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# DIABETIC RETINOPATHY CLASSIFICATION WITH DEEP NETWORKS AND FEW-SHOT LEARNING ON IMBALANCED RETINAL DATA

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**ABSTRACT**

A consequence of diabetes called diabetic retinopathy (DR) has been caused by damage to the vessels of blood that carry photosensitive cells in the eyes. If this issue is not identified in its early stages, vision loss follows. Diabetic retinopathy occurs in five stages: proliferative, mild, moderate, severe, and no DR. Conventional approaches for DR detection are time-consuming. The availability of sufficient data for training would be necessary for an autonomous and accurate model, however, this is not the case. Aside from No DR, the publicly accessible dataset is wildly unbalanced for other classes, particularly proliferative and severe classifications. The performance of Deep Learning (DL) models has been negatively impacted by issues with imbalanced datasets, inconsistent annotations, fewer sample images, and improper performance evaluation measures. The current state-modern-the-art DL (deep learning) techniques, particularly CNN architectures, have been applied to numerous issues and have demonstrated remarkable efficacy in learning balanced datasets. Furthermore, a sizable dataset is needed to train the model using DL-based approaches. The main obstacle to creating deep learning models is the sheer volume of data that is unavailable, particularly for uncommon and emerging retinal disorders. few-shot When a sizable dataset is not available for training, learning can be used as a substitute for developing deep learning models. To solve the aforementioned problems, the researchers in this study established DR-FSL-DNet, a FSL-based deep network model for DR classification. Few-Shot learning (FSL) produced better results than DL models by guiding the DR classification model with a comparatively limited number of samples. First, The DR-FSL-DNet framework utilizes episodic learning to train its model on few-shot classification tasks. Later, applied resampling technique (i.e., Focus Loss function) to balance data and classes in training data. Finally, a prototype meta-learning network is applied for DR detection and classification. On public datasets DRIVE, STARE, and CHASEDB1, the proposed network DR-FSL-DNet is applied by comparing it with modern-of-the-art works. The experiment shows that DR-FSL-DNet contributes to the desirable performance of DR classification. The proposed network outperforms compared to standard methods and achieved better scores in Accuracy, Sensitivity, Specificity, Precision, and F1-Score metrics.

**Keywords**: *Diabetes Retinopathy, Deep Learning, FSL, Class Imbalance, and Retinal Data.*

## 1. INTRODUCTION

Diabetes mellitus, which already affects 463 million people globally and is predicted to make 750 million by the year 2050, is regarded as a serious public health concern [1]. The negative effects of diabetes are typically observed in the retina, which can cause significant vision impairments in the later stages of the disease. DR is the most common eye condition related to diabetes, affecting at least one-third of those with the disease [2]. The retina's blood vessels have elevated sugar levels, which is the cause of this problematic disorder. Clinical diagnosis of diabetic retinopathy can be made using fundus photography, optical coherence tomography, or other imaging methods that involve examination of the retinal fundus. Therefore, early DR diagnosis is essential to rescuing the patient from this potentially fatal circumstance and saving their life.

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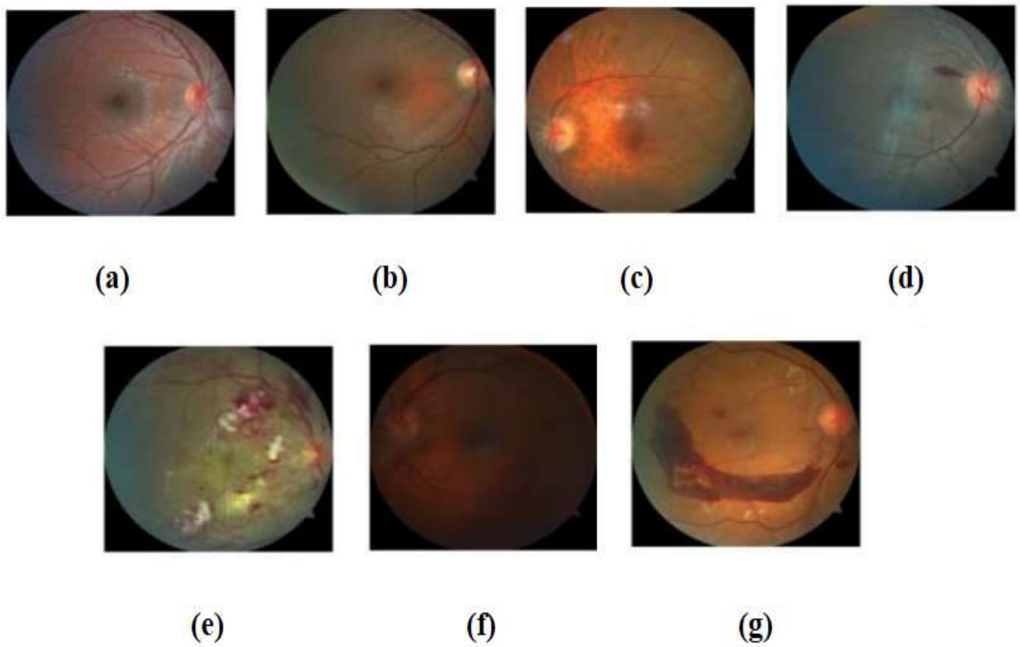


*Fig 1: The Stages Of DR (A) No DR (B)Mild Or NPDR (No Proliferative Diabetic Retinopathy) (C)Moderate NPDR (D)Severe NPDR (E)Very Severe NPDR (F) PDR (No Proliferative DR) (G) Advanced PDR*

The International Clinical Diabetic Retinopathy Scale has four levels for Diabetic Macular Edema and five levels for Diabetic Retinopathy, requiring fewer Fields of View. The levels of International Clinical Diabetic Retinopathy, as shown in Figure 1, are discussed in Table 1.

*Table 1: The Description Of Stages Of DR By The International Clinical Illness Severity Scale (ICDSS)*

| Stage | Observations by Ophthalmologist during screening |
|---|---|
| No DR | There are no DR |
| Mild NPDR | the first stage of diabetic retinal hemorrhage (DR), marked by microscopic patches of expansion in the retinal blood vessels called microaneurysms (MA) and no significant retinal nerve bleeding. |
| Moderate NPDR | blood leakage from the occluded retinal arteries occurs, Hard Exudates (Ex) may also exist, and the appearance of Venous beads (VB). |
| Severe & very severe NPDR | intraretinal hemorrhages (IHE) and intraretinal microvascular abnormalities (IRMA) exist in fundus all quadrants. Results a thin, swollen vessel of blood, red dots with small, and sharp edges. |
| PDR and advanced PDR | The development of new blood vessels in the retina, known as neovascularization (NV), raises the possibility of fluid leakage and the creation of fibrous tissue. Different functional visual issues, such as blurriness, a reduced field of vision, and, in rare cases, total blindness, are brought on by proliferative DR. |

Deep learning techniques can now be applied much more easily thanks to recent advancements in computer hardware, which have tremendously benefited the biomedical field. Therefore, compared to more conventional methods, the use of deep learning has led to a notable improvement in the diagnosis of DR. CNNs have advanced significantly in the last several years and are now extensively used in computer vision. CNNs have made significant advancements in tasks like image classification, object recognition, and semantic segmentation by combining feature removal and classification in an end-to-end manner. Despite the positive outcomes that CNN-based DR Classification systems have produced, the task's intricacy makes actual clinical implementation of these methods difficult. To train the model, any deep neural network [3] needs a sizable dataset. The main obstacle to creating deep learning models is the sheer volume of data that is unavailable, particularly for uncommon and emerging retinal disorders. Another problem is that only a tiny percentage of DR data—abnormal fundus images—is distributed evenly across grades. The model's capacity to generalize will be impacted by the unbalanced data distributions, which will force it to concentrate on DR grades having much more samples (DR 0 & DR 2) and disregard those with fewer samples (DR 1, DR 3, and DR 4). FSL, a meta-learning-based technique, has gained popularity recently for developing deep-learning models in situations where a huge, unbalanced dataset is not available for training. With this method, the model is trained on a related task first (meta-training), and after seeing only a smaller number of training instances, this knowledge is subsequently generalized over additional data (meta-testing). Therefore, using a small sample of retinal fundus images, this research aims to construct FSL-based deep network models for DR categorization and new retinal illness detection. The DR-FSL-DNet framework trains its model on few-shot classification tasks through the use of episodic learning. After episodic learning, training data is rescaled using a technique called the Focus Loss function in order to balance the data and tasks. Finally, the DR detection and categorization are done using a prototype meta-learning network.

The significant contributions of this research are:

1. Proposed a DR-FSL-DNet model, which is a combination of Deep Network and FSL, for classifying DR retinal images.
2. A meta-learning-based loss function is applied to balance the data and tasks associated with training data.
3. A FSL approach based on a Prototype Network is applied to learn image embeddings using only a few sample images.
4. Evaluated the performance of the proposed model using three benchmark datasets STARE, DRIVE, and CHBASE_DB1.

The structure of the paper is as follows. FSL mechanisms have been reviewed in section 2 together with previous efforts on DR classification using deep networks. The research methodologies utilized in this study are presented in Section 3. Section 4 explains the suggested network architecture and the training procedure. Section 5 represents the outcomes of the experiments, and Section 6 concludes the paper.

## 2. RELATED WORK

One of the most interesting challenges in computer vision is the early detection of DR. The goal of detection with diagnostic transparency criteria is to categorize diabetic retinopathy using the International Clinical Diabetic Retinopathy Grading System. Thus, the last several decades have seen positive advancements in automated diabetic retinopathy (DR) pathology screening. The field of computer vision has recently seen a dramatic shift due to deep learning techniques. CNNs are being considered by many researchers as a means of classifying images. The utilization of DL algorithms for medical analysis has advanced significantly in recent years. DR grading benefits greatly from deep learning, particularly when using CNNs. In particular, a CNN could be trained end-to-end as a feature extractor, recognizing delicate features “straight from fundus images without the need for human intervention or specialized domain knowledge [4] created a new deep network and got decent results by utilizing different filter sizes to learn fine-grained features for the recognition of DR on 2 public datasets. Attained good outcomes by applying the Inceptionv3 architecture for the automated identification of diabetic” macular edoema and DR in retinal fundus pictures. Use a CNN (LeNet-5) model to extract characteristics from images in order to deal with the segmentation of blood vessels. Two publicly accessible databases of retinal images were used for the experiment (DRIVE and STARE). Using the APTOS dataset, deep transfer learning models such as Res-Net18, Alex Net, Google Net, Squeeze Net, VGG19, and VGG16 are utilized for medical DR detection. Three novel deep neural networks—Densenet201, Resent101, and EfficientNetbo[5]—are employed for classification tasks in diabetic retinopathy settings. Prior research has shown that deep learning techniques perform well on DR grading assignments. Even yet, it remains problematic since small lesions like hard exudates and microaneurysms are impossible to capture using conventional deep-learning models. Although deep learning techniques are well recognized for their cutting-edge performance on numerous tasks, they frequently need to be trained on sizable, labeled datasets in order to generalize successfully to new samples. Large datasets, however, could be expensive to acquire and annotate [6]. The requirement for a positive user experience, the existence of uncommon categories, or the requirement to execute tasks in real time make this a particularly restrictive problem in many real-world scenarios [7]. By specifying a distribution among tasks, FSL reduces this burden. Each job comprises a set of target data (query set) and a fewer labeled data points (support set) that correspond to the same set of classes.

Unbalanced class distribution hinders the effectiveness of the current research and may lead to skewed categorization results. An FSL architecture for the detection of DR "and other common pathologies is based on a 2-stage network comprised of a probabilistic detector for rare diseases and a multi-task detector for common pathologies [8]. In a dataset of 1000 sample fundus images, a current FSL model on the basis of a deep residual network and the Earth Mover's Distance (EMD) algorithm" classifies images into 39 categories. Furthermore, the current FSL models for detection of DR are more computationally demanding, come with an inherent complexity in their design, and combine statistical exploratory approaches like PCA with other machine learning techniques like SVM. As a result, it is now obvious that a simpler FSL framework is needed for the identification and grading of DRs.

## 3. MATERIALS AND METHODS

This section explains the basic concepts & approaches utilized in the study for building the suggested network model.

### 3.1. Class Imbalance

When a class (the majority class) has more samples than the other classes, there is an imbalance (the minority classes). If left unmonitored, traditional supervised losses such as (multi-class) cross-entropy induce bias as well as weak generalization towards the class of minority. The study of class imbalance has made use of real-world datasets and distributions that replicate real-world dynamics. Real-world instances of class unbalanced issues include text recognition, credit card fraud detection, and, critically, medical diagnoses. Three categories of classical imbalance techniques can be distinguished: algorithm-level, data-level, and hybrid [9]. Random Over Sampling (ROS) [10], which resamples data points through the minority classes at random, is a popular data-level technique. Strategies at the algorithmic level make use of loss/cost function minimization or regularization. A popular method is called "weighted loss," in which each sample's loss is proportionately weighted by the inverse frequency of its class. Focal loss [11] concentrates training on more difficult-to-classify samples while down-weighing simple predictions. The weighted loss is enhanced by CB loss [12] according to the efficient number of samples. Hybrid approaches incorporate many tactics (e.g., 2 Phase Training [13]). While CI strategies were explored for a variety of object identification tasks, there hasn't been much study done on how well they generalize to more contemporary FSL techniques.

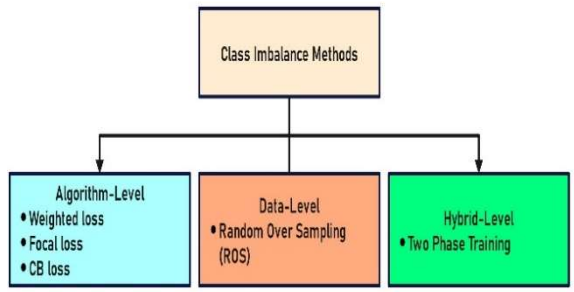


*Figure. 2. Classical Class Imbalance Approaches*

The Majority Of Real-World Biomedical Datasets Are Known To Be Imbalanced, And A Significantly Skewed Class Distribution Was Seen In Datasets Related To Diabetic Retinopathy. Nonetheless, It Is Equally Crucial To Identify The Majority Classes And The Underrepresented Classes (Minority Classes) In Order To Have An Effective Diagnostic Technique. Effective Models That Can Reliably Diagnose Diabetes And Identify Its Type Based On Automated Diagnosis Through Classification Tasks Are Required.

### 3.2. Class Imbalance in FSL

Vast volumes of labeled data are typically not available for real-world applications, and normal deep-learning approaches are not well suited to train such large amounts of data. FSL is a novel type of learning methodology that uses meta-learning to train models on a small amount of data. FSL approaches could learn a class representation which could be utilized to generalize to a new class. Three kinds of imbalance are generated in FSL which include Task Imbalance, Dataset Imbalance, and Hybrid Imbalance. The Task imbalance, either in the support set & the query-set class imbalance can be viewed, and it influences both the learning and evaluation tasks. It also stems from meta-training tasks, in which the distribution of tasks may not be readily observable or managed. A class imbalance in the query or support sets having a direct impact on the processes of assessment and learning. employs

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unbalanced support sets to build a benchmark for meta-learning that is more difficult and realistic.

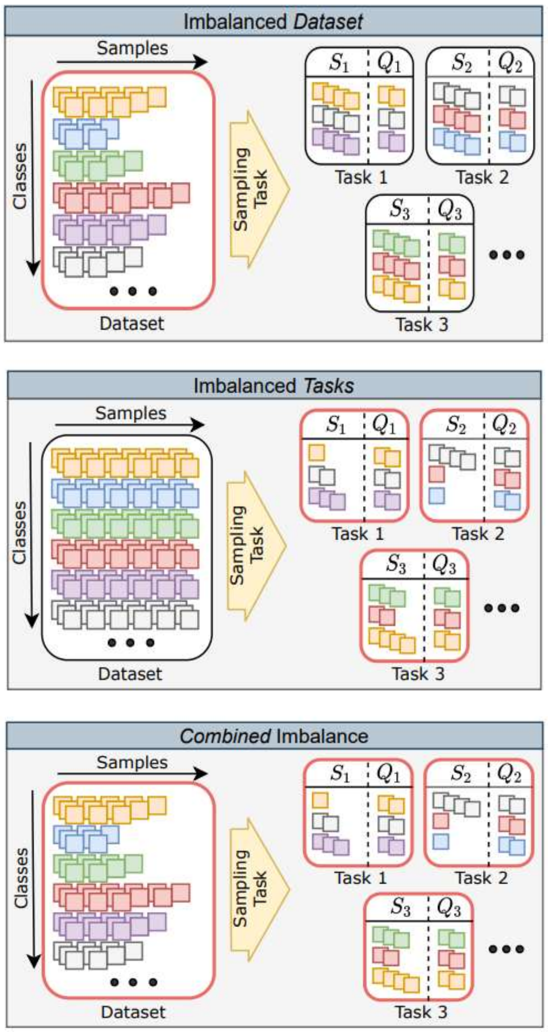


*Figure 3 Imbalance In FSL*

Generally, most of the real-world applications require a task balance approach which should be less expensive in computation, and easily adapted to the FSL. Hence, task sampling approaches under these considerations are classified into their types of Random shot Meta Sampling, Random Over-Sampling, and Rebalancing Losses respectively. Unplanned picture In the phase of meta-training, meta-sampling is a model for imbalanced tasks; hence, it might also be intentionally employed to train models for imbalanced assessment tasks. Similar to the traditional episodic meta-training [14], random-shot meta-training substitutes with $K_{min} - K_{max}$ shot random-distribution tasks for the balanced tasks. We maintain the same number of classes between tasks in order to isolate imbalance. By selecting data points at random from the minority classes, Random Over-Sampling automatically rebalances the data. Rebalancing Losses, the variety of approaches to take, Losses categorized as weighted, focal, and class balancing.

### 3.3. FSL for Classification

Three general categories can be used to group FSL methods: transfer-learning, optimization-based, and metric-learning. The query's label is predicted using metric-based meta-learning techniques as a weighted sum of the labels across the support samples. Prototypical Networks [15], Relation Networks [16], Matching Networks [17], MetaOptNet [18], and other popular metric-based meta-learning techniques are examples. A generalized version of nearest-neighbors classification on the basis of the Euclidean distance is carried out using matching networks. A sample is classified by Prototypical Networks using a Euclidean distance function that is computed between the sample's embedding and a representative class centroid. Relation Networks utilize a relation module, which is built on a neural network, to calculate the degree of similarity among the support & query sample embeddings for every class. In order to quantify the generalization error on query set samples, MetaOptNet [19] uses a linear SVM (Support Vector Machine) that has been trained on labelled support set samples as the comparator. A limited number of gradient steps are used by optimization-based meta-learning techniques, such as the Model-Agnostic Meta-Learning (MAML) [20], Proto-MAML, LEO [21], and others, to adjust the model parameters. In order to identify a highly adaptive set of parameters, MAML continuously modifies the initial meta-learned parameter set on the basis of success achieved on the episodic tasks. First-Order MAML (FO-MAML): during parameter optimization, it solely makes use of first-order gradients. Lastly, few-shot classification fine-tuning a model pre-trained on a much bigger dataset is addressed by transfer learning.

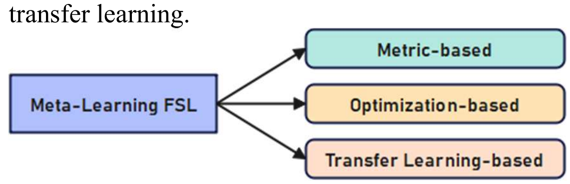


*Figure 4. Meta-Learning Based FSL Methods To Handle Class Imbalance*

2 transfer learning methods (i.e. Fine-Tuning & Freezing). Fine-tuning, learning the initial model parameters through tasks, and refining the weights. When a new task is provided, freezing (TLFZ) stops the embedding function's weights and permits the model head's weights to be updated.

## 4. Proposed method DR-FSL-DNet

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The DR classification problems with the proposed DR-FSL-DNet are described in detail in Fig 5. First, The DR-FSL-DNet framework utilizes "episodic learning to train its model on few-shot classification tasks". Later, applied resampling technique (i.e., Focus Loss function) to balance data and classes in training data. Finally, a prototype meta-learning network is applied for DR classification and detection.

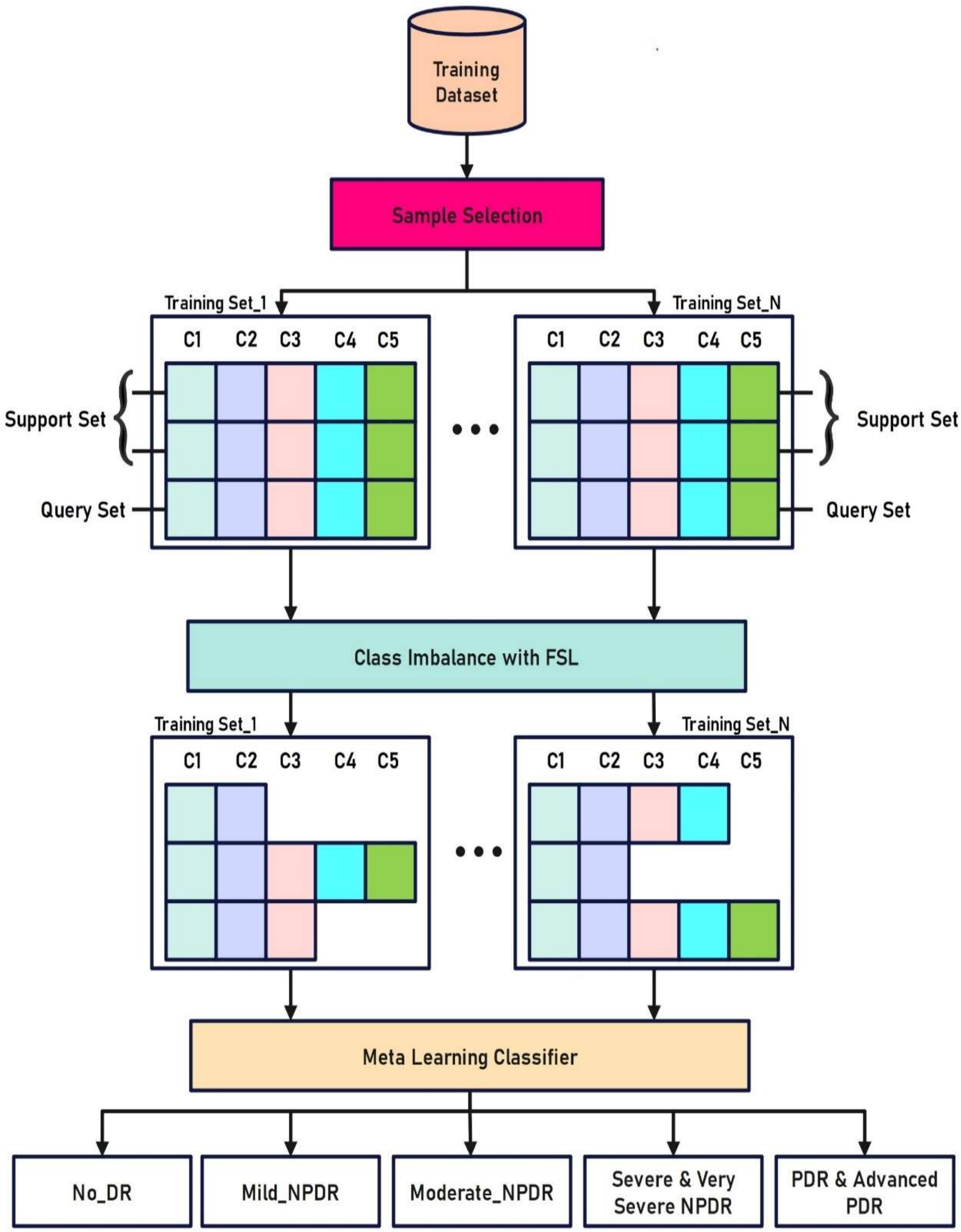


*Figure 5. The Suggested Framework DR Detection And Classification.*

### 4.1. Episodic Sampling

It is used to sub-samples few-shot tasks from a large base dataset. It is essentially an optimal meta-model for a certain set of episodes. A support set and a query set make up each episode. Model specialization and imitating the small datasets used for adaption during testing are done with the help of the support set. Given the customized model, the training loss is optimized using the Query set.

An episode $\vartheta$ is called N-way and K-shot, in this, the total training data is divided into two sets known as Support Set $S_\vartheta$ with $K$ labeled examples for every of the $N$ classes & Query Set $Q_\vartheta$.

$$S_\vartheta = \{(x_i, y_i), y_i = N\}_{i=1}^{k} \quad (1)$$

$$Q_\vartheta = \{(x_i^*, y_i^*) \setminus S_\vartheta, y_i = N\}_{i=1}^{k} \quad (2)$$

From the eq.(1) & (2) both $S_\vartheta$ $Q_\vartheta$ are subsets of training data $Z$ and need to be retrieved with minimum loss and it can be represented as:

$$f_{min}(x_n) = \frac{1}{\sum_i S_{\vartheta,i}} \sum_{S_\vartheta \subseteq x_n} S_{\vartheta,n} |S_\vartheta| \quad (3)$$

$$f_{min}(x_n) = \frac{1}{\sum_i Q_{\vartheta,i}} \sum_{Q_\vartheta \subseteq x_n} Q_{\vartheta,n} |Q_\vartheta| \quad (4)$$

This procedure results in episodes that are more diverse and possibly unbalanced.

| **Algorithm1:** *Episode Learning* |
| --- |
| *Input :* **Retinal Image Training Data set with** $n$ **samples** $Z$ <br> *Output :* $R \leftarrow$ *Subset of* $Z$ <br> *Step1 : Read Training Data set with n samples* $Z = \{(x_i, y_i)\}_{i=1}^{n}$ <br> *Step2 : Find* $R_n$ *subset of* $Z_n$ *by loss funtion* $f_{min}(x_n) = \frac{1}{\sum_i R_i} \sum_{R \subseteq x_n} R_n \lvert R \rvert$ <br> *Step3 : for each Episode* $\vartheta$ *do* <br> *Step4 : Generate* <br> $S_\vartheta = \{(x_i, y_i), y_i = N\}_{i=1}^{k}$ <br> $Q_\vartheta = \{(x_i^*, y_i^*) \setminus S_\vartheta, y_i = N\}_{i=1}^{k}$ <br> *Step5 : end for* |

### 4.2. Resampling with FSL

The class imbalance problem during training is solved with various approaches in this study focused on loss-based techniques to resolve the issue. The issue of category imbalance in the dataset utilized for this study will have an impact on the model's accuracy. The proportion of the loss value generated when a particular category's sample number is tiny also tends to be small, deviating from the multiclassification model's high-performance characteristics for all classification categories. Resampling the dataset is a popular solution to this issue. One of the loss techniques is the focal loss function used to solve the class imbalance in multiclassification. The multiclassification focal loss function is described as:

$$Loss_{FL}(y) = \sum_{i=1}^{N} \alpha y^* (1-y)^\gamma \log(y^*) \quad (5)$$

where $N$ shows the total number of classes, $y^*$ and shows the predicted value of an original $y$ sample. To improve the DR-based multiclassification an additional regularized term is adapted to the regular loss function. The issue of the impact of class imbalance on classification network learning can be resolved by adding the regular term in accordance with the original loss function.

$$Loss_{RFL}(y) = -\sum_{i=1}^{N} \alpha y^{*}(1-y)^{\gamma} \log(y^{*}) + \lambda \left\| y^{*} - y \right\|_2^2 \quad (6)$$

where,

| | |
|---|---|
| $N$ | total number of classes |
| $y^{*}$ | predicted value of the original $y$ sample |
| $\alpha$ | equilibrium factor |
| $\lambda$ | coefficient of the weight of the regular term |

The network's convergence can be expedited by the loss function by incorporating an additional norm as a regular term.

### 4.3. Meta-Learning for DR Classification

In this paper, the grading and DR detection are formulated as multiclass classification tasks, respectively. For five-class classification, a multi-class classifier is trained to distinguish among the NDR, moderate, mild, proliferative, and severe DR. To calculate the DR severity in the image of the test, the multi-class classifier has been trained with a collection of training photos, each of which has its DR severity labeled.

Given a training set $Z = \{(x_i, y_i) \mid x_i \in R_d; y_i \in R\}$ of retinal images & labels, the task of the multi-class classifier has to learn a decision function $f_{mc}(x)$ which maps a new test image $x$ to a label as in the "given Eq. (7),

$$f_{mc}(x) = \arg\max_{k \in (1-5)} [\delta(x) = k] \quad (7)$$

where $\delta(x)$ represents the predicted DR grade of the severity for $x$ & $k$ represented as a number of classes".

Usually, well-liked along with successful approaches for FSL, which is employed as an embedding mechanism in DR classification, is the prototype network.

During training, episodes comprising a support set $S_{\vartheta}$ along with the query set $Q_{\vartheta}$ are represented in eq (1) and (2)

$$S_{\vartheta} = \{(x_i, y_i), y_i = N\}_{i=1}^{k}$$

$$Q_{\vartheta} = \{(x_i^{*}, y_i^{*}) \setminus S_{\vartheta}, y_i = N\}_{i=1}^{k}$$

Next, a prototype is calculated for every class $k$ by taking the mean embedding of the samples from the class-related support set:

$$C_{\vartheta} = \frac{1}{S_{\vartheta}} * \sum_{(S_i, y_i) \in S_{\vartheta}} f_{\theta}(S_i) \quad (8)$$

where $f_{\theta}$ represents a deep neural network having parameters $\theta$ learned.

Let $C = \{(c_1, y_1), \ldots, (c_k, y_k)\}$ be the prototypes set along with the corresponding labels. The loss could be written as follows:

$$Loss_{PN} = \frac{-1}{Q_{\vartheta}} \sum_{(q_i, y_i) \in Q_{\vartheta}} \log\left( \frac{\exp - \left\| f_{\theta}(q_i) - c_{y_i} \right\|^2}{\sum_{k^{*}} \exp - \left\| f_{\theta}(q_i) - c_{k^{*}} \right\|^2} \right) \quad (9)$$

where $k^{*}$ denoted as an index which goes over all classes.

## 5. Experimental Results

TensorFlow and Keras libraries were used in the Python development of each network. Google Colab provided an NVIDIA Tesla P4 GPU for the models' training. We tested a standard PC having 8 CPU cores (AMD FX-8320 @ 3.5GHz) & 8GB RAM for the evaluation process. The design of the newly suggested FSL-AUNet-AM, aims to increase the traditional U-Net networks' accuracy in the context of retina image segmentation.

### 5.1. Dataset Description

We have conducted extensive tests on "the public retinal image datasets, namely, DRIVE, CHASE_DB, & STARE, to evaluate the performance of the suggested model on the basis of DR-FSL-DNet framework and show the good potential of the paradigm. In our trials, just 10 photos (i.e., 10 classes) have been utilized as the candidate set for building episodes consisting of the query & support sets for each dataset. The remaining images have been divided into the validation as well as testing sets. Four groups of C-way H-shot modes namely, 2-way 1-shot, 2-way 3-shot, 3-way 1-shot, and 3-way 3-shot, are set up to build various episodes for the training of above vessel segmentation models", correspondingly.

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**5.2. Evaluation Metrics**

This section provides a thorough evaluation of the proposed model DR-FSL-performance DNets in the validation, training, and testing procedures. The evaluation is based on the segmentation metrics, which include specificity (Spe), sensitivity (Sen), F1-score (F1), accuracy (Acc), and AUC, as well as the actual segmentation findings on the images of testing.

As a measure of a model's overall correctness, accuracy is calculated as the ratio of correctly classified occurrences to overall occurrences, as stated in Eq (10).

$$\text{Accuracy} = \frac{[T_P + T_N]}{[T_P + T_N + F_P + F_N]} \quad (10)$$

The model's recall serves as a measure of how well it predicts favorable examples. It is calculated using the equation provided in Eq. (11) and reported as the proportion of accurately detected positive samples to all positive samples.

$$\text{Recall} = \frac{T_P}{[T_P + F_N]} \quad (11)$$

Specificity is a metric used to assess how well a model predicts negative cases. It is the proportion of the overall number of the negative samples, as stated in Equation (12), to the correctly anticipated negative cases.

$$Specificity = \frac{T_N}{[T_N + F_p]} \quad (12)$$

The number of samples that are accurately identified out of all the positive samples that are anticipated as per Equation (13) is known as precision.

$$\text{Precision} = \frac{T_P}{[T_P + F_p]} \quad (13)$$

To create a balance among the 2, the F1-score assigns equal weight to the metrics of sensitivity and precision. Equation (14) can be used to calculate the F1-score, which has a range of 0 to 1. The classifier's worst performance is shown by the lowest value (0), while its best performance is indicated by the highest value (1).

$$\text{F1-Score} = 2 * \frac{[Pre * Rec]}{[Pre + Rec]} \quad (14)$$

where $F_p$, $T_P$, and $F_N$ have been the number of false positive, true positive, and false negative samples per class, correspondingly.

**5.4. Results Analysis**

To further verify the efficacy of the suggested network for DR classification, experiments on the three datasets DRIVE, STARE, and CHASEDB1 are conducted. The prediction results of the deep networks are compared in terms of five performance metrics: Acc, Sen, Spe, Pre, and F1. To more clearly see the improvement of the accuracy of DR classification by each module (i.e., Embedding of Resampling and Few Shot Learning with Prototype Networks is proposed in the model, the classification performance of different methods is shown in Table 2. The methods compared include CNN, U-Net, U-Net with loss function, and proposed network DR-FSL-DNet which has the capability of performing episodic and embedding in a better way.

*Table 2: Results Of Deep Networks For DR Detection On DRIVE Dataset*

| Technique/Metric | Accuracy (Acc) | Sensitivity (Sen) | Specificity (Spe) | Precision (Pre) | F1-Score (F1) |
|---|---|---|---|---|---|
| CNN | 90.72% | 73.31% | 93.53% | 76.29% | 84.01% |
| U-Net | 91.97% | 74.50% | 94.80% | 77.48% | 85.23% |
| U-Net with Loss function | 95.88% | 79.98% | 98.23% | 83.26% | 88.71% |
| Proposed Network DR-FSL-DNet | 98.41% | 82.68% | 99.06% | 84.68% | 90.47% |

As shown in Table 2, The performance of basic CNN and U-Net is very limited and produced low scores in all metrics. However, after adapting the resampling strategy with loss function U_Net was improved the performance Acc =95.88%, Sen=79.98%, Spe=98.23%, Pre=83.26%, F1=88.71% when balanced output is added to basic U-Net, improved classification performance compared to the Standard U_Net.

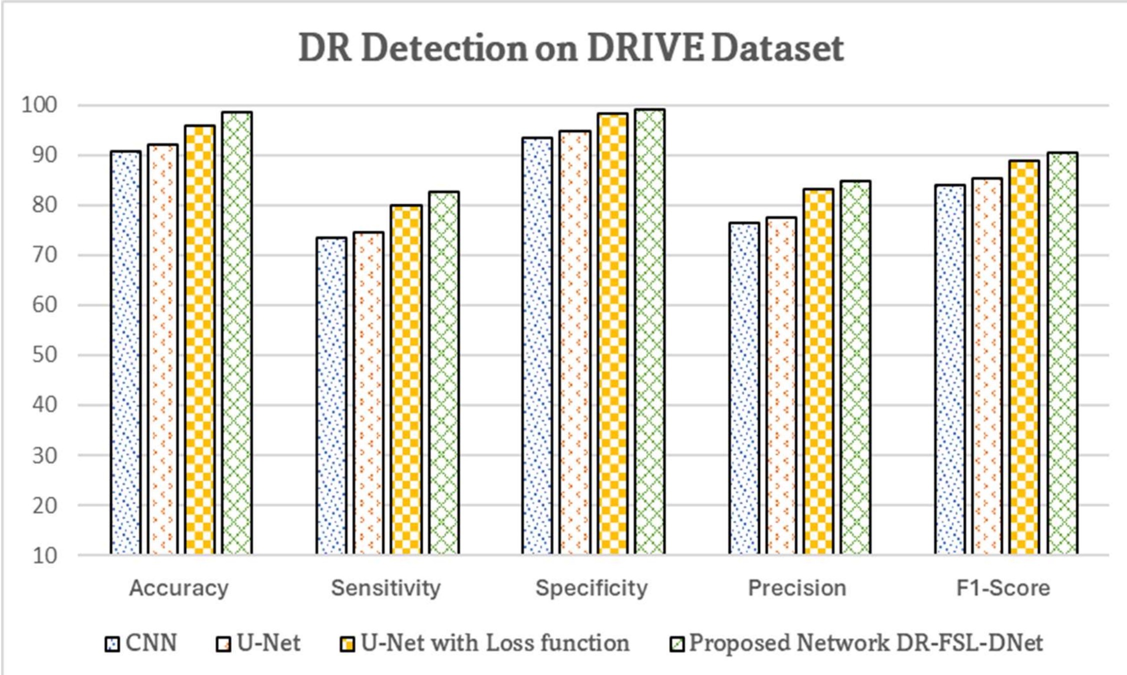


*Figure 6. Results of Deep Networks for DR Detection on DRIVE Dataset*

After adding the resampling and prototype network embedding to the deep network Acc =98.41%, Sen=82.68%, Spe=99.06%, Pre=84.68%, F1=90.47% are higher than U-Net with loss function and U-Net, respectively, which verifies the effectiveness of the meta-learning and FSL. It is shown that the proposed network is effective in DR classification performance, which shows their rationality and effectiveness. Therefore, the proposed method has advantages in DR classification. It shows from the last row of Table 2, that the values of Acc, Sen, Spe, Pre, and F1 of the suggested network are increased from standard CNN and U-Net variants respectively. Experiments show that using the resampling and prototype networks of the embedding module can improve the DR

*Table 3. Results of Deep Networks Techniques for DR Detection on STARE Dataset*

| Technique/Metric | Accuracy (Acc) | Sensitivity (Sen) | Specificity (Spe) | Precision (Pre) | F1-Score (F1) |
|---|---|---|---|---|---|
| CNN | 91.87% | 74.82% | 94.22% | 74.98% | 83.41% |
| U-Net | 93.46% | 78.26% | 94.80% | 77.43% | 86.88% |
| U-Net with Loss function | 98.11% | 84.41% | 99.89% | 83.58% | 91.03% |
| Proposed Network DR-FSL-DNet | 99.18% | 86.59% | 99.40% | 84.79% | 92.35% |

As shown in Table 3, The performance of basic CNN and U-Net is very limited and produced low scores in all metrics. However, after adapting the resampling strategy with loss function U_Net was improved the performance Acc =98.11%, Sen=84.41%, Spe=99.89%, Pre=83.58%, F1=91.03% when balanced output is added to basic U-Net, improved classification performance compared to the Standard U_Net

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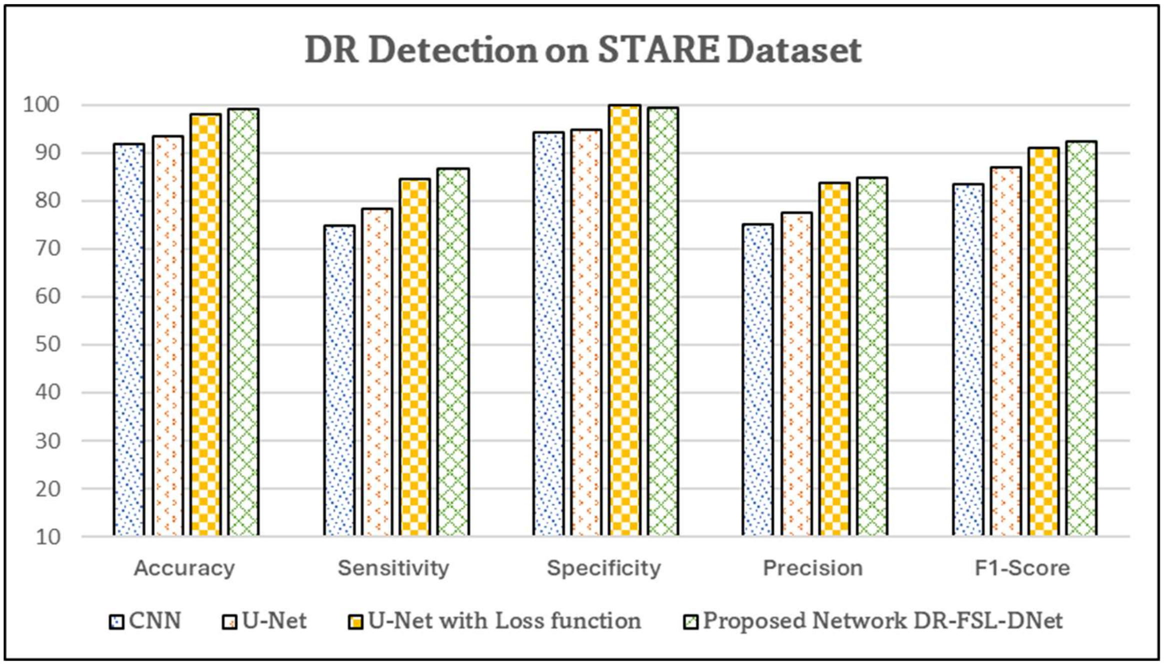


*Figure 7. Results Of Deep Networks For DR Detection On STARE Dataset*

After adding the resampling and prototype network embedding to the deep network Acc =99.18%, Sen=86.59%, Spe=99.40%, Pre=84.79%, F1=92.35% are higher than U-Net with loss function and U-Net, respectively, which verifies the effectiveness of the meta-learning and Few-shot learning. It is shown that the proposed network is effective in DR classification. It shows from the last row of Table 3, that the values of Acc, Sen, Spe, Pre, and F1 of the suggested network are increased from standard CNN and U-Net variants respectively. Experiments show that using the resampling and prototype networks of the embedding module can improve the DR classification performance, which shows their rationality and effectiveness. Therefore, the proposed method has advantages in DR classification.

*Table 4. Results Of Deep Networks Techniques For DR Detection On CHASEDB1 Dataset*

| Technique/Metric | Accuracy (Acc) | Sensitivity (Sen) | Specificity (Spe) | Precision (Pre) | F1-Score (F1) |
|---|---|---|---|---|---|
| CNN | 90.75% | 73.21% | 92.76% | 70.57% | 80.12% |
| U-Net | 91.21% | 76.34% | 94.99% | 72.01% | 82.30% |
| U-Net with Loss function | 95.11% | 80.58% | 99.41% | 78.20% | 86.77% |
| Proposed Network DR-FSL-DNet | 97.09% | 82.01% | 99.88% | 79.34% | 88.04% |

As shown in Table 4, The performance of basic CNN and U-Net is very limited and produced low scores in all metrics. However, after adapting the resampling strategy with loss function U_Net was improved the performance Acc =95.11%, Sen=80.58%, Spe=99.41%, Pre=78.20%, F1=86.77% when balanced output is added to basic U-Net, improved classification performance compared to the Standard U_Net.

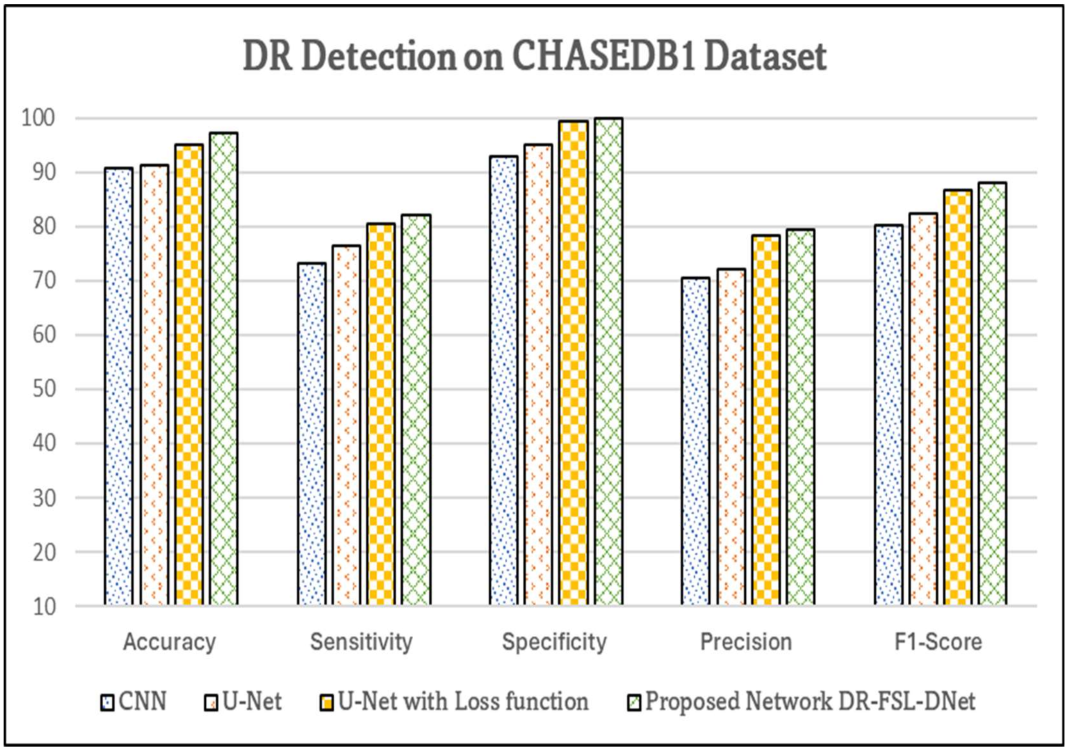


*Figure 8. Results Of Deep Networks For DR Detection On CHASEDB1 Dataset*

After adding the resampling and prototype network embedding to the deep network Acc =97.09%, Sen=82.01%, Spe=99.88%, Pre=79.34%, F1=88.04% are higher than U-Net with loss function and U-Net, respectively, which verifies the effectiveness of the meta-learning and Few-shot learning. It is shown that the proposed network is effective in DR classification. It shows from the last row of Table 4, that the values of Acc, Sen, Spe, Pre, and F1 of the suggested network are increased from standard CNN and U-Net variants respectively. Experiments show that using the resampling and prototype networks of the embedding module can improve the DR classification performance, which shows their rationality and effectiveness. Therefore, the proposed method has advantages in DR classification.

Five popular FSL algorithms, including the MAML [22], Prototype Net [23], Relation Net [24], and others, were chosen as the comparative algorithms in order to measure the superiority of our suggested approach. As the experimental findings in Table 5 demonstrate, our technique performed best on 2-way 1-shot and 5-shot for the DRIVE Dataset. In particular, our approach beat the cutting-edge technique by 5% and 7% in 1-shot and 5-shot, correspondingly. Similarly, the suggested strategy improves outcomes on 2-way 1-shot & 5-shot by 5% and 7% in 1-shot & 5-shot, correspondingly, in the STARE Dataset. Results generated on 2-way 1-shot and 5-shot by the suggested method are improved by 5% and 7% in 1-shot & 5-shot, correspondingly, in the CHASEDB1 Dataset.

*Table 5. The Accuracy Comparison Of Different Methods On The Three Datasets.*

| Dataset | Method | MAML | Prototype Net | Relation Net | Proposed |
|---|---|---|---|---|---|
| DRIVE | 1-shot | 65.34 ±2.35% | 68.71±3.38% | 74.61±2.19% | 76.69±1.92% |
| | 5-shot | 74.43±3.08% | 74.81±3.22% | 74.92±3.20% | 82.03±2.87% |
| STARE | 1-shot | 66.35± 1.75% | 66.35± 1.14% | 68.45± 1.32% | 73.66±1.10% |
| | 5-shot | 70.19± 2.03% | 71.24± 2.05% | 74.79± 2.01% | 81.52±1.91% |
| CHASEDB1 | 1-shot | 60.81± 1.61% | 61.39± 1.81% | 65.67± 1.61% | 70.95±1.54% |
| | 5-shot | 68.77± 2.42% | 72.98± 2.33% | 60.35 ± 2.14% | 77.25±2.09% |

Table 5 displays the experimental findings on the three datasets, demonstrating the superior performance of our strategy above all other approaches. Table 5 displays the outcomes obtained from the DRIVE dataset. Our approach yielded the best results, with the highest accuracy and the lowest

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confidence interval. A similar performance is produced in the other two datasets also.

## 6. CONCLUSION

A novel network (i.e., DR-FSL-DNet) using few-shot-based resampling is done for effective DR detection and classification. The proposed network is focused on solving class and task imbalance faced in training with focused loss and prototype networks. The FSL that utilizes a relatively smaller number of training images to guide the DR classification resulted in effective performance. The structure utilizes episodic learning to train its model on few-shot classification tasks. Applied resampling technique (i.e., Focus Loss function) to balance data and classes in training data. Finally, a prototype meta-learning network is applied for DR detection and classification. On public datasets DRIVE, STARE, and CHASEDB1, the proposed network DR-FSL-DNet is applied and comparing it with state-of-modern-art works. The experiment shows that DR-FSL-DNet contribute to the desirable performance to DR classification. The proposed network outperforms compared to standard methods and achieved better scores in Accuracy, Sensitivity, Specificity, Precision, and F1-Score metrics.

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