácias de teste com ruído (0.942 e 0.939);
- O relatório de classificação do Dropout 0.2 apresenta a melhor acurácia ponderada (weighted avg accuracy $\approx$0.94) com maior consistência nas métricas de Precision e Recall entre as classes (menos erros graves);
- Para o 0.2, a Classe 5 ainda é a mais fraca (recall 0.85 e precision 0.93) e a Classe 8 é fraca em recall (0.85), mas o desempenho é superior ao 0.3,0.4 e 0.5;
- Embora o 0.1 tenha a maior acurácia absoluta, o Dropout de 0.2 oferece uma performance quase idêntica, mas com um comportamento de treinamento mais saudável e estável;