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DRGNet: Diabetic Retinopathy Grading Network Using Data Balancing Integrated Transfer Learning with Graph-based KNN Classification

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Abstract: Diabetic retinopathy (DR) is a prevalent and potentially blinding eye disease that affects individuals with diabetes. On the other hand, internet of medical things (IoMT) incorporation into DR grading classification offers a promising future for the field of eye health. It optimizes the diagnostic process, increases accessibility to healthcare services, and ultimately improves patient care and outcomes. Therefore, accurate and timely grading of DR severity is crucial for effective disease management. In this article, DR-grading network (DRG-Net) is proposed, which is a comprehensive approach for DR labels classification using the indian diabetic retinopathy image dataset (IDRiD) dataset. To address the imbalanced nature of the dataset, synthetic minority over-sampling technique (SMOTE) is employed for data balancing, ensuring representative samples for each severity level. Then, transfer learning based residual network-50 (ResNet50) architecture is used to extract features from SMOTE outcome, which is a deep learning model renowned for its ability to learn complex image representations. Finally, graph-based K-nearest neighbours (GKNN) classification which utilizes the spatial relationships between samples to make informed decisions, considering the similarity of retinal images in a graph-based representation is introduced for enhanced grading classification of DR. The simulation results show that, the proposed DRG-Net resulted in improved performance as compared to state-of-the-art approaches such as MSA-ResNetGB, DLCNN-MGWO-VW, OHGCNet, and E-DenseNet BC-121 with an accuracy of 99.93%, and F1-score of 99.85%.

Keywords: Diabetic retinopathy, Synthetic minority over-sampling technique, Residual network, Convolution neural network, Graph-based k-nearest neighbours.

1. Introduction

DR is a common complication of diabetes that affects the eyes and can lead to vision loss or blindness if left untreated. Early detection and accurate classification of DR are crucial for timely intervention and effective management of the condition [1]. The traditional approach to diagnosing DR involves manual examination of retinal images by ophthalmologists, which can be time-consuming and subjective. However, with the advent of the internet of medical things (IoMT) [2], there is an opportunity to leverage interconnected devices and technologies to automate and improve the DR classification process. The manual classification of DR is a labour-intensive and error-prone process that can be challenging for ophthalmologists to perform consistently and accurately [3]. Additionally, the growing prevalence of diabetes worldwide has resulted in an increasing number of patients requiring regular screening for DR, putting a strain on healthcare systems. Therefore, there is a need for a reliable and efficient solution to automate the DR classification process, allowing for early detection and timely treatment.

IoMT enables the integration of retinal imaging devices with internet connectivity. These devices can capture high-resolution images of the patient's retina and transmit them in real-time to a cloud-based platform [4]. This allows for remote access by ophthalmologists, who can then review the images and classify the presence and severity of DR. Wearable devices such as smart glasses or contact lenses equipped with sensors can continuously monitor various parameters related to the eyes, such as intraocular pressure, blood flow, or glucose levels. These sensors can provide valuable data for early detection and monitoring of DR [5]. The collected data can be transmitted wirelessly to a centralized system, where it can be analysed using machine learning algorithms for DR classification. IoMT facilitates remote consultations between ophthalmologists and patients. Through video conferencing and secure data transmission, ophthalmologists can remotely assess retinal images or sensor data and provide timely guidance or treatment recommendations. This can improve access to specialized care, especially in rural or underserved areas where ophthalmologists were scarce. Finally, IoMT can support ophthalmologists by providing decision support systems that analyse patient data and generate personalized recommendations for DR management [6]. These systems can assist in treatment planning, monitoring disease progression, and suggesting appropriate interventions based on evidence-based guidelines.

Data analytics and machine learning based DR, a vast amount of data can be collected from various sources, including retinal images, patient health records, and sensor data. Machine learning algorithms can be trained on this data to develop accurate classification models for DR. These models can then be deployed on edge devices or cloud platforms to provide real-time classification results, allowing for prompt medical interventions when necessary. Machine learning algorithms [7] can be trained on large datasets of labelled retinal images to develop accurate classification models for DR. These models learn from patterns and features present in the data, enabling them to distinguish between healthy retinas and those affected by DR. The training process involves feeding the algorithms with labelled images, where the ground truth diagnosis is known, and the algorithms adjust their internal parameters to optimize their performance. Once trained, these machine learning models can be deployed on edge devices or cloud platforms, enabling real-time classification of retinal images [8]. Edge devices such as smartphones or portable devices equipped with image sensors can analyse retinal images on-site, without the need for a stable internet connection. This capability is particularly beneficial in remote areas or regions with limited healthcare infrastructure. On the other hand, cloud platforms provide scalability and computational power, allowing for the analysis of large volumes of retinal images in a short period. This approach can be useful in busy clinics or hospitals, where multiple images need to be processed simultaneously. Cloud-based solutions can also facilitate collaboration and data sharing among healthcare professionals, improving the accuracy and efficiency of DR diagnosis [9]. By leveraging data analytics and machine learning, healthcare providers can harness the power of big data to improve the detection, diagnosis, and management of DR. The integration of these technologies can lead to faster and more accurate diagnosis, timely interventions, and ultimately, better patient outcomes [10].

However, it is important to ensure the privacy and security of patient data when implementing these solutions, adhering to ethical and legal standards to maintain patient trust and confidentiality. The novel contributions of this work are as follows:

- The SMOTE data balancing technique is used to mitigating class imbalance issues and improving overall classification performance.
- Additionally, the ResNet50 feature extraction method yields rich and discriminative representations, enabling accurate classification of DR severity.
- The GKNN algorithm utilizes the spatial relationships between samples to make informed decisions, considering the similarity of retinal images in a graph-based representation.

Rest of this article is organized as follows: section 2 contains various existing DR grading methods, section 3 contains the detailed analysis of DRG-Net with SMOTE data balancing, ResNet-50 feature extraction, and GKNN classification. Section 4 contains the detailed analysis of simulation results, and section 5 concludes the article.

2. Related work

In [11], the authors proposed a deep learning approach for the joint classification of DR and diabetic macular edema (DME) using a modified grey-wolf optimizer with variable weights. The method utilized a convolutional neural network (CNN) for feature extraction and classification. However, the performance heavily depends on the choice of optimizer and weight configurations, which can be time-consuming and challenging to optimize. In [12], the authors presented a hybrid graph convolutional network model called OHGCNet for the joint classification of DR and DME. The model incorporated optimal feature selection to improve classification performance. However, the OHGCNet requires constructing and processing the graph structure, which can be computationally expensive for large datasets.

Mohanty, et al. [13] proposed a gradient boosting CNN for the classification of DR grades. They aimed to improve the accuracy of the classification model by incorporating attention mechanisms at multiple scales. Xiaoxue et al. [14] presented a multi-task learning and multi-branch network for joint grading of DR and DME. Their work aimed to improve the accuracy and efficiency of DR and DME grading. Eman et al. [15] developed a computer-aided diagnosis system for detecting various grades of DR based on a hybrid deep learning technique. Their approach combined different deep learning models to achieve accurate classification. Zhang [16] proposed a deep graph correlation network for DR grading on retinal images without manual annotations. Their approach aimed to improve the efficiency and reduce the reliance on manual annotations. Miao et al. [17] proposed a fine-grained attention and knowledge-based collaborative network for DR grading. Their approach aimed to incorporate both attention mechanisms and knowledge-based collaboration to improve the accuracy of the grading system. Mohamed et al. [18] proposed a feature extraction method using encoded local binary patterns for the detection and grading of DR. The approach aimed to capture discriminative features from retinal images. Jena et al. [19] presented a novel approach for DR screening using asymmetric deep learning features. Their work aimed to improve the accuracy and efficiency of DR screening.

In [20], the authors presented a multi-scale attention-based mechanism integrated into a gradient boosting CNN for the classification of DR grades. The proposed model focused on capturing important features at multiple scales to improve the classification accuracy. However, the multi-scale attention mechanism increases the model's complexity and may require more computational resources for training and inference. In [21], the authors introduced modified residual networks for the severity stage classification of DR. The modified residual networks aimed to capture and utilize both low-level and high-level features for improved classification performance. However, the modified residual networks may suffer from the vanishing gradient problem, especially when the network becomes deeper, which can affect the training convergence and overall performance. In [22], the authors' paper presented GO-DBN, a Gannet optimized deep belief network based wavelet kernel extreme learning machine (ELM) for the detection of DR. The model combined deep belief networks and wavelet kernel ELM to enhance the detection accuracy. However, the integration of multiple techniques may introduce additional hyperparameters, making the model more complex to optimize and prone to overfitting. In [23], the authors proposed a hinge attention network, which was a joint model for DR severity grading. The model leveraged attention mechanisms to focus on informative regions in retinal images and accurately classify the severity levels of DR. However, the performance heavily relies on the effectiveness of the attention mechanism, which may struggle to capture subtle features or variations in certain cases.

In [24], the authors presented an AI-based automatic detection and classification system for DR using U-Net and deep learning. The U-Net architecture was employed for accurate segmentation and classification of retinal images. However, the U-Net architecture, while effective for segmentation tasks, may not capture high-level features and contextual information as effectively for classification, potentially limiting its overall performance. In [25], the authors introduced UNIConv, an enhanced U-Net based on the InceptionV3 convolutional model for semantic segmentation of DR in retinal fundus images. The proposed model utilized the U-Net architecture with additional enhancements from the InceptionV3 model to improve the accuracy of semantic segmentation. However, the enhanced U-Net may require more computational resources and training data compared to the standard U-Net architecture, which can be a limitation in resource-constrained settings.

3. Proposed methodology

DR grading plays a crucial role in assessing the severity of the disease and guiding appropriate treatment strategies. The proposed DRG-Net in this study aims to address the challenges associated with DR grading using the IDRiD dataset. Fig. 1 shows the proposed DRG-Net block diagram. The primary objective is to accurately grade the severity of DR, considering its imbalanced nature. To address this issue, the SMOTE is employed to balance the dataset, ensuring that each severity level has representative samples. The next step in the proposed approach is feature extraction using the ResNet50 architecture, which is a transfer learning-based deep learning model. ResNet50 is known for its ability to learn complex image representations by utilizing residual connections. By applying this model to the SMOTE-balanced dataset, the researchers aim to extract high-level features that capture discriminative patterns

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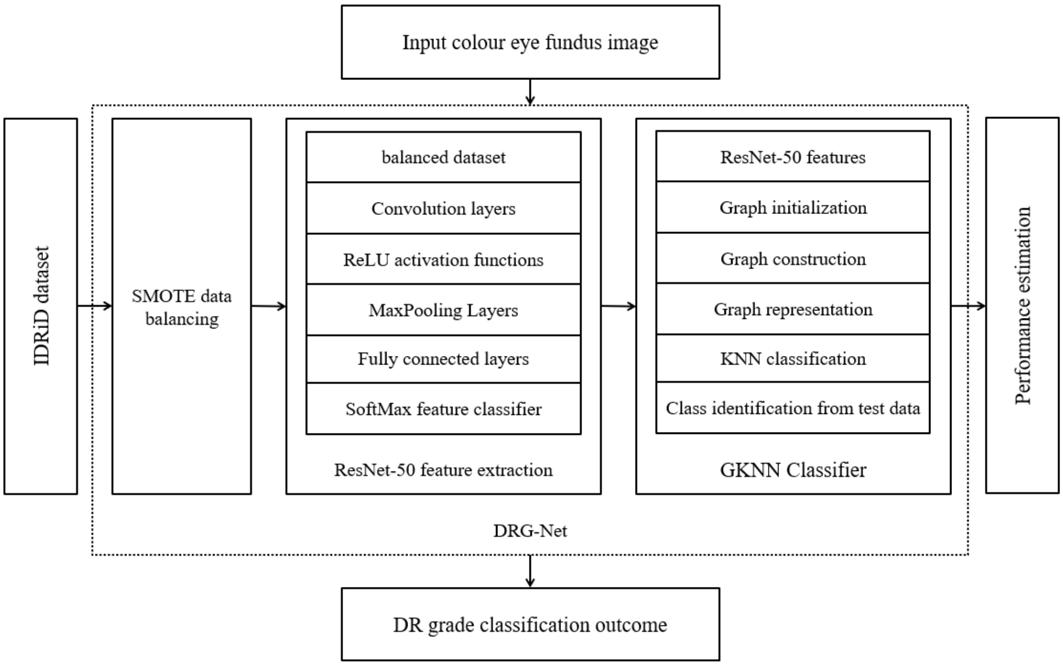

Figure. 1 Proposed DRG-Net block diagram

associated with different stages of DR. Furthermore, the study introduces the GKNN classification algorithm to effectively grade DR. The GKNN algorithm considers the spatial relationships between samples by considering the similarity of retinal images in a graph-based representation. This approach leverages both the intrinsic characteristics of retinal images and the learned features from ResNet50, leading to enhanced classification performance.

Finally, the combination of SMOTE data balancing, ResNet50 feature extraction, and GKNN classification offers several advantages. The SMOTE technique addresses the imbalanced nature of the IDRiD dataset, ensuring that the model is trained on a representative distribution of each severity level. The ResNet50 architecture enables the extraction of rich and discriminative features from the SMOTE-balanced dataset, allowing for a more comprehensive representation of DR patterns. Finally, the GKNN algorithm utilizes the spatial relationships between samples to make informed decisions, taking advantage of the graph-based representation and further enhancing the classification accuracy.

3.1 Data balancing SMOTE

A resolution to the issue of class imbalance was given by Chawla et al. in the form of a heuristic oversampling approach called SMOTE. Fig. 2 shows the SMOTE data balancing block diagram. It has significantly solved the problem of over-fitting, which was produced by the non-heuristic random oversampling technique; as a result, it has found considerable application in the field of class imbalance in the recent years. SMOTE is based on the principle of inserting new samples that are produced randomly between minority class samples and their neighbours. This can both improve the situation regarding class imbalance as well as increase the quantity of samples coming from underrepresented groups in the population. If the dataset has a sampling magnification of N, N samples are selected at random from the KNN (there must be more than N neighbours total), and the N samples that were selected are recorded as $y_1, y_2, \dots, y_N$.

The data samples X and y_i are correlated, and the associated random interpolation operation is carried out using the correlation formula between X and y_i $(i = 1,2, \dots, N)$ to create the interpolated sample pi. The data samples X and y_i are correlated to generate the interpolated sample p_i. This enables the generation of N matching minority class samples for each data sample that is collected. The formula for interpolation is provided below in the following format:

$$p_i = X + rand(0,1) \times (y_i - X), i = 1,2, \dots, N \quad (1)$$

Here, X is a data sample obtained from the minority class samples, rand (0,1) is a random integer generated from the range (0,1). The y_i is the i^{th} of the KNN of the data sample X. The degree of imbalance present in the dataset will determine the

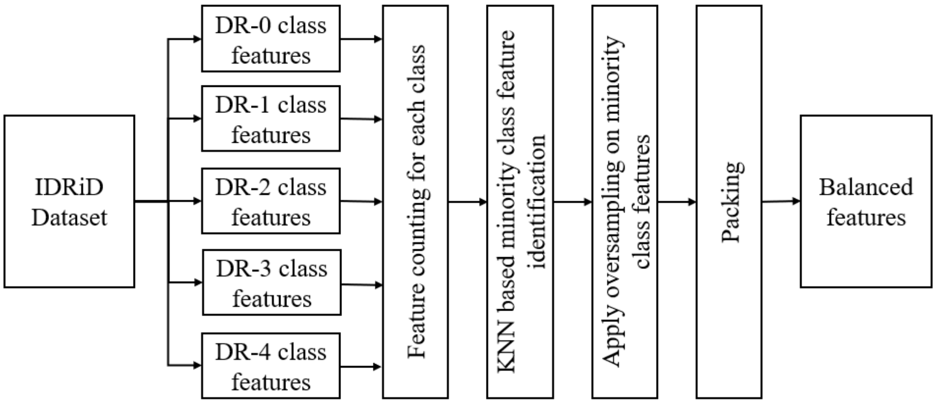

Figure. 2 SMOTE data balancing approach with IDRiD dataset

sample magnification, which is indicated by the letter "N." The formula that must be used to determine the imbalance level (IL) between the majority class and the minority class of the dataset is shown below.

$$N = round(IL) \tag{2}$$

Here, round (IL) is the value that is obtained by bringing the IL up to the next whole number after it has been rounded down.

By performing the interpolation process, it is feasible to achieve a satisfactory equilibrium between the samples taken from the majority class and those taken from the minority class, which ultimately leads to an improvement in the classification accuracy of unbalanced datasets. It is assumed that there is a two-dimensional dataset, and one of the data sample points X is taken from it. The coordinates for this point in the dataset are (8,4). A random value of 0.5 has been assigned to the $rand$ (0,1) variable, and the coordinates of a nearby sample point of X have been assigned the values (2,6). The findings are attainable by using Eqs. (1, 2), as shown below:

$$p_3 = X + rand(0,1) \times (y_3 - X) \tag{3}$$

To put it another way, the freshly created interpolation is denoted by p_3. The procedure of interpolation that is used to produce new data is shown on an axis that only has two dimensions. During the process of sampling for SMOTE, it is revealed that a random interpolation operation on the line between the data sample and its nearest neighbour is taking place, as can be seen in the picture. This approach was thought of as a linear interpolation, but in comparison to the straightforward duplication of the original data samples, its influence has been significantly strengthened and shows significant improvement.

3.3 ResNet50 for feature extraction

The ResNet50 is DLCNN model, which removes some layers of its network by means of skip connections. Fig. 3 shows the ResNet50 layers architecture. The vanishing gradients issue in the DLCNN is helped to be solved and the amount of time spent training is reduced using skip connections. In between the layers that were skipped, non-linear activation functions are used. In addition to this, batch normalization is carried out between the shortcut connections. It is necessary to make use of a weight matrix to compute the weights of the jump connections. The fundamental component of a ResNet is seen in Fig. 4.

Various iterations of the residual block are use in various places around the network. The mapping from x to $f(x)$ is something that is learnt in a DLCNN. A feed-forward neural network is responsible for the mapping in the basic block of the residual network. This network has shortcut connections that are referred to as jump or skip connections; the formula for these connections is $x = f(x) + g(x)$. If the output dimensions and the input dimensions are the same, then the function $g(x)$ is an identity connection. If they are not the same, then zero padding is applied. Eq. (4) was used to determine the residual block for the network's stacked layers with the same dimensions.

$$y = f(x, w_i) + x \tag{4}$$

The function $f(x, w_i)$ is the representation of the convolution layer mapping that is found when the model is being trained. A fully connected layer is used in the end of the ResNet50 CNN that was provided with SoftMax classifier. It extracts the features from the SMOTE data balanced images.

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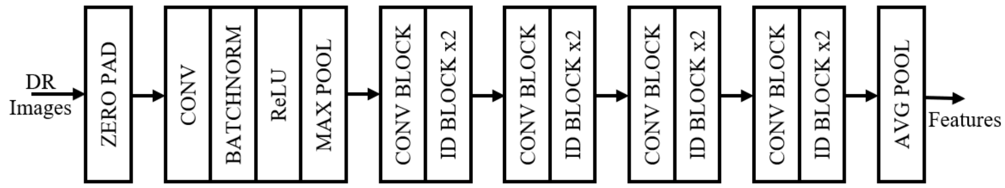

Figure. 3 ResNet50 feature extraction

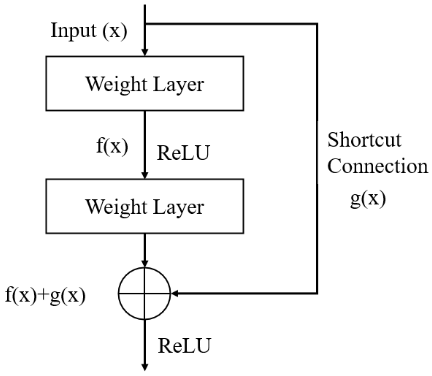

Figure. 4 Building block of a ResNet

3.4 GKNN classification

The GKNN algorithm is a non-parametric classification algorithm that determines the class of a sample by looking at the classes of its neighbouring samples in a graph representation of the dataset. It is a simple yet powerful algorithm for classification and can also be used for regression tasks. Fig. 5 shows the GKNN block diagram. Here is a detailed analysis of the GKNN algorithm:

Step 1 - Apply DGCN features: The GKNN algorithm requires a dataset consisting of samples and their corresponding class labels. Each sample in the dataset is represented by a feature vector. The algorithm assumes that the dataset is labelled, meaning each sample is associated with a known class label.

Step 2 - Graph construction: The first step in the GKNN algorithm is to construct a graph representation of the dataset. Various methods can be used to construct the graph, epsilon-nearest neighbours, or fully connected graphs. The choice of graph construction method depends on the characteristics of the dataset and the problem at hand.

Step 3 - Graph representation: Once the graph is constructed, each sample in the dataset becomes a node in the graph. The edges of the graph connect neighbouring samples based on their similarity or proximity in the feature space. The graph can be represented as an adjacency matrix or an adjacency list.

Step 5 - KNN classification: To classify a new, unlabelled sample using the GKNN algorithm, the following steps are performed:

- Calculate the similarity or distance between the new sample and all the labelled samples in the dataset.
- Select the KNN based on the similarity or distance metric.
- Determine the class label of the new sample by a majority vote or weighted voting among its KNN. Each neighbour's vote is weighted based on its proximity to the new sample.

Step 6 - Choice of K: The parameter K in KNN represents the number of nearest neighbours considered during classification. The selection of K depends on the dataset and the problem domain. A smaller value of K may lead to more local decision boundaries, while a larger value of K may result in smoother decision boundaries but could introduce more bias. The choice of K can be determined through cross-validation or other model selection techniques.

Step 7: Distance metrics: The GKNN algorithm relies on distance metrics to calculate the similarity or proximity between samples. Commonly used distance metrics include Euclidean distance.

Step 8 - Output: The smallest distance indicates maximum similarity between test data and trained samples, which resulted in the classification outcome.

4. Results and discussion

This section gives the detailed analysis of simulation results. Further, the performance of proposed method is compared with existing methods using IDRiD dataset.

4.1 Dataset

The IDRiD is used to evaluate the experimental outcomes of DR detection in the proposed framework [26]. A significant concern with publicly available healthcare datasets is their scarcity, which limits the options for the research community. Consequently, researchers often must rely on the few available datasets, leading to a lack of variability in the types

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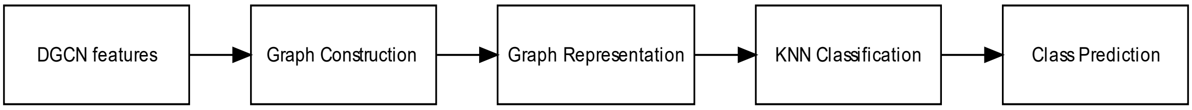

Figure. 5 GKNN classifier block diagram

of applications that can be developed. Moreover, models developed based on such datasets may not be suitable for generalized widescale applications. Therefore, it is crucial to extensively characterize the data to assess the quality of such datasets for researchers and model developers. This characterization involves a thorough breakdown of the features present in the dataset. In this context, the IDRiD dataset has been critically examined in the current study. The IDRiD dataset comprises 516 retinal fundus images, which are categorized into three groups: segmentation, clinical grading, and localization of the images. The segmentation process includes 81 authentic colour fundus images, while the localization and disease-grading process involve 516 authentic colour fundus images.

The quality metrics used to evaluate the proposed model includes four metrics such as true positive (TP), false positive (FP), true negative (TN), and false negative (FN).

Accuracy: Accuracy is the ratio of the number of correct predictions to the total number of predictions made by the model.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + TN + FN)} \tag{16}$$

Precision: Precision is the ratio of the number of true positives to the total number of positive predictions made by the model.

$$Precision = \frac{TP}{(TP + FP)} \tag{17}$$

Recall: Recall is the ratio of the number of true positives to the total number of actual positive instances

$$Recall = \frac{TP}{(TP + FN)} \tag{18}$$

F1-Score: The F1-score is the harmonic mean of precision and recall. It provides a balanced measure of both precision and recall.

$$F1 - Score = 2 * \frac{(precision * recall)}{(precision + recall)} \tag{19}$$

4.2 Subjective analysis

In Fig. 5, the prediction results of the DRG-NET Model for various eye fundus images are presented. The estimated predicted probabilities (EPP) are measured for each eye fundus image. These EPP values are arranged in a row matrix format, such as {Normal, Mild NPDR, Moderate NPDR, Severe NPDR, PDR}, representing the probability values for each category. To determine the predicted outcome, the maximum value in the EPP matrix for each image is considered. For instance, if the EPP is {0.8, 0.03, 0.03, 0.03, 0.01}, the maximum value of 0.8 is in the first position, indicating that the predicted outcome is normal for that image. Furthermore, Fig. 5 (a), Fig. 5 (b), Fig. 5 (c), Fig. 5 (d), and Fig. 5 (e) specifically display the predicted outcomes for the grades of Normal, Mild NPDR, Moderate NPDR, severe NPDR, and PDR, respectively.

4.3 Objective analysis

Table 1 shows the performance comparison of various DR grading classifiers. Here, the proposed DRG-Net resulted in superior performance as compared to MSA-ResNetGB [13], DLCNN-MGWO-VW [11], OHGCNet [12], and E-DenseNet BC-121 [15]. Compared to DLCNN-MGWO-VW [11], the proposed DRG-Net achieves a higher accuracy of 99.93%, surpassing it by 7.7%, while exhibiting a slightly lower precision of 98.49% by 1.2%, a higher recall of 99.95% by 6.74%, and a higher F1-Score of 99.85% by 5.22%. Compared to MSA-ResNetGB [13], the proposed DRG-Net demonstrates a significant improvement in accuracy, achieving 99.93% accuracy compared to 94.17% of MSA-ResNetGB [13]. Compared to OHGCNet [12], the proposed DRG-Net achieves a slightly lower accuracy of 99.93% compared to 98.67% of OHGCNet [12], but exhibits higher precision, recall, and F1-Score by 0.37%, 1.19%, and 1.18%, respectively. Compared to E-DenseNet BC-121 [15], the proposed DRG-Net achieves a higher accuracy of 99.93% compared to 93.0% of E-DenseNet BC-121 [15], while exhibiting a significantly higher sensitivity of 99.56% by 2.86%.

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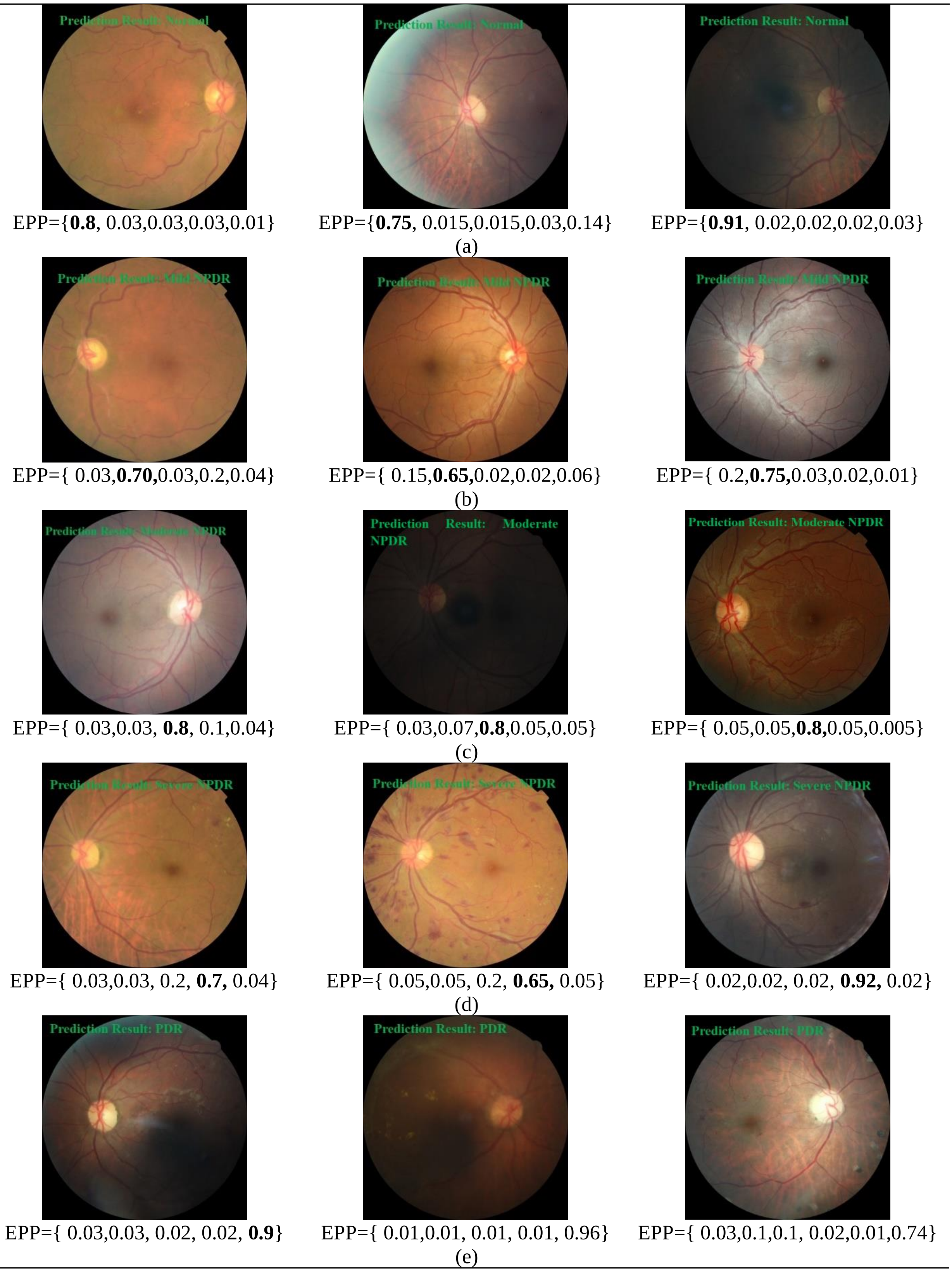

Figure. 5 Prediction results of DRG-NET model: (a) Predicted oucomes as normal, (b) Predicted oucomes as Mild NPDR, (c) Predicted oucomes as moderate NPDR, (d) Predicted oucomes as severe NPDR, and (e) Predicted oucomes as PDR

Table 1. Performance comparison of various DR grading classifiers.

Metric	MSA-ResNetGB [13]	DLCNN-MGWO-VW [11]	OHGCNet [12]	E-DenseNet BC-121 [15]	Proposed DRG-Net
Accuracy	94.17	92.23	98.67	93.0	99.93
Precision	91.48	96.69	99.04	-	98.49
Recall	91.57	93.21	98.76	-	99.95
F1-Score	91.45	94.63	98.88	-	99.85
Sensitivity	-	-	-	96.7	99.56
Specificity	-	-	-	72.0	99.19

Table 2. Performance comparison of various DR grading classifiers on messidor dataset

Metric	DGCN [16]	FA-Net [17]	ULBPEZ [18]	ADLF [19]	Proposed DRG-Net
Accuracy	91.8	94.10	98.37	94.80	99.14
Precision	-	95.7	96.2	89.86	99.15
Recall	-	90.0	98.08	87.04	99.19
F1-Score	-	92.8	98.08	88.23	99.99
Sensitivity	90.2	-	100.0	-	99.99
Specificity	93.0	-	97.2	95.67	99.98

4.4 Case study

Table 2 shows the performance comparison of various DR grading classifiers on Messidor dataset. Here, the DRG-Net resulted in superior performance than the existing DGCN [16], FA-Net [17], ULBPEZ [18], and ADLF [19]. Compared to DGCN [16], the Proposed DRG-Net achieves a higher accuracy of 99.14% compared to 91.8% of DGCN [16], while having a slightly higher precision, recall, and F1-Score by 3.45%, 9.19%, and 7.19%, respectively. Compared to FA-Net [17], the proposed DRG-Net demonstrates higher accuracy, precision, recall, and F1-Score by 4.04%, 3.45%, 0.8%, and 7.19%, respectively. Compared to ULBPEZ [18], the Proposed DRG-Net achieves a slightly lower accuracy of 99.14% compared to 98.37% of ULBPEZ [18], but exhibits higher precision, recall, and F1-Score by 2.95%, 0.11%, and 1.91%, respectively. Compared to ADLF [19], the Proposed DRG-Net shows a higher accuracy, precision, recall, and F1-Score by 4.34%, 9.29%, 12.15%, and 11.76%, respectively. The Proposed DRG-Net achieves a significantly higher sensitivity of 99.99% compared to 90.2% of DGCN [16] and exhibits higher specificity by 6.98% compared to 93.0% of DGCN [16].

4 Conclusion

This work proposed the DRG-Net as a comprehensive approach for the classification of DR labels using the IDRiD dataset. The imbalanced nature of the dataset was addressed by employing the SMOTE, which ensured representative samples for each severity level. Then, the transfer learning based ResNet50 architecture to extract features from the SMOTE outcome. ResNet50 is a deep learning model known for its ability to learn complex image representations. Additionally, the GKNN classification algorithm was employed for effective grading of DR. This algorithm utilized the spatial relationships between samples, considering the similarity of retinal images in a graph-based representation. The simulation results demonstrated that the proposed DRG-Net outperformed other approaches in terms of various metrics such as accuracy, precision, recall, F1-score, sensitivity, and specificity. The improved performance of DRG-Net suggests its effectiveness in accurately classifying DR labels in the IDRiD dataset. In the future, this could involve experimenting with different graph learning models, optimization models to potentially improve feature extraction and classification accuracy.

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

“Conceptualization, Swetha Presaru; methodology, Swetha Pesaru; software, Swetha Pesaru; validation, Swetha Pesaru; formal analysis Swetha Pesaru; investigation, Swetha Pesaru; resources, Swetha Pesaru; data curation, Swetha Pesaru; writing—original draft preparation, Swetha Pesaru; writing—review and editing, Swetha Pesaru, B Vishnu Vardhan; visualization, Swetha Pesaru; supervision, Naresh K Mallenahalli, B Vishnu Vardhan; project administration, B Vishnu Vardhan;

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