FixMatch

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Motivação

1. Ausência de dados rotulados de qualidade e alto custo para produzí-los
2. Modelos de aprendizado semi-supervisionado demasiadamente complexos

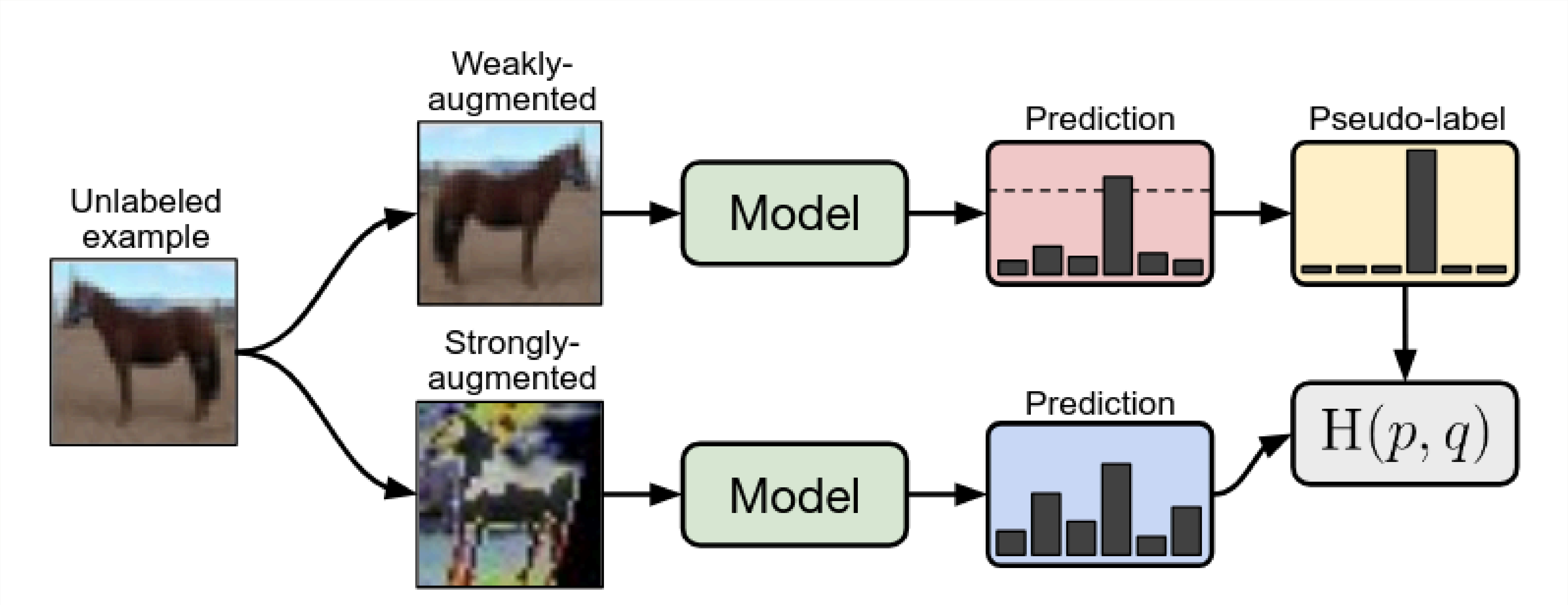
Pilares

1. **Reg. Por Consistência:** O modelo deve ser robusto e lidar bem com pequenas variações
2. **Pseudo-Rotulagem:** Usar o próprio modelo como gerador de rótulos (apenas para previsões com probabilidade alta)

Metodologia

1. Seleciona uma imagem não rotulada e aplica uma augmentation fraca
2. Passa a imagem pelo modelo e gera uma previsão com uma certeza associada
3. Se a certeza for alta, atribui esse rótulo à imagem
4. Seleciona a imagem original e aplica uma augmentation forte
5. Passa a imagem pelo modelo e a ideia é reconhecer o rótulo mesmo com a transformação

Metodologia



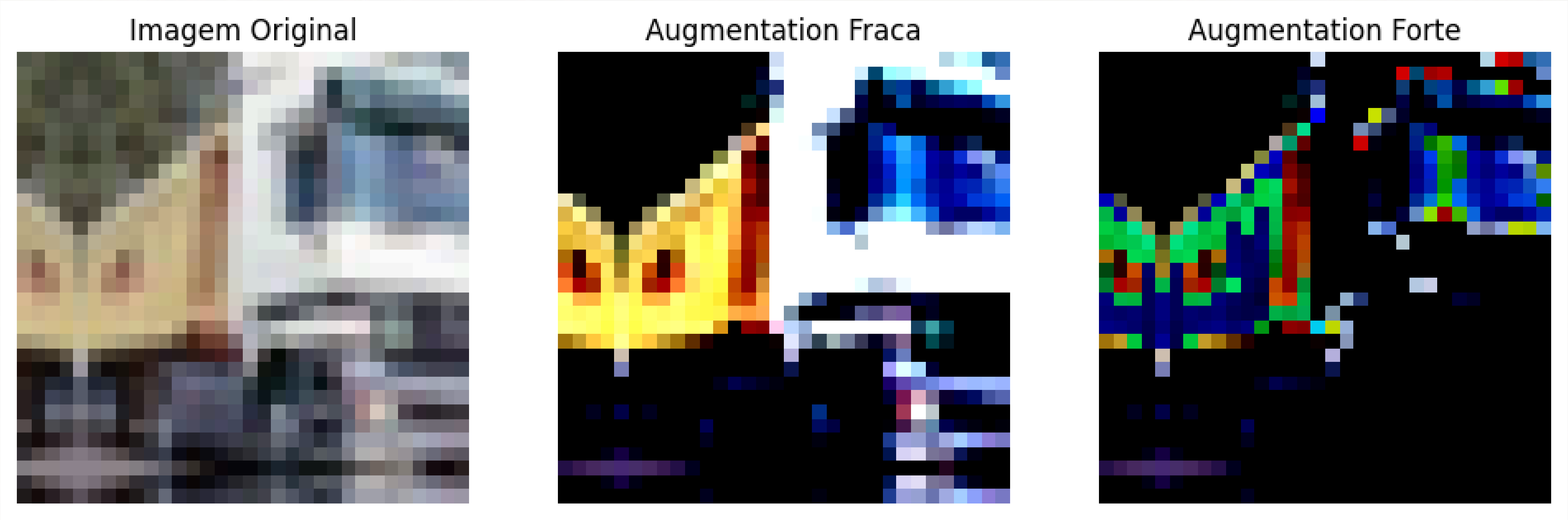
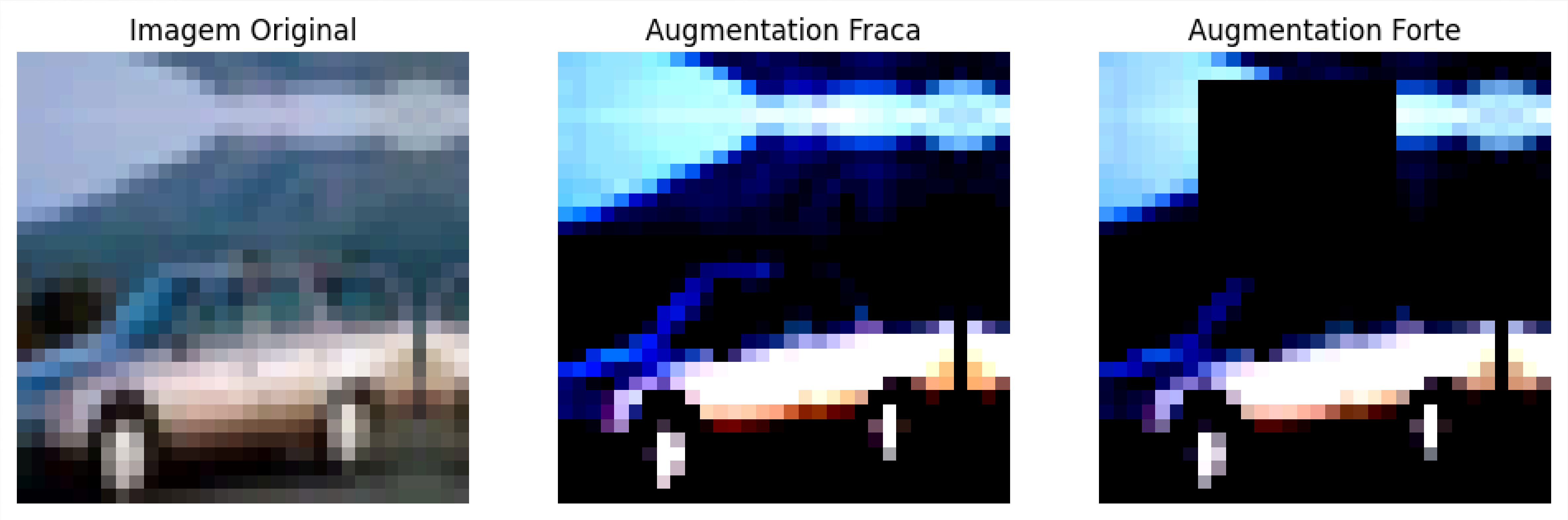


Imagem Original
Augmentation Fraca
Augmentation Forte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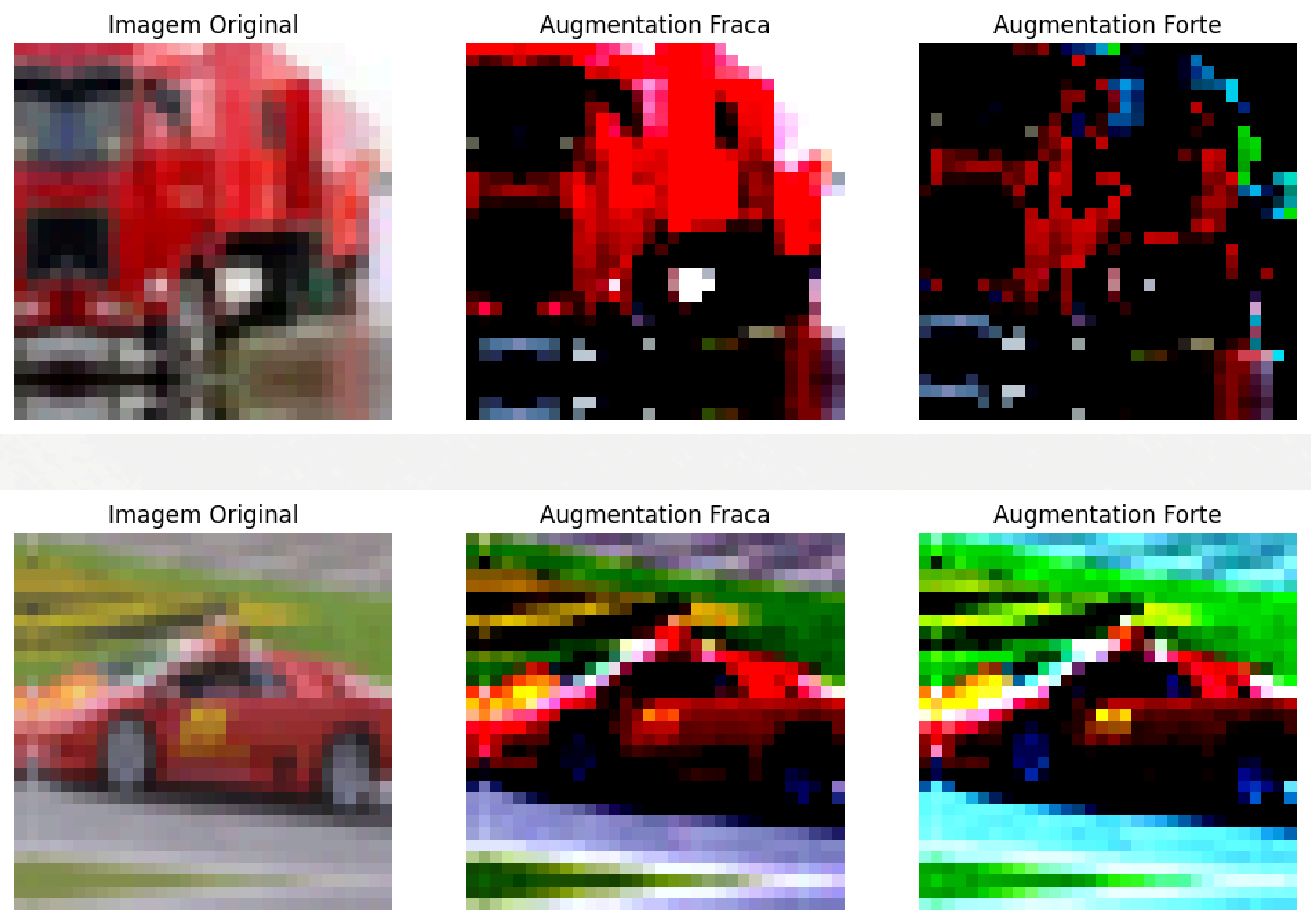
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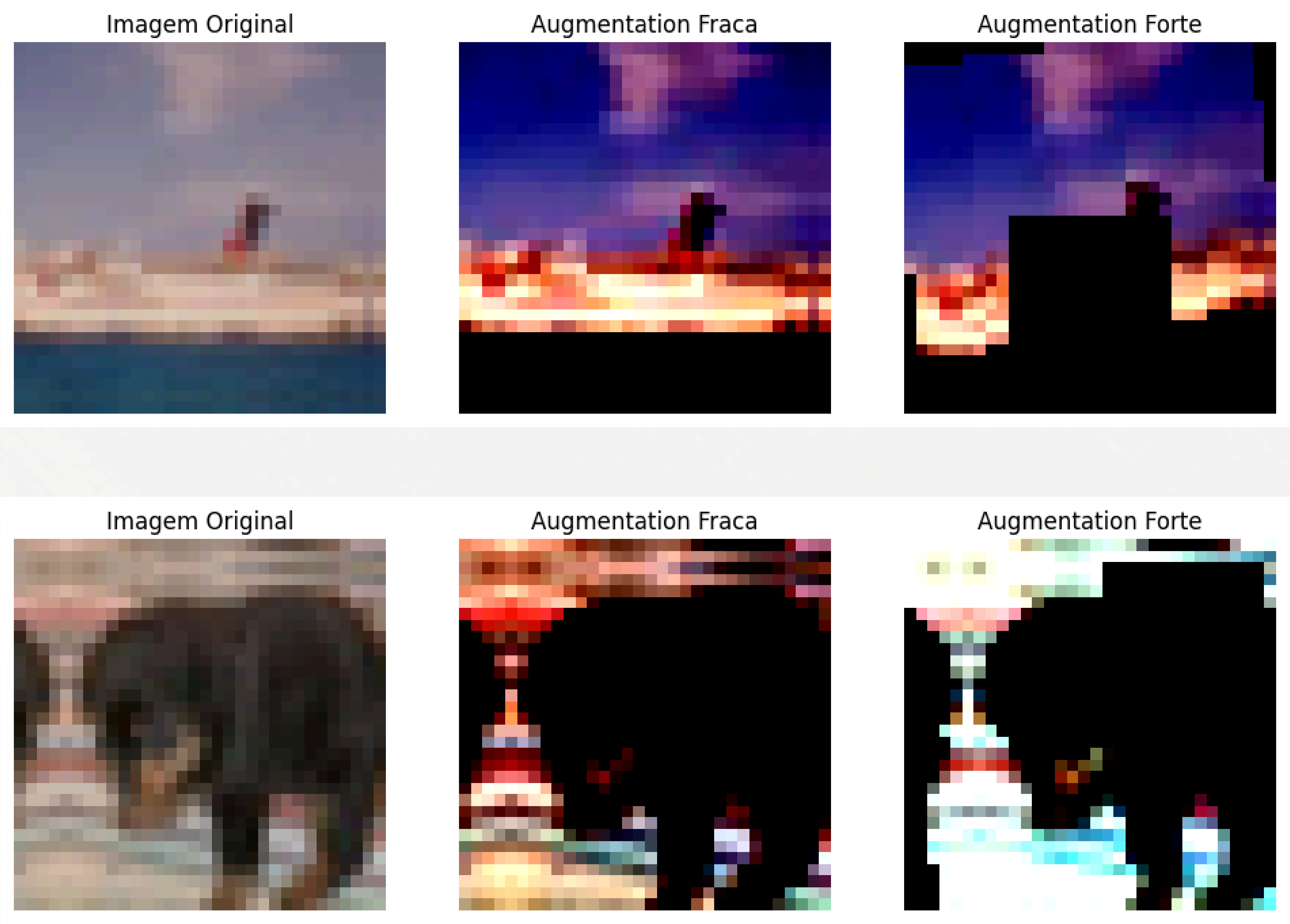
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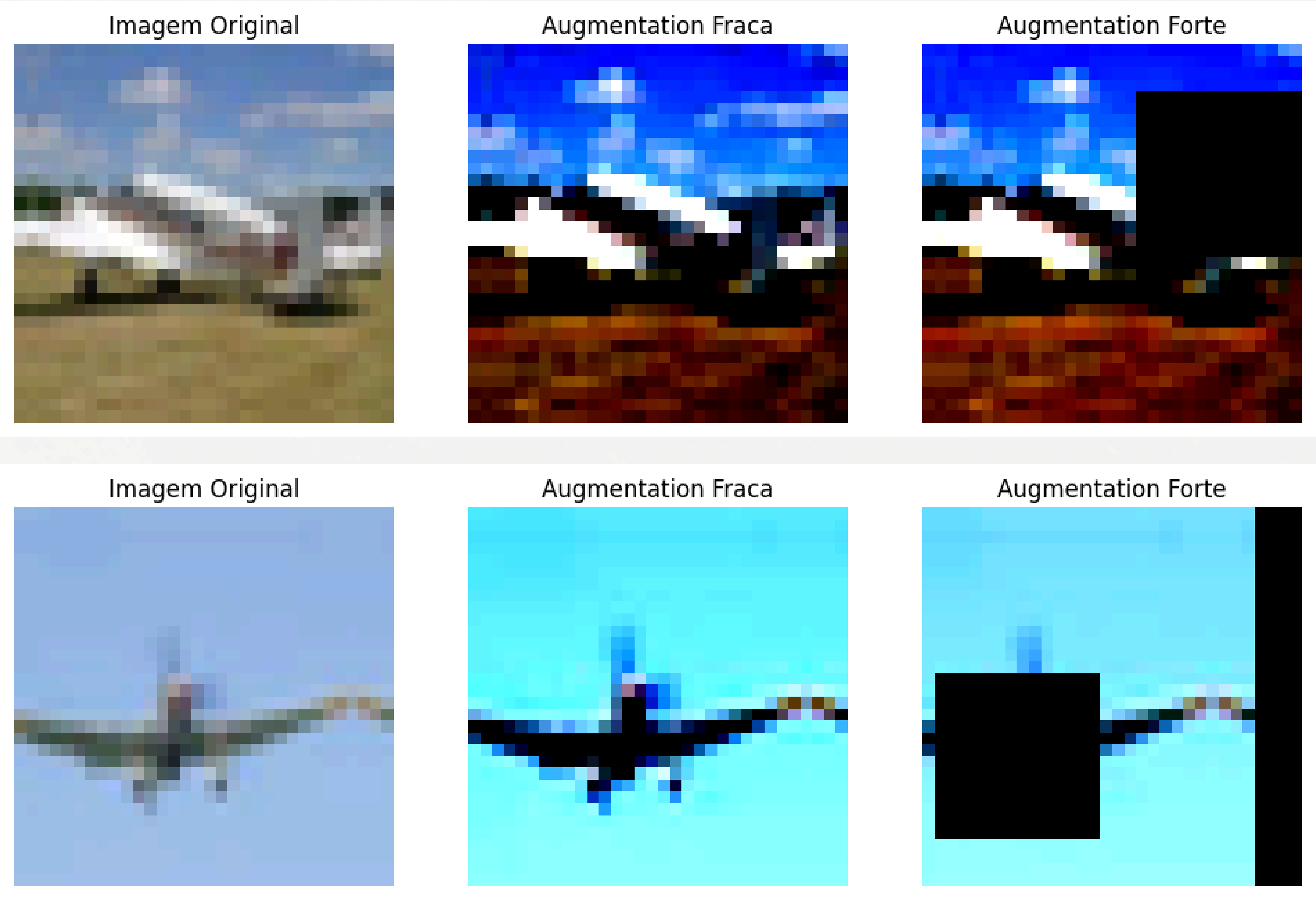


Imagem Original
Augmentation Fraca
Augmentation Forte
Imagem Original
Augmentation Fraca
Augmentation Forte

Metodologia

-> O limiar de confiança atua como um “afiador” que torna a distribuição mais decisiva (0.95)

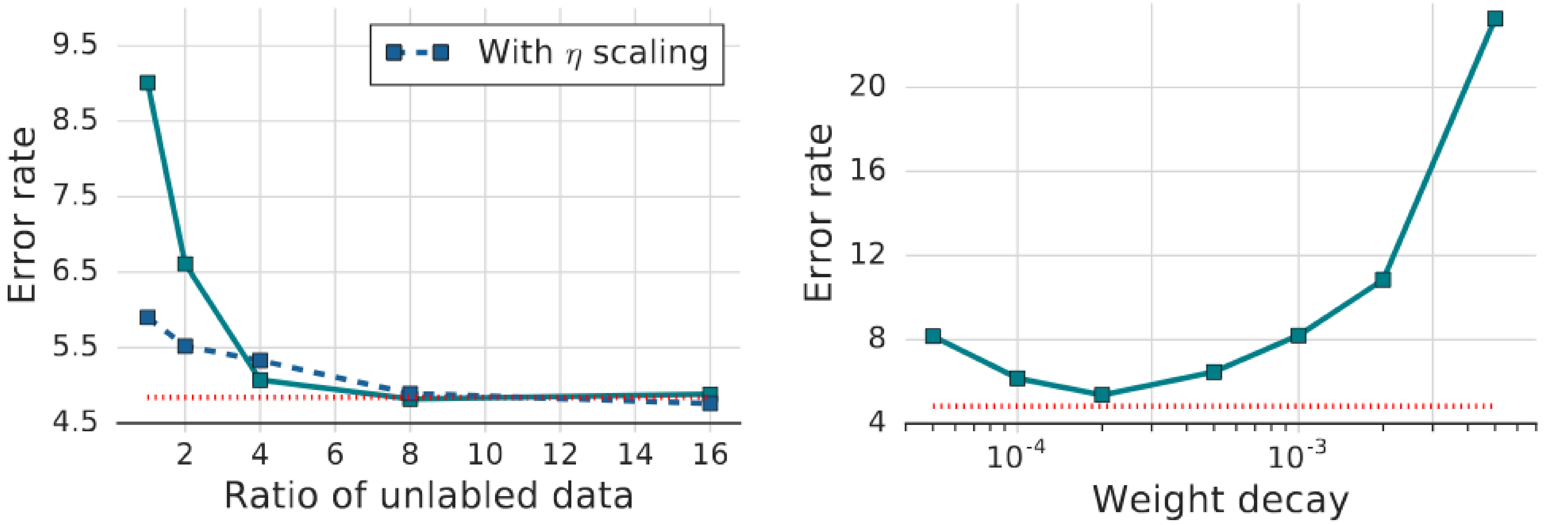
-> Aprendizado contínuo, aprende a rotular imagens fáceis, incorpora isso no modelo e parte para imagens mais complicadas

-> Atribuem grande parte do sucesso do modelo à augmentation assimétrica

-> Weight-decay, otimizador com nesterov momentum e decaimento cosseno para o learning rate se mostraram importantes.

-> Constataram a existência de um ratio mínimo entre dados rotulados e não rotulados

Metodologia



(a)

(b)

Metodologia

Algorithm	Artificial label augmentation	Prediction augmentation	Artificial label post-processing	Notes
TS / Π-Model	Weak	Weak	None	
Temporal Ensembling	Weak	Weak	None	Uses model from earlier in training
Mean Teacher	Weak	Weak	None	Uses an EMA of parameters
Virtual Adversarial Training	None	Adversarial	None	
UDA	Weak	Strong	Sharpening	Ignores low-confidence artificial labels
MixMatch	Weak	Weak	Sharpening	Averages multiple artificial labels
ReMixMatch	Weak	Strong	Sharpening	Sums losses for multiple predictions
FixMatch	Weak	Strong	Pseudo-labeling	

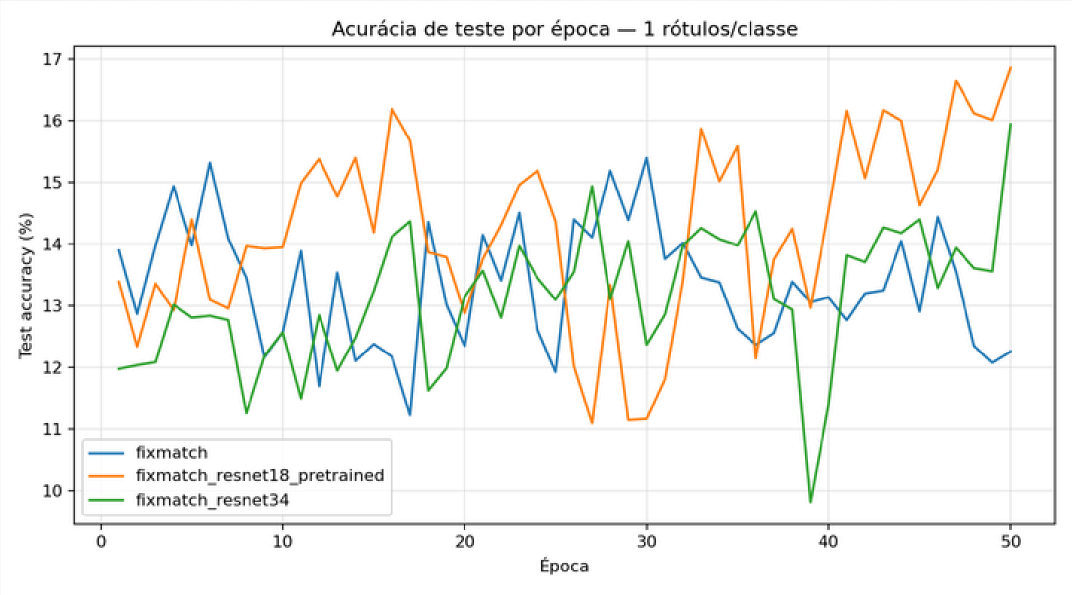
Table 1: Comparison of SSL algorithms which include a form of consistency regularization and which (optionally) apply some form of post-processing to the artificial labels. We only mention those components of the SSL algorithm relevant to producing the artificial labels (for example, Virtual Adversarial Training additionally uses entropy minimization [17], MixMatch and ReMixMatch also use MixUp [59], UDA includes additional techniques like training signal annealing, etc.).

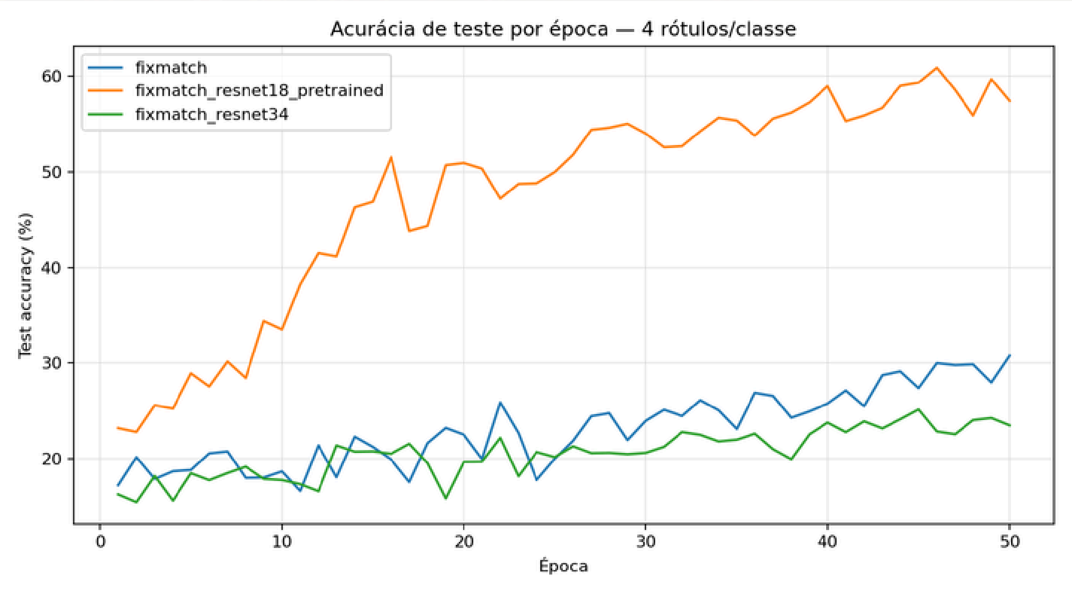
Metodologia

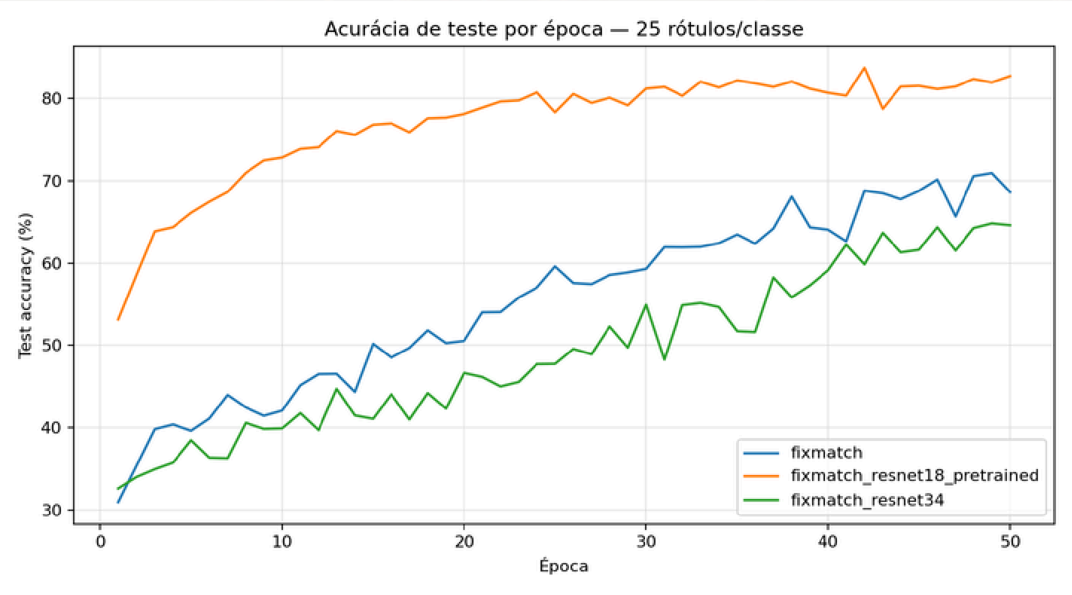
	CIFAR-10			CIFAR-100			SVHN			STL-10
Method	40 labels	250 labels	4000 labels	400 labels	2500 labels	10000 labels	40 labels	250 labels	1000 labels	1000 labels
Π-Model	-	54.26±3.97	14.01±0.38	-	57.25±0.48	37.88±0.11	-	18.96±1.92	7.54±0.36	26.23±0.82
Pseudo-Labeling	-	49.78±0.43	16.09±0.28	-	57.38±0.46	36.21±0.19	-	20.21±1.09	9.94±0.61	27.99±0.83
Mean Teacher	-	32.32±2.30	9.19±0.19	-	53.91±0.57	35.83±0.24	-	3.57±0.11	3.42±0.07	21.43±2.39
MixMatch	47.54±11.50	11.05±0.86	6.42±0.10	67.61±1.32	39.94±0.37	28.31±0.33	42.55±14.53	3.98±0.23	3.50±0.28	10.41±0.61
UDA	29.05±5.93	8.82±1.08	4.88±0.18	59.28±0.88	33.13±0.22	24.50±0.25	52.63±20.51	5.69±2.76	**2.46**±0.24	7.66±0.56
ReMixMatch	**19.10**±9.64	**5.44**±0.05	4.72±0.13	**44.28**±2.06	**27.43**±0.31	**23.03**±0.56	**3.34**±0.20	**2.92**±0.48	2.65±0.08	**5.23**±0.45
FixMatch (RA)	**13.81**±3.37	**5.07**±0.65	**4.26**±0.05	48.85±1.75	28.29±0.11	**22.60**±0.12	**3.96**±2.17	**2.48**±0.38	**2.28**±0.11	7.98±1.50
FixMatch (CTA)	**11.39**±3.35	**5.07**±0.33	**4.31**±0.15	49.95±3.01	28.64±0.24	23.18±0.11	7.65±7.65	**2.64**±0.64	**2.36**±0.19	**5.17**±0.63

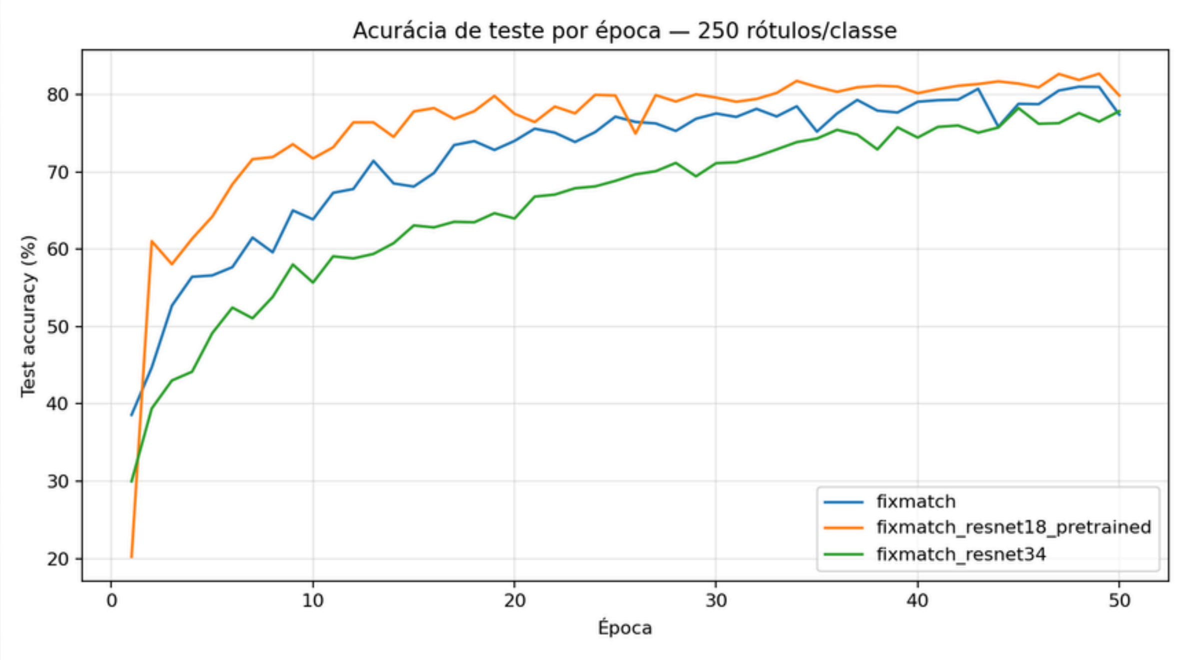
Table 2: Error rates for CIFAR-10, CIFAR-100, SVHN and STL-10 on 5 different folds. FixMatch (RA) uses RandAugment [11] and FixMatch (CTA) uses CTAugment [3] for strong-augmentation. All baseline models (Π-Model [43], Pseudo-Labeling [25], Mean Teacher [51], MixMatch [4], UDA [54], and ReMixMatch [3]) are tested using the same codebase.

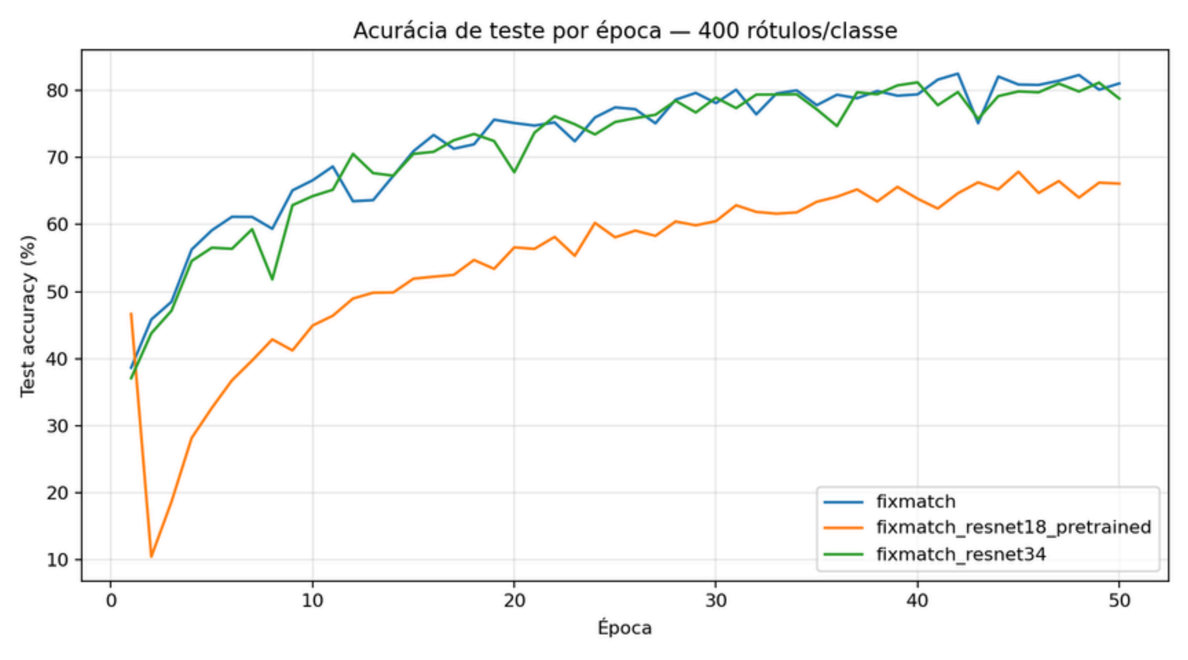
Acurácia por Época



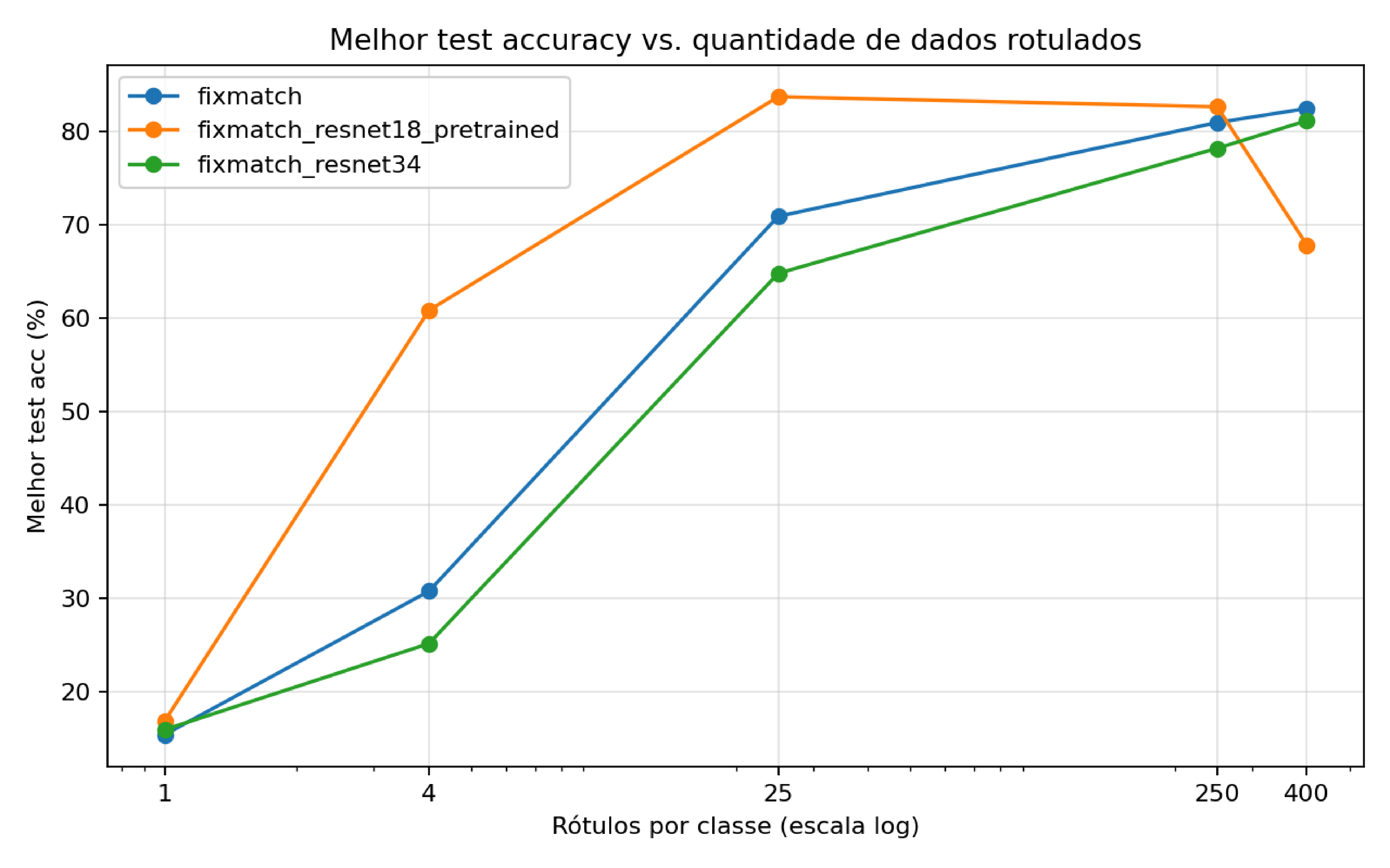




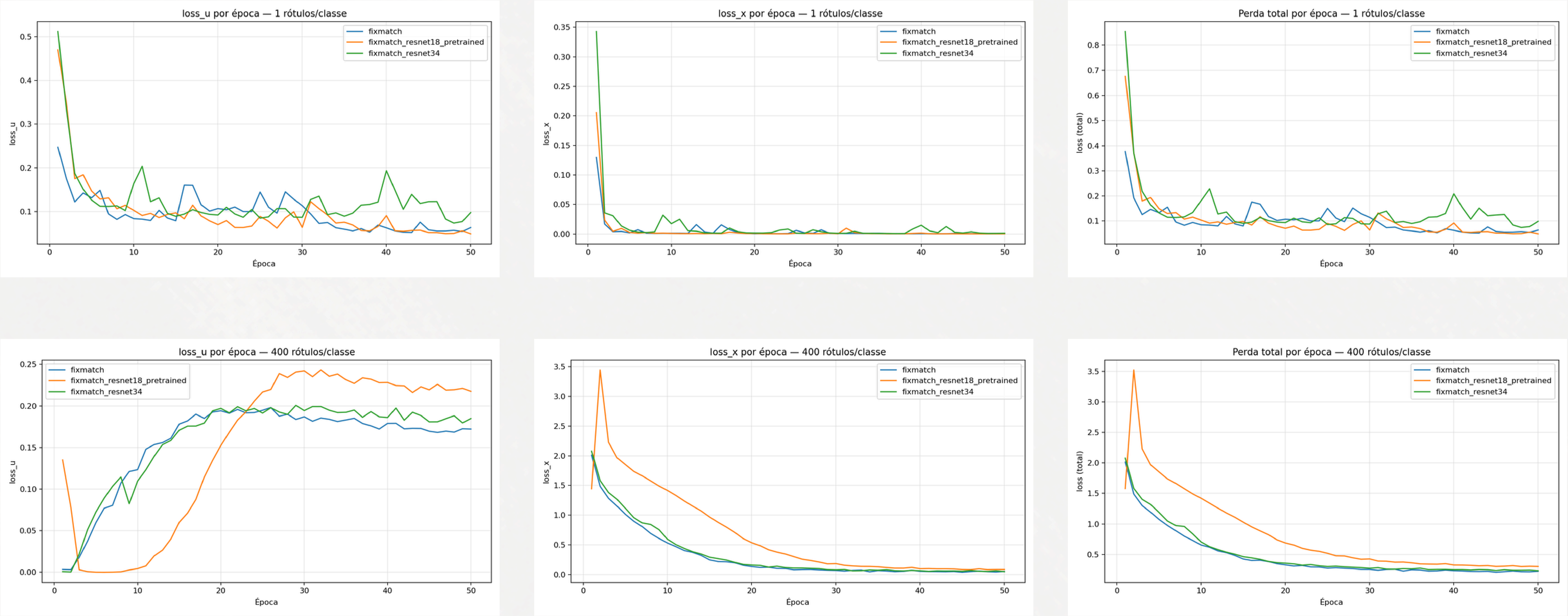




Comparação Melhor Acurácia



Perda Segmentada por Época



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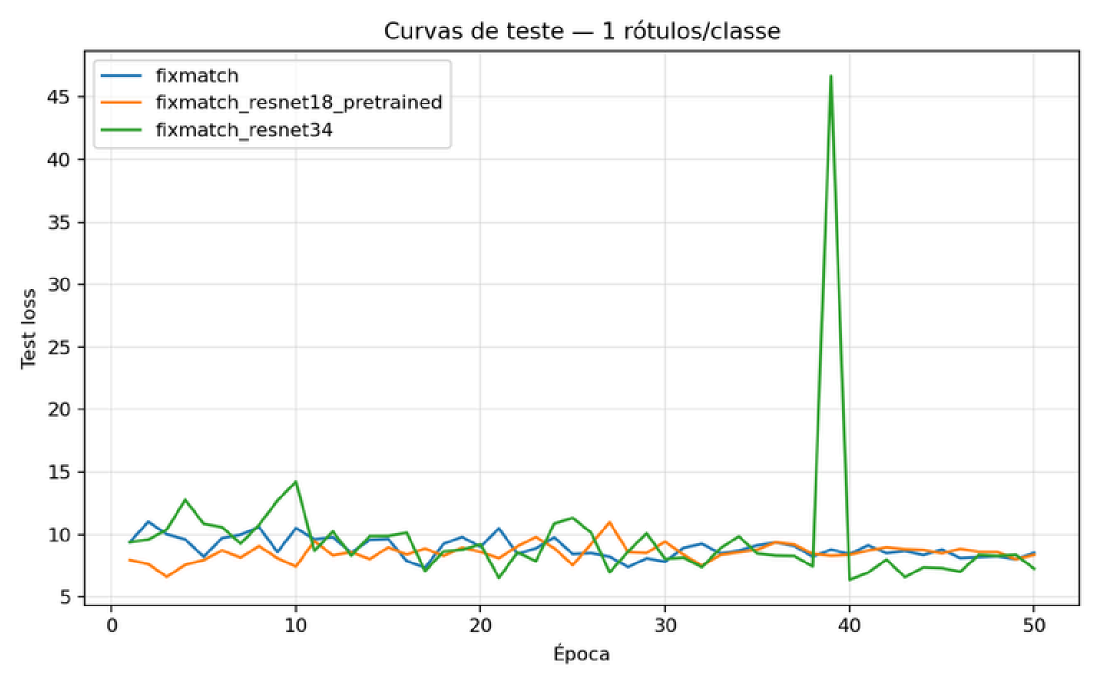

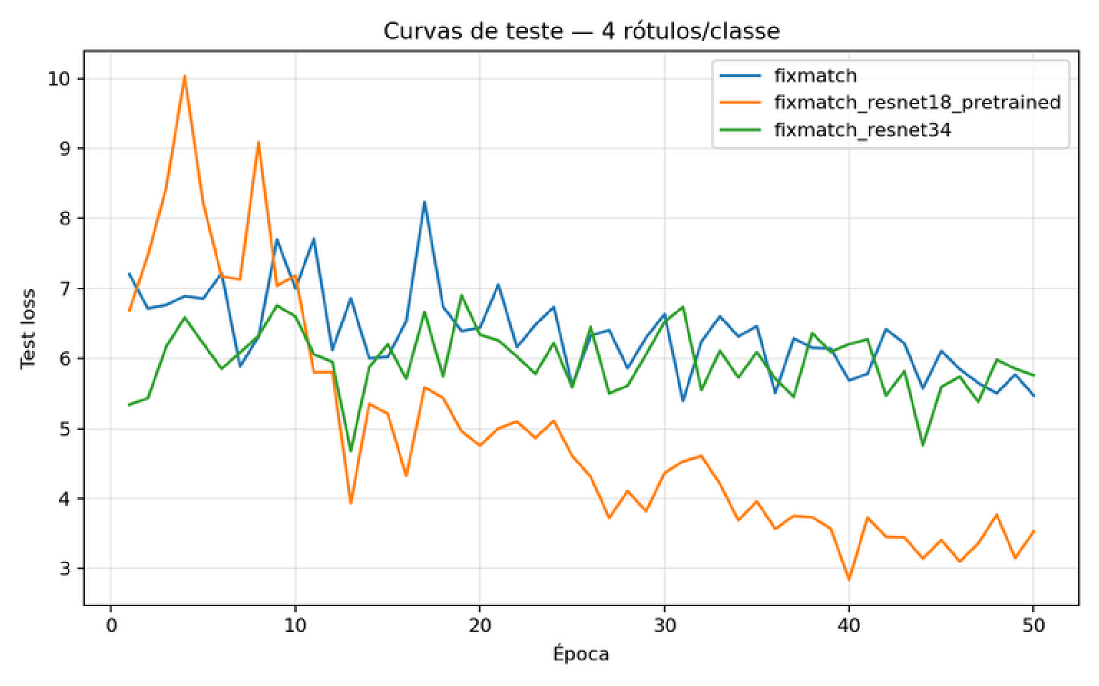

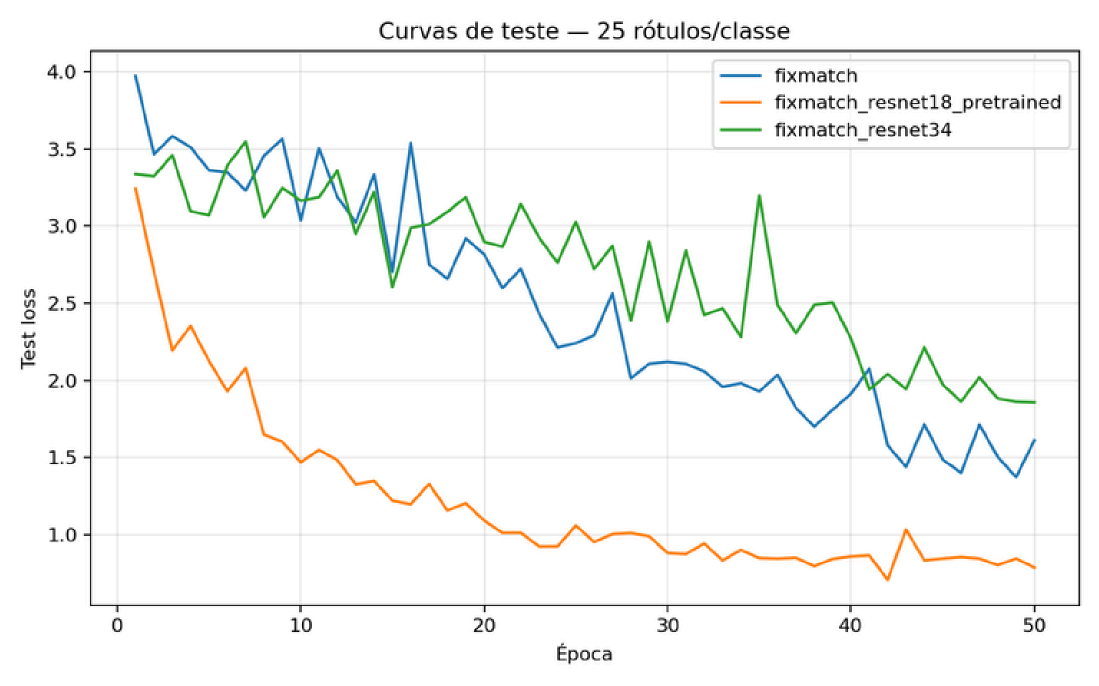

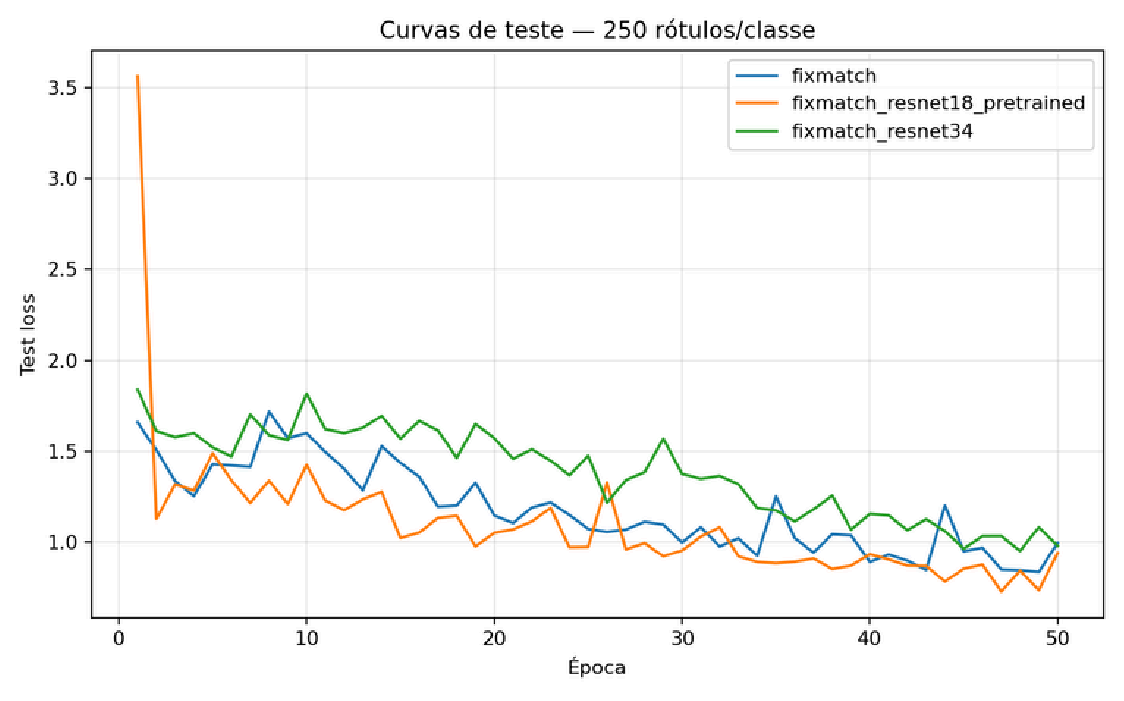

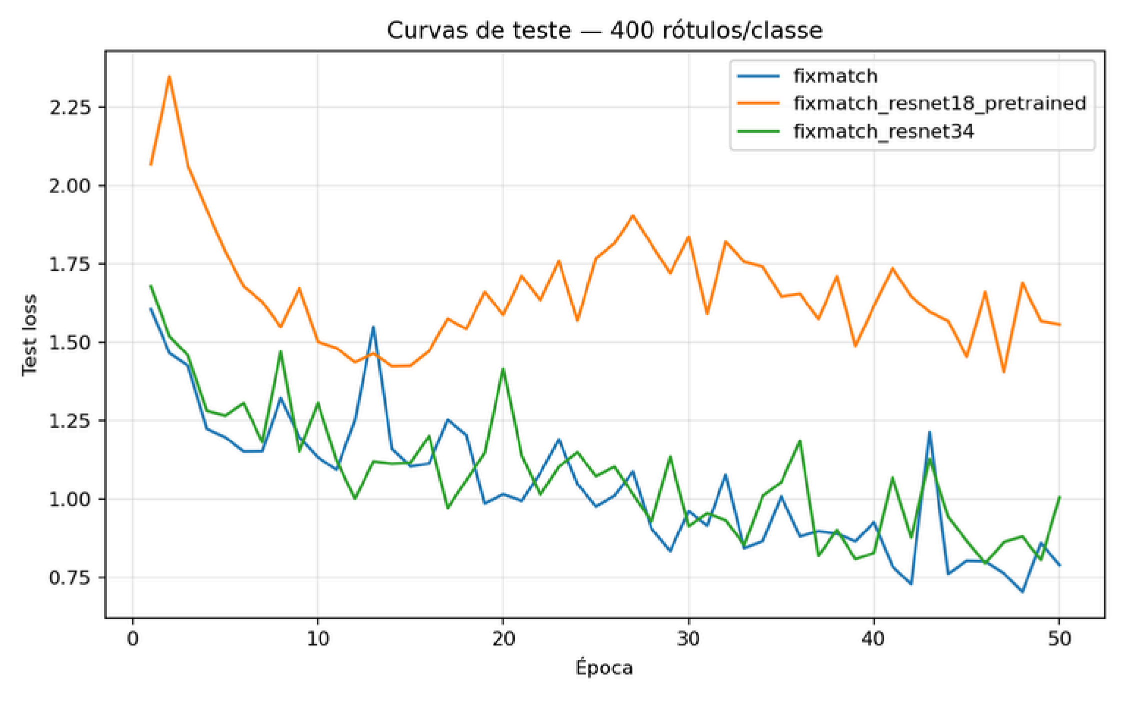

Obrigado!

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