International Journal of Computational and Electronic Aspects in Engineering
Volume 6, Issue 3, July 2025, pp 168 - 179
https://doi.org/10.26706/ijceae.6.3.20250607

Prospective Detection of Diabetic Retinopathy Using Modified CNN Models on Fundus Images: A Study at Al-Noor Institute, Al-Nasiriya

Atyaf Jarullah Yaseen

Department of Computer Science, College of Computer Science and Mathematics, University of Thi-Qar, Iraq

Correspondence: atyafjarallah82@utq.edu.iq

Article – Peer Reviewed
Received: 1 June 2025
Accepted: 11 July 2025
Published: 25 July 2025

Cite this article: Atyaf Jarullah Yaseen, "Prospective Detection of Diabetic Retinopathy Using Modified CNN Models on Fundus Images: A Study at Al-Noor Institute, Al-Nasiriya", *International Journal of Computational and Electronic Aspects in Engineering*, RAME Publishers, vol. 6, issue 3, pp. 169-179, 2025.
https://doi.org/10.26706/ijceae.6.3.20250607

Abstract: Diabetic retinopathy (DR) is considered to be the most common microvascular complication with diabetes mellitus and continues to be the main disease that causes vision impairment and blindness all over the world. Early-stage outcomes are, however, difficult to identify; they require highly qualified clinical retinal fundus photos interpretation to detect DR at an opportune stage in order to avert visual disability that would most probably be irreversible. The aim of this prospective study was to consider a deep learning-based diagnostic model, which is based on the modified convolutional neural network (CNN) trained and tested on a proprietary dataset and estimated in Al-Noor Institute in Al-Nasiriya in the Ophthalmology department. The goal of the model was to evaluate the quality of input fundus images, and group them in such categories as DR-positive, and DR-negative. Clinical ophthalmologists were used to check the production of the model and certify the results of model accuracy. The study used 398 patients (232 males and 166 femals) screened over a five weeks period. Compared to the expert-labeled ground truth, the proposed model had an accuracy of 93.72%, sensitivity of 97.30%, and a specificity of 92.90% initialization. This evidence underlines the feasibility of deep learning applications in helping to detect diabetic retinopathy early and especially in low-resource environments.

Keywords: Diabetic retinopathy. Fundus imaging, convolutional neural networks, deep learning, automated diagnosis, ophthalmology.

1. Introduction

Diabetic retinopathy (DR) has been identified as the most common microvascular complication attributed to diabetes mellitus and one of the major causes of blindness and sight deficiency in different parts of the world. Epidemiologic estimates indicate that more than 200 million will be afflicted by this condition by the year 2040 [1]. The destruction of the small blood vessels within the retina, or light-sensitive tissue at the back of the eye, is the main work of DR and causes gradual loss of vision.

Studies have shown DR to fall in two clinical categories of: Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR). The initial phases of the condition (NIH NPDR), retinal microvasculature is destroyed as a result of swelling and rupture of the capillaries. This condition commonly leads to macular edema, where the central part of the retina (macula) is swollen and this is one of the reasons of mild to moderate visual loss. By contrast, PDR manifests the advanced form of the disease, during which unusual neovascularization takes place on the retinal surface. These weak new vessels tend to burst, resulting in hemorrhage to the vitreous, fibrosis and in the end serious loss of vision. Some risk factors are related to the emergence and development of DR among which it is possible to distinguish type 1 and type 2 diabetes, hypertension, hyperlipidemia, pregnancy, the ethnicity, and positive family history.

Clinical progression of DR, though not specific has been known to include blurred vision, floaters, dark or blank spots in the sight and reduction in night vision [2].

An illustrative overview of DR types and associated clinical symptoms is presented in Figure 1.

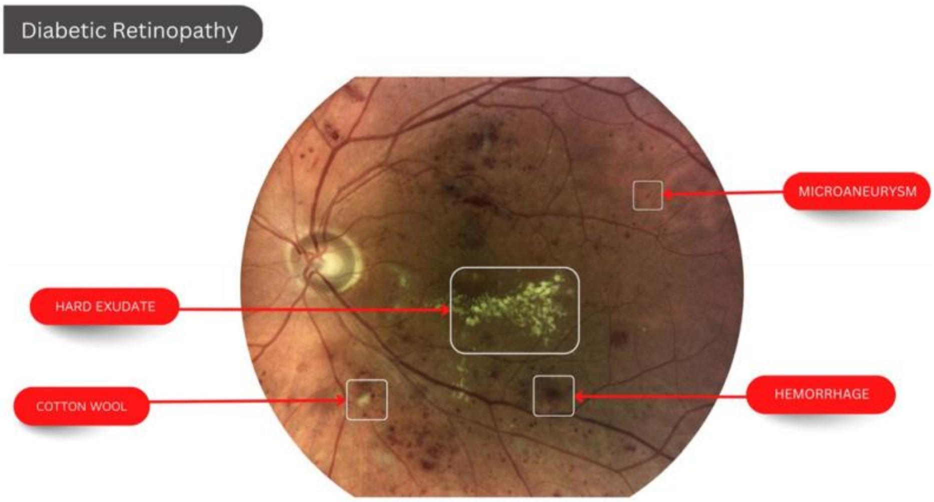


Figure 1: Diabetic Retinopathy [1].

Diabetes retinopathy (DR) presently constitutes the main cause of visual impairment among adults of working age in Iraq. The occurrence of this is directly linked with the length of diabetes mellitus and unless addressed early enough; it may develop to become permanent blindness. The percentage of people affected by DR grew by an estimated 89 percent between 2000 and 2025 to 7.69 million people as per the Centers of Disease Control and Prevention (CDC) data. This amount is expected to increase two-fold in the world by the year 2050 [3].

The National Diabetes Survey reported in Iraq [4] showed a dramatic rise in the cases of diabetes with an approximate figure of 27.4 million being affected now when compared to the cases albeit small in 1998. The prompt identification of DR has high chances of getting appropriate treatment and preventing vision impairment [5]. But many patients have no symptoms in the early periods of their disease, and they do not notice visual loss until after they have sustained considerable damage to their retina in the later stages of the condition [6].

Fundus photography is the most commonly used non-invasive imaging method to detect the presence of DR because they are of high quality, cheap, and easy to store and transmit digitally. Although manual interpretation by ophthalmologists is effective, it is time consuming, subject to inter-observer and is prone to diagnostic errors. Consequently, the demand in automated diagnostic systems is growing using the benefits of the image processing and machine learning techniques to enhance the accuracy and efficiency of the DR screening [7].

Machine learning has shown significant potential in helping accomplish quick and solid DR diagnosis. As an example, Sambyal et al. [8] came up with one hybrid machine learning method, which exploited the features of two classifiers, Optimum Path Forest (OPF) and Restricted Boltzmann Machine (RBM). They assessed their model with respect to common performance measures of accuracy, sensitivity, or specificity. The greatest accuracy of diagnostics was obtained using the RBM-1000 configuration, which amounted to 89.47%.

Over the past years, deep learning, specifically, convolutional neural networks (CNNs) has emerged as the dominant tool in the classification process of complex medical images, such as retinal scans. The Khan et al. presented deep-learning model to assign ocular images to one of the categories DR-positive or DR-negative by means of combining the Xception classifier with dense neural network. The empirical results indicated that the training accuracy was 96.68 and the validation accuracy was 90.82, which is evidence to the effectiveness of deep-learning methods as far as the identification of retinal ailment is concerned.

The current examination is an update of the recent research on the deep learning of objects detection through a new architecture of the convolutional neural network (CNN). The literature review, included in the Sect. 2, sets the research context that includes a survey of existing methods of image-based object detection and the discussion of technical limitations. Sect. 3 subsequently explains that proposed CNN model making use of multiscale feature fusion and also integrates low-level and high-level features through an attention mechanism. Sect. 4 provides the experimental design, presents the results obtained, and makes an in-depth analysis of performance. Sect. 5 offers an outline of the results showing the higher level of detection accuracy when using multiscale fusion and attention-based feature fusion. Lastly, there are the open questions, as well as future directions, listed in Sect. 6.

2. Related Work

The introduction of modern advances in deep learning has significantly increased possibilities of automated probabilistic diagnostic systems in medical imaging. According to Ali et al. (2021) [10], deep learning models have the potential to improve diagnostic means and efficiency, to a large extent, with the manifestation of Incremental Modular Networks (IMNets). In their design, a possible growth of IMNets begins with some modular elements implemented to meet the needs of particular features or patterns, making them especially worthy of complicated medical applications. The authors of the investigations, however, draw particular attention to the fact that these systems must be used as supplemental tools of trained medical workers but not as alternatives.

In [11], a hybrid deep learning solution has been suggested to identify diabetic retinopathy. They combined convolutional neural networks (CNN) with already trained modules, including VGG16 and VGG19 to learn and predict the features of the retina. The model has levels of DR severity: no DR, mild, moderate, severe and proliferative DR. Testing on both sets of APTOS-2019 and Messidor-2 and a local DR dataset showed good results with accuracies of 90.60%, an F1-score of 94% and a recall of 85%.

To handle the complexity that exists in the detection of DR in retinal images, there is an attempt by Gunasekaran et al. [12] of proposing a deep recurrent neural network (RNN) structure. The architecture of RNN-based model was made to capture temporal and spatial aggregations in image data, leading to the precision of the model in diabetic retinopathy prediction at 95.5%.

Khan et al. [13] tested various deep neural network structures- VGGNet, ResNet, InceptionV3 and also carried out transfer learning operations. Before fitting the model, a Gaussian filter was used to reduce noise and enhance original images. These models were then trained and tested on data that involved five diabetic retinopathy (DR) categories. InceptionV3, however, in all studied models, showed the best results: training accuracy equal to 81.2% and testing accuracy equal to 79.4%.

Fang et al. [14] also proposed a Directed Acyclic Graph (DAG) network model of classification of DR with a multi-feature fusioning. Retinal hemorrhagic plaques, varices and neovascularization were extracted as three important indicators by special algorithms that were implemented in the system. The DAG network combined and analyzed such features and made it possible to perform effective classification. The validation of the model was performed on the real-time clinical set and publicly available DIARETDB1 set.

In a different submission, Elloumi et al. [15] proposed a lightweight diagnosis framework to study the DR images acquired through smartphone devices, which usually have low image quality. The feature extraction used by the authors was the NasNetMobile architecture, and it was performed on an 440 fundus image dataset involving cross-validation. This model demonstrated excellent performance: 95.91 % of accuracy, 95.71 % of precision, 94.44 % of sensitivity and 96.92 % of specificity.

Kanakaprabha et al. [16] performed a comparison among some deep learning cutting edge architectures some of them did CNN, VGG16, VGG19, InceptionV2, ResNet50, MobileNetV2, and DenseNet architects with the purpose of detecting and diagnosing diabetic retinopathy. Their paper helped in giving an important insight into the trade-offs of different models on their performance regarding accuracy, computational performance and stability of various datasets.

Convolutional Neural Networks (CNNs) have proven to be very resourceful in classification of medical images and especially Diabetic Retinopathy (DR). Sridhar [17] has suggested a CNN-based DR detection system that was trained with a publicly available Kaggle dataset. The model was successful in extracting the relevant features of the retinal fundus images and classified them to be whether DR or not with high rates of detection accuracy showing better results than the traditional methods.

Das et al. [18] proposed a DR classification model that was founded on narrative features retrieved on segmented fundus images. To remove false segmentations in images, such preprocessing operations as morphological operations and adaptive histogram equalization were used. This type of classifier based on CNN, which is tested through DIARETDB1 dataset, demonstrated a precision of 97.2% and an accuracy of 98.7, which makes the classification much better than the traditional methods.

Vives-Boix et al. [19] presented some other work in which they have come up with the novel approach that combines synaptic meta-plasticity in a CNN structure with the architecture of InceptionV3. Analyzing a DR model on a publicly released dataset, it brought the classification accuracy of an 95.56%, F1-score of 94.24%, recall of 90%, and precision of 98.9%.

Having identified the limitations of a single-view approach to analyzing images, Luo et al. [20] proposed a multi-view CNN design to screen out diabetic retinopathy (DR). The network is based on the modular architecture to apply two parallel convolutions pathways where the latter is supplied with an attention module that makes the difference of the areas prevalent caused by the lesions in various views of the fundus. Tested against a multi-view DR dataset the model achieved the results in terms of classification metrics superior to traditional systems.

Adriman [21] performed the experiments of comparing the performance of DR detection systems with different deep learning models, namely ResNet, DetNet, VGG16 and DenseNet. Compared with the APTOS 2019 Blindness Detection dataset, the models got 96.25%, 93.99%, 76.21% and 84.05% performances in classification respect. In order to improve the process of feature extraction, local binary patterns (LBP) were used, which stress on the texture features of the retinal images.

Fatima [22] suggested a hybrid neural network model to enhance the visibility of the retinal structures aided by entropy-based image enhancement algorithm. This procedure when used on images e.g. MESSIDOR-2, UWF, and APTOS showed strong results in fundus image classification. In the same sense, another study [23] also used the same optimization algorithm with the entropy but used the Archimedes Optimization Algorithm with Kapur Entropy (AOA-KE) to optimize the quality of images before classifying them.

Qureshi [24] introduced an Active Deep Learning CNN (ADL-CNN) architecture for automatic DR detection and severity classification. The system segmented regions of interest and identified five severity levels. Trained on the EyePACS dataset, ADL-CNN achieved 98.0% accuracy, 95.10% specificity, 92.2% sensitivity, and a 93.0% F1-score.

Kalyani et al. [25] introduced a Capsule Network-based DR detection model to be enhanced by deep learning. The convolutional and capsule layers along with SoftMax classification created an accuracy of 97.98%, 97.65%, 97.65%, and 98.62% in the presence of healthy retinas and stages 1 through 3 in the MESSIDOR dataset.

Gayathri et al. [26] in their 2018 research paper suggest an automated diagnosis framework that checks diabetic retinopathy (DR) through a Multi-path Convolutional Neural Network (M-CNN) as feature extractor. The obtained feature vectors are further used by three machine-learning classifiers, i.e., Random Forest, Support Vector Machine, and J48. This framework is tested on two open datasets namely IDRiD and MESSIDOR and the performance is measured against various indicators such as accuracy, precision, F1- score and specificity. The findings indicate that the approach has strong classification performance in each dataset and measure, which implies the prospect of the M-CNN architecture as a tool of automatized DR screening.

The work by Bodapati et al. [27] presented a classification scheme based on severity where a complex deep neural network with the gated-attention mechanism was used. Multi-channel encoding method involved use of pre-trained convolutional neural networks (CNNs) whose feature descriptions were then aggregated through spatial pooling operation which maintained critical spatial material as well as reducing the dimensions. The proposed system was evaluated and compared to that of prior methods by an experiment, done on the APTOS-2019 dataset and established significant benefits in terms of lesion region detection and the level of precision in classification.

Math et al. [28] present an adaptive machine learning model of categorizing DR based on the features extracted by a pre-trained CNN at the level of segments at the sensitivity of 96.37%, a specificity of 96.37, and the AUC of 0.963 on the Kaggle dataset.

The study of Gao [29] develops a DR grading scheme in fundus fluorescein angiography imaging and evaluates the effectiveness of the use of VGG16, DenseNet and ResNet50 when processing the Xian and Ningbo datasets. VGG16 is the best model among the competing structures, showing the accuracy of 94.17% as well as the AUC of 0.972.

Kobat et al. [30] used a pre-trained DenseNet design to classify diabetic retinopathy (DR) -negative fundus-images. Its classification pipeline was based on the partitioning of the source images into horizontal tiles and vertical tiles and then using a type of convolutional network that classified this image set. The model was evaluated using the 10-fold cross-validated using two different sets of data and an overall accuracy of 84.90 was achieved.

3. Proposed Methodology

The high-level architecture of the Diabetic Retinopathy (DR) classification model is illustrated in Fig. 2 and it consists of three main stages, namely, training, validation, and testing. During training, a closed dataset of 57,625 retina fundus images was collected in Al-Noor Institute of Ophthalmology in Al-Nasiriyah. These images were labeled by skilled ophthalmologists and divided into two groups, on the one hand, DR-positive and, on the other hand, DR-negative. The data set was then split into training and validation sets whereby 80 percent was assigned training set, and the rest 20 percent assigned the validation set.

The training subset was used to estimate the parameters of the model, but the validation subset was also used to track and monitor performance across training iterations continuously to address overfitting. The images labeled were then given as the input to a CNN based classification model that assigned DR labels. This deep learning structure promoted automatic extraction of features and hierarchical learning hence improving the ability of the model to generalise across variations of retinal fundus images.

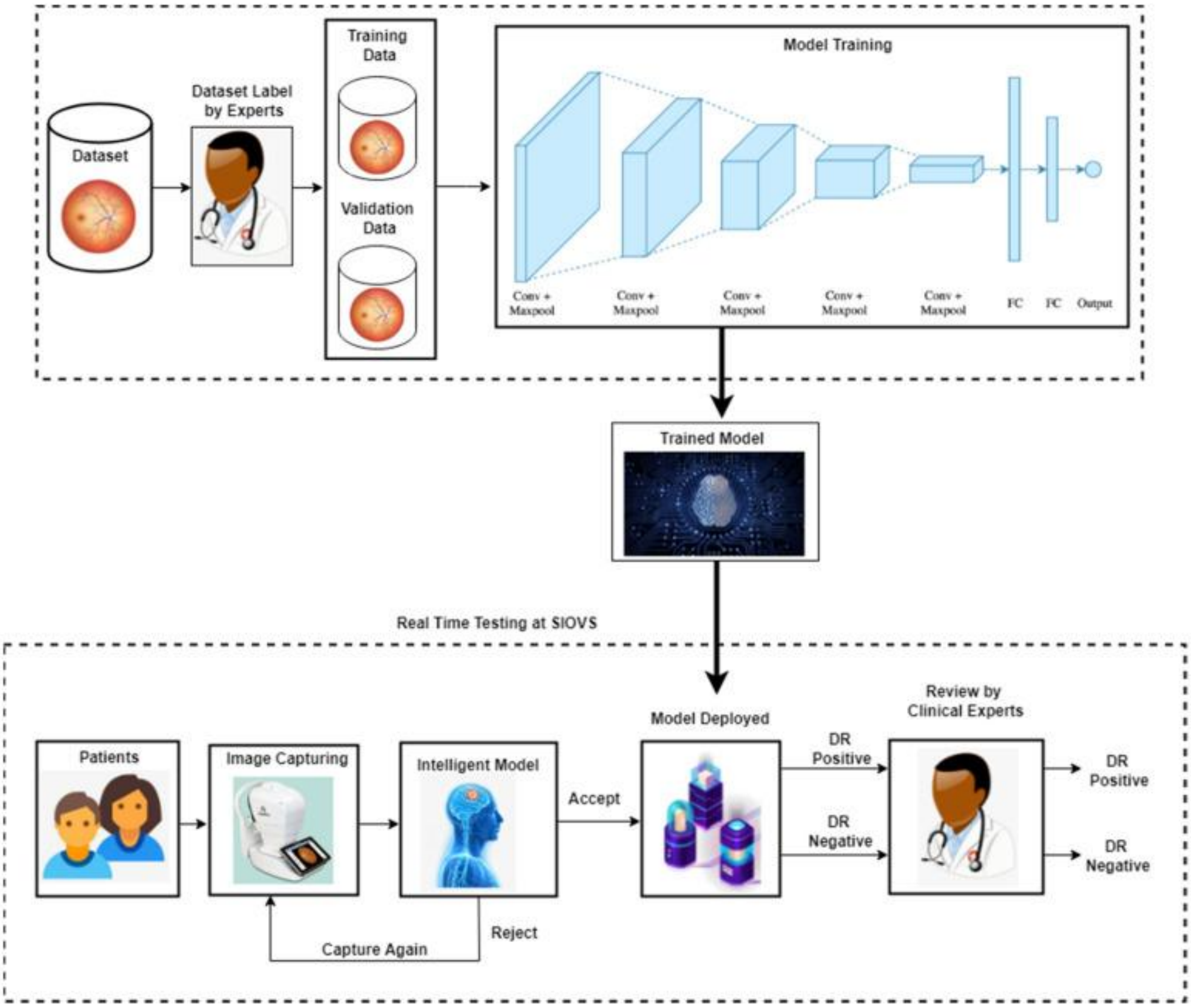


Figure 2: Diabetic Retinopathy detection architecture.

The testing stage was based on the data of the patients taken at the Al-Noor Institute of Ophthalmology. The retinal imagery was captured through high-resolution tools and then was included in the experimentation pool. The modular structure of the proposed Diabetic Retinopathy detection framework will include several convolutional and pooling blocks that will perform the hierarchical features extraction on the one hand and the dimensional reduction in the spatial domain on the other.

In the convolutional layers the operation of feature detection is based on filters with different kernel dimensions used to extract the most essential features of the input volume. The aligned output, called a feature map or an activation map, codes spatial and textural due to the fact of DR diagnosis. To support the non-linearity of the model, Rectified Linear Unit activation function was implemented that allows transforming linear input features to non-linear representation.

After a convolution operation, in additional layers, pooling operations were performed to shrink the activation maps and hence, decreasing the dimensionality of the said maps. Out of the surveyed types of pooling, max pooling, average pooling, min pooling, and sum pooling, the given study used some pooling mechanisms to preserve important elements of images and restrict spatial resolution as much as possible. One-dimensional vectors of flattened features in these reduced feature maps were then fed through what were then learning-managed multiple fully connected layers, and the last layer output with binary responses to determine whether an input image was DR-positive or DR-negative.

The second phase was the collection of real time data of the participants over five weeks of individuals diagnosed with Type II diabetes. All acquired images were subjected to assessment module before the first level to assess quality of the diagnosis. Images that did not meet the expected standards were discarded and repeated again to achieve a sound diagnosis. The images passed through this quality screening were only those that were conceded to be acceptable and then submitted to the trained CNN to be classified.

The eventual results of the automatized system of classification were then focused by clinical ophthalmologists and the results were observed to provide expert confirmation of the speculation. Such an iterative review procedure allowed the model to be evaluated comprehensively concerning the real-world situation connected with its use in the clinical domain and the purpose of comparing its performance directly with that of expertly trained human interpretation.

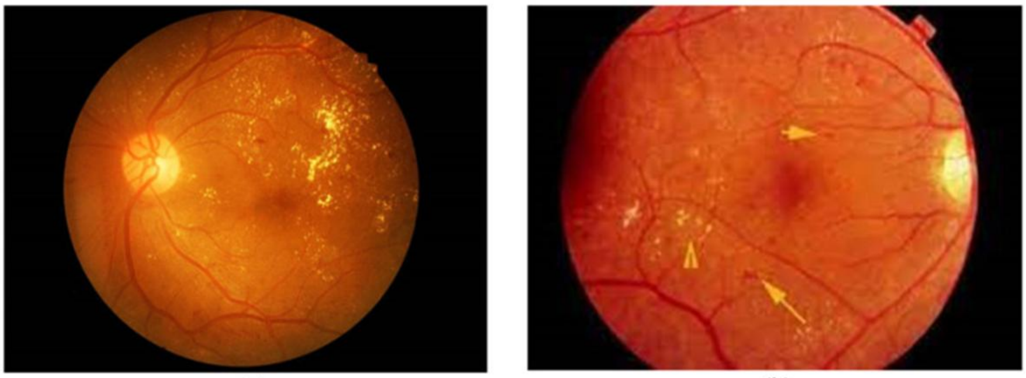
4. Results and Discussion

The given work represents a comprehensive assessment of a deep-learning model, used to automatically classify Diabetic Retinopathy (DR). It intends to classify retinal fundus images as DR-positive or DR-negative. The label DR-positive indicates the presence of the manifestations of DR hence the need to involve clinical intervention and therapeutical management. On the other hand, DR-negative diagnosis denotes a lack of DR pathology and thus the lack of a prompt medical care.

This model was trained, validated and tested on a proprietary database of 57625 retinal fundus images accrued by the Al-Noor Institute of ophthalmology, and manually annotated with respect to presence or absence of DR-related features using expert ophthalmologists. In order to carry out model building processes, the dataset was shared between training with 80 % and validation within the training with 20 % in order to control generalization modeling and offset the chances of overfitting.

Table 1 summarises the performance measures that were obtained in the course of the experiment of the research. The general predictive performance of the classifier was 96 % (93.597.19% confidence interval), and it was followed by the area under the receiver operating characteristic curve (AUC) of 0.99. Its sensitivity was 95 % (93.1 to 96.6 %), and the specificity was 97 % (95.5 to 98.5 %).

In order to ensure robustness, the validation elements (such as the validation set) and an independent, real-time testing data set were adopted to measure model performance. The training process was performed through supervised learning and accuracy, precision, recall, and F1-score were used as the metrics of quantifying classification effectiveness. The depicted images presented in Fig. 3a as an example of DR-positive and DR-negative ones.



(a) (b)

Figure 3: Diabetic Retinopathy images (a) DR Negative. (b) DR Positive.

In order to deplete the performance of the suggested Diabetic Retinopathy (DR) classification model to a suitably good level of credibility, all typical statistical evaluation measures, being accuracy [31], sensitivity [32], and specificity [33], were used. The given indices provide quantitative criteria that can be used to compare the ability of the model to recognize patients with or without DR. They are written as equations, and their mathematical representations are as shown below (Equations 1 _ 2).

$$Accuracy = \frac{(TN+TP)}{(TN+FN+FP+TP)} \tag{1}$$

$$Sensitivity = \frac{TP}{(TP+FN)} \tag{2}$$

$$Specificity = \frac{TN}{(TN+FP)} \tag{3}$$

The confusion matrix that is related to the validation stage of the proposed model can be seen in Table 1. For the validation of the retinal fundus images, 11,525 images were employed, which were labeled into DR-Negative and DR-Positive classes with the help of expert experts. Of this, the model recognized the following correctly, namely, 5,210 pictures as true negatives (TN) or positively identified the DR-Negative cases. But there were 614 instances of false positives (FP) where the image was wrongly identified as DR-Positive though it belongs to a DR-Negative category. On the other hand, 147 of the images that were in effect DR-Positive were deciphered to be DR-Negative (false negatives, FN). The model registered 5,554 true positives (TP) in the DR-Positive cases.

According to this confusion matrix, the validation accuracy of this model was 93.40%, the sensitivity 97.42%, specificity 89.45%, which represents the strong results of the model in differentiating between the DRs and non-DRs groups of cases.

Table 1. Confusion matrix of Diabetic Retinopathy for model validation.

		Predicted Label	
		DR Negative	**DR Positive**
Actual Label	DR Negative	True Negative (TN) 5210	False Positive (FP) 614
	DR Positive	False Negative (FN) 147	True Positive (TP) 5554

Table 2 contains the overview of the testing dataset utilized in the real-time examination of the suggested Diabetic Retinopathy (DR) classification model. Total 398 samples of fundus images are included in the dataset, which are gathered in the process of clinical usage with the patients. Among them 232 samples were collected over male patients and 166 over female patients. The mean age of the men patients was 49.83 years and that of the women patients was 49.71 years. Mean age of all the subjects was 49.76 years.

Table 2. Summary of data collection at Al-Noor institute.

Gender	No. of Samples	Age (Years) (Mean ± SD)
Male	232	49.83 ± 12.67
Female	166	49.71 ± 11.73
Total	398	49.76 ± 12.1

The results of classification of the presented Diabetic Retinopathy (DR) model on a real-time testing data taken during a period of five weeks are shown in Table 3. The data has a total of 398 fundus image records of patients with diagnosis of Type II diabetes. The proportion of 232 male patients categorized as DR-Negative were 196 and the remaining persons were 36 as DR-Positive. Out of the 166 female patients, 128 patients were DR-Negative and 38 were DR-Positive according to the model.

Table 3. Results of Diabetic Retinopathy model for data at Al-Noor institute.

Gender	No. of Samples	DR Negative	DR Positive
Male	232	196	36
Female	166	128	38
Total	398	324	74

Table 4 shows the assessment of the model prediction after analyzing it by the clinical specialists. Of 324 samples that were identified by the model as DR-Negative, the samples that were identified as DR-Negative by the experts were 301 with the remaining 23 samples as DR-Positive. Out of the 74 samples the model showed that it was DR-Positive, the clinicians confirmed 68 samples to be true DR-Positive and 6 samples were re-categorized to be DR-Negative. After this expert review, the model showed classification accuracy of 93.72%, sensitivity with 97.30%, and specificity with 92.90%, which means that predictions by the model are significantly close to the expert clinical evaluations.

Table 4. Confusion Matrix of the Diabetic Retinopathy Classification Model Following Clinical Expert Review.

		Predicted Label	
		DR Negative	**DR Positive**
Actual Label	DR Negative	True Negative (TN) 301	False Positive (FP) 23
	DR Positive	False Negative (FN) 2	True Positive (TP) 72

Figure 4 shows the sample image of representative samples of the confusion matrix in Table 4. In image (a), the model classified this image as DR-Negative whilst the clinical expert concurred with this classification. The image (b) which was initially classified as DR-Positive in the model subsequently became DR-Negative in the expert review. Image (c) was however predicted as a DR-Negative in the model whereas the clinical expert predicted it as a DR-Positive. Finally, the model and the clinical expert agreed on image (d) being DR-Positive.

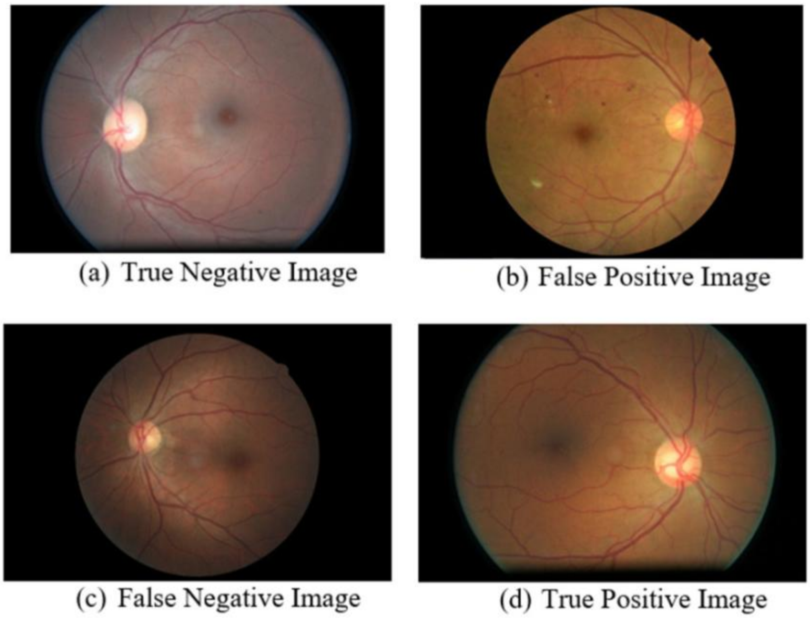


Figure 4. Results of classified images reviewed by clinical experts.

Figure 4 shows the sample image of representative samples of the confusion matrix in Table 4. In image (a), the model classified this image as DR-Negative whilst the clinical expert concurred with this classification. The image (b) which was initially classified as DR-Positive in the model subsequently became DR-Negative in the expert review. Image (c) was however predicted as a DR-Negative in the model whereas the clinical expert predicted it as a DR-Positive. Finally, the model and the clinical expert agreed on image (d) being DR-Positive.

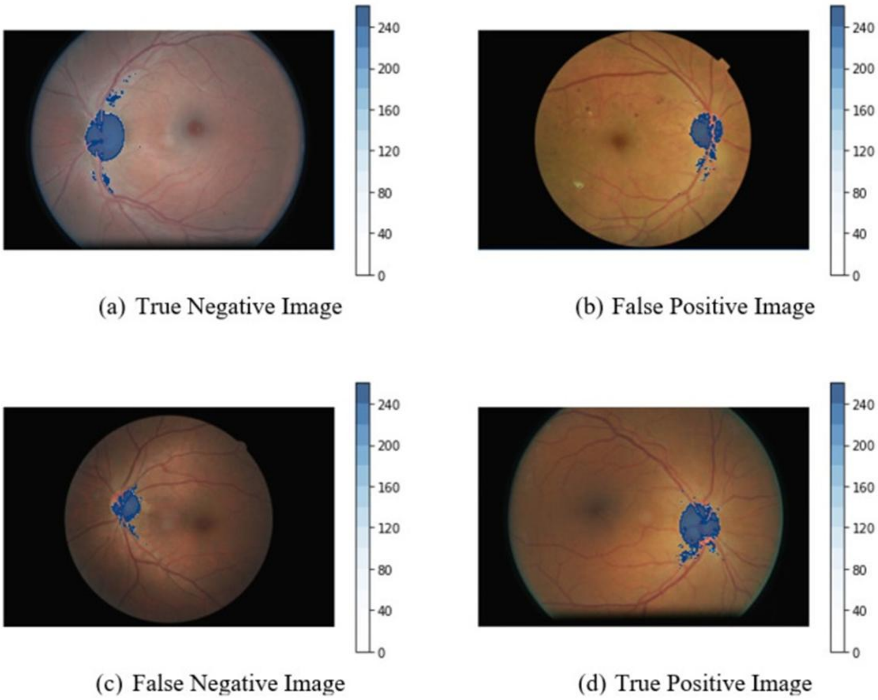


Figure 5. The heat map generated from the final convolutional layer is superimposed onto the original image.

The receiver operating characteristic (ROC) curve is applied in this research to assess the performance of Diabetic Retinopathy (DR) classification model. There are two parameters that characterize the profile of the ROC curve namely the True Positive Rate (TPR) and the False positive rate (FPR). Figure 6 is the ROC curves of the model results with each dataset corresponding to the performance of the model on each of the real-time testing sets that was collected on patients at Al-Noor Institute of Ophthalmology, separated by gender: Figure 6a shows the real-time testing dataset results involving male patients, Figure 6b, shows the results of the real-time testing datasets involving female patients, and Figure 6c shows the joint dataset result of both male and female patients involved in the real-time testing test. These Area Under the Curve (AUC) values are 0.975 and 0.951 in male and female patients respectively as well as 0.969 in the total patient population.

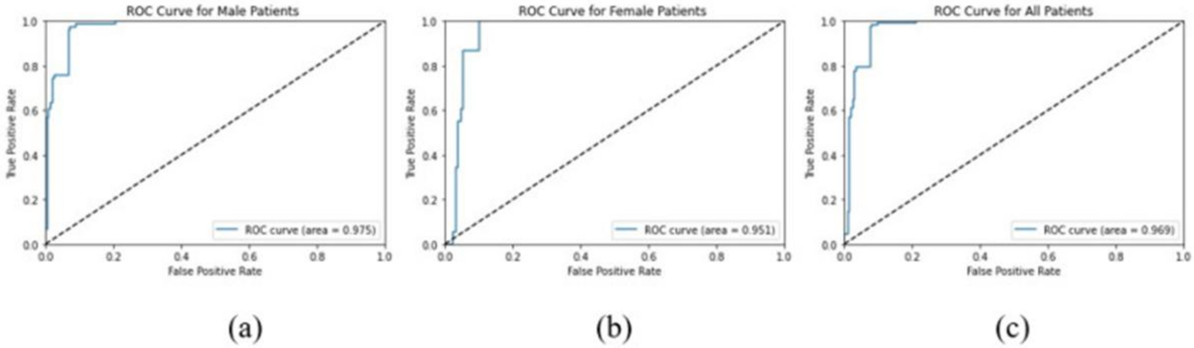


Figure 6. ROC curve of the Diabetic Retinopathy model for (**a**) males, (**b**) females, and (**c**) all of the patients.

5. Conclusions

This research paper initiated this process by retrieving the Diabetic Retinopathy (DR) data sets using various sources and annotating the data sets expertly by clinicians. A modern deep learning system was created, trained, and checked with the labeled data. In the validation, the model recorded a 93.40 percentage accuracy, a sensitivity of 97.42 percent and a specificity of 89.45 percent. The model was then implemented to conduct real-time evaluation in Al-Noor Institute of Ophthalmology. A smart quality assessment system was the one that accepted only high-quality retinal fundus images to investigate. These images were categorized using the model as DR-Positive and DR-Negative and the results of this classification were independently analyzed by clinical experts as a measure of how the model performed in a real-life setting. Its accuracy, sensitivity, and specificity were 93.30%, 97.30%, and 92.90% based on expert assessment. Moreover, the Area under the Curve (AUC) values (separately calculated with respect to male/female/combined patients groups) supported strong and dependable capability of the classification model.

References

[1] Yau J.W.Y., Rogers S.L., Kawasaki R., Lamoureux E.L., Kowalski J.W., Bek T., Chen S.J., Dekker J.M., Fletcher A., Grauslund J., et al. Global Prevalence and Major Risk Factors of Diabetic Retinopathy. Diabetes Care. 2012;35:556–564. doi: 10.2337/dc11-1909. [DOI] [PMC free article] [PubMed] [Google Scholar]

[2] Diabetic Retinopathy|AOA. [(accessed on 12 April 2022)]. Available online: https://www.aoa.org/healthy-eyes/eye-and-vision-conditions/diabetic-retinopathy?sso=y.

[3] Diabetic Retinopathy Data and Statistics|National Eye Institute. [(accessed on 12 April 2022)]; Available online: https://www.nei.nih.gov/learn-about-eye-health/outreach-campaigns-and-resources/eye-health-data-and-statistics/diabetic-retinopathy-data-and-statistics.

[4] Diabetic Retinopathy: A Growing Challenge in Pakistan|Blogs|Sightsavers. [(accessed on 5 August 2022)]. Available online: https://www.sightsavers.org/blogs/2021/06/diabetic-retinopathy-in-pakistan/

[5] Li X., Hu X., Yu L., Zhu L., Fu C.W., Heng P.A. CANet: Cross-Disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading. IEEE Trans. Med. Imaging. 2020;39:1483–1493. doi: 10.1109/TMI.2019.2951844. [DOI] [PubMed] [Google Scholar]

[6] Kumar P.N.S., Deepak R.U., Sathar A., Sahasranamam V., Kumar R.R. Automated Detection System for Diabetic Retinopathy Using Two Field Fundus Photography. Procedia Comput. Sci. 2016;93:486–494. doi: 10.1016/j.procs.2016.07.237. [DOI] [Google Scholar]

[7] Zhu C.Z., Hu R., Zou B.J., Zhao R.C., Chen C.L., Xiao Y.L. Automatic Diabetic Retinopathy Screening via Cascaded Framework Based on Image- and Lesion-Level Features Fusion. J. Comput. Sci. Technol. 2019 346. 2019;34:1307–1318. doi: 10.1007/s11390-019-1977-x. [DOI] [Google Scholar]

[8] Sambyal N., Saini P., Syal R., Gupta V. Modified Residual Networks for Severity Stage Classification of Diabetic Retinopathy. Evol. Syst. 2022:1–19. doi: 10.1007/s12530-022-09427-3. [DOI] [Google Scholar]

[9] Khan A.I., Kshirsagar P.R., Manoharan H., Alsolami F., Almalawi A., Abushark Y.B., Alam M., Chamato F.A. Computational Approach for Detection of Diabetes from Ocular Scans. Comput. Intell. Neurosci. 2022;2022:1–8. doi: 10.1155/2022/5066147. [DOI] [PMC free article] [PubMed] [Google Scholar]

[10] Ali R., Hardie R.C., Narayanan B.N., Kebede T.M. IMNets: Deep Learning Using an Incremental Modular Network Synthesis Approach for Medical Imaging Applications. Appl. Sci. 2022;12:5500. doi: 10.3390/app12115500. [DOI] [Google Scholar]

[11] Menaouer B., Dermane Z., El Houda Kebir N., Matta N. Diabetic Retinopathy Classification Using Hybrid Deep Learning Approach. SN Comput. Sci. 2022;3:357. doi: 10.1007/s42979-022-01240-8. [DOI] [Google Scholar]

[12] Gunasekaran K., Pitchai R., Chaitanya G.K., Selvaraj D., Annie Sheryl S., Almoallim H.S., Alharbi S.A., Raghavan S.S., Tesemma B.G. A Deep Learning Framework for Earlier Prediction of Diabetic Retinopathy from Fundus Photographs. Biomed Res. Int. 2022;2022:1–15. doi: 10.1155/2022/3163496. [DOI] [PMC free article] [PubMed] [Google Scholar] [Retracted]

[13] Khan A., Kulkarni N., Kumar A., Kamat A. D-CNN and Image Processing Based Approach for Diabetic Retinopathy Classification. Appl. Inf. Process. Syst. 2022;1354:283–291. doi: 10.1007/978-981-16-2008-9_27. [DOI] [Google Scholar]

[14] Fang L., Qiao H. Diabetic Retinopathy Classification Using a Novel DAG Network Based on Multi-Feature of Fundus Images. Biomed. Signal Process. Control. 2022;77:103810. doi: 10.1016/j.bspc.2022.103810. [DOI] [Google Scholar]

[15] Elloumi Y., Abroug N., Bedoui M.H. End-to-End Mobile System for Diabetic Retinopathy Screening Based on Lightweight Deep Neural Network. Lect. Notes Comput. Sci. (Incl. Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinform.) 2022;13205 LNCS:66–77. doi: 10.1007/978-3-031-01333-1_6/COVER. [DOI] [Google Scholar]

[16] Kanakaprabha S., Radha D., Santhanalakshmi S. Diabetic Retinopathy Detection Using Deep Learning Models. Int. 2022;302:75–90. doi: 10.1007/978-981-19-2541-2_7. [DOI] [Google Scholar]

[17] Sridhar S., PradeepKandhasamy J., Sinthuja M., Sterlin Minish T.N. Diabetic Retinopathy Detection Using Convolutional Nueral Networks Algorithm. Mater. Today Proc. 2021 doi: 10.1016/j.matpr.2021.01.059. [DOI] [Google Scholar]

[18] Das S., Kharbanda K., Suchetha M., Raman R., Dhas E. Deep Learning Architecture Based on Segmented Fundus Image Features for Classification of Diabetic Retinopathy. Biomed. Signal Process. Control. 2021;68:102600. doi: 10.1016/j.bspc.2021.102600. [DOI] [Google Scholar]

[19] Vives-Boix V., Ruiz-Fernández D. Diabetic Retinopathy Detection through Convolutional Neural Networks with Synaptic Metaplasticity. Comput. Methods Programs Biomed. 2021;206:106094. doi: 10.1016/j.cmpb.2021.106094. [DOI] [PubMed] [Google Scholar]

[20] Luo X., Pu Z., Xu Y., Wong W.K., Su J., Dou X., Ye B., Hu J., Mou L. MVDRNet: Multi-View Diabetic Retinopathy Detection by Combining DCNNs and Attention Mechanisms. Pattern Recognit. 2021;120:108104. doi: 10.1016/j.patcog.2021.108104. [DOI] [Google Scholar]

[21] Adriman R., Muchtar K., Maulina N. Performance Evaluation of Binary Classification of Diabetic Retinopathy through Deep Learning Techniques Using Texture Feature. Procedia Comput. Sci. 2021;179:88–94. doi: 10.1016/j.procs.2020.12.012. [DOI] [Google Scholar]

[22] Fatima, Imran M., Ullah A., Arif M., Noor R. A Unified Technique for Entropy Enhancement Based Diabetic Retinopathy Detection Using Hybrid Neural Network. Comput. Biol. Med. 2022;145:105424. doi: 10.1016/j.compbiomed.2022.105424. [DOI] [PubMed] [Google Scholar]

[23] Ragab M., Aljedaibi W.H., Nahhas A.F., Alzahrani I.R. Computer Aided Diagnosis of Diabetic Retinopathy Grading Using Spiking Neural Network. Comput. Electr. Eng. 2022;101:108014. doi: 10.1016/j.compeleceng.2022.108014. [DOI] [Google Scholar]

[24] Qureshi I., Ma J., Abbas Q. Diabetic retinopathy detection and stage classification in eye fundus images using active deep learning. Multimed Tools Appl. 2021;80:11691–11721. doi: 10.1007/s11042-020-10238-4. [DOI] [Google Scholar]

[25] Kalyani G., Janakiramaiah B., Karuna A., Prasad L.V. Narasimha Diabetic Retinopathy Detection and Classification Using Capsule Networks. Complex Intell. Syst. 2021;2021:1–14. doi: 10.1007/S40747-021-00318-9. [DOI] [Google Scholar]

[26] Gayathri S., Gopi V.P., Palanisamy P. Diabetic Retinopathy Classification Based on Multipath CNN and Machine Learning Classifiers. Phys. Eng. Sci. Med. 2021;44:639–653. doi: 10.1007/s13246-021-01012-3. [DOI] [PubMed] [Google Scholar]

[27] Bodapati J.D., Shaik N.S., Naralasetti V. Composite Deep Neural Network with Gated-Attention Mechanism for Diabetic Retinopathy Severity Classification. J. Ambient Intell. Humaniz. Comput. 2021;12:9825–9839. doi: 10.1007/s12652-020-02727-z. [DOI] [Google Scholar]

[28] Math L., Fatima R. Adaptive Machine Learning Classification for Diabetic Retinopathy. Multimed. Tools Appl. 2021;80:5173–5186. doi: 10.1007/s11042-020-09793-7. [DOI] [Google Scholar]

[29] Gao Z., Jin K., Yan Y., Liu X., Shi Y., Ge Y., Pan X., Lu Y., Wu J., Wang Y., et al. End-to-End Diabetic Retinopathy Grading Based on Fundus Fluorescein Angiography Images Using Deep Learning. Graefe's Arch. Clin. Exp. Ophthalmol. 2022;260:1663–1673. doi: 10.1007/s00417-021-05503-7. [DOI] [PubMed] [Google Scholar]
[30] Kobat S.G., Baygin N., Yusufoglu E., Baygin M., Barua P.D., Dogan S., Yaman O., Celiker U., Yildirim H., Tan R.S., et al. Automated Diabetic Retinopathy Detection Using Horizontal and Vertical Patch Division-Based Pre-Trained DenseNET with Digital Fundus Images. Diagnostics. 2022;12:1975. doi: 10.3390/diagnostics12081975. [DOI] [PMC free article] [PubMed] [Google Scholar]
[31] Latif G. DeepTumor: Framework for Brain MR Image Classification, Segmentation and Tumor Detection. Diagnostics. 2022;12:2888. doi: 10.3390/diagnostics12112888. [DOI] [PMC free article] [PubMed] [Google Scholar]
[32] Butt M.M., Iskandar D.N.F.A., Abdelhamid S.E., Latif G., Alghazo R. Diabetic Retinopathy Detection from Fundus Images of the Eye Using Hybrid Deep Learning Features. Diagnostics. 2022;12:1607. doi: 10.3390/diagnostics12071607. [DOI] [PMC free article] [PubMed] [Google Scholar]
[33] Naseer I., Masood T., Akram S., Jaffar A., Rashid M., Iqbal M.A. Lung Cancer Detection Using Modified AlexNet Architecture and Support Vector Machine. Comput. Mater. Contin. 2023;74:2039–2054.
[34] Shaimaa H.Mohammad, Israa Z. Chyad Alrikabi, Hayder Rahm Dakheel al- fayyadh, "Number Plate Recognition System Based on an Improved Segmentation Method", International Journal of Computational and Electronic Aspects in Engineering, RAME Publishers, vol. 6, issue 1, pp. 42-50, 2025. https://doi.org/10.26706/ijceae.6.1.20250207 .
[35] Serri Ismael Hamad, "Utilizing Convolutional Neural Networks for the Identification of Lung Cancer", International Journal of Computational and Electronic Aspects in Engineering, RAME Publishers, vol. 6, issue 1, pp. 35-41,2025. https://doi.org/10.26706/ijceae.6.1.20250206 .
[36] Hiyam Hatem, "improved deep learning models for plants diseases detection for smart farming", international journal of computational and electronic aspects in engineering,rame publishers, vol. 6, issue 1,pp. 10-21, 2025. https://doi.org/10.26706/ijceae.6.1.20250204 .