International Journal of Innovative Research in Advanced Engineering (IJIRAE) ISSN: 2349-263
Volume 7, Issue 03 (March 2020) www.ijirae.com
Special Issue – 6th International National Level Conference- "MEEMIC-2020"

DIABETIC RETINAL AND FOOT DISEASE DIAGNOSIS USING MACHINE LEARNING ALGORITHM

Dr.R.Sathish Kumar.[1], Naveena.M.,[2]
[1]Principal, Sengunthar College of Engineering, Tiruchengode.
[2], PG Scholar,
Department of Medical Electronics Engineering,
Sengunthar College of Engineering. Tiruchengode,Tamil Nadu, INDIA
[1],harsiga@gmail.com, [2]navimadhav95@gmail.com

Manuscript History
Number: **IJIRAE/RS/Vol.07/Issue03/Special Issue/01.MRAESCE10100**
Received: 15, February 2020
Final Correction: 27, February 2020
Final Accepted: 10, March 2020
Published: **14, March 2020**
Editor: Dr.A.Arul Lawrence selvakumar, Chief Editor, IJIRAE, AM Publications, India

Abstract—Artificial intelligence in combination with modern technologies including medical screening devices has the potential to deliver better management services to deal with chronic diseases with higher accuracy, efficiency, and satisfaction. With the recent evolution in digitized data acquisition, computer vision and machine learning, AI solutions are spreading into areas which were previously examined by well-trained clinicians. Early diagnosis of diabetic retinopathy (DR) and foot ulcers (DFU) occurrence through image analysis is in high demand as many individuals are left without any supervision due to the limited resources such as trained clinicians or suitable equipment especially, in rural areas. Furthermore, the existing system will become even more insufficient as the number of people with diabetes increases. In this research paper, we propose a prototype that involves an autonomous system called an Intelligent Diabetic Assistant (IDA), which decides the diagnosis and the treatment prioritization depending upon the observations appeared in the screen. The IDA consists of knowledge-based modules for severity level-based classification, clinical decision support and near real- time foot ulcer detection and boundary screening. We use the System Usability Scale (SUS) in terms of performance; learn ability, and satisfaction to measure the usability of the IDA. The mean SUS score was 88.5, demonstrating good but not exceptional system usability. We perform our experiments with clinicians who have been involved in diabetic care.
Keywords—Retinopathy, foot ulcers, telemedicine, deep learning, transfer learning, image retrieval, instance based segmentation, classification

INTRODUCTION

Diabetic Mellitus is one of the most pandemic and expensive chronic diseases. It affects an estimated 415 million individuals globally, accounting for 12% of the world's health expenditures, and yet 1 in 2 persons remain undiagnosed and untreated [1]. Consequently, life-threatening complications due to diabetes mellitus such as neuropathy, nephropathy, retinopathy, cardiomyopathy, and strokes have spiked all over the world today. Nowadays patients and caregivers remain on a question related to diabetes management. For example, frequently diagnosis and provide necessary instructions for patients in self- management are required to prevent acute terrible complications and minimize the risk of life-long conditions. With the increase of the high amount of real-world data gathered during treatments has produced tremendous excitement in diabetic care. Among these data, imagery records provide a high impact to develop novel insights and disrupt the current understanding of diabetic care. In the current arena, medical imaging widely used for diagnosis, treatment prioritization and assessing response to treatments in modern medicine. The major reason is that the workload of a medical expert increases significantly due to a large number of patients participating in population screening and therefore patients must have to wait in a long queue.

Artificial intelligence is progressively automating medical practices and offers higher accuracy, efficiency, and satisfaction. With the recent evolution in digitized data acquisition, computer vision and machine learning, AI solutions are spreading into clinical decision-making processes which were previously examined under the direct supervision of human experts. During the recent past, CNNs have revealed their extraordinary performance and the remarkable learning power in tasks that severely rely on feature extraction, such as image classification [2], object recognition [3], video analysis [4] and other several vision-related task.CNN based architectures usually outperform other techniques in the aforementioned research areas, which shows that CNNs can learn strong features that capture the semantic details of the images. Thus, the most appropriate technique is to use deep learning to analyze medical images.

Our research work represents a diverse and complex set of novel CNN-based architectures that purpose to improve diabetic care in main areas such as severity level based classification for automated screening and treatment prioritization, clinical decision support by using content-based image retrieval for diabetic retinopathy and near real-time foot ulcer detection and boundary screening to identify the majority of anomalies at the initial observation of diabetic ulcer imagery. With the selected technology stack, our results show a promising accuracy of over 98% for classification systems, over 99% mean average precision (mAP) for image retrieval system for diabetic retinopathy and over 87% of mAP at Intersection over Union (IoU) threshold of 0.5 for foot ulcer boundary detection system. The ultimate goal of our research is to provide a telemedicine system which can be used to improve the efficiency of diabetic care. It will be a great opportunity for society since everyone will receive the service nearly within an hour instead of spending more time on manual inspection of the deceased. Furthermore, this application will be a better solution to the problem of overload too much patients per consultant. This is where deep learning will play a major role in the future. Our solution will not be diagnosing patients and replacing consultants, it will be enhancing their ability to diagnose abnormal lesions that they need to treat for a patient and present it in a precise, easily digestible format.

RELATED WORK

Inadequate efforts have been made in autonomous diabetic management according to the literature. Previous studies have been explored autonomous systems for diagnosing DR and DFU separately as described below. Wang. L et.al [6] had implemented a system for real-time wound assessment based on image analysis. They have used mean shift based algorithm and this system outputs wound area, healing score and color segmented wound areas. This system provides only the semantic segmentation and it does not provide any classification. Therefore the user of the system cannot identify the severity stage of the patient for treatment planning. Suriyal.S et.al [7] had implemented a mobile assisted diabetic retinopathy detection system. The authors have used MobileNet [8] model for the implementation of the system. This system only provides the binary classification of DR to identify the input image is DR or non-DR. And also they had achieved 73.3 % of accuracy and 74.5% of sensitivity and 63% of specificity.

ARCHITECTURE

The IDA is designed and developed according to the requirements for effective diagnosis and delivering the treatment plans for diabetic patients. It affords an interaction mechanism with the health- care practitioner at a rural area and diagnosed severity level to suggests treatment plans, ulcer detection and boundary screening to visualize infected areas and image retrieval to identify the similar cases as per the given query image. The IDA consists of four sub-modules to perform the different responsibilities. Fig. 1 illustrates the overall system architecture of the IDA.

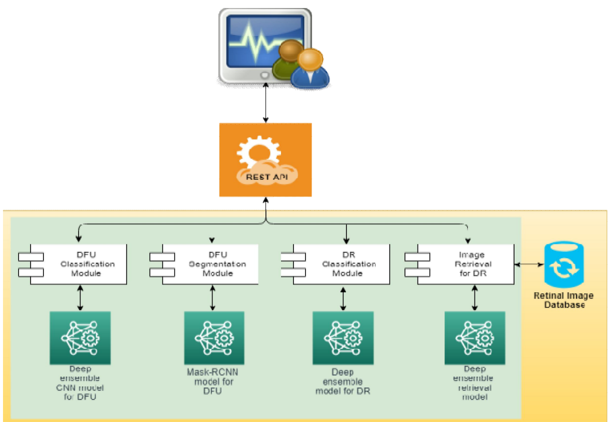


Fig. 1. System Architecture of IDA

We use two retinal and one diabetic foot ulcer imagery datasets for this study. One retinal dataset was collected from an eye hospital in Sri Lanka (744 fundus images) and the other one was drawn from a recent Kaggle competition [9]. Diabetic foot ulcer dataset (400 images) was collected from a diabetic clinic in Sri Lanka.

Severity Stage Classification Module for Diabetic Retinopathy

In this section, we describe the rationale behind the methodology of this module that has been used to perform the severity scale classification for diabetic retinopathy. Ophthalmologists and well-trained practitioners often use a five-class grading system to describe the severity stages of DR as follows: diabetes without retinopathy (Non-DR), Mild non-proliferative DR (Mild-NPDR), Moderate non-proliferative DR (Moderate- NPDR), severe non-proliferative DR (Severe-NPDR) and Proliferative diabetic retinopathy (PDR) [10]. Traditional diagnosis of DR requires manual evaluation process, which is time- consuming and depend heavily on the expertise of ophthal mologists and well-trained practitioners.

In order to assist and speed up the screening process and treatment planning for DR, we have developed an ensemble model to improve the prediction of DR using deep CNNs with transfer learning. The input to this module is a retinal image submitted by the SO. If the query image contains extra black spaces on either side of the retina, then as the initial step, our module will remove this unwanted background. The query images are in different dimensions and aspect ratios, therefore this module standardized all query images by resizing into 224px x 224px before feeding into the ensemble model. The ensemble model built using the combination of Dense Net201[11],

ResNet-18 [12] and VGG-16 [13] pre-trained CNNs as feature extractors followed by a global average pooling layer [14] and SVD, and a single hidden layer ANN as a feature classifier. The output appeared in the screen is a class label indicating the severity stage of DR. This classification module shows a promising accuracy of over 98%, which is a considerable performance gain with respect to the state-of-the-art approaches.

Image Retrieval module to identify similar cases for diabetic retinopathy

This module aims to develop an efficient content- based image retrieval technique to search and retrieve images from the retinal image database. Numerous features are mined from the retinal images through deep semantic hash code embedding [15] for the retrieval. This module consists of three main sub-modules. The first sub-module is the supervised learning of an ensemble CNN on the retinal dataset in order to learn rich mid-level image sig- natures. In the second sub-module, we feed extracted features from the previous step to another single hidden layer (28 neurons with sigmoid activation) ANN to learn binary hash codes. The final stage is to retrieve similar clinically relevant retinal images according to the visual features in the query image using a coarse-to-fine strategy [16] that utilizes the learned compact binary codes and mid-level image representations. First, we retrieve a group of candidates which are similar to the query image according to the hamming distance computed using the generated binary codes. Subsequently, we sort the retrieved candidate list by taking the cosine similarity with the query image based on the rich mid-level image representations which are extracted through the feature extractor of our classification model. The retrieval performance of the proposed module is tested using the 30 test retinal images. The retrieval performance assessed based on mAP(mean average precision) and we have achieved a promising mAP of over 99% (for top 10 ranked retinal images) which is a remarkable performance with respect to the state-of-the-art approaches.

Diabetic Wounds Detection & Boundary Screening Module

This module mainly focuses on the core process of wound assessment; wound detection and boundary segmentation. This process will help to analyze the spread of the wound over the limb and for further calculations of wound properties. In order to achieve more accurate and more generalized solution, we have built a Mask-RCNN [17] model. This model enables to identify multiple wounds separately, it allows to detect even very small wounds and it detects irregular boundaries with a higher accuracy rate. Since this model is using only the query images instead of handcrafted features or thresholds, this approach perform better accuracy than traditional image processing techniques and also it reduces the user interaction with the system. We have achieved over 87% mAP at IoU threshold 0.5.

Severity Stage Classification Module for Diabetic Wounds

The responsibility of this module is to predict the severity stage of the given ulcer imagery. This classification module performs based on the Wagner Ulcer Grading Scale which is most commonly used by practitioners and regarded as the gold standard. This scale has six grades to describe the severity stages of ulcers as follows: Grade 0 (No open lesions, but have deformations or cellulitis), Grade 1 (infected area with superficial ulcers), Grade 2 (Deep ulcers to tendon or joint capsule), Grade 3 (Deep ulcer with abscess, osteomyelitis or joint sepsis), Grade 4 (Local Gangrene forefoot or heel), Grade 5 (Gangrene in entire foot) [18].

We have built a deep CNN ensemble model as described in section III-A in order to achieve better accuracy for diabetic foot ulcer classification. After uploading an ulcer query image by the SO, the module will resize into 224px x 224px before feeding into the ensemble model. The final outcome, which is the prediction label of the severity stage, displays in the screen. This classification module achieves a promising accuracy of over 97%. This is an improvement on the current state-of-the- art approaches.

SYSTEM EVALUATION

Evaluation & Results of Modules

In order to evaluate our IDA medical system, we have involved five clinicians. We gave 10 retinal fundus images and 10-foot ulcer images to classify into severity stages. Table II indicates the comparison of classification accuracy between clinician's point of view and predicted results from our system. Fig. 2 indicates the ground truth ulcer boundary annotated through VGG Annotator tool [19] vs Segmented Ulcer boundary from the system. Mean average precision (mAP) at IoU threshold 0.5 was used to evaluate this model and it was over 87%. We have used a ranking based approach [20] for the evaluation of our image retrieval module for diabetic retinopathy. Given a query image and a similarity measure, a rank can be assigned for each retinal image in the dataset. We have evaluated the ranking of top k (e.g. k=10) retinal images with respect to the query images by calculating the mAP by taking the mean of the average precision over all query images and reported as a single score. Precision at each point when a relevant (according to the severity stage) retinal image is encountered in the ranked list calculated as follows (1).

$$Precision@k = \frac{\sum_{i=1}^{k} Relevance(i)}{k} \qquad (1)$$

Here Relevance(i) represents the ground truth relevance between a given query image and the ith ranked image. In our evaluation, we consider only the severity class label in measuring the relevance where Relevance(i) is equal to 1 if the query and the ith image have the same class label and zero otherwise. Table I shows the top five similar retinal images retrieved from the dataset according to the each given query image.

System Usability Evaluation

Usability studies are essential on practitioners point of view and mobile-based health-care interaction performance because such systems are becoming more common in the current arena for chronic disease management. This shortfall is addressed by our quantitative usability study of a mobile-based diabetes TABLE I

TOP 5 RETRIEVED IMAGES FROM RETINAL IMAGE DATASET

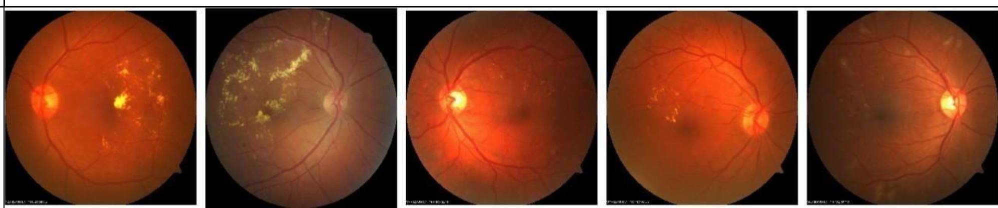
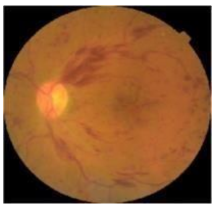
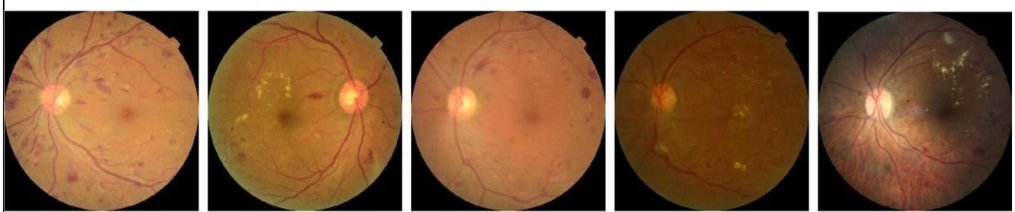
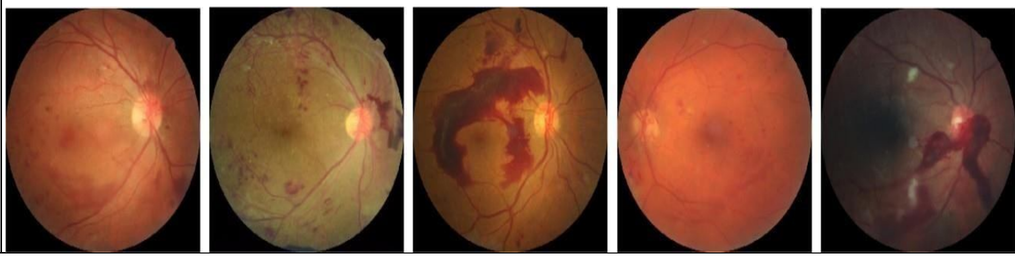
Query Image	Top 5 Retrieved Images
	
	
	

TABLE II CLASSIFICATION ACCURACY OF SYSTEM VS FIVE CLINICIANS

Classification	System Accuracy	C 1	C 2	C 3	C 4	C5
DR	98%	70 %	70 %	60 %	70 %	80 %
DFU	97%	80 %	80 %	70 %	80 %	70 %

system evaluating practitioners task performance, learnability, and satisfaction. Performance denotes to the accuracy and completeness of users in accomplishing the specified system functionalities. Accuracy refers to the error rate which calculates by considering the errors made by participant for each single system functionality and completeness refers to the percentages of given system functionalities that are successfully completed by the given participant (task completion rate). Learnability is one of the measurements for effectiveness and completion rate of the tasks given during the evaluation it assists with participants abilities in functioning the system.

TABLE III TASKS AND INPUTS SCENARIO

Task	Description
1	Starts the application
2	Navigates to DR Analyzer screen
3	Uploads a retinal query image
4	Clicks on ”Predict” button
5	Clicks on ”Retrieve”button to retrieve similar cases
6	Navigates to DFU Analyzer screen
7	Uploads a foot ulcer query image
8	Clicks on ”Predict” button
9	Clicks on ”Detect” button to detect ulcer boundary

Satisfaction indicates the participants insights and opinions of the system. We use System Usability Scale (SUS) [21] to measure the usability of the IDA and this scale consists of a 10 questionnaire with five response options (from strongly agree to strongly disagree) for the participants. For this study, 10 participants were involved and they were asked to operate the given scenario of the IDA. The scenario consists of numerous tasks in a sequential manner. Table III describes the above- mentioned tasks with the input values that user needs to conduct. Almost all participants did not come across any substantial difficulties in completing the tasks given.

Fig. 4 illustrates the We have classified encountered errors into three types namely input error, navigation error, and comprehension error. Input error indicates the incorrect input options or values from the user control. Navigation error indicates invalid gestures (tap, click, swipe) for certain tasks. Comprehension error indicates uncertainty of specified task completion. Table IV demonstrates the number of errors identified on each task.

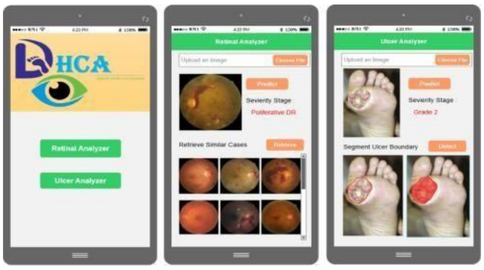
There are no considerable errors in tasks 1,2,6 and 9. In tasks 3 and 7, five input errors were encountered by the participants because they had to upload irrelevant images. Moreover, in tasks 4,5 and 8, five comprehension errors were encountered because of no guideline to perform the next step. In order to evaluate the system usability scale in terms of satisfaction, a deeper inspection was conducted for each question of the aforementioned SUS questionnaire. Fig. 5 illustrates the result of participant satisfaction degree that ranging from 0 to 100 in a nutshell. The mean SUS score was 88.5 that obtained from the SUS questionnaire given.

Social Impact

Our automated system is applicable in diabetic care, especially targeted to rural areas in Sri Lanka, where limited dedicated diabetic care centers are located. This system could easily be amalgamated in mobile health-care centers or health camps. The patient who feels difficult to reach main hospitals in urban areas can get treatment efficiently from these mobile health-care centers, which use the services of our system. Furthermore, this system would save the workload of the clinician and time consumption in analyzing medical images with no evidence of any clinical signs of diabetic mellitus and only images which belong to a severity stage can be separated and then sent to the appropriate practitioners to obtain the treatment plan.

In addition to the mobile health-care centers, the medical schools also able to use this system as a standard for their teaching, and students will obtain their knowledge in diabetic care. Thus, our IDA aims at enlightening opportunities in the health-care industry in the developing countries, and also this cost-effective system is in high demand in the developed countries where health care expenses are very high.

TABLE IV- THE NUMBER OF ERROR ENCOUNTERED



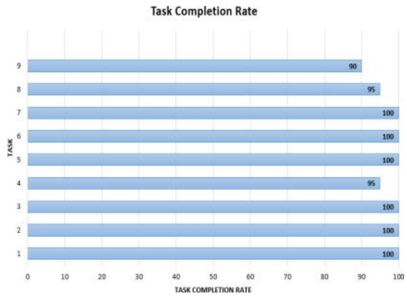


Fig. 2. Visualization of Ulcer Boundary detection Results: Green contour indicates the ground truth boundary and the red contour indicates the predicted contour through Mask-RCNN model.

Fig. 4. Task Completion Rate

Task	Types of Error		
	In.Error	Nav.Error	Comp.Error
1	0	0	0
2	0	0	0
3	2	0	0
4	0	0	1
5	0	0	2
6	0	0	0
7	3	0	0
8	0	0	2

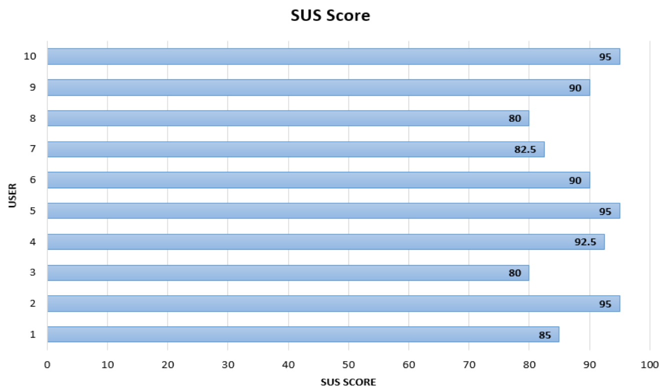


Fig. 5. SUS Score

CONCLUSION

The prototype IDA medical system that has been described above is suitable to the prevailing situation of diabetic-care for the patients who live in rural areas to reduce their traveling efforts to reach the hospitals or health-care centers at long distances. Moreover, this cost-effective medical system is ideal for developing countries to promote better diabetic- care assessment and make it available to one and all. This is potentially a prevailing tool for the next- generation implementation of ubiquitous diabetic- care systems. This system captures the images submitted by the system operator and applies deep learning algorithms to facilitate decision making such as treatment planning, wound boundary detection and identifying similar cases according to the severity level for the initial screening process. With the selected technology stack, our results show a promising accuracy of over 98% for classification systems, over 99% mean average precision (mAP) for image retrieval system for diabetic retinopathy and over 87% of mAP at Intersection over Union (IoU) threshold of 0.5 for foot ulcer boundary detection system.

We here considered three usability aspects namely performance, learnability and satisfaction. The aim of this study is to provide the best user performance for the IDA mobile application usability by evaluating the implemented user interfaces. A higher number of participants were able to accomplish the given scenario without any significant problems in the IDA. Therefore, we can conclude that the user interface of the application is understandable and there are no significant usability issues in terms of performance. There exists a considerable relationship between user experience for standard widgets and usability difficulties in our learnability evaluation. Due to the restriction of interaction model in mobile devices, upcoming research studies for the problems had to be conducted to deliver better illustrations to the design and development of the novel mobile-based application widgets and UIs in order to provide better performance in terms of smart-phone based application usability. Moreover, there are no significant issues encountered in user satisfaction evaluation criteria for the IDA.

ACKNOWLEDGMENTS

The authors would like to express their heartiest gratitude towards Dr. Manel Pasquel& Dr.Manilka Sumanathilake for providing us advice and support us through the problems we faced during the research. Moreover, they would like to thank Mr. Amila Chandrasekara for sharing his expert knowledge in the field and spending his valuable time to guide us through the research. This research was funded by the SRC Grant in University of Moratuwa of Sri Lanka.

REFERENCES

1. W. H. Organization, "Global report on diabetes," WHO, Tech. Rep., 2016.
2. J. Schmidhuber, U. Meier, and D. Ciresan, "Multi-column deep neural networks for image classification," in CVPR. IEEE, 2012, pp. 3642– 3649.
3. C. Szegedy, A. Toshev, and D. Erhan, "Deep neural networks for object detection," in NIPS, 2013, pp. 2553–2561.
4. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, and L. Fei-Fei, "Large-scale video classification with convolutional neural networks," in CVPR, 2014, pp. 1725–1732.
5. J. Long, E. Shelhamer, and T. Darrell, "Fully convolutional networks for semantic segmentation," in CVPR, 2015, pp. 3431–3440.
6. L. Wang, P. C. Pedersen, D. M. Strong, B. Tulu, E. Agu, R. Ignotz, and Q. He, "An automatic assessment system of diabetic foot ulcers based on wound area determination, color segmentation, and healing score evaluation," Journal of Diabetes Science and Technology, vol. 10, 2016.
7. P. Prasanna, S. Jain, N. Bhagat, and A. Madabhushi, "Decision support system for detection of diabetic retinopathy using smartphones," in 7th International Conference on Pervasive Computing Technologies for Healthcare and Workshops. IEEE, 2013, pp. 176–179.
8. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang,
9. T. Weyand, M. Andreetto, and H. Adam, "Mobilenets: Efficient convo- lutional neural networks for mobile Vision applications," arXiv preprint arXiv: 1704.04861,2017.
10. Kaggle datasets: Diabetic retinopathy detection.[Online]. Available: https://www.kaggle.com/c/diabetic-retinopathy-detection/kernels
11. S. Department, "Diabetic retinopathy guidelines," The Royal College of Ophthalmologists, Tech. Rep., 2012.
12. Satish Kumar.R. and Sanavullah, M.Y.," Theoretical and Experimental identification of cooking spot for shell eggs without explosions in a domestic Microwave Oven", Canadian Journal on Electrical and Electronics Engineering, Vol. 1, No. 4, pp.71-78, June 2010.

13. Satish Kumar.R, K.Uma Devi, and Sanavullah, M.Y.," Performance Analysis of using Exterior Rotor Permanent Magnet Brushless DC (ERPMBLDC)Motor", Improvement by a Novel Peak Torque Excitation Technique", International journal of Innovative research in Advanced Engineering, Vol. 1, 2012, pp. 1-7 (Impact factor 1.311).
14. Dr.R.Satish Kumar and Dr.K.Umadevi " Finite Element Analysis of an Exterior Rotor Permanent Magnet Brushless DC Motor for Torque Improvement by a Novel Peak Torque Excitation Technique", International journal of Innovative research in Advanced Engineering, Vol. 1, 2014, pp. 1-6 (Impact factor 1.311).
15. Raja, G P& Mangai, S 2017, 'Firefly Load Balancing Based Energy Optimized Routing for Multimedia Data Delivery in Wireless Mesh Network', Cluster Computing-The Journal of Networks Software Tools and Applications, SCOPUS Indexed Journal (Springer) - (E ISSN No: 1573-7543).Published Online: 27th Dec 2017, https://doi.org/10.1007/s10586-017-1557-1 .IF: 2.040.
16. Geetha. E & Nagarajan. C , 2019, 'Stochastic Rule Control Algorithm Based Enlistment of Induction Motor Parameters Monitoring in IoT Applications', Springer, Wireless Personal Communications. October 2018, Volume 102, Issue 4, pp 3629 - 3645.

