ISSN 1870-4069

SS-DTL: Semantic Segmentation with Dual Transfer Learning in Leukemic Retinopathy Using Knowledge from Diabetic Retinopathy

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Abstract. Leukemic retinopathy encompasses ocular pathologies affecting the retina, typically manifesting in leukemia's early stages. However, the scarcity of images limits the training of semantic segmentation models for lesion-level analysis. To address this, a Dual Transfer Learning (DTL) approach leverages the morphological similarities between lesions of diabetic and leukemic retinopathy, overcoming data limitations. Initially, Transfer Learning is applied in a U-Net network using ResNet-18, AlexNet, and VGG16 models trained with diabetic retinopathy images. The best-performing model, VGG16, achieves 95.34% accuracy and is selected for a second transfer stage. In this phase, the stored model is adapted to a modified U-Net architecture and retrained with leukemic retinopathy images. Results show that VGG16 attained a DICE coefficient of 95.16% and an IoU of 90.77% for diabetic retinopathy. For leukemic retinopathy, it achieved a DICE of 94.11% and an IoU of 88.88%. This demonstrates the effectiveness of DTL in addressing data scarcity, improving segmentation performance by transferring knowledge from better-studied diseases. The proposed method highlights the value of utilizing data from similar pathologies, representing significant progress in detecting leukemic retinopathy and advancing the study of lesser-known medical conditions.

Keywords: Semantic segmentation, dual transfer learning, diabetic retinopathy, leukemic retinopathy.

1 Introduction

Leukemia is a heterogeneous group of hematological neoplasms, arising from an abnormal increase of leukocytes in the bone marrow and peripheral blood [8]. Leukemic retinopathy (LR), on the other hand, is an ocular manifestation that occurs when leukemic cells infiltrate the retina, potentially extending to the optic nerve or optic disk [13, 19] his infiltration can cause various visual manifestations, such as hemorrhages, cotton-wool spots, Roth's spots, and exudates [33, 37]. Various case studies [26, 16, 41], have documented patients with leukemia developing these ocular manifestations.

Table 1. Comparison of SS and DTL related work.

Author/year	Image	Disease	Category	SS	DTL
[34]/2024	O.D.	Glaucoma	Medical	X	-
[21]/2023	O.D. and O.C.	Glaucoma	Medical	X	-
[15]/2023	O.D. and O.C.	Glaucoma	Medical	X	-
[4]/2020	O.D. and O.C.	Glaucoma	Medical	X	-
[43]/2021	DDD17	-	Driving scene	X	X
[24]/2024	Brain MRI	Neurological	Medical	X	X
[6]/2022	COCO and ADE	-	Objects	X	X
[35]/2018	Plants	-	Vegetation	X	X
Proposed	**O.D.**	**D.R. and L.R.**	**Medical**	**X**	**X**

There is evidence [1, 11, 39, 3] that these manifestations can be the first visible signs of a possible leukemia, highlighting the importance of early ophthalmological detection in patients with non-specific symptoms. However, their accurate diagnosis presents significant challenges due to the need for high skill in differentiating types of retinopathies. In this context, deep learning presents itself as a solution. It is worth noting that, to date, only one study has been identified on detecting LR, focusing on disease classification [28].

This lack highlights an important area of opportunity, such as semantic segmentation, which could significantly improve the differentiation of this disease. Classical segmentation divides an image into distinct regions based on characteristics such as color, texture, or depth, grouping related pixels without assigning them to a specific class. In contrast, semantic segmentation [20, 14] assigns a specific label to each pixel, identifying classes such as “car,” “person,” or “tree,” providing a more detailed and specific understanding of the image. Model training for semantic segmentation requires images with segmented masks. However, no specific data for LR were found in public repositories, only for diabetic retinopathy (DR) [29, 9].

This lack of data hinders the training of deep learning models. In addition, the generation of synthetic images requires disease specific data, and the complex morphological characteristics of the lesions make this process even more difficult. As a solution, Dual Transfer Learning with DR databases is proposed. Transfer learning (TL) facilitates the adaptation of a model designed for one task to a second related task and is particularly effective when data are scarce or difficult to obtain [24, 42].

There are two approaches: feature extraction and fine-tuning. In feature extraction, all layers of a pretrained model are frozen, and a new classifier is added, ideal for large datasets. In fine-tuning, the last layers of a pretrained network are unfrozen, which is ideal for small datasets. The combination of both approaches is called Dual Transfer Learning (DTL). This methodology takes what is learned by one method and transfers it to the other [23]. In ophthalmology, specifically in DR, TL is adequate despite the complexity and variability of retinal images, providing positive results in the semantic segmentation of lesions in fundus images, as observed in [40, 44, 25, 36, 22].

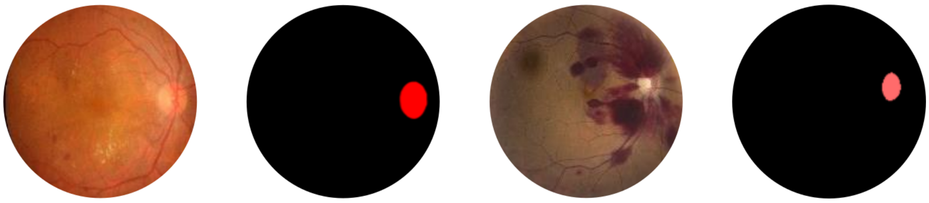


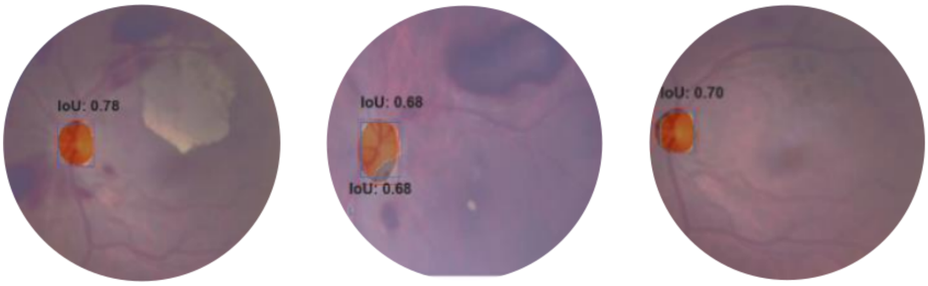
Fig. 1. Fundus images and true masks: a) DR, b) True mask DR, c) LR, d) True mask LR.

Fig. 2. Fundus images: a) DR, b) LR.

Therefore, a DTL approach is proposed, starting with DR images and then applying it to leukemia retinopathy images. Before conducting the TL tests, the elements to be semantically segmented in the fundus images were selected, opting for a bi-class segmentation focused on the optic disc. The selection and identification of the optic disc is of paramount Semantic Segmentation with DTL importance in DR and related conditions, as it provides crucial information about the presence and progression of the disease [2, 17, 45, 27]. After selecting the data type, the first TL was applied using different CNN models (ResNet-18, AlexNet, VGG16), adapting them to a U-Net network. First, manually segmented LR images were used to observe the behavior with little data; subsequently, DR images were tested. The resulting model was stored.

Then, DTL was applied, employing the model previously trained with DR images, but this time training it with LR images. In the first case, we faced the problem of generating poor masks due to the limited data available for LR, so we applied the DTL strategy. This approach demonstrated better performance in generating masks associated with LR. The results obtained highlight the main objective of this study, which is to explore the effectiveness of the DTL technique in U-Net models for semantic segmentation of retinopathy images in data-constrained contexts. The main contributions of this paper are:

– Introduce a method using deep learning techniques for semantic segmentation of the optic disc in fundus images associated with LR.
– Propose a procedure to exploit the knowledge acquired from previously semantically segmented elements in DR images and adapt it to LR in scenarios where data are scarce or difficult to obtain.
– Present an alternative solution in data-scarce contexts where it is impossible to generate synthetic images of the condition due to the lack of data and the complexity of the lesions.



(a) (b) (c)

Fig. 3. Predicted optic disc masks for LR.

2 Related Works

In this section, the works related to this research are presented. Although there are numerous studies on classical segmentation [38, 7, 47, 46, 48], our focus is specifically on semantic segmentation and double TL techniques, as detailed below: The study in [34] proposes an ensemble semantic segmentation method to improve glaucoma detection using fundus images and deep learning models such as U-Net 3Plus, Deep Lab V3P, PSPNET, and UW-Net. On the other hand, [21] presents an encoder-decoder network for optic disc and optic cup segmentation in fundus images using a pretrained ConvNext encoder and a lightweight decoder enhanced with the Dual-Path Response Fusion Attention (DPRFA) module.

In addition, [15] introduces a modified U-Net model for optic disc and optic cup segmentation in fundus images, using a modified Atrous Spatial Pyramid Pooling (ASPP) module to capture detailed spatial data and improve segmentation accuracy. Finally, [4] proposes a deep learning-based approach for automatic segmentation of the optic disc and optic cup and a model for glaucoma detection in fundus images.

On the other hand, with regard to DTL related work, this study [43] suggests a DTL method for event-based final task prediction by converting events into detailed images containing more structural information. This information is transferred to the EEL branch, improving its ability to perform complex tasks. On the other hand, [24] discusses the unsupervised adaptation of a skull-stripping model on brain MRI images, which was trained with adult data to work with newborn images.

Also, [6] presents SimFormer, a method for semantic segmentation that reduces the need for detailed pixel-level labels. Based on MaskFormer, Sim-Former uses dual similarity transfer to learn new classes with image-level labels, transferring proposal-pixel similarities from known classes to new classes and learning inter-pixel similarities to improve segmentation. Finally, [35] explores the applicability of a fully convolutional network for plant segmentation using a two-step transfer method.

First, learning is transferred from a domain with many labeled data to a central category in the plant domain. Then, this major category is adapted to a minor category with little data. In Table 1, the reviewed articles are presented, detailing the author and year of publication under the “Author/Year” column; the type of medical image used, which includes Optic Disc (O.D.); Optic Cup (O.C.); DDD17 (DAVIS Driving Dataset 2017); COCO (Common Objects in Context); and ADE (ADE20K Dataset); the

Table 2. Comparison with other models using DR images.

Model	Accuracy	Loss	DICE	IoU
AlexNet	0.9082	0.0097	0.9122	0.8386
ResNet18	0.9416	0.0056	0.9520	0.9084
VGG16	**0.9560**	**0.0052**	**0.9581**	**0.9196**

disease studied; the application category; and the application of semantic segmentation (S.S.) and DTL techniques. The proposal of this research, listed at the end of Table 1, stands out for the joint application of semantic segmentation and Dual Transfer Learning (DTL) in diabetic retinopathy (DR) and leukemic retinopath (LR) images. This approach is particularly significant as, after the literature review, it is concluded that there is very little documentation on semantic segmentation using DTL in the medical field. Specifically, no previous studies have been found that address LR with these advanced techniques.

3 Characteristics of the Dataset Used

3.1 Dataset

The IDRID dataset [29], composed of segmented color fundus images, was used to perform this research. This set includes 81 images, divided into 54 for training and 27 for testing, all in JPG format. In addition, each image has its respective masks in TIF format. On the other hand, concerning the images of LR, an exhaustive review of medical publications was carried out to identify representative images of this condition. As a result of this search, 40 images were selected from various sources specialized in this disorder [12, 10, 18, 37, 32].

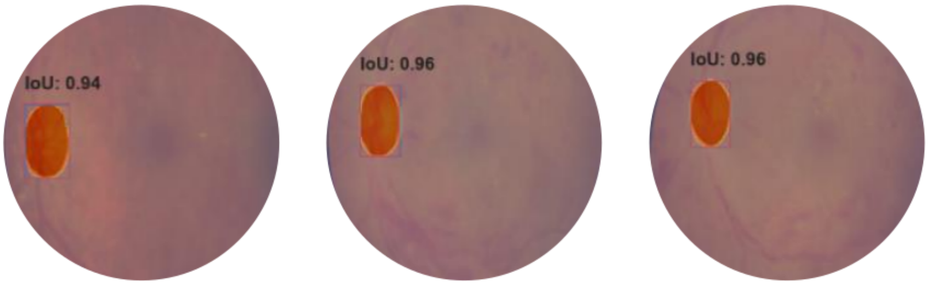
3.2 Dataset Distribution

The training set includes 54 optic discs for DR imaging. The test set includes 27 optic disc images. For the LR images, manual semantic segmentation of the optic disc was performed on each image using the freely licensed ImageJ program [30]. The dataset was organized into two groups: 32 images for training and 8 images for testing.

In both cases, the training and testing are done using the full fundus images in RGB format and the true masks of the optic disc corresponding to each case. The Fig. 1, shows the shape of the masks for each condition.

3.3 Comparison of the Optic Disc Between Retinopathies

The optic disc is a crucial structure in ophthalmologic evaluation, standing out as an oval area within the retina where blood vessels converge to exit into the eye. It generally presents a coloration that varies from pink to yellow; the temporal half is paler than the rest, and the nasal half has a less delineated border. These characteristics may be altered in the presence of certain diseases. Below are two images showing the presence of lesions and how they are associated with each retinopathy.



(a) (b) (c)

Fig. 4. Predicted optic disc masks for DR.

The Fig. 2, shows two fundus images of DR and LR, respectively. In the first image, we can see that the optic disc shows clarity in its well-defined borders; the disc coloration is normal, varying from pink to pale yellow, with no signs of pallor or hyperemia, suggesting good vascularization and absence of acute inflammation. In addition, the disc structure is intact, with no signs of hemorrhage or neovascularization.

On the other hand, in the second image, the optic disc shows several prominent pathologic features: the disc borders appear blurred, the disc shows an unusually pale coloration, especially in its temporal half, and hemorrhages are seen within the disc, indicative of possible vascular disorders or retinal damage. Although the optic discs in both retinopathies may appear different at first glance, crucial specific similarities justify using the transfer of learning approach. This approach allows leveraging previously acquired knowledge to improve diagnostic accuracy in less well-studied diseases.

4 Methodology Proposed

4.1 Proposed DTL Semantic Segmentation Model

This study proposes a methodology involving several tests with images of diabetic and LR to evaluate the effectiveness of TL. CNN models (ResNet18, AlexNet, VGG16) previously trained on ImageNet were selected and adapted to function as U-Net network's encoders. Subsequently, these adapted models were retrained and evaluated using data sets specific to each type of retinopathy. A plan was established that included three critical tests. The first aims to evaluate the effectiveness of TL using exclusively LR images to semantically segment the optic disc in fundus images, even with a limited number of images of this pathology.

In the second test, selected models are retrained by TL, applying a fine-tuning technique with DR images in a U-Net network. This process involves the partial freezing of the internal layers of the model and the adaptation of the final layers to the study's specific context. After this adjustment, the modified model is retained for further use. The third test focuses on LR using the model already adjusted for DR. A feature extraction strategy is implemented, freezing all the layers of the model, which are then adapted in the U-Net coding stage.

Table 3. Results obtained using DTL in LR images.

Model	Accuracy	Loss	DICE	IoU
VGG16	**0.9143**	**0.0090**	**0.9411**	**0.8888**

Table 4. Comparison of results for LR applying both techniques: TL vs DTL.

Image	Technique	Accuracy	Loss	DICE	IoU
Leukemia	TL	0.8351	0.0172	0.8765	0.7801
Leukemia	**DTL**	**0.9143**	**0.0090**	**0.9411**	**0.8888**

This model undergoes a new training process with the LR dataset, thus allowing the exploitation of previously learned features from the DR dataset to obtain a better semantic segmentation of the optic disc in LR images, even when the available data are limited.

4.2 Performance Metrics

Several metrics have been selected to evaluate the performance of the deep learning model in semantic segmentation tasks and provide different perspectives on its performance. Accuracy measures the proportion of correct predictions and gives an overview of the model's performance. The Loss function evaluates how much the model's predictions deviate from the actual values and is crucial for optimization during training. The DICE coefficient and the Jaccard Index (IoU) are specific metrics for segmentation quality assessment, measuring the similarity and overlap between model predictions and true annotations. The equation (1) presents the DICE coefficient [5]:

$$\mathrm{DICE} = \frac{2\,(X \cap Y)}{|X| + |Y|}, \tag{1}$$

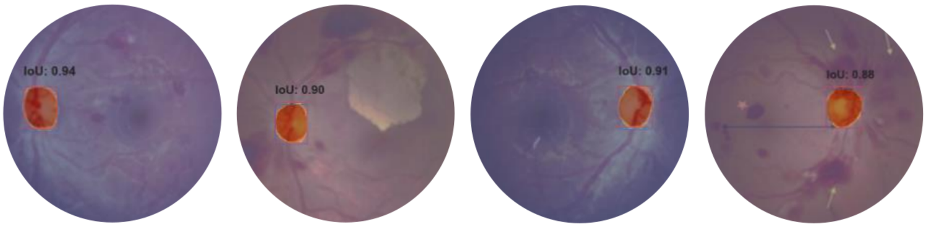
where, X represents the set of pixels predicted as positive (i.e., the segmentation performed by the model), and Y is the set of true positive pixels (the ground truth or real segmentation). On the other hand, the Jaccard Index [31], also known as Intersection over Union (IoU), is calculated by the equation (2):

$$\mathrm{IoU} = \frac{|X \cap Y|}{|X \cup Y|}. \tag{2}$$

In this metric, X is the model prediction, and Y represents the ground truth. The IoU evaluates the effectiveness of the segmentation by dividing the size of the intersection of the sets X and Y by the size of their union, providing a clear indicator of the accuracy of the segmentation.

5 Results

In the first test, which was trained exclusively with images of LR, the U-Net architecture was used with a pretrained VGG16 model. The results obtained for the first test, including the predicted optic disc masks and the calculated Index of Overlap (IoU), are presented in Fig. 3. In the second test, DR images were used, and TL was applied



(a) (b) (c) (d)

Fig. 5. Optical disc predicted masks with DTL in LR images.

with a fine-tuning approach using various pretrained models adapted to the U-Net architecture. The results obtained are presented in Table 2, and the predicted mask along with the calculated Index of Overlap (IoU) is shown in Fig. 4. In the third test, a DTL approach focused on feature extraction was implemented by adapting the U-Net network with the model previously trained with DR data. Subsequently, this model was retrained using LR images, taking advantage of the knowledge acquired in the context of DR. The outcomes are displayed in Table 3, while Fig. 5. exhibits the predicted mask along with the calculated Index of Overlap (IoU). As shown in Table 4, DTL showed better performance compared to TL by leveraging prior knowledge from DR. This behavior indicates that DTL is more effective at transferring knowledge between similar domains, significantly improving the results in the segmentation of LR images.

6 Discussion

As could be seen in Fig. 3, which was trained only with LR images, the evaluated model fails to fully satisfy the requirements of accurate semantic segmentation for the optic disc. The predicted masks do not cover the entire optic disc in cases a), b), and c), reaching overlap indices (IoU) of 0.78, 0.68, and 0.70, respectively. This result indicates that the match between the predicted mask and the actual region of the optic disc is insufficient, especially when the model is trained exclusively with images of LR. In the second test, as seen in Table 2, the VGG16 model proved superior to the others, achieving an (Accuracy) of 0.9560, notably higher than the 0.9416 of ResNet18 and the 0.9082 of AlexNet. In addition, VGG16 achieved the highest values in the DICE (0.9581) and IoU (0.9196) metrics, highlighting its efficiency in optic disc specific semantic segmentation.

The results of the predicted masks, shown in Fig. 4, with Index of Overlap (IoU) values of 0.94 for a), 0.96 for b), and 0.96 for c), confirm that VGG16 offers a significant improvement in terms of semantic segmentation accuracy and quality compared to other evaluated models. In the third test, which employed a DTL approach using LR images, the VGG16 model achieved remarkable results, as shown in Table 3. The Accuracy obtained was 0.9143, while the value of the Loss function was recorded at 0.0090. Additionally, the model demonstrated high performance in the semantic segmentation evaluation metrics, with a DICE coefficient of 0.9411 and an Index of Overlap (IoU) of 0.8888. On the other hand, Fig. 5, presents the predicted masks for the optic disc using the DTL approach on DR images.

The Index of Overlap (IoU) values for each image are as follows: for image a) an IoU of 0.94 was achieved, image b) reached an IoU of 0.90, c) repeated an IoU of 0.91, and finally, image d) recorded an IoU of 0.88. Finally, a comparison was made applying both techniques with the LR dataset. The Table 4 shows that the DTL technique significantly outperforms TL in all metrics (accuracy, loss, DICE, IoU) for leukemia retinopathy images.

These results illustrate the variability in semantic segmentation accuracy and highlight the positive impact of using advanced techniques such as DTL to improve optic disc identification and delineation in complex pathological conditions. In addition, they emphasize the advantages of applying this technique in situations where little information is available, demonstrating its usefulness in managing diagnostic challenges such as those presented in this research.

7 Conclusion

This research addressed the problem of missing data and the difficulty in generating synthetic images due to the morphological characteristics of lesions and the scarcity of data in LR. In these scenarios, DTL enabled leveraging prior knowledge acquired in one specific domain to improve performance in another significantly. This approach optimized the use of limited data. It improved the results obtained in the semantic segmentation model, proving an effective solution to data limitation and difficulty in generating synthetic images.

8 Future Works

Future steps of this research involve expanding semantic segmentation to other lesions characteristic of diabetic and LR, such as microaneurysms, hemorrhages, exudates, Rorh's spots, and leukemic infiltrates. These elements present additional challenges due to their greater variability and lower frequency than the optic disc.

Acknowledgments. We would like to thank the Consejo Nacional de Humanidades, Ciencias y Tecnologías (Conhacyt) for the financial support through the doctoral scholarship.

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