Transfer learning data adaptation using conflation of low-level textural features

Raphael Wanjiku[1], Lawrence Nderu[1], and Michael Kimwele[1]

[1]Jomo Kenyatta University of Agriculture and Technology

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Abstract

Adapting the target dataset for a pre-trained model is still challenging. These adaptation problems result from a lack of adequate transfer of traits from the source dataset; this often leads to poor model performance resulting in trial and error in selecting the best performing pre-trained model. This paper introduces the conflation of source domain low-level textural features extracted using the first layer of the pretrained model. The extracted features are compared to the conflated low-level features of the target dataset to select a higher quality target dataset for improved pre-trained model performance and adaptation. From comparing the various probability distance metrics, Kullback-Leibler is adopted to compare the samples from both domains. We experiment on three publicly available datasets and two ImageNet pre-trained models used in past studies for results comparisons. This proposed approach method yields two categories of the target samples with those with lower Kullback-Leibler values giving better accuracy, precision and recall. The samples with the lower Kullback-Leibler values give a higher margin accuracy rate of 6.21% to 7.27%, thereby leading to better model adaptation for target transfer learning datasets and tasks

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