RN-DRC: A relation network-based few-shot learning framework for Diabetic Retinopathy Detection and severity grading

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Abstract: Diabetic Retinopathy (DR) has become a leading cause of visual impairment and blindness globally, where early diagnosis and assessment of disease severity are important for providing timely clinical treatment. Traditional deep learning-based DR classification approaches commonly demand large amounts of annotated data, which is costly and time-consuming to collect in medical image processing applications. In order to overcome this challenge, this paper presents the framework of Few-Shot Learning using a Relation Network for Diabetic Retinopathy Detection and Severity Grading (RN-DRC), which can effectively learn discriminative features from a few labelled samples and generalize to unseen retinal images. Specifically, in our proposed framework, we integrate VGG16 as the feature embedding component while utilizing ResNet18 as the relation module. The proposed model is tested on the APTOS 2019 dataset for both binary DR Detection and multiclass DR severity grading tasks. The proposed model achieved an accuracy of 99.64% with an AUC of 0.9982 for binary DR detection, and an accuracy of 96.92% with an AUC of 0.9729 for multiclass DR severity grading, demonstrating its effectiveness in distinguishing subtle retinal disease severity levels. Moreover, we conduct ablation studies to evaluate the impact of the number of training episodes on the stability of the model's performance.

Keywords: Diabetic Retinopathy, Few-Shot Learning, Relation Network, Retinal Fundus Images.

1. Introduction

Diabetic Retinopathy (DR) is a serious challenge associated with type 2 diabetes, which affects the retina and can eventually result in partial or total blindness. It occurs when high blood sugar causes repeated damage to small blood vessels in the retina. According to recent systematic reviews, almost 22-34.6 per cent of diabetic patients worldwide develop DR, with a higher prevalence rate in the cases of low - and middle-income countries. In 2014, it was reported that there were 422 million people with diabetes according to the WHO, and the figures have been steadily increasing. Consequently, DR has become one of the major causes of vision impairment across the globe and a major societal health concern in the context of increasing global diabetes trends.

Lack of proper screening at diagnostic facilities can lead to loss of sight for some patients who may not be able to have the procedures done in time due to the limited access to such facilities in various countries. The disease is also largely economically demanding on health systems, and the global direct medical expenses of the disease are estimated at over 500 million USD per year. That is why it is critical to use sophisticated technological solutions to detect and grade DR in a fast and accurate manner. This may assist healthcare workers in detecting the severity of any disease early enough and thus be able to treat it before it results in blindness.

Presently, the procedure of fundus photography is regarded as the traditional method of diagnosis and grading of DR. The clinical examination may result in high-quality retinal images due to this non-invasive method of imaging. Nonetheless, the process of determining the manual interpretation of fundus images captured by ophthalmologists turns out to be resource-intensive and time-consuming in large-scale population-based screening programs. Consequently, automated diabetic retinopathy detection provides an effective solution for improving the efficiency of early diagnosis and large-scale screening to increase the effectiveness of early diagnosis and screening.

https://doi.org/10.33436/v36i2y202607

Recent advances in computer vision and deep learning have demonstrated a great deal of promise for automating the identification and evaluation of DR. Conventional techniques for DR using machine learning classification generally require a lot of annotated training data. The acquisition of such labelled medical data can be very costly and time-consuming, and it demands skilled labour. To address this issue, Few-Shot Learning (FSL) has become a powerful method that allows the model to learn meaningful patterns using a limited number of labelled examples and still attain a good generalization to previously unseen data.

The Relation Network is an architecture of neural networks that has been developed specifically to be applied to FSL. It uses similarity patterns within sample sets and applies these patterns to offer a prediction of unseen data. The architecture comprising it consists of two main elements: a feature extraction component that transforms the input samples into feature representations and a relation component that assesses the similarity or connection between pairs of feature vectors. Relation Networks have demonstrated strong performance across various challenges involving FSL, such as image categorization, the processing of natural language, and object detection. In the identification and grading of DR, this approach can be used to build a few-shot classifier that gains knowledge from sparse labelled data and generalizes effectively to new retinal images.

The principal contributions of this study are summarized as follows:

1. A relation network-based FSL framework is proposed, labelled RN-DRC, to identify and grade DR correctly.
2. The theoretical argument behind using FSL and Relation Networks, which addresses the challenges caused by limited labelled data in medical imaging applications and a lack of marked information in the medical imaging field.
3. The RN-DRC is tested using the APTOS dataset with ablation analysis of the impact of different training episodes.
4. RN-DRC is contrasted with state-of-the-art FSL models (Prototypical Networks, Matching Networks, MAML, and DRNet), and the models prove to be superior using a variety of evaluation measures.

2. Related work

DR is a diabetic point of contention that damages the retina's blood vessels, the light-sensitive layer located at the back of the eye. It is considered one of the primary causes of adult blindness and vision impairment. The causes of the condition arise through the long-term effects of excessive blood glucose that damage the small blood vessels in the retina in the long run (Gupta et al., 2018). Several factors predispose to the development of DR: a longer period of diabetes, elevated blood pressure, elevated cholesterol, and lack of glycemic control.

DR is another complication of diabetes, which presents no symptoms in the initial phases (Yun et al., 2008). There are two categories of DR: Proliferative (PDR) and Non-Proliferative (NPDR). NPDR has been discovered by leaking blood vessels and fluid build-up. PDR involves the formation of fragile vessels that may leak blood, block vision, or detach the retina and cause blindness. Prevention involves early diagnosis of diabetes, effective management, and eye check-ups. Treatment options include laser surgery and the use of anti-VEGF injection, as well as vitrectomy (in severe cases) (Zhao and Cheng, 2019). Image-based interventions for DR are an essential part of the early detection, diagnosis, and management of such a complication that endangers vision (Cole et al., 2016). Various techniques of Retinal imaging available to clinicians include fluorescein angiography, optical coherence tomography (OCT), and fundus photography, among others, which assist clinicians with early diagnosis and effective treatment to reduce the risk of visual loss. These screening processes based on images are especially effective at identifying DR at the earliest stages, even when the patient is not yet showing symptoms, so that it is possible to receive treatment early and reduce the chances of severe visual impairment (Ting et al., 2016).

Machine learning has already shown that it can be used to manage DR (Bhatia et al., 2016) by analysing retinal images automatically to provide early warning (DL- based management) and identify risk factors (ML-based risk factors). These methods are based on the methods of extracting hand-crafted characteristics, e.g., blood vessel structure, texture patterns, and lesion appearance, to train classifiers (Acharya et al., 2009). Yet, these models also have limitations since they require expert knowledge, feature engineering is both time-consuming and error-prone, which has an impact on performance (Rajalakshmi et al., 2018). Convolutional Neural Network (CNN) and deep learning models have become promising solutions to DR management since they can easily extract hierarchical features of images in an automated way without further feature extraction (Abramoff et al., 2018). This benefit would render these models more precise and powerful because they can identify hidden and sophisticated patterns in retinal scans (Ting et al., 2017).

The broad review of deep learning-based systems for detecting DR is given (Alyoubi et al., 2020). A custom CNN is used in the breakthrough study of DR detection based on deep learning introduced by (Pratt et al., 2016). This architecture comprises several fully associated layers of the final classification and convolutional blocks of the initial layers. In case DR grading is a five-class classification problem, the model achieves an accuracy of 75% and a sensitivity of 95%. Here, (Gulshan et al., 2016) used the Inception-v3 architecture (Szegedy et al., 2016) to identify DR. It resulted in impressive performance of the method, 97.5% sensitivity and 93.4% specificity in EyePACS (Cuadros & Bresnick, 2009), and 96.1% sensitivity and 93.9% specificity in Messidor-2.

The mechanism of Weighted Path CNN (WP-CNN) (Liu et al., 2019) employs the use of a weighted path to extract discriminative features and remove redundancy during the detection of referable DR (RDR). This strategy enhances the attention of the model to critical features. It has a specificity of 95.74%, as well as a sensitivity of 90.94% and an accuracy of 94.23%. A Region-based Fully CNN (R-FCN) is suggested to perform the task of DR grading and lesion detection by modifying the ResNet-101 model to extract features and using an object detector known as Region Proposal Network (RPN) (Wang et al. 2020). The R-FCN gives a sensitivity of 92.59% and specificity of 96.20% on the Messidor dataset. Nevertheless, owing to the lack of annotated training data, the model has a low precision in detecting small lesions such as microaneurysms and hemorrhages. A patch-based DERA system (Zago et al., 2020) is an alternative to DR detection that uses a personalized CNN as a selection model to examine patches of an image, detect red lesions, and create a map of the probability of these lesions. The CF-DRNet (Wu et al., 2020), which works with five-stage DR classification, includes two subnetworks: one called the coarse network, which is a DR detector, and another broader network referred to as the fine network, which is a grader of DR-positive images detected by the former. The two subnetworks share the same ResNet18 structure, and a coarse network module adds attention to seek the discriminative DR features. Nevertheless, this framework has a detection accuracy of 56.19% on the IDRiD data (Porwal et al. 2018).

The DeepDR model (Dai et al., 2021) consists of the main network and three dedicated sub-networks trained to assess the quality of images, lesion segmentation, and DR grading. The main network uses an already trained ResNet, and the parameters are shared with the subnetworks. At testing, an input image is fed through each subnetwork to carry out the required function in the subnetwork. The lesion-aware subnetwork is used to draw significant features, which are combined with the features provided by the DR grading network to give the ultimate classification. Non-Diabetic. The model comprises six categories of DR: No Diabetic Retinopathy (NDR), Mild NPDR, Moderate NPDR, Severe NPDR, Proliferative DR, and Referable DR. The DeepDR framework demonstrates high performance in the identification of PDR with an AUC of 0.961%, sensitivity of 93.2%, and specificity of 86.2%. Nevertheless, the framework is a relatively more difficult one compared to several other models covered in the literature. (Zang et al. 2022) have introduced a deep learning-based classification of the DR, based on OCT Angiography (OCTA) images. The framework was able to achieved an AUC of 0.96 with a variance of 0.01 and a quadratic-weighted kappa value of 0.83 with a variance of 0.04 in referable DR (RDR) classification. For vision-threatening DR (vtDR), it obtained an AUC of 0.92 ± 0.02 and a kappa score of 0.73 ± 0.04. The model had a 0.83 -0.03 quadratic-weighted kappa of the multi-class DR classification test (non-referable DR, accessible non-vtDR, and vtDR).

The study under consideration (Ryu et al. 2022) has suggested the use of an automated DR staging system built on OCTA imaging using a deep CNN. The recommended CNN had an accuracy of 0.728, sensitivity of 0.675, specificity of 0.944, F1-score of 0.683 with a quadratic-weighted kappa of 0.908 applicable in the six-stage DR classification test. These results are much better than human expertise and traditional machine learning methods. Also, the findings indicate that the CNN achieved higher results on the merged datasets and larger OCTA image sets than when trained on single OCTA layers.

FSL classifiers are recent models that receive a lot of interest as an alternative to traditional ones, primarily because they can learn with sparse training data (Guan et al., 2020). A variety of meta-learning approaches, such as the Prototypical Network (Snell et al., 2022) and a Relation Network (Zheng et al., 2022), have been developed to construct classification systems, which combine base learners trained on various data subsets. However, the use of FSL in medical image diagnosis has been barely utilized, with a small number of studies examining the potential of its use. Indicatively, a two-stage FSL architecture of DR and other retinal diseases is an integration of a multi-task detector of more common diseases and a probabilistic module of rare abnormalities (Quellec et al., 2020). This model performed best on frequent condition classification with an AUC of 0.966 using an Inception-based architecture. The method uses PCA projection and KNN regression during learning and inference, and t-SNE when dimensionality is being reduced following a log transformation, even though it is expensive to run.

Another FSL-based approach that employs a deep residual network with Earth Mover Distance (EMD) is FEDI (Pan et al., 2021), which classifies 39 categories of a fundus image with 1000 images. The residual network step in this framework extracts features, and EMD assesses them in the same manner as used in classification. The maximum accuracy of all categories had been reported in experimental results, but this was not given. On the same note, DRNet (Murugappan et al., 2022) was suggested to detect and grade DR with the aid of a prototypical network with an attention mechanism to enhance performance in limited-data cases. It was trained on the APTOS 2019 repository and enhances the representation of features by employing the gradient-based activations and aggregate transformations. The model showed good results in automated diagnosis with an accuracy of 99.73% and 98.18% in DR detection and DR grading, respectively.

With the recent development of algorithms related to analyzing retinal images, transformer networks such as Vision Transformer (Ramesh Dadi et al., 2026) and Swin Transformer (Praveena Mallampalli et.al., 2025) have been widely applied because of their capability of modelling long-range contextual dependencies. Transformer algorithms achieve superior accuracy in tasks such as detecting and classifying diabetic retinopathy. Additionally, novel few-shot learning algorithms, such as transductive few-shot learning and cross-domain few-shot learning (Ruoxian Song et.al., 2025) have attracted more attention from researchers due to their ability to deal with the problems of having insufficient labelled data and domain shift.

Several recent studies have reported that attention-based deep learning architectures can improve diabetic retinopathy analysis by emphasizing clinically relevant retinal regions, thereby enhancing feature representation and classification performance in fundus image analysis (Sagenela, V.K. et al., 2026). However, most of the currently existing FSL-based DR models are sophisticated and often incorporate other methods like PCA, which requires more computer resources. Such difficulties highlight the necessity of a more efficient and lightweight FSL structure for DR analysis. It is possible to propose a Relation Network-based FSL model, which helps to increase the recognition of DR, evaluation, and diagnosis, especially in cases of limited labelled data. This kind of network works by capturing the associations between input images and the class to which they belong, which is accomplished by comparing the unseen samples to a small number of annotated instances. The reason why FSL is best applicable in the DR grading process is the lack of annotated medical data. The use of Relation Networks is advantageous since they calculate similarities in features at a pair-wise level in an end-to-end fashion, given the ease with which features of varying amounts of DR severity can be differentiated. The ResNet18 and VGG16 backbone architectures are chosen since they have a high level of functionality and performance regarding the extraction of medical image features, as well as their efficiency in terms of computational cost during execution.

Despite the promising classification performance achieved by traditional convolutional neural network-based diabetic retinopathy approaches, many existing methods rely heavily on large annotated datasets and often exhibit limited generalization capability under constrained training-data conditions. Similarly, existing Few-Shot Learning approaches for diabetic retinopathy analysis may encounter challenges in effectively capturing relational similarities among retinal fundus images corresponding to different diabetic retinopathy severity levels. Such limitations motivate the need for a more effective similarity-learning mechanism for diabetic retinopathy grading under limited labelled -data settings. To address these challenges, the proposed RN-DRC framework adopts a Relation Network-based episodic learning strategy that enables effective similarity learning between support and query retinal fundus images. In addition, the integration of dual-backbone feature extraction using VGG16 and ResNet18 enhances discriminative feature representation for improved diabetic retinopathy detection and grading performance.

3. Intelligent detection and grading of Diabetic Retinopathy

This study addresses diabetic retinopathy (DR) analysis through both binary classification (DR detection) and multiclass classification (DR grading). Binary classification identifies whether a retinal image contains signs of DR, whereas multiclass classification predicts the severity stage of DR, including No DR, Mild, Moderate, Severe, and Proliferative DR.

The objective of learning a decision function f_b (x) is the goal of the binary classifier, which assigns a binary outcome to a given test image *x.* In this study, the decision function is formulated as presented in Equation (1), where δ(*x*) denotes the predicted probability of DR for the input image.

$$f_b(x) = 1\{\delta(x) > 0.5\} \tag{1}$$

The objective of a multiclass classifier is to predict the appropriate severity level for an unseen test image. The mission of the decision function f_m (x) must be learned by the multiclass classifier to predict the appropriate class designation for a specific input image *x*, as expressed in Equation (2). In this context, δ(*x*) indicates the estimated degree of DR severity for the image, while *k represents* the total number of classes.

$$f_m(x) = arg \max_{k \in \{1,\dots 5\}} \delta_k(x) \tag{2}$$

Few-Shot Learning (FSL) is particularly suitable for medical image analysis, where annotated datasets are limited due to costly and labour-intensive labelling procedures. Relation Networks are effective in this scenario because they learn pairwise similarity metrics in an end-to-end manner, enabling robust generalization from limited labelled samples and improving discrimination among subtle DR severity levels.

4. System design

The proposed study presents the RN-DRC, which is an FSL classification framework. In this section, the author defines the framework of the RN-DRC model and the methodologies that can be used to implement the proposed framework in the following subsections. The RN-DRC is built upon the concept of Relation Network in FSL and incorporates the pre-trained Deep learning models such as VGG16 and ResNet18. The architecture of these networks and workflows is described below.

4.1. Overview of relation network

The Relation Network is an FSL method that models the relationship between input samples and class labels using a neural network. It is well-suited for scenarios with limited labelled data, as it can learn effectively from just a few examples. The architecture includes fundamental classifiers with relation modules that operate on high-dimensional embeddings and determine similarity between samples and classes for classification. This design enables efficient and accurate prediction even with minimal training samples. The general design of the suggested RN-DRC framework is presented in Figure 1.

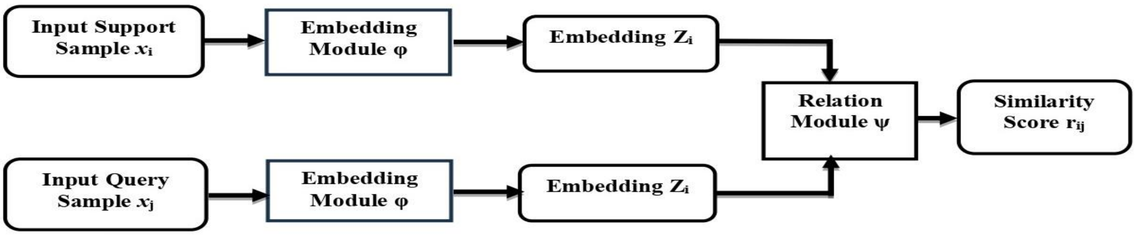

Figure 1. Overview of the proposed RN-DRC framework (Source: author's own elaboration)

Support and query sets are jointly processed by the embedding system (VGG16/ResNet18) to obtain a feature representation. The extracted embeddings are then provided to the relation module, which calculates relation scores between the embeddings of the query and support samples. These calculated scores are then applied to the binary and multi-class classification of DR and severity grading, respectively.

The relation module works as a neural network that provides a similarity score between two pairs of embeddings, where the score is difficult to predict without either input. Using a relation function that can be learned through multiple embedding pairs, the module can learn complex relationships between labels and samples that could not be learned by ordinary classifiers, by examining a variety of embedding pairs. Once these relationships have been calculated, the weighted sum of embeddings is produced. It is an integrated representation that serves as the final feature representation of individual samples and has been used for class prediction. Overall, the Relation Network learns to measure multiple relationships within the classification stage, which increases its ability to extrapolate and apply to unseen samples. The mathematical model of the RN-DRC model is provided below.

Let the support set be represented as $s = \left(x_i, y_i\right)_{i=1}^{N}$ wherein x_i represents the i-th input sample, and y_i stands for the class label that corresponds to it. Likewise, the query set is expressed as $Q = \left(x_j\right)_{j=1}^{M}$. The Relation Network aims to understand a classification function $f(x_j)$. This approach predicts the label y_j for a query instance x_j using only a limited number of labelled examples from the support set S. An embedding module and a relation module are the two primary components of the Relation Network framework. Input samples are transformed into a high-dimensional feature space using the embedding module so that $(x_i) = z_i$ and $(x_j) = z_j$. Equation (3) describes how the relation module then determines similarity between the feature representations of the query and support samples.

$$\psi\left(z_i , z_j\right) = r_{ij} \tag{3}$$

The classification function $f(x_j)$ assigns the label y_j to the query sample by utilizing the similarity scores r_{ij}, as specified in Equation (4). Here, y denotes the set of all potential class labels, and 1 is an indicator function, which gives 0 otherwise and 1 under the given condition.

$$y_i = \underset{y_k \in Y}{arg\ max} \sum_{i=1}^{N} 1 \left(y_i = y_k\right). rij \tag{4}$$

The Relation Network can be trained to properly classify query samples based on the defined loss function by reducing it to a smaller value.

Embedding Module: VGG16 has been proposed to be embedded in the proposed system. VGG16 has been selected due to its demonstrated ability to extract discriminative features by virtue of its ubiquity in medical imaging research. A neural network called the embedding module converts input samples through a high-dimensional attribute representation. The input sample xi embedded module produces its feature vector zi according to Equation (5), with θϕ representing the learnable Embedding Network parameters. These embeddings encode the key properties of the incoming data and are used to carry out classification in the Relation Network's later phases.

$$z_i = \phi\left(x_i; \theta_\phi\right) \tag{5}$$

Relation Module: The proposed system uses ResNet18 to obtain the relation Score. ResNet18 was selected because its vanishing gradient problems are lessened by residual connections, enabling deeper and more efficient feature learning. The relation module ψ is designed to calculate the resemblance among embeddings obtained from both the query and support sets. For a support set embedding z_i and a query set embedding z_j, the segment produces a comparison value r_{ij}, which is expressed in Equation (6)

$$r_{ij} = \psi\left(z_i, z_j; \theta_\psi\right) \tag{6}$$

Using both architectures (VGG16 and ResNet18), the proposed RN-DRC framework demonstrates robustness across shallow and deep CNN backbones, ensuring that more than one feature extractor is responsible for the observed speed improvements.

4.2. Model architecture

Figure 2 illustrates the general components of the RN-DRC model with episode selection, feature embedding, and classification. The training stage involves the use of embeddings formed by the training set, whereas the testing stage involves embeddings generated from previously unseen images.

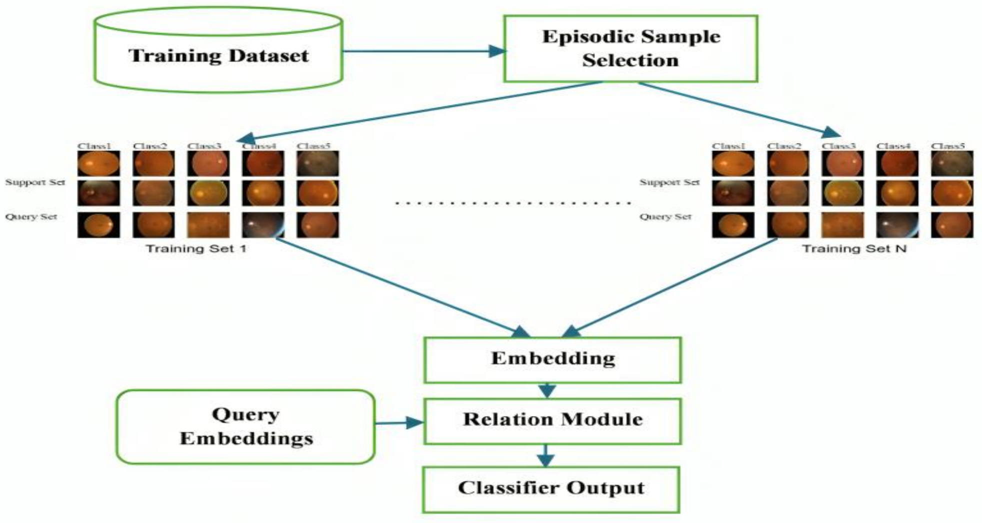

Figure 2. Proposed System Architecture (Source: Author’s own elaboration)

The architecture introduced in Figure 2 shows the novel RN-DRC dual-backbone design, in which VGG16 is used to extract low-level retinal features, and ResNet18 is used to calculate the relation scores. Such a complementary representation enhances the ability of the model to detect small changes among classes in clinically challenging DR grading, such as Mild versus Moderate DR. By customizing the relation network framework to the specifications of the medical image analysis, RN-DRC exists beyond traditional FSL configurations while also offering a unique contribution to the medical image analysis.

4.3. Proposed methodology

This section provides a detailed description of the approach used to formulate the proposed RN-DRC model. It discusses the aspect of data preparation and the training process.

Dataset: The APTOS2019 dataset is used in this project and consists of 3662 retinal fundus images labelled according to five severity grades, including Non-DR (NDR), Mild (mnDR), Moderate (modDR), Severe (SnDR), and Severe Proliferative (SPDR). In our experiments, we used a stratified 70/30 split of the dataset, giving 2564 training images and 1098 test images. Table 1 provides a summary of the distribution of both binary DR detection and five-class DR grading samples.

To guarantee an unbiased assessment, a strict demarcation between the training and test sets was maintained throughout all experiments, thereby reducing the risk of any unintentional data leak during the assessment process.

Table 1. APTOS 2019 Dataset Distribution

DR Class	**DR Detection**		**DR Grading**	
	Training Images	**Testing Images**	**Training Images**	**Testing Images**
NDR	1264	541	1264	541
DR (any)	1300	557	-	-
Mild DR (mnDR)	-	-	259	111
Moderate DR (monDR)	-	-	699	300
Severe DR (SnDR)	-	-	135	58
Severe Proliferative DR (SPDR)	-	-	207	88
Total	**2564**	**1098**	**2564**	**1098**

Model Training: An episodic learning framework that is FSL-oriented is used to train the model. In this method, the training data are structured into episodes comprising a query set and a support set. For every class, there are only a certain number of labelled instances in the support set, whereas the query set comprises samples for which the labels need to be inferred. Each episode represents a standard FSL environment. Below is a description of the episodic training procedure.

In the introduced RN-DRC, a 5-way 1-shot episodic learning setting is used, where an episode involves five classes of diabetic retinopathy along with a labelled support image for each class. The query images are unlabelled retinal fundus images that will be categorized based on the relation scores obtained from the learning process. While the data is split into training and test sets in a ratio of 70/30 in a stratified manner, model training is done by generating episodes of tasks. This episodic approach allows the framework to work with limited labelled data and aligns with few-shot learning.

Algorithm 1: Episodic Learning

```
Data   : Task distribution P(T), amount of episodes E
Result: Trained model parameters $\theta_\Phi$ and $\theta_\psi$
Initialize: Model parameters $\theta_\Phi$ and $\theta_\psi$
1. For episode $ e=1 to E do
    a. Sample a task T
    ~ P(T) with support set S = $(x_i, y_i)$ (i=1)$^N$ and query set Q= $(x'_j)^M_{(j=1)}$
    b. For each sample $x_i$ in S do:
        i. Compute the Embedding $z_i = \Phi(x_i ; \theta_\Phi)$
    c. For each sample $x'_j$ in Q do:
        i. Calculate the Embedding $z'_j = \Phi(x'_j ; \theta_\Phi)$
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        ii.  Calculate pairwise relation scores $r_{ij} = \psi(z_i, z'_j; \theta_\psi)$
        iii. Calculate the predicted label
             $Y'_i = argmax \sum_{i=1}^{n} 1(y_i = y_k).r_{ij}$
2. Calculate the loss function
3. Update model parameters $\theta_\Phi$ and $\theta_\psi$ to minimize the loss L
```

4.4. Implementation details

We used PyTorch for implementation. The Adam optimizer was used to train the model, with a batch size of 32, a learning rate of 1 × 10^{-4}, and, unless otherwise specified (as in the ablation study), all experiments, including the comparison with other FSL models, were trained for 1000 episodes to ensure fairness and consistency. Data augmentation (rotation, flipping, CLAHE) was applied. Experimentation was performed on an NVIDIA Tesla V100 GPU.

5. Model evaluation

The evaluation metrics employed to gauge the effectiveness of the RN-DRC model, along with the corresponding experimental results, are presented below.

5.1. Performance of RN-DRC model with its metrics

Metrics such as sensitivity, specificity, accuracy, precision, F1-score, and Matthews Correlation Coefficient (MCC) are used to evaluate the performance of the classification model. True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are among the classification outputs from which these metrics are computed.

Accuracy is a ratio of correctly classified samples to the total samples, and equation (7) calculates the accuracy, which implies the general soundness of the forecast.

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (7)$$

Sensitivity evaluates how well affirmative examples are identified by the model. Equation (8) expresses sensitivity as the proportion of correctly identified positive events to all actual positive samples.

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (8)$$

Specificity quantifies the model's skill to appropriately categorize negative cases. The ratio of accurately anticipated negative cases over the total number of actual negative cases determines the specificity, as defined in Equation (9).

$$Specificity = \frac{TN}{(TN + FP)} \quad (9)$$

Precision calculates the ratio of true positive predictions to all samples that were projected to be positive, as described in Equation (10).

$$Precision = \frac{TP}{(TP + FP)} \quad \ldots\ldots(10)$$

Each of the above evaluation metrics ranges from 0 to 1, with 0 being the lowest performance and 1 being the ideal performance of the model. The F1-score and MCC, among others, are especially useful in measuring the classifiers of imbalanced datasets. The F1-score combines the sensitivity and accuracy by assigning both measures the same weight, thus providing a levelled assessment. It is calculated as shown in Equation (11), where values near 1 signify better performance and values near 0 represent poorer performance.

$$F1 = 2 \cdot \frac{(Precision \cdot Recall)}{(Precision + Recall)} \tag{11}$$

A performance measurement technique based on the concept of correlation is the Matthews Correlation Coefficient, which measures the quality of classification using the confusion matrix technique that considers true positive, true negative, false positive, and false negative cases and the extent of agreement between actual class labels and the model prediction, as compared in Equation (12).

$$MCC = \frac{(TP \cdot TN - FP \cdot FN)}{\sqrt{((TP+FP)(TP+FN)(TN+FP)(TN+FN))}} \tag{12}$$

5.2. Classification presentation analysis

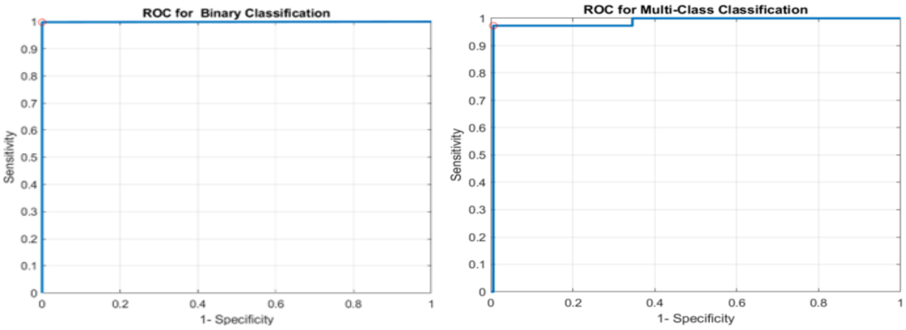
The suggested model is evaluated in the context of binary and multiclass classification, and the relevant evaluation measures are presented in Table 2. The findings not only show the general performance but also the class-based performance of the model. The comparison reveals that the model performs better when compared to the multiclass option in binary classification. Moreover, the values of specificity are higher than those of sensitivity, which shows that the model is efficient in rating the samples in the dataset with high reliability. In addition, the high MCC and F1-score demonstrate the model's resilience and its capacity to learn from unequal class distributions.

Table 2. Classification performance analysis

Metrics	**Classification Type**	
	Binary Classification (DR Detection)	**Multi-Class Classification (Five Classes – DR Grading)**
Accuracy	0.9964	0.9692
Sensitivity	0.9946	0.9428
Specificity	0.9982	0.9925
Precision	0.9982	0.9339
F1	0.9964	0.9382
MCC	0.9927	0.9304

5.2.1 ROC curves and confusion matrix:

The efficacy of the model for learning is measured in terms of binary and multi-class Receiver Operating Characteristic (ROC) curves, as shown in Figure 3a and Figure 3b. The ROC curve illustrates the trade-off between true positive rate and the false positive rate across multiple decision thresholds. The Area Under the Curve (AUC) shows how well the classifier can distinguish between classes in relation to the false-positive rate.

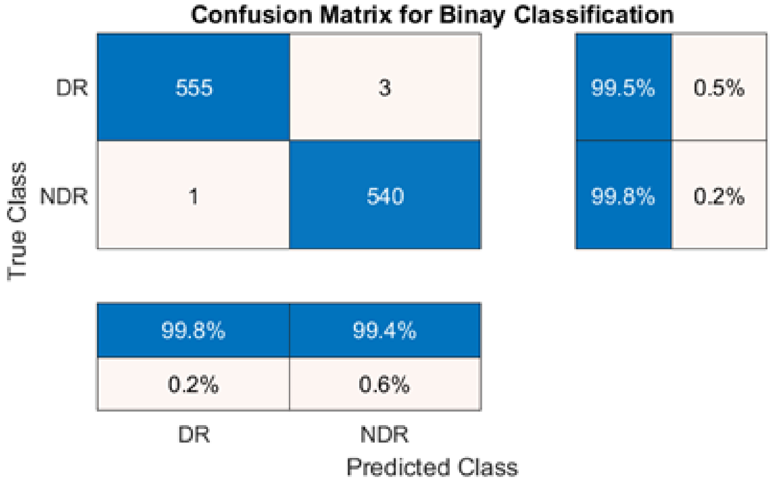


ROC for Binary Classification (b)ROC for Multiclass Classification

Figure 3. ROC Curves: (a) Binary Classification, (b)Multiclass Classification
(Source: author's own elaboration)

The ideal ratio between false positive and false negative rates is represented by the Optimal Operating Point (OOP), which is located close to the upper-left corner of the ROC curve. The AUC score ranges from 1.0, which denotes flawless classification, to 0.5, which denotes random performance. The constructed binary and multiclass models showed outstanding discriminative abilities with AUCs of 0.9982 and 0.9729, respectively.

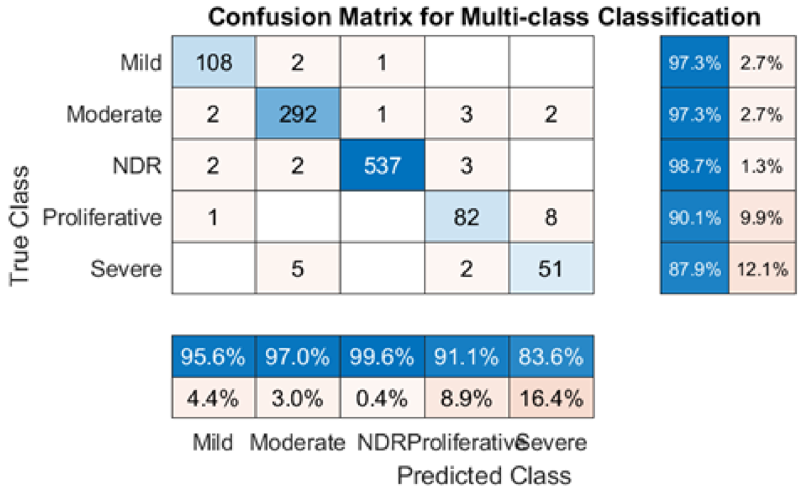
Figures 4 and 5 display the confusion matrices illustrating the RN-DRC model's effectiveness in both binary and multiclass classification problems.



Confusion Matrix for Binay Classification

True Class \ Predicted Class	DR	NDR		
DR	555	3	99.5%	0.5%
NDR	1	540	99.8%	0.2%
	99.8%	99.4%		
	0.2%	0.6%		

Figure 4: Confusion Matrix for Binary Classification (Source: Author's own elaboration)



Confusion Matrix for Multi-class Classification

True Class \ Predicted Class	Mild	Moderate	NDR	Proliferative	Severe		
Mild	108	2	1			97.3%	2.7%
Moderate	2	292	1	3	2	97.3%	2.7%
NDR	2	2	537	3		98.7%	1.3%
Proliferative	1			82	8	90.1%	9.9%
Severe		5		2	51	87.9%	12.1%
	95.6%	97.0%	99.6%	91.1%	83.6%		
	4.4%	3.0%	0.4%	8.9%	16.4%		

Figure 5. Confusion Matrix for Multiclass Classification (Source: Author's own elaboration)

The above figures illustrate the classification behaviour of the RN-DRC model for binary and multiclass tasks, respectively. All the elements in the confusion matrix represent the number of test samples that were predicted belonging to a specific class. The diagonal entries exhibit correctly identified samples, while the off-diagonal entries represent misclassifications.

Strong diagonal dominance in the binary classification (Figure 4) strongly indicates that most of the Normal and DR samples are correctly recognized as such, which indicates the model can make a clear distinction between diseased and non-diseased cases. In the multiclass scenario (Figure 5), the diagonal values are dominant with mild off-diagonal values between the adjacent grades, especially between Mild and Moderate or Moderate and Severe DRs, indicating the clinical similarity of these two categories. These findings reveal that the RN-DRC model is effective in separating the levels of DR severity, and that implementing lesion-level features or attention-related details in the future could further reduce the misclassification of borderlines.

5.3. Performance comparison

Performance comparison values in relation to the Few-Shot Learning model are given below, which are obtained from the references mentioned in each study. The objective of these comparisons is to show how well the proposed RN-DRC model performed on the APTOS 2019 Dataset.

Table 3. Performance comparison of RN-DRC with other FSL models for multiclass diabetic retinopathy grading on the APTOS 2019 dataset.

Various Models	Accuracy	Precision	Recall	F1-Score
Prototypical Networks	0.912	0.905	0.896	0.900
Matching Networks	0.918	0.910	0.901	0.905
MAML	0.926	0.910	0.910	0.914
DRNet	0.944	0.936	0.930	0.933
RN-DRC (Proposed)	**0.969**	**0.962**	**0.958**	**0.960**

In Table 3, the results of the comparative analysis are shown concerning the performance of the proposed RN-DRC framework in multi-class diabetic retinopathy grading using the APTOS 2019 dataset. In particular, it is noteworthy to state that the RN-DRC accuracy of 0.969 relates to the accuracy of multi-class grading (0.9692), as provided in Table 2. Furthermore, the RN-DRC accuracy was chosen as a criterion for comparing the proposed approach with other Few-Shot Learning models.

The superiority of the proposed RN-DRC framework in classification can be explained by the efficiency of its learning similarity mechanism based on Relation Networks, which enables the learning of feature correlations between support and query retinal fundus images under limited conditions of labelled data availability. Moreover, due to the utilization of a dual backbone embedding mechanism and a relation module dedicated to diabetic retinopathy diagnosis, efficient feature representation across different classes becomes possible.

5.4. Ablation study

The number of training episodes ranged from 100 to 1000 to assess the impact of training episodes. According to Table 4, an increase in performance is observed with the increase in training episodes, which proves the efficiency of RN-DRC under the conditions of training data scarcity. These findings confirm that the simulated RN-DRC model produces consistent and predictable routines despite having few training episodes, which demonstrates the claim that the model will not need large amounts of labelled data.

Table 4. Ablation study on the number of training episodes.

Episodes	Accuracy	F1-Score
100	0.925	0.910
300	0.944	0.930
500	0.958	0.945
1000	0.969	0.938

5.5. Limitations and future work

In this case, the limitation of RN-DRC is that the quality of features depends on the type of backbone networks chosen. Moreover, our experiments performed on the APTOS dataset show high accuracy, but our results on more miscellaneous datasets must be authenticated to confirm greater generalizability. The domain-specific features, like lesion localization, could also be introduced in future work to reduce misclassification rates.

Despite the success shown by the proposed RN-DRC model on the APTOS 2019 Retinal Dataset, it should be noted that the current research findings are achieved with a fixed experimental setting. Future work will be done to repeat the experiment with confidence, including interval testing, perform ablation tests, as well as the use of other retinal datasets.

However, the current ablation study mainly aims at evaluating the impact of training epochs on the model's performance. Future studies should include a more comprehensive ablation study of individual components, evaluating the impact of different architectures for feature extraction, relation learning models, different pre-processing techniques like CLAHE enhancement, and single or dual backbone approaches.

6. Conclusion

The research presented the RN-DRC framework, a Few-Shot Learning architecture based on relation networks for detecting and grading diabetic retinopathy from a few retinal fundus images. The performance of the proposed model was analysed using the APTOS 2019 dataset, and excellent classification performance was achieved for both binary and multiclass DR classification. A comparison between RN-DRC and several popular models, such as prototypical networks, matching networks, MAML, and DRNet, shows that RN-DRC performs favourably across multiple evaluation metrics. Furthermore, ablation studies indicate that RN-DRC can maintain reliable performance even with a small number of training episodes, making the algorithm suitable for medical imaging scenarios with limited data availability. Further investigation is needed on the use of larger datasets of retinal images to determine the generalizability of the approach. In future work, attention mechanisms will be investigated.

Author contributions

Conceptualization: R. Seethalakshmi and R. Priyadharsini; Data Curation: R. Seethalakshmi; Methodology: R. Seethalakshmi and R. Priyadharsini; Writing – Original Draft Preparation: R. Seethalakshmi; Writing – Review & Editing: R. Priyadharsini; Supervision: R. Priyadharsini. All authors have read and agreed to the published version of the manuscript.

Submission received: 16 February 2026; Revised: 02 June 2026; Accepted: 09 June 2026.; Published: 30 June 2026.

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