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Research Article

Optimizing Diabetic Retinopathy Classification with Transfer Learning: A Lightweight Approach Using Model Clustering

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ABSTRACT

Accurate and rapid classification of diabetic retinopathy is critically significant in order to prevent vision loss. The advent of artificial intelligence introduces novel and potent methodologies for enhancing the classification of diabetic retinopathy as derived from medical imaging. Due to the large size of the model make it unsuitable in real world. This research paper is dedicated to the classification of diabetic retinopathy utilizing constrained resources while achieving elevated accuracy levels. We implemented weighted clustering technique within deep convolutional neural networks and transfer learning architectures: VGG 19, DenseNet 121, and EfficientNet B6. To mitigate the challenge posed by considerable model sizes without sacrificing accuracy, the best fit results were observed with EfficientNet-B6, where applying weighted clustering reduced the model size by a factor of 12 while maintaining high accuracy results of 92% for the APTOS-2019 data. This underscores the efficacy of employing lightweight techniques to enhance the practicality of extensive models for the early diagnosis of diabetic retinopathy.

***Keywords:* Diabetic Retinopathy; deep convolutional neural network; transfer learning; weighted clustering**

1. INTRODUCTION

This Diabetes mellitus represents a persistent metabolic condition delineated by the inadequate secretion of insulin by the pancreas or the organism's incapacity to effectively utilize insulin. Prolonged duration of this condition may precipitate significant health complications, one of which is diabetic retinopathy, a prevalent sequel that can profoundly impair visual acuity. [1] The principal etiological factor contributing of diabetes is the elevation of blood glucose concentrations, which, when sustained over prolonged durations, may inflict damage upon the vascular structures of the retina. Diabetic retinopathy (DR) does not elicit visual disturbances during its initial phases. The optimal strategy for safeguarding the patient's visual acuity necessitates prompt diagnosis and appropriate intervention [2].

Typically DR is classified into various grades, no DR, mild NPDR, moderate NPDR, severe NPDR, and PDR [3]. Each stage serves as an indicator of the disease's severity and the degree of retinal damage incurred. As the severity of diabetic retinopathy is directly associated with the retinal lesions. Such lesions may encompass microaneurysms, hemorrhages, and exudates, which exhibit an increased occurrence as the disease advances [4].

In light of advancements in Artificial Intelligence, technology autonomously evaluates the health status of patients and swiftly diagnoses issues by utilizing medical images. Diabetic Retinopathy represents one such condition that this article endeavors to explore [5]. CNN, represent a category of deep learning architectures characterized by multiple

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layers of interconnected neurons. Each neuron within a given layer exhibits connections to all neurons within the subsequent layer [6]. CNN have capability to autonomously acquire sophisticated feature information of images, and have demonstrated commendable efficacy in the domain of image classification [7], the development of models that are both robust and precise presents' considerable challenges in the context of medical issues. Transfer Learning effectively addresses this challenge, specifically by enhancing the learning process in one task through the transference of knowledge acquired from a previously learned task. Nonetheless, this approach will be significantly more expedient and accurate than initiating the training process from the ground up [8].

The principal contributions of this proposed system can be given as follows:

1. Class Balancing: Enhance dataset performance by balancing class distribution through augmentation techniques, optimizing model training.

2. Data Preprocessing: Standardize image data with resizing and Gaussian blur, employing weighted masking for edge enhancement, ensuring improved image clarity.

3. Deep Learning Classification: Employ state-of-the-art models like VGG19, DenseNet121, and EfficientNetB6 for precise retinopathy classification, ensuring high efficiency and accuracy.

4. Lightweight Techniques: Implement clustering weight to streamline model size while preserving classification accuracy, facilitating deployment on resource-limited devices.

The work is organized as follows. Related work for clustering classification are discussed in Section 2. Section 3 describes the proposed system design. Methodology description in section 4. Weight clustering in section 5. The evaluation criteria and results are discussed in Section 6.Finally, the work is concluded in Section 7.

2. RELATED WORK

In this section, many related works to this study are reviewed:

Vasantrao et al. [10] provide approach for heart diagnosis utilizing a weighted clustering technique. The current methodologies for heart diagnosis formulate a decision by examining the correlation between the feature vector of the query sample and the pre-existing knowledge within the system. For the execution of the proposed research, the Cleveland Dataset has been employed. The results indicate that the weighted clustering methodology not only augments the accuracy and sensitivity associated with the heart disease diagnosis but also enhances processing efficiency in comparison to prevailing techniques

Huang et al. [11] provide a framework possesses the capability to collaboratively assimilate the hierarchical semantics acquired by each respective layer. The instances belonging to the same category are systematically compelled to converge progressively in a low-dimensional space, which proves advantageous for the ensuing clustering endeavor. Several datasets used Handwritten (HW), 3 sources, BBC, BBCSport, CiteSeer, and Reuters the model achieves accuracy 80.35 when the layer size p is searched (50 C) by using HW dataset

Li et al. [12] present a sophisticated framework that integrates clustering methodologies with deep learning techniques to forecast stock prices utilizing three well-established deep learning predictive models. They used three deep learning models (LSTM, RNN, and GRU) for the purpose of stock prices prediction. The dataset stock prices from the public data platform Kaggle. LSTM model provide best predictive capabilities in comparison to the other models when it comes to forecasting stock prices.

Sharma et al.[13] proposed a comprehensive framework that organizes the patches derived from a whole slide image (WSI) into k distinct groups, subsequently samples k′ patches from each designated group for the purpose of training, and employs an adaptive attention mechanism to facilitate slide-level predictions; Cluster-to-Conquer (C2C). Many datasets used Celiac Disease Dataset, CAMELYON16 Dataset, MNIST-bag Dataset, and Gastrointestinal Dataset. Best accuracy obtained with C2C 86.2.

.Dang et al [14] introduced an innovative deep clustering paradigm that focuses on the extraction of semantically proximate neighbors at both local and global level, referred to as nearest neighbor matching (NNM). They used CIFAR-10 and CIFAR-100 and STL-10. NNM showed a 3.7% improvement in performance with CIFAR-100 dataset.

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3. PROPOSED SYSTEM DESIGN

The proposed system, illustrated in Figure 1, comprises multiple sequential phases. These phases encompass the preliminary input and preprocessing of the retinopathy dataset, followed by the systematic division of the pre-processed retinopathy images into separate testing and training cohorts, the execution of various deep learning techniques, and the assessment of the system's efficacy through a range of comprehensive evaluation metrics. Subsequently, the by a thorough evaluation of its performance. This evaluation aims to compare the results obtained after the implementation of the lightweight techniques with those derived prior to their application.

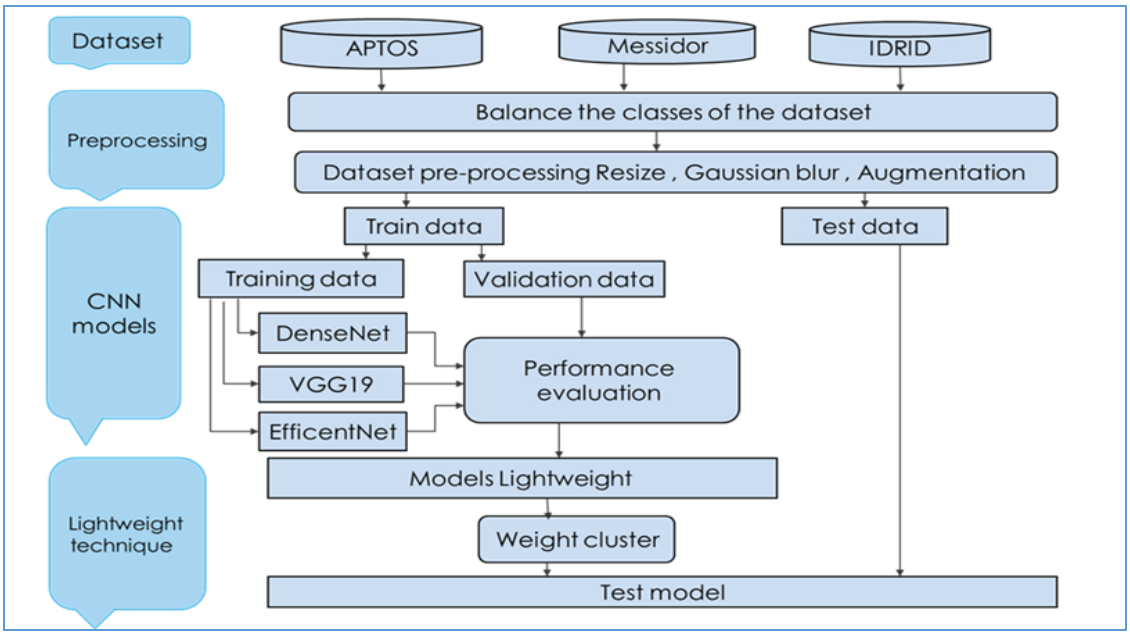

Fig. 1. Stages of retinopathy classification using weight clustering deep learning

3.1 Retinopathy Datasets

In the proposed system, two distinct datasets are employed; the first dataset comprises the APTOS-2019 multi-class retinopathy collection, while the second dataset constitutes an amalgamation of two multi-class retinopathy datasets, namely IDRiD and Messidor-2, which are combined for accurately classifying more retinal images.

- The APTOS-2019 dataset [15] constitutes the most extensive dataset employed for the diagnosis of diabetic retinopathy. It is imbalanced and involves 3662 images collected in a real-world environment.
- IDRiD [16] constitutes a widely employed benchmark dataset comprising images of normal retinas and those exhibiting retinopathy, specifically formatted at a resolution of 4288×2848, tailored for the Indian demographic. This dataset encompasses a cumulative total of 516 retinal images, with 413 images specifically assigned for the training phase, whereas the remaining 103 images are reserved for the testing phase.
- [17] The dataset involved 1748 high-caliber images, of which 1058 images were sourced from the Messidor dataset, along with an additional 690 images gathered between the years 2009 and 2010. . The dataset distribution are depicted in Table I.

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TABLE I. Number of retinal images in each class

Dataset	Normal	Mild	Moderate	Severe	Proliferative
APTOS-2019	1805	999	370	295	193
Messidor- 2	1017	270	347	75	35
IDRID	129	22	156	84	64

The quantity of retinal images present in the APTOS-2019 dataset is deemed adequate; however, the individual counts of retinal images in the Messidor-2 and IDRiD datasets are regarded as insufficiently effective. Consequently, in this study, we combine the two datasets, Messidor-2 and IDRiD. By undertaking this action, the dataset has been augmented, which may subsequently improve the efficacy of the learning process. Figure 2 shows the retinopathy classes distribution after the dataset augmentation.

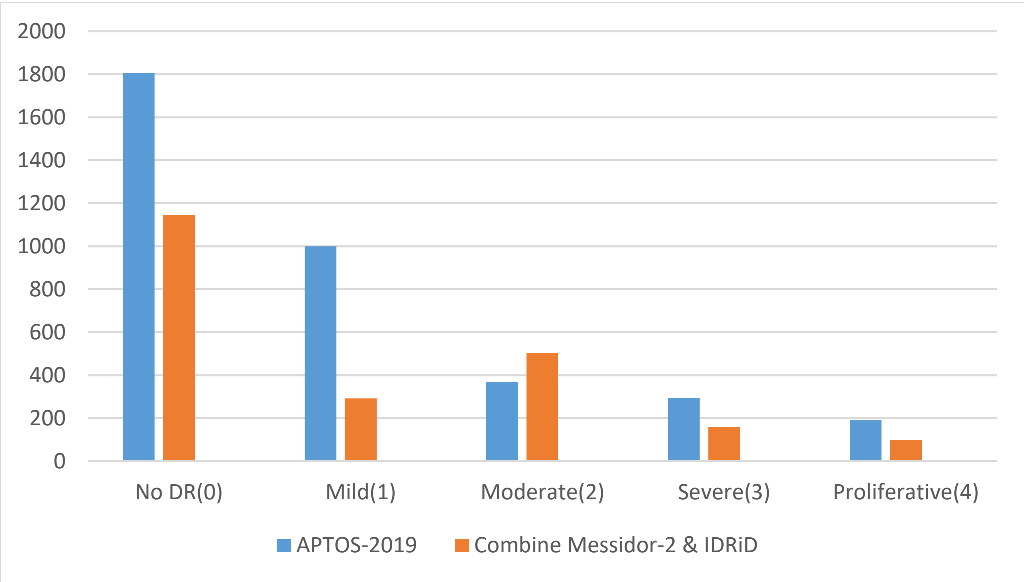

Fig. 2. Distribution of the retinopathy classes in each utilized dataset

3.2 Pre-processing Retina Images

As shown in figure 3 Retinal images are standardized to dimensions of 224×224 pixels with three color channels (RGB) to ensure uniformity and compatibility with various models. Gaussian blur is employed to mitigate noise and augment smoothness by computing a weighted mean for adjacent pixels, regulated by the parameter of standard deviation. Weighted masking serves to accentuate or attenuate specific regions of the image in accordance with designated weights. SMOTE is employed to address class imbalance, improving model performance. Techniques of data augmentation, including rotation and scaling, facilitate the creation of additional diverse training images. These preprocessing methodologies result in the expansion of the APTOS-2019 dataset to 10,108 images and the amalgamated IDRiD and Messidor-2 dataset to 7,217 images, consequently improving the accuracy and generalization of the model.

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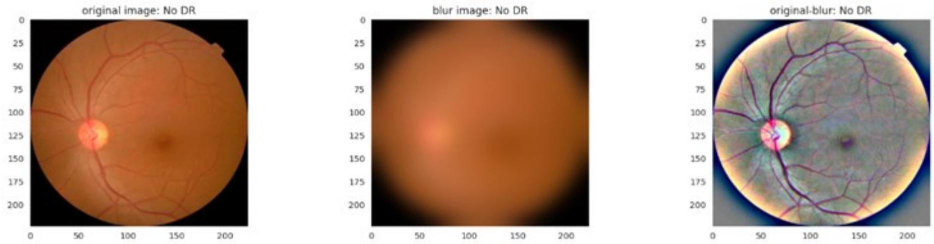

Fig. 3 An example of the retinal image pre-processing

In figure 3, three images are shown. The first is the original image. In the second image, the Gaussian blur has been applied, which reducing noise and smoothing out the image. In the third image, the weighted image has been applied, which enhances edges and details in the image. These operations are used in image processing tasks to provide more image analysis or feature extraction.

4. METHODOLOGY

The following segment exemplifies the utilization of effective methodologies, particularly weight clustering or weight sharing, to diminish the total number of unique weight values within a model. This reduction contributes to advantageous outcomes during deployment. The weights of each layer are organized into N clusters, which the centroid value of each cluster is shared among all the weights associated with it. This method yields enhancements through model compression techniques, notably in architectures like Convolutional Neural Networks (CNNs), DenseNet121, Vgg19, and EfficientNet B6 to classify diabetic retinopathy. By embracing this framework, substantial memory footprint enhancements can be achieved, proving pivotal for the deployment of deep learning models on embedded systems characterized by constrained resources.

Prior to the initiation of the training procedure, the dataset is partitioned into two distinct segments: 80% designated for training purposes and 20% reserved for testing, subsequent to this, a proportion of 10% of the training dataset is designated for the purpose of validation.

4.1 Convolution neural network

The architectural design commences with a pair of Conv2D layers that incorporate 32 filters, advances to an additional pair possessing 64 filters, and subsequently transitions to a tertiary set equipped with 128 filters. The terminal convolutional layers amalgamate 512 filters. Subsequent to this phase, the model employs global average pooling, succeeded by three fully connected layers consisting of 1024, 512, and 256 units respectively, culminating in a final dense layer dedicated to the classification of inputs into five discrete categories, as show in Figure 4.

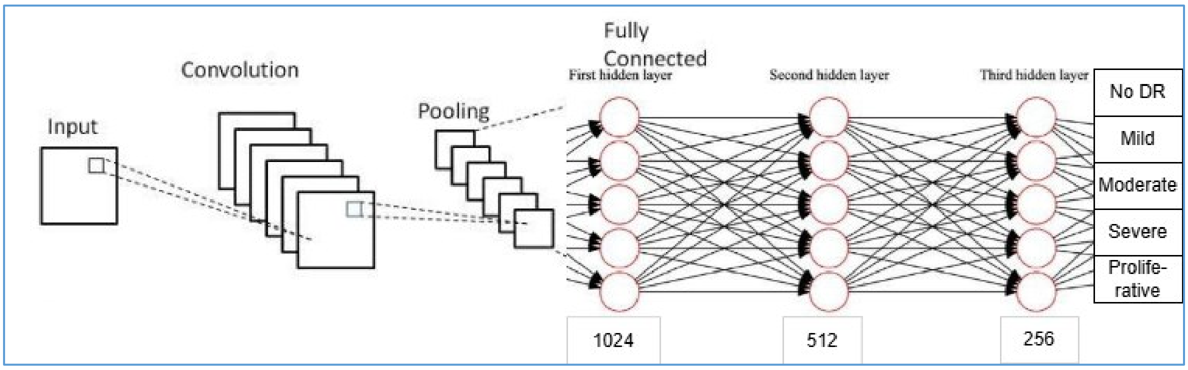

Fig. 4 Diagram of Convolution Neural Network hidden layer

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4.2 Transfer learning techniques

We adopted three models in our study:

- DenseNet121: [18] Exemplifies the concept of dense connectivity, which is defined by the complex interrelations among all layers in a feed-forward configuration. This architectural framework promotes the reutilization of features and increases the propagation of features throughout the network, consequently improving gradient flow and the process of feature extraction.
- VGG19: [19] The VGG19 consists of 19 layers, more specifically 16 convolutional layers and 3 fully connected layers. This model has been widely utilized in various image classification tasks, exhibiting exceptional effectiveness across multiple datasets.
- EfficientNet B6: [20] The framework is based on the EfficientNet model lineage, utilizing a compound scaling strategy to augment the model's dimensions regarding depth, width, and resolution in a coordinated fashion.

The feature maps produced by the CNN or a pre-trained architecture are subsequently transmitted through a global average pooling layer. Following this, a sigmoid activation function and binary cross-entropy loss to optimize the feature vector, thereby facilitating the classification of fundus images into five distinct classifications within a multi-label classification framework.

5. WEIGHT CLUSTERING

Weight Clustering represents a scheme optimization or compression method utilized in deep transfer learning to minimize the scheme size and improve the efficiency of computation and memory without considerably donating performance [21]. Particularly, this method is beneficial for utilizing lightweight deep transfer learning schemes in resource-restricted environments. Rather than holding singular weight values to every connection in the network, these weights can be grouped into restricted clusters, and every weight is substituted with the closest cluster center. This leads to minimizing the count of singular weight values and thus considerably compressing the scheme's size. However, Weight Clustering may decrease the schemes' accuracy (particularly, when the cluster count is insufficient) and increase the schemes' complexity as well [22].

There are many types of clustering methods such as Hard clustering (exclusive clustering) delineates each object to a singular cluster, precluding any overlap or ambiguity. Conversely, soft clustering (overlapping clustering) permits objects to be affiliated with multiple clusters, exhibiting varying degrees of membership. Fuzzy C-means (FCM) generates soft partitions by enabling data points to be associated with several clusters concurrently. The Expectation Maximization algorithm progressively enhances model parameters through an expectation phase followed by a maximization phase, particularly suited for incomplete datasets. K-means represents a widely recognized partition clustering methodology that categorizes data into k non-overlapping clusters. The selection of initial centroids within K-means is conducted randomly, which significantly influences the algorithm's efficiency and the total number of iterations required [23].

In our proposed work, the Weight Clustering methodology employs the Linear Centroid technique to ascertain the centroids of the designated clusters. The determination of these centroids is conducted through the application of the arithmetic mean in accordance with the subsequent equation:

$$Cj = \frac{1}{Nj}\sum_{i=1}^{Nj} Wi \qquad (1)$$

Cj: The centroid or center, of the designated cluster j.

Nj: This denotes the total quantity of weights encompassed within cluster j.

Wi: The entirety of weights residing within cluster j, indexed from i=1 to i=Nj [24].

Weight clustering involves grouping similar weights in neural networks into clusters, thereby restructuring the model's parameterization. This process reorganizes weights without altering their values, aiming to improve model efficiency

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through reduced redundancy. By clustering weights, the model's parameter space is effectively compressed, potentially leading to faster inference and reduced memory footprint.

6. EXPREMENTAL RESULT

In this section, the proposed classification system for retinopathy is rigorously evaluated utilizing the designated testing sets, and the efficacy of the deep learning methodologies is scrutinized and juxtaposed with other pertinent studies concerning performance evaluation metrics such as sensitivity, precision, F1-Score, and accuracy.

The formulations for the performance evaluation metrics are delineated as follows:

$$\mathrm{Acc} = \frac{\sum_{i=1}^{N} \mathrm{TP(Ci)}}{\sum_{i=1}^{N}\sum_{j=1}^{N} \mathrm{Ci,j}} \quad (2)$$

$$Sens = \frac{TP}{FN+TP} \quad (3)$$

$$Pre = \frac{TP}{TP+FP} \quad (4)$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP+ FN}} \quad (5)$$

$$\mathrm{F1(Ci)} = \frac{2*\mathrm{TPR(Ci)}*\mathrm{PPV(Ci)}}{\mathrm{TPR(Ci)}+\mathrm{PPV(Ci)}} \quad (6)$$

Table II, III and IV shows the testing performance with five assessment measurements. Observation for two types of datasets is compared the result without using clustering, It is important to note that after using the clustering technique, the model size is significantly reduced without affecting the accuracy results as show in table V. Additionally Clustered EfficientNet-B6 shows the best results among the others for both datasets, while VGG-19 providing unsatisfactory results in terms of accuracy when using combined data.

TABLE II. Accuracy without lightweight

Dataset	CNN	VGG-19	enseNet-121	ficientNet B6
APTOS 2019	80%	88%	91%	94%
ıbined Messidor-2 & IDRiD	69%	80%	88%	90%

TABLE III. Results using APTOS-2019 dataset

Classes	Clustered DCNN			Clustered VGG-19			Clustered DenseNet-121			Clustered EfficientNet-B6			Support
	Pre	Sens	F1Score	Pre	Sens	F1Score	Pre	Sens	F1Score	Pre	Sens	F1Score	
0	0.72	0.78	0.75	0.78	0.83	0.81	0.84	0.77	0.80	0.89	0.86	0.87	377
1	0.62	0.65	0.63	0.69	0.65	0.67	0.68	0.68	0.68	0.86	0.80	0.83	355
2	0.96	0.96	0.96	0.94	0.97	0.96	0.95	0.99	0.97	0.94	0.99	0.97	358
3	0.80	0.50	0.62	0.70	0.62	0.66	0.67	0.77	0.72	0.83	0.91	0.87	363
4	0.90	0.97	0.94	0.92	0.95	0.93	0.96	0.93	0.94	0.98	0.97	0.98	1074
Acc	0.83			0.84			0.86			**0.92**			2527
Macro-Average	0.80	0.77	0.78	0.81	0.80	0.80	0.82	0.83	0.82	0.90	0.91	0.90	2527
Weighted-Average	0.83	0.83	0.82	0.84	0.84	0.84	0.86	0.86	0.86	0.92	0.92	0.92	2527

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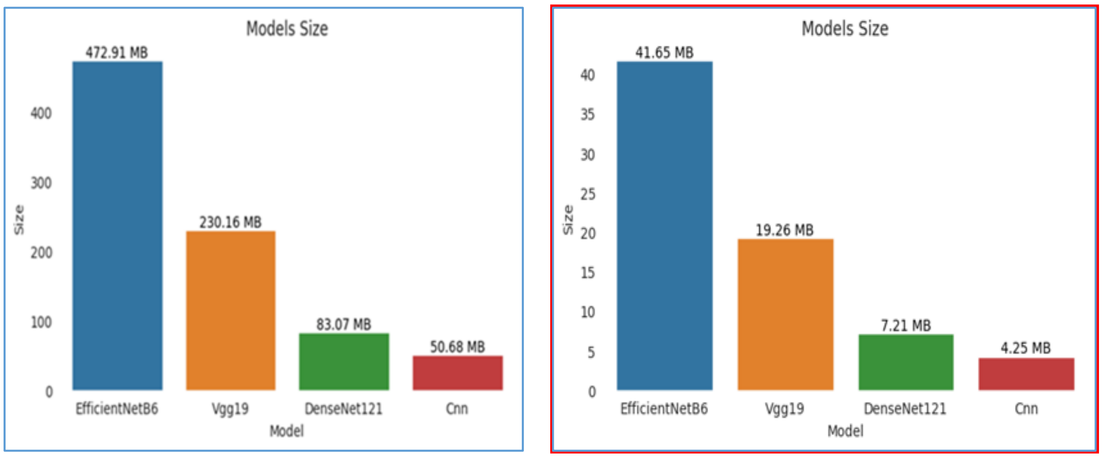
TABLE IV. Results using IDRiD & Messidor-2 dataset

Classes	Clustered DCNN			Clustered VGG-19			Clustered DenseNet-121			Clustered EfficientNet-B6			Support
	Pre	Sens	F1Score	Pre	Sens	F1Score	Pre	Sens	F1Score	Pre	Sens	F1Score	
0	0.58	0.61	0.60	0.00	0.00	0.00	0.75	0.61	0.67	0.73	0.82	0.77	244
1	0.33	0.34	0.33	0.16	0.46	0.24	0.45	0.51	0.48	0.74	0.63	0.68	235
2	0.70	0.58	0.63	0.08	0.18	0.11	0.73	0.73	0.73	0.86	0.75	0.80	230
3	0.69	0.76	0.73	0.19	0.32	0.24	0.59	0.73	0.65	0.88	0.97	0.92	229
4	0.91	0.90	0.90	0.00	0.00	0.00	0.91	0.85	0.88	0.98	0.99	0.98	667
Acc	0.71			0.14			0.73			0.87			1605
Macro-Average	0.64	0.64	0.64	0.09	0.19	0.12	0.69	0.69	0.68	0.84	0.83	0.83	1605
Weighted-Average	0.71	0.71	0.71	0.06	0.14	0.08	0.75	0.73	0.74	0.87	0.87	0.87	1605

Table V. The Models size

Model	CNN	DenseNet-121	VGG-19	EfficientNet-B6
Original model	50.68 MB	83.07 MB	230.16 MB	472.91 MB
Model after clustering	4.25 MB	7.21 MB	19.26 MB	41.65 MB



(a) (b)

Fig. 5 model size for (a) original model (b) clustering model

In Figure 5, we notice that the original size of the CNN model was 50.68MB. Nevertheless, subsequent to the implementation of clustering techniques, the size of the model diminished to 4.25MB, without any notable effect on its accuracy. Likewise, for the rest of the models VGG-19, DenseNet-121, and EfficientNet B6, their size decreased from 230.16MB, 83.07MB, 472.91MB and became 19.26MB, 7.21MB, and 41.65MB respectively. This reduction signifies a 12-fold decrease in the models' original sizes while maintaining accuracy levels, underscoring their efficiency and viability for deployment on resource-constrained devices.

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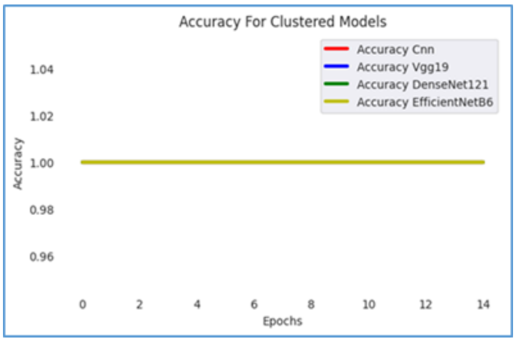
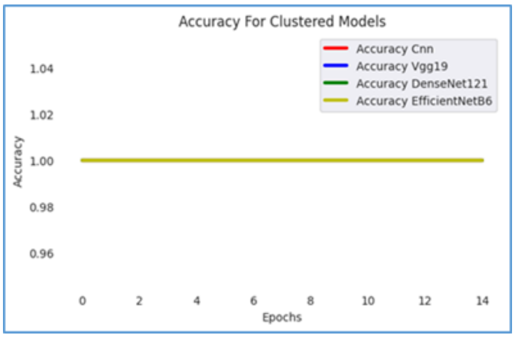
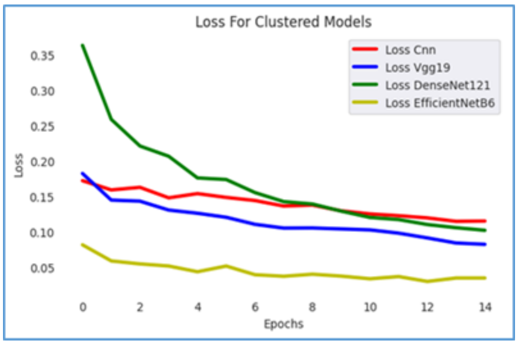


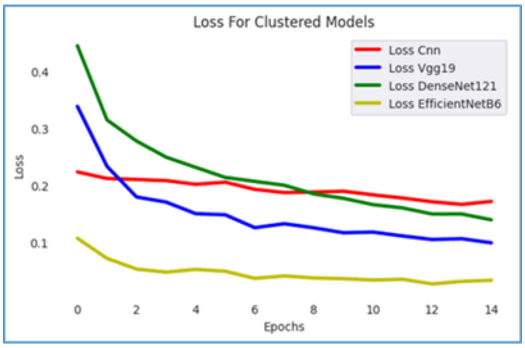
APTOS-2019



Messidor-2 & IDRiD



APTOS-2019



Messidor-2 & IDRiD

Fig. 6 Training Accuracy and losses using weight clustering technique for both dataset.

Figure 6 shows the performance of the proposed framework during training. The training and testing results prove the ability of the proposed framework to perform early detection in a good way and the possibility of using it on devices with limited resources.

7. CONCLUSION

The precise classification of diabetic retinopathy is imperative for facilitating early intervention and mitigating the risk of vision impairment, particularly when utilized in conjunction with simple, portable devices that possess the capability to capture and analyze retinal images in real-time. To render these technological advancements practicable for extensive adoption, particularly in resource-constrained environments, it is critical to develop lightweight models that achieve an optimal equilibrium between accuracy and operational efficiency. Weight clustering has emerged as a commendable strategy in this context, as evidenced by its effective implementation within the EfficientNet-B6 architecture. This methodology not only substantially decreased the model's size but also preserved a high degree of accuracy, thereby rendering it suitable for deployment on devices characterized by limited computational capabilities. By incorporating such optimized models, it becomes feasible to deliver precise, real-time diagnoses of diabetic retinopathy, thereby enhancing the accessibility of advanced healthcare services to a wider demographic. Future research endeavors should investigate the synergistic effects of combining clustering with additional lightweight methodologies.

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