Detection of Lesions for Diabetic Retinopathy By using Machine Learning Algorithms

Mohamed Jebran P, Shweta Gupta

Abstract: ***In this paper existing writing for computer added diagnosis (CAD) based identification of lesions that might be connected in the early finding of Diabetic Retinopathy (DR) is talked about. The recognition of sores, for example, Microaneurysms (MA), Hemorrhages (HEM) and Exudates (EX) are incorporated in this paper. A range of methodologies starting from conventional morphology to deep learning techniques have been discussed. The different strategies like hand crafted feature extraction to automated CNN based component extraction, single lesion identification to multi sore recognition have been explored. The different stages in each methods beginning from the image preprocessing to classification stage are investigated. The exhibition of the proposed strategies are outlined by various performance measurement parameters and their used data sets are tabulated. Toward the end we examined the future headings.***

Keywords : Diabetic Retinopathy (DR), microaneurysms (MA), hemorrhages (HEM), Exudates (EX), SVM, KNN, NB, BOVW, CNN

I. INTRODUCTION

The worldwide inescapability of Diabetes Mellitus (DM) among grown-ups over the 18 years old has ascended from 4.7% in 1980 to 8.5% in 2014 [1], [2]. As per the WHO, 31.7 million individuals were impacted by diabetes mellitus (DM) in India in the year 2000. This figure is evaluated to ascend to 79.4 million by 2030, the biggest number in any country on the planet [3]. Very nearly two-third of all Type 2 and practically all Type1 DM persons are inclined to Diabetic Retinopathy (DR) over some stretch of time [4]. Diabetic Retinopathy harms the veins inside the retinal tissue making them release liquid or hemorrhage, leading to obscured vision in its most exceptional stage and thereby blindness [5].

Contusions found in the DR contacted retina are categorized as red sores and bright lesions. Microaneurysms (MA) and hemorrhages (HEM) are red lesions while Hard Exudates (HE) and Cotton Wool Spots (CWS) also known as soft exudates are bright lesions. Microaneurysms (MA) are the most obvious side effects of DR. They are the red injuries portrayed by red spots, round shape with sharp edges and dimensional range between 20µm to 200µm. Bleeding of liquid occurs from delicate vessels in hemorrhages. They are portrayed by sporadic edge and thickness, with estimation ordinarily more conspicuous than 125 µm. Further they are named dot HEM, BlotHEM and Flame HEM. Dot HEM bear a striking resemblance to MA. This makes them both difficult to isolate from each other. Hard Exudates appear when fluid consisting of proteins and other discharges leaks from retinal veins. HEs are arranged in White or off-white stores with piercing edges. Blockages in arteriole causes soft exudates known as CWS [5].

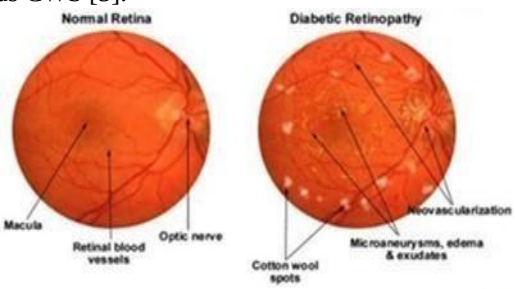

Fig. 1.Clinical Features found in the normal and DR retina.

DR lesions found in the DR effected retina is shown in Fig.1 [6]. DR can be broadly classified as NPDR and PDR [7]. NPDR (non-proliferative diabetic retinopathy) can be identified by the closeness of sores, as exhibited in MA, HEM, HE and microinfarcts. The Early Treatment Diabetic Retinopathy Study (ETDRS) has scaled the acuteness of the disease as mild to moderate NPDR by the proximity of bright and red lesions in the fundus images, medium to extreme on the account of the closeness of signs like substantial hemorrhages in retina as well as MA or CWS, or walls of retinal veins losing their normal alignment or abnormality of the main capillaries to the retina, last stage shows all above symptoms present at any rate. The PDR has stages like Neovascularization of the disc, followed with high- threat of Vitreous hemorrhage discharge and new vessels on the disc and last stage will be PDR with cutting edge eye ailment where tractional retinal separation is seen.

The remainder of the paper is sorted out as pursues: in area II audit the various procedures for distinguishing the MA, HEM and EX. In segment III, examine the results, lastly reach inference on segment IV.

II. LITERATURE SURVEY

Diabetic retinopathy is identified by the presence of microaneurysms [7]. The detection of red lesion MA plays a significant part in early diagnosis of DR. One of the major challenge in the detection of lesions is their difference with respect to their dimensions, structure and closeness to other normal features of the retina. This sometimes results in false detection or wrong classifications.

Revised Manuscript Received on January 15, 2020
***** Correspondence Author
Mohamed Jebran P*, Research Scholar, Department of Electronics and Communication, Jain University, Bangalore, India.
Shweta Gupta, Associate Professor, Department of Electronics and Communication, Jain University, Bangalore, India.

A. Peak Detection Method

MAs show Gaussian like intensity distribution. This property helps decide the possibility of MA, as proposed by Lazar and Hajdu [8]. At first the image is preprocessed and number of pixels are confined by taking into consideration the local maxima. Intensity detection is applied on every candidate to identify a group of characteristics that depict the dimensions, and state of the focal peak. A feature bundle list is created which depends on the factual proportion of these qualities as the direction of cross area changes. These list of statuary is applied to the Naïve Bayes (NB) classifier to separate between obvious MA applicants from the non-MA hopefuls. The proposed strategy is tried on publically accessible Retinopathy Online Challenge (ROC) data set and a private data set. Alongside the cross segment profile [8], a lot of local features, for example, Hessian Matrix based, shape and intensity are proposed by Bo Wu et al. [9]. In all 27 features are extracted. For image preprocessing the green channel fundus is utilized in addition to applying Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm for magnification of MA applicants. The MA candidate choice is arrived at by using peak detection technique and region growing strategy is connected to get back the original shape of the lesions, for which a dynamic transformation is used. Different classifiers are analyzed, for instance, KNN, NB and adaboost to find the best classifier for this sort of future set.

During the process of identifying a true MA candidate various false contenders were included alongside, especially when the MAs were found close to veins. S. Wang et al. [10] proposed a technique wherein candidates were segregated based on dark object filtering followed by singular spectrum Analysis (SSA) the purpose of which is to isolate the bogus candidate. These picked contenders were then scaled on Correlation coefficient (CC) score. In all, 11 features which were subjected to the scaled profiles were used by KNN classifier.

B. Dictionary learning method

MA identification strategy built on the sparse coding and dictionary learning is presented by W. Zhou et al. [11]. The procedure consists of image preprocessing, candidate extraction, multi feature dictionary learning and classification. Preprocessing step is performed to expel the uneven brightening and clamor. In the candidate extraction step all the conceivable MA hopefuls are separated by applying Multi Scale Correlation Filtering (MSCF). During the training phase eight features were extracted from every MA and non- MA patch which is obtained from the second step, and a fusion matrix is created and by utilizing K-Singular Value Decomposition (K- SVD) a sub dictionary is built. Finally, for the test images preprocessing and candidate extraction procedure is rehashed. With the assistance of multi feature fusion dictionary (MFDL) reference, MA competitor were grouped dependent on the total reconstruction error. Discriminative Dictionary Learning (DDL) is proposed by Malihe Javidi et al. [12] with the two targets one with the precise location of vein and second with the MA recognition. DDL algorithms are utilized rather than fixed dictionary learning because these dictionaries not only use discriminative data of preparation data sets proficiently, in addition they adjust to the context of the image. Here two dictionaries were learned for MA and non-MA candidates both each, and Morlet wavelet strategy is applied for MA candidate extraction.

C. Class imbalance classifier

At the point when the minority class for example MA are a lot littler or rarer than a greater part class for example non-MA brings about uneven informational collection. This class irregularity issue affects the proficiency of the conventional classifiers. This class unevenness issue is overcome by re-adjusting the class appropriation by random selection of the occurrences of the splinter group, one such procedure is the Synthetic Minority Over-sampling TEchnique (SMOTE) [13]which generates the synthetic samples. F. Ren et al. [14] presented a novel structure which is an amalgamation of versatile over-sampling method for example SMOTE with the ensemble classifiers, for example, Boosting, Bagging and Random subspace to improve the MA location by diminishing the false positive MA candidates. So as to distinguish the MA, image preprocessing, and vessel evacuation by multi-scale top- hat transform, thereafter, Gaussian filter with 7X7 arithmetic kernel is implemented to cut off clatter. Feature extraction procedure brought about twenty six features from numerous angles for example, intensity, shape and gradient distribution were drawn out from domain of concern for every prospective MA. M. Habib et al. proposed ensemble classifier with bagging [15] for the MA grouping from the false applicants. Whole identification procedure has three stages. After the first phase of image preprocessing, in the second stage a closing operator is utilized for the vein's expulsion, pursued by the Gaussian matched filter for removing noise, lastly region growing is connected to upgrade the state of the recognized MA applicants. At long last 70 features are used in tree ensemble classifier. Since the proportion of non- MA and genuine MA candidates are imbalanced, RUSBoost which is an adaptive boosting classifier is utilized as a class imbalance classifier by B. Dai et al. [16].

D. Red lesion detection

During the division of veins numerous authentic lesions were lost, when lost they can't be recovered back in the process, in order to beat this downside Lama Seoud et al. [17] incorporates another shape feature Dynamic Shape Features(DSF) for the identification of red sores i.e. both MA and HEM. DSF have qualities that permit the separation between the lesions and vessel sections, it does not require exact division of the veins, and is robust. The Random Forest classifier is utilized to separate among extruders and different structures like vessel fragments. The course of action of images as DR and no-DR has been done by M. Gegundez-Arias et al. [18] by recognizing the MA and HEM. In the primary stage identification of the MA and HEM applicants is performed. This stage incorporates the procedure of background homogenization, MA and HEM enhancement in the image and Thresholding steps.

Likewise, so as to diminish the bogus negatives, optic disc, fovea and veins division is performed. Second stage is the identification of MA and HEM sores. This stage includes extraction and grouping process. A regularized local regression is utilized as a supervised classifier. The preparation for the classifier is given from the private data set.

To defeat the issue of bogus recognition of red lesions at veins and changed size of the red sores, a filter based on Frangi filters and a Multiple Kernal learning (MKL) is proposed by Ruchir Srivastava et al. [19]. These channels have the capability to recognize extended structures and bead like structure of red sores. To distinguish the fluctuated size of the sores, the image is isolated into various patches, and data from these sub-images are incorporated by utilizing MKL which creates a vector which was utilized with SVM, to foresee if a lesion is present in the image.

E. Multi lesion detection (bright and red lesions)

The multi lesions identification and reviewing the seriousness level of DR is proposed in [20]. Features optimization based on weighting technique is done by utilizing Adaboost. The whole procedure is separated into three phases, in the primary stage division of optic disc and vasculature will be done, trailed by the lesion grouping and sorting as bright and red sores in the second stage, at last, seriousness reviewing will be finished by counting the tally of MA and HEM on per image basis. For grouping reason, assortment of feature classifiers are examined, for example, GMM, KNN, SVM, Adaboost and hybrid classifiers, and it is discovered that for the bright lesions order GMM classifier and for the red sore characterization KNN is the best classifiers. A multi lesion, for example, MA, HEM and exudates discovery framework is proposed by Kar et al. [21] where preprocessing is done independently for the dark and bright sore, for that curvlet based edge enhancement system is utilized for dark sores and ideal band pass filter for red. Applicant lesions identification is performed in the third step, for which matched filter and Laplacian of Gaussian separating is utilized. Differential Evaluation algorithm is utilized to decide the limit esteems for classification.

F. Feature optimization

In a DR screening framework displayed by S. Sreng et al [22]. There around 208 features were isolated, in light of pixel density, spatial arrangement, complexion and magnitude of fragmented lesions. Optimization of list of features is necessary so as to reduce the computational time and layoff of unnecessary features. Distinctive element optimization procedures were discussed, for example, Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Hybrid Ant Colony Optimization (HACO) and Hybrid Simulated Annealing (HSA). The simulated outcomes demonstrate that Hybrid Simulated Annealing is the best feature optimizer. The yield of these improved features are inputted to different classifiers, for example, Support Vector Machine (SVM), Decision Tree (DT), Logistic Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN), Ensemble Bagging (EB). Of these Ensemble Bagging (EB) classifier outflanked over others. In [23] a strategy to recognize the fundus images as ordinary or unusual is suggested by J. Koh et al. Fundus photo is crumbled by using 2D-Continuous Wavelet Transform (CWT), then energy and entropy features were extricated from the crumbled images, class imbalance issue is addressed by adaptive synthetic sampling. The feature ranking and optimization were performed by utilizing particle swarm optimization, at last, chosen features were utilized to train the random forest classifier. Two dimensionality reduction techniques for feature space by using Principal Component Analysis and RF feature importance is proposed by Wen Cao et al. [24].

G. Multiple Instance Learning (MIL) framework -Bag of Visual Word (BOVW)

The regular methodologies for DR distinguishing proof used to be done by perceiving simply explicit kind of lesions, and besides pixel wise lesions notation understanding must be trained which makes this methodology costly and monotonous. This issue is overpowered by using Multiple Instance Learning (MIL) structure — Bag of Visual Word (BOVW) methodology. The procedure proposed by R. Pires et.al [25] is based on using two-layered image depiction which incorporates low level feature using Speeded-Up Robust Features (SURF) as low rank descriptors and mid-level features reliant on semi-soft encoding with max pooling. These component vectors are used by maximum margin SVM classifier. On a similar structure M. Islam et.al in [26] included additional progression at the outset as image pre-processing. On the equivalent lines, DR recognition and severity ranking by using the blend of BOVW model with multiclass classifiers proposed by Sagar Honnungar et.al [27]. It involves image preprocessing, trailed by the low level element extraction, for instance, SURF, LBP and HOG are considered and by using these, midlevel feature vector are constructed. Multi class classification is performed by using multinomial logistic regression, SVM and random forest. The previously mentioned [25] [26] lesion based referable strategy is having the three phases, which incorporates acknowledgment of individual lesions, blend of individual lesions responses and final classifier. So it requires two decision makers one for the individual lesions and other for conclusive order. This technique will lose the critical information, for instance, count, intensity and localization of lesion. To crush these drawbacks R. Pires et al. [28] proposed a method in which image patches of different grids frameworks are used, from which SURF are extracted. For the mid-level highlights alongside the customary BOVW strategy two new mid-level features such as BossaNova and Fisher Vector are researched. Finally, for the twofold separation referable versus non-referable, SVM is used. Another novelty is proposed by Pedro costa et.al [29] concerning BOVW method, in which encoding and classification stages are combined as single stage. K.S.Sreejini et al. [30] proposed Probabilistic latent semantic analysis (pLSA) model which is one of the feature dimension reduction system reliant on topics instead of words.

Here First features are picked by using Local Binary Pattern (LBP), Scale Invariant Feature Transform (SIFT), Local Directional Pattern (LDP), and color descriptors. K-means gathering is associated to make BOVW vectors. Then topic modeling pLSA is utilized to cut down the feature dimension by utilizing the concept of topics rather than words. At the last vector is given to the linear SVM classifier to classify the image as infected or normal.

H. Deep learning method

A three-phase MA detection framework is pro- posed by Piotr Chudzik et al. [31] by utilizing fully Convolution neural network. Besides how knowledge transfer between the small data set for recognition of MA is shown. Feature extraction is mechanized, it doesn't require manual hand created features for the characterization. In [32] spiral sequence of gray level values are used for the candidate extraction. Umit Budak et al. utilized Deep Convolutional Neural Network (DCNN) architecture, in which convolution and pooling tasks develop the features and classification is performed by utilizing fully connected layers with reinforcement sample learning strategy. Preparing the CNN requires lesion level clarified information, so marking images at the lesion level is exorbitant. J. Orlando et al. [33] displayed a strategy which exploits light CNN design for feature extraction. This arrangement of features is then enlarged, by joining handmade features. These outfit vectors are utilized to prepare RF classifier.

In CNN learning method to envision the learning procedure a convolutional representation layer is presented by R. Gargeya et al. [34]. Data augmentation is performed after the image pre- processing step. Profound learning system learns the data driven features from this data set. To envision the learning procedure visualization layer is implanted in the mechanized learning system. Feature extraction will be performed from the global average pooling layer and metadata high- lights are likewise included. A second level gradient boosting classifier which is decision tree classifier model is used to produce final conclusion for DR.

The DR identification and five class seriousness reviewing of DR by utilizing CNN is proposed by H. Pratt et al. [35]. The CNN alongside information growth helps in finding complex features associated with the detection of the lesions, for example, MA, exudates and hemorrhages so that appropriate reviewing can be performed. It essentially comprises of image preprocessing, training and enlargement steps. For preparing this system a top of the line NVIDIA K40c GPU is utilized. Another significant prerequisite for this sort of system is availability of enormous dataset collection. Kaggle dataset collection is utilized for this reason. The CNN techniques for grouping the DR endures real downside of over-fitting. One of the answer for this issue is proposed by S. Wan et al. [36] by actualizing transfer learning and hyper parameter tuning techniques.

To assemble clinical application with 4 degree seriousness evaluation zhentao gao et.al [37] proposed CNN technique which is investigated on a moderate estimated new dataset and the model is hosted on a cloud platform, also used for pilot demonstrative administrations.

I. Detection of Exudates

The morphological contrasts between the veins and exudates can be utilized to sort out the blood vessel segments. Elaheh Imani et al. [38] utilized Morphological Component Analysis (MCA) deterioration algorithm to isolate the veins so it clears a path for different lesions which can be effectively fragmented. Finally, the dynamic thresholding and morphological operators are utilized for the exudate division. Javeria Amin et al. [39] proposed a 2 class classification as exudate area or non-exudate locale. The fundus image is preprocessed by grayscale change. For upgrading the odds of lesion recognition Gabor filter is applied, furthermore to decrease the pseudo discovery of lesions, optic disc is sectioned and expelled. Exudates division is performed. 4 principle descriptors, region, edge, circularity, and diameter were extricated from the portioned applicants. Separated component vector is used in various classifiers such as different types of SVM, NB, fine, medium and weighted k- Nearest neighbor (KNN) and ensemble bagged tree-based, are utilized for characterization as exudates or non- exudates.

M. Moazam Fraz et al. [40] proposed an ensemble based bootstrapped decision tree for the localization and division of exudates. Due to the varied size of the exudate candidate region two level candidate region extraction will be per-formed. The coarse level candidate extraction is performed by Gabor filtering and morphological reproduction, trailed by top hat transformation as a fine grain level applicant extraction. For false positive reduction, bright and dark artifacts present in the retinal image are eliminated. A couple of region based features are removed from candidate for pixel based classification. The ensemble classifier has a significant quality, which is that the significance of the feature utilized in the basic classification can be judged appropriately.

Locating the exudate region patches and segmenting the exudate from that patch is exhibited by Qing Liu et al. [41]. The whole procedure is divided into three phases, an anatomic structure evacuation, matched filter based fundamental vessels division technique and a saliency based optic disc division strategy. The subsequent stage is identifying the exudate regions, for which random forest classifier is utilized. To learn a classifier, histograms of completed local binary pattern (CLBP) are separated from the exudate and non- exudate patches, to portray the surface structures. So the classifier characterizes the patches as exudate and non-exudate patches. For the division of exudate from the variances around the exudate areas, the earlier size of the exudate areas and the earlier local contrast are utilized for localizing the lesions.

For exudate classification Wei Zhou et al. [42] proposed a series of super pixel exudate candidates which is a simple linear iterative clustering.19 multi-channel intensity features and a global element are presented as contextual feature. Contextual feature is the mean gray estimation of every candidate. Fisher Discriminant Analysis (FDA) concludes them as exudate or non-exudate. Optic disc is expelled post procedure, by key point extraction and template matching.

Table I: Evaluation outcome of MA & HEM detection methods

Authors	Methods	Data Base	Lesion	Classifier	Performance Measure
Lazar et al [8]	Intensity detection	ROC	MA	NB	FROC=0.423
Bo Wu et al. [9]	Peak detection, region growing	ROC	MA	KNN	FROC= 0.202
W.Zhou et al. [11]	MSCF, K-SVD	ROC	MA	MFDL	FPPI= 0.285
M. Javidi et al.[12]	Morlet wavelet	ROC	MA	FDDL	FROC=0.2679
F. Ren et al.[14]	SMOTE	ROC	MA	ASOBoost	SE=0.425,FPI=5.7
B. Dai et al[16]	gradient vectors	ROC	MA	RUSBoost	SE=0.433
L.Seoud et al[17]	DSF	ROC	MA, HEM	RF	ACC=0.420
M. Gegundez-Arias et al [18]	Tamura texture signature	MESSIDOR	MA,HEM	Regularized local regression	SE=0.9380, SP=0.5098
S.Roychowdhury et al[20]	OD and BV segmentation	DIARETDB1	MA, HEM, CWS, HE	GMM,kNN	Red lesion SE=80%,SP=85% Bright lesion SE=74.2%,SP=98%
S. Kar et al.[21]	laplacian of Gaussian filtering	DRIVE, STARE, DIARETDB1, MESSIDOR, ROC	MA, HEM	Differential Evaluation algorithm	MA-SE=95.23%, ACC-97.23% HEM-SE=97.67% ACC-96.99%
R. Pires et al.[28]	BOVW, BossaNova Fisher Vector	DR2	-	SVM	AUC=94.2%
K. Sreejini et al[30]	BOVW,pLSA	STARE	-	SVM	SE=94.44%,SP=96.88 %, Acc=96 %
P. Chudzik et al.[31]	Batch normalization	EOPHTHA	MA	CNN	FPI=0.562
U. Buda et al.[32]	DCNN	ROC	MA	Reinforcement sample	FROC=0.221

Independent of the varieties of intensities, brightness and faint edges in the retinal image, Jaskirat Kaur et al. [43] proposed a vigorous exudate division technique dependent on dynamic decision thresholding. For precise recognition and elimination of veins, a feature extraction and classification by neural network, an adaptive blood vasculature normalization procedures are performed. Union of blood vasculatures approach is utilized for the OD disposal. To get the genuine exudates from the fake applicants, adaptive image quantization and thresholding approach is utilized. For generalization both public and private data set is used.

An exudate division technique for fundus images which contain the artifacts is proposed by X.Zang et al. [44]. At first preprocessing step is performed post which Mathematical morphology based exudate division takes place. A lot of contextual and textural features are extricated from the entire candidates, as well as from various littler divergence candidates. Random Forest classifier is utilized for the genuine exudate classification.

For the purpose of improving the exactness without utilizing the classifiers, another strategy for the exudate division is suggested by kittipol wisaeng et al. [45]. The morphological closing operator is utilized to circumscribe the OD and binary dilation is utilized to recreate the image with a superior OD identified image. At that point coarse division of exudate and non-exudate areas is done by mean shift algorithm. Fine tune segmentation of exudate region only, is obtained by applying mathematical morphology algorithm procedure.

III. COMPARISON OF RESULTS

The table of result comparison for the detection of red lesion group members such as MA and HEM is presented in the Table I. Similarly, the detection of exudates is presented in the Table II. The results are tabulated with respect to the various measurement parameters as specificity (SP), sensitivity (SE), Accuracy (ACC), False Positive per Image (FPPI), Positive Prediction Value (PPV), FROC (Free Response Receiver Operating Characteristics) and Area under ROC curve (AUC).

Table II: Evaluation Outcome of Exudate detection method

Authors	Techniques	Dataset	Classifier	Performance Measure
E. Imani et al.[38]	MCA algorithm (Thresholding Method)	DIARETDB, HEI-MED,	-	AUC=96.1,94.8,93.7%
J. Amin et al. [39]	OD and BV segmentation	public and local	KNN	AUC=98%
M. Fraz et al.[40]	Gabor filtering, top hat transformation	HEI-MED	Ensemble (Bootstrapped decision trees)	AUC=0.9842
Q. Liu et	CLBP	E-OPHTHA	Random Forest	SE=76%,
W. Zhou et al.[42]	Multi-channel intensity, Contextual feature.	DIARETDB1, E-OPHTHA, EX	FDA	SE=88%, SP=95%, AUC=0.9655
J. Kaur et al[43]	adaptive blood vasculature normalization	658 images	Dynamic decision thresholding	SE=88.85%, SP=96.15%, ACC=93.46%

IV. CONCLUSION

Diabetic Retinopathy is a dynamic disease primarily found in the working age individuals who have diabetes mellitus for quite a long while. It causes gathering of red and splendid lesions in the retina. The number and sort of lesions present on the retina decide the seriousness of the infection. The red lesions like MA are the most obvious indications of DR. Building up a programmed DR screening system is fundamental which not just decreases the remaining task at hand for ophthalmologists, lessens the time, and in addition improves the exactness of location of clinical features. This paper displays a diagram of late techniques and classification algorithms utilized for distinguishing, identification, and grading of DR. The discovery procedure for the most part comprises of different procedural advances like preprocessing, candidate extraction, feature extraction and grouping. Enhancements have been done in each phase so as to improve the exactness level. Despite the fact that significant progress has been achieved in the early discovery of sores, challenges still exist in lessening the pseudo positives, improving the sensitivity, specificity, accuracy and severity evaluation. By utilizing the highly discriminative feature set and the best classifier, lesion based DR detection can be investigated. A collaboration of deep learning based model and domain based feature set can be utilized for DR decision and its severity level. Furthermore DR activation maps can be used for compelling clinical references, with the intention to help enable the ophthalmologist interpret in all respects proficiently. What features a deep neural system learns, to make decision as DR or no-DR is another zone of future research. How the knowledge transfer of the small datasets can be done while utilizing the deep learning model is another captivating zone. Aside from the DR recognition, study of other eye disease identification, for example glaucoma, age macular degeneration from the fundus image in the same framework can be investigated.

REFERENCES

1. Emerging Risk Factors Collaboration, "Diabetes mellitus, fasting blood glucose concentration, and risk of vascular disease: a collaborative meta-analysis of 102 prospective studies", Lancet 375," 9733. [Online]. Available: 10.1016/s0140-6736.
2. W. int, "Diabetes", Who.int, 2019. [Online]. Available: https://www.who.int/news-room/factsheets/
3. Q. M. S. Gadkari and B. Nayak, "Prevalence of diabetic retinopathy in India: The All India Ophthalmological Society Diabetic Retinopathy Eye Screening Study 2014," Indian Journal of Ophthalmology, vol. 64, pp. 38– 10, 2016. [Online]. Available: 10.4103/0301-4738.178144.
4. L. Drake, "Prevention of Blindness from Diabetes Mellitus Report of a WHO Consultation Prevention of Blindness from Diabetes Mellitus - Report of a WHO Consultation, Nursing," Standard, vol. 21, no. 32, p. 30. [Online]. Available: 10.7748/ns2007.04.21.32.30.b604.
5. M. Clinic, "Diabetic retinopathy - Symptoms and causes. [Online] Available at," 2019, conditions/diabetic-retinopathy/symptoms-causes/ syc-20371611. [Online]. Available: https://www.mayoclinic.org/diseases
6. Hoque, "Diabetic Retinopathy," 2019. [Online]. Available: https://www.slideshare.net/fahmidahoque1/
7. A. Alghadyan, "Diabetic retinopathy – An update," Saudi Journal of Ophthalmology, vol. 25, p. 111, 2011. [Online]. Available: 10.1016/j.sjopt.2011.01.009
8. A. H. Lazar, "Retinal Microaneurysm Detection Through Local Rotating Cross-Section Profile Analysis," IEEE Transactions on Medical Imaging, vol. 32, no. 2, pp. 400–407, 2013. [Online]. Available: 10.1109/tmi.2012.2228665.
9. B. Wu, W. Zhu, F. Shi, and S. Z. X. Chen, "Automatic detection of microaneurysms in retinal fundus images", Computerized Medical Imaging and," Graphics, vol. 55, pp. 106–112, 2017
10. S. Wang, "Localizing Microaneurysms in Fundus Images Through Singular Spectrum Analysis," IEEE Transactions on Biomedical Engineering, vol. 64, no. 5, pp. 990–1002, 2017. [Online]. Available: 0.1109/tbme.2016.2585344.
11. W. Zhou, C. Wu, D. Chen, and Z. Wang, "Automatic Microaneurysms Detection Based on Multifeature Fusion Dictionary Learning," Computational and Mathematical Methods in Medicine, pp. 1–11, 2017. [Online]. Available: 10.1155/2017/2483137.
12. M. Javidi, H. Pourreza, and A. Harati, "Vessel segmentation and microaneurysm detection using discriminative dictionary learning and sparse representation, Computer Methods and Programs in Biomedicine 139," p. 108, 2017. [Online]. Available: 10.1016/j.cmpb.2016.10.015.
13. N. Chawla and W. Kegelmeyer, "SMOTE: Synthetic Minority Over-sampling Technique," Journal of Artificial Intelligence Research, pp. 321–357, 2002. [Online]. Available: URL10.1613/jair.953.
14. F. Ren, P. Cao, and W. Li, "Ensemble based adaptive over-sampling method for imbalanced data learning in computer aided detection of microaneurysm", Computerized Medical Imaging and Graphics, 55, pp. 54–67, 2017.
15. M. Habib, R. Welikala, and A. Hoppe, "Detection of microaneurysms in retinal images using an ensemble classifier," Informatics in Medicine Unlocked, vol. 9, pp. 44–57, 2017. [Online]. Available: 10.1016/j.imu.2017.05.006.
16. B. Dai, X. Wu, and W. Bu, "Retinal Microaneurysms Detection Using Gradient Vector Analysis and Class Imbalance Classification," PLOS ONE, vol. 11, pp. 8–0 161 556, 2016. [Online]. Available: 10.1371/journal.pone.0161556.

17. L. Seoud, T. Hurtut, and J. Chelbi, “Red Lesion Detection Using Dynamic Shape Features for Diabetic Retinopathy Screening”, IEEE Transactions on Medical Imaging, vol. 35, no. 4, pp. 1116–1126, 2016. [Online]. Available: 10.1109/tmi.2015.2509785.
18. M. Gegundez-Arias, “A tool for automated diabetic retinopathy pre-screening based on retinal image computer analysis”, Computers in Biology and Medicine, vol. 88, pp. 100–109, 2017.
19. R. Srivastava, L. Duan, D. Wong, J. Liu and T. Wong, "Detecting retinal microaneurysms and hemorrhages with robustness to the presence of blood vessels", Computer Methods and Programs in Biomedicine, vol. 138, pp. 83-91, 2017. Available: 10.1016/j.cmpb.2016.10.017.
20. S. Roychowdhury, D. Koozekanani and K. Parhi, "DREAM: Diabetic Retinopathy Analysis Using Machine Learning", IEEE Journal of Biomedical and Health Informatics, vol. 18, no. 5, pp. 1717-1728, 2014. Available: 10.1109/jbhi.2013.2294635.
21. S. Kar and S. Maity, "Automatic Detection of Retinal Lesions for Screening of Diabetic Retinopathy", IEEE Transactions on Biomedical Engineering, vol. 65, no. 3, pp. 608-618, 2018. Available: 10.1109/tbme.2017.2707578.
22. S. Sreng, N. Maneerat, K. Hamamoto and R. Panjaphongse, "Automated Diabetic Retinopathy Screening System Using Hybrid Simulated Annealing and Ensemble Bagging Classifier", Applied Sciences, vol. 8, no. 7, p. 1198, 2018. Available: 10.3390/app8071198.
23. J. Koh et al., "Diagnosis of retinal health in digital fundus images using continuous wavelet transform (CWT) and entropies", Computers in Biology and Medicine, vol. 84, pp. 89-97, 2017. Available: 10.1016/j.compbiomed.2017.03.008.
24. W. Cao, N. Czarnek, J. Shan and L. Li, "Microaneurysm Detection Using Principal Component Analysis and Machine Learning Methods", IEEE Transactions on Nano Bioscience, vol. 17, no. 3, pp. 191-198, 2018. Available: 10.1109/tnb.2018.2840084.
25. R. Pires, H. Jelinek, J. Wainer, E. Valle and A. Rocha, "Advancing Bag- of-Visual-Words Representations for Lesion Classification in Retinal Images", PLoS ONE, vol. 9, no. 6, p. e96814, 2014. Available: 10.1371/journal.pone.0096814.
26. M. Islam, A. Dinh and K. Wahid, "Automated Diabetic Retinopathy Detection Using Bag of Words Approach", Journal of Biomedical Science and Engineering, vol. 10, no. 05, pp. 86-96, 2017. Available: 10.4236/jbise.2017.105b010.
27. S.Honnungar, 2019. [Online]. Available http://cs229.stanford.edu/proj2016/report/HonnungarMehraJoseph-DRISC-report.pdf. [Accessed: 30- Jul- 2019].
28. R. Pires, S. Avila, H. Jelinek, J. Wainer, E. Valle and A. Rocha, "Beyond Lesion-Based Diabetic Retinopathy: A Direct Approach for Referral", IEEE Journal of Biomedical and Health Informatics, vol. 21, no. 1, pp. 193-200, 2017. Available: 10.1109/jbhi.2015.2498104.
29. P. Costa, A. Galdran, A. Smailagic and A. Campilho, "A Weakly-Supervised Framework for Interpretable Diabetic Retinopathy Detection on Retinal Images", IEEE Access, vol. 6, pp. 18747-18758, 2018. Available: 10.1109/access.2018.2816003.
30. K. Sreejini and V. Govindan, "Retrieval of pathological retina images using Bag of Visual Words and pLSA model", Engineering Science and Technology, an International Journal, vol. 22, no. 3, pp. 777-785, 2019. Available: 10.1016/j.jestch.2019.02.002.
31. P. Chudzik, S. Majumdar, and F. Calivá, “Microaneurysm detection using fully convolutional neural networks,” Computer Methods and Programs in Biomedicine , no. 158, pp. 185–192, 2018. [Online]. Available: 10.1016/j.cmpb.2018.02.016.
32. U. Budak, A. S¸engür, Y. Guo, and Y. Akbulut, “A novel microaneurysms detection approach based on convolutional neural networks with reinforcement sample learning algorithm,” Health Information Science and Systems, vol. 5, pp. 10–1007, 2017. [Online]. Available: 10.1007/s13755- 017-0034-9.
33. J. Orlando, E. Prokofyeva, M. Fresno, and M. Blaschko, “An ensemble deep learning based direct approach for red lesion detection in fundus images”, Computer Methods and Programs in Biomedicine 153, pp. 115– 127, 2018. [Online]. Available: 10.1016/j.cmpb.2017.10.017.
34. R. Gargeya and T. Leng, “Automated Identification of Diabetic Retinopathy Using Deep Learning,” Ophthalmology, vol. 124, pp. 7–962, 2017. [Online]. Available: 10.1016/j.ophtha.2017.02.008.
35. H. Pratt, F. Coenen, D. Broadbent, S. Harding, and Y. Zheng, “Convolutional Neural Networks for Diabetic Retinopathy”, Procedia, Computer Science, vol. 90, 2016. [Online]. Available: 10.1016/j.procs. 2016.07.014.
36. S. Wan, Y. Liang, and Y. Zhang, “Deep convolutional neural networks for diabetic retinopathy detection by image classification,” Computers & Electrical Engineering, vol. 72, pp. 274–282, 2018. [Online]. Available: 10.1016/j.compeleceng.2018.07.042.
37. Z. Gao, J. Li, J. Guo, Y. Chen, Z. Yi and J. Zhong, "Diagnosis of Diabetic Retinopathy Using Deep Neural Networks", IEEE Access, vol. 7, pp. 3360-3370, 2019. Available: 10.1109/access.2018.2888639.
38. H. P. Imani, “A novel method for retinal exudate segmentation using signal separation algorithm”, Computer Methods and Programs in Biomedicine, 133, 2016. [Online]. Available: 10.1016/j.cmpb.2016.05. 016.
39. J. Amin, M. Sharif, M. Yasmin, H. Ali and S. Fernandes, "A method for the detection and classification of diabetic retinopathy using structural predictors of bright lesions", Journal of Computational Science, vol. 19, pp. 153-164, 2017. Available: 10.1016/j.jocs.2017.01.002.
40. M. Fraz, W. Jahangir, S. Zahid, M. Hamayun and S. Barman, "Multiscale segmentation of exudates in retinal images using contextual cues and ensemble classification", Biomedical Signal Processing and Control, vol. 35, pp. 50-62, 2017. Available: 10.1016/j.bspc.2017.02.012.
41. Q.Liu et. al., “A location-to-segmentation strategy for automatic exudate segmentation in colour retinal fundus images”, Computerized Medical Imaging and Graphics, 55, pp. 78–86, 2017. [Online]. Available: 10.1016/j.compmedimag.2016.09.001.
42. W. Zhou, C. Wu, Y. Yi and W. Du, "Automatic Detection of Exudates in Digital Color Fundus Images Using Superpixel Multi-Feature Classification", IEEE Access, vol. 5, pp. 17077-17088, 2017. Available: 10.1109/access.2017.2740239.
43. J. Kaur and D. Mittal, "A generalized method for the segmentation of exudates from pathological retinal fundus images", Bio cybernetics and Biomedical Engineering, vol. 38, no. 1, pp. 27-53, 2018. Available: 10.1016/j.bbe.2017.10.003.
44. Zhang, “Exudate detection in color retinal images for mass screening of diabetic retinopathy,” Medical Image Analysis, vol. 18, no. 7, pp. 1026– 1043, 2014. [Online]. Available: 10.1016/j.media.2014.05.004.
45. K. Wisaeng and W. Sa-Ngiamvibool, "Exudates Detection Using Morphology Mean Shift Algorithm in Retinal Images", IEEE Access, vol. 7, pp. 11946-11958, 2019. Available: 10.1109/access.2018.2890426.

AUTHORS PROFILE

Mohamed Jebran P received M.Tech degree in Electronics and Communication from DSCE, Bangalore, India, in 2010. He is currently pursuing the Ph.D. degree in the department of Electronics and Communication, Jain University, Bangalore, India. His research interest include medical image processing and machine learning.

Dr. Shweta Gupta is Ph.D. in Electronics and Communication from Dr. K. N. Modi University, Rajasthan, India. M.S from Bits Pilani and B.E from Pune University and Executive M.B.A from I.I.M, Lucknow. She is all INDIA topper of C.B.S.E Board in 1997. Her research areas are Biomedical electronics with specialization in Epilepsy and Parkinson’s disease. She is currently working as Associate Professor in School of Engineering and Technology, Jain University, Bangalore. She was awarded by DST-SERB, Govt. of India as senior Scientist to present her research paper in Singapore in ICBBT 2015.