Misr International University

جامعة مصر الدولية

Automatic Classification Of The Preliminary Diabetic Retinopathy Stages

Presented By : Mahmoud Hazem, Mohamed Alaa, Omar Khaled, Youssef Talaat

Supervised By : Dr. Alaa hamdy, ENG. Yomna Ibrahim

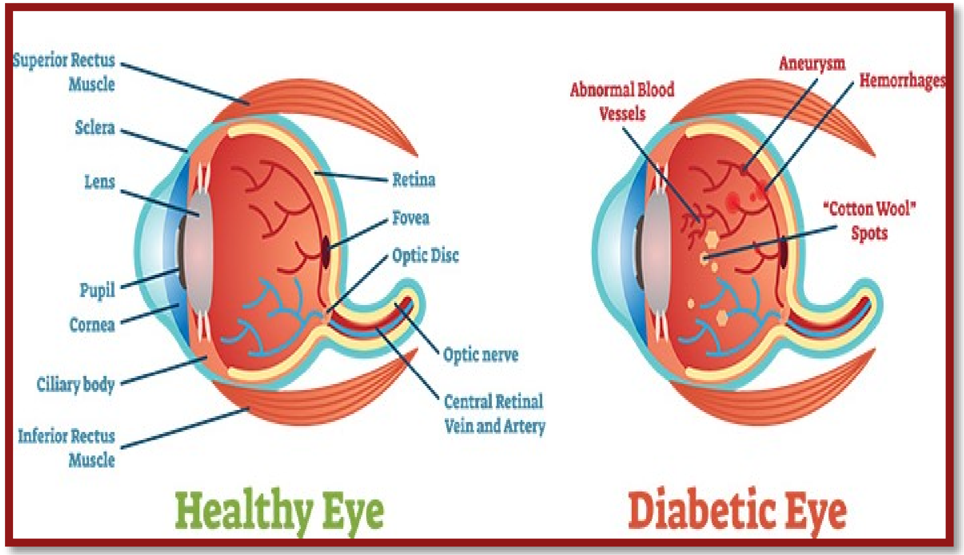
OUTLINE

INTRODUCTION & MOTIVATION

- Too much sugar in the blood, can cause damage throughout the body, including the eyes [1].

- One third of people suffering from Diabetes Mellitus are expected to also be diagnosed with Diabetic Retinopathy [2].

- Diabetic Retinopathy is a retinal disease that is caused by too much sugar in the blood, over an extensive period of time.



[1] "Diabetic Retinopathy." Mayo Clinic, Mayo Foundation for Medical Education and Research, 30 May 2018, https://www.mayoclinic.org/diseases-conditions/diabetic-retinopathy/symptoms-causes/syc-20371611. Accessed 8 Oct. 2019.

[2]- Lee, Ryan, Tien Y. Wong, and Charumathi Sabanayagam. "Epidemiology of diabetic retinopathy, diabetic macular edema and related vision loss." Eye and vision 2.1 (2015): 17.

SUPPORTIVE DOCUMENT

Re: Diabetic Retinopathy project

DH Dina Hossam <drdhossam@yahoo.com>

10/2/2019 9:45 PM

To: Mohamed Mohamed Alaa Eldine Hanafi Mohamed

Dear Mohamed

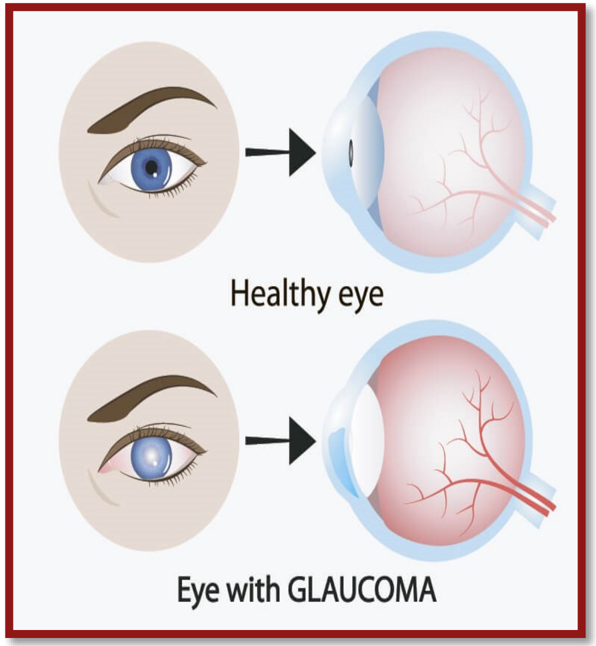
It is my pleasure supervising your valuable project and i am willing to provide you with any information needed about Diabetic Retinopathy, which is considered one of the most prevalent preventable eye diseases in Egypt and the middle east. The success of setting a comprehensive screening and management program for Diabetic Retinopathy in Egypt will definitely have an extremely positive impact on the rates of blindness among the Egyptian population.

Good luck in your project and best wishes.

Dr. Dina Hossam Hassanein, MD, FRCS
Assistant Professor of Ophthalmology
Cairo University

CHALLENGES

- Diabetic Retinopathy can eventually evolve and lead to more severe complications, such as total blindness and/or Glaucoma.
- Manual Classification of (DR) is not always accurate.
- Offer a usable and reliable assistive system to doctors.



- Eye Affected By Glaucoma

PROBLEM STATMENT

- Automatically detecting the presence of Diabetic Retinopathy and Classifying the different Stages of the disease in the patient’s eye.

- We aim to minimize and reduce the inaccurate diagnosis of (DR), and increase the classification accuracy rate among the four different stages of the disease.

RELATED WORK

Paper	No. of Images Used	Classification classes	Classifier	Accuracy	Sensitivity	Specificity
Bhattacharjee et al.[3]	13,402	5	Random Forest	76.50%	77.20%	93.30%
Kumar et al. [4]	89	2	SVM	-	96.00%	92.00%
Cisneros et al. [5]	130	2	SVM	92.00%	87.30%	84.60%
Tjandrasa et al. [6]	149	2	SVM (Soft Margin)	90.54%	-	-
Carrera et al. [7]	400	4	SVM	85.00%	95.00%	-
Sangwan [8]	96	3	SVM	92.60%	-	-
Junjun et al. [9]	35,126	5	ResNet	78.40%	-	-
Jain et al. [10]	35,126	5	VGG16, VGG19, Inception V3	76.90%	43.10%	-
Kwasigroch et al.[11]	37,000	5	VGG-D	81.70%	-	-
kajan et al.[12]	49,272	5	ResNet50	92.64% (Yes/No) 70.29% (Stages)	-	-
Suriyal et al. [13]	16,798	2	MobileNets	73.30%	-	-
Harangi et al. [14]	552	5	CNN	83.35%	64.58%	88.00%
Khan et al.[15]	1,200	5	5 Layered CNN Model	98.15%	98.94%	97.87%
Zeng et al. [16]	35,126	5	Inception V3	-	82.20%	70.70%
Carson et al.[17]	36,200	5	CNN	57.2% - 74.5%	-	-

DATASET

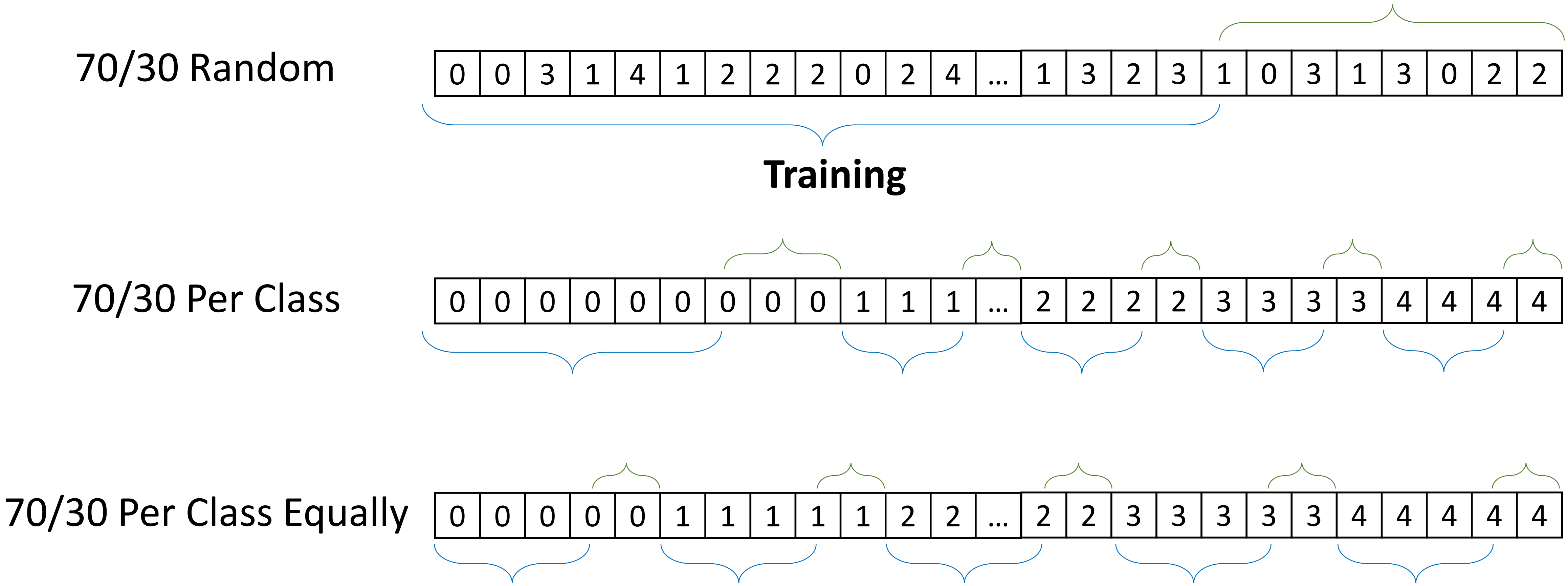
- The Dataset we intend to use in our project is provided by a Kaggle competition called "EyePacs"[18].
- In total, there are 88,702 images of left and right eyes.
- The images are labeled in five stages: Normal (0), Mild (1), Moderate (2), Severe (3) and Proliferative DR (4).

Figure 1. Some samples in the EyePACS dataset

[18] "Diabetic retinopathy (resized)," May 2019. [Online]. Available: https://www.kaggle.com/tanlikesmath/diabetic-retinopathy-resized.csv

DATASET EXPERIMENTS 1/3

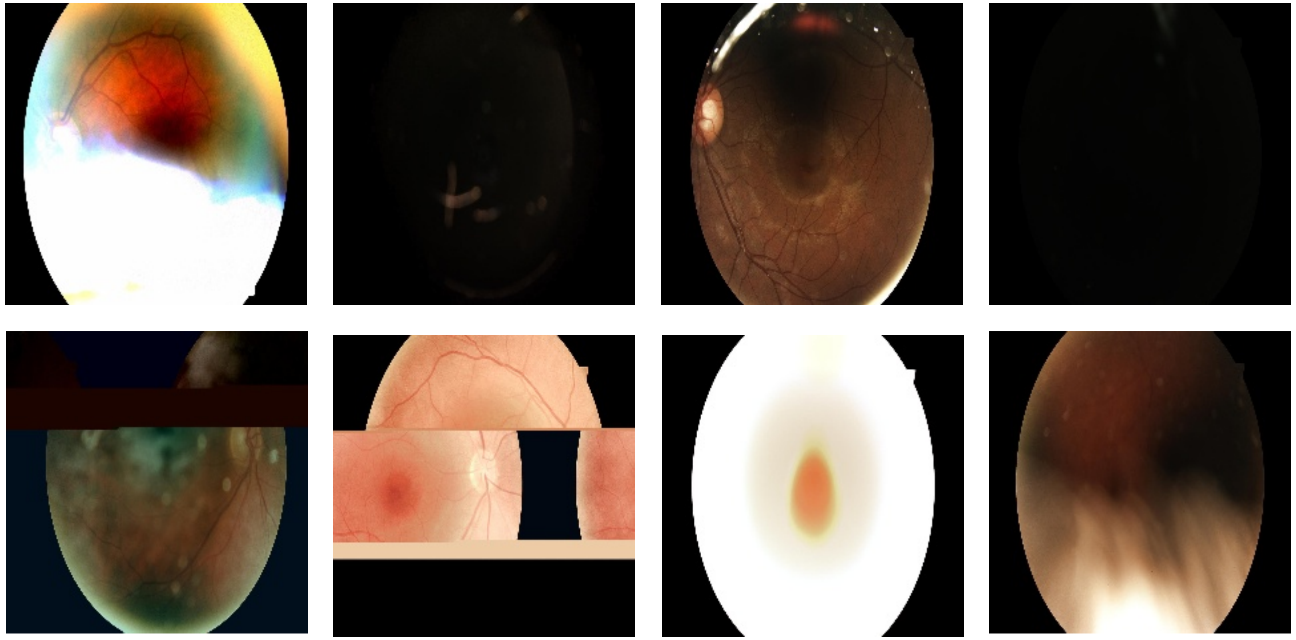
- Dataset splitting :



DATASET EXPERIMENTS 2/3

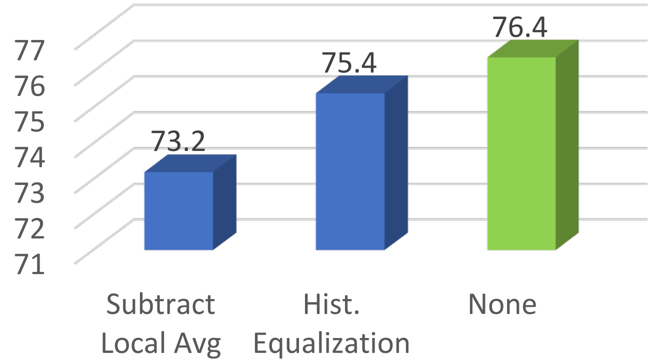
- Dataset Filtering :

Around 245 images of the dataset was corrupted and might cause distraction to the model while training.

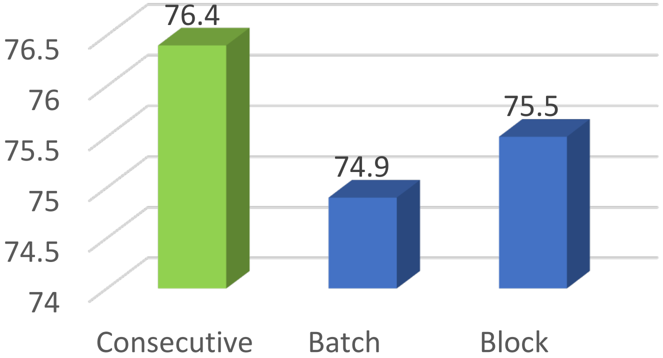


DATASET EXPERIMENTS 3/3

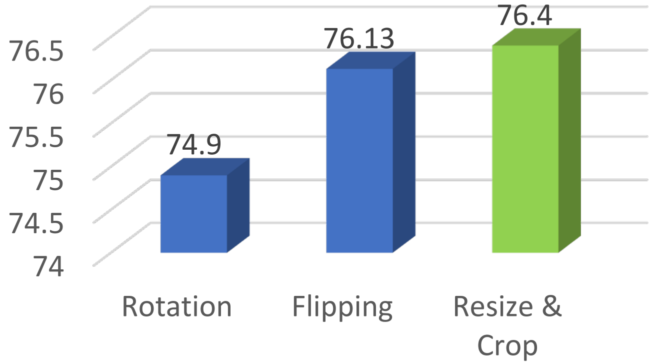
Preprocessing Techniques



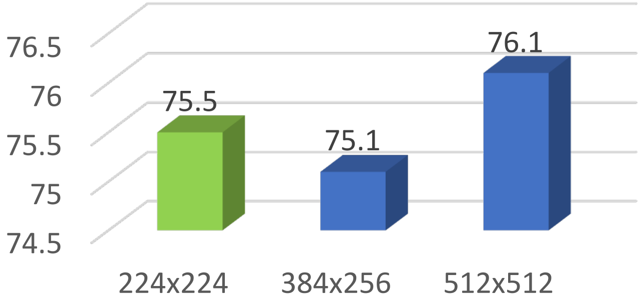
Images Distribution



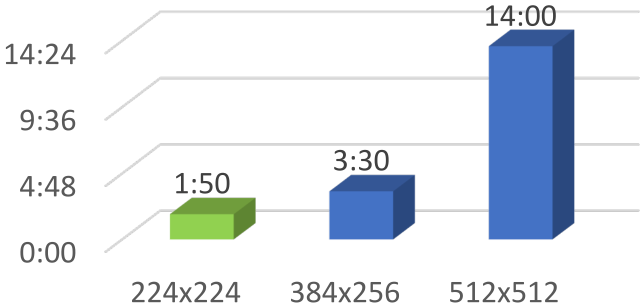
Sampling Techniques



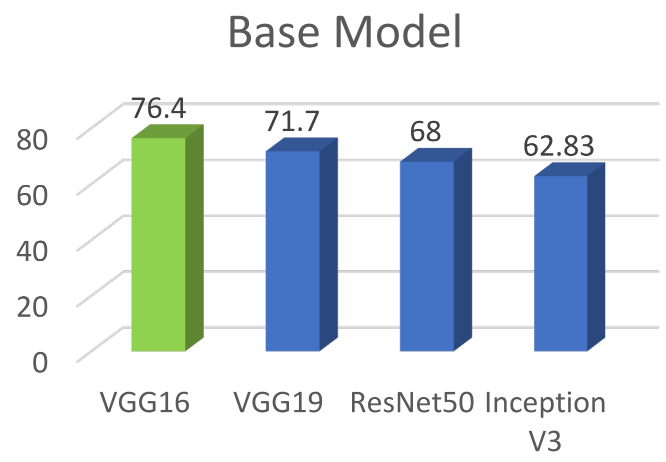
Images Dimensions (Accuracy)

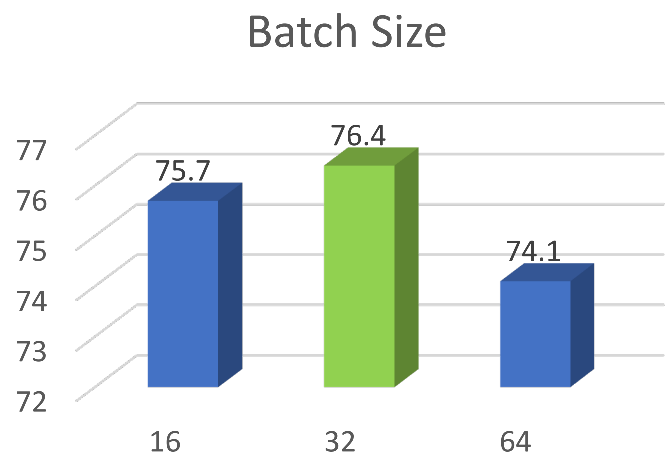


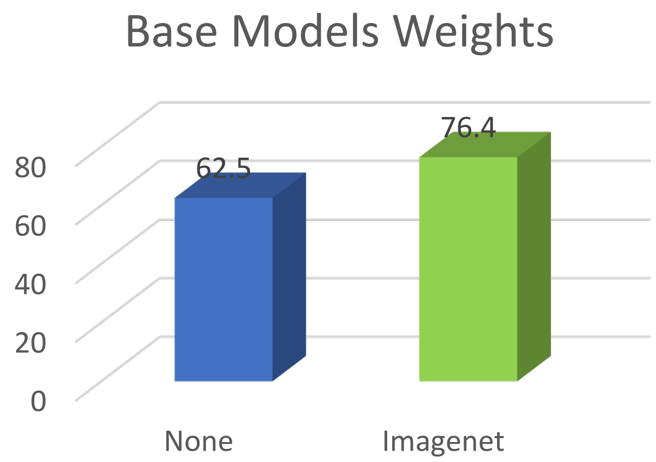
Images Dimensions (Time Taken)

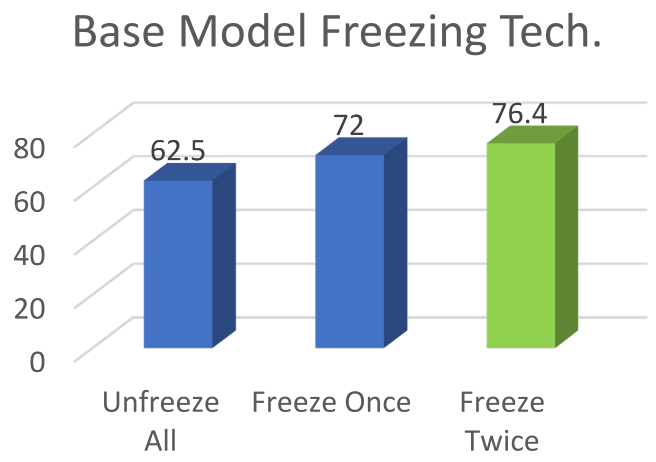


CNN MODEL EXPERIMENTS 1/3

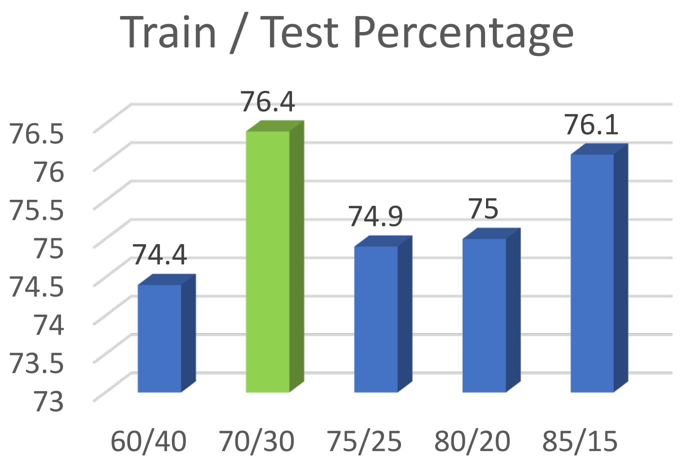


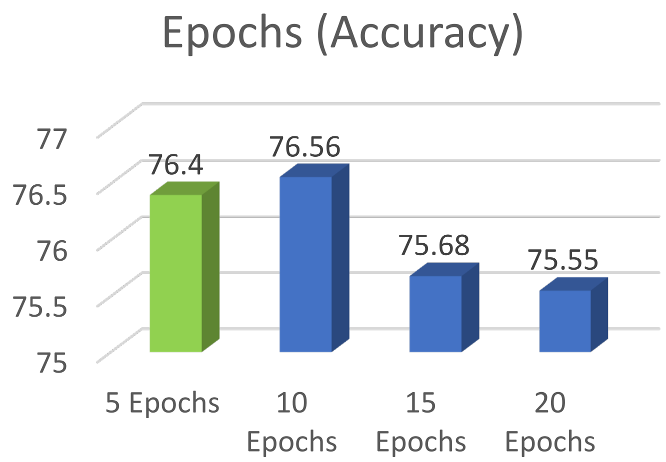


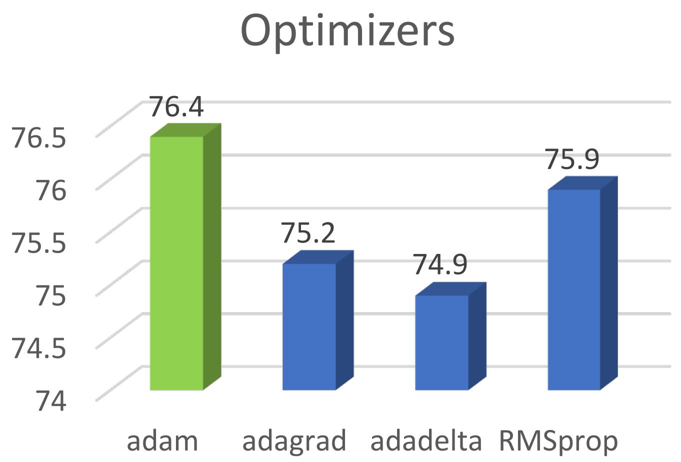


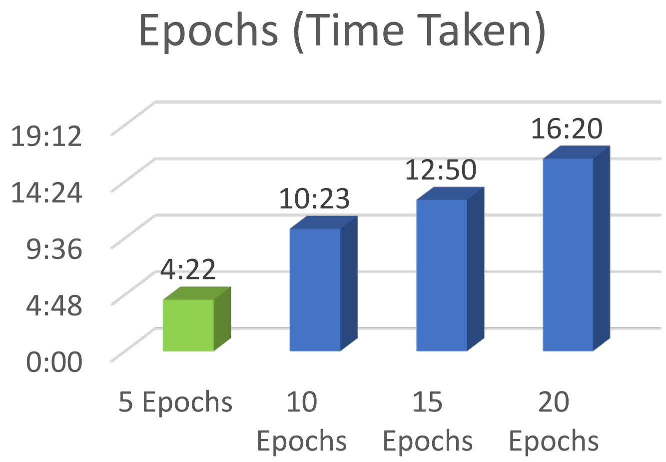


CNN MODEL EXPERIMENTS 2/3





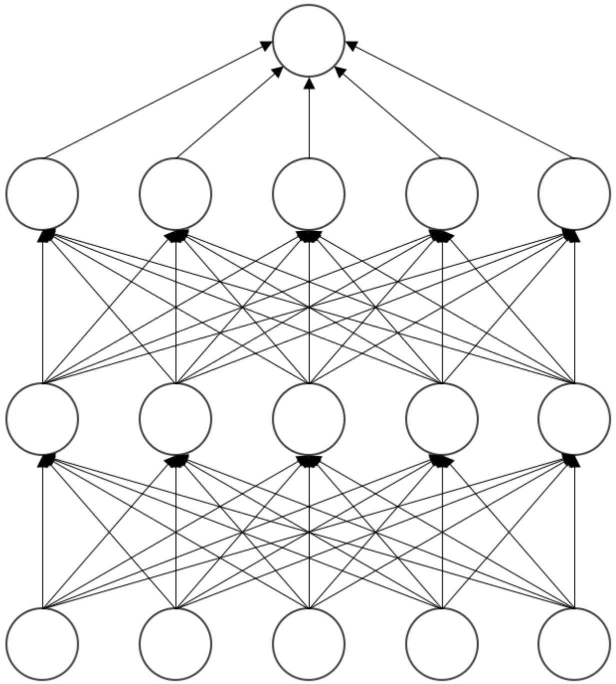




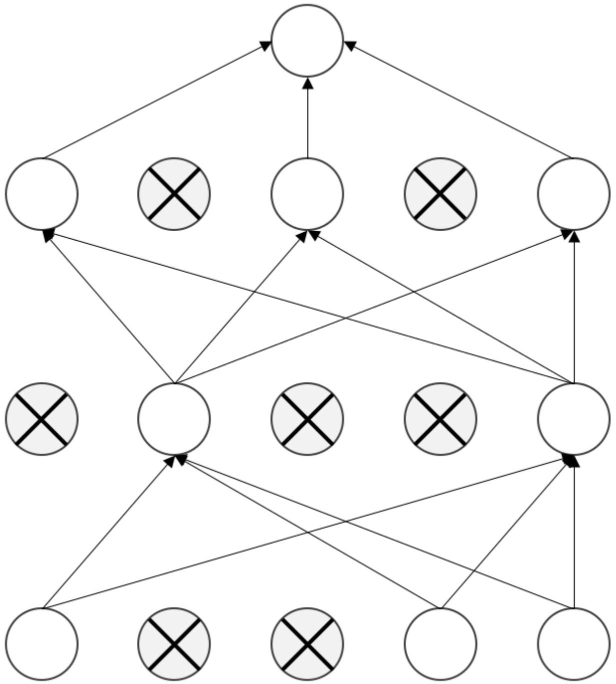
CNN MODEL EXPERIMENTS 3/3

- Overfitting :

We included dropout layers in our model and made sure of applying generalization to avoid overfitting.

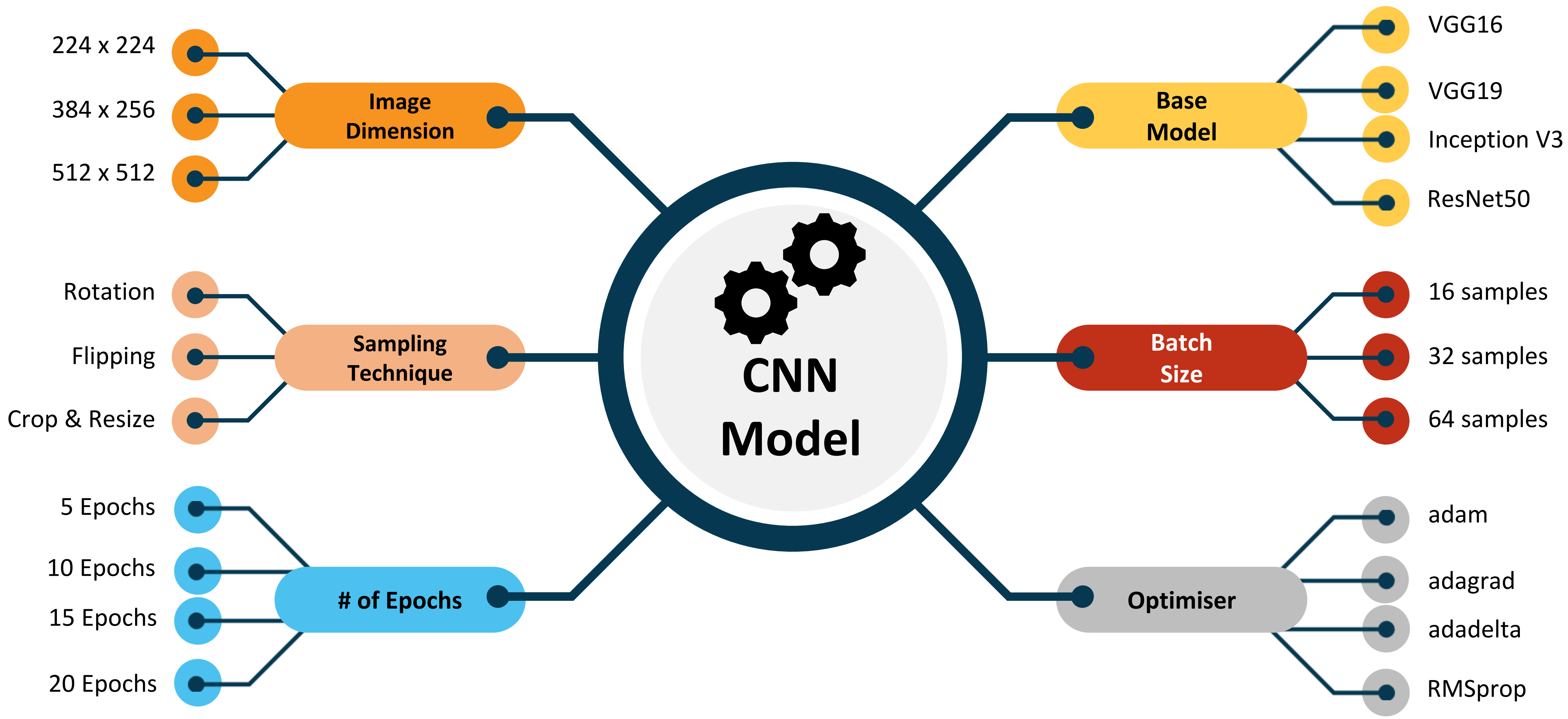


Standard Neural Net

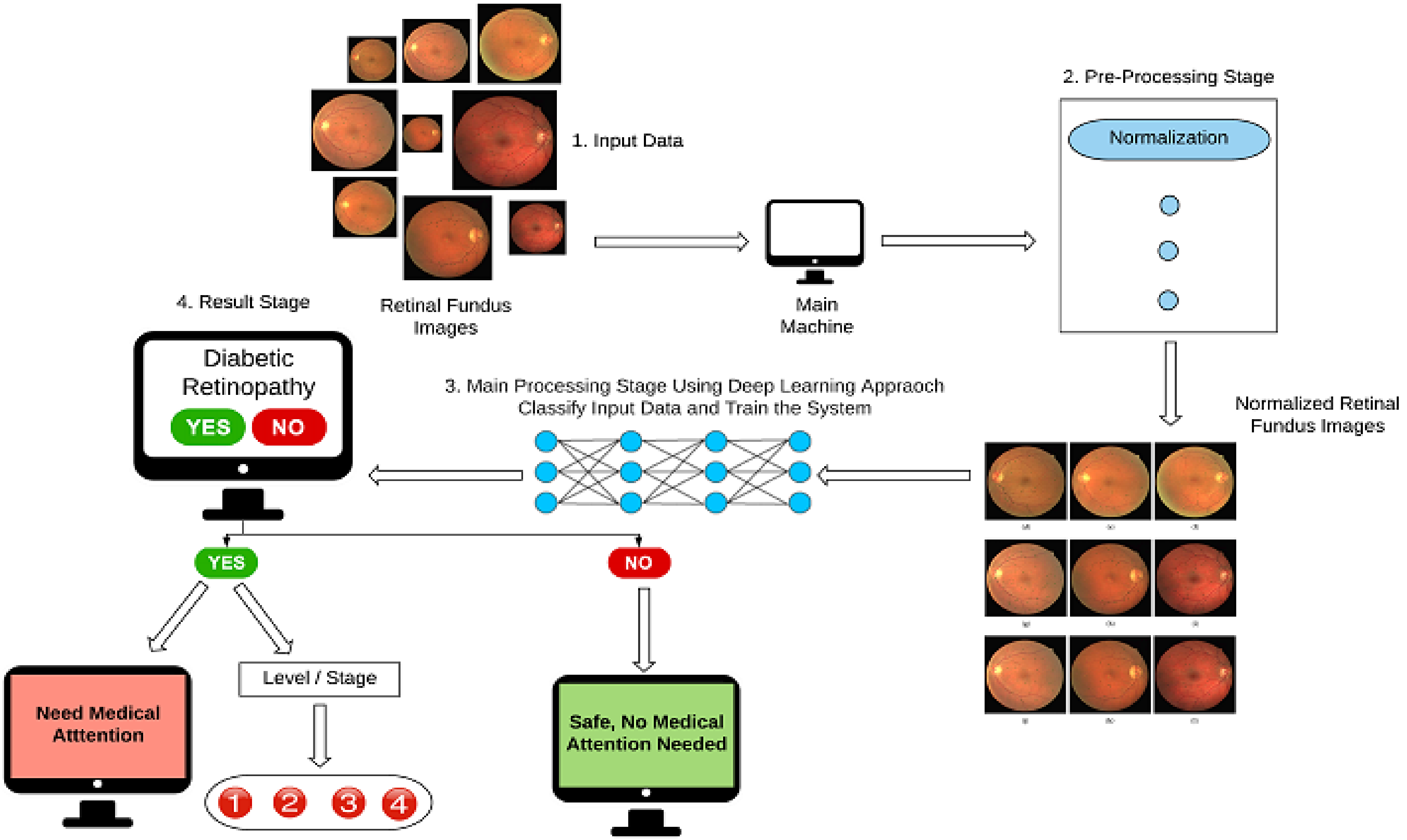


After applying dropout

SYSTEM PARAMETERS

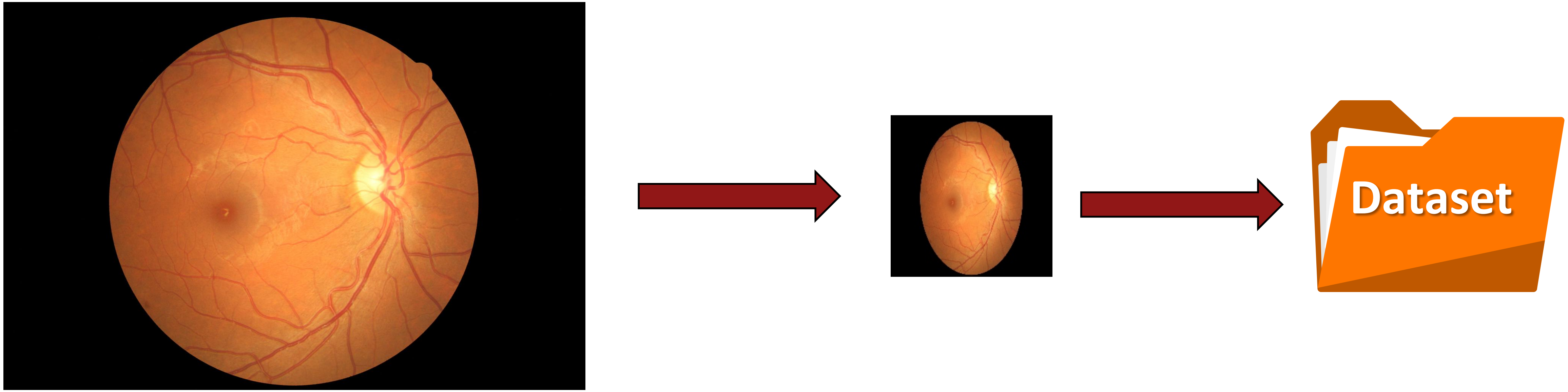


SYSTEM OVERVIEW



PREPROCESSING TECHNIQUES

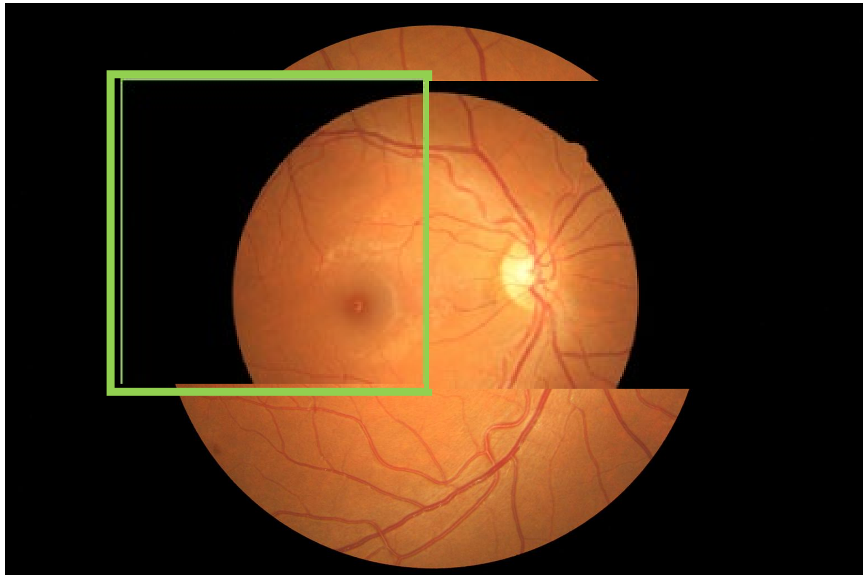
- All input images are resized to the model’s input size (224x224).



1536 x 1024 **224 x 224**

SAMPLING TECHNIQUES

- Crop & Resize



1536 x 1024

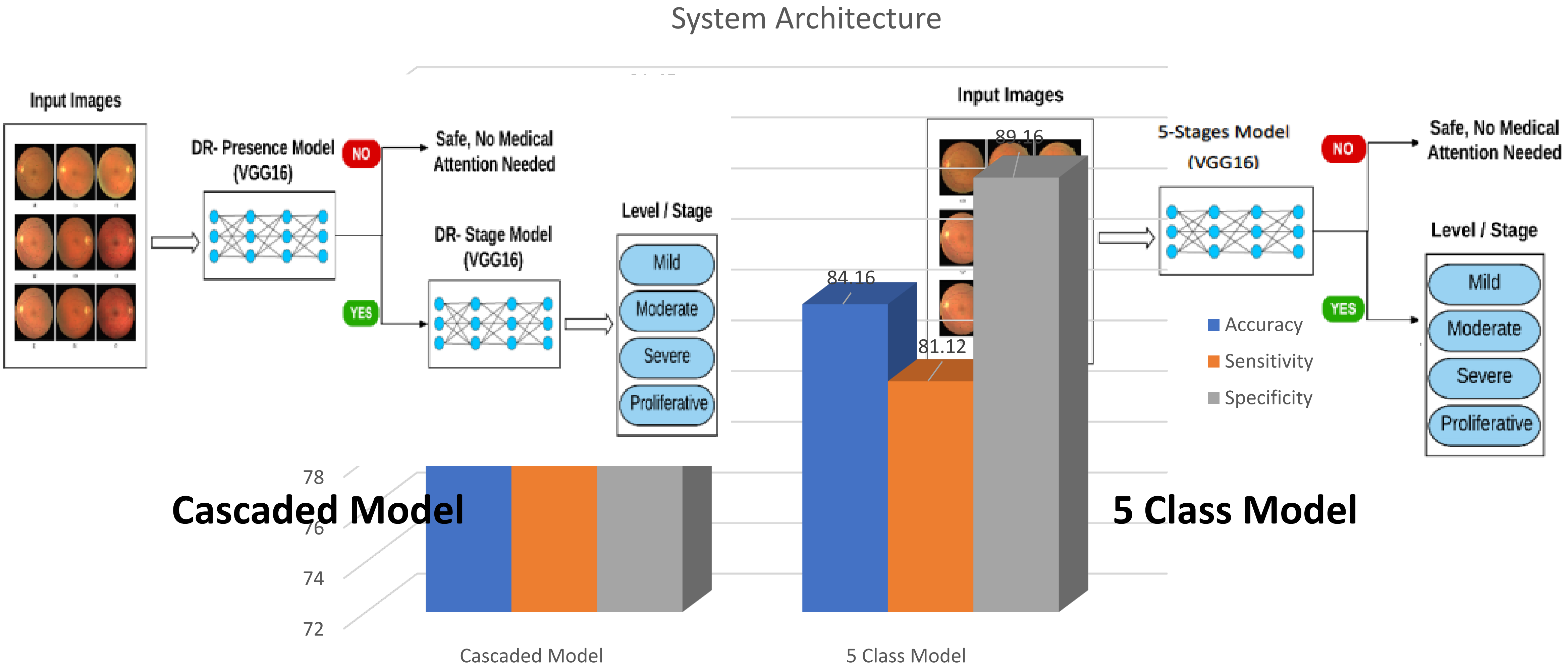
- Maintain the images' aspect ratio to avoid any data loss.
- Enable us to increase the original dataset size.
- Had the best performance compared to the other sampling techniques.

DATASET USAGE

	Original Images	Original Images (After Filtration)	Input Images		
			Original Images Used	Augmented Images	Images Used
Class 0 (No DR)	65,343	65,167	17,740	0	17,740
Class 1 (Mild)	6,205	6,190	6,205	11,535	17,740
Class 2 (Moderate)	13,153	13,116	13,153	4,587	17,740
Class 3 (Severe)	2,087	2,083	2,087	15,653	17,740
Class 4 (Proliferative)	1,914	1,901	1,914	15,826	17,740
Total	88,702	88,457	41,099	47,601	88,700

- Original Images Used : **41,099** Images (**46.3%** of Original Dataset).
- Total Input Images Used : **88,700** Images.
- Data Split : 70% Training (**12,418** Images per Class) – 30% Testing (**5,322** Images per Class).

RESULTS 1/3



Cascaded Model

5 Class Model

RESULTS 2/3

- DR Detection Accuracy : **82.73 %**.
- Sensitivity : **81.12 %**.
- Specificity : **89.16 %**.

		Predicted Labels	
		No DR	**DR**
True Labels	**No DR**	4,745	577
	DR	4,019	17,269

RESULTS 3/3

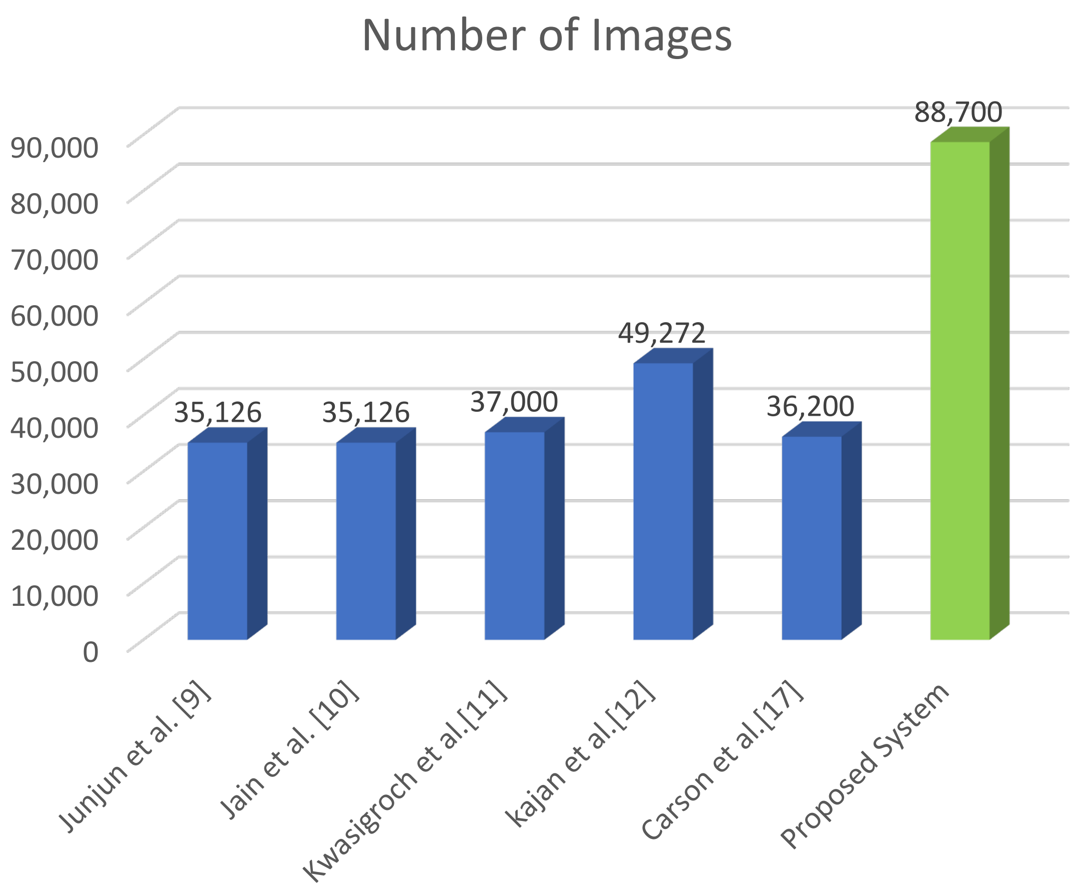
Accuracy Per Class

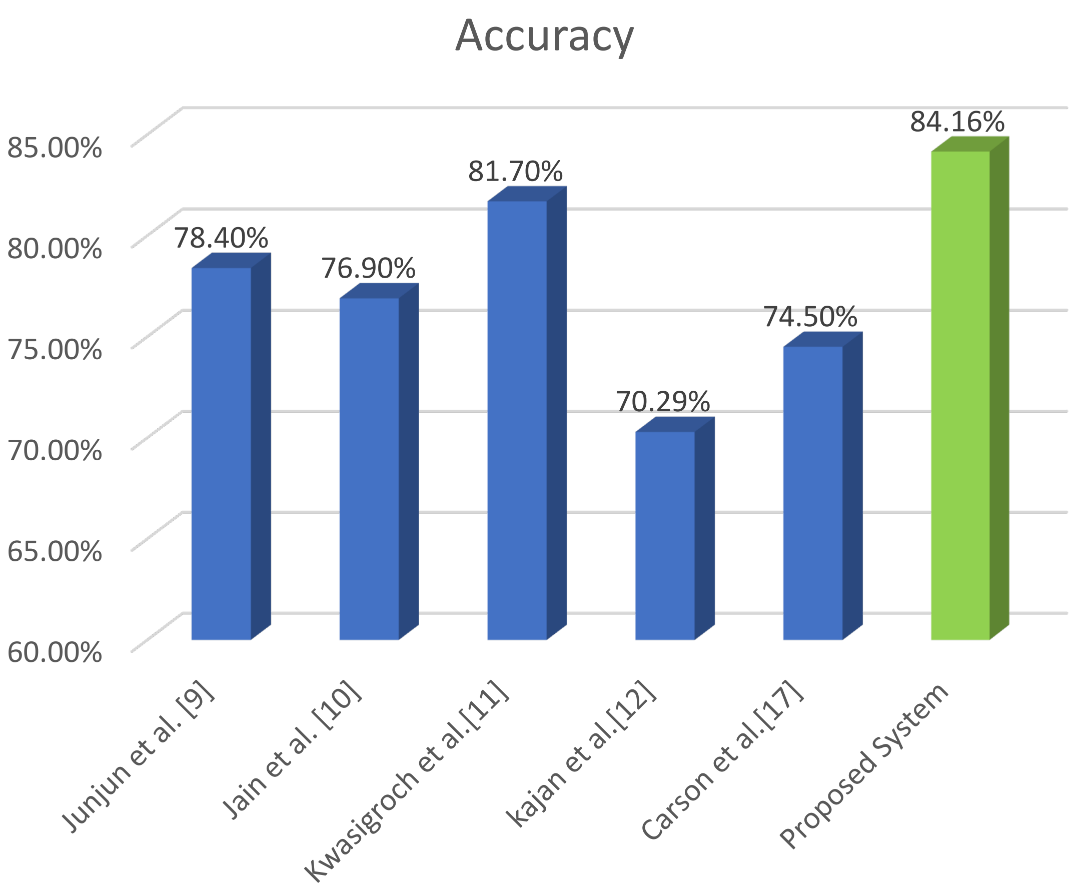
- Class 0 : **82.73 %**
- Class 1 : **85.53 %**
- Class 2 : **80.94 %**
- Class 3 : **83.69 %**
- Class 4 : **87.93 %**

		Predicted Labels				
		Class 0	**Class 1**	**Class 2**	**Class 3**	**Class 4**
True Labels	**Class 0**	4,745	1	518	3	55
	Class 1	1,624	2,905	230	426	137
	Class 2	2,213	670	1,578	544	317
	Class 3	119	605	370	3,278	950
	Class 4	63	157	211	1,322	3,569

Overall Accuracy = **84.16 %**

FINAL SYSTEM EVALUATION





FUTURE WORK

- Trying different techniques or models to improve the system's performance.

- In addition to using real data to prove the system's applicability and measure its performance.

COMPETITIONS & CONTRIBUTIONS

- DELL (EMC) – Shortlisted for the final stage of the Dell Technologies Envision the Future Competition.

Envision The Future

Dell Technologies Graduation Project Competition for Turkey, Middle East, and Africa

- ICSIE 2020 – Notification of Acceptance, and paper will be included and published in the upcoming conference.

ICSIE 2020

Doctor DEMO

Healthcare Template

localhost/DR_Project/

HEALTHCARE

111-222-333
99-222-333

88 Route West 21th Street,
Suite 721 New York NY 10016

Login To Your Portal

Helping to improve quality

Login To Portal

Username

Username

Password

Password

Please fill out this field.

Login

Patient DEMO

Healthcare Template

localhost/DR_Project/

HEALTHCARE

111-222-333
99-222-333

88 Route West 21th Street,
Suite 721 New York NY 10016

Login To Your Portal

Helping to improve quality

Login To Portal

Username

Username

doctor
admin
patient
omar
seif
Damco

Password

Password

Login

Admin DEMO

Healthcare Template

localhost/DR_Project/

HEALTHCARE

111-222-333
99-222-333

88 Route West 21th Street,
Suite 721 New York NY 10016

Login To Your Portal

Helping to improve quality

Login To Portal

Username

Username

Password

Password

Login

THANK YOU

ANY QUESTIONS?

APPENDIX

3. “Diabetes facts and figures,” (2019, December 13).©2020 International Di-abetes Federation. https://idf.org/aboutdiabetes/what-is-diabetes/facts-figures.html.[Online]. Available: https://idf.org/aboutdiabetes/what-is-diabetes/facts-figures.html.

4. I. Bhattacharjee and T. Mahmud, “Diabetic retinopathy classification from retinalimages using machine learning approaches,” Ph.D. dissertation, 02 2020.

5. S. Kumar and B. Kumar, “Diabetic retinopathy detection by extracting area and num-ber of microaneurysm from colour fundus image,” in2018 5th International Conferenceon Signal Processing and Integrated Networks (SPIN). IEEE, 2018, pp. 359–364.

6. F. Cisneros-Guzḿan, S. Tovar-Arriaga, C. Pedraza, and A. Gonź alez-Gutierrez, “Clas-sification of diabetic retinopathy based on hard exudates patterns, using images pro-cessing and svm,” in2019 IEEE Colombian Conference on Applications in Computa-tional Intelligence (ColCACI). IEEE, 2019, pp. 1–5.

7. H. Tjandrasa, R. E. Putra, A. Y. Wijaya, and I. Arieshanti, “Classification of non-proliferative diabetic retinopathy based on hard exudates using soft margin svm,” in2013 IEEE International Conference on Control System, Computing and Engineering.IEEE, 2013, pp. 376–380.

8. E. V. Carrera, A. Gonź alez, and R. Carrera, “Automated detection of diabetic retinopa-thy using svm,” in2017 IEEE XXIV International Conference on Electronics, Electri-cal Engineering and Computing (INTERCON). IEEE, 2017, pp. 1–4.

9. S. Sangwan, V. Sharma, and M. Kakkar, “Identification of different stages of diabeticretinopathy,” in2015 International Conference on Computer and Computational Sci-ences (ICCCS). IEEE, 2015, pp. 232–237.

10. P. Junjun, Y. Zhifan, S. Dong, and Q. Hong, “Diabetic retinopathy detection based ondeep convolutional neural networks for localization of discriminative regions,” in2018International Conference on Virtual Reality and Visualization (ICVRV). IEEE, 2018,pp. 46–52.

APPENDIX

11. A. Jain, A. Jalui, J. Jasani, Y. Lahoti, and R. Karani, “Deep learning for detection andseverity classification of diabetic retinopathy,” in2019 1st International Conference onInnovations in Information and Communication Technology (ICIICT). IEEE, 2019,pp. 1–6.

12. A. Kwasigroch, B. Jarzembinski, and M. Grochowski, “Deep cnn based decision sup-port system for detection and assessing the stage of diabetic retinopathy,” in2018International Interdisciplinary PhD Workshop (IIPhDW). IEEE, 2018, pp. 111–116.

13. S. Kajan, J. Goga, K. Lacko, and J. Pavloviˇcov́a, “Detection of diabetic retinopathyusing pretrained deep neural networks,” in2020 Cybernetics & Informatics (K&I).IEEE, pp. 1–5.

14. S. Suriyal, C. Druzgalski, and K. Gautam, “Mobile assisted diabetic retinopathy de-tection using deep neural network,” in2018 Global Medical Engineering Physics Ex-changes/Pan American Health Care Exchanges (GMEPE/PAHCE). IEEE, 2018, pp.1–4.

15. B. Harangi, J. Toth, and A. Hajdu, “Fusion of deep convolutional neural networks formicroaneurysm detection in color fundus images,” in2018 40th Annual InternationalConference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE,2018, pp. 3705–3708.

16. S. H. Khan, Z. Abbas, S. D. Rizviet al., “Classification of diabetic retinopathy imagesbased on customised cnn architecture,” in2019 Amity International Conference onArtificial Intelligence (AICAI). IEEE, 2019, pp. 244–248.

17. X. Zeng, H. Chen, Y. Luo, and W. Ye, “Automated diabetic retinopathy detectionbased on binocular siamese-like convolutional neural network,”IEEE Access, vol. 7,pp. 30 744–30 753, 2019.

Appendix

5 Class Model															
	0	**1**	**2**	**3**	**4**	**Sum**	**TP**	**TN**	**FP**	**FN**	**Accuracy**	**Sensitivity (Recall)**	**Specificity**	**Precision**	**F-Score**
0	4745	1	518	3	55	5322	4745	17269	4019	577	82.73%	89.16%	81.12%	54.14%	67.37%
1	1624	2905	230	426	137	5322	2905	19855	1433	2417	85.53%	54.58%	93.27%	66.97%	60.14%
2	2213	670	1578	544	317	5322	1578	19959	1329	3744	80.94%	29.65%	93.76%	54.28%	38.35%
3	119	605	370	3278	950	5322	3278	18993	2295	2044	83.69%	61.59%	89.22%	58.82%	60.17%
4	63	157	211	1322	3569	5322	3569	19829	1459	1753	87.93%	67.06%	93.15%	70.98%	68.97%
						Sum	16075	95905	10535	10535					
						Calculated					84.16%	60.41%	90.10%	60.41%	60.41%

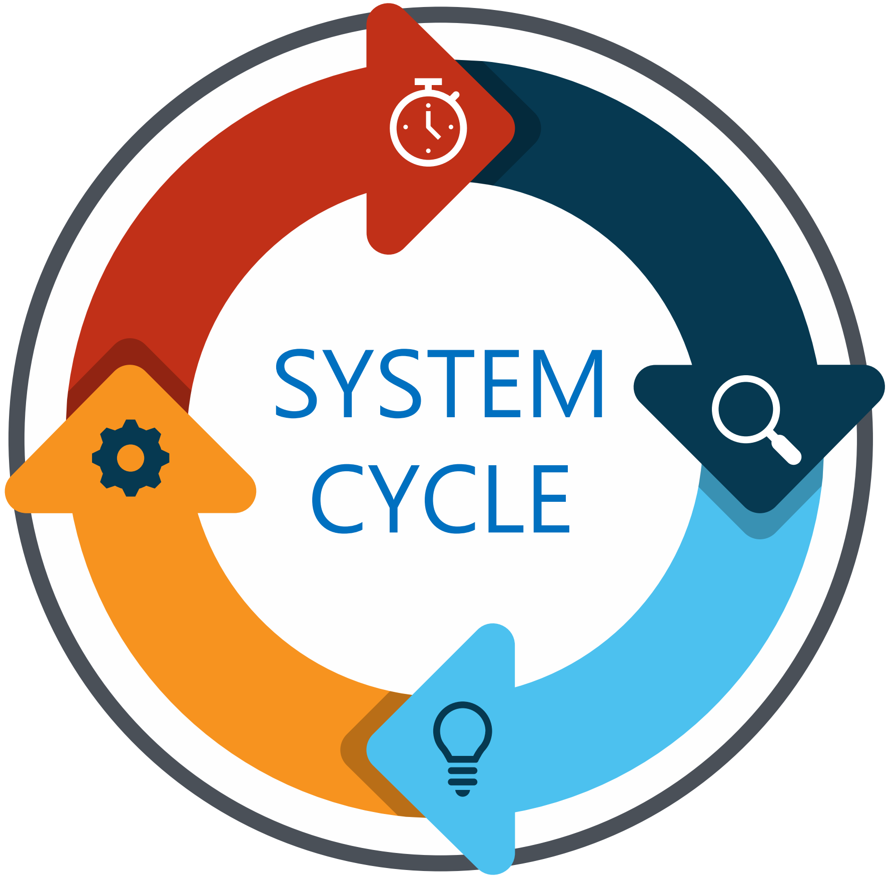
5 Class Model												
	0	**1**	**Sum**	**TP**	**TN**	**FP**	**FN**	**Accuracy**	**Sensitivity (Recall)**	**Specificity**	**Precision**	**F-Score**
0	4745	577	5322	17269	4745	577	4019	82.73%	81.12%	89.16%	96.77%	88.26%
1	4019	17269	21288									

APPENDIX

- Accuracy = $\dfrac{TP + TN}{TP + TN + FP + FN}$
- Sensitivity = $\dfrac{TP}{TP + FN}$
- Specificity = $\dfrac{TN}{TN + FP}$

Appendix

The system will use the image and doctor's feedback, to Re-Train itself and improve its classification accuracy by time.



Take an input image (Fundus Images) from the patient

The doctor will provide his/her feedback on the system results.

The system starts classifying the input image and recognizing its stage.