SciEn
Journal of Engineering Advancements Vol. 02(04) 2021, pp 221-227 https://doi.org/10.38032/jea.2021.02.008

Predicting Retinal Diseases using Efficient Image Processing and Convolutional Neural Network (CNN)

*Asif Mohammad, Mahruf Zaman Utso, Shifat Bin Habib, Amit Kumar Das**

Department of Computer Science and Engineering, East West University, Dhaka, Bangladesh

Received: October 20, 2021, Revised: December 21, 2021, Accepted: December 22, 2021, Available Online: December 27, 2021

ABSTRACT

Neural networks in image processing are becoming a more crucial and integral part of machine learning as computational technology and hardware systems are advanced. Deep learning is also getting attention from the medical sector as it is a prominent process for classifying diseases. There is a lot of research to predict retinal diseases using deep learning algorithms like Convolutional Neural Network (CNN). Still, there are not many researches for predicting diseases like CNV which stands for choroidal neovascularization, DME, which stands for Diabetic Macular Edema; and DRUSEN. In our research paper, the CNN (Convolutional Neural Networks) algorithm labeled the dataset of OCT retinal images into four types: CNV, DME, DRUSEN, and Natural Retina. We have also done several preprocessing on the images before passing these to the neural network. We have implemented different models for our algorithm where individual models have different hidden layers. At the end of our following research, we have found that our algorithm CNN generates 93% accuracy.

Keywords: Retinal Disease, Deep Learning, Image Processing, Neural Network, Convolutional Neural Network.

1 Introduction

Drum Scanner is the first scanner which is developed for use with a computer [1]. Since then the technology has advanced day by day, and lots of technology for scanning and loading pictures on a computer are available. With the availability of these technologies, researchers started to build and develop systems to analyze these images. The advancement of the image processing system is still going on in the present time, and it progressed from a ruled-formed method to a machine learning procedure. Even now, Machine learning methods take part in a prominent role [2]. Experts mostly write the features in hand used in machine learning algorithms, which is one of the significant drawbacks of machine learning approaches. For image processing, the algorithm needs to be created, which will be able to extract features and complete calculations. This is where a deep learning method is applied in image processing. For the availability of vast amounts of imagery data, ANN and CNN deep learning algorithms play a prominent role [3]-[6].

Because of advanced technology, medical researchers can take more precise images of x-ray and inner organs than before. That is why vast amounts of image data are generated in x-ray and other image reports. Deep learning techniques are critical for dealing with such massive amounts of data. Deep learning algorithms are used in numerous branches of medical study that are related to retinal sickness prognosis [7], Cancer prognosis [8], abdominal and musculoskeletal prognosis [9].

The deep learning technique is a machine learning approach in which various neural networks are implied for prognosis and categorization. Deep learning is used over massive imagery datasets for prediction and classification. Critical neural networks used in large imagery datasets are the ANN, CNN, RNN, and LSTM [10]-[12]. Some basic concepts of neural networks will be talked about below. Neurons are considered the modeling chunks of a neural network that looks like organic neurons in the interior of our brain. There are three distinct layers (input layer, hidden layer, and output layer). Input layer's each neuron extracts a sole attribute from the dataset and gives it to the hidden layer. Hidden layer's every neuron is attached to a former layer and preceding layer along with weights. When the hidden layer neuron gets the former layer's signal, each neuron is multiplied by the correlated weights. Then the multiplications of each neuron are added and then given to the activation function to find if the hidden layer neuron will roll the signal to the next layer or not. The architecture of neural networks is shown in Fig. 1.

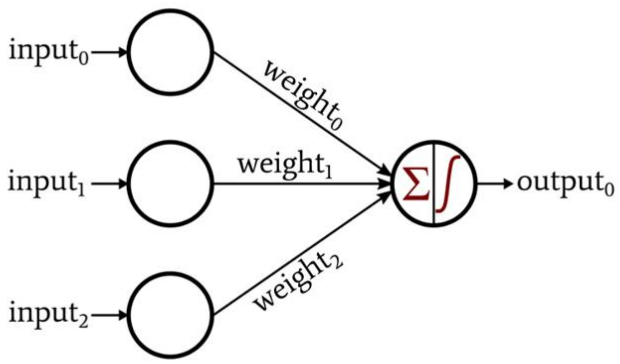

Fig. 1 The simple architecture of neural networks [13].

The weights of the neurons are assigned randomly at the beginning. Then during the training of the datasets, the value of the weight gets updated. In this way, neural networks learn to differentiate one object from another. The number of hidden layers used in neural networks plays a vital role in classification and regression. Various hidden layers are used in a model, and the optimal result is selected. The backpropagation technique is popular in neural networks for supervised learning, making deep learning more popular nowadays. This technique helps a machine learn distinct features from the datasets without the intervention of humans.

*Corresponding Author Email Address: akdas@ewubd.edu

Retinal disease is one of the common diseases in the present time. With the advancement of medical technology and computational science, many learning techniques are being invented for predicting and classifying disease accurately. As a substantial medical image database is available, deep learning techniques are becoming more suitable for classification and prediction [14]. Among deep learning approaches, CNN was used for our research paper to process the retinal images and categorize those different images into different disease classes.

Our research paper aims to develop and implement a deep learning model called CNN (Convolutional Neural Networks) to predict and label retinal illness by perceiving retinal pictures with higher reliability.

In medical research, retinal disease is one of the crucial sectors. The medical hardware is advancing day by day. With its advancement, a massive amount of imagery medical datasets are available in which doctors can take more explicit retinal images and other organ images. Deep learning technology is becoming popular for classification and prediction for the enormous medical imagery dataset. There are many pieces of research in which deep learning techniques were introduced to predict and classify retinal diseases. More and more research is also developing in which deep learning approaches are used to improve prediction and classification accuracy.

2 Literature Review

Several research papers include image datasets and deep learning algorithm techniques. In one research paper [15], the author examined RNFL (Retinal Nerve Fiber Layer) width and VF (Visual Field) and fetched some candidate attributes for the glaucoma prediction model. After that, the paper's author developed synthesized features and selected the most pleasing attributes for categorization (diagnosis) by implying feature evaluation. Then, the paper implemented machine learning approaches that are C5.0, Random Forest, SVM, and KNN. The dataset includes 100 cases of data for testing and 399 cases of data for training. Being a small dataset causes drawbacks as deep learning techniques need a vast dataset to predict precision.

The research paper [16] implied CNN deep learning approach to perceive Glaucomatous Optic Neuropathy by observing color fundus pictures. The size of the dataset of that particular paper is 48,000 images. The paper's author labeled the data with the help of experts and then applied CNN deep learning to categorize the pictures. This paper was one of the inspirational papers for our research as we processed a much larger dataset and used convolutional neural networks (CNN) after processing.

CNN is applied to perceive diabetic retinopathy by observing fundus images of the retina in another research paper [17]. The dataset size is 127125 images of the retina, which 54 licensed ophthalmologists grade. Nevertheless, they focused on only one sickness and used the fundus picture dataset, unlike our research's OCT image datasets.

Multiple classifications of retinal diseases are discussed in another note-worthy paper [18]. These diseases include AMRD, diabetic eye diseases, etc. To classify images into different image category the author of the paper used deep CNN and SVM classifiers. In the end, the author discussed the difficulties of the classification for the likelihood of the disease.

OCT images were used to categorize pictures into a distinct class of diseases in Ref. [19]. Here CNN is also implied, and the outcome is compared with the human ophthalmology experts categorizing these sicknesses. In another study [20], a deep learning technique was used to predict Age-related macular degeneration (AMD). The dataset size for this paper color fundus pictures of 120,656 pictures in which 13 categories were represented for prediction. The research paper's authors have tried various combinations of convolutional neural networks among different deep learning algorithms. Nonetheless, images are classified into only one sickness, and fundus pictures were used for this research's dataset.

A convolutional neural network (CNN) was used in another research paper [21] to detect eye glaucoma eye disease on retinal fundus imaging. The dataset size of that paper was 1200 retinal images. In this research paper, an unsupervised convolutional neural network (CNN) was used to draw out the features from raw images. Then the author of the research paper applied the DBN technique to the extracted attributes by CNN to detect the optimal finest feature for the implementation in this research. And lastly, the softmax linear classifier was used to differentiate between two classes, glaucoma and not glaucoma. Like the previous paper, fundus images were used as datasets, and the images were classified into only one disease.

Deep Learning was also used by the researchers [22] to assess cardiovascular risk factors from retinal fundus photographs. The research paper's authors have trained 284,335 patients on a dataset and validated their findings into two separate datasets. The size of the one separate dataset contains the data of 12,026 patients, and another separate dataset contains the data of 999 patients. Besides their excellent results, we think it would be better to use a larger dataset for more accurate validation findings. In a review paper [23] researchers discussed different deep learning approaches that can cause prognosis diabetic retinopathy in a person's retina. Other authors' papers discuss how deep learning algorithms are used to generate better prediction values. This paper is not that type of research paper where the authors launch a new model and attempt to attest their claim, but it can be helpful for further deep learning algorithm research. In Ref. [24] the authors applied deep learning approaches to predict diabetic retinopathy in the retina. The dataset for this research is collected from 1612 diabetic patients, which contains 1796 retinal fundus pictures. Nevertheless, we think that dataset size is small-scaled as deep learning algorithms need a larger dataset for more accurate results.

In another paper [25], deep learning was used on OCT images for Macular fluid's fully automated method for detecting and quantifying. The author's method based on a deep learning algorithm automatically detects IRC (Intraretinal cystoid) fluid and SRF (Subretinal) fluid. The dataset size for this research paper is 1200 volumes of OCT images.

In Ref. [26] we can see the discussion about the detection of diabetic retinopathy of different ethnicities of diabetic patients. The author used various deep learning algorithms for this detection and used a vast dataset of 494661 retinal images. They classified the image data into different ethnicities as people from different corners of the world have different food habits, and food habit is the primary concern on maintaining diabetes. This paper is different from other papers because it focuses on different ethnicities, which draws a different aspect.

In Ref. [27] the researchers applied CNN and ANN in 84,494 image datasets to predict retinal diseases and compared each algorithm predicting accuracy. This paper is such an inspiration to us. However, we applied only convolutional neural networks (CNN) to the same dataset. Still, we have better-predicting accuracy for different image processing approaches and other convolutional neural networks (CNN) algorithm implementation systems.

3 Methodology

To classify the diseases, we have used a Convolutional Neural Network (CNN), an artificial neural network that is very popular for organizing dataset images [28]-[29]. Our dataset contains a total of 84,484 images. These images are in Optical Coherence Tomography (OCT) form. We have divided our dataset into three categories: 80% for training, 15% for validation, and 5% for test. In the following steps, we have explained our research procedure in detail. Then we have also explained in a flowchart.

3.1 Input Data

First, we have imported our dataset into the model. In our dataset, images are organized into four different categories. Three represent a particular disease, and the remaining one category represents normal no-disease.

3.2 Preprocessing

3.2.1 Removing Duplicate Images

Our dataset had a total of 7676 identical images. We have removed those images from the dataset to make our prediction and algorithm learning unbiased. Repeating the same image may affect the learning of our algorithm.

3.2.2 Filling Up Blank Spaces

Some images had empty spaces by the border areas. We have filled up those empty spaces with the same background color, which happens to be black in our images. Filling up blank spaces of the images helps to make the images of our dataset consistent.

3.2.3 Image Resizing

Image resizing is an essential process in deep learning models. Models train faster if they are fed smaller images. Smaller images have more computational advantages compared to larger images. Also, many deep learning models require the image to be the same size. In our case, we have resized the images into 200x200 sizes. Resizing them any smaller can lead us to information loss. On the other hand, larger images might also negatively affect our model regarding power drain and production time.

3.2.4 Image Blurring

Image blurring is often used in image classifications before inserting the image model to reduce unnecessary noises in the data. When we work with image datasets, we see pictures with various attributes. Some images will have too much noise. Image blurring is applied to collect data from these noisy images. Blurring will help to remove noises from those images. We have used total variation filtering, a noise removal process, to denoise the dataset. But we have to maintain it carefully because if we blur the image too much, we will lose necessary information from the images. Here in Fig. 2, the demonstration of the Image Blurring process is shown.

3.2.5 Image Standardization

Standardization is an important technique used as a preprocessing step. When it comes to pictures, the input data set features significant differences between their ranges. These differences in the ranges of elements can cause trouble for many machine learning models. We have used standardization techniques to scale the pixel values of the images.

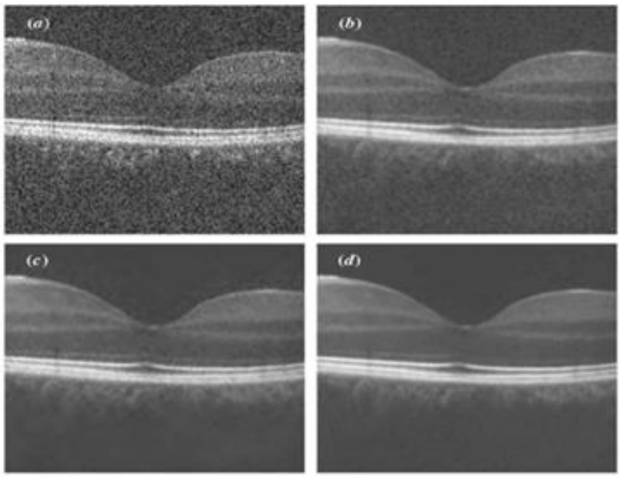

Fig. 2 Image Blurring process [30].

3.3 Image Recognition

3.3.1 Architecture of the Proposed Model

Deep Learning is becoming the primary tool for problems that try to understand images, human voice, and robots. With our dataset, our main target is the implementation of CNN for recognizing images.

The primary purpose of our proposed model is to have a proper grasp of CNN and customize the algorithm for recognizing images for the dataset.

CNN uses filters to bring out the feature maps from 2D pictures. It considers mapping image pixels with the neighborhood space instead of fully connected neuron layers. CNN has become an innovative and vastly acclaimed algorithm for processing images. It is also gaining attention in recognizing handwriting, object classifications, and computer vision. It is becoming a better option than others.

When someone begins to gather ideas about deep learning and neural networks, the Convolutional Neural Network (CNN) is one of the most used deep learning techniques.

The primary purpose of designing CNN is to find visual patterns straight from pictures with as low preprocessing as possible. Most CNNs try to apply convolutional layers to the input. By raising the feature map's quantity, CNN also down-samples the spatial dimensions called max pooling.

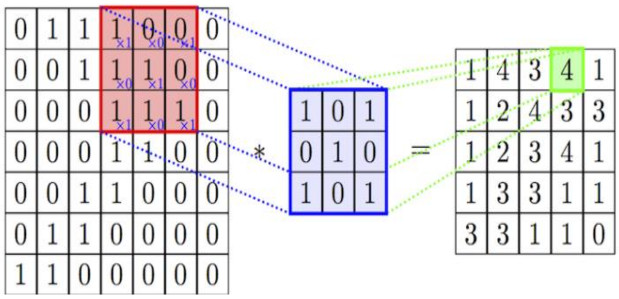

Fig. 3 Convolution Operation [31].

However, convolutional, pooling, and fully connected layers are the most significant among all the operations of CNN. Therefore, we would like to present these layers before introducing our proposed model.

The first layer extracts features from the images, the Convolutional layer. The convolution preserves the connection among different parts of a picture. It happens because one single pixel is only connected to the adjacent and closest pixel. Also, convolution filters the picture with a smaller pixel filter to bring down the picture size so that it does not lose the relationship between pixels. For example, if convolution is applied to a 7x7 image and if we use a filter of size 3x3, which has a 1x1 stride, it will be a 5x5 output. Convolution Operation Demonstrated in Fig. 3.

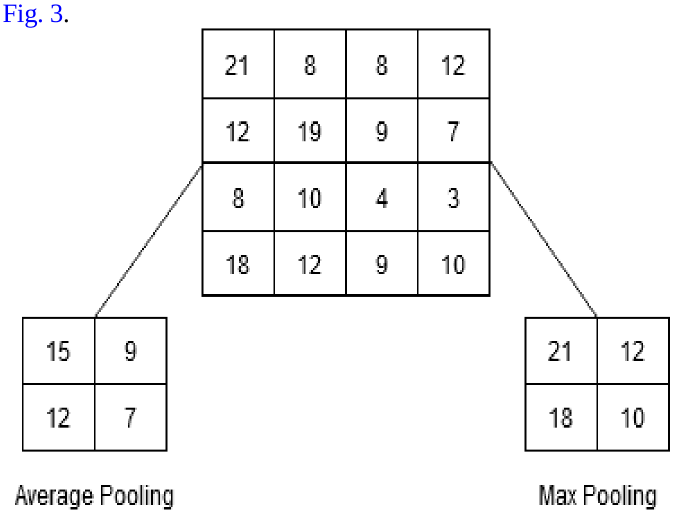

Fig. 4 Max pooling and Average pooling operation.

Inserting pooling layers after every convolution layer is a common practice. We do this while constructing CNN to decrease the size of the actual representation. This layer reduces the counts of the parameter. By doing that, also helps to reduce the computational complexity. Moreover, when it comes to overfitting problems, pooling layers try to solve them. We try to find the maximum, average, or sum values inside the pixels. To reduce the parameters count. We also select a pooling size. Max pooling and Average pooling operation Demonstration shown in Fig. 4.

If every neuron in one layer connects to every neuron in the next layer in an artificial neural network, it can be identified as a fully connected neural network.

We can decrease time-space complexity by a significant margin if we use pooling and convolutional layers. After doing all this, a fully connected network can be built to classify the images.

3.3.2 Explanation of the models

Fig. 5 shows the structures of our proposed CNN models. The first layer of each model gets the preprocessed image as the input of size 200*200. Each conv2D layer has filter size 3*3 with stride 1, padding='same', and activation function 'ReLU' (Rectified Linear Unit). The number of filters is mentioned in Fig. 5.

We have used (2*2) max-pooling layers with a string of 2. The dropout rate is set to 0.2.

Because our dataset is unbalanced, we have utilized class weight. This dictionary maps class indices to a weight value that may be used to urge the model to "pay more attention" to samples from an under-represented class. Equation (1) shows the used formula to determine the weights of the corresponding classes.

$$Weight\ of\ a\ class = \frac{number\ of\ samples}{num\ of\ unique\ class * number\ of\ samples\ in\ corresponding\ class} \quad (1)$$

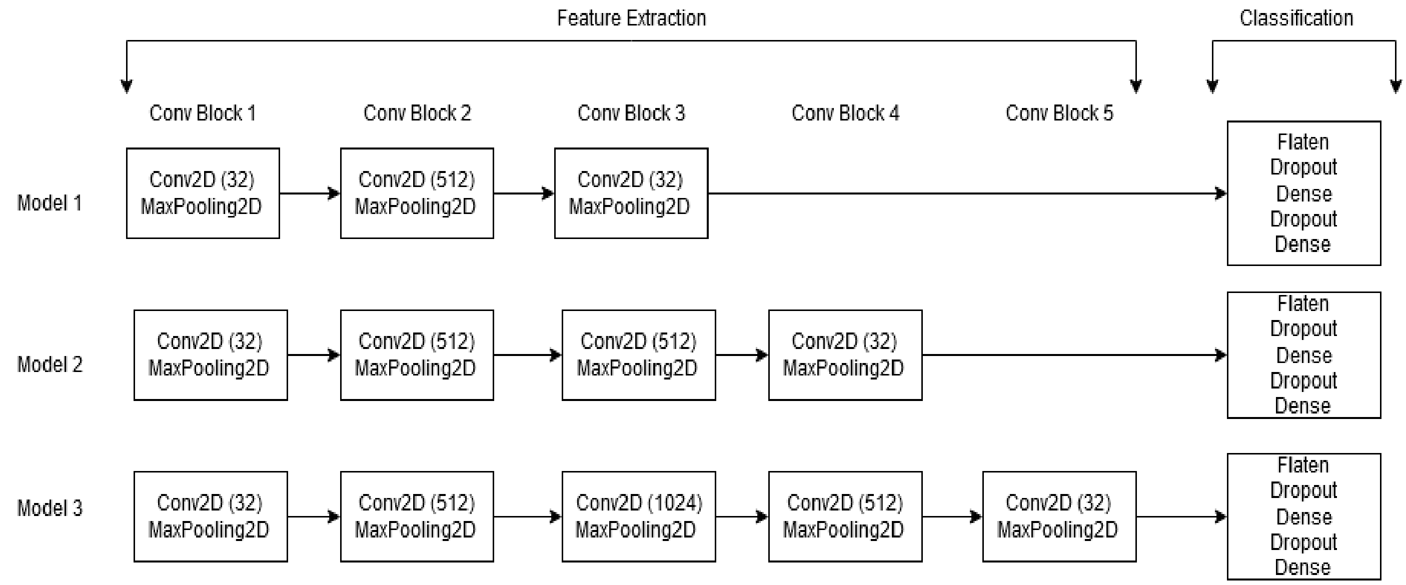

Fig. 5 CNN Model Structures.

4 Results and Discussion

4.1 Dataset Description

The dataset of our research paper [32] consisted of 84,495 numbers of OCT (Optical Coherence Tomography) pictures of the retina. Four categories separate these pictures. They are CNV, DME, DRUSEN, and normal retinal pictures.

The images of this dataset were taken from five institutes. The institutes are

1. Beijing Tongren Eye Center, Beijing.
2. The Shanghai First People's Hospital, Shanghai
3. MCOA,
4. CRRF, California, USA
5. Shiley Eye Institute, San Diego, USA

There are three disease categories and one normal category in five categories in the dataset. The disease categories are shortly discussed below:

CNV: CNV stands for choroidal neovascularization disease, which arises on the retina. This disease causes the massive growth of new vessels which carry blood in the choroid, a layer under the retina. Unlike normal vessels and occasionally red blood cells, new vessels let fluids from the blood.

DME: DME stands for Diabetic Macular Edema retinal disease, which transpires due to fluid leaking in the Macular's retina part. This disease generally arises in diabetic patients. It can damage blood vessels in the retina. This disease has to be treated within a certain time; otherwise, the eye can be damaged.

DRUSEN: the white or yellow-colored spots that transpire in the Bruch's membrane named retinal layer can be identified as DRUSEN. There can be several causes of this disease, and one of the common causes is gathering waste products from rods and cones. If this disease is not treated within a particular time, it can cause permanent blindness.

Our research studied different layers to discover the optimal CNN algorithm model. Here, features of this particular algorithm were selected by the algorithm's built-in nature.

The prediction quality was measured into four rates: accuracy, sensitivity, specificity, and precision by using 3, 4, 5, vgg16, and vgg19 layer models. Here Eqs. (2) - (5) are used to calculate accuracy, precision, sensitivity and specificity [33]-[37].

$$Accuracy = \frac{Predicted\ correctly}{Number\ of\ total\ images} \tag{2}$$

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Negative} \tag{4}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{5}$$

In Table 1, we can see that all 3, 4, 5, vgg16, and vgg19 layers are almost close in forms of accuracy, sensitivity, specificity, and precision in percentage. When we observe precisely, we can see that the five hidden layer model gives the highest accuracy (93.26%), sensitivity (93%), specificity (97%), and precision (93%), and the vgg16 model provides the lowest accuracy (90.02%) and sensitivity (90%), specificity (94%). The hidden layer models 3, 4, vgg16, and vgg19 have the same precision (92%).

Table 1 Different Hidden Layer models of Convolutional Neural Network (CNN) comparison.

Hidden Layer	Accuracy	Sensitivity	Specificity	Precision
3	91.52	92	96	92
4	91.57	92	96	92
5	93.26	93	97	93
Vgg16	90.02	90	94	92
Vgg19	91.91	92	96	92

Table 2 Comparison of Different Hidden Layer model of Convolutional Neural Network (CNN) to accurately predict disease.

Hidden Layer	CNV	DME	DRUSEN	Normal
3	90.98	87.23	82.98	96.47
4	93.35	86.68	82.2	94.25
5	92.07	92.15	85.34	97.47
Vgg16	89.51	93.07	85.86	90.57
Vgg19	95.33	89.42	70.42	95.17

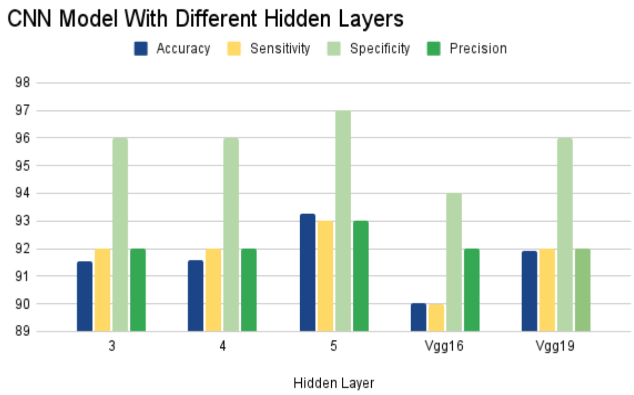

Fig. 6 Comparison of Different Hidden Layer model of Convolutional Neural Network (CNN) in terms of accuracy, sensitivity, specificity, and precision.

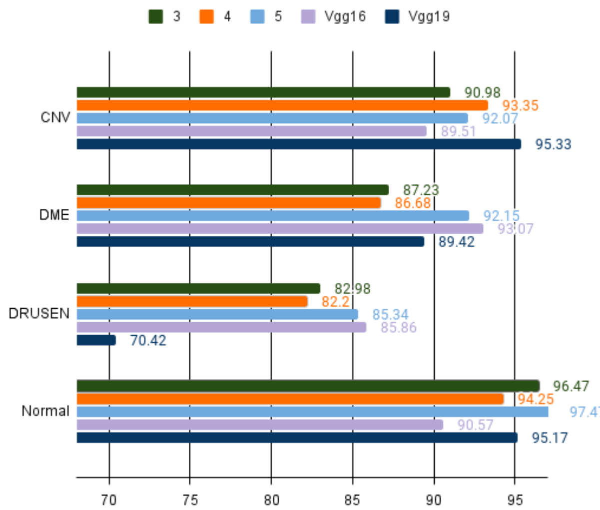

Fig. 7 Comparison of Different Hidden Layer model of Convolutional Neural Network (CNN) to accurately predict disease.

Also, if we carefully compare all the hidden layers, we will see a pattern of increment in accuracy, sensitivity, specificity, and precision among hidden layers 3, 4, and 5. It indicates that five hidden layers were more effective than 3 and 4 layers. Even between Vgg16 and Vgg19, Vgg19 showed better results than vgg16. We also measured the prediction accuracy in CNV, DME, DRUSEN disease, and regular eye prediction for 3, 4, 5, vgg16, and vgg19 layer models.

In Table 2, we can observe that the vgg19 layer model gives the highest accuracy for CNV disease prediction (95.33%). The vgg16 layer model offers the best accuracy (93.07%). In the case of DRUSEN disease prediction, the vgg16 layer model provides the best accuracy (85.86%). The 5 layer model gives the best accuracy (97.47%). Here Fig. 6 and Fig. 7 are the graphical representation of what is shown in Table 1 and Table 2.

In [27], research on the same dataset was conducted. They also used convolutional neural networks. In their paper, a model with four hidden layers produces the best result among all. Their four hidden layer model shows an accuracy score of 86.71. In contrast, our created five hidden layer model shows an accuracy score of 93.26. Their sensitivity, specificity, and precision scores are 85.04, 86.08, and 85.41, respectively, with four hidden layers. Our model's sensitivity, specificity, and precision scores are 93, 97, and 93, with five hidden layers.

5 Conclusion

In the forms of data analysis and data prediction, machine learning algorithms have surpassed all statistical models in the present time. But with the increasing amount of data, the limitations of the machine learning algorithms became clearer. That is the time the deep learning algorithm stepped up. Deep learning algorithms can select features independently and perform complex non-linear equations even though these algorithms are machine learning algorithms. For that reason, deep learning algorithms have taken up machine learning algorithms in various fields. Convolutional Neural Networks (CNN) dominate in the image processing sector.

The medical sector generates a massive quantity of image data, like ophthalmology. With this vast amount of imagery data, researchers used deep learning algorithms to predict diseases that might happen in our eyes. We inspired those research papers and applied Convolutional Neural Network (CNN) to separate three retinal diseases from normal vision.

Nevertheless, in the future, we would like to develop the algorithm to get more accuracy and also would like to apply other deep learning algorithms to compare and observe whether it performs better than Convolutional Neural Network (CNN) or not. Moreover, we can think of learning techniques that may be unsupervised in the future to see whether it surpasses convolution neural deep learning algorithms or not. Lastly, we would like to apply the same approach to other imagery datasets available for medical sectors and in other sectors where massive image datasets are used to classify and predict.

References

[1] Kantengwa, S., 2020. *Origin of ordinary things: Scanner*. The New Times, accessed 12 October 2021, Website: https://www.newtimes.co.rw/lifestyle/origin-ordinary-things-scanner

[2] Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M., Van Der Laak, J.A., Van Ginneken, B. and Sánchez, C.I., 2017. A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, pp.60-88.

[3] Islam, J., Mubassira, M., Islam, M.R. and Das, A.K., 2019, February. A speech recognition system for Bengali language using recurrent neural network. In *2019 IEEE 4th international conference on computer and communication systems (ICCCS)* (pp. 73-76). IEEE.

[4] Mumu, T.F., Munni, I.J. and Das, A.K., 2021. Depressed people detection from bangla social media status using lstm and cnn approach. *Journal of Engineering Advancements*, *2*(01), pp.41-47.

[5] Hossain, M.T., Hasan, M.W. and Das, A.K., 2021, January. Bangla Handwritten Word Recognition System Using Convolutional Neural Network. In *2021 15th International Conference on Ubiquitous Information Management and Communication (IMCOM)* (pp. 1-8). IEEE.

[6] Das, A.K., Ashrafi, A. and Ahmmad, M., 2019, February. Joint cognition of both human and machine for predicting criminal punishment in judicial system. In *2019 IEEE 4th International Conference on Computer and Communication Systems (ICCCS)* (pp. 36-40). IEEE.

[7] De Fauw, J., Ledsam, J.R., Romera-Paredes, B., Nikolov, S., Tomasev, N., Blackwell, S., Askham, H., Glorot, X., O'Donoghue, B., Visentin, D. and van den Driessche, G., 2018. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature Medicine*, *24*(9), pp.1342-1350.

[8] Xiao, Y., Wu, J., Lin, Z. and Zhao, X., 2018. A deep learning-based multi-model ensemble method for cancer prediction. *Computer Methods and Programs in Biomedicine*, *153*, pp.1-9.

[9] Weston, A.D., Korfiatis, P., Kline, T.L., Philbrick, K.A., Kostandy, P., Sakinis, T., Sugimoto, M., Takahashi, N. and Erickson, B.J., 2019. Automated abdominal segmentation of CT scans for body composition analysis using deep learning. *Radiology*, *290*(3), pp.669-679.

[10] Rakib, O.F., Akter, S., Khan, M.A., Das, A.K. and Habibullah, K.M., 2019, December. Bangla word prediction and sentence completion using GRU: an extended version of RNN on N-gram language model. In *2019 International Conference on Sustainable Technologies for Industry 4.0 (STI)* (pp. 1-6). IEEE.

[11] Das, A.K., Al Asif, A., Paul, A. and Hossain, M.N., 2021. Bangla hate speech detection on social media using attention-based recurrent neural network. *Journal of Intelligent Systems*, *30*(1), pp.578-591.

[12] Hossain, M.M., Labib, M.F., Rifat, A.S., Das, A.K. and Mukta, M., 2019, June. Auto-correction of english to bengali transliteration system using levenshtein distance. In *2019 7th International Conference on Smart Computing & Communications (ICSCC)* (pp. 1-5). IEEE.

[13] Bombini, A., 2019. *Using CNN to classify images w/PyTorch*, *Kaggle*. accessed 12 October 2021, Website: https://www.kaggle.com/androbomb/using-cnn-to-classify-images-w-pytorch

[14] Ker, J., Wang, L., Rao, J. and Lim, T., 2017. Deep learning applications in medical image analysis. *Ieee Access*, *6*, pp.9375-9389.

[15] Kim, S.J., Cho, K.J. and Oh, S., 2017. Development of machine learning models for diagnosis of glaucoma. *PloS one*, *12*(5), p.e0177726.

[16] Lee, C.S., Baughman, D.M. and Lee, A.Y., 2017. Deep learning is effective for classifying normal versus age-related macular degeneration OCT images. *Ophthalmology Retina*, *1*(4), pp.322-327.

[17] Gulshan, V., Peng, L., Coram, M., Stumpe, M.C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J. and Kim, R., 2016. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *Jama*, *316*(22), pp.2402-2410.

[18] Arunkumar, R. and Karthigaikumar, P., 2017. Multi-retinal disease classification by reduced deep learning features. *Neural Computing and Applications*, *28*(2), pp.329-334.

[19] Kermany, D.S., Goldbaum, M., Cai, W., Valentim, C.C., Liang, H., Baxter, S.L., McKeown, A., Yang, G., Wu, X., Yan, F. and Dong, J., 2018. Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*, *172*(5), pp.1122-1131.

[20] Grassmann, F., Mengelkamp, J., Brandl, C., Harsch, S., Zimmermann, M.E., Linkohr, B., Peters, A., Heid, I.M., Palm, C. and Weber, B.H., 2018. A deep learning algorithm for prediction of age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. *Ophthalmology*, *125*(9), pp.1410-1420.

[21] Abbas, Q., 2017. Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning. *Int J Adv Comput Sci Appl*, *8*(6), pp.41-5.

[22] Poplin, R., Varadarajan, A.V., Blumer, K., Liu, Y., McConnell, M.V., Corrado, G.S., Peng, L. and Webster, D.R., 2018. Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning. *Nature Biomedical Engineering*, *2*(3), pp.158-164.

[23] Raman, R., Srinivasan, S., Virmani, S., Sivaprasad, S., Rao, C. and Rajalakshmi, R., 2019. Fundus photograph-based deep learning algorithms in detecting diabetic retinopathy. *Eye*, *33*(1), pp.97-109.

[24] Sayres, R., Taly, A., Rahimy, E., Blumer, K., Coz, D., Hammel, N., Krause, J., Narayanaswamy, A., Rastegar, Z., Wu, D. and Xu, S., 2019. Using a deep learning algorithm and integrated gradients explanation to assist grading for diabetic retinopathy. *Ophthalmology*, *126*(4), pp.552-564.

[25] Schlegl, T., Waldstein, S.M., Bogunovic, H., Endstraßer, F., Sadeghipour, A., Philip, A.M., Podkowinski, D., Gerendas, B.S., Langs, G. and Schmidt-Erfurth, U., 2018. Fully automated detection and quantification of macular fluid in OCT using deep learning. *Ophthalmology*, *125*(4), pp.549-558.

[26] Ting, D.S.W., Cheung, C.Y.L., Lim, G., Tan, G.S.W., Quang, N.D., Gan, A., Hamzah, H., Garcia-Franco, R., San Yeo, I.Y., Lee, S.Y. and Wong, E.Y.M., 2017. Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes. *Jama*, *318*(22), pp.2211-2223.

[27] Hasib, M.H., Sultana, T. and Chowdhury, C., 2020. *Efficient image processing and machine learning approach for predicting retinal diseases* (Doctoral dissertation, Brac University).

[28] Bhuiyan, M., Rahman, A., Ullah, M. and Das, A.K., 2019. iHealthcare: Predictive model analysis concerning big data applications for interactive healthcare systems. *Applied Sciences*, *9*(16), p.3365.

[29] Labib, M.F., Rifat, A.S., Hossain, M.M., Das, A.K. and Nawrine, F., 2019, June. Road accident analysis and prediction of accident severity by using machine learning in Bangladesh. In *2019 7th International Conference on Smart Computing & Communications (ICSCC)* (pp. 1-5). IEEE.

[30] Thapa, D., Raahemifar, K. and Lakshminarayanan, V., 2015. Reduction of speckle noise from optical coherence tomography images using multi-frame weighted nuclear norm minimization method. *Journal of Modern Optics*, *62*(21), pp.1856-1864.

[31] Pamar, R., 2018. *Demystifying Convolutional Neural Networks, towards data science*, accessed 12 October 2021, Website: https://towardsdatascience.com/demystifying-convolutional-neural-networks-384785791596.

[32] Mooney, Paul.(2017, October). *Retinal OCT Images (Optical Coherence Tomography)*, Version 2. accessed july 20,2021 , Website: www.kaggle.com/paultimothymooney/kermany2018.

[33] Ullah, M.R., Bhuiyan, M.A.R. and Das, A.K., 2017, September. IHEMHA: Interactive healthcare system design with emotion computing and medical history analysis. In *2017 6th International Conference on Informatics, Electronics and Vision & 2017 7th International Symposium in Computational Medical and Health Technology (ICIEV-ISCMHT)* (pp. 1-8). IEEE.

[34] Emon, E.A., Rahman, S., Banarjee, J., Das, A.K. and Mittra, T., 2019, June. A deep learning approach to detect abusive bengali text. In *2019 7th International Conference on Smart Computing & Communications (ICSCC)* (pp. 1-5). IEEE.

[35] Drovo, M.D., Chowdhury, M., Uday, S.I. and Das, A.K., 2019, June. Named entity recognition in bengali text using merged hidden markov model and rule base approach. In *2019 7th International Conference on Smart Computing & Communications (ICSCC)* (pp. 1-5). IEEE.

[36] Khan, M.S.S., Rafa, S.R. and Das, A.K., 2021. Sentiment Analysis on Bengali Facebook Comments To Predict Fan's Emotions Towards a Celebrity. *Journal of Engineering Advancements*, *2*(03), pp.118-124.

[37] Islam, S., Khan, S.I.A., Abedin, M.M., Habibullah, K.M. and Das, A.K., 2019, July. Bird species classification from an image using VGG-16 network. In *Proceedings of the 2019 7th international conference on computer and communications management* (pp. 38-42).