Binary Classification of Hypertensive Retinopathy Using Deep Dense CNN Learning

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Summary
A condition of the retina known as hypertensive retinopathy (HR) is connected to high blood pressure. The severity and persistence of hypertension are directly correlated with the incidence of HR. To avoid blindness, it is essential to recognize and assess HR as soon as possible. Few computer-aided systems are currently available that can diagnose HR issues. On the other hand, those systems focused on gathering characteristics from a variety of retinopathy-related HR lesions and categorizing them using conventional machine-learning algorithms. Consequently, for limited applications, significant and complicated image processing methods are necessary. As seen in recent similar systems, the preciseness of classification is likewise lacking. To address these issues, a new CAD HR-diagnosis system employing the advanced Deep Dense CNN Learning (DD-CNN) technology is being developed to early identify HR. The HR-diagnosis system utilized a convolutional neural network that was previously trained as a feature extractor. The statistical investigation of more than 1400 retinography images is undertaken to assess the accuracy of the implemented system using several performance metrics such as specificity (SP), sensitivity (SE), area under the receiver operating curve (AUC), and accuracy (ACC). On average, we achieved a SE of 97%, ACC of 98%, SP of 99%, and AUC of 0.98. These results indicate that the proposed DD-CNN classifier is used to diagnose hypertensive retinopathy.

Keywords:
Retinography images, Hypertensive-retinopathy, deep-neural network, Transfer learning, convolutional neural network.

1. Introduction

Hypertension is a public, universal illness that affects approximately 9.5 million people in the United States [1], and the figure is expected to rise. Because of the increase in blood pressure, HR causes many changes in the retina as well as the vessels in the retina. Indeed, early detection of HR is critical since it can lead to cardiovascular risk and microcirculation in the retina. Many hypertensive individuals have been diagnosed with these two disorders caused by HR. Many people lose their vision when HR symptoms [2] occur. Many studies have recently demonstrated that using a fundus digital camera, retinal microvascular alterations can be observed. Because it is inexpensive [3,] simple to use, and most anatomical features of lesions are visible in this type of imaging, this fundus camera is used to screen many HR patients non-invasively.

Hypertension is caused by an increase in arterial pressure [4], and it is also the most common type of eye disease that has recently spread globally. Several humanoid organs, including the retina, heart, and kidneys, are damaged by hypertension [5]. Among all these consequences, HR [6] is the main cause of cardiovascular disease, which leads to death. Generally, HR is an abnormality that occurs in the retina and is triggered by an excessive rise in blood pressure level. The existence of signs such as hemorrhage (HE) spots in the retina, cotton wool patches, and micro-aneurysms is a strong sign of HR-related eye illness. Early detection and accurate treatment of HR-related eye illnesses [7] are critical for saving human lives.

An ophthalmologist, who is a medical professional, analyses microscopic images of the retina to assess the existence of HR illness in a cost-effective and non-invasive manner. The major goal of utilizing automated systems [8] is to decide the existence of HR while relieving ophthalmologists of the burden of vast image assessment early and quickly. Many research efforts have previously established procedures for retinal image analysis, including image enhancement, segmenting HR lesions as well as retinal vessels, extracting features, and lastly, supervised machine learning classifiers for HR illness [9].

A significant HR indication is the unusual wideness of the retinal veins, which reduces the A/V ratio (the mean artery to vein diameter). The detection of retinal vessels' diameter [10] and other features such as AVR are difficult tasks when using an image analysis system to diagnose HR-related eye disease. Furthermore, getting precise measurements of vascular diameters is quite difficult for ophthalmologists.

Ophthalmologists use automatic analysis of digital fundus images to identify HR by observing abnormalities in retinography photos. As previously stated, these

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abnormalities harm HR-related lesions as well as other key eye regions. If these alterations are not noticed early enough, they can progress to HR. It was found that HR-related eye disease can be reversed [11], whereas DR-related eye illness cannot be reversed. Ophthalmologists can use CAD systems to diagnose certain retinal diseases, such as HR-related eye illnesses. These technologies help academics and the health care industry by enabling self-diagnosis. Such systems are used by ophthalmologists to diagnose and treat eye-related diseases, particularly HR-related diseases. The authors provided a recent survey for automated HR identification techniques in the literature.

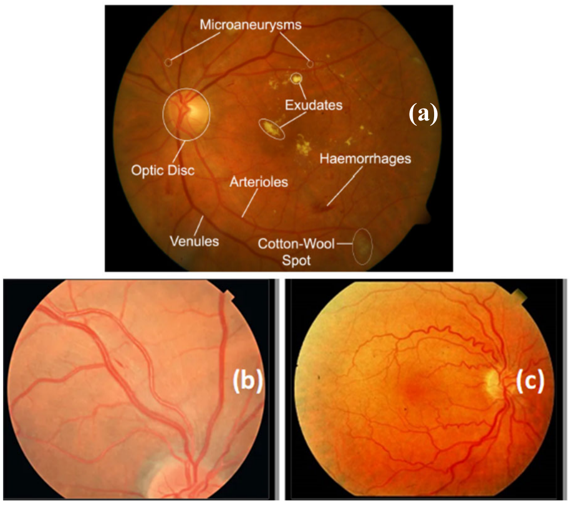

Figure 1. A visual example of hypertensive retinopathy (HR), where figure (a) shows the sample of different HR-related lesions, and figures (b, c) represents the HR images.

2. Background

Feature extraction and recognition tasks based on deep learning models (DLMs) have been widely used in previous systems to recognise objects. A novel active deep learning-based convolutional neural network (ADL-CNN) was implemented to overcome multilayered network architecture training challenges. In practice, the ADL-CNN architecture is simple to train. In addition, the CNN model has been applied in a great deal of research with the purpose of picture recognition on a broad scale. The ADL-CNN model surpasses other models in performance when compared to other models for use with minimal training datasets. In previous studies, the researchers reported that the CNN model automatically learned distinguishing features from the raw samples.

In the past, the most common methods for identifying HR-related lesions within retinal images were conventional image processing techniques as well as machine learning algorithms. However, those traditional arts are slow and difficult to apply in real-time environments. With the development of hierarchical deep learning methods, it is now possible to tackle all the previously described issues. There are a wide variety of deep learning approaches, including convolutional networks, deep belief networks (DBN), reinforcement learning machines (RBM), and deep reinforcement learning network (DRN) models.

The pre-training procedure is applied in a wide variety of computer vision applications to acquire characteristics for the purpose of resolving a variety of issues. The transfer learning technique is an example of the pre-train networks used in numerous computer vision systems. There are several pre-trained models that have been developed, including VGG, InceptionV3, and ResNet50. The ImageNet dataset was utilized in the performance evaluation process of these pre-trained networks. A substantial number of pre-trained models utilized in transfer learning are based on large CNNs. The high performance and easy training of CNN have raised the network's popularity level in recent years. A basic CNN model's architecture consists of two parts: a convolutional base composed of feature maps and pooling layers. Convolutional filters of various sizes were used to create the feature map layer. In addition, the SoftMax classifier, which recognizes classes, is a second component. It's common for the classification layer to be fully interconnected in practice. The features extracted during the first layer of CNN's deep learning architecture are more generic, whereas the features defined during the last layer are the most specialized. The process by which generic characteristics are transformed into more specific features is referred to as "feature transformation."

Although several machine learning (ML) techniques for classifying retinal fundus images into normal and HR have been implemented, there are still several substantial challenges with those ML methods. Using complicated pre- or post-image processing procedures, it is extremely hard to discover and determine relevant features for HR symptoms from retinography photos to describe HR qualities. The lack of datasets labelled "normal" and "high risk" by a skilled medical person makes training and evaluating the network difficult. As a result, automated systems have a bad habit of detecting illness.

The researchers used hand-crafted features for training their networks and compared the accuracy of their models with the literature. As a result, finding the top attributes dictates the use of an automated methodology rather than relying on hand-crafted features. Numerous distinct models are developed that undoubtedly acquire features using a deep-learning methodology; nonetheless, they all share identical weights at every layer. Then, it gets harder for layers to send weight parameters to the next stages of the network to make accurate decisions.

The main goal of this research is to implement a deep-learning model for completely automated retinography image processing, particularly for HR disease. In this effort, neither image processing nor traditional machine learning techniques, which both require domain-expert knowledge, are used to extract clinical information. Multilayer DD-CNN will be used to implement a CAD-HR diagnosis system. To accurately detect HR, the training process of the DD-CNN model employed several HR images that include anatomic components. To identify distinct abnormalities from fundus photos, a transfer-learning methodology is proposed in this study.

3. Related Work

According to the survey of the literature, detecting hypertensive retinopathy from fundus images should be done using a segmentation-based methodology [12]. The scientists employed a machine-learning classification technique to identify HR from retinography photos in their experiments after first detecting distinct HR-related characteristics. In [13–17], the artery to vein diameter ratio (A/VR), the optic disc (OD) location, the mean fractal dimension (mean-D), papilledema indicators, and the index of tortuosity are hand-crafted features that are used in automated approaches to figure out the irregularities in the retina, such as graded HR and vascular bifurcation. Aimed at subdivision and neat tasks, the Gabor 2D or Cake-Wavelet was utilized, together with the Canny edge detector. To evaluate the performance of such systems, the DRIVE, AVR-DB, IOSTAR, STARE, DR/HAGIS, INSPIR/AVR, and VICAVR datasets were employed.

The authors used a novel technique to detect HR-related eye illness in their paper [18]. Cotton wool spots (CWS) were discovered by the academics and are among the most significant medical indications for determining HR illness. Researchers enhanced candidate regions with the Gabor filter bank, then binaries the image with the adaptive threshold approach. To categorize the different retinal blood vessel types, [19] used a several-layered neural network that was supplied with invariant moment indicators in addition to Gabor and wavelet coefficients. They achieved much better segmentation results on the DRIVE dataset.

The authors in [20] describe a nine-step automated system for extracting the OD region, segmenting vessels, detecting color features, calculating the A/V ratio, differentiating between veins and arteries, calculating the AM/FM characteristics as well as the mean RED intensity, and finally classifying the images into HR or normal fundus photos. A 0.84 AUC was attained on a collection of 74 color fundus pictures, while 90% sensitivity and 67% specificity were achieved. Furthermore, in [21], an ICA (independent component analysis) was performed on a wavelet sub-band for identifying retinal alterations that appear in the retinography photos, including the optic disc, blood vessels, hemorrhages, macula, exudates, and drusen. This approach was put to the test on 50 photos, and the results were correct.

Whereas in [22], the authors described a method for detecting HR by figuring out characteristics from previously handled color retinography photos. Firstly, it used CLAHE to transform the retinography photos into green-channel images, resulting in a clearer view of the retinal vessels. Secondly, it used morphological closure to eliminate the optic disk. Subtraction was used to remove the backdrop. Then, utilizing zoning, characteristics were retrieved. Finally, as a classifier, a neural network with back propagation was utilized. It had a 95% accuracy rate. Moreover, in [23], the authors describe a method for segmenting retinal vessels from fundus pictures using the ELM classifier. A vector of 39 local, morphological, and other characteristics was fed into the classifier as input features. On the DRIVE dataset, this approach has a 96% accuracy, a 71.4% sensitivity, and a 98.6% specificity. By means of any of the learning-based methods, there is a distinct approach to classifying fundus images. Pre-processing of the fundus is minimized in these methods. Many image-processing tasks, such as segmentation and feature extraction, may be accomplished directly with deep-learning architectures.

In [7], an architecture for a deep learning model (DLM) for identifying HR was developed. They used 32x32-scaled consignments of grayscale-transformed retina images to train a CNN. The CNN produced either HR or regular output. The accurateness of the detection was 98.6%. In [24], they used an architecture that combined the random Boltzmann machine (RBM) and deep neural network (DNN) methods to measure the alteration of arterial blood vessels. They have distinct characteristics for the deep learning method using the AVR ratio and the OD region. In that study, they discovered a much higher accuracy. Furthermore, in [25], the authors described a CNN-based approach for extracting the OD, the retina's arteries, and the fovea centralis. There were seven layers in the CNN architecture. The fovea centralis, OD, the retina's arteries, and the background of the retina were represented by four nodes in the output of their CNN design. On the DRIVE dataset, a mean accuracy of classification of 92.6% was attained. CNN was used by several researchers to segment and categories the retinal vasculature into arteries and veins [26–28]. The accuracy of these approaches was high: 88.9% for a 100-photo poor-quality dataset and 93+% for the DRIVE data set. Finally, in [29], the authors described a CNN automated approach for detecting exudates in retinography photos. During CNN's training procedure, all the features were retrieved. CNN was fed odd-sized patches as input, with the processed pixel at the patch's center. Convolutional layers were employed to determine whether each separate pixel belongs to an exudate or not. Exudates do not appear in the OD region. Hence, it is excluded. Aside from the input and output layers, the CNN design has four convolutional and pooling layers. Using the DRiDB dataset, the approach was found to have identical performance measures for positive predictive value (PPV) and sensitivity, while having a 77% F-score.

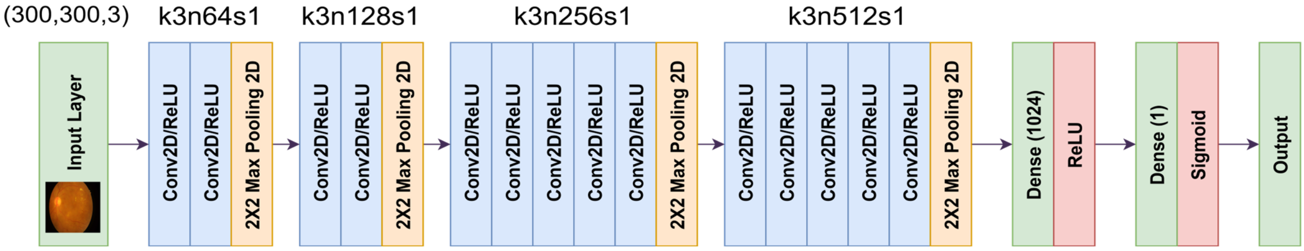

Figure 2. A systematic flow diagram of proposed deep-dense CNN model

4. Methodology

4.1 Data Acquisition

To advance the DD-CNN Diagnosis System, we need to create a dataset with a manageable number of retinography images. Thus, to evaluate and contrast the suggested DD-CNN diagnostic methods, we created 800 HR retinography photographs and 600 regular retinography photos. The creation of the training dataset needed a skilled ophthalmologist (to manually distinguish the HR and regular fundus photos from different datasets). To create a gold standard, the doctor examined all the HR-related traits in a collection of 1400 fundus photographs, as seen in figure 1. The generation of the training dataset includes a description of the three distinct datasets (used to create our training and testing fundus sets) with various lighting (manually distinguishing the HR and regular fundus photos from different datasets). To create a gold standard, the doctor examined all the HR-related traits in a collection of 1400 fundus photographs, as seen in figure 1. A description of the three distinct datasets used to create our training and test dataset collection. To conduct the research, all those photographs were downsized to (300 × 300) pixels. As part of a routine process for identifying people with hypertension, images were taken. The procedure of preparing HR and non-HR datasets for ground truth examination also involves a qualified ophthalmologist. An example of a fundus picture from the study's databases.

4.2 Proposed Methodology

A deep learning (DL) network design known as a convolutional neural network (CNN), sometimes referred to as ConvNet, does not require manual feature extraction because it learns directly from the input data. The CNNs are highly useful at identifying patterns in images, allowing them to discern between things like people, objects, and scenes. They may be adept at classifying non-image data, such as audio, time series, and signal data, and they are quite helpful. Because of the following three key benefits, the CNNs are increasingly being used for deep learning. For example, CNNs eliminate the need for manually extracting features because they learn the features directly. The outcomes of CNN recognition are remarkably precise. By retraining CNNs to do other types of recognition tasks, you may expand upon already-formed networks. Figure 2 depicts CNN's operational mechanism. With the help of our DD-CNN model, we were able to diagnose hypertensive retinopathy in binary form (HR). To create feature maps from input pictures and forecast the right labels for the diagnosis of HR, the proposed DD-CNN uses 14 convolutional layers.

To conduct DR diagnosis, the suggested DCNN architecture was modified from the VGG-16 design. It consists of four convolutional layer stages (Fig. 2), each separated by a (2×2) 2-D Max-Pooling layer that reduced the input image's resolution by two. Small 33-sized kernels were utilized in each convolutional layer, and the rectified linear unit (ReLU) was employed as the activation function. The (300×300) pixel scaled and colored originals are trained using an 8-batch size. A layer with 1024 neurons and the ReLU activation function receives the output of the final convolutional stage. The final layer consists of a single neuron with the Sigmoid activation function for binary classification provided by:

$$ReLU(x) = \max(0; x) \quad (1)$$

Adapted and modified from the VGG-16 [19] architecture to carry out DR diagnostics. It had four convolutional layer stages (Fig. 2), each separated by a 2x2 2D Max pooling layer that downscaled the input picture by two. Small (3X3) sized kernels were utilized in each convolutional layer, and the rectified linear unit (ReLU) was employed as the activation function.

The 300x300-pixel scaled, and colored originals are trained using an 8-batch size. A layer with 1024 neurons and the ReLU activation function receives the output of the final convolutional stage. A single neuron with the sigmoid activation function for binary classification, as provided by this equation, makes up the final layer.

$$S(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The Adam [15] optimizer was selected to optimize the network. It has a learning rate of 0.0002 and a binary cross-entropy loss *JBC* that can be calculated using Eq. (3).

$$JBC = -\frac{1}{m}\sum_{i-1}^{m} y_i.\log \begin{matrix}(p(y_i) + (1-y_i) \\ .\log(1-p(y_i)))\end{matrix} \tag{3}$$

Where, the parameter y_i is the actual label, $p(y_i)$ is the predicted probability of y_i and m is the number of training/test examples. These parameters are used to develop the DD-CNN classifier for recognition of HR.

4. Results

To evaluate the efficiency of the suggested DD-CNN strategy based on deep learning. In every experimental trial, datasets are divided into a training set and a testing set using a 3:1 split, which means that three-quarters of the data are used for training and the remaining one-fourth are used for testing. These retinal pictures came from three different online sources and one private source. All 1400 images were scaled to 700 x 600 pixels in order to carry out feature extraction and classification activities. The two deep learning methods known as VGG16, and deep CNN are combined to develop our proposed system. Digital fundus benchmarks with varying imaging techniques are shown in Figure 1.

To build and programmed our DD-CNN system, a computer with a core i7 CPU, 16GB of RAM, and a 4GB Gigabyte NVIDIA GPU was used. On this computer, TensorFlow (version 2.7) and Keras deep learning libraries are set up using Windows 10 Professional 64-bit edition. Various kernel dimensions are methodically used to develop feature maps from the previous step to build or train the CNN architecture. The convolutional layer's weight settings are altered since the project typically uses kernel sizes of either 3 x 3 or 5 x 5. Various window widths and values obtained from the excitation objective function of each feature map are used to convolute the convolutional layers. The pooling layer was made using a similar procedure to the convolutional layer. There is only one difference: a window size of 2 x 2 and sliding increments of 2 are utilized to maximize the features gathered from the previous layer. This stage reduces the convolutional weights while increasing the network's overall speed. This average pooling's output is fed into a fully linked layer.

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With VGG16 serving as the foundation architecture for training, accuracy, and validation, along with a training loss and a validation loss function, we start testing our suggested DD-CNN model on the various datasets. Figure 3 shows how well our proposed DD-CNN model performs. It required just 10 total iterations of the training and validation processes to achieve a training accuracy and validation accuracy of above 96%. Additionally, we were able to obtain a very low loss function for both the training and validation data that was below 0.1, providing further proof of the viability of our suggested approach. We must first gather the confusion matrix in order to properly assess detection performance.

Even with a small dataset training sample for the model, the p label for each category does not become jumbled. The two categories have been correctly classified. As a result, the confusion matrix showed that the detection accuracy of our recommended model, DD-CNN, is higher. Additionally, table 1 demonstrates that the DD-CNN model outperformed other systems in terms of SE, SP, ACC, and AUC values. The training step is completed in different CNN and VGG19 architectures with eight to sixteen stages to perform comparisons on the retinal fundus datasets with pre-processing to improve the contrast. The findings are illustrated in Figure 4. It's important to note that all of the CNN and VGG16 deep learning models were trained using the same quantity of epochs. The network with the highest performance is selected, and an identical classic convolutional network is trained, with a validation accuracy of 59%. Sensitivity, specificity, accuracy, and AUC metrics were used to evaluate the performance of the proposed CAD system against the capabilities of conventional CNN, DRL, trained-CNN, and trained-DRL models. The results for SE, SP, ACC, and AUC for the trained-CNN model on this dataset were 81.5%, 83.2%, 81.5%, and 0.85, respectively. Figure 13 clearly illustrates the similarities between DLM systems and AUC systems in terms of the AUC graph. The DD-CNN model produced metrics values for SE, SP, ACC, and AUC of 82.5%, 84%, 83.5%, and 0.86, respectively. By combining the capabilities of DD-CNN on four annotated fundus sets that are not susceptible to overfitting issues, the generated DD-HR system produced results that were superior to those of deep-learning models.

Table 1: Performance of the developed DD-CNN system compared to other DL systems on 1400 samples.

No.	Technique	SE	SP	ACC	AUC
1	Triwijoyo-2017 [7]	78.5%	81.5%	80%	0.84
2	Pradipto-2017 [8]	81.5%	82.5%	84%	0.86
3	DD-CNN model	97%	99%	98%	0.98

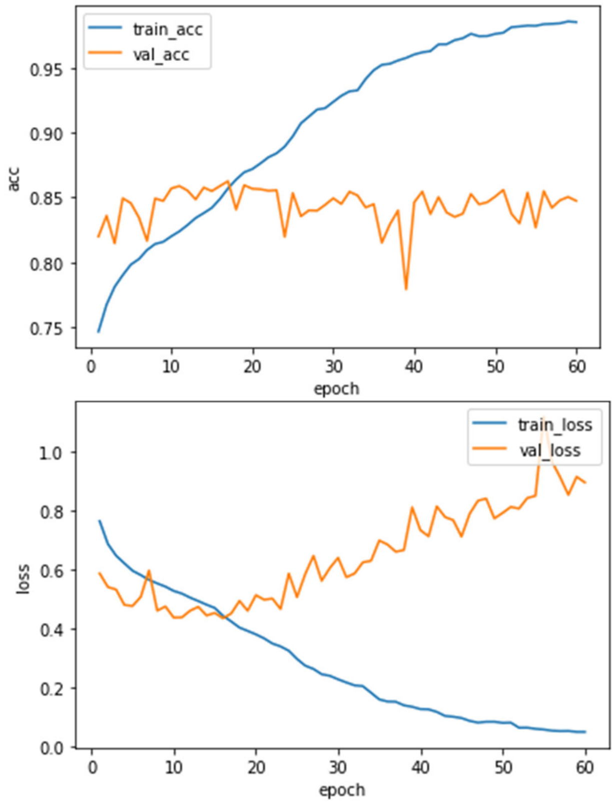

Figure 3. Train and validation Loss versus accuracy of the proposed DD-CNN model.

5. Discussions

The implementation of DD-CNN used VGG16 as a pretrained model and a trained CNN model as an input to deep CNN architectures to categorize HR. By creating a multilayered hierarchical structure, the learning process for specialized features was completed without the need for complicated feature selection and image processing techniques. This multi-layer architecture used learning methods to extract information from the input image without the aid of a person. To construct the suggested architecture, the VGG16 was updated to integrate DD-CNN and convolutional blocks in order to provide more generalizable features. The VGG16 layer acquires localized and trained features from four HR-related lesions using a scratch-based training method. Convolutional, pooling, and fully connected layers make up the majority of the layers in the CNN model for learning deep features. These layers must be trained and proven to be efficient at retrieving valuable information before being used to build the model. These characteristics are not the best for detecting HR in retinograph images. Deep residual connections were therefore incorporated, providing highly specialized characteristics as opposed to feature-based classification techniques that needed human involvement.

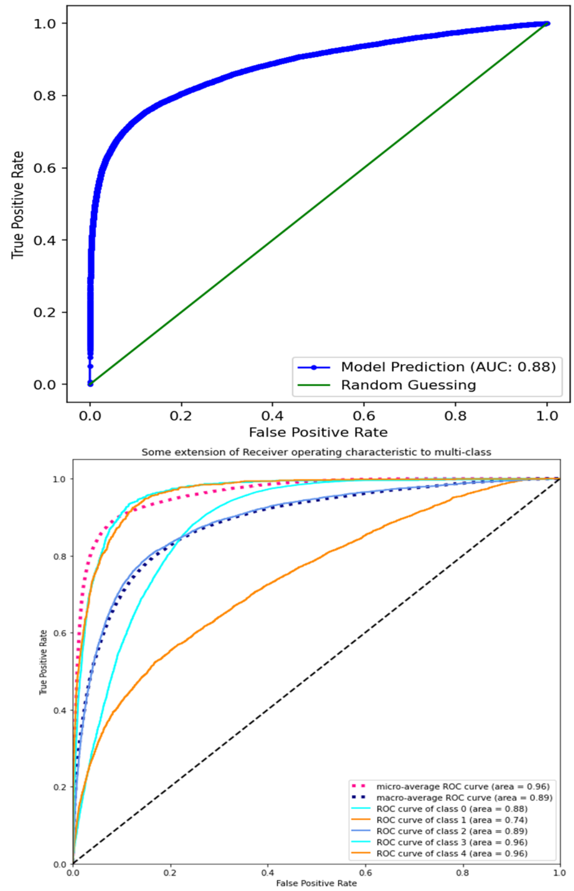

Figure 4. Area under the curve (AUC) compared to other approaches

Several categorization schemes for both HR-related and non-HR-related eye conditions have been created in the past, as discussed in Section 3. Instead of using conventional machine learning techniques, these systems employ deep learning techniques. There were several significant challenges when HR automated systems were established using traditional methods. The first issue is that in order to identify and extract pertinent HR-related pathological characteristics from retinograph pictures in order to calculate HR parameters, one must utilize complex pre- or post-image processing techniques. For training and testing the network, there are no datasets with clinical expert annotations characterizing these HR-related lesion patterns. As a result, it is difficult for automated systems to recognize certain disease features. The authors trained the network with manually created characteristics and evaluated the effectiveness of both conventional and stateof-the-art deep learning models in accordance with the literature. Consequently, to find the best characteristics, an automated method is required. Deep-learning models produce better results than the traditional method. Other models, on the other hand, used trained models created entirely from scratch to automatically learn features, although they all used the same weighting methodology throughout. Then, transferring precise decision-making weights to deeper network levels may be challenging for layers. An independent features learning strategy enabled the successful identification of HR. However, the handcrafted-based classification systems for diagnosing HR illnesses rely on computationally expensive algorithms for pre-processing, segmentation, and localization of HR-related data. Researchers only paid close attention to extracting the required components as opposed to other important symptoms like cotton wool spots or hemorrhage detection. Instead of focusing on image processing algorithms, the DD-CNN system is developed in this work to address the issues by categorizing pictures into HR and non-HR using two multi-layer deep learning approaches. Here we outline the major contributions of the DD-CNN system. This study used residual blocks and a convolutional neural network (CNN) to construct two novel deep learning techniques. The first CNN model, which was used to establish the hierarchy of features, was trained using four different HR lesions. The feature maps with the most valuable information were found using the second residual blocks, which increased the learning procedure's efficiency. It is the first HR classification system developed in this work, and it is based on a color space that is perceptually oriented. The DD-CNN model and a softmax classifier are used to classify the deep features. This is the first effort we are aware of to automatically detect HR disease. The multilayer deep learning network must be trained on several samples in order to achieve higher feature generalization while building the DD-CNN system presented in this study. An innovative deep learning-based approach was developed to automatically learn features using a DD-CNN with three residual blocks. However, a few samples are incorrectly classified by the suggested DD-CNN method. Figure 1 provides a visual explanation. It was a case of severe hypertensive retinopathy (HR), and we will address this issue in further studies. In terms of HR recognition accuracy, the DSC-HR system outperformed the most recent systems, Triwijoyo-CNN-2017 [7] and Pradipto-CNN-RBM-2017 [8]. This is due to the fact that the DD-CNN system is constructed using learned features and deep residual learning approaches. In addition, three CNN blocks that extract localized and specialized information were added to the VGG16 architecture. Instead of using commercially available pre-trained models to create specialized features, the authors upgraded deep residual network blocks with three shortcuts to address the difficulty of recovering HR-related lesions.

Future improvements to the DD-CNN HR detection system might include providing a bigger library of retinograph pictures that have been obtained from diverse sources. It might be possible to integrate hand-crafted features to increase the model's classification accuracy rather than just using deep features. DR-related lesions were segmented from retinograph images using the saliency maps approach in numerous studies, and those lesions were subsequently retrieved from the images using a train classifier. In those investigations, just the segmentation stage was carried out. The accuracy of classifying HR eye-related diseases will increase with the eventual incorporation of these saliency maps. The different HR severity levels will also be assessed in the future. Recent studies have indicated that clinical traits are important indications for figuring out the degree of HR severity. On the other hand, the degree of HR illness will be identified by the extraction of those HR-related lesions with different thresholds. Because of this, practitioners may find it helpful to employ them to address the hypertension issue.

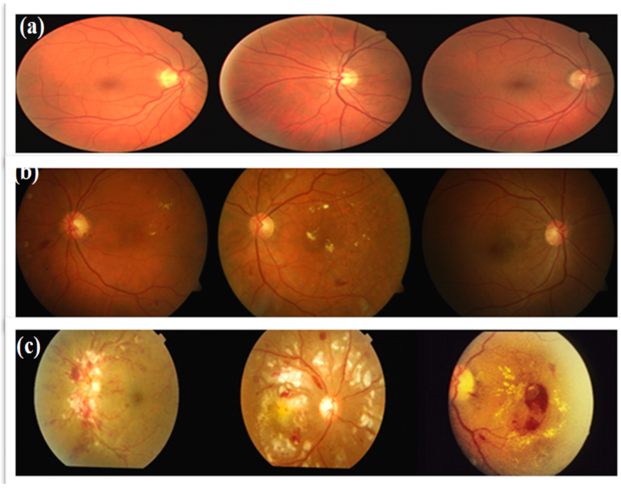

Figure 5. An illustration of three distinct HR datasets that were used to develop and test the DSC-HR system, with figure (a) showing the Drive dataset, figure (b) representing the DDB1 dataset, and figure (c) showing the Imam-DB dataset.

6. Conclusion

A condition of the retina known as hypertensive retinopathy (HR) is connected to excessive blood pressure. The severity and persistence of hypertension are closely correlated with the occurrence of HR. To avoid blindness, it is essential to recognize and assess HR as soon as possible. A few computer-aided systems are now available that can detect HR issues. On the other hand, such systems focus on gathering characteristics from a variety of retinopathy-related HR lesions and categorizing them using conventional machine learning techniques. Therefore, significant, and challenging image processing techniques are required for a small number of applications. Recent comparable techniques have shown that classification precision is also poor. To solve these problems, a brand-new CAD HR-diagnosis system utilizing cutting-edge Deep Dense CNN Learning (DD-CNN) technology is now being created. A convolutional neural network that had previously been trained as a feature extractor was used by the HR-diagnosis system. The implemented system's correctness is evaluated statistically using more than 1400 retinography pictures, employing performance measures including specificity (SP), sensitivity (SE), area under the receiver operating curve (AUC), and accuracy (ACC). AUC was 0.98, SP was 99%, ACC was 98%, and SE was 97% on average. These findings suggest that hypertensive retinopathy is diagnosed using the suggested DD-CNN classifier.

Few computational methods have been created to date that can identify HR from colored fundus pictures. Modern approaches, on the other hand, focus on characterizing a range of HR-related lesions and categorizing them using machine learning algorithms. To create the HR identification system, domain expertise in feature selection and image processing is necessary. There aren't many systems that classify disorders of the HR eye using deep learning models (DLMs) at the moment. Because such methods had only been evaluated on a small dataset, it was difficult to use them as a screening tool for HR detection. The categorization accuracy is also subpar. In this study (HR), for the classification of hypertensive retinopathy, a novel multi-layer deep CNN (DD-CNN) with a features-training approach using the VGG-16 model is created. The DD-CNN method extracts characteristics from retinal fundus images and classifies them as HR- or non-HR-related illnesses using a multilayer architecture made up of DD-CNN trained features and deep residual learning blocks. Furthermore, by changing the VGG16 network architecture, the DD-CNN system automatically learns and categorizes features. The DD-CNN technology can detect HR, which will assist the ophthalmologist in making a wise choice. Additionally, it aids in screening sizable groups of people. The outcomes of the tests demonstrate that the DD-CNN system can make a precise diagnosis of hypertensive retinopathy.

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