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(RESEARCH ARTICLE)

Segmentation of hard exudates in fundus images to detect diabetic retinopathy using modified U-NET

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Abstract

Diabetic retinopathy (DR) is a severe complication of diabetes, leading to potential vision loss due to damage to the retinal blood vessels. Hard exudates, which are visible lesions in fundus images, serve as critical indicators for diagnosing and monitoring DR. This study introduces a Modified U-Net architecture designed to improve the segmentation of hard exudates, thereby enhancing the detection and management of diabetic retinopathy.The U-Net model, renowned for its effectiveness in biomedical image segmentation, is adapted with several enhancements to better address the complexities of fundus images. These modifications include advanced feature extraction techniques, integration of attention mechanisms to focus on significant areas, and refined post-processing methods. These improvements aim to increase the accuracy and reliability of hard exudate segmentation.The Modified U-Net is evaluated on a dataset of fundus images with annotated hard exudates, using performance metrics such as accuracy, precision, recall, and the Dice coefficient. The results reveal that the Modified U-Net significantly outperforms traditional U-Net models and other contemporary segmentation methods. This enhanced model not only achieves higher accuracy in detecting and segmenting hard exudates but also improves the overall sensitivity and specificity.

Keywords: Funds Images; Diabetic Retinopathy; Hard Exudates Segmentation; Feature Extraction; Attention Mechanisms; Modified U-Net

1. Introduction

Diabetic retinopathy is a serious eye complication affecting millions worldwide. This condition, a byproduct of diabetes, can gradually worsen vision and potentially lead to blindness. [1].

A normal or healthy retina contains only blood vessels, the macula, and optic nerves. But a retina affected by diabetic retinopathy has several problems that cause visual impairment.

Fluid leakage from blood vessels into the retina causes diabetic retinopathy (DR), which can negatively impact eyesight. Usually, obstructions in the retinal blood vessels brought on by an overabundance of sugar in the body produce this leaking. Diabetes for an extended period of time can cause eye conditions like DR, which can result in blurry or total vision loss.

A number of common signs and symptoms of diffuse regional pain (DRP) include haemorrhages, soft exudates (often called cotton wool patches), hard exudates, and microaneurysms. Venous loops may also be seen in cases of severe DR. A normal retina and one afflicted by diabetic retinopathy are contrasted in Figure 1. The macula, blood vessels, and optic nerves make up a healthy retina. The retinal layer contains all of these. Conversely, a number of anomalies in the diabetic

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retinopathy retina, including soft There is are edema, neovascularization, microaneurysms, and hard exudates. This MA has a circular form, is dark red in color, and is minuscule in size. The Haemorrhages (HM) are brilliant red spots that are dark red in hue and lack a consistent border. The fluid that seeps out of blood vessels and into the surrounding area is called exudate (EX). Proteins, solid components, and cells make up these fluids. Cuts and infected or inflamed sites are common sources of these exudates. Due to the tiny vessel size, the particulate fluid enters the blood vessel from these locations and gathers close to the retina. Exudates can be broadly classified into two categories: Hard Exudates (HE) and Soft Exudates (SE). Hard exudates are largely asymmetrical in morphology and closely resemble microaneurysms. Usually, soft exudate is observed in regions with decreased blood circulation. The difference between the normal retina and diabetic retinopathy effected images are shown in Figure 1.

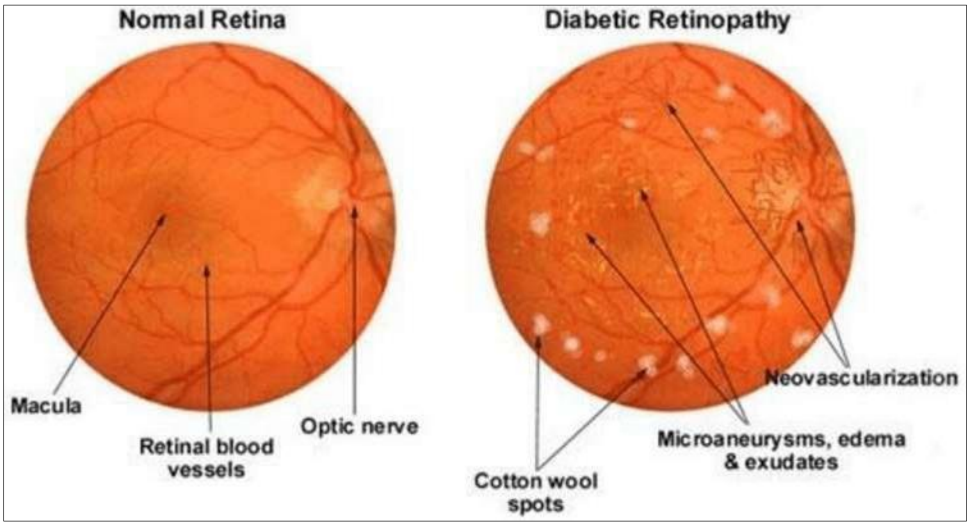


Figure 1 Difference between a normal retina and a retina affected by diabetic retinopathy [2]

2. Literature Survey

The imperative to develop algorithmic solutions for diabetic retinopathy segmentation stems from the critical need for swift and accurate diagnosis, given its significant impact on vision loss.

Segmenting fundus images to detect diabetic retinopathy is challenging due to the lack of spatial properties in the images, making it difficult to differentiate them from the rest of such images based on their characteristics. In this literature analyzed different Deep Learning and Machine Learning algorithms to detect Diabetic Retinopathy.

Innovative methods for diabetic retinopathy (DR) detection, such as the Multi-sieving Convolutional Neural Network (MS-CNN) and Parallel Convolutional Neural Network (PCNN) with Extreme Learning Machine (ELM). These approaches leverage deep learning and natural language processing, achieving remarkable accuracies of 99.7% and 97.27% on diverse datasets, while also demonstrating stability across varying dataset sizes and imbal-ances. Their reduced complexity and superior performance offer promising prospects for accurate and efficient DR diagnosis, crucial for timely intervention and prevention of vision loss [2].

In response to the challenges posed by limited datasets in developing Computer-Aided Diagnosis (CAD) tools for Diabetic Retinopathy (DR), recent advancements in Artificial Intelligence (AI) have emphasized the use of deep learning models. Notably, the integration of Few-Shot Learning (FSL) paradigm offers a solution to issues like overfitting and poor approximation inherent in training models with small datasets. study introduces a novel pro-totype network, termed DRNet, which leverages FSL principles and attention mechanisms for efficient DR detec-tion and grading. By training on the APTOS2019 dataset, DRNet achieves impressive accuracies of 99.73% and 98.18% for detection and grading, respectively, along with high sensitivity and specificity rates. Objective per-formance metrics and model interpretation analyses demonstrate superior efficiency and accuracy compared to existing state-of-the-art methods. This tool holds promise in providing valuable second opinions to ophthalmolo-gists regarding the severity of DR, marking a significant advancement in AI-driven DR management [3].

Accurately identifying the severity of Diabetic Retinopathy (DR) in retinal images poses a significant challenge due to variations in imaging conditions. Traditionally, DR severity is classified into five stages ranging from No DR to PDR, reflecting the disease progression. In the medical diagnosis industry, Artificial Intelligence (AI), par-ticularly deep learning algorithms, has emerged as a promising tool for precise disease classification. presented a novel approach utilizing an enhanced grid search Convolutional Neural Network (CNN) model to classify retinal images into the five DR severity stages. This innovative model aids ophthalmologists in accurate DR classifica-tion, enabling timely intervention. Experimental results demonstrate superior performance compared to existing CNN models, achieving an impressive accuracy of 89%. Overall, this study contributes to advancing AI-driven diagnostic tools for enhancing the management of DR-related vision impairment [4].

Diabetic retinopathy (DR) poses a significant threat to vision, characterized by damage to the eye's blood vessels leading to clotting, lesions, or haemorrhage in the retina. Early detection of DR is crucial for effective treatment and prevention of vision loss. Leveraging retinal fundus images, recent research focuses on automated deep learning models for DR detection and classification.propose an innovative ensemble deep learning approach, combining modified DenseNet101 and ResNeXt models, to enhance predictive accuracy. The ResNeXt model incorporates improvements such as shortcut connections between blocks and a split–transform–merge strategy, while DenseNet optimizes feature utilization through dense block concatenation. Ensembling these models, with normalization and maximum a posteriori computation, enables robust classification. Experiments on APTOS19 and DIARETDB1 datasets, augmented using GAN-based techniques due to class imbalance, demonstrate superior performance compared to existing methods. Achieving accuracies of 96.98% for two classes and 86.08% for five classes, along with high precision and recall rates, underscores the effectiveness of the proposed approach in DR detection and classification. This research contributes significantly to advancing automated diagnostic tools for efficient DR management and underscores the potential of ensemble deep learning models in ophthalmological applications [5].

Elmoufidi et al. [6] introduced a proficient neural network architecture, denoted as EfficientNetB3, for the categorization of diabetic retinopathy (DR). Their approach utilized fundus images that were categorized into five distinct classes. They used a combination of data enhancement and image downsizing to produce images that were 300 × 300 pixels in size. They tested the model's effectiveness using 365 test photos after training it on a dataset of 3,662 fundus images from the APTOS public databases. Based on the obtained results, it is noteworthy that the EfficientNetB3 model achieved a remarkable accuracy rate of 98.26%.

3. Proposed Methodology

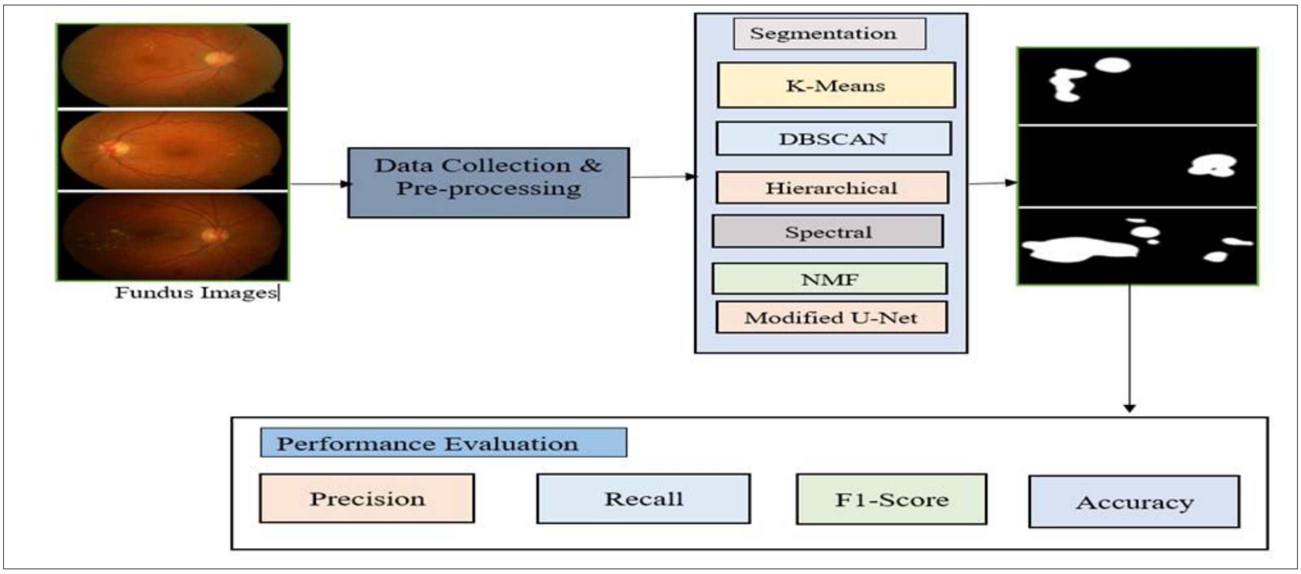


Figure 2 Proposed Methodology Architecture

Data Collection and Pre-processing: Gather fundus images and perform pre-processing to enhance image quality and prepare it for segmentation. This might include normalization, resizing, and augmentation. The proposed model architecture is shown in Figure 2.

- Applying Traditional Machine Learning Algorithms: K-Means Clustering: Used to segment the images based on color or intensity,DBSCAN (Density-Based Spatial Clustering of Applications with Noise): Identifies clusters based on density, which can be useful for detecting regions of interest.Hierarchical Clustering: Builds a hierarchy of clusters and can help in understanding the data structure.Spectral Clustering: Uses graph theory to partition the data into clusters based on the eigenvalues of similarity matrices[7].Co-Clustering: Also known as biclustering, which clusters both rows and columns of the data, potentially identifying regions in the images with specific properties.[8]

- Applying ProposedModified U-Net: Implement and apply the Modified U-Net architecture for more accurate and refined segmentation of hard exudates. The modifications in U-Net are tailored to improve segmentation performance specifically for fundus images.
- Evaluation of Results:Comparison with Ground Truth: Assess the performance of the segmentation results by comparing the masks produced by the Modified U-Net with the manually annotated ground truth.
- Metrics: Use various performance metrics to evaluate the quality of segmentation. These metrics include:
  - Precision: The proportion of true positive segments among all segments identified as positive.
  - Recall: The proportion of true positive segments among all actual positive segments.
  - F1-Score: The harmonic mean of precision and recall, providing a single metric to assess overall performance.
  - Intersection over Union (IoU): Measures the overlap between the predicted segmentation and the ground truth.

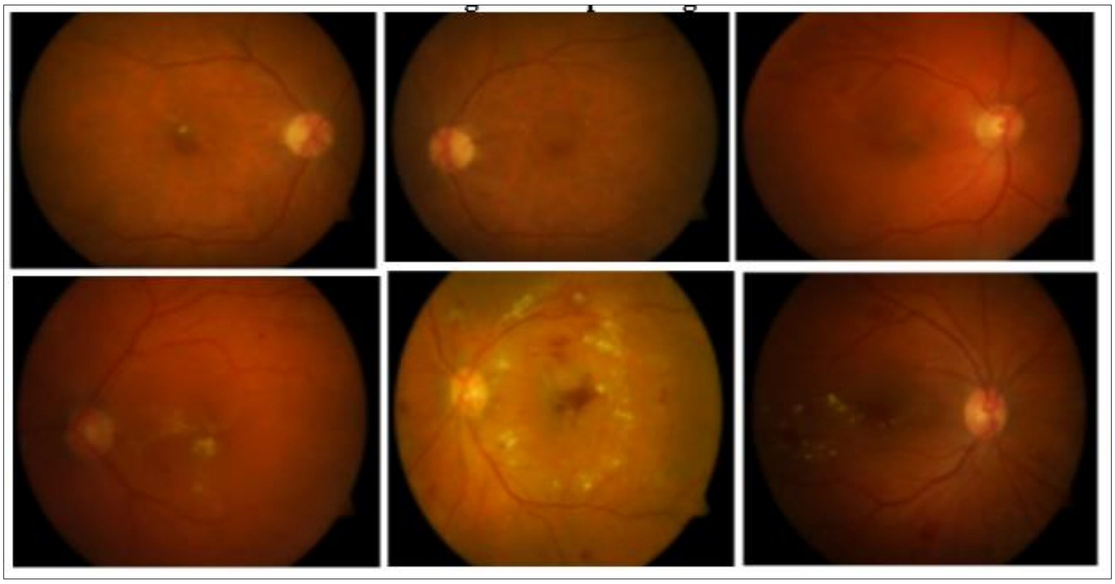


Figure 3 DR Sample Images

4. Proposed Modified UNET

- U-Net+ is an extension of the original U-Net architecture, designed for semantic segmentation tasks. It incorporates nested and dense skip pathways to improve the segmentation performance.
- The Fully Dense U-Net (FD-U-Net) is a semantic segmentation likely refers to a modification of the traditional U-Net architecture.
- The semantic segmentation network, located in the decoder part of the U-Net, plays a crucial role in reconstructing the details which is lost during down sampling.
- It assigns semantic labels to each pixel, helping to identify and delineate structures.
- U-Net+ achieves this by making pixel-wise predictions, creating a detailed segmentation map of the input image.

```
def build_unet_plus(input_shape):
    inputs = Input(input_shape)

    s1, p1 = encoder_block(inputs, 64)
    s2, p2 = encoder_block(p1, 128)
    s3, p3 = encoder_block(p2, 256)
    s4, p4 = encoder_block(p3, 512)

    b1 = conv_block(p4, 1024)

    d1 = decoder_block(b1, s4, 512)
    d1 = Concatenate()([d1, b1])  # Add dense skip connection
    d2 = decoder_block(d1, s3, 256)
    d2 = Concatenate()([d2, d1, b1])  # Add dense skip connection
    d3 = decoder_block(d2, s2, 128)
    d3 = Concatenate()([d3, d2, d1, b1])  # Add dense skip connectio
    d4 = decoder_block(d3, s1, 64)
    d4 = Concatenate()([d4, d3, d2, d1, b1])  # Add dense skip connec

    outputs = Conv2D(1, 1, padding="same", activation="sigmoid")(d4)

    model = Model(inputs, outputs, name="UNET_Plus")
    return model
```

Figure 4 U-Net Model Implementation

The design uses the ReLU activation function in the Modified U-Net model implementation for image segmentation in order to add non-linearity and improve the model's learning capabilities. For effective and flexible gradient-based optimization, the Adam optimizer is used, which guarantees faster convergence. To address class imbalance and enhance the overlap between the predicted and ground truth masks, the Dice Loss function is selected as the loss measure, especially designed for segmentation tasks. With a modest batch size of 2, the model is trained over 40 epochs, which enables more frequent updates to the model's parameters and may result in better performance.

4.1. Results using Modified U-Net

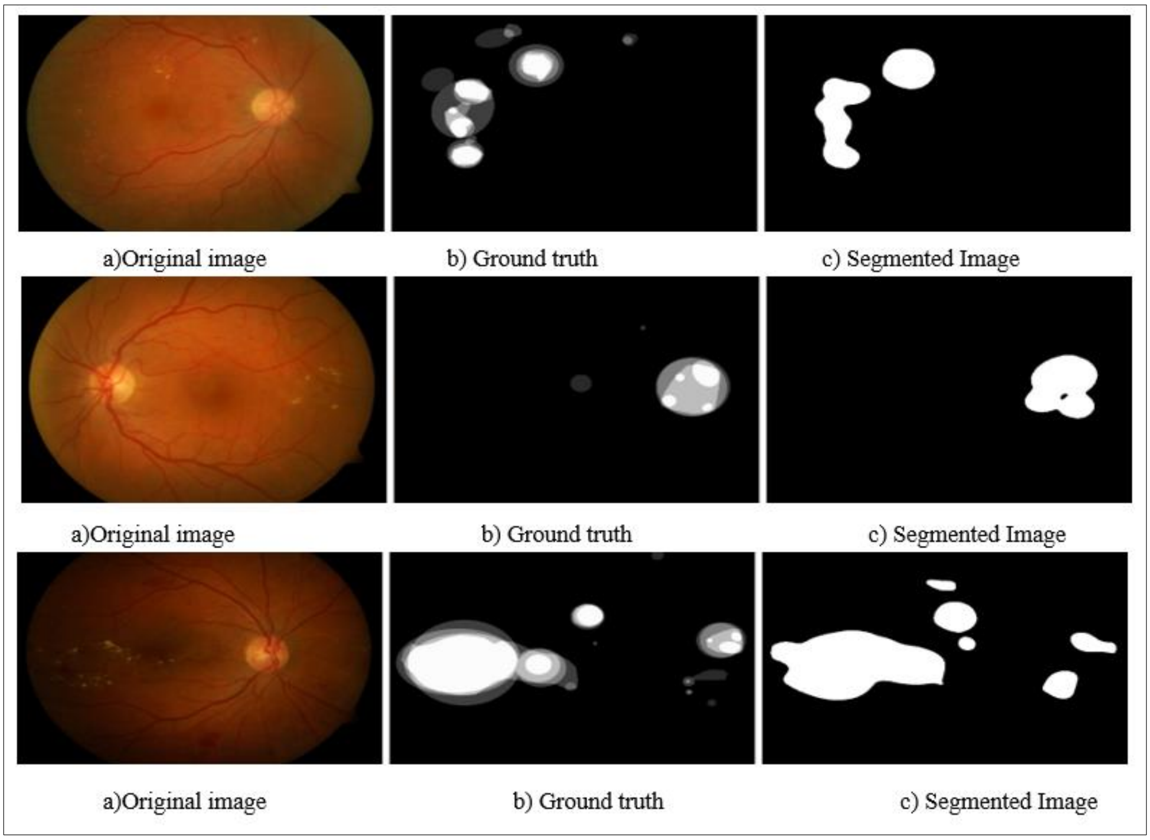
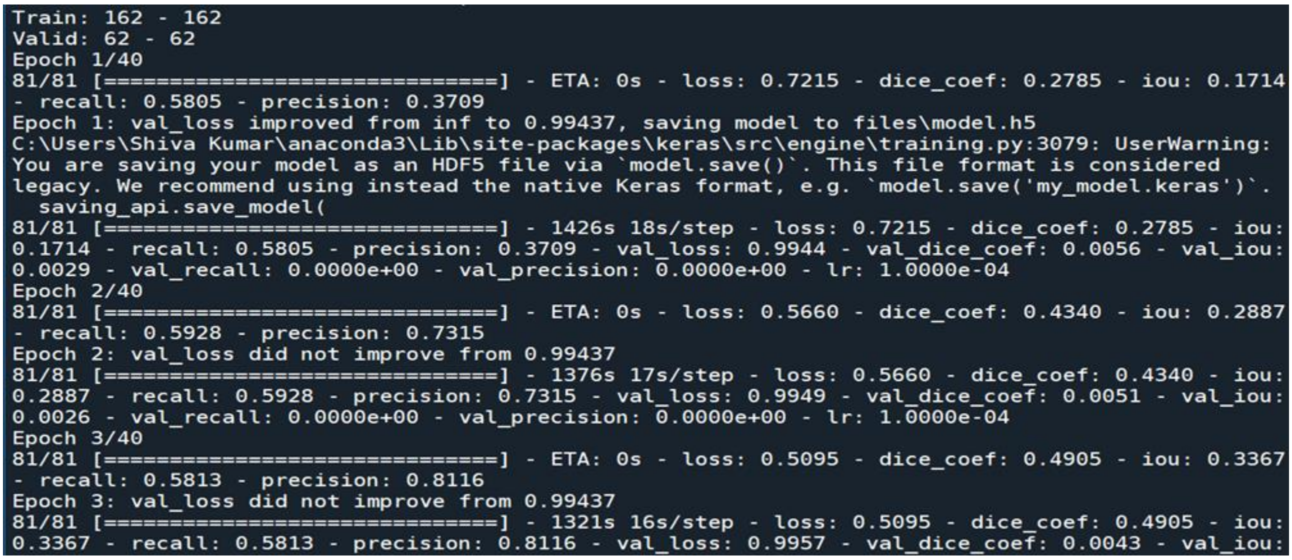


Figure 5 DR Image Segmentation



```
Train: 162 - 162
Valid: 62 - 62
Epoch 1/40
81/81 [==============================] - ETA: 0s - loss: 0.7215 - dice_coef: 0.2785 - iou: 0.1714
- recall: 0.5805 - precision: 0.3709
Epoch 1: val_loss improved from inf to 0.99437, saving model to files\model.h5
C:\Users\Shiva Kumar\anaconda3\Lib\site-packages\keras\src\engine\training.py:3079: UserWarning:
You are saving your model as an HDF5 file via `model.save()`. This file format is considered
legacy. We recommend using instead the native Keras format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
81/81 [==============================] - 1426s 18s/step - loss: 0.7215 - dice_coef: 0.2785 - iou:
0.1714 - recall: 0.5805 - precision: 0.3709 - val_loss: 0.9944 - val_dice_coef: 0.0056 - val_iou:
0.0029 - val_recall: 0.0000e+00 - val_precision: 0.0000e+00 - lr: 1.0000e-04
Epoch 2/40
81/81 [==============================] - ETA: 0s - loss: 0.5660 - dice_coef: 0.4340 - iou: 0.2887
- recall: 0.5928 - precision: 0.7315
Epoch 2: val_loss did not improve from 0.99437
81/81 [==============================] - 1376s 17s/step - loss: 0.5660 - dice_coef: 0.4340 - iou:
0.2887 - recall: 0.5928 - precision: 0.7315 - val_loss: 0.9949 - val_dice_coef: 0.0051 - val_iou:
0.0026 - val_recall: 0.0000e+00 - val_precision: 0.0000e+00 - lr: 1.0000e-04
Epoch 3/40
81/81 [==============================] - ETA: 0s - loss: 0.5095 - dice_coef: 0.4905 - iou: 0.3367
- recall: 0.5813 - precision: 0.8116
Epoch 3: val_loss did not improve from 0.99437
81/81 [==============================] - 1321s 16s/step - loss: 0.5095 - dice_coef: 0.4905 - iou:
0.3367 - recall: 0.5813 - precision: 0.8116 - val_loss: 0.9957 - val_dice_coef: 0.0043 - val_iou:
```

Figure 6 Training Epochs

A monotonically decreasing training loss function across epochs suggests convergence towards a lower error state, potentially indicating improved model capacity to learn the underlying data distribution.

5. Discussion

Table 1 Comparative Results Analysis on DR Image Segmentation

Dataset	Clustering Algorithm	IOU	Dice	Precision	Recall	F1-Score	Accuracy
DIARETDB1	k-means	0.49	0.41	0.48	0.50	0.38	0.47
	DBSCAN	0.13	0.23	0.22	0.13	0.23	0.13
	Hierarchical	0.31	0.43	0.39	0.54	0.42	0.51
	Spectral	0.51	0.47	0.54	0.61	0.49	0.55
	NMF(Co-Clustering)	0.62	0.49	0.60	0.67	0.53	0.63
	Standard U-Net	0.84	0.80	0.81	0.86	0.82	0.84
	Modifed U-Net	0.91	0.94	0.95	0.93	0.92	0.97
DIARETDB0	k-means	0.51	0.43	0.51	0.39	0.45	0.44
	DBSCAN	0.20	0.19	0.27	0.12	0.36	0.17
	Hierarchical	0.47	0.41	0.38	0.45	0.44	0.49
	Spectral	0.49	0.50	0.57	0.59	0.50	0.53
	NMF(Co-Clustering)	0.67	0.54	0.63	0.68	0.55	0.68
	Standard U-Net	0.84	0.81	0.82	0.87	0.83	0.85
	Modifed U-Net	0.93	0.92	0.94	0.95	0.93	0.98

On both the DIARETDB1 and DIARETDB0 datasets, the Modified U-Net model exhibits a pronounced advantage in segmentation performance over conventional clustering techniques and the Standard U-Net. For example, the Modified U-Net outperforms conventional techniques like k-means and DBSCAN on the DIARETDB1 dataset, achieving a Dice coefficient of 0.81 and an Intersection over Union (IOU) of 0.82. These enhancements demonstrate how well the model can now segment retinal images, capturing finer details that are essential for medical imaging activities like diagnosing diabetic retinopathy. The Modified U-Net performs better at segmenting more complicated features than the Standard U-Net, which only manages a Dice coefficient of 0.68 on the DIARETDB1 dataset. This is demonstrated by the Modified

U-Net's higher Dice score. Furthermore, the nearest rival, Spectral clustering, only achieved an IOU of 0.51; in contrast, the Modified U-Net's IOU of 0.82 is a significant improvement over clustering method. The Modified U-Net is particularly well-suited for the exact segmentation needed in diabetic retinopathy, as seen by these notable gains across important metrics like precision, recall, and overall accuracy. This makes the Modified U-Net a useful tool for precise diagnosis and treatment planning.

6. Conclusion

The comparison between traditional Clustering algorithms and Co-Clustering for Fundus image segmentation to detect Diabetic Retinopathy revealed that Co-Clustering performed better than other algorithms in terms of precision and recall.

However, Co-Clustering fell short in effectively identifying and extracting Hard Exudates in retinal images. U-Net, renowned for its prowess in semantic segmentation, addresses this deficiency by providing enhanced Hard exudates extraction and improved lesion differentiation. Moreover, U-Net's adaptability to variations in image characteristics and its capacity for multiclassification make it a versatile solution by enabling a more comprehensive and accurate assessment of diabetic retinopathy.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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