Automated Decision Making ResNet Feed-Forward Neural Network based Methodology for Diabetic Retinopathy Detection

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***Abstract*—The detection of diabetic retinopathy eye disease is a time-consuming and labor-intensive process, that necessitates an ophthalmologist to investigate, assess digital color fundus photographic images of the retina, and discover DR by the existence of lesions linked with the vascular anomalies triggered by the disease. The integration of a single type of sequential image has fewer variations among them, which does not provide more feasibility and sufficient mapping scenarios. This research proposes an automated decision-making ResNet feed-forward neural network methodology approach. The mapping techniques integrated to analyze and map missing connections of retinal arterioles, microaneurysms, venules and dot points of the fovea, cottonwool spots, the macula, the outer line of optic disc computations, and hard exudates and hemorrhages among color and back white images. Missing computations are included in the sequence of vectors, which helps identify DR stages. A total of 5672 sequential and 7231 non-sequential color fundus and black-and-white retinal images were included in the test cases. The 80 and 20 percentage rations of best and poor-quality images were integrated in testing and training and implicated the 10-ford cross-validation technique. The accuracy, sensitivity, and specificity for testing and analysing good-quality images were 98.9%, 98.7%, and 98.3%, and poor-quality images were 94.9%, 93.6%, and 93.2%, respectively.**

Keywords*—Retinal lesion (RL); Fundus Images (FunImg); Microaneurysms (MAs); Principal Component Analysis (PCA); Standard Scaler (StdSca); Feed-Forward Neural Network (FFNN); cross pooling (CxPool)

I. INTRODUCTION

Diabetic Retinopathy (DR) eye disease (ED) is correlated with chronic type diabetes, which is the primary trigger of sightlessness in children, workforce employees, and elderly people across the globe, and it is impacting more than 96 million people [1]. DR is a type of diabetes that causes damage to the retinal blood vessels (BV). Primarily, it is symptomless and changes vision-based issues. As it becomes more severe, it disturbs both eyes and ultimately causes partial to complete vision loss. It principally arises when blood sugar levels are uncontrollable. The premature detection of DR can prevent the possibility of permanent blindness. Consequently, it needs an effective screening scheme [2]. Detection of the initial stages of DR-ED is one of the challenging tasks in the DR diagnosis process, it helps in the advancement to vision loss, which can be decelerated, but it can be complicated as DR-ED regularly indicates rare symptoms until it is extremely late to deliver efficient medication [4] [5]. Consequently, uncovering DR at an early stage is crucial in preventing the complications of this illness, as shown in Fig. 1 [2]. CNN in DL manages to deliver helpful results while it comes up to the job of classification of medical images [5].

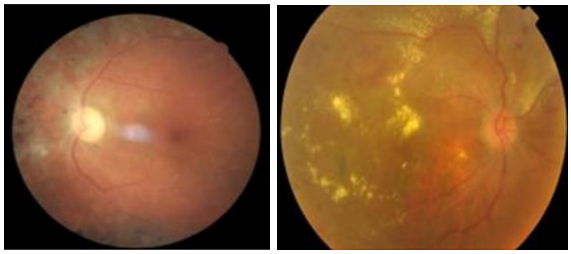

Fig. 1. Hard exudates, hemorrhages, abnormal growth of blood vessels, aneuryam and cotton wool sports of DR affected retina.

Recognition of the initial clinical signs of DR initiation is a crucial constraint for interference-free and efficient medication. Ophthalmologists qualified to detect DR focus on analyzing minor fluctuations in patient microaneurysms (MAs) of the eyes, retinal bleeds, macular edema, and fluctuations in retinal blood vessels. Segmentation of MAs is another crucial constraint for primary identification of DR, which has attracted the major attention of the research community across the early years [27]. According to the International Clinical DR Disease Severity Scale, DR seriousness is marked into five degrees, such as non-DR, mild-NPDR, moderate-NPDR, PDR, or severe-NPDR [7] [8]. Mild-NPDR is specified as the occurrence of microaneurysms. Moderate NPDR is specified as being further than exactly micro-aneurysms, although less severe NPDR produces CWS, retinal hemorrhages, and hard exudates. DME was analyzed if difficult exudates were identified in the interior of 500μm of the macular centre corresponding to the specification of the initial medication for DR research [9]. Ascribable-DR is specified as DME, moderate NPDR, or both. Based on the recommendations for image procurement and clarification of DR assessment in China [10], the image quality was rated conferring to requirements specified in terms of three characteristic factors such as field definition (FD), clarity, and artifacts (AF). The overall result was equivalent to a grade for transparency plus a

grade for FD and minus the score for AF; the overall count was less than 12, which counted as ungradable [8]. Recognizing the first clinical signs of DR is a significant barrier to effective intervention and treatment. Ophthalmologists who are trained to identify DR focus on analyzing minute changes in patient microaneurysms (MAs), retinal bleeding, macular edema, and changes in retinal blood vessels. Another important barrier to the initial identification of DR is the segmentation of MAs, which has received significant attention from the academic community in recent years.

The article is planned in a section wise manner: Section I included an introduction and research objectives; Section II comprised the associated works along with the background of the research; and Section III included the proposed methodology of the Automated Decision Making ResNet Feed-Forward Neural Network (RNFFNN) Methodology for Recognition of DR Stages and its executional scenarios. Section IV described the experimental setup and analysis through Image Normalization Principal Component Analysis (PCA) and Multi-level ConvNets based Pooling and Feature Integrations, along with the results and discussion; Section V contains the results and discussions. Finally, Section VI addresses the conclusion and future direction.

II. Related Work

DR is one of the significant interests that have captured the healthy world. Accepting the interest from numerous scientists to discover the ideal solutions for initial recognition of DR disease, subsequently prominent to avoidance of early oscillations in eyesight. Several investigations were performed and continued in this field with the intention of improving the lives of patients. This section articulates an analysis of DR-related research [2].

The author, Anumol Sajan et al., proposed the detection of DR stages using deep learning (DL). It proposed an automatic classification system, in which it analyzes fundus images (FunImg) with fluctuating illumination and fields of assessment and produces a severity grade for DR using ML replicas such as VGG-16, Convolutional Neural Network (CNN), and VGG-19 through five groups of classified images ranging from 0 to 4, where 0 is no DR and 4 is proliferative DR. It accomplishes 82%, 80%, and 82% accuracy, sensitivity, and specificity, respectively [1]. Author Mushtaq et al. proposed detection of DR using DL-based densely connected CNN (DenseNet-169) for identification of early recognition of DR, which categories the FunImgs based on their levels of severity: Proliferative-DR, Severe, Moderate, Mild, and No-DR with integration of DR-Recognition-2015 and Aptos-2019-Blindness-Recognition from Kaggle in the inclusion of data-gathering, pre-processing, augmentation, and modeling levels and achieved 90% accuracy (ACU) [2]. The fifth most common cause of blindness in the world is now diabetes. One of the main causes of vision loss and blindness among diabetes individuals worldwide is diabetic retinopathy. According to the WHO, diabetic retinopathy is a serious eye condition that needs to be addressed right once by government agencies and medical specialists. [3]. Image artifact, clarity, and field definition are the three main criteria used to evaluate the quality of fundus images. Unfortunately, the majority of quality assessment techniques now in use only consider overall image quality without providing comprehensible quality feedback for real-time correction. Furthermore, these models frequently lack generalizability under various imaging settings and are susceptible to the particular imaging devices [11].

The author, J. De Calleja et al. [31], integrated a 2-stage scheme for DR recognition. FE was processed through local binary patterns, and the classification stage was processed through ML-based Support Vector machines (SVM) and Random Forest (RF) and attained a 97.46% ACU rate with a test case of 71 images. M. Gandhi et al. [32] proposed automatic DR recognition through SVM by sensing exudates from FunImgs with manual FE with DL for J. Orlando et. al. [24] integrated CNN with manual and enhanced features for FE for sensing RED-lesion in the retina eye. U. Acharya et al. [33] integrated 331 FunImgs through MAs, BV, haemorrhages, exudates-based features using SVM and attained 85% of ACU. K. Anant et. al. [26] integrated texture and wavelet features for DR recognition in basic level analysis with involvement of DM and IP on the DIARETDB1 database and accomplished 97.95% of ACU. In a different study, 331 fundus images were analyzed and morphological image processing and support vector machine (SVM) techniques were utilized for the automatic detection of eye health [34]. S. Preetha et al. [14] described DM and ML methods in their analysis for the prediction of various diabetic-related diseases such as DR, skin cancer, and heart disease. S. Sadda et al. [13] used a quantitative based method to recognize new parameters for sensing proliferative DR based on hypotheses of lesions location, surface area, number, and distance from the ONH canter, which progressed the prediction procedure of DR with the involvement of imaging data and quantitative lesion parameters. The authors, J.Amin et al. [27], deliver an assessment of numerous practices for DR by sensing hemorrhages, MAs, exudates, and BV and analyzing numerous outcomes obtained from these practices experimentally. Y. Kumaran et. al. [18] emphasize the dissimilar types of pre-processing and segmentation methods typically used for the detection of DR in the human eye, which contain several classification models. I. Sadek et al. [25] proposed automatic DR detection through DL with the integration of four CNNs to categorize DR into three classes: normal, exudates, and drusen and achieved 91%–92% ACU. G. Zago et al. [6] proposed a lesion localization model using a deep NN through CNN with integration of regions in the place of segmentation localization processes and 2-CNNs implicated for training through the Standard DR Database and DIARETDB1 and achieved 95% sensitivity. P. Kaur et al. [17] proposed the NN method for the categorization of several RIs using the MATLAB environment. A comparison study was done among the proposed methods using SVM. SVM helped generate an accurate result.

M. Voets et al. [12] proposed a study that integrated the Kaggle dataset EyePACS for finding DR from retinal FunImgs test cases and experimented on existing work on several data sets that provided 95% of ACU [2]. It aimed to improve the performance of detecting certain retinal lesions (RL) with their grading levels through a cost-effective ResNet implicated RL-aware sub-network (RLASN) for reducing vanishing gradient complexity, which was improved with more sensitive FE for

small lesions compared to VGG and Inception's existing net designs [15]. The RLASN included a feature pyramid structure that was intended to describe features of multi-scale and dig out lesion types and position relationships [16] [23]. Identifying several types of RLs can help with making decisions in the clinical process, like fenofibrate for patients with hard excaudate [19] and antiplatelet drugs used thoroughly in patients with bleeding retina [20]. Progression is another major problem in DR screening, as advancement of RLs is symptomatic of improving sight-threatening DR [21–23]. It stated that, as a substitute for direct end-to-end training from FunImgs to DR grades, a cost-effective RLASN was established to improve the capability of acquiring features of lesion [26]. For the purpose of ultimately detecting nonproliferative diabetic retinopathy, the author outlined different ways for detecting microaneurysms, hemorrhages, and exudates. Techniques for detecting blood vessels are also covered for proliferative diabetic retinopathy [28].Author Veena Mayya et al. [30] proposed an analytical study through automated MAs recognition and segmentation for DR early diagnosis, which was achieved using color fundus photography, optical coherence tomography angiography, or fluorescein angiography images. This study was categorized into classical IP, conventional ML, and DL based practices and achieved significant analytical progress.

This section articulates the DR study based on the accessibility of FunImgs data. A fundus camera is utilized to acquire two-dimensional digital RIs. The highly accessible early-stage DR recognition works make use of databases, including images obtained by dilating the pupil. While many RI datasets such as Kaggle DR [38] [39], MESSIDOR [35] [36], STARE [30], DeepDR [41], HRF [37], ODIR [40], UoA-DR [42], DRIVE [31], and so on are openly accessible for the persistence of DR research studies, MAs are generally the initial visible sign of DR; their recognition can decrease beyond difficulties and loss of vision. The present manual assessment is hard to scale and a time-consuming process for a large patient population. Efficient automated detection and segmentation (ADS) of MA will be able to decrease the liability of ophthalmologists to a certain level by computerizing the assessment activity and assisting in the early stages of DR diagnosis. The research society for ADS in MA has developed numerous methodologies for early DR diagnosis [29]. In order to evaluate deep learning models and further investigate the clinical applications, particularly for lesion recognition, the author T. Li et al. [43] developed a new dataset called DDR. Using the ideas of mathematical morphology, the authors B. Lay et. al. [44] devised a computerized method for the detection of microaneurysms (MA) in fluorescein angiograms.

The authors, Wejdan L. et al. [45], proposed an analysis of the detection of DR using DL practices. It has reviewed various detection and classification techniques using DL techniques, which analyze DR stages based on color fundus retina images. Author S. Mishra et al. [46] proposed DR recognition using DL. It integrated artificial intelligence (AI) techniques and used DenseNet to train the model on a massive dataset consisting of 3662 images to instinctively distinguish the DR stage, which has been categorized as having superior FunImgs resolution. It integrated APTOS data derived from Kaggle with DR's five stages, categorized into 1 to 4 numbers. By using patients' fundus eye images as input, DenseNet's FE process produced results through activation function, achieved 0.9611 ACU, and described the distinction between the VGG16 and DenseNet121 designs. The authors, Ayala et al. [47], proposed DR-improved detection using DL. It integrated CNN to perform a fundus oculi image to identify the structure of the eyeball and establish the occurrence of DR. The factors improved using the TL approach for mapping an image with the subsequent labeling structure. Training, testing are accomplished with a medical fundus oculi image dataset, and a pathology seriousness scale appears in the eyeball as labels and attains 97.78% of ACU.

Author M. Mohsin Butt et al. [48] proposed a multi-channel CNN-based approach for the detection of DR from eye fundus images. It integrated 35,126 images from EyePACS and achieved 97.08% ACU. The authors, Fatima, Muhammad Imran, et al. [49], proposed a unified method for entropy improvement-based DR recognition using a hybrid NN. It devised manipulating the discrete wavelet transforms to enhance the visibility of medical imaging by making the delicate features more prominent, and it classified images for further stages. It integrated three datasets, such as those from the Asia Pacific Tele Ophthalmology Society (APTOS), Ultra-Wide Filed (UWF), and MESSIDOR-2. The authors, Yuhao Niu, Lin Gu, et al. [50], intended explicable DR recognition through RIs. It has proven a direct relationship between the lesions and isolated neuron activation for pathological justification. Initially, it described new pathological signifiers using triggered neurons of the DR detector to determine both lesions appearance and spatial data, then visualized the DR indication encoded in the descriptor through Patho-GAN, which was used to produce medically possible RIs. The author, Abdel Maksoud E. et al. [51], proposed the E-DenseNet computer-aided diagnosis system for detecting various diabetic retinopathy grades based on a hybrid DL technique. E-DenseNet integrated DenseNet and EyeNet versions based on TL. It modified conventional EyeNet by incorporating blocks of dense and improving the resultant hyperparameters of blended E-DensNet versions. The author, Sikder, N. et al. [52], proposed classification of DR severity with integration of collaborative learning algorithmic sequences through examining RIs. It included various additional IP practices and steps of FE and feature selection and attained 94.20% classification accuracy with 0.32% boundary error and a 93.51% F-measure with 0.5% boundary error.

The authors, Nikos Tsiknakis, Dimitris, et al. [53], proposed DL integrated recognition and classification for DR based on FunImgs. It included a description of all DR recognition stages, such as DR grading, complexity levels. The author, M. T. Al-Antary et al. [54], integrated features to enhance the interpretation, and after that, a pyramid of multi-scale features was incorporated to define the retinal structure in a distinct region. It has trained a model in the traditional sense using cross-entropy loss to categorize severity levels of DR through healthy and non-healthy RTs, and it has integrated EyePACS and APTOS datasets. The author, Veena Mayya et al. [55], proposed a study on automated MAs recognition for early diagnosis of DR with a description of various DR

diagnosis techniques with their advantages and limitations. The author, Shah P. et al. [56], proposed validation of deep CNN-based algorithmic sequences for recognition of DR-AI against the screening clinician process. The authors, Chetoui M. et.al. [57], proposed reasonable end-to-end DL for DR recognition across multiple datasets. It included 90,000 images from nine open datasets, which were employed to evaluate the effectiveness of the planned procedure. The planned DL process tunes a pre-trained deep CNN for DR recognition. The author, Sebti, R. et al. [58], proposed a DL-based methodology for the recognition of DR. It presented an automated classification scenario from a certain set of RI to identify the DR. An automatic retinal image analysis (ARIA) method has been created by authors Shi, C. et al. [59] that combines transfer net ResNet50 deep network with the automatic features generation approach to automatically assess image quality and differentiate between eye abnormalities and artefacts that are associated with poor quality on color fundus retinal images. According to individual risk variables, authors Alfian, G. et al. [60] suggest using a deep neural network (DNN) in conjunction with recursive feature elimination (RFE) to offer an early diagnosis of diabetic retinopathy (DR). Color fundus photography, fluorescein angiography, B-scan ultrasonography, and optical coherence tomography are a few of the crucial imaging modalities that are utilized to diagnose diabetic retinopathy [61].

A multi-classification prototype has been generated through CNN algorithmic sequences with numerous parameters on a dataset of DR with several structures. The authors R K. Jha et al. [64] stated an analysis to assess various categorization algorithmic sequences for estimation of HD where several conventional processes like SVM, KNN, DT-DNN, NB, and RF [65–66] were utilized to be valid selection of features over the Rapid Minor (RM) instrument to train-learn employing the Cleveland dataset from the UCI repository environment [67–72]. The Diabetic Retinopathy Debrecen Data Set from the UCI machine learning repository was taken into account by the author Nagaraja Gundluru et. al. [73] who then designed a deep learning model with principal component analysis (PCA) for dimensionality reduction and Harris hawks optimization algorithm to extract the most crucial features. To distinguish the stages of DR, the author Asia, A.-O et al. [74] use fundus photography and a deep learning tool called a convolutional neural network (CNN). The Xiangya No. 2 Hospital Ophthalmology (XHO), Changsha, China, provided the study's pictures dataset, which is very vast, sparse, and labeled in an uneven manner. A hybrid method for the detection and classification of diabetic retinopathy in fundus pictures of the eye is proposed by author Butt, M.M. [75]. On pre-trained Convolutional Neural Network (CNN) models, transfer learning (TL) is applied to extract features that are then combined to produce a hybrid feature vector. The literature on AI approaches to DR, such as ML and DL in classification and segmentation, that has been published in the open literature within six years (2016-2021), is covered by author Lakshminarayanan, V [76]. A thorough list of the accessible DR datasets is also presented. The PICO (Patient, I-Intervention, C-Control, O-Outcome) and Preferred Reporting Items for Systematic Review and Meta-analysis (PRISMA) 2009 search methodologies were both used to create this list. Many researchers have achieved significant progress in early DR diagnosis and detection, but various complexities and disparities still occur, emphasizing a significant possibility for the advancement of completely automated early DR diagnosis [29].

III. METHODOLOGY

The Deep Convolutional Neural Network (D-CNN) designs are extensively used in multi-labeling mapping and classification, which improves the analysis of the various DR grades such as normal, mild, moderate, severe, proliferative DR, and non-proliferative DR. DR degrees are articulated by seeming multiple DR lesions concurrently on the color retinal FunImgs. The various lesion types have numerous features that are difficult to segment and recognize by employing conventional methods. Consequently, the practical solution is to utilize an effective CNN model with a dual image ResNet mapping approach. Retinal diagnosis promotes early detection of DR stages, which helps with timely treatment.

To accelerate the screening process, this research uses the Automated Decision Making ResNet Feed-Forward Neural Network (RNFFNN) Methodology to detect early-to-late stages of DR. The majority of the uses for CNN's high-level features are in the detection and classification of retinal lesions. This research is mainly focused on developing the best RI interpretation, which further helps to enhance the implementation of DR detection simulations. To obtain the best possible interpretation, features obtained from various pre-trained ConvNet simulations were intermingled using the intended multi-modal blended module.

The final stage of descriptions is employed to train a D-CNN used for DR recognition and severity level prediction. Each ConvNet obtains unique features, blending them using 1D and cross pooling, which leads to improved interpretation compared to using features extracted from a single ConvNet. This research will adopt deep learning-based convolutional neural networks to achieve varying objectives. First, an exploratory research study is to be carried out to gain an in-depth understanding of AD. The second objective is the core objective of my research, in which we are going to propose a new framework and apply this framework to the public dataset. The proposed methodology module for training the image with labeled deep understanding could satisfy unlabeled data because deep learning could satisfy supervised and unsupervised segmentation. Finally, to check the feasibility of the proposed framework, an empirical evaluation will be carried out. The classification and detection of DR stages are integrated using the dual image approach of integration and aggregation of color fundus images and black-and-white images. Both photos are analyzed separately and combined with the missing points of each image sequence of the color fundus and black-and-white images. This research has integrated more than ten thousand images from different age groups, such as 10 to 25 years, 26 to 35 years, 3 years, 46 to 55 years, and above 56 years. Initially, all color fundus images are collected from the various age-group patients; we consider these to be the primary input images. In data collection, all gathered color fundus images are classified into two groups: sequential and non-sequential images.

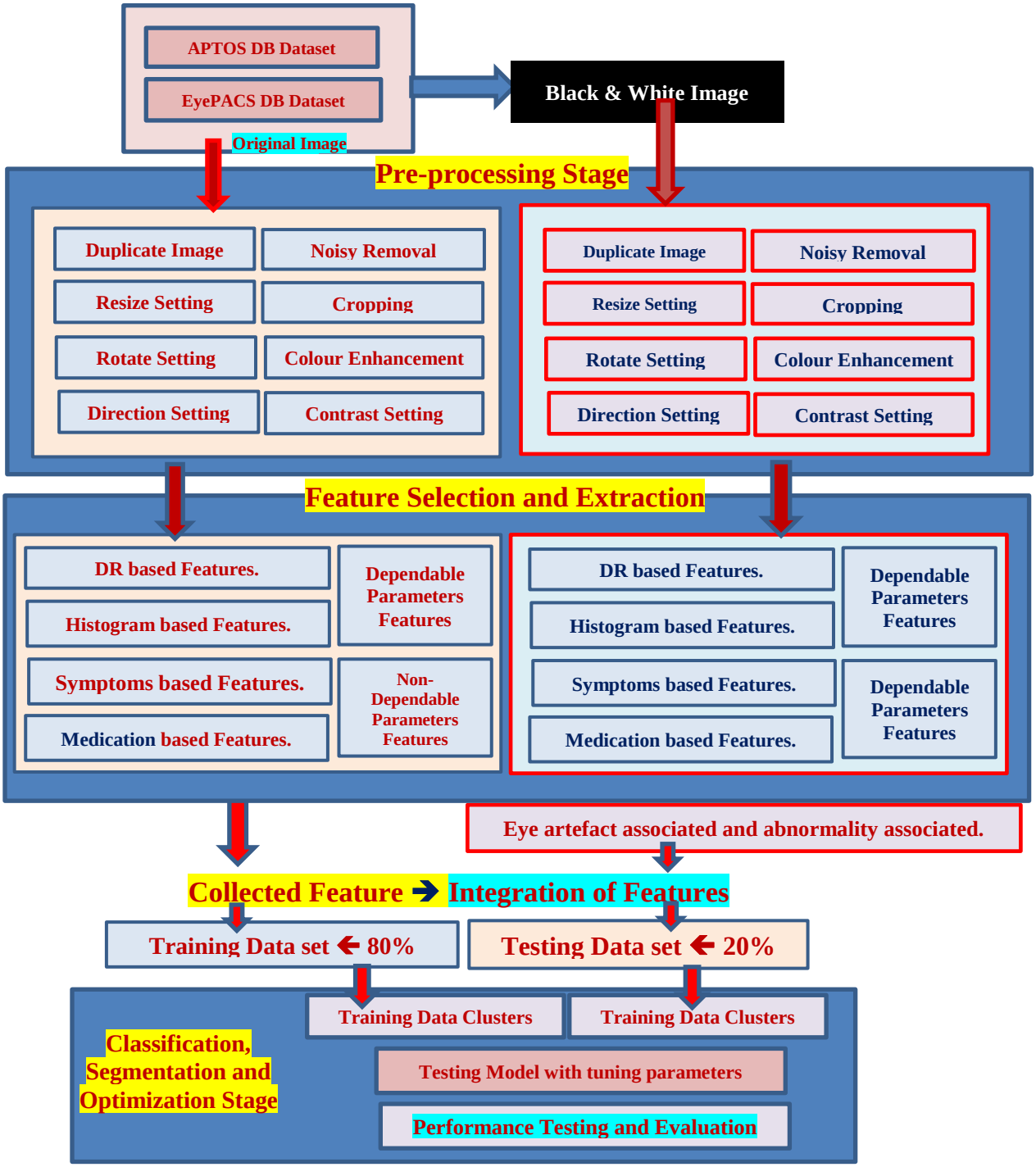

Fig. 2. Dual-image multi-layer mapping methodology for identification of DR early stages.

The sequential images are the images that have been picked from the same patient and age group. The various sequential images hold a slight variation in the color fundus and help the research generate the best outcomes and high predictions for the five stages of DR. The automated system feels complex when it tries to tune non-sequential images. The proposed methodology for training proficiency completely depends on balanced error-free data, so it's required to tune the data for training and testing purposes to process it further in the proposed deep learning-based CNN implicated dual-image multi-layer mapping approach. The color fundus and black-and-white image-based data uniformly divide according to every DR stage, such as Non-DR, MiDR, MoDR, SeDR, and PrDR, which helps the model minimize any inequality during the training and progression of the proposed approach. All input color fundus and black-and-white images are equally sized, then processed in a systematic series way that is elected the combination images for analyzing the grading for further predictions as shown in Fig. 2. The classification task is mainly performed based on the deep learning Inception-Resnet model.

Furthermore, the classification task has initiated the cross-entropy loss function based on two variations: binary-class and multi-class classification.

IV. Experimental Setup

The integration of dual-type sequential and non-sequential cluster images is required for auto-detection of DR stages. This research proposes an auto-fine-tuning system for the recognition of DR stages using a dual-image ResNet mapping approach. The sequential and non-sequential images were processed parallelly in the pre-processing and classification stages. The mapping techniques integrated to analyze and map missing connections of retinal arterioles, microaneurysms, venules and dot points of the fovea, cottonwool spots, the macula, the outer line of optic disc computations, and hard exudates and hemorrhages among color and back white images Missing computations are included in the sequence of vectors, which helps identify DR stages. A total of 5672 sequential and 7231 non-sequential color fundus and black-and-white retinal images were included in the test cases. The 80 and 20 percentage rations of best and poor-quality images were integrated in testing and training and implicated the 10-ford cross-validation technique.

The proposed methodology's training ability is variable on reasonable error-free data, which is essential to tune the data for training-testing purposes and manage it for the advanced process in the anticipated deep learning-based CNN (DL-CNN) implicated dual-image multi-layer mapping approach. The color fundus and black-and-white image-based data uniformly divide according to every DR stage, such as Non-DR, MiDR, MoDR, SeDR, and PrDR, which helps the model eliminate any inequality during the progression of training and testing the proposed approach. All input color fundus and black-and-white images are equally sized, then processed and tuned in a systematic series way, which are elected as the combination images for analyzing the grading for further predictions. The Fig .3 representing the dual-image Structural design of custom-built DL-CNN based network stem segment with extracted features

A. Image Normalization Principal Component Analysis (PCA)

The Eq. (1) has integrated for normalizing the dataset features, X signifies the features of dataset, μ signifies mean value for separately feature x(i) of dataset, and σ signifies subsequent standard deviation. This normalization method was executed using the scikit-learn based Standard Scaler (StdSca) [62] and employed Principal Component Analysis (PCA) for dimensionality decrease if in case of MNIST and Fashion-MNIST which has selected for representing features of image data. Which is achieved using the scikit-learn based PCA.

$$z = \frac{X - \mu}{\sigma} \tag{1}$$

It has implicated a feed-forward neural network (FFNN) and CNN, mutually come up with two different classification functions such as ReLU and SoftMax. DL solutions to classification difficulties typically utilize the SoftMax function to perform classification task, which indicates a discrete probability distribution (DPD) for K classes, expressed as

$$\sum_{k=1}^{K} Pk \tag{2}$$

If it takes x as the activation at the penultimate layer of a neural network, and θ as its weight parameters at the SoftMax layer, it has 'o' as the input to the SoftMax layer,

$$o = \sum_{i}^{n-1} \theta i x i \tag{3}$$

Subsequently, yˆ is expected class.

$$Pk = \frac{\exp(Ok)}{\sum_{k=0}^{n-1} \exp(Ok)} \tag{4}$$

$$y^{\wedge} = \max \arg \max pi \quad i \in 1,\ldots\ldots, N \tag{5}$$

ReLU is an activation function presented by, which has strong biological and mathematical Underpinning [63].

$$y^{\wedge} = \text{argmax; i} \in 1, \ldots, \text{N; max (0, o)} \tag{6}$$

$$l(\theta) = -\sum y.\log(\max(0, \theta x + b)) \tag{7}$$

Let the input x be replaced the penultimate activation output h,

$$\frac{\partial l(\theta)}{\partial h} = \frac{\theta . y}{\max(0, \theta h + b) . 1n\ 10} \tag{8}$$

The backpropagation algorithm as shown in the eq. 8. is the same as the conventional SoftMax-based deep neural network.

$$\frac{\partial l(\theta)}{\partial \theta} = \sum_{i} \left[\frac{\partial l(\theta)}{\partial pi} \left(\sum_{k} \frac{\partial pi)}{\partial Ok} \frac{\partial Ok)}{\partial \theta} \right) \right] \tag{9}$$

B. Multi-level ConvNets based Pooling and Feature Integrations

This research has integrated two distinct pooling-based methods such as cross pooling (CxPool) and 1D pooling (1DPool) to merge multi-level feature extraction from VGG32 through fc1 and fc2 with integration of Xception net environment. The CxPool has implicated with two distinct feature vectors (FV) of A and B are adopted as input and a further FV C is produced, where A, B, C ∈Rd. Every feature element ci, of the output vector C, is processed employing through the Eq. (10) to Eq. (13).

$$ci = \max (ai, bi)\ \forall\ i \in \{1,2\ldots d\} \tag{10}$$

$$ci = \min (ai, bi)\ \forall\ i \in \{1,2\ldots d\} \tag{11}$$

$$ci = \text{mean } (ai, bi+1)\ \forall\ i \in \{1,2\ldots d\} \tag{12}$$

$$ci = ai+bi+1 \forall i \in \{1,2\ldots d\} \tag{13}$$

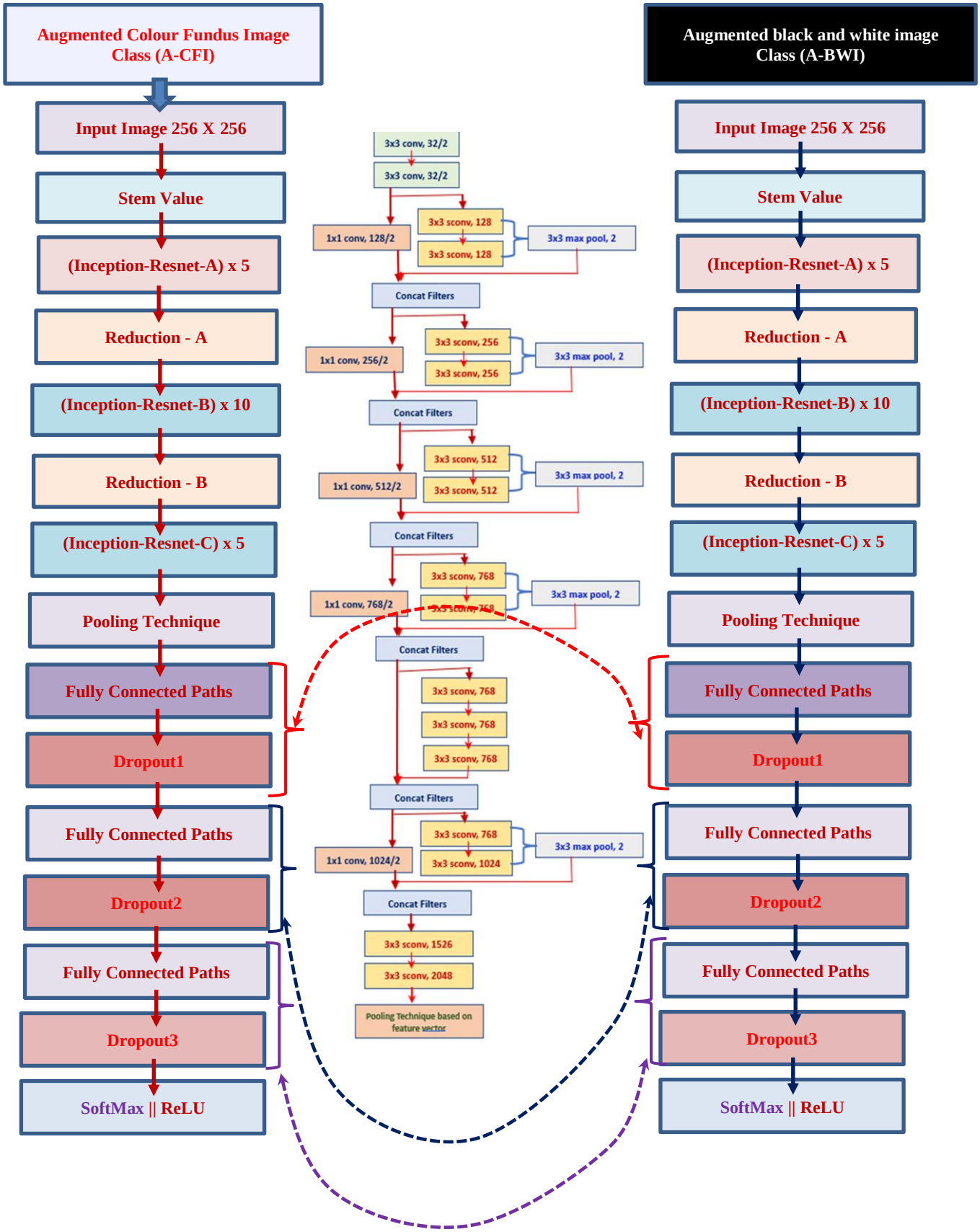

Fig. 3. The Structural design of custom-built DL-CNN based network stem segment with extracted features.

The 1DPool is employed to choose leading regional features from every VGG32 region, where the Cr-Pool permits accumulating the leading features achieved by 1DPool with global interpretation of Xception net environment. The 1DPool based synthesis brings one FV 'K' as an input and which generates a further FV of K^, where K belongs to Rd1, K^ belongs to Rd2 with the executional condition of d2≤d1. K^ is a decreased interpretation of K, where K={k1,k2…kd1} and K^={k^1,k^2…k^d1}. In this environment, every feature element k^i, of the output vector K^, is calculated employing through the Eq. (14) to Eq. (17).

$$k^i = \max (ki*2, ki*2+1) \; \forall \; i \in \{1,2\ldots d2\} \quad (14)$$

$$k^i = \min (ki*2, ki*2+1) \; \forall \; i \in \{1,2\ldots d2\} \quad (15)$$

$$k^i = \text{mean} (ki*2, ki*2+1) \; \forall \; i \in \{1,2\ldots d2\} \quad (16)$$

$$k^i = ki*2 + ki*2+1 \quad \forall \; i \in \{1,2\ldots d2\} \quad (17)$$

The 1DPool has been employed individually on extracted features of VGG32 based fc1 and fc2 layers. After that, the CxPool method has been employed on the subsequent pooled features, which FV has unified with the extracted features from the Xception, which are generated from the two individual sets of input image classes, such as the Augmented Color Fundus Image Class and the Augmented Black and White Image Class sets, using CrPool, as shown in Fig. 3 and 4. As the final FV is a unified form of the global and local interpretations of the RIs, it offers robust hyper features.

V. Results and Discussion

The multi-decision Inception-ResNet blended hybrid model has integrated with multi-layers of dual image-based parameters that process sequential and non-sequential images. The proposed model has been trained with a multi-layered transfer learning mechanism that has been tuned with 172 weighted multi-layers, of which 86 weighted layers are connected with color fundus images and 86 more weighted layers are connected with black-and-white images. The images are graded manually on a scale of 0 to 4 (0, normal DR; 1, mild; 2, moderate; 3, severe; and 4, proliferative DR) to indicate different severity levels, and the grading process has been extended to binary bit form, such as:

Dual Labeling Mechanism (P, Q)🡐🡒 (~P, ~Q).

where Q1 = {q1 / q1∈{000, 001, 010, 011, 100}} and Q2 = {q2 / q2∈{00, 01, 10, 11}}.

Q1 representing primary case of labeling and Q2 representing secondary case of labeling based on positive (1), true-positive (11), true-negative (10), false-positive (01), false-negative (00).

Grade-0: Normal 🡐000.00.

Grade-1: Mild DR 🡐 001 Various levels 🡒 {001.01, 001.10, 001.11}.

Grade-2: Moderate DR 🡐 010 Various levels 🡒 {010.01, 001.10, 001.11}.

Grade-3: Severe DR 🡐 011 Various levels 🡒 {011.01, 001.10, 001.11}.

Grade-4: Proliferate DR 🡐 100 Various levels 🡒 {100.01, 001.10, 001.11}.

The DL-CNN based Layered Integration with training and testing scenario with grading process has shown in the Fig. 4 which are integrated for detection of DR stages. The data has collected for training and testing purpose which are clustered according to the DR stage and according to the DR symptoms through binary bit formation which is shown in the Table I.

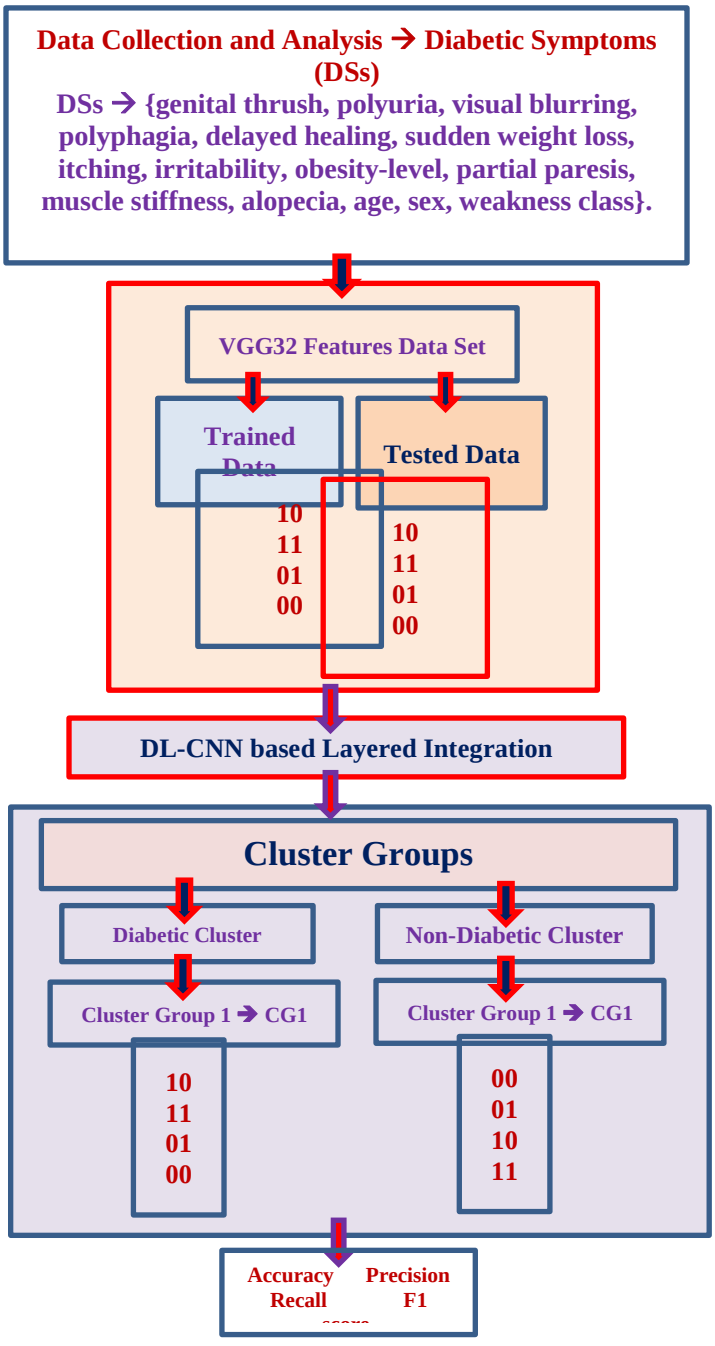

Fig. 4. DL-CNN based Layered Integration with training and testing scenario for detection of DR stages.

TABLE I. INTEGRATED SET OF IMAGES AND DR GRADING CLASS

DR Stages / Grade	Impact	Base binary class	Supporting sub-class	Sampling	Sequential and Non-sequential Images	Single / Dual Image Processing
Grade-0	Normal	000	000.00	2150	Sequential	Dual Image
Grade-1	Mild DR	001	{001.01, 001.10, 001.11}	526	both	Dual Image
Grade-2	Moderate DR	010	{010.01, 001.10, 001.11}	1325	both	Dual Image
Grade-3	Severe DR	011	{011.01, 001.10, 001.11}	372	both	Dual Image
Grade-4	Proliferate DR	100	{100.01, 001.10, 001.11}	158	both	Dual Image

TABLE II. PARAMETERS TURNING AND INTEGRATION FOR CLASSIFICATION-BASED DECISION MAKING, AND TEST-CASE CONDITIONS BASED ON STOCHASTIC GRADIENT DECENT OPTIMIZATION (SGD) ← PARAMETERS TURNING AND INTEGRATION

Test conditions	Epochs Value	Image Learning Rate (imlr)	Momentum1
Test condition 1 (TC1)	epochs>70 then	0.0001	0.4
Test condition 2 (TC2)	epochs>140 then	0.0002	0.5
Test condition 3 (TC3)	epochs>210 then	0.0003	0.6
Test condition 4 TC4	epochs>280 then	0.0004	0.7
Test condition 5 (TC5)	epochs>350 then	0.0005	0.8

The Table II is representing the dual-image-based multi-layer mapping approach based on classification and regression → used at the end to classify the five stages of DR based on the features extracted from a series of networks. Each stage consists of the following data. The Table III representing the A dual-image-based multi-layer mapping approach based on classification and regression which used at the end to classify the five stages of DR based on the features extracted from a series of networks for further decision making (dm).

Every dual image based multi-layer mapping approach.

imlr1 = 0.001, momentum1 = 0.4.

imlr2 = 0.005, momentum2 = 0.8.

cim1 ← first moment of color image based exponential decomposition rate in AOpt.

cim2 ← second moment of color image based exponential decomposition rate in AOpt.

bwim1 ← first moment of black-white image-based exponential decomposition rate in AOpt.

bwim2 ← second moment of black-white image-based exponential decomposition rate in AOpt.

cim1 =0.7, cim2=0.890.

bwim1=0.7, bwim2=0.890.

The experimental scenarios are framed based on the Kaggle APTOS dataset, which has shown that the proposed trained modelized approach represents a greater contribution to the active methodologies through blended features. The proposed methodology has been compared with the existing approaches based on integrated DR symptoms, their affecting factors, data metrics, and dual image processing techniques. This research has experimented with dual images, which has helped to analyze the images in depth for detection of DR stages and has helped to identify and map the missing patches with color fundus images and black-and-white images.

TABLE III. A DUAL-IMAGE-BASED MULTI-LAYER MAPPING APPROACH BASED ON CLASSIFICATION AND REGRESSION WHICH IS USED AT THE END TO CLASSIFY THE FIVE STAGES OF DR BASED ON THE FEATURES EXTRACTED FROM A SERIES OF NETWORKS FOR FURTHER DECISION MAKING (DM)

Test Condition stage1	Test Condition stage2	Each epoch range	tiny cluster	cim1	cim2	bwim1	bwim2
initialized Adaptive Moment Estimation → bhm	Adaptive Moment Estimation (Adam) ← Parameters turning and integration.	1 to 70	for each tiny-cluster1 ➔ (Pmini, Qmini) ∈ (P, Q)	0.7	0.890	0.4	0.5
initialized Adaptive Moment Estimation → bhm then.	Adaptive Moment Estimation (Adam) ← Parameters turning and integration.	71 to 90	for each tiny-cluster2 (Pmini, Qmini) ∈ (P, Q)	0.7	0.890	0.5	0.6
Adaptive Moment Estimation ➔	Update the multitasking parameters	above 90	If validation error is not improving for four epochs, then imlr1 = avg ((imlr1 * 0.01) + ((imlr2 * 0.01)) imlr2 = avg ((imlr1 * 0.01) + ((imlr2 * 0.01))	0.7	0.890	0.7	0.8

VI. CONCLUSION

A trained clinician or ophthalmologist must analyze and estimate digital color fundus photographs of the retina to identify DR based on the presence of lesions associated with the vascular malformations brought on by the disease. This labour-intensive and manual process takes time. This study suggested ResNet feed-forward neural network technology for automated decision-making. In the pre-processing and classification steps, the sequential and non-sequential pictures were analyzed concurrently. The mapping approaches combined to evaluate and map the hard exudates and hemorrhages, microaneurysms, venules and dot points of the fovea, cottonwool spots, the macula, the outside line of computations of the optic disc, and retinal arterioles between color and black-white pictures. Missing computations are incorporated into the vector sequence, which makes it easier to recognize DR phases. The test cases comprised a total of 5672 sequential and 7231 non-sequential color fundus and black and white retinal pictures. The 10-ford cross-validation technique was used in testing and training using the 80 and 20% ratios of high- and low-quality photos. For testing and analyzing high-quality photographs, the ACU, sensitivity, and specificity were 98.9%, 98.7%, and 98.3%, respectively; for low-quality images, they were 94.9%, 93.6%, and 93.2%.

AUTHORS' CONTRIBUTION

Conceptualization: A., AK, and Henge. S.K.; Methodology: Henge. S.K., and Bhagat., A.; Software: A., AK, and Henge. S.K.; Validation: A., AK, and Henge. S.K., Mandal. S.K.; Formal analysis: Henge. S.K. and Bhagat., A; Investigation: Bhagat., A, and A., AK; Resources: A., AK and Henge. S.K.; Data curation: A., AK, Mandal. S.K. and Henge. S.K.; Writing—original draft preparation, A., AK, Bhagat., A and Henge. S.K.; Writing—review and editing: A., AK, and Henge. S.K.; Visualization: Bhagat., A, and A., AK; Supervision: Henge. S.K.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

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