JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

A Review on Deep Convolutional Neural Networks for Diabetic Retinopathy detection by image classification

Nayanbhai Soni
Research Scholar
Dept. of Computer Science
Sabarmati University
Ahmedabad, India
nynsoni@gmail.com

Dr. Mukta Agarwal
Associate Professor
Dept. of Computer Science
Sabarmati University
Ahmedabad, India
mukta09agarwal@gmail.com

Abstract-The main reason for blindness in India and other nations is diabetic retinopathy. Millions of individuals worldwide are impacted by DR, which results in blindness and vision loss. Early detection of diabetes mellitus is crucial for avoiding the potential loss of vision that can occur if the condition is not treated for an extended length of time. As diabetic retinopathy can result in blindness in people with uncontrolled diabetes, it is becoming more and more crucial to identify it early using automated technologies rather than human screening techniques like fluorescein angiography, optical coherence tomography, etc. On machine learning and deep learning-based DR detection systems, numerous papers have been published.We examine the fundamentals of cutting-edge AI technologies utilized in DR analysis and early detection in this research. Reviewing DR detection methods from several perspectives, including datasets, picture preprocessing, methods, machine learning and deep learning-based approaches, and performance measurements, is the goal of this paper. It includes both the review's findings and the authors' observations.In the area of DR detection, many public datasets were accessible. Based on shape, texture, and statistical data, the Artificial Neural Network outperformed previous machine learning techniques for DR detection. This study's goal is to review the performance of the Convolutional Neural Network (CNN).

Keywords: Convolutional Neural Network (CNN), Retinal Fundus Images, Ophthalmology, Diabetic Retinopathy(DR), Artificial Intelligence,Machine-learning, Deep-learning, Deep Neural Network.

I. Introduction

India currently ranks among the nations with the highest rates of diabetes; the disease affects practically all of the body's organs, particularly the eye. Diabetes can cause blindness in those with high blood sugar in a matter of days. A diabetes complication that can affect the eyes is diabetes eye disease. Therefore, diabetic eye problems are a possibility for diabetic people. Without proper diagnosis and care, diabetes-related illness can cause significant vision loss or even eventual blindness. Due to modifications inside the fundus of the eye's blood vessels, DR is currently the main cause of vision loss brought on by diabetes. The retina, a membrane of tissue that is light-sensitive, is located inside the back of the eye.For clear vision, a healthy retina is essential. In diabetics, blood vessels develop on the retina's surface and may enlarge, rupture, or leak blood or fluid. If we catch DR as soon as feasible, it will get less serious. Some signs include floating dots in the field of vision or general eyesight blurriness. Early detection of DR is essential for its prevention or delay. In that situation, AI is essential for detecting

DR as soon as possible. Nearly all facets of human life have been touched by technological advancements during the past several years. Human work capacity has been successfully transferred to machines in the developing field of AI.Since the human capacity is insufficient to fulfil people's everyday living standards, the machine automation sector has been called upon as the human population has increased. We investigated this area with artificial intelligence and discovered a response to the query, "Why can't the machine have some intelligence?" Machine learning (ML) and deep learning (DL) are created in this manner. ML enables the machine to reason about and react to specific circumstances based on the knowledge gained from the enhanced dataset. Since many diseases are closely linked and are challenging to distinguish based solely on their symptoms, artificial intelligence (AI) has found tremendous utility in the field of medical research.Although it takes time to consider all options, a human's intelligence can aid in the diagnosis and prediction of diseases. Patients with these conditions don't have enough time to survive as a result of the significant scale efficiency, which prompted the introduction of AI in medicine, where the AI domain was thoroughly investigated. Through the use of ML and DL analysis, AI has been able to better utilize its power. ML is used to train and learn the system by building a variety of neural-based models for categorizing the issues based on various learning artefacts.In contrast, DL leverages the knowledge gained by ML as a platform to teach the machine how people behave by exploring the possibilities in both the known and new scenarios for the prediction and diagnosis of diseases.

Deep Learning uses a CNN, an artificial neural network with a convolutional structure, to identify objects in a picture. We have evaluated a number of CNN architectures for image classification in this study. The most advanced image categorization system is CNN.

II. Convolutional Neural Network

Convolutional neural networks (CNNs or ConvNets) are a type of deep learning network design that learns directly from data, doing away with the requirement for manual feature extraction. CNNs are especially helpful for identifying patterns in photos that can be used to identify objects, faces, and sceneries.A CNN is made up of four layers: a convolution layer, a fully linked layer, and an output layer, as shown in Figure 1.

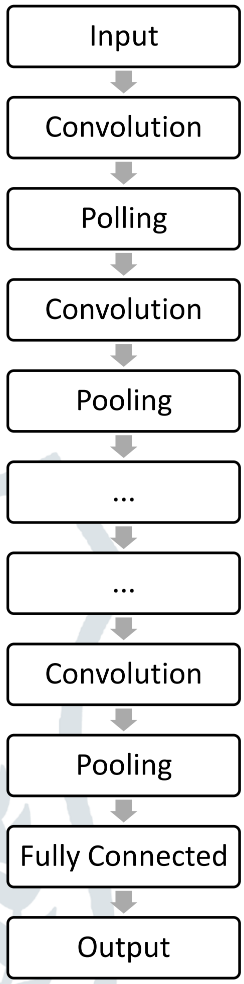

Fig. 1: Building block of a typical CNN

2.1 Convolutional Layer

CNNs are based on convolutional layers (conv layers) which serve as the core of the algorithm. Images are generally stationary, meaning that there are no difference between the features learned in different areas of the image. A large image is constructed by passing a small section between all points on the large image (input) and then combining all the points as an output (output). Each small section is the kernel, which passes between the large image and the small section.Afterwards, filters are configured based on back propagation. An example of a convolutional operation can be seen in figure 2.

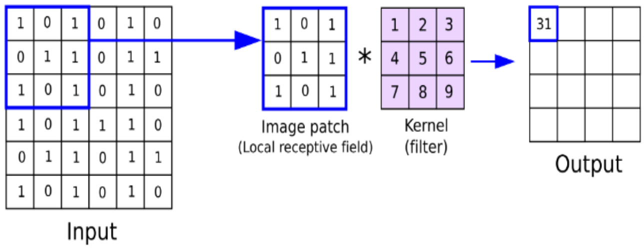

Fig. 2: Convolutional Layer

2.2 Sub-sampling or Pooling Layer

Using a tiny area of a convolutional output as the input and subsampling it to produce a single output is the notion behind pooling. There are numerous types of pooling, including maximum, average, and mean pooling. As seen in picture 3, max pooling considers the biggest pixel value in a region. By doing this, it is possible to compute fewer parameters while still maintaining the network's invariance.

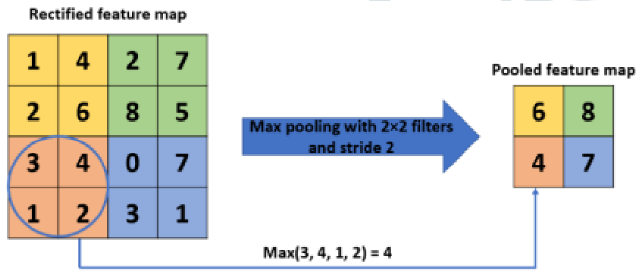

Fig. 3: Max Pooling operation

2.3 Fully-connected Layer (FC Layer)

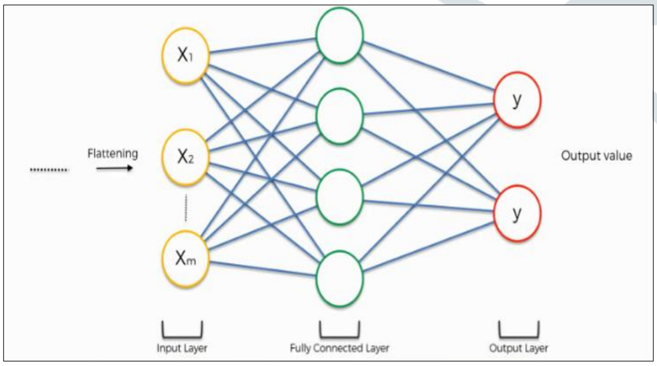

Fig. 4: Fully-connected Layer

As seen in figure 4, the final layer of a CNN is essentially a fully linked layer that processes each neuron in the current layer using information from the layer before it.

III. Related Work

DR can be effectively identified at an early stage thanks to automated DR picture detection. Delaying or avoiding vision deterioration requires early detection and treatment. Refer to [1] [2] for a summary of these techniques. Deep learning approaches have recently experienced an unprecedented shift in the field of computer vision. Many scholars are interested in using CNNs to accomplish picture categorization. Segmentation of these traits as well as blood vessels is a topic of research in this area [3] [4]. Deep CNNs structures were first proposed as a way to classify images naturally, and current research has made significant strides on classifying DR fundus images. In order to extract picture characteristics for addressing blood vessel segmentation, Wang et al. [5] use a CNN (LeNet-5) model.These techniques have various drawbacks. First off, as the features in the dataset are manually and empirically extracted, their accuracy cannot be ensured. Second, it is impossible to assess the effectiveness of the algorithms in the experiment due to the limited size and poor quality of the data sets, which are often only a few hundred or perhaps a few dozen fundus images with a comparatively single collection environment. Since Alex et. al. [6] [7] .'s presentation of the AlexNet architecture for notable performance enhancements at the 2012 ILSVRC competition, deep CNNs have seen a significant explosion in their use in computer vision.After a number of great CNNs architectures, such VggNet [8] [9], GoogleNet [10], have been suggested. ResNet [11], one of the most significant network models, was put forth in 2015 and improves the performance of CNNs in image categorization. Transfer learning and hyperparameter tuning are employed in this study because creating a model from scratch is laborious and time-consuming. These architectural designs are available in [12] [13] [14] [15] [16] [17]. Transferring learning is used to speed up the learning process, and performance is compared with AlexNet, VggNet, GoogleNet, and ResNet. This results in an automatic and accurate detection that allows for the least amount of visual damage possible.Our review provides classification performance.

III. METHODS

CNNs have accomplished a lot thanks to their successful image categorization abilities. We have employed the most recent Deep CNNs, AlexNet,VggNet,GoogleNet, and ResNet, together with transfer learning and hyper-parameter tuning, and discuss how effectively these models categorize using the DR image dataset. On the effectiveness of the models, a comparative discussion for retinopathy detection studies is offered. The last completely connected layer of a previously trained CNN is removed and used as a feature extractor in the transfer learning technique. We train a classifier on the new dataset once we have successfully extracted all of the features for all of the medical photos.It is vital to tweak and optimize these parameters in accordance with the results of training the DR image in order to improve performance because the parameters of the hyper parameter-tuning approach are not initialized by the network itself.

IV. COMPARITIVE STUDY

For this investigation, we reviewed the following three published papers w.r.t. (1)Amnia Salma et. al. [18], (2) Akhilesh Kumar et. al. [19], and (3) Hassan Tariq et. al. [20]. They all used the same open source Kaggle's dataset.We identified three indicators: accuracy, sensitivity, and specificity. Sensitivity is the proportion of patients out of the actual total of patients with DR that were accurately identified as having DR. The percentage of patients correctly recognized as lacking DR out of the actual total of those truly lacking DR is known as specificity. Accuracy is defined as the total number of patients with a proper classification, according to Amnia Salma et al. [18]. Their model's training as a result had an accuracy of 88%, a sensitivity of 75%, and a specificity of 52%.On the same dataset, the another author named Akhilesh Kumar et. al.[19]who obtained a test accuracy of 82.18%.As well as according to HassanTariq et. al. [20] experimental findings, the pre-trained CNN model outperformed all other pre-trained models with a classification accuracy of 97.53% for the same dataset and on each CNN architecture, they ran five separate trials. As a result, a five-degree categorization has a minimum accuracy of 84.01%. Hence we can conclude that Hassan Tariq et. al. [20]'s CNN model has better performed among these three papers.

V. LIMITATION AND RESEARCH GAP IDENTIFICATION

Following are the limitations and research gaps identified by the literature study based on the various models used to detect DR.

1. Although current approaches work admirably when used on huge datasets, their effectiveness when used on smaller datasets is in doubt.
2. While there are a few solutions for DR detection based on machine and deep learning techniques, they are ineffective.
3. Because of the quantity, quality, and resolution of the images, present technologies are unable to produce consistent findings on any dataset.
4. Most plans fall short in properly re-purifying, segmenting, and extracting features from the data.

VI. THE DETECTION OF DR REQUIRES SOME IMPROVEMENT FROM SOME VIEWPOINTS

1. Constructing a reliable segmentation technique for retinal pictures.
2. For retinal images, an effective model for feature extraction must be created.
3. Creating a machine learning system for DR categorization.
4. Create effective models that can be applied to datasets of retinal pictures in any dimension.

X. REFERENCES

[1] Walter T, Klein J-C, Massin P, Erginay A. , "A contribution of image processing to the diagnosis of diabetic retinopathy-detection of exudates in color fundus images of the human retina," *IEEE Trans Med Imag,* Vols. 2002;21(10):1236-43.

[2] Zeiler MD, Fergus R., "Visualizing and understandin convolutional networks," *European Conference on Computer Vision, Springer*, pp. 818-33, 2014.

[3] Wang Z, Yang J., "Diabetic retinopathy detection via deep convolutional networks

for discriminative localization and visual explanation," *arXiv:170310757*, 2017.

[4] Yehui Yang, Tao Li, Wensi Li, Haishan Wu, Wei Fan & Wensheng Zhang , "Lesion Detection and Grading of Diabetic Retinopathy via Two-Stages Deep Convolutional Neural Networks," *Springer: MICCAI 2017*, pp. 533-540, 2017.

[5] Shuangling Wang, Yilong Yin, Guibao Cao, Benzheng Wei, Yuanjie Zheng, Gongping Yang, "Corrigendum to “Hierarchical retinal blood vessel segmentation based on feature and ensemble learning”," *Neurocomputing, Volume 226, 22 February 2017*, vol. Volume 226, pp. 270-272, 2017.

[6] Krizhevsky, A., Sutskever, I., & Hinton, G. E., "Imagenet classification with deep convolutional neural networks," *Advances in Neural Information Processing Systems (NIPS). Neural Information Processing Systems Foundation, La Jolla, CA.*, 2012.

[7] Szegedy C, Loffe S, Vanhoucke V, Alemi AA, "Inception-v4, inception-resnet and the impact of residual connections on learning," *AAAI*, vol. 4, no. 2017, p. 12.

[8] Parkhi, O. M., Vedaldi, A., & Zisserman, A., "Deep face recognition," 2015.

[9] Simonyan K, Zisserman A., "A Very deep convolutional networks for large-scale image recognition," *arXIv preprint arXIv: 14091556*, 2014.

[10] Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erthan D, Vanhoucke V, Rabinovich A. et. al., "Going deeper with convolutions," *CVPR*, 2015.

[11] He K, Zhang X, Ren S, Sun J., "Deep residual learning for image recognition," *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770-778, 2016.

[12] H. -C. Shin et al.,, "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," *In IEEE Transactions on Medical Imaging*, vol. 35, no. doi: 10.1109/TMI.2016.2528162, pp. 1285-1298, 2016.

[13] N. Tajbakhsh et al., "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?," *In IEEE Transactions on Medical Imaging*, Vols. 35, no. 5, no. doi: 10.1109/TMI.2016.2535302, pp. 1299-1312, 2016.

[14] Nitish Srivastava et. al., "A Simple Way to Prevent Neural Networks from Overfitting," *Journal of Machine Learning Research 15*, pp. 1929-1958, 2014.

[15] Wan S, Yang H., "Comparision among methods of ensemble learning," *In: Biometrics and Security Technologies (ISBAST)*, pp. 286-90, 2013 Internaional Symposium on, IEEE.

[16] Szegedy C, Vanhoucke V, loffe S, Shlens J, Wojna Z., "Rethinking the inception architecture for computer vision," *In: Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, pp. 2818-26, 2016.

[17] Wan S, Liang Y, Zhang Y, Guizani M. , "Deep multi-layer perceptron classifier for behavior analysis to estimate parkinson's disease severity using smart phones," *IEEE*, vol. 6, 2018.

[18] Amnia Salma *, Alhadi Bustamam, Devvi Sarwinda, "Diabetic Retinopathy Detection Using GoogleNet Architecture of Convolutional Neural Network Through Fundus Images," *Bioinformatics and Biodiversity Conference*, no. http://dx.doi.org/10.11594/nstp.2021.0701, 2021.

[19] Akhilesh Kumar Gangwar, Vadlamani Ravi, "Diabetic Retinopathy Detection Using Transfer Learning and Deep Learning," *Advances in Intelligent Systems and Computing 1176*, pp. https://doi.org/10.1007/978-981-15-5788-0_64, 2021.

[20] Tariq, H.; Rashid, M.; Javed, A.; Zafar, E.; Alotaibi, S.S.; Zia, M.Y.I., "Performance Analysis of Deep-Neural-Network-Based Automatic Diagnosis of Diabetic Retinopathy," *Sensors 2022*, *22*, *205*, no. https://doi.org/10.3390/s22010205.