SBC-Based Diabetic Retinopathy and Diabetic Macular Edema Classification System using Deep Convolutional Neural Network

Anicia Coleen S. Reyes, Gem Ryan C. Milan, James Marvin M. Quilaton, Bryant Exel G. Sigue, Steven Valentino E. Arellano, Kenneth C. Karamihan

Abstract: This Raspberry Pi Single-Board Computer-Based Diabetic Retinopathy (DR) and Diabetic Macular Edema (DME) Classification System using Deep Convolutional Neural Network through Inception v3 Transfer Learning and MATLAB digital image processing paradigm based on International Clinical DR and DME Disease Severity Scale with Python application, which would capture the image of the retina of diabetic patients to classify the grade, severity, and types of DR; and the grade of DME without using dilating drops. It would also display, save, search and print the partial diagnosis that can be done to the patients. Diabetic patients, endocrinologists and ophthalmologists of one of the medical centers in City of San Pedro, Laguna, Philippines tested the system. Obtained results indicated that the classification of DR and DME, and its characteristics using the system were accurate and reliable, which could be an assistive device for endocrinologists and ophthalmologists.

Keywords: Diabetic retinopathy, diabetic macular edema, deep convolutional neural network, digital image processing, transfer learning

I. INTRODUCTION

Diabetes mellitus (diabetes) is a non-transmittable disease, which is a metabolic disorder due to disfigurement of insulin secretion in the body [1]. Diabetic retinopathy (DR) is a highly specific problem of both types including type 1 and 2, respectively. DR is also the most recurring cases of blindness among people aging around 20 years of age and above. Moreover, diabetic macular edema (DME) is one of the most common causes of blindness among diabetic patients. Almost 2.6% of global blindness can be attributed to diabetes and a major public health concern since 1980 [2]. The widespread presence has increased by 110% to men and 58% to women, although through 7.9% and 9% of global commonness within 2014. The high rate of level is alarmingly will be doubled with the population growth and high age has now nearly led to quadruple of numerous adults with diabetes, which is now estimated be 422 million, and assuming it will enhance to be 629 million by the year 2045 [3]. However, there were over 3,721,900 instances of diabetes in the Philippines since 2017. Furthermore, diagnosing DR and DME is through retina by the use of fundus photography of dilated pupils, which the dilating drops will be put in the eyes of the patient, which it will widen (dilate) the pupil for the ophthalmologist will have a better sight of the retina through the eyes of the patient. In addition, the said drops can cause side effects to the eyes that can cause the vision to blur until it will be wear off for several hours or up to four weeks [4]. Currently, the implementation of deep convolutional neural network (DCNN) model towards the Raspberry Pi (RPi) single-board computer (SBC) with Inception v3 transfer learning and embedded camera could make the system portable. Additionally, transfer learning is a machine learning technique, which it can train a model by reusing these parts or modules of existing developed models and haste the time it takes to train and develop a pre-trained DCNN model [5] through MATLAB and Python applications, which can be utilized to build a prototype of the software (graphical user interface—GUI) application rapidly and it also provides an interface for working with SQLite (Structured Query Language) database [6] while Matrix Laboratory (MATLAB) is the much-preferred mathematical computing software of the researchers utilizing system designs and algorithms to define input data sets in a simulation environment. The developed system could help the patients to prevent the stated diseases to be more severe, and for the doctors, to provide an ease, cheaper and reliable way of diagnostic examination. It is an assistive device and also a way of helping the endocrinologists and ophthalmologists from classifying the diabetic retinopathy and diabetic macular edema and its characteristics without the use of dilating drops. Consequently, the transformation of modern technology resulted to the increasing of productivity and which helps lessen the effort of work force.

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***** Correspondence Author

Anicia Coleen S. Reyes*, Computer Engineering Department, College of Engineering, University of Perpetual Help System Laguna, City of Biñan, Laguna, 4024 Philippines. E-mail: aniciacoleensalvaniareyes@gmail.com

Gem Ryan C. Milan, Computer Engineering Department, College of Engineering, University of Perpetual Help System Laguna, City of Biñan, Laguna, 4024 Philippines. E-mail: gemryanmilan@gmail.com

James Marvin M. Quilaton, Computer Engineering Department, College of Engineering, University of Perpetual Help System Laguna, City of Biñan, Laguna, 4024 Philippines. E-mail: jamquilaton@gmail.com

Bryant Exel G. Sigue, Computer Engineering Department, College of Engineering, University of Perpetual Help System Laguna, City of Biñan, Laguna, 4024 Philippines. E-mail: bryantexel@yahoo.com

Steven Valentino E. Arellano, Computer Engineering Department, College of Engineering, and Graduate School, University of Perpetual Help System Laguna, City of Biñan, Laguna, 4024 Philippines. E-mail: arellanostevenvalentino@gmail.com

Kenneth C. Karamihan, Computer Engineering Department, College of Engineering, University of Perpetual Help System Laguna, City of Biñan, Laguna, 4024 Philippines. E-mail: kckaramihan@gmail.com

A. Conceptual Model

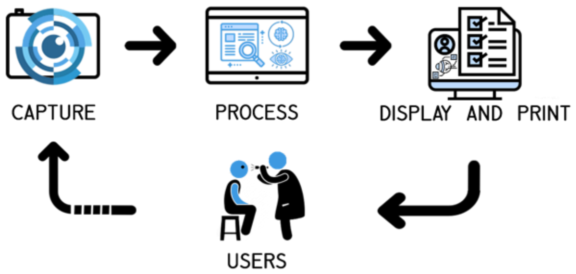


Fig. 1. The Conceptual Model of the System.

Fig. 1 indicates the visionary model of the system for endocrinologists, ophthalmologists and patients through the use of the captured image of the patient's eye specifically the retina. The system performed an operation wherein the captured image serves as the input data then the machine learning algorithm executed by the single-board computer (SBC) serves as the processing phase. It also generates the existence and state of DR and DME, through the monitor of the system. The image of the retina was analyzed using the camera embedded with the SBC. The output phase is the analyzed image with to classify the grade, severity, and types of DR and the grade of DME being displayed on the touch-enabled liquid crystal display (LCD) monitor of the system to show the generated results to the users.

B. Scope and Delimitation

The system enables to classify the grade, severity, and types of DR and the grade of DME from the captured images of retina to the patients. The application (app) has a database that would store, save, search, and delete the profile of the patient including the results of the test using the developed system. The ophthalmologists who have the privilege to use the app and access the database must provide their registered username and password on the system. The database contained the name, age, occupation, medical history and the results of the diagnostic tests, which are printable in Portable Document File (PDF) format.

Other possible interruptions should be considered as delimitation such as power disruption and patients with pupils less than 4mm (millimeters) wide upon dilation. Also, patients with sore eyes and those under the influence of drugs and alcohol. This can be used by both the endocrinologists and ophthalmologists for diagnostic examinations.

II. METHODOLOGY

Waterfall System Development Life Cycle (SDLC) model was used in developing the system, in which the development process flows through separate phases. The population of this study was composed of 75 diabetic patients, 2 endocrinologists, 3 ophthalmologists, 6 engineers and 4 IT professionals for a total of 93 respondents. Stratified sampling was used as the primary data source and split into two groups of endocrinologists and their out-patients. The locale of this study was in Westlake Medical Center National Highway, Pacita Complex San Pedro, Laguna, Philippines, which provides DR and DME consultation to patients. This is one of the medical centers, which handles patients with health conditions such as diabetes, hypertensions, tuberculosis, and other range of diseases.

A. Transfer Learning

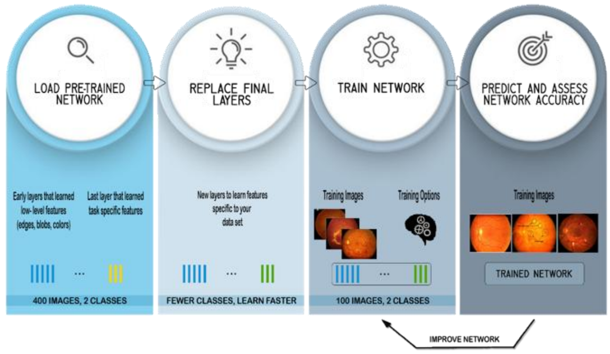


Fig. 2. DCNN Model.

Transfer learning (TL) removes the information from other domains like raw data, features, or classification domain, this is to re-do the lack of labeled data from the examined subject. TL is a method used to enhance the accuracy of classifier trained from one state by transferring useful data from other state [7]. Fig. 2 shows the DCNN model of the system used for transfer learning.

B. Datasets

In summary, the Messidor-2 dataset image consists of the fundus image regarding Diabetic Retinopathy and Diabetic Macular Edema graded to be trained. Messidor-2 differs from the original Messidor dataset of 1200 images having a more reliable and accurate dataset for more credibility for the developed system [8].

Table - I: Rate of Accuracy Evaluation for Different Dataset Sizes

Data Set	Size	Test Images (80)				Accuracy Percentage
		TP	TN	FP	FN	
A	250 images	12	8	23	21	45.00%
B	500 images	27	13	15	18	58.75%
C	750 images	38	15	8	11	76.25%
D	1000 images	45	15	4	2	92.50%

Note.
TP (True Positive) - Positive instances classified
TN (True Negative) - Negative instances classified
FP (False Positive) - Positive instances misclassified
FN (False Negative) - Negative instances misclassified

Table - II: Independent Rate of Accuracy Evaluation for Different Dataset Sizes

Data Set	TP Rate	TN Rate	FP Rate	FN Rate
A	42.50%	47.50%	57.50%	52.50%
B	62.50%	55.00%	37.50%	45.00%
C	80.00%	72.50%	20.00%	27.50%
D	90.00%	95.00%	10.00%	5.00%

TABLES I and II show the confusion matrix defining the accuracy level of the type of diabetic retinopathy. Moreover, TABLE I shows the level of accuracy of the evaluation for different data set sizes in this study, and it was tested using eighty (80) separate eye images given by the locale of the study.

As such, the most accurate data set size was data set D with the size of 1000 images and accuracy of 92.50%, On the other hand, TABLE II shows the independent accuracy values for each instance classified on each dataset size with

dataset D as the most accurate set size in the data with 10.00% and 5.00% on various instances.

Even though neural network models need to be evaluated to determine whether the model would be sufficiently efficient to accurately classify the input data, sets of tests were performed, which illustrated an improvement in the data set sizes that had positive effects on the model's accuracy, therefore providing a stronger guide for the classification of DR and DME for each increase. Moreover, this increase was tested until enough accuracy rates had been met.

C. Image Preprocessing

Set enhancement methods was used to encode different invariances in the deep feature learning process. Data set increase is a process of implementing image transformations through a sample data set to boost the distribution of the image while retaining the prognostic qualities of the image itself. Another essential concept in fundus diagnosis is that the disease classification is rotationally invariant; recognition and classification of pathological structures is locally defined in relation to main anatomical structures, regardless of the position. A rotational invariance was encoded in assumptions by spontaneously rotating each image before propagating these images to the model. Through applying specific predictions for arbitrarily rotated images, the model's capacity was enhanced to generalize and accurately distinguish fundus images in various orientations through multiple types in fundus imaging instruments without losing precision. Other essential features were the color and brightness of the images [9].

D. Image Feature Extraction

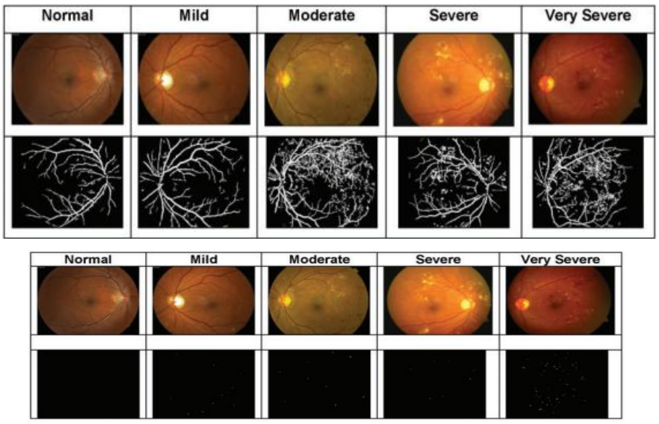


Fig. 3. Blood Vessel and Microaneurysms Feature Extraction.

Image representation and pattern recognition was used \to allow the extracting of features in every layer prior to the actual person responsible for classification and to use this data for better decision-making. Feature extraction method is extremely flexible because it enables to use different machine learning algorithms [10]. Moreover, the next phase is the feature extraction, which the features of the fundus image taken from the patient are extracted, such as the area of the blood vessels, exudates, and micro aneurysms show in Fig 3. Feature extraction was used also to calculate the area of blood vessels, exudates, and micro aneurysms from the final segmented images [11].

E. Neural Network Layer Model Implementation

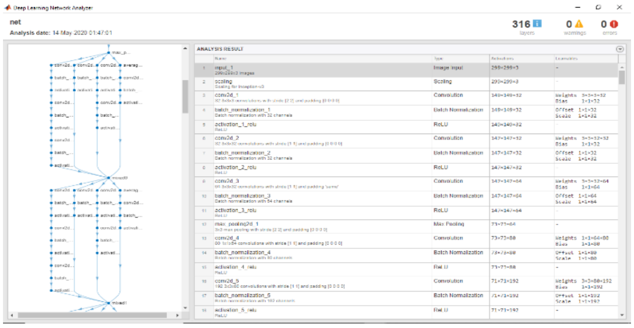


Fig. 4. Deep Learning Network Analyzer.

Fig. 4 shows the interactive design of the network architecture of Inceptionv3 and basic details about the layers. It is a mixture of all those layers namely, 1×1 Convolutional Layer, 3×3 Convolutional layer, 5×5 Convolutional layer, and max pooling layer with their output filter banks linked into a single output vector forming the input of the next stage. CNN layers obtain features of the preprocessed image that classifies the input image using the last learnable layer and the final classification layer. The last layer produced the data on how the features of the preprocessed image extract into class probabilities, a loss factor, and expected labels that can be combined. Also, new layers will substitute the final classification layer and retrain a pre-trained network to identify different images of the eyes with different layers that adjust to a new dataset.

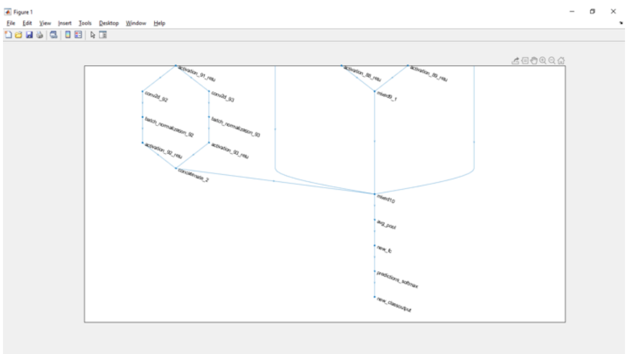


Fig. 5. Network Layers.

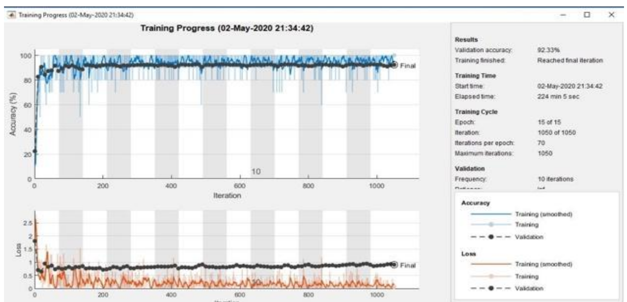


Fig. 6. Training Progress Result.

Fig. 5 shows the development of the newly created layer design and the final layers of the network to distinguish if the layer networks are attached correctly. Moreover, the network layers which are compatible with every eye type and classes can be frozen to hurry the process of network training and decrease network training time.

Fig. 6 shows the progress result using MATLAB, which lasted for about 4 hours. In addition, the DCNN model acquired a 92.33% validation accuracy rate for the data set size D illustrated in TABLE I. Specifically, MATLAB digital image processing paradigm was responsible with the DR and DME classification by extracting the ROI, producing binarized image and color comparison.

F. Image Classification

Table - III: International Clinical Diabetic Retinopathy and Diabetic Macular Edema Disease Severity Scale

Diabetic Retinopathy	Findings Observable on Dilated Ophthalmoscopy
No apparent DR	No abnormalities
Mild nonproliferative DR	Microaneurysms only
Moderate nonproliferative DR	Microaneurysms and other signs (e.g., dot and blot hemorrhages, hard exudates, cotton wool spots), but less than severe nonproliferative DR
Severe nonproliferative DR	Moderate nonproliferative DR with any of the following: • Intraretinal hemorrhages (≥20 in each quadrant); • Definite venous beading (in 2 quadrants); • Intraretinal microvascular abnormalities (in 1 quadrant); • and no signs of proliferative retinopathy
Proliferative DR	Severe nonproliferative DR and 1 or more of the following: • Neovascularization • Vitreous/preretinal hemorrhage

Diabetic Macular Edema	Findings Observable on Dilated Ophthalmoscopy*
No DME	No retinal thickening or hard exudates in the macula
Noncentral-involved DME	Retinal thickening in the macula that does not involve the central subfield zone that is 1mm in diameter
Central-involved DME	Retinal thickening in the macula that does involve the central subfield zone that is 1mm in diameter

Note. Retrieved from "ICO Guidelines for Diabetic Eye Care", by International Council of Ophthalmology, 2017, *1*(1), p. 2.

TABLE III shows the labels that are provided by professionals who rank the presence of DR and DME in each image by a scale of D0, D1, D2, D3, D4, M0, M1, and M2 which stands for no DR, mild, moderate, severe, proliferative DR, no DME, Noncentral-involved DME and Central-involved DME respectively. Even though the low-quality image generates incorrect results, preprocessing is an essential operation to enhance the image quality, the results of which are regarded as the original input for the training data that identifies the images. Due to the incomplete data and the limited number of datasets, pre-process standardization and data increase schemes were adopted [12].

G. System Requirements and Specifications

Table - IV: System Requirements and Specifications

System Requirements	Characteristic Properties
Operating System Used:	Raspbian 9 (Jessie) – Raspbian 10 (Buster)
Programming Language(s):	MATLAB R2018a Python 3.0-3.7
Database Language(s):	SQLite 3.0.0 – 3.26.0
Integrated Development Environments (IDEs):	Thonny IDE 2.1.19 - 3.2.3 MATLAB IDE R2018a
Input Data/Device(s):	Captured Eye (Retina) Image Touch-Enabled LCD Monitor
Output Data/Device(s):	Touch-Enabled LCD Monitor SMT47WD/850D Coaxial LED PDF File (Inkjet Printer)
No. of LEDs Used:	2
Sensor(s) / Camera(s):	Raspberry Pi Camera V2
No. of Sensor(s) / Camera(s) Used:	1
Single-Board Computer(s):	Raspberry Pi 4 Model B
No. of Single-Board Computer Used:	1
Switch(es):	SPST (Single-Pole, Single-Throw)
No. of Switch Used:	1
Power Source:	DC Power Supply • Input: 100~240V_{ac} 50/60Hz • Output: 5V_{dc} 0.6A-3A

H. System Schematic Diagram

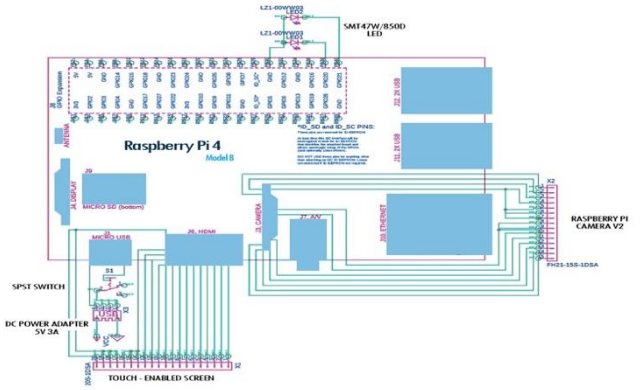


Fig. 7. System Schematic Diagram.

I. System Flowchart Diagram

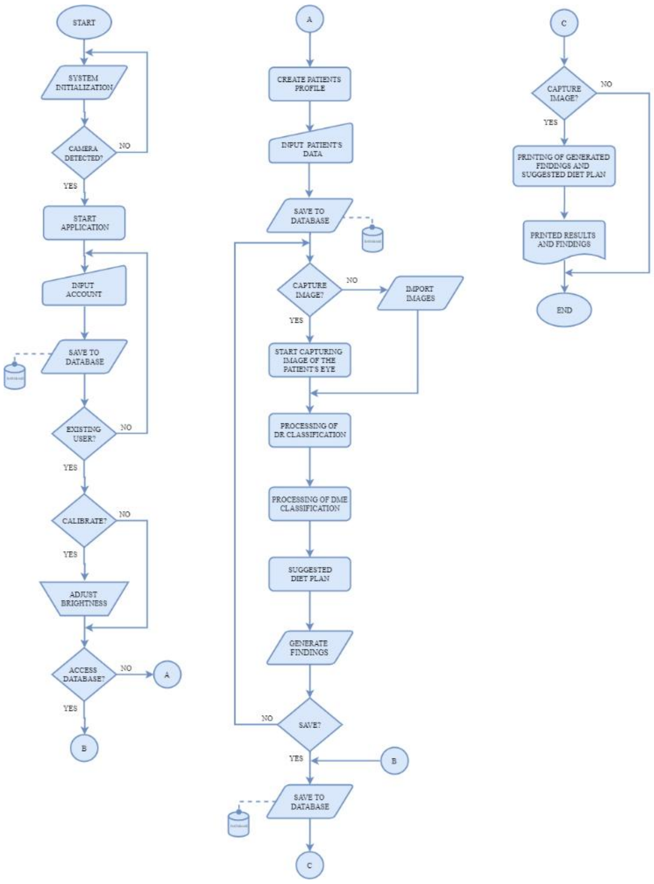


Fig. 8. System Flowchart Diagram.

Fig. 8 shows that the system flow begins from the initialization of the system, and the camera can be identified. The user can open the application to input their account. By signing in, the user can modify the luminosity of the system, create a profile for the patients and access the database to display or print the results produced and then recommend a diet plan for the patients. Furthermore, after calibrating and creating a profile for the patients the user can select the operation of DR and DME classification to the application. Upon recognition, the system generates the results showing the captured image of the DR and DME with its type, severity and grade, it also shows the suggested diet plan for the patients. The results will be recorded in the database, if not, the patient should take a picture again.

Additionally, the patient could print the results and generate a PDF file.

J. System Hardware Architecture

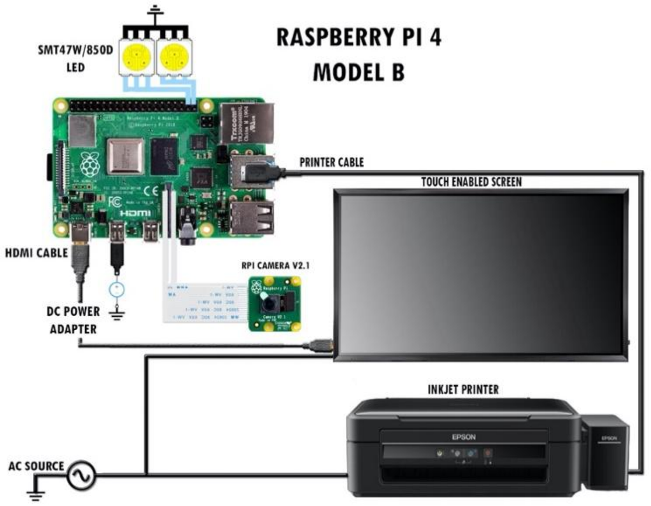


Fig. 9. System Hardware Architecture.

Fig. 9 shows the main supply of the system comes from the 5V 3A $_{DC}$ Power Adapter, which is connected to a 220V$_{AC}$ outlet to activate the main components of the developed system, which is the Raspberry Pi 4 Model B SBC. Furthermore, a USB type A and B were used to interconnect the RPi 4B SBC and the Inkjet Printer. The HDMI cable connects the Touchscreen LCD Monitor to the RPI 4B SBC. Additionally, the camera module was connected to the Raspberry Pi board through the CSI connector, and the SMT47W/850D LED connected with a 4pin LED strip connector to light an infrared light while to place the eye in the proper position, then capture the image with a white flash of light.

K. System Software Architecture

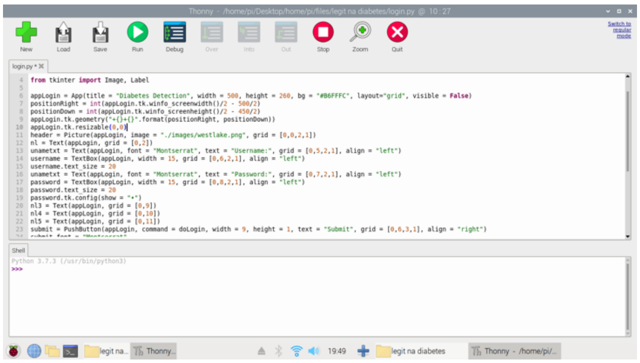


Fig. 10. Thonny (Python) IDE Window.

L. System Structural Architecture

Fig. 11. System Structural Architecture and its Logo.

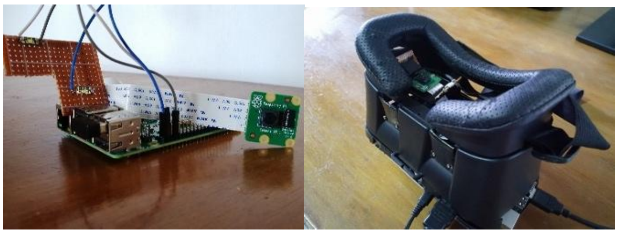


Fig. 12. Actual System Prototype.

M. System Implementation

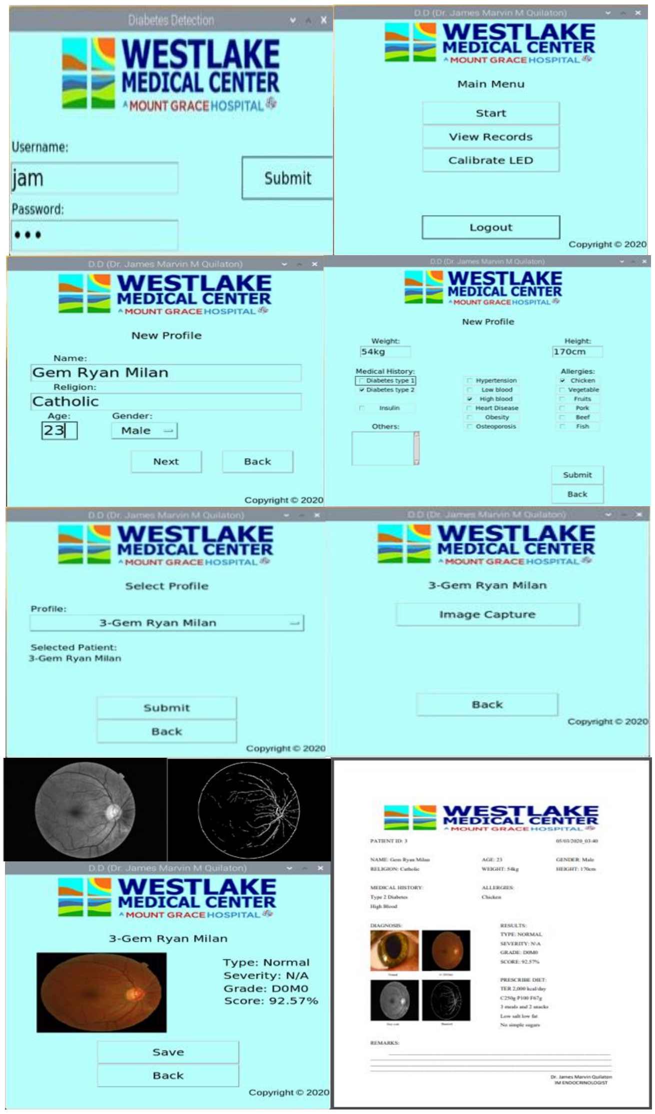


Fig. 13. User Interface of the System and PDF Result.

III. RESULTS AND DISCUSSIONS

Table - V: Likert Scale Used for Evaluating the Rate of Reliability of the System

Numerical Value	Reliability Percentage Yield	Interpretation
5	91% - 100%	Very Reliable
4	81% - 90%	Reliable
3	71% - 80%	Fairly Reliable
2	61% - 70%	Unreliable
1	60% and below	Very Unreliable

Note. Retrieved from "SBC-Based Cataract Detection System using Deep Convolutional Neural Network with Transfer Learning Algorithm", by K. Karamihan, et. al., 2019, *International Journal of Recent Technology and Engineering*, *8*(2), p. 4610.

TABLE V shows the Likert Scale which was used in evaluating the rate of reliability of the developed system. In addition, the scale served as the basis of the researchers in terms of the classifications of DR and DME with its characteristics.

Table - VI: Rate of Reliability of the System for Diabetic Retinopathy Classification

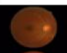
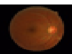
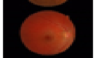
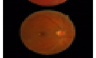
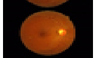
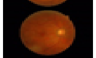
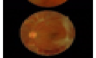
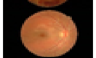
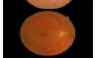
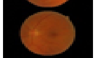
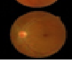
Sample	Image	Diabetic Retinopathy Classification using the Developed System				
		Type	Severity	Grade	RPY	Interpretation
1		No DR	N/A	D0	100%	Very Reliable
2		No DR	N/A	D0	100%	Very Reliable
3		NPDR	Mild	D1	100%	Very Reliable
4		NPDR	Severe	D3	80%	Reliable
5		PDR	Severe	D4	80%	Reliable
6		PDR	Severe	D4	80%	Reliable
7		NPDR	Moderat	D2	80%	Reliable
8		No DR	N/A	D0	100%	Very Reliable
9		No DR	N/A	D0	100%	Very Reliable
10		NPDR	Mild	D1	80%	Reliable
Composite Mean					90%	Very Reliable

Table - VII: Rate of Reliability of the System for Diabetic Macular Edema Classification

Sample	Image	Diabetic Retinopathy Classification using the Developed System		
		Grade	RPY	Interpretation
1		M0	100%	Very Reliable
2		M0	100%	Very Reliable
3		M1	80%	Reliable
4		M1	80%	Reliable
5		M1	80%	Reliable
6		M0	100%	Very Reliable
7		M1	80%	Reliable
8		M0	100%	Very Reliable
9		M0	100%	Very Reliable
10		M0	100%	Very Reliable
Composite Mean			92%	Very Reliable

TABLES VI and VII presents the results of assessing the developed system in terms of the rate of reliability. The aforementioned tables show the DR and DME classifications for the DR type, severity, and grade, as well as classifications for the DME grade obtained from ten (10) tests performed at the Westlake Medical Center. In addition, the Likert scale exhibited from TABLE V was used to assess the results while the grading classification was based in TABLE III. As such, the results portrayed that the developed system was very reliable with a Reliability Percentage Yield of 90% for DR and 92% for DME in comparison with the data from the MESSIDOR dataset. Both results in TABLES VI and VII with an average of 91% proves that the system could be an assistive device for ophthalmologists, endocrinologists and diabetic patients.

IV. CONCLUSION AND RECOMMENDATIONS

The approach in the development of the assistive device's design to be allowed to view the inner part of the eye through the 20D condensing lens by having the proper angle and lighting. The design also had proper portability for the ease of use for both the doctor and the patient. The developed system successfully implemented DCNN through the use of MATLAB IDE in using transfer learning via the pre-trained model inceptionv3. The generated model had an accuracy of 92.5% in the classification of both DR and DME. The developed system encountered a set of tests and was able to achieve a high rate of reliability since it provided a relevant result with the readings of the MESSIDOR dataset as reference. Moreover, this proved that the system was capable of being a reliable assistive device for the Endocrinologists in both DR and DME classification. To further improve the system, the combining different eye problem detection such as glaucoma and cataract into one classification system device to be used. Furthermore, using of different pre-trained models and additional datasets to provide higher accuracy and reliability in classifying both DR and DME; and also, the use of different method in preprocessing the dataset to make the region of interest more visible. Minimizing the time of diagnostic examination by improving the hardware structure by not changing the portability of the assistive device. Lastly, creating a smaller casing and taking up lesser space to lessen the strain on the patient while wearing the device. could increase in the portability of the device.

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REFERENCES

1. Z. Punthakee, R. Goldenberg, and P. Katz. (2018). Definition, Classification and Diagnosis of Diabetes, Prediabetes and Metabolic Syndrome. *Canadian Journal of Diabetes* [Online]. 42(1), pp. S10-S15. Available: https://guidelines.diabetes.ca/docs/cpg/Ch3-Definition-Classification-and-Diagnosis-of-Diabetes-Prediabetes-and-Metabolic-Syndrome.pdf
2. World Health Organization (2016). Diabetes Country Profiles-Philippines [Online]. Available: https://www.who.int/diabetes/country-profiles/phl_en.pdf?ua=1
3. R. Cheloni, S. A. Gandolfi, C. Signorelli, and A. Odone. (2019). Global prevalence of diabetic retinopathy: protocol for a systematic review and meta-analysis. *BMJ Open* [Online]. 9(3), e022188. Available: http://dx.doi.org/10.1136/bmjopen-2018-022188
4. Mayo Clinic (2018). Diabetic Retinopathy [Online]. Available: https://www.mayoclinic.org/diseases-conditions/diabetic-retinopathy/diagnosis-treatment/drc-20371617
5. B. Curry. (2018, July 27). An Introduction to Transfer Learning in Machine Learning [Online]. Available: https://medium.com/kansas-city-machine-learning-artificial-intelligen/an-introduction-to-transfer-learning-in-machine-learning-7efd104b6026
6. Mindfire Solutions. (2017, October 3). Python: 7 important Reason Why You Should Use Python [Online]. Available: https://medium.com/@mindfiresolutions.usa/python-7-important-reasons-why-you-should-use-python-5801a98a0d0b
7. A. M. Azab, J. Toth, L. S. Mihaylova, and M. Arvaneh, "Signal Processing and Machine Learning for Brain-Machine Interfaces", 1st ed. vol. 114, The Institution of Engineering and Technology, London, United Kingdom, 2018, pp. 81-101.
8. M. D. Abràmoff, Y. Lou, A. Erginay, W. Clarida, R. Amelon, J. C. Folk, and M. Niemeijer. (2016). Improved Automated Detection of Diabetic Retinopathy on a Publicly Available Dataset Through Integration of Deep Learning. *Investigative Ophthalmology & Visual Science* [Online]. 57(13), pp. 5200-5206. Available: https://doi.org/10.1167/iovs.16-19964
9. R. Gargeya, and T. Leng. (2017). Automated Identification of Diabetic Retinopathy Using Deep Learning. *Ophthalmology* [Online]. 124(7), pp. 962-969. Available: https://doi.org/10.1016/j.ophtha.2017.02.008
10. D. K. Prasad, L. Vibha, and K. P. Venugopal. (2015, December). Early detection of diabetic retinopathy from digital retinal fundus images. *Recent Advances in Intelligent Computational Systems (RAICS) IIEE* [Online]. 1(1) pp. 240-245. Available: https://doi.org/10.1109/RAICS.2015.7488421
11. R. Pires, S. Avila, J. Wainer, E. Valle, M. D. Abramoff, and A. Rocha. (2019). A data-driven approach to referable diabetic retinopathy detection. *Artificial Intelligence in Medicine* [Online]. 96(1), pp. 93-106. Available: https://doi.org/10.1016/j.artmed.2019.03.009
12. S. Wan, Y. Liang, and Y. Zhang. (2018). Deep convolutional neural networks for diabetic retinopathy detection by image classification. *Computers & Electrical Engineering* [Online]. 72(1), pp. 274-282. Available: https://doi.org/10.1016/j.compeleceng.2018.07.042

AUTHORS PROFILE

Engr. Anicia Coleen S. Reyes acquired her Bachelor of Science in Computer Engineering (BSCpE) degree at University of Perpetual Help System Laguna (UPHSL). During her college years, she once served as the President of Computer Engineering Department's MicroSociety with four years of service on different positions. At the same time, she was also the Director for Finance of Institute of Computer Engineers of the Philippines Student Edition (ICpEP.SE) Region 4A and Secretary of the Engineering, Architecture and Aviation Student Council of the University. She was part of EngGenius: the Official Student Publication of the College of Engineering as Cartoonist, Chief Layout Artist and Chief Illustrator also the Digital Graphic Designer of Engineering Student Council of the University. During the 4th ICpEP General Assembly, She was recognized as 2nd Runner Up in the ICpEP.SE Region 4A CpE Challenge 2018 fastest breadboarding competition held at Collegio de San Juan de Letran Calamba and also recognized as the Best in On the Job Training for year 2019.

Engr. Gem Ryan C. Milan is a graduate of Bachelor of Science in Computer Engineering (BSCpE) degree at University of Perpetual Help System Laguna (UPHSL). During his college years, he once served as a Graphic Designer and Director for Documentation for the Computer Engineering Department's MicroSociety. He is also a member of the Institute of Computer Engineers of the Philippines Student Edition (ICpEP.SE) Region 4A.

Engr. James Marvin M. Quilaton is a graduate of Bachelor of Science in Computer Engineering (BSCpE) degree at University of Perpetual Help System Laguna (UPHSL). During his college years, he was the Auditor; and Public Relations Officer for Internal Affairs of the Computer Engineering Department's MicroSociety. He was also a member of the Institute of Computer Engineers of the Philippines Student Edition (ICpEP.SE) Region 4-A.

Engr. Bryant Exel G. Sigue is a graduate of Bachelor of Science in Computer Engineering (BSCpE) degree at University of Perpetual Help System Laguna (UPHSL). During his college years, he was the 5th year representative of the Computer Engineering Department's MicroSociety; and a member of the Institute of Computer Engineers of the Philippines Student Edition (ICpEP.SE) Region 4A.

Engr. Steven Valentino E. Arellano, CpE, MSME was born in the City of Manila, Philippines on June 21, 1992. He is a degree holder of Master of Science in Management Engineering (MSME) conferred last 2017 at University of Perpetual Help System Laguna (UPHSL) in City of Biñan, Laguna, Philippines. He finished his Bachelor of Science in Computer Engineering (BSCpE) degree program last 2015 at the same university. He is a Freelance Digital Graphic Designer and Editor; Web Developer; Undergraduate Thesis/Research Adviser for Computer, Electrical, and Electronics Engineering of UPHSL; and Professional Member of Institute of Computer Engineers of the Philippines (Region IV-A), respectively. During his college years, he once served as Vice President-Internal, Treasurer, and Business Manager of MicroSociety (Computer Engineering Society) of UPHSL. He was the Chief Layout Artist, Writer, and Editor of EngGenius (Engineering) Magazine; and Digital Graphic Designer of Engineering Student Council and College of Engineering. Through his dedication with graphic design, he was once recognized as Best in Digital Graphic Design in the said university. The official logo of the National Collegiate Athletic Association (NCAA) South 16th Season was one of his graphic designs. During the 40th Commencement Exercises of UPHSL held in Philippine International Convention Center, Pasay City, he was awarded a Plaque of Recognition for his Outstanding Graduate Thesis entitled "Child Detector Android Application through Smartphone Using Bluetooth Low Energy (BLE) Beacon Technology", which was also published in the International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249-8958, Volume 8, Issue 2, December 2018. He had also scholarly published researches in different international research journals such as the International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume 7, Issue 12, September 2018, entitled "Sign Language and Speech Translation Wearable Device for Special Education Schools in the Philippines"; and International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume 8, Issue 2, July 2019, entitled "SBC-Based Cataract Detection System Using Deep Convolutional Neural Network with Transfer Learning Algorithm", respectively. IJEAT, IJITEE and IJRTE are published by Blue Eyes Intelligence Engineering and Sciences Publication.

Engr. Kenneth C. Karamihan acquired his Bachelor of Science in Computer Engineering (BSCpE) degree last 2019 at University of Perpetual Help System Laguna (UPHSL). He is currently a Junior Research and Development Engineer for Enterprise Business Solutions Department of Advanced World Solutions, Inc. (AWS) located at 3/F Multinational Bancorporation Center, 6805 Ayala Avenue, Bel-Air, Makati City, Metro Manila. During his AWS Center for Technology Incubation (ACTION) Training, he was recognized as the topnotcher of Batch 33C for General IT Concepts, Technical, Business Basics and Japanese Language (N4 Level). In addition to his work achievements, he was awarded with Project Achievement (Technical Contribution) Award by the company for his outstanding contribution as a developer and sub-leader during July 2020 Monthly General Meeting (MGM) and Company Fiscal Year Awarding. He is also an Undergraduate Thesis/Research Adviser for Computer, and Electronics Engineering of UPHSL. During his college years, he once served as the President of Institute of Computer Engineers of the Philippines Student Edition (ICpEP.SE) in Region 4A for two consecutive years with four years of service on different positions. He was also the President of the Computer Engineering Department's MicroSociety and the Vice President for External Affairs of the Engineering, Architecture and Aviation Student Council of the university. He was the Associate Layout Artist of EngGenius Magazine and Digital Graphic Designer of Engineering Student Council and College of Engineering. During the 3rd ICpEP General Assembly, he was recognized as Regional Champion in the ICpEP Region 4A CpE Challenge 2017 Quiz Bowl Competition held at Lyceum of the Philippines University, Batangas City, Batangas, and became the 4th Runner-Up in the National ICpEP CpE Challenge 2017 at the same category held at Legazpi City, Albay. He was also recognized with Proficiency in Computer Programming, Best in Object-Oriented Programming, Best in On-the-Job Training, Dean's Lister and ICpEP Leadership Award. His undergraduate thesis was recognized as Best in Design Project in Computer Engineering program and the 8th Engineering Research Forum Outstanding Research Paper. He had also scholarly published his undergraduate research in International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume 8, Issue 2, July 2019, entitled "SBC-Based Cataract Detection System Using Deep Convolutional Neural Network with Transfer Learning Algorithm". IJRTE is published by Blue Eyes Intelligence Engineering and Sciences Publication.