Uncertainty Inclusive Contrastive Learning for Leveraging Synthetic Images

Supplementary Material

0.1. Manual Weights UniCon Experiment Results

Here, we report our results from our UniCon experiments in which we manually set the values for the class-specific weights in the UniCon loss function as described in Eq. **??**. We report our results from testing on Flowers10 and Fitzpatrick40 datasets with DALL-E-generated synthetic images [**?**]. We compare UniCon to SupCon-Real and SupCon-Mixed. As shown in Table 1, we observe that training UniCon on real and synthetic images with lower weightings, $w = 0.0$ and $w = 0.4$, yields an improvement ranging from 0.95% to 3.55% in accuracy over training SupCon with only real images for the Flowers102 dataset. UniCon with the optimal weightings additionally performs better than SupCon-Mixed, indicating UniCon can use the weighting to better adapt to synthetic images rather than making no distinction between synthetic and real images as does SupCon-Mixed. In the few shot case of $k = 8$ for the Fitzpatrick40 experiments, we notice that SupCon-Mixed performs worse than SupCon with only original images but find that UniCon weighting synthetic images at $w = 0.4$ yields a 3.33% increase in accuracy over SupCon with original images and a 6.88% increase over SupCon where synthetic images are weighted the same as real images. This suggests UniCon can discern uncertainty in synthetic images when they can be leveraged to improve performance, especially crucial in few-shot learning scenarios like skin diseases where real data is scarce.

0.2. UniCon Optimal Weights

Figure 1 and Figure 2 illustrate the output of the UniCon method's optimization process for the Flowers10 and CUBS10 datasets, presenting a heatmap of the optimal weights for synthetic images. The varying shades indicate how much each class should rely on synthetic data, with darker tones showing higher reliance. These weights, learned through the UniCon method, adaptively modulate the contribution of synthetic images from both DALL-E and Stable Diffusion experiments, enabling a tailored approach to enhance classification performance on fine-grained image datasets.

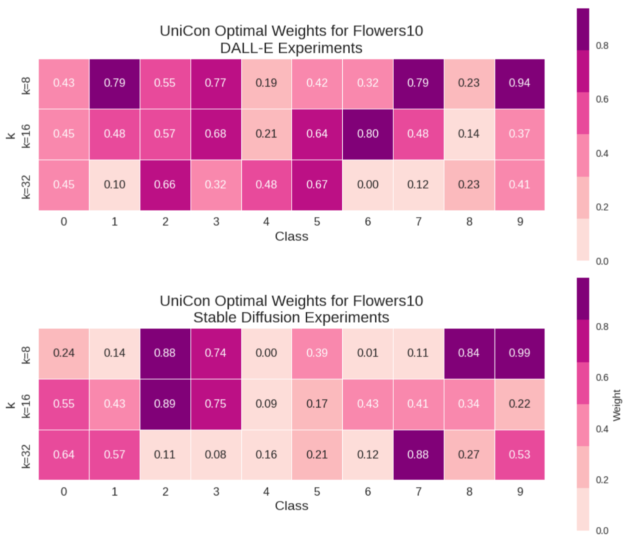

Figure 1. UniCon Optimal Weights for Flowers10 Experiments Experiments

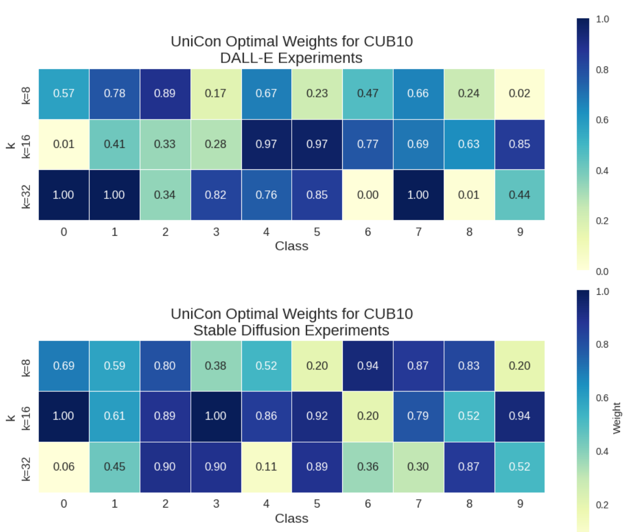

Figure 2. UniCon Optimal Weights for CUBS10 Experiments Experiments

Table 1. **Fine-Grained Classification Performance for Flowers102 and Fitzpatrick40** UniCon with the best weighting outperforms both SupCon-Real and SupCon-Mixed, in classification accuracy across all k. We highlight the UniCon model and optimal w parameter that yields the highest average test accuracy.

	Flowers102			**Fitzpatrick40**		
k	**8**	**16**	**32**	**8**	**16**	**32**
SupCon-Real	85.70 (2.86)	89.55 (1.77)	91.45 (3.20)	50.86 (5.09)	52.47 (4.40)	59.68 (5.80)
SupCon-Mixed	84.20 (2.30)	88.45 (2.75)	92.50 (1.50)	47.31 (3.53)	52.26 (4.14)	60.32 (2.82)
UniCon $w = 0.0$	**86.65 (2.62)**	91.80 (1.45)	**95.00 (1.02)**	51.29 (3.66)	51.29 (5.87)	62.58 (4.71)
UniCon $w = 0.2$	84.70 (4.14)	92.10 (3.51)	94.40 (1.14)	51.18 (6.07)	53.87 (6.24)	**63.44 (3.37)**
UniCon $w = 0.4$	84.55 (4.46)	**92.40 (2.12)**	94.50 (1.48)	**54.19 (3.37)**	54.52 (3.16)	59.57 (3.34)
UniCon $w = 0.6$	85.00 (3.64)	92.25 (2.88)	94.55 (1.06)	53.76 (4.19)	**55.16 (5.31)**	58.39 (3.97)
UniCon $w = 0.8$	86.15 (3.41)	91.35 (3.15)	94.95 (0.88)	52.80 (4.23)	54.84 (2.93)	59.68 (4.36)
UniCon $w = 1.0$	86.30 (1.45)	92.40 (2.58)	94.90 (0.54)	52.04 (4.91)	54.30 (4.96)	59.68 (3.73)