

Declaration

I hereby declare that the work presented in this Thesis titled “*Quality Assessment and Enhancement of Retinal Fundus Images using Deep Learning Methods*” submitted to the Indian Institute of Technology Jodhpur in partial fulfilment of the requirements for the award of the degree of Doctor of Philosophy, is a bonafide record of the research work carried out under the supervision of *Dr. Anil Kumar Tiwari*. The contents of this Thesis in full or in parts, have not been submitted to, and will not be submitted by me to, any other Institute or University in India or abroad for the award of any degree or diploma.

A handwritten signature in black ink, appearing to read 'Aditya Raj', with a horizontal line underneath it.

Aditya Raj
P15VSS201

Certificate

This is to certify that the Thesis titled “*Quality Assessment and Enhancement of Retinal Fundus Images using Deep Learning Methods*”, submitted by *Aditya Raj (P15VSS201)* to the Indian Institute of Technology Jodhpur for the award of the degree of *Doctor of Philosophy*, is a bonafide record of the research work done by him under my supervision. To the best of my knowledge, the contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Dr. Anil Kumar Tiwari
Ph.D.Thesis Supervisor

Acknowledgments

This thesis represent not only my research contributions but it also includes the hard work and dedication done by my supervisor and me in the last five years. I owe my deepest gratitude and respect to my Ph.D. Thesis Supervisor, Dr. Anil Kumar Tiwari, for always encouraging me to explore the research area independently. In the process, I have learned many technical and non-technical aspects of professional work. I am grateful to him for his time, patience, excellent guidance, and invaluable support as well as for continually reminding me to be perfect in the little things that I do each day. I would like to thank him for calmly correcting all my mistakes and failures during the entire Ph.D. duration. I am also thankful to God for the good health and courage that were necessary to complete this thesis.

I am grateful to Department of Biotechnology, India, and British Council, United Kingdom, for selecting me for the prestigious “Newton Bhabha PhD Placement Program 2019”. I am also very grateful to Prof. Maria G. Martini, for accepting me as intern. Her ideas, enlightening discussions, and excellent suggestions helped me to progress, during my research internship at Kingston University, London, United Kingdom. Also, I am indebted to my doctoral committee members, Dr. Gaurav Harit, Dr. Gaurav Bhatnagar, and Dr. Rajlaxmi Chouhan, for their valuable comments, suggestions, and continued guidance during the research work.

Further, I am thankful to the Director of IIT Jodhpur for providing such excellent facilities and making my stay at the Institute comfortable and fruitful. I would also like to thank the Department of Electrical Engineering for providing the research facilities. I am also thankful to the faculty members of the department who were always supporting and helping. Also, I would like to thank all the staff members of the department for providing all sorts of support during my studies.

I am grateful to the Ministry of Electronics and Information Technology (MeitY), Government of India, for initiating the visionary Visvesvaraya Ph.D. Scheme for Electronics and IT. The financial support provided through this scheme is gratefully acknowledged. I also wish to thank Dr. Sunil Moreker from Apolo Hospital, Navi Mumbai, Dr. S. Meena from All India Institute of Medical Sciences (AIIMS) Jodhpur, and Dr. A. Chouhan from Mathura Das Mathur (MDM) Hospital, Jodhpur, and their colleagues for their valuable inputs and suggestions.

I wish to thank my lab-mates, Kumar Rahul, Tushar Shankar Shinde, Deepak, Naveen Mangal, Puneet Jain, and Shabari Nath for all their help. I especially want to thank my friend Nisarg A. Shah for his help in my research work. My stay at the Institute was a wonderful experience because of my friends, Anuj Bharti, Amrik Singh, and Ankit Agarwal. I wish to thank them all for the liveliness they infused into the non-academic part of the days at IIT Jodhpur. Finally, I acknowledge and thank my family, especially my parents, my sister, Smriti, and my wife, Dr. Pratistha, for their relentless belief in me. I owe my deepest gratitude to my father Sri. Alok Srivastava and mother Smt. Sarita Srivastava, who have devoted their everything to my education with invariant love and enthusiasm. They have made tremendous sacrifices to survive this family in tough days. I could never have gone this far without every bit of their faith. I feel proud to thank my family, who taught me many great things in simple ways that helped me to survive the ups and downs of my life. Lastly, I want to dedicate my Thesis work to my son Arjun.

Aditya Raj
Ph.D. Student

List of Figures

Figure	Title	page
1.1	Sample fundus image indicating different structures in a fundus image: (i) Optic disc, (ii) Macula, and (iii) Blood vessels.	2
1.2	Advanced fundus image acquisition devices: (a) D-EYE, (b) Panoptic Ophthalmoscope. Image Credits: D-EYE [HOSPEQ, 2020], and Panoptic Ophthalmoscope [EYEWIRE.News, 2020]	2
1.3	Distribution of the naturalness values of the examples of natural images	5
1.4	Distribution of the naturalness values of the examples of fundus images	6
1.5	Commonly occurred distortions in fundus images	7
2.1	Classification of fundus IQA algorithms	11
2.2	Sample fundus images; (a) Good Quality, (b) Poor Quality.	12
2.3	Normalized histogram of both fundus images	12
2.4	Pie chart summarising the analysis of the fundus IQA algorithms in the literature.	25
2.5	Examples of average quality fundus images: (a) Blur, (b) Dark, (c) Uneven Illumination, and (d) Bright.	26
3.1	Samples of the fundus images from FIQuA dataset.	30
3.2	Samples of the fundus images taken from each category of FIQuA dataset.	31
3.3	Graph showing the range of Opinion Score values for all the six features for the three classes of quality: (a) Good, (b) Fair, and (c) Poor. Here (+) indicates the outlier values.	32
3.4	Confusion Matrices for the each of the four classification results shown in Table 3.3.	33
4.1	Comparison Flow Chart of the state of the art fundus IQA methods and the proposed method.	36
4.2	Proposed Model. FC: Fully Connected Layer, FC1: 1024×1 , FC2: 512×1 , FC3: 120×1 , FC4: 24×1 , FC5: 12×1 , FC6: 480×1 , FC7: 120×1 , FC8: 24×1 , FC9: 12×1 , FC10: 6×1 , CR: Classification Result.	37
4.3	Feature-wise plot of the predicted scores versus actual opinion scores.	40
4.4	Confusion matrix of the prediction results obtained on FIQuA data-set from the proposed fundus IQA model.	42
4.5	Sample images with different distortions from the Fair category of the FIQuA data-set that are correctly classified by the proposed model. Here (a) and (b) represent the images distorted with Blur and Uneven Illumination distortion, respectively.	42
5.1	Fundus images from three categories of image quality: (a) Good, (b) Fair, and (c) Poor.	46
5.2	Samples of naturally distorted and corresponding synthetically distorted fundus images. Here pair (a,f) represents MUI, (b,g) represents BUI, (c,h) represents bright, (d,i) dark, and (e,j) haze.	48
5.3	Comparison Flow Chart of the state of the art fundus enhancement methods and the proposed method.	49
5.4	Architecture of (a) residual block with single skip connection. Here, O_i represents the output obtained from the i^{th} layer, and (b) residual dense block (RDB) with 3 conv layers. For an i^{th} RDB block, X_{i-1} and X_i represent the input and output, and $X_{i,n}$ represents the n^{th} conv layer. $X_{i,LFF}$ represents the reduced feature map obtained after applying the 1×1 conv layer. Here, LFF: local feature fusion.	49

5.5	Architecture of the proposed fundus image denoising model. RDB: Residual Dense Block, d: Depth of the feature map at each layer of the network model.	50
5.6	Architecture of the proposed ensemble model built using the proposed RDC-UNet architecture (shown in Fig. 5.5). Here, d indicates the depth of the feature map at each layer of the network model.	51
5.7	Visual comparison of the results obtained from the proposed model using state-of-the-art methods with synthetically distorted images.	54
5.8	Performance of the proposed ensemble model in terms of visual clarity. Here (a) and (c) represent naturally distorted images containing multiple distortions, and (b) and (d) are the corresponding enhanced images.	55
5.9	Comparative performance of RDC-UNet based ensemble model with state-of-the-art methods in terms of visual observation over naturally degraded fundus images.	56
5.10	Samples of the quality evaluation results obtained from the MvRCNN model. Here, column (a,c) represents naturally distorted fundus images, (b) shows the predicted images labelled as good, and (d) shows the images labelled as fair quality.	57
5.11	Predicted segmentation map results obtained for the synthetically distorted and respective enhanced images from the DRIVE dataset.	58
5.12	Predicated segmentation map results obtained for naturally distorted and respective enhanced images.	59
6.1	An example of the fundus image acquisition process through smartphone funduscopy Espinosa [2022]	64

List of Tables

<i>Table</i>	<i>Title</i>	<i>page</i>
2.1	Summary of Similarity based fundus IQA algorithms. NS: Not Specified	13
2.2	Summary of Segmentation based fundus IQA algorithms. SN: Sensitivity, SP: Specificity, SC: Spearman's Correlation	16
2.3	Summary of Machine learning based fundus IQA algorithms divided on the basis of feature extraction approach. GIS: Generic Image Statistics, DT: Decision tree, FC: Fuzzy classification, ANN: Artificial neural network, SP: Specificity, SN: Sensitivity, MF: Membersip function.	23
3.1	Classification of the six quality parameters for the subjective quality assessment	29
3.2	Sample of the subjective scores and corresponding quality class graded by the ophthalmologists for the respective images shown in Fig. 3.1	30
3.3	Comparison table of accuracy (in %) of various classifiers for individual classes and overall. SVM: Support Vector Machine (Polynomial Kernel); NB: Naive Bayesian; RF: Random Forest; SF: SoftMax.	33
3.4	Coefficient values obtained for F1-F6 from SVM (Polynomial Kernel) classification method.	33
4.1	Correlation coefficients for the predicted values of F1-F6	39
4.2	Performance evaluation of different models for classification results on FIQuA data-set..	41
4.3	Performance evaluation of proposed method over DRIMDB and Eye-Quality (EyeQ) data-set	43
4.4	Performance summary of recent fundus IQA works over DRIMDB and EyeQ data-set. Here (+) indicates that the work also includes fundus images from other proprietary data-sets.	43
5.1	Information of the number of images in each distortion category along with its train and test split.	51
5.2	Comparative performance analysis in terms of PSNR and SSIM values. P: PSNR, S: SSIM.	60

List of Symbols

Symbol	Description
I	An image
m	Horizontal dimension of image I
n	Vertical dimension of image I
$I(i, j)$	Pixel in I at location (i, j) with $i \in \{1, 2, \dots, m\}$ and $j \in \{1, 2, \dots, n\}$
$\mu(i, j)$	Local Mean in I for pixel $I(i, j)$
$\sigma(i, j)$	Local standard deviation in I for pixel $I(i, j)$
$\omega_{k,l}$	Circularly-symmetric 2D Gaussian weighting function
\hat{X}_i	Input feature vector for the i^{th} image
\hat{W}_i	Weight matrix for the i^{th} image
\hat{Y}_i	Predicted score vector for the i^{th} image
\hat{E}_i	Corresponding error matrix for the i^{th} image
L_{MSE}	Mean squared error loss function
L_{CCE}	Categorical cross entropy loss function
L_{MAE}	mean absolute error function
L_{SSIM}	SSIM Loss function
A	classification accuracy
P	Precision
R	Recall
F_m	F-measure
R	Radius of a circle
DI	Darkness intensity
hI	Pixel value with highest frequency near border region of a fundus image
gI	Heuristically chosen intensity value

List of Abbreviations

Abbreviation	Full form
<i>2D</i>	Two-Dimensional
<i>3D</i>	Three-Dimensional
<i>ADAM</i>	Adaptive moment estimation
<i>AIIMS</i>	All India Institute of Medical Sciences
<i>ARIES</i>	Automatic retinal interest evaluation system
<i>B</i>	Blue Channel
<i>CAD</i>	Computer Aided Diagnosis
<i>CLAHE</i>	Contrast limited adaptive histogram equalization
<i>CNN</i>	Convolutional neural network
<i>CPBD</i>	Cumulative probability blur detection
<i>CSF</i>	Contrast sensitivity function
<i>CT</i>	Computed tomography
<i>DD</i>	Disk diameters
<i>DIBR</i>	Depth-image-based-rendering
<i>DR</i>	Diabetic Retinopathy
<i>FC</i>	Fully connected
<i>FIQuA</i>	Fundus image quality assessment
<i>FOV</i>	Field of view
<i>FR</i>	Full-Reference
<i>G</i>	Green Channel
<i>GAN</i>	Generative adversarial networks
<i>GVD</i>	Global vessel density
<i>HVS</i>	Human Visual System
<i>IQA</i>	Image Quality Assessment
<i>ISC</i>	Image structure clustering
<i>ITU</i>	International Telecommunication Union
<i>JNB</i>	Just noticeable blur
<i>k – NN</i>	K-nearest neighbor
<i>KROCC</i>	Kendall rank-order correlation coefficient
<i>LFF</i>	Local feature fusion
<i>LRL</i>	Local residual learning
<i>LVD</i>	Local vessel density
<i>MAD</i>	Most Apparent Distortion
<i>MAE</i>	Mean absolute error
<i>MDM</i>	Mathura Das Mathur
<i>ML</i>	Machine learning
<i>MRI</i>	Magnetic resonance imaging
<i>MSE</i>	Mean square error
<i>NR</i>	No-Reference
<i>pdf</i>	Probability density function
<i>PLCC</i>	Pearson Linear correlation coefficient
<i>PLS</i>	Partial least square
<i>PSNR</i>	Peak signal-to-noise ratio
<i>R</i>	Red Channel
<i>RDB</i>	Residual Dense Blocks
<i>RDC</i>	Residual-Densely Connected
<i>ReLU</i>	Rectified linear unit
<i>RMSE</i>	Root-mean-square error
<i>RR</i>	Reduced-Reference
<i>SVD</i>	Singular value decomposition
<i>BUI</i>	Uneven illumination over border region
<i>MUI</i>	Uneven-illumination over macular region
<i>SROCC</i>	Spearman rank-order correlation coefficient
<i>SSIM</i>	Structural Similarity Index
<i>SURF</i>	Speeded Up Robust Feature
<i>SVM</i>	Support Vector Machine
<i>VAE</i>	Variational autoencoders
<i>VIF</i>	Visual Information Fidelity