Reverse Knowledge Distillation: Training a Large Model using a Small One for Retinal Image Matching on Limited Data (Supplemental Material)

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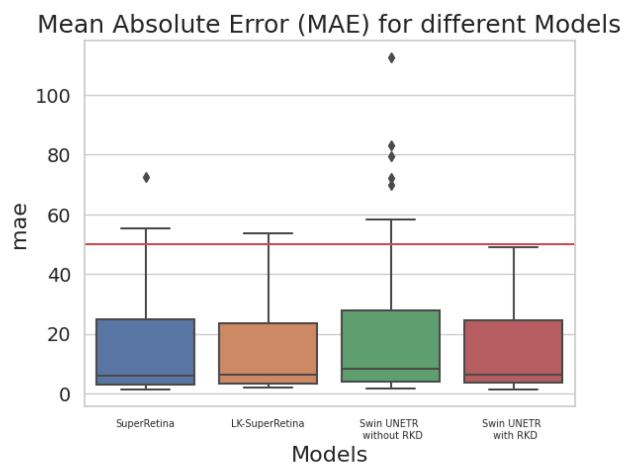

Figure 1. The mean absolute error of different models across all images in the testing dataset [2].

[1]

1. Evaluation Metrics: MAE and MEE

We compute the Euclidean distance between each query point p_q in I_q and its corresponding reference point p_r in I_r. The maximum of these distances gives the Maximum Error (MAE), as shown in Fig. 1. The median distance across all query images is known as the Median Error (MEE), depicted in Fig. 2. Our proposed approach evaluates the performance of the Swin-based encoder-decoder model, which initially showed suboptimal results for both Mean Euclidean Error (MEE) and Mean Absolute Error (MAE). Applying reverse knowledge distillation led to a significant performance enhancement compared to other models. To assess accuracy, we used the red lines defined as thresholds in the SuperRetina paper, which served as a reference.

[1] * Indicates equal contribution

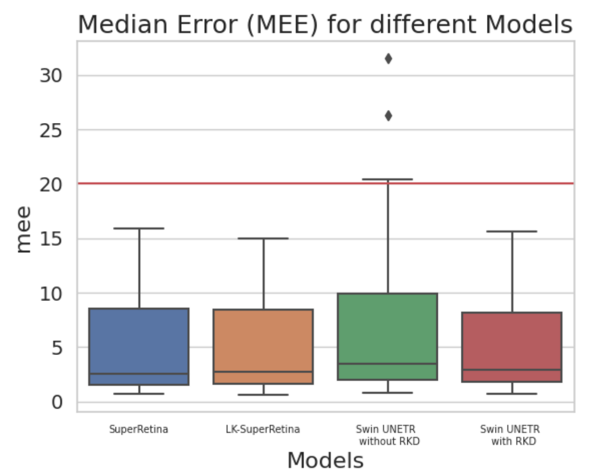

Figure 2. The median of different models across all images in the testing dataset [2].

2. MeDAL-Retina dataset

In Figure 3, you can see samples from two sources: our dataset [1] and the FIRE dataset [3]. The initial and second rows exhibit pictures from the e-ophtha dataset and the retinal disease classification dataset, correspondingly. These images are complemented by our annotated keypoints superimposed on them. As for the third row, it presents images taken from the FIRE dataset, accompanied by their respective annotations for reference.

Fig. 4 depicts how the keypoints are distributed across the images in our dataset.

3. The Wider Facial Landmarks in-the-wild

The Wider Facial Landmarks in-the-wild (WFLW) dataset comprises 10,000 faces, with 7,500 designated for training and 2,500 for testing [4]. These faces are equipped with 98 meticulously annotated landmarks. In addition to

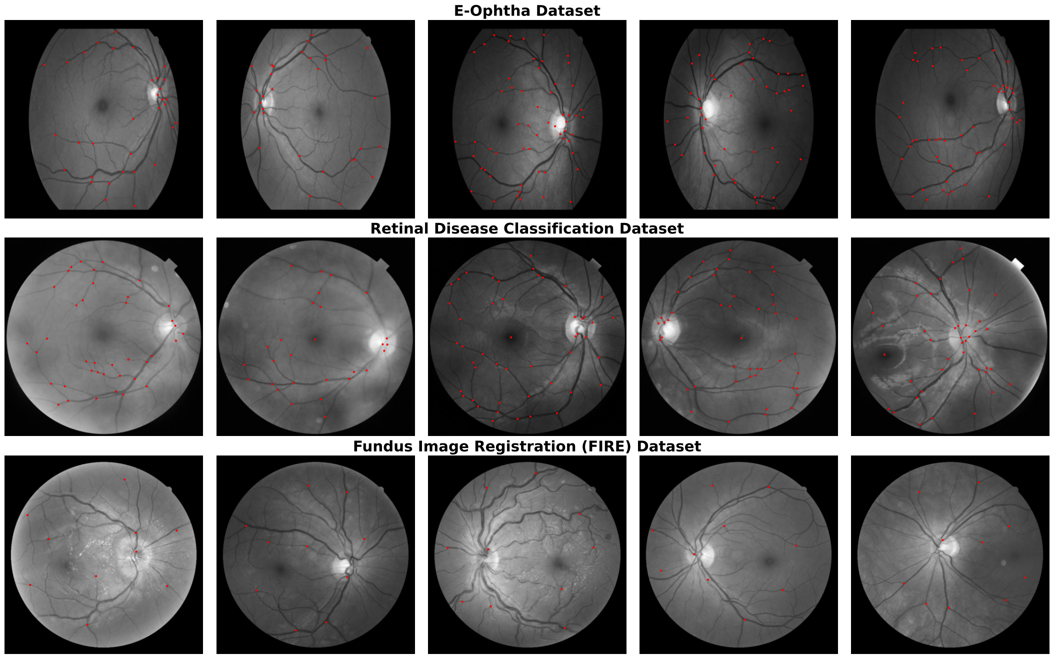

Figure 3. Samples from our dataset and the FIRE dataset [2]. The first, second, and third rows exhibit images from the e-ophtha dataset, retinal disease classification dataset, and FIRE dataset, respectively. We showcased our annotations as keypoints overlaid on the images in the first and second rows. Similarly, the annotations of the FIRE dataset are displayed on the images in the third row.

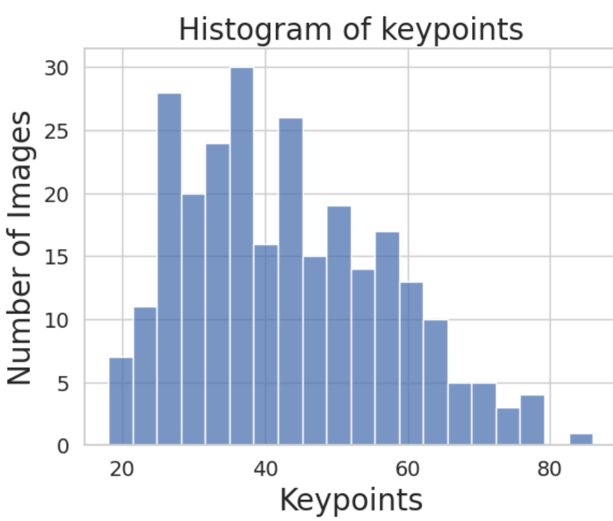

Figure 4. Illustration of keypoint distribution across images in our dataset.

these landmarks, the dataset features extensive attribute annotations, encompassing aspects such as occlusion, pose, make-up, illumination, blur, and expression. This comprehensive attribute information allows for thorough analysis of existing algorithms.

Unlike previous datasets, this dataset introduces significant variations in expressions, poses, and occlusions among the faces. This variability provides a robust basis for evaluating the performance of algorithms concerning pose, occlusion, and expression. Consequently, there's no need to navigate between multiple evaluation protocols across different datasets; the dataset suffices for assessing these attributes.

References

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[2] Carlos Hernandez-Matas, Xenophon Zabulis, Areti Triantafyllou, Panagiota Anyfanti, Stella Douma, and Antonis A Argyros. Fire: fundus image registration dataset. *Modeling and Artificial Intelligence in Ophthalmology*, 1(4):16–28, 2017. 1, 2

Figure 5. Examples sourced from the Wider Facial Landmarks in-the-wild (WFLW) dataset [4].

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[4] Wayne Wu, Chen Qian, Shuo Yang, Quan Wang, Yici Cai, and Qiang Zhou. Look at boundary: A boundary-aware face alignment algorithm. In *CVPR*, 2018. 1, 3