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A Review on Dristipatalagata Roga(Diabetic Retinopathy) Detection Using Deep Learning

Tejaswini V Gudigar[1], Sushma Chandrashekhar Yallakkanavar[2], Varshitha A R[3], Sriharshith[4],

tejaswinigudigar6@gmail.com , sushmapunith248@gmail.com , varshithav501@gmail.com ,

sriharshith44@gmail.com,

Abstract— An introduction to the automatic diagnosis and categorization of diabetic retinopathy (DR) utilizing retinal pictures through the use of convolutional neural networks (CNNs). It talks about the difficulties in making manual diagnoses, stresses the need of early detection, and highlights the need of precise classification methods. The approach for training and assessing CNN models is covered in detail, as is the mathematical formulation of DR detection using CNNs. The study addresses improvements in model performance and preprocessing techniques, underlines the value of continued research in enhancing early-stage diagnosis and patient outcomes, and demonstrates the effectiveness of deep learning techniques in DR detection. Overall, the paper emphasizes how deep learning techniques can revolutionize the diagnosis of diabetic retinal disease (DR) and seeks to improve patient care while lowering the prevalence of the condition worldwide.

I.INTRODUCTION

Diabetes mellitus is a chronic illness marked by elevated blood sugar levels due to insufficient pancreatic production of insulin [13]. This disease has become more common over time [3]; 422 million individuals worldwide were impacted in 2014[20]. Diabetes can cause damage to important organs such as the kidneys, heart, and eyes [4]. Diabetic retinopathy, or DR, is a condition that can result from diabetes and is the leading cause of blindness in individuals under 50 [5]. Diabetic renal disease (DR)-related blood vessel blockages can result in fluid leakage, edema, and blindness. Preventing the impact of diseases like diabetes requires early detection. DR may lead to abnormal blood vessel growth in the retina, which may result in bleeding, scarring, and blindness. To find DR, screening must be done often.

Diabetic renal disease (DR) is associated with high hemoglobin A1c, prolonged diabetes, and elevated blood pressure. As per the World Report on Vision, 11.9 million individuals globally suffer from visual impairments linked to DR [6], glaucoma, and trachoma [7].

Recent studies have shown that in order to diagnose diabetic retinopathy (DR), a physician will usually employ retinal imaging to identify particular types of lesions and record the form and appearance of these lesions. Microaneurysms (MA), hemorrhages (HM), soft and hard discharges (EX), and hemorrhages (HM) are the four types of lesions that are most often detected [8]. Diabetic retinopathy diagnosis requires the identification of five stages: no DR, mild DR, moderate DR, severe DR, and proliferative DR [1].

Due to inter- and intra-grader differences, even highly trained practitioners have trouble conducting evaluations for manual DR detection [9]. Thus, such issues might be mitigated by automated DR detection with precise machine-learning approaches. Several attempts have been made to classify OCT pictures.

Hemorrhage and exudate features are easily diagnosed with computer-aided diagnostics (CAD). By grouping them into proliferative and non-proliferative cases, this enables the separation of mild and severe vascular abnormalities from low-level, less significant lesions on fundus photographs. Both proliferative and nonproliferative DR (NPDR) are the two main stages of depression that fall into two groups. The growth of new arteries along the retina's vascular arcades is often thought to be the cause of neovascularization. The latter stage of DR, known as proliferative DR, is an angiogenic retinal response. This study reviews the stateof-the-art in deep learning classification research, emphasizing the use of deep learning techniques in categorization.

Diabetic retinopathy (DR), a specific kind of diabetes, can cause major retinal damage and consequent visual issues. Vision distortion results from DR's impact on the retinal tissue's veins, which causes fluid leaks. Together with glaucoma and cataracts, this disease is among the most prevalent causes of vision impairment. The characteristics and symptoms of the five DR phases—0, 1, 2, 3, and 4—vary. Nevertheless, early detection of DR with traditional imaging is challenging. Using a fundus camera, medical personnel can obtain images of the veins and nerves behind the retina to diagnose retinopathy. It is challenging diagnose this illness in its early stages because there are no DR symptoms.

To provide timely therapy, numerous CNN (Convolutional Neural Network) techniques have been employed for early diagnosis. The dataset used in this work was donated by

"Aravind Eye Hospital" may be accessed on Kaggle with the username "APTOS (Asia Pacific Tele Ophthalmology Society)" [10]. In this study, the performance of two CNN architectures—DenseNet121 and VGG16—is presented and compared [11]. Keywords: VGG16 Architecture, DenseNet121 Architecture, Fundus Camera, Diabetic Retinopathy (DR), Deep Learning [10].

Diabetic retinopathy (DR) comprises five phases, denoted as 0, 1, 2, 3, and 4. Doctors are unable to distinguish between stages using standard imaging techniques because each has unique symptoms and characteristics. The lengthy and frequently ineffective current techniques of diagnosing DR increase the risk of receiving the wrong therapy. However, recent studies have demonstrated that artificial intelligence (AI) models—specifically, "Deep Learning" models—can correctly identify the various phases of diabetes by analyzing medical photos [24]. This can help with better medical decision-making and increased care [12].

Diabetic Retinopathy is a disorder that mostly affects the retina and is caused by the expansion and rupture of blood vessels. The advanced-stage symptoms are not easily noticeable and can result in visual impairment if not treated promptly. The current DR screening process is time-consuming and made more difficult by the lack of qualified ophthalmologists. It entails performing fluorescein angiography, dilation of the eye, retinal imaging, and a clinical assessment.

Diabetes-related retinopathy is expected to affect 5 million people globally, making up 5% of all cases of blindness. In rural locations where diabetes patients are more common, a major issue is the shortage of qualified medical workers. Proliferative DR, Severe Non-Proliferative DR, Moderate Non-Proliferative DR, and Mild Non-Proliferative DR (NPDR) are the five stages of disease response. Due to symptoms such as decreased retinal pericytes, fast leukocyte adhesion, and delayed retinal blood flow, diagnosing moderate NPDR might be difficult.
Intraretinal microvascular anomalies, venous caliber alterations, and the formation of microaneurysms are the hallmarks of moderate non-proliferative diabetic retinopathy. Severe NPDR results in the growth of blood vessels to the point of severe blood flow restriction, where damaged blood vessels replace newly formed ones. New, delicate blood vessels in proliferative DR soon burst, resulting in irreversible blindness.
It is separated into multiple sections. A summary of the literature on DR image classification can be found in Section II. Comprehensive information about the dataset is provided in Section III. Section IV talks about the architectural methodology used by DL. The primary findings of the project are presented in Section V, and the paper's conclusion is found in Section VI.

Diabetes Mellitus is a chronic disease caused by inadequate production of insulin or insulin release from the pancreas, resulting in high blood sugar [13]. Diabetes, which is more common than before, can cause damage to the body such as kidneys, liver, heart, joints and eyes. Diabetes is the most common cause of blindness in people under 50. Due to blockage in the blood vessels that feed the retina, Diabetic retinopathy (DR) caused by diabetes is caused by swelling, blood, or fluid, Air can cause eye damage. Diagnosis of DR can occur in five stages but can be difficult to define as it requires knowledge and special equipment.

According to research, at least 90% of diabetic retinopathy (DR) cases can be prevented with appropriate medication and specialized eye care. Diabetes lasts longer, and DR risk. When vision loss is severe, DR can cause eye bleeding or scarring, which can lead to blindness. 2.6% of all blindness cases are associated with DR, which affects 11.9 million people worldwide. Early diagnosis is important to prevent complications of chronic diseases such as diabetes. Diabetic patients need to be checked regularly for early diagnosis of DR. The most important factors associated with the development of DR include hyperglycated hemoglobin, hypertension, and duration of diabetes.

Diagnosing diabetic retinopathy (DR) typically involves a doctor employing retinal imaging to assess the appearance and form of various lesion types. The four types of lesions that are commonly diagnosed are hemorrhages (HM), microaneurysms (MA), soft and hard discharges (EX), and hemorrhages (HM) [6]. Due to the weakening of the vessel walls, little red circular patches on the retina known as microaneurysms (MA) can be detected in the early stages of diabetic retinopathy. Sharp edges, no larger than 125 micrometers, characterize the dots. All six microaneurysm subgroups receive the same treatment, however they can be identified apart.

II. DIABETIC RETINOPATHY (DR) CLASSIFICATION

Diabetic retinopathy has four individual stages (DR), each with its own set of symptoms and characteristics [16]. Traditional methods of diagnosis rely on medical professionals to manually review retinal images, which can be time-consuming and prone to human error. Advances in artificial intelligence (AI), particularly in deep learning models, have shown promise in accurately diagnosing different drug resistance (DR) stages using medical picture analysis. Deep learning models are helpful for tasks like evaluating pictures used in medicine because they are very good at extracting complex patterns and attributes from large datasets. Given that these models are developed using annotated retinal images representing different stages of DR, they can automatically identify and classify the severity of the condition.

The application of DL models to DR diagnosis has several benefits. First and foremost, it can greatly shorten the time needed for diagnosis, freeing up doctors to concentrate on the treatment of patients and planning [22]. Additionally, AI models can provide assessments that are more objective and consistent than those made by humans, which may reduce the likelihood of misdiagnosis and ensure that patients receive the required medication on schedule.

Furthermore, by using the insights provided by AI models, medical professionals can make more informed judgments about patient care and treatment strategies. By accurately identifying the stage of DR, medical practitioners can tailor therapy to each patient's needs. This may increase the effectiveness of treatment and reduce the likelihood of issues.

Applying AI—more specifically, deep learning models—to the diagnosis of diabetic retinopathy has considerable promise for bettering patient outcomes. Healthcare providers can improve diagnosis accuracy, expedite workflow, and consequently treat patients with diabetes-related vision disorders more efficiently by evaluating medical photographs using machine learning algorithms.

III.MATHEMATICAL FORMULATION FOR DETECTING DR

Two stages are typically distinguished in the mathematical formulation of diabetic retinopathy (DR): a) early-stage, such as non-proliferative DR (NPDR), which might be mild, moderate, or severe.
b) Proliferative DR (PDR) and maculopathy, or DME, were examples of advanced phases.
To analyze medical images, the Mathematical Formulation for Detection (DR) employs a convolutional neural network (CNN) [21]. To recognize faces, people, DR, and other visual data, the convolutional neural network (CNN) employs algorithms [16].
The fully linked layer, the convolutional layer, activation function (ReLU), pooling layer (Max Pooling), training, and backpropagation are the components of a convolutional neural network (CNN)[19].

1. *Image Preprocessing*

Before feeding images into the model, they are pre-processed to enhance features and reduce noise. Common preprocessing steps include resizing, normalization, and augmentation.

2. *Convolutional Layer (CNN)*

Layers are often used to extract features from input images. Each convolution layer creates a unique map by convolving the input image with a set of learnable filters or kernels.

Convolution operation
$Y(l)[i,j]=f(\sum m=0M-1\sum n=0N-1$
$X\,[i+m,j+n].W(l)[m,n]+b(l))$

The filter's dimensions are M and N, its bias term is b(l), its activation function is f, its output feature map is Y(l), and its input image is X.

3. *Pooling Layer (Max Pooling)*

Apply pooling layers (e.g., max pooling) to reduce the spatial dimensions of the feature maps while retaining important information. Pooling can help make the model more robust to variations in input.

Pooling operation:

$P(l)[i,j]=\max m,n(Y(l)[i+m,j+n])$

$P(l)$ is the output of the pooling layer.

4. *Fully Connected Layer*

Flatten the output of the last pooling layer and feed it into one or more fully connected layers to perform classification.

$Y(l)=f(\sum i=1NWi(l).Xi(l)+b(l))$

$Y(l)$ is the output, $X(l)$ is the input to the fully connected layer, $Wi(l)$ is the weights, $b(l)$ is the bias term, N is the number of neurons, and f is the activation function.

5. *Activation Function (ReLU)*

Rectified Linear Unit (ReLU) activation function commonly uses the convolutional and fully connected layers [19].

Mathematically, Relu is defined as:

$f(x)=\max\,(0,\,x)$

ReLU is commonly used as the activation function in CNNs.

6. *Output Layer*

The output layer typically consists of a SoftMax activation function for multi-class classification, where each class represents a stage of diabetic retinopathy.

7. *Training and Backpropagation*

The network was trained using the backpropagation algorithm to minimize the loss function, which measures the difference between predicted and actual labels. Gradients are computed and used to update the network parameters (weights and biases) iteratively until convergence.

To achieve accurate classification of DR severity levels in retinal images, the mathematical formulation for detecting DR using deep learning involves a combination of Image Preprocessing, Convolutional Layer (CNN), Pooling Layer (Max Pooling), Connected Layer, and Output layer, along with optimization techniques and model evaluation.

IV. DATASET

The imaging data source used in this investigation is publicly available data from The Arvind Eye Hospital [10]. This information, especially 4. The results of the Asia Pacific Tele-Ophthalmology Society (APTOS) Eye Vision Research 2019 are easily accessible via the Kaggle platform [17]. The largest public has reliable data used before the CNN architecture or model, the convolutional neural network. Describes the content of data, which includes multiresolution retinal images from various imaging techniques. Image capture technology refers to the use of a fundus camera to capture color images of diabetic retinopathy. A fundus camera is a low-energy camera used to take pictures of the inside of the eye [25]. Fundus images are used as standard information for patients with diabetic retinopathy because they provide clear information that facilitates identification [18].

Five groups represent different stages of diabetic retinopathy (DR), they are class 0 (no DR), class 1 (mild DR), class 2 (moderate DR), class 4 (severe DR), and class 5 (PDR, or proliferative DR).
The dataset's structure is explained, along with its many files, including sample_submission.csv, train.csv, test.csv, and train pictures. The names of fundus eye images and the accompanying severity levels (classes) are contained in the train.csv file, but the test.csv file just contains the names of eye images and is meant to be tested following CNN architecture training.

V. METHODOLOGY

One of the main reasons diabetics have visual impairment is diabetic retinopathy. It is brought on by damage to the small blood vessels that supply the retina with vital nutrients and oxygen. Ophthalmologists or clinical specialists often use visual examination of retinal images to diagnose diabetic retinopathy. This approach, however, has the potential to result in mistakes, incorrect diagnoses, protracted processing times, and higher patient costs. Ophthalmologists or clinical specialists often use visual examination of retinal images to diagnose diabetic retinopathy. To overcome these constraints, automated systems that include numerous business rules with an expert system have been created. However developing such systems requires significant time, money, and coding commitment.

Additionally, the problems encountered in coding methods for managing large image datasets demonstrate the negative impact of inconsistencies in datasets on the accuracy of existing algorithms. That's why hospitals still rely on traditional diagnostic methods. Most experts use modified statistical methods for text and code entry. This technique is less useful when processing image datasets. Recent advances in deep learning and machine learning have demonstrated the potential to increase the accuracy of electronic systems in diagnosing diabetic retinopathy. Although automation has many benefits, there are still many problems with the current method, such as improper training, high coding requirements, too much time consumption, high prices, and poor quality [19]. Therefore, further research and advancements are needed to improve the accuracy, efficiency, and technology economics of diabetic retinopathy diagnosis [23].

Highlighting how important it is to use deep learning methods to detect and diagnose diabetic retinopathy. How crucial it is to maintain data integrity by making sure that class labels are correct and by enhancing dataset quality using preprocessing methods like contrast limited adaptive histogram equalization (AHE) [1]. Additionally, it investigates how transfer learning and customized deep feature extraction methods might increase the accuracy of diabetic retinopathy classification. In conclusion, the session concludes with a discussion of the creation of an automated deep-learning method that can accurately and consistently distinguish between various stages of diabetic retinopathy using fundus images, exhibiting a high level of specificity and sensitivity [1].

Accuracy is improved, especially for the DenseNet121 design, by utilizing a Convolutional Neural Network (CNN) architecture that has been pre-trained using the ImageNet dataset [19]. ImageNet is a vast collection of handpicked photographs that can be used to construct algorithms or models in computer vision, artificial intelligence (AI), machine learning (ML), and deep learning (DL). Subsets of the ImageNet datasets are used by models, algorithms, and annual competitions and challenges. Details are provided about the ImageNet dataset, which includes information on its vast size and 14 million distinct photos from a range of categories, such as images of flora, animals, and medical objects [13]. The primary goal of the ImageNet dataset was to offer a resource for advancing research and development in the fields of computer vision, artificial intelligence (AI), machine learning (ML), and deep learning (DL).
By using a Convolutional Neural Network (CNN), a deep learning system that can efficiently examine a substantial quantity of erratic and unlabeled fundus pictures, the suggested cure seeks to overcome issues with the current diagnostic system. The CNN-based approach simulates human-like activities and provides time efficiency, cost-effectiveness, and reliability. CNN has received a lot of attention for its accuracy in processing unlabeled image data; fundus images are particularly sensitive to its training. The online platform Kaggle, which conducts competitions and datasets for data science and machine learning projects, provided the training dataset that was used. The dataset is made up of several fundus photos, each of which has a label on a severity scale that runs from 0 to 4, signifying varying degrees of diabetic retinopathy severity [26]. The CNN model is trained on the dataset, and predictions are based on the model's prior knowledge gained from training on the test set. The steps involved in creating a CNN model are as follows: importing libraries, preprocessing data, initializing the neural network model, adding input and hidden layers, adding an output layer, and compiling the neural network model.
There was an uneven distribution of classes in the training dataset: there were more cases classified as '0' and fewer occurrences in classes '3' and '4' [22]. The dataset was used to create a histogram that showed the distribution of patients during the five phases of diabetic retinopathy [2]. An architectural representation of the convolutional network is used to construct the CNN model [19].

An explanation of convolutional neural networks (CNN) pooling and convolutional layers, as well as their importance for efficiently processing image data:

1. *Convolutional Layer*

The convolutional layer helps the network understand spatial hierarchies of features by applying filters or kernels to input data. To calculate the dot products between the filter and image patches, it convolves the filters across the input image. A feature map is created by this method, which extracts important patterns from the input. Convolutional layers allow for efficient feature learning with spatial information preservation.

2. *Pooling Layer*

Precisely, the pooling layer is essential for down sampling the input's spatial dimensions, which helps to lower the network's overall parameter count and computational complexity. The maximum or average value within each pooling zone is retained by common pooling techniques like max pooling and average pooling, respectively. By eliminating variables that are less relevant or non-maximal, this technique guarantees the retention of the most prominent traits. Additionally, pooling layers provide the network some translational invariance, which strengthens its resistance to small input translations.

3. *Architecture Design*

The convolutional layers in the suggested design are arranged without the use of intermediate spatial pooling layers. By expanding the receptive field, convolutional layer stacking enables the network to cover a greater range of spatial patterns. Disabling spatial pooling is one technique to keep geographical resolution intact throughout the network. This strategy improves the capacity to learn features and make discriminative judgments by making it simpler to construct deeper architectures with fewer learnable parameters.

Convolutional and pooling layers work together to provide a powerful CNN architecture that preserves important spatial information while handling large amounts of picture input and capturing discriminative characteristics.

When a histogram is used to visually represent the imbalanced distribution of classes in the training dataset, the following steps could be taken to create a Convolutional Neural Network (CNN) for diabetic retinopathy classification:

1. *Preprocessing*

Data is divided into sets for testing, validation, and training. adding extra data to the dataset (maybe by flipping, rotating, scaling, or employing other methods) to boost the representation of minority groups in the dataset and make it more balanced.

2. *Design of Model Architecture*

Convolutional, pooling and fully linked layers are incorporated into the architecture while building the CNN's structure. It is essential to match the right number of layers, filter sizes, and activation functions to the task complexity and processing power [28]. Furthermore, to avoid overfitting, methods such as batch normalization and dropout must be taken into account.

3. *Training of Models*

Using a suitable optimizer (like Adam or RMSprop) and loss function (such categorical cross-entropy for multi-class classification), the model is put together at this stage. The CNN model is then trained using pre-processed training data. It's critical to monitor the model's performance on the validation set to avoid overfitting. During this process, hyperparameters may need to be changed for the optimum results [21]. During this stage, the model is built using an appropriate optimizer (like Adam or RMSprop) and a suitable loss function (such as categorical cross-entropy for multi-class classification). The CNN model is then trained using pre-processed training data. It's critical to keep a tight eye on the model's performance on the validation set to avoid overfitting. It might be essential to adjust the hyperparameters for optimal results.

Subsequently, the trained model's generalization ability is assessed using an unidentified test dataset in an evaluation step. The efficacy of the model in distinguishing the phases of diabetic retinopathy is assessed through the computation of performance metrics, such as accuracy, precision, recall, F1-score, and a confusion matrix.

Specifically, great care is taken to ensure that there is no bias in favor of the majority class by assessing the model's performance for minority classes ('3' and '4' in this instance).

4. *Modification and Simplifying*

The model architecture and hyperparameters are continuously adjusted based on the evaluation findings to enhance performance, particularly for the minority classes. examining cutting-edge methods like transfer learning when the dataset is minimal or it is possible to obtain models that have already been trained on comparable problems [19].

5. *Observation*

Deploying the learned model in a real-world setting to put it into action. creating systems for monitoring the model's performance over time and retraining it frequently to account for concept drift and modifications in the data distribution. By taking these steps, it will be possible to systematically apply a Convolutional Neural Network (CNN) for the categorization of diabetic retinopathy. This approach ensures that the dataset is applied methodically and maximizes the performance of the model.

VII. CONCLUSION

The paper concludes with a thorough investigation of the use of deep learning methods for the early diagnosis of diabetic retinopathy (DR). It highlights how deep learning in particular, Deep Convolutional Neural Networks, or CNN has revolutionized the diagnosis of diffuse radiative illness by utilizing enormous datasets and cutting-edge methods. The paper focuses on how deep learning techniques outperform conventional methods in identifying disease-related traits and aiding early-stage identification, which is essential for prompt intervention and the avoidance of visual loss.

Various techniques, such as data augmentation, transfer learning, and evaluation of various CNN architectures, are presented throughout the review to improve the accuracy of DR classification [27]. In addition, the need of preserving dataset integrity and utilizing preprocessing methods for picture improvement is emphasized, in addition to investigating new deep learning architectures and the requirement for standardized assessment criteria.

All things considered, the assessment notes the noteworthy advancements in the use of deep learning for DR detection as well as the continuous work to improve methods for more effective and precise diagnosis. The review aims to enhance patient outcomes and lessen the worldwide burden of diabetic retinal disease by merging insights from medical imaging and artificial intelligence. This lays the foundation for future developments in the field.

REFERENCES

[1] SujithKumar, S. B., and Vipula Singh. "Automatic detection of diabetic retinopathy in non-dilated RGB retinal fundus images." *International Journal of Computer Applications* 47.19 (2012): 26-32.

[2] Alwakid, Ghadah, Walaa Gouda, and Mamoona Humayun. "Deep Learning-based prediction of Diabetic Retinopathy using CLAHE and ESRGAN for Enhancement." *Healthcare*. Vol. 11. No. 6. MDPI, 2023.

[3] Feng, Xingyu, et al. "Nomogram for individually predicting overall survival in rectal neuroendocrine tumours." *BMC cancer* 20 (2020): 1-7.

[4] Tayel, Safaa I., et al. "Biochemical and molecular study on interleukin-1β gene expression and relation of single nucleotide polymorphism in promoter region with type 2 diabetes mellitus." *Journal of Cellular Biochemistry* 119.7 (2018): 5343-5349.

[5] Mobley, R. Keith. *An introduction to predictive maintenance*. Elsevier, 2002.

[6] Sari, Ade Malia, and Kusnanto Kusnanto. "THE RELATIONSHIP BETWEEN TRIAGE ACCURACY AND SERVICE RESPONSE TIME IN THE EMERGENCY ROOM (IGD) AT RSIA BUNDA JAKARTA IN 2023." *HEARTY: Jurnal Kesehatan Masyarakat* 12.1 (2024): 149-154.

[7] Monji, Akira, et al. "Laminin inhibits both Aβ40 and Aβ42 fibril formation but does not affect Aβ40 or Aβ42-induced cytotoxicity in PC12 cells." *Neuroscience letters* 266.2 (1999): 85-88.

[8] Jahan, Rownak, et al. "Ethnopharmacological significance of Eclipta alba (L.) hassk.(Asteraceae)." *International scholarly research notices* 2014 (2014).

[9] SujithKumar, S. B., and Vipula Singh. "Automatic detection of diabetic retinopathy in non-dilated RGB retinal fundus images." *International Journal of Computer Applications* 47.19 (2012): 26-32.

[10] Nguyen, Quang H., et al. "Diabetic retinopathy detection using deep learning." *Proceedings of the 4th international conference on machine learning and soft computing*. 2020.

[11] Farhadi, Hadi, and Mohammad Najafzadeh. "Flood risk mapping by remote sensing data and random forest technique." *Water* 13.21 (2021): 3115.

[12] Cui, Miao, et al. "International Journal of Scientific Engineering and Research (IJSER)."

[13] Jangsavang, Sangdaw, and SUPIT SIRIARUNRAT. Factors predicting blood glucose control behavior among pregnant women with gestational diabetes mellitus. Diss. Burapha University, 2020.

[14] Asemi, Asefeh, Ali Safari, and A. Asemi Zavareh. "The role of management information system (MIS) and Decision support system (DSS) for manager's decision making process." *International Journal of Business and Management* 6.7 (2011): 164-173.

[15] Ochei, Laud Charles, Julian M. Bass, and Andrei Petrovski. "Degrees of tenant isolation for cloud-hosted software services: a cross-case analysis." *Journal of cloud computing* 7.1 (2018): 22.

[16] Chen, Yueh-Peng, Tzuo-Yau Fan, and Her-Chang Chao. "Wmnet: A lossless watermarking technique using deep learning for medical image authentication." *Electronics* 10.8 (2021): 932.

[17] Mishra, Supriya, Seema Hanchate, and Zia Saquib. "Diabetic retinopathy detection using deep learning." *2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE)*. IEEE, 2020.

[18] Qureshi, Mohammad Farhan, Shoeb Qureshi, and Viquar Fatima Qureshi. "International Journal of Medical Science and Innovative Research (IJMSIR)." (2019).

[19] Kang, Min-Joo, and Je-Won Kang. "Intrusion detection system using deep neural network for in-vehicle network security." PloS one 11.6 (2016): e0155781.

[20] Maksymov, Ivan S. "Magneto-plasmonics and resonant interaction of light with dynamic magnetisation in metallic and all-magneto-dielectric nanostructures." Nanomaterials 5.2 (2015): 577-613.

[21] Albattah, Waleed, et al. "Artificial intelligence-based drone system for multiclass plant disease detection using an improved efficient convolutional neural network." Frontiers in Plant Science 13 (2022): 808380.

[22] Berns, Jeffrey S., et al. "Hemoglobin variability in epoetin-treated hemodialysis patients." Kidney International 64.4 (2003): 1514-1521.
[23] Yehia, Sami, et al. "Translation of SIMD instructions in a data processing system." U.S. Patent No. 8,505,002. 6 Aug. 2013.
[24] Mustaqim, Muh Firman, and S. Kp Arum Pratiwi. Gambaran Kecemasan pada Lanjut Usia dengan Penderita Diabetes Melitus di Posyandu Desa Praon Nusukan Surakarta. Diss. Universitas Muhammadiyah Surakarta, 2016.
[25] Zhang, Sheng, et al. "Kinetics and fusion characteristics of municipal solid waste incineration fly ash during thermal treatment." Fuel 279 (2020): 118410.
[26] Harshitha, Chava, et al. "Predicting the stages of diabetic retinopathy using deep learning." 2021 6th international conference on inventive computation technologies (ICICT). IEEE, 2021.
[27] Thorat, Sumit, et al. "Diabetic retinopathy detection by means of deep learning." 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2021.
[28] Doshi, Darshit, et al. "Diabetic retinopathy detection using deep convolutional neural networks." 2016 international conference on computing, analytics and security trends (CAST). IEEE, 2016.
[29] Atwany, Mohammad Z., Abdulwahab H. Sahyoun, and Mohammad Yaqub. "Deep learning techniques for diabetic retinopathy classification: A survey." IEEE Access 10 (2022): 28642-28655.
[30] Qiao, Lifeng, Ying Zhu, and Hui Zhou. "Diabetic retinopathy detection using prognosis of microaneurysm and early diagnosis system for non-proliferative diabetic retinopathy based on deep learning algorithms." IEEE Access 8 (2020): 104292-104302.