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RESEARCH ARTICLE

Multi-Class Retinal Diseases Detection Using Deep CNN With Minimal Memory Consumption

ASIF NAWAZ[1], TARIQ ALI[1], GHULAM MUSTAFA[1], MUHAMMAD BABAR[2], (Member, IEEE), AND BASIT QURESHI[3], (Senior Member, IEEE)

[1]University Institute of Information Technology (UIIT), PMAS-Arid Agriculture University, Rawalpindi 46000, Pakistan
[2]Robotics and Internet of Things Laboratory, Prince Sultan University (PSU), Riyadh 11586, Saudi Arabia
[3]College of Computer and Information Sciences, Prince Sultan University (PSU), Riyadh 11586, Saudi Arabia

Corresponding author: Asif Nawaz (asif.nawaz@uaar.edu.pk)

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ABSTRACT Machine Learning (ML) such as Artificial Neural Network (ANN), Deep learning, Recurrent Neural Networks (RNN), Alex Net, and ResNet can be considered as a broad research direction in the identification and classification of critical diseases. CNN and its particular variant, usually named U-Net Segmentation, has made a revolutionary advancement in the classification of medical diseases, specifically retinal diseases. However, because of the feature extraction complexity, U-Net has a significant flaw in high memory and CPU consumption while moving the whole feature map to the corresponding decoder. Furthermore, it can be concatenated to the unsampled decoder feature map avoids reusing pooling indices. In this research work, a convolutional neural network (CNN) model is proposed for multi-class classification problems with the efficient use of memory consumption. The proposed model has been evaluated on a standard benchmark dataset of Eye Net, having 32 classes of retinal diseases. From experimental evaluation, it has been concluded that the proposed model performs better regarding memory management and accuracy. The overall comparison has been performed based on precision, recall, and accuracy with different numbers of epochs and time consumption by each step. The proposed technique achieved an accuracy of 95% on the Eye-net dataset.

INDEX TERMS Classification, CNN, deep learning, EyeNet, retina, U-Net.

I. INTRODUCTION

Retinal diseases are spreading widely among humans of all ages. The retina contains a layer of optic nerve tissue called photosensitive in the human eye. This layer transforms the light focused by the lens into brain impulses. Macula, positioned in the retina's middle, performs the sensing process. Information acquired by the macula is processed by the retina and transferred to the brain for visual recognition through the optic nerve [1]. Different types of diseases can cause abnormality in perception, such as age-related macular degeneration (AMD), optic disc drusen, Rothspot diabetic macular edema (DME) [2], etc. In most of the developed countries, people belonging to the age group of 50 to 60 are losing vision due to AMD. According to recent research, in the United States (US), this abnormality is found in about 35% of adults in the age group of 80 [3]. Identifying retinal diseases is the most challenging task, as accurate diagnosis needs a highly experienced ophthalmologist due to the diversity of retinal diseases. Similarly, with computer-aided diagnostic systems (CAD), retinal diseases can easily be identified and treated at early stages [4].

Technology advancements have immense benefits in almost every field of life, especially in the medical domain. Several approaches and models have been presented to improve the efficacy and quality of medical solutions. A significant improvement has been observed in the social health system with the advancement in Automatic Disease Detection (ADD) [5]. Furthermore, an ADD application, namely retinal symptom analysis, provides a unique opportunity to improve

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eye care globally [6]. Recently, many state-of-the-art ML and Deep Learning (DL) models have been proposed for the classification, segmentation, and identification of retinal diseases. We observe that data collection and labeling are significant challenges in the implementation of ADDs, as presented by authors in [7] and [8], due to the development of several machine learning (ML) and deep learning (DL) models, including Recurrent Neural Network (RNN), Convolution Neural Network (CNN), Alex Net ResNet and VGN. These have enabled researchers and physicians to detect and categorize such vital disorders [9] readily. An ML-based Hybrid technique is presented for the classification of retinal diseases automatically. Researchers in [10] have proposed to use U-Net segmentation for image pre-processing; they have also used a Support Vector Machine (SVM) classifier for the classification. The proposed technique achieved a diagnostic accuracy of 89.3%. Yang et al. also provided the first labeled EyeNet dataset containing 32 retinal diseases. It was noted by authors in [10] that the U-Net has a significant flaw of high memory consumption in moving the whole feature map to the corresponding decoder. Deep learning plays a vitol role in the classification of images [11], [12], [13].

This research proposes a CNN model based on deep learning for classifying multi-class eye disease detection. The proposed model has been evaluated on EyeNet Dataset. The EyeNet dataset includes 32 folders, each containing related images for specific. 70% has been used for training and the rest for validation. From experimental evaluation, it has been observed that the proposed model achieved 95% of accuracy.

The deep learning-based CNN model has been applied for retinal-based crucial diseases to boost the conventional diagnostic method. This is the primary contribution of this study. The key contributions of the paper are as follows.

- A deep learning-based CNN model has been utilized to strengthen the traditional diagnosis process for retinal-based crucial disease.
- The proposed CNN model produces better outcomes while consuming low memory than standard state-of-art techniques.
- Experimental evaluation reveals that the performance of the proposed model on the multi-class EyeNet dataset produces higher accuracy.

The remainder of the paper is structured as follows: Section II presents the related works. In Section III, we offer the proposed architecture along with a detailed description of the dataset used. Section IV details the result of the experimental evaluation, including the performance of the given CNN model. Section V contains the analysis and the discussion. Finally, section VI concludes the research work with future directions.

II. LITERATURE REVIEW

In the current era, DL and ML models are widely used in image processing and classification. Similarly, many models have been introduced to include optical coherence tomography (OCT) for the classification of retinal diseases. Authors [14] proposed the OCT-NET model, which uses a Deep learning approach to classify diabetic-based retinal diseases. The model was evaluated on two public datasets incorporating classes, A2A SD-OCT and SERI-CUHK. Their proposed model can classify these mentioned diseases with significant accuracy. In [15], Mahendran et al. used machine learning algorithms to analyze retinal diseases. The proposed methodology uses a decision tree classifier to classify images as normal or disease-affected images. Bilateral filtering methods are used to reduce the noise in the dataset images. Next, Otsu's segmentation was used for the segmentation of the macula region, and then regional structures were forwarded to the classifier that, results in 92% accuracy.

Authors in [16] compare four algorithms for machine learning (SVM, KNN, C5.0 and random forest) for glaucoma prediction [16]. Maximum entropy transformation on retinal fundus pictures from an online dataset was used to identify age-related eye disorders early [17]. A flower pollination optimization-configured convolution neural network (CNN) extracted information from processed photos (FPOA). FPOA adjusted CNN training hyperparameters. The network's efficiency and accuracy improved. Four pre-trained CNN algorithms diagnose seven retinal defects in pictures with and without illnesses [18]. Bayesian optimization selects suitable hyperparameter values, and image augmentation improves model applicability. This study evaluates the suggested models. DenseNet201's classification accuracy on the Retinal OCT Imaging dataset is 99.9%, compared to prior methods that can only identify a few retinal diseases. The authors build a multiclass model-based DED classification system [19]. Multiple Diabetic Eye Disease (DED) diagnoses using retinal fundus pictures are essential clinical research. Ophthalmologist-annotated retinal fundus photographs were assessed.

A segmentation approach employing the ensemble classifier for subsequent classification is presented for identifying and categorizing Oppositional defiant disorder (ODD) illnesses. The classification between normal and abnormal blood vessels is observed with an accuracy of 81% [24]. The transfer learning technique is used to reduce training time and resource consumption. A fine-tuned version of VGG-19 is proposed for feature extraction and classification of a retinal database in [25]. A CNN based fine-tuned Inception-Resnet-v2 model is proposed that is implemented on publicly available data called SERI [26] with 100% classification accuracy. A CNN-based ResNet model for the classification of diabetic retinopathy (DR) severity level has been presented by Zhang et al. Image cropping techniques such as oversampling and cost-sensitive learning with the aid of the Kaggle dataset are used to handle the issue of imbalance classes. By introducing extra layers, the increased regularization in training and accuracy achieves datside-outputis81% [27].

According to the published literature, it is found that the maximum state-of-the-art models are implemented and evaluated for the datasets having 2 or

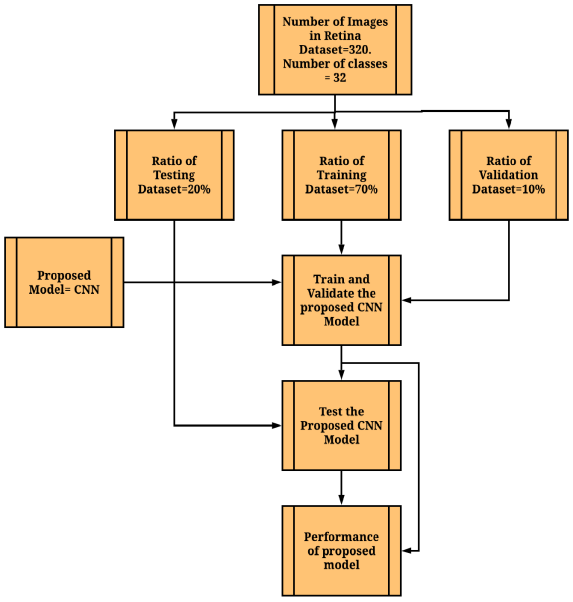

FIGURE 1. Workflow diagram of the proposed model.

4 classes [20], [21], [22], [23]. Moreover, only two of these are implemented for a dataset having 15 classes and 32 classes [19], providing very low accuracy of 80.93% and 89.3%, respectively. Most of these focused on preprocessing techniques such as segmentation and transfer learning. Many of them these work with pre-trained CNN weights and pre-processed images instead of taking raw images without any preprocessing. However, all the models presented achieved high recognition rates greater than 85%.

CNN and its derivative, sometimes called U-Net Segmentation, have achieved a breakthrough leap in categorizing medical disorders, particularly retinal diseases. Due to the intricacy of feature extraction, U-Net has a main memory and CPU usage fault when transporting the whole feature map to the associated decoder. In addition, concatenating it with the unsampled decoder feature map prevents the reuse of pooling indices. In this study, a convolutional neural network (CNN) model with optimal memory consumption is developed for multi-class classification problems.

III. METHODOLGY

This section also discusses the dataset used and the proposed CNN architecture. In Figure 1, the proposed methodology has been demonstrated stepwise.

A. DATASET

The EyeNet dataset provided by Yang et al. [10] has been used. They offered a labeled collection of 32 sorts of clinical data. Historically, most model implementations were performed using STARE or Drive datasets, as these datasets are identified with four or two classes at most. On the other hand, Table 1 Eye-Net dataset with 32 retinal disease types is used. The whole model implementation is performed on this dataset. The photos inside the following dataset are categorized with the appropriate labels. The dataset was extracted from the source on GitHub [30].

TABLE 1. Dataset description.

Dataset	Class Label
Eye-net	Adult Coats' Disease
	AdultFoveomacularDystrophy
	Age- Related Macular Degeneration
	AMNMacularNeuroretinopathy
	Antiphospholipid Antibody Syndrome
	Behcet's disease
	Bilateral Macular Dystrophy
	Bull's Eye Maculopathy Chloroquine
	Central Serous Chori- oretinopathy
	Choroidal Nevus
	CMV Chorioretinitis
	Cone -Rod Dystrophy
	Congenital Syphillis
	Diabetic Maculopathy Multiple Myeloma with Retinal Detachment
	Giant Retinal Tear
	North Carolina Dystrophy
	Leber's Stel- late Maculopathy
	Multifocal Exudative Detachments
	Macular Dystrophy
	Myelinated Nerve Fibers
	Juxtafoveal Telangiectasis DM Diabetes
	Optic Disc Drusen
	Roth Spot disease
	Pattern Dystrophy Simulating Fundus Flavimaculatus
	Retinal Folds Following Retinal Reattachment Surgery
	Reticular Pattern Dystro- phy
	Retro hyaloid Hemorrhage
	Solar Retinopathy Familial
	Susac's Syn- drome
	Self-Applied Retinal Detachment
	Terson's Syndrome
	Wyburn-Mason Syndrome

B. PROPOSED MODEL

Deep learning is the most widespread technology in the present day. Many processing layers inside the framework of DL enable the computational models to learn data patterns with multiple levels of abstraction. These models primarily identify voice, objects, visual objects, and several other discovery domains. DL technology is inspired by the deep structure of the human brain [31]. CNN is the most potent and effective DL model [32]. Although researchers have expanded its applicability to other disciplines, CNN is primarily used in the medical industry [33]. A method for developing a DL-based model for retinal illness categorization in which the DL model sequentially processes retinal pictures. At first, the low-level features are extracted then the middle and high-level refined features are extracted for classification. These final extracted features are passed to the trainable classifier for classification.

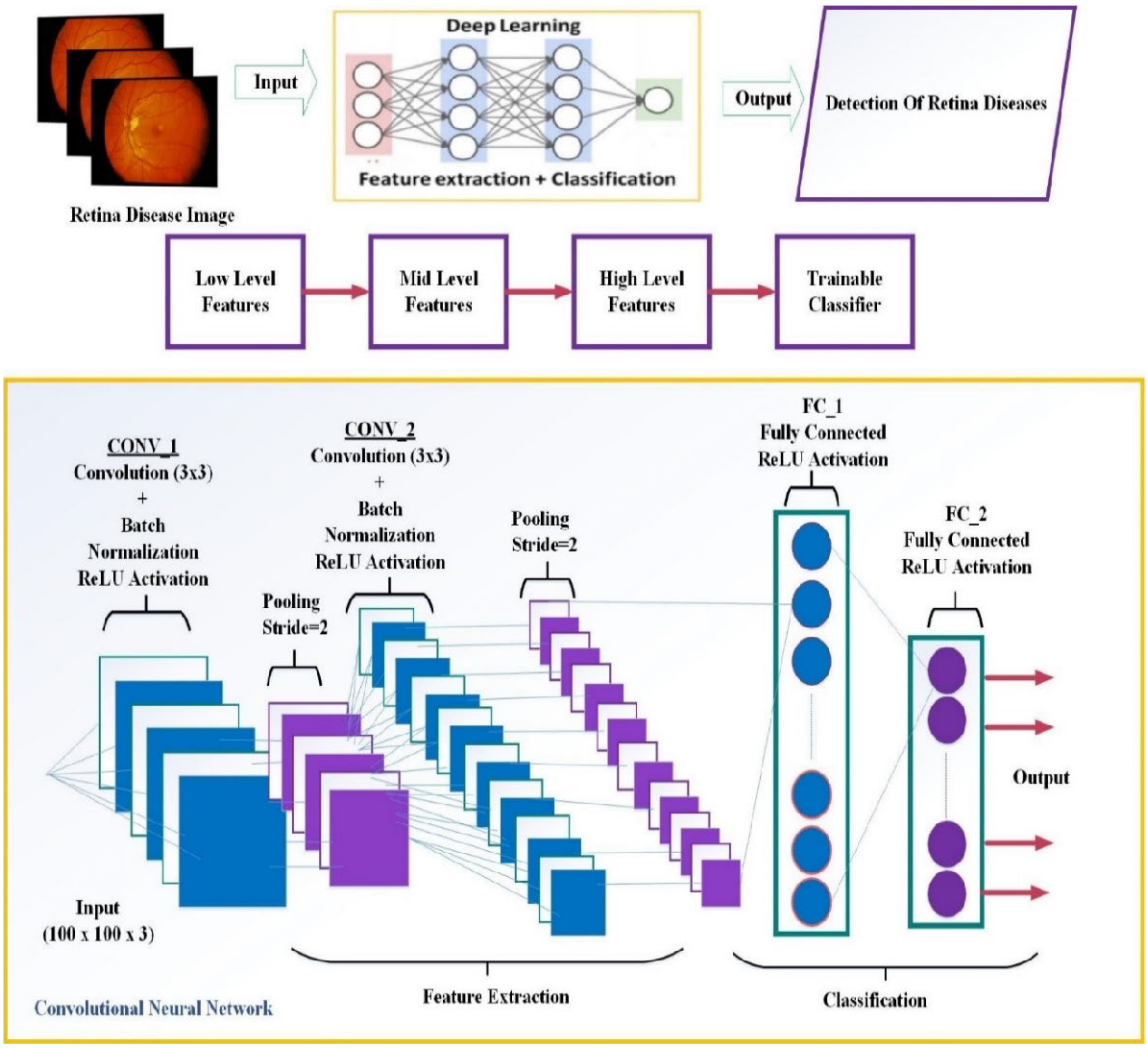

FIGURE 2. The proposed model architecture.

1) CONVOLUTIONAL NEURAL NETWORK MODEL

CNN contains hidden layers; these layers perform convolution, a sub-sampling technique to extract features of data from a low level to a high level. In the proposed model, ten convolution layers are used. In Figure 2, the arrangement of layers is shown. On the abstract, retina images are input to the CNN model, which gives label prediction for the normal or affected eyes. The presented model minimized the number of layers compared to the traditional models. Models such as AlexNet are implemented with 25 layers, Densnet201 with 201 layers, Inception3 with 48 layers, and ResNet-10 with 101 layers. In addition, these pre-trained networks are usually implemented with transfer learning techniques in the medical field for classification. A network with fewer layers is presented so the training time can be reduced. Batch normalization layers are used so that higher learning rates can be achieved and used, which improves the training speed. Detailed information about the proposed CNN model is given in Table 2.

The graphical illustration of the model is given in Figure 2. In the proposed model, feature extraction is done in three steps. The first level includes low-level features of images, and then these extracted features are passed to the mid-level for further refinement. The high level consists of the detailed features which basically involved in the training process and then used for classification.

C. DATA AUGMENTATION

Data augmentation technique is used for enough data to be available for the training. Data augmentation is also used to avoid overfitting. The parameters we have used in augmentation are rescaling, zooming, and flipping [28], [29]. We augmented data using various random transformations so the model could not face the same image again. This technique helps the model from overfitting as well as better generalization. In Keras, augmentation is done by ImageData Generator. Data augmentation in our proposed model

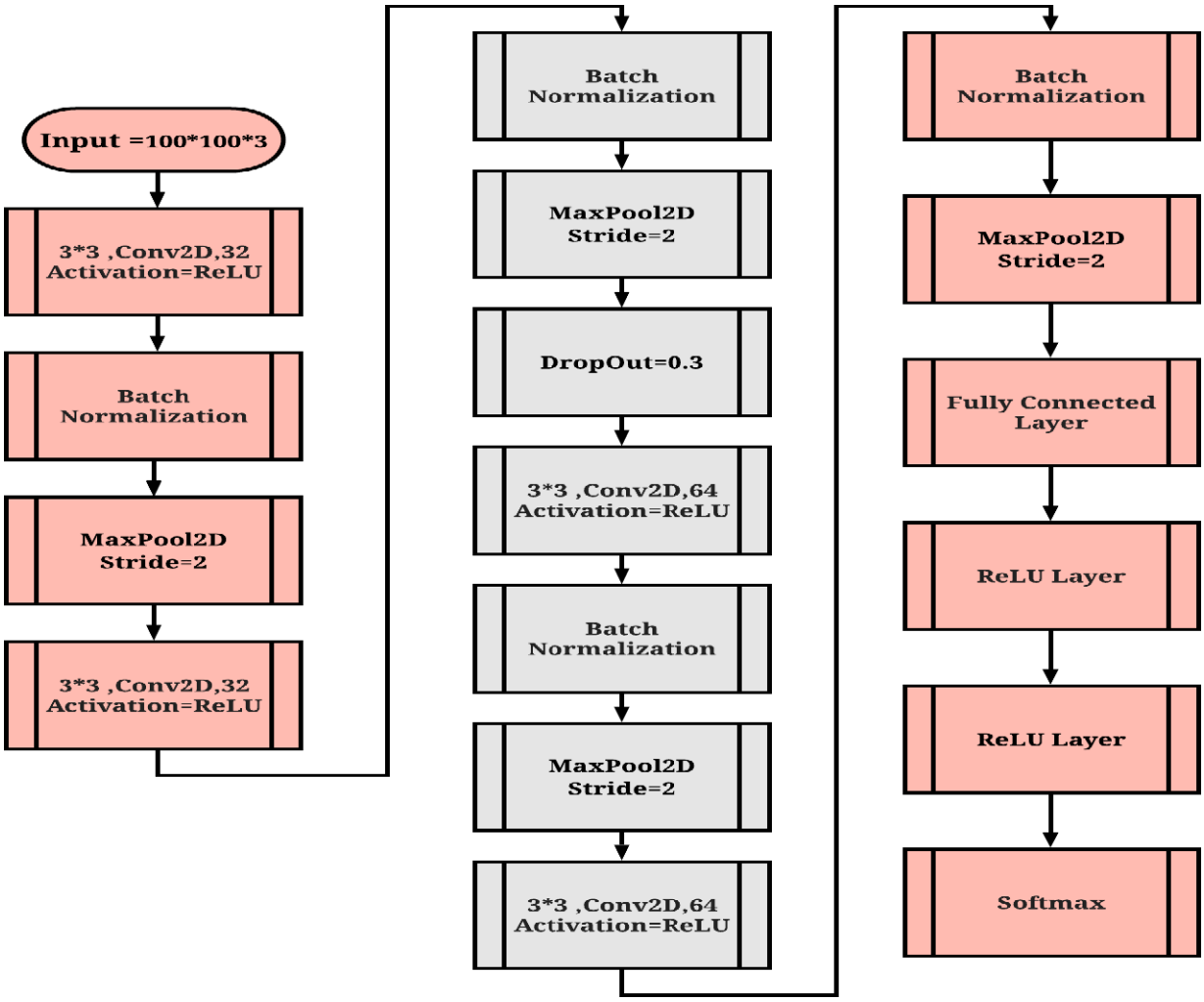

FIGURE 3. CNN model.

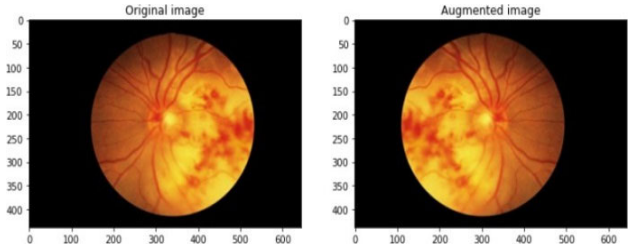

FIGURE 4. Saturated.

includes six basic steps. Each step transforms the image to the new level.

In Figure 3, data augmentation steps saturation has been shown. Data augmentation is beneficial for enhancing the performance and results of machine learning models by adding additional and distinct training samples. If the dataset used in a machine learning model is extensive and comprehensive, the model will perform better and more precisely. The original image is saturated, which increases the opacity of the image. This also enhances the visibility of the essential features to diagnose the disease better. Figure 4 depicts another augmentation in which the original image is converted into a grayscale image. The grayscale technique changes the colors of the original image into grayed contrast. In Figure 5, the original image is flipped. In this technique, the direction of the original image is changed. Figure 6 depicts the brightening step of the augmentation technique. Figure 7 displays the zoom step. The selection of augmentation steps or processes may vary in every research.

D. ADAPTIVE MOMENT ESTIMATION

The optimization algorithms, based on stochastic gradient, have a significant impact and usage in science and engineering-related fields [35]. Adaptive moment estimation, also called Adam, is one of the optimization algorithms [35]. The Adam optimization technique is a stochastic gradient descent predicated on the adaptive estimate of first- and second-order moments. The approach is easy to develop, has low memory needs, is computationally efficient, is invariant

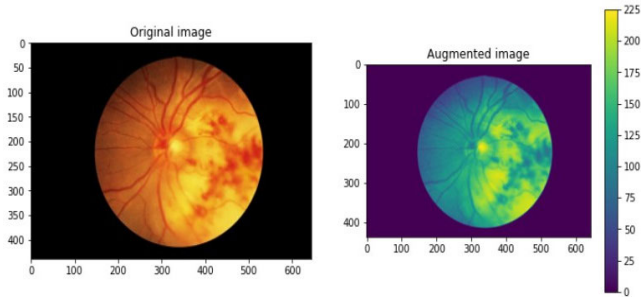

FIGURE 5. Gray scaled.

TABLE 2. CNN layers distributions.

Layer	Type	Number of Layers	Size/ Information	Activation	Stride
0	Input	01	100 x 100	---	
1	Convolution 2D	10	Output Channel 32	ReLU	
2	Batch Normalization	07	---	---	---
3	Max Pooling	08	---	---	02
4	Convolution 2D	--	Output channel 64	ReLU	
5	Batch Normalization	--	----		
6	Max Pooling	--	----		02
7	Flattening	--	---	---	
8	Fully Connected/Dense	--	1024 nodes	ReLU	
9	Dense	--	32 as per Classes	SoftMax	

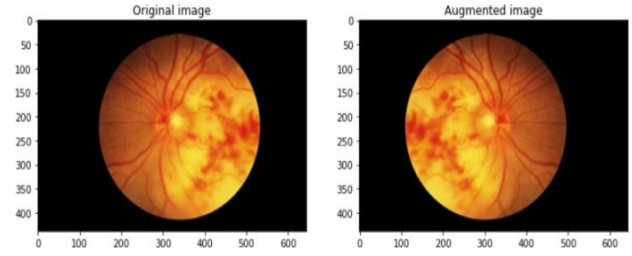

FIGURE 6. Flipped.

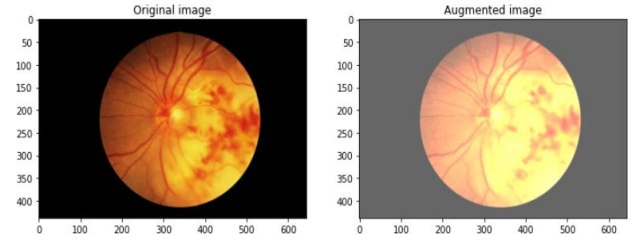

FIGURE 7. Brighten.

to diagonal re-scaling of the gradients, and is a good fit for applications that involve a significant amount of data or parameters. The approach is also suitable for use with

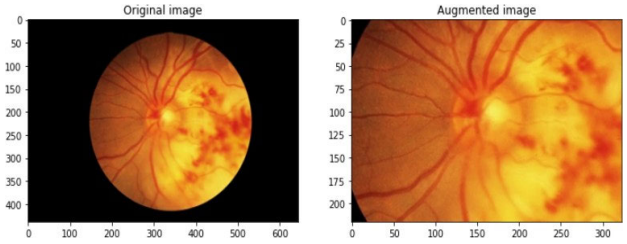

FIGURE 8. Zoom.

non-stationary goals and issues that include highly noisy or sparse gradients. The hyper-parameters may be interpreted straightforwardly and usually require very little fine-tuning [35]. It can be used to update the network weights iteratively based on training data instead of the classical stochastic gradient descent procedure. It is specifically designed to work with complex optimization problems. In this research, Adam is used because of its low memory consumption and efficiency in computation. The implementation of Adam is done by using built-in Kara's library.

IV. PERFORMACE EVALUATION

To determine how well the suggested model performs, the output of the categorization model has been contrasted with the labels that correspond to it. The labeling of images is done by the ophthalmologist [11]. We evaluate the model on the bases of these labels. In Figure 9, the confusion matrix is plotted to analyze the performance of CNN. Figure 10 depicts the results of the classification report generated by implementing the proposed model. The precision is also known as a positive predictive value, and recall is a true positive rate or actual values (presented in equation 1 and equation 2)

$$precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

The dataset contains 32 retinal diseases; therefore, the performance measures are computed against each class. All the classes are classified correctly with 100% precision and 99% recall. The class AMN has 91% precision and 100% recall. On the other hand, the minimum precision in the classification report is 77% of the class Adult Fovemacular Dystrophy Appearance. Similarly, the class RH has a minimum recall value of 70% of results analyzed at 10 and 15 epochs. In both cases model performed outclass.

V. RESULTS AND DISCUSSIONS

The dataset is divided into two subsets such as training and validation. The implementation is done in python by using Keras. The implementation is executed on Intel(R) Core (TM) i5-7200CPU at 2.70GHz. The Google GPU is used for the training. We tested the model with different optimizers; among them, Adam gave the best results. The learning rate used for the optimizer is 0.001. All the other hyperparameters

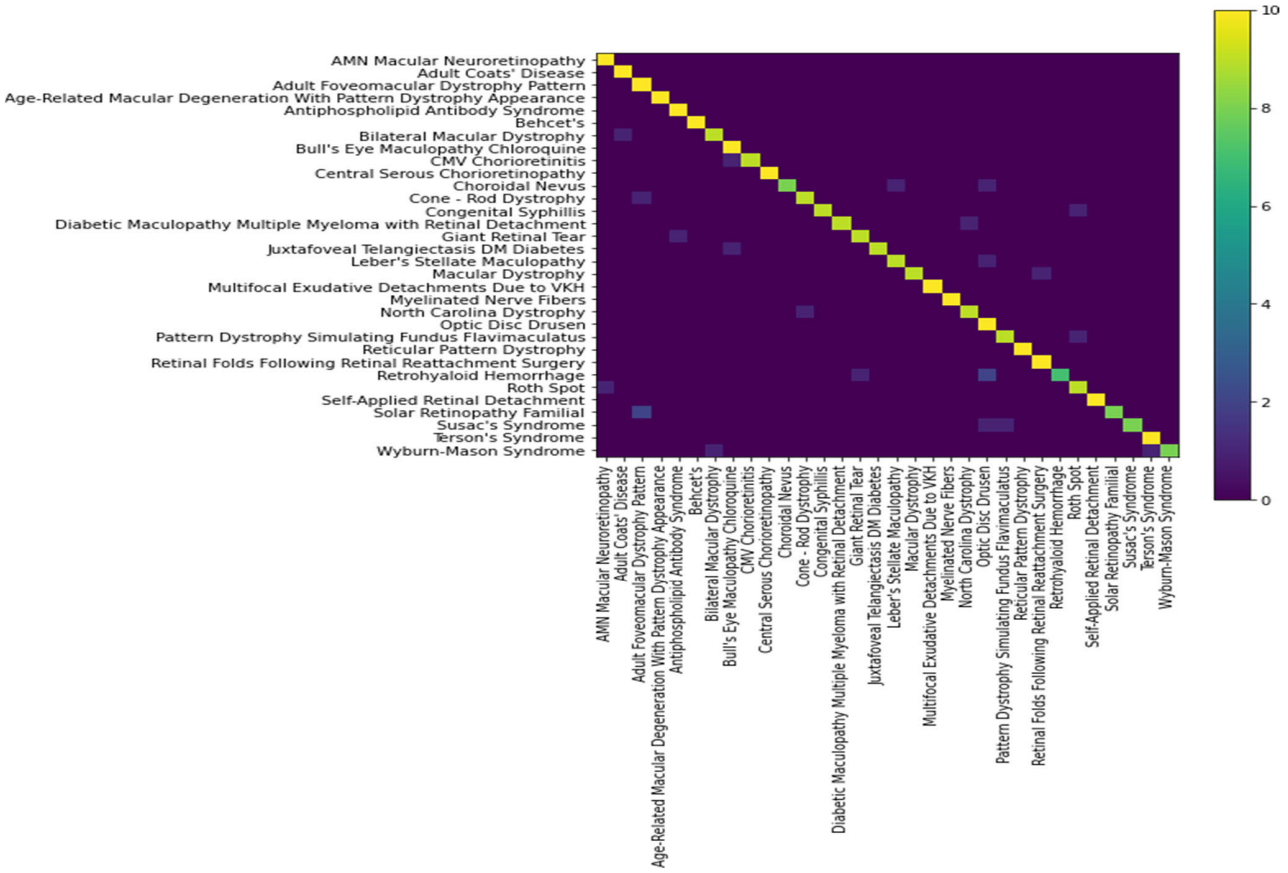

FIGURE 9. Confusion matrix.

	precision	recall
AMN Macular Neuroretinopathy	0.91	1.00
Adult Coats' Disease	0.91	1.00
Adult Foveomacular Dystrophy Pattern	0.77	1.00
Age-Related Macular Degeneration With Pattern Dystrophy Appearance	1.00	1.00
Antiphospholipid Antibody Syndrome	0.91	1.00
Behcet's	1.00	1.00
Bilateral Macular Dystrophy	0.90	0.90
Bull's Eye Maculopathy Chloroquine	0.83	1.00
CMV Chorioretinitis	1.00	0.90
Central Serous Chorioretinopathy	1.00	1.00
Choroidal Nevus	1.00	0.80
Cone - Rod Dystrophy	0.90	0.90
Congenital Syphillis	1.00	0.90
Diabetic Maculopathy Multiple Myeloma with Retinal Detachment	1.00	0.90
Giant Retinal Tear	0.90	0.90
Juxtafoveal Telangiectasis DM Diabetes	1.00	0.90
Leber's Stellate Maculopathy	0.90	0.90
Macular Dystrophy	1.00	0.90
Multifocal Exudative Detachments Due to VKH	1.00	1.00
Myelinated Nerve Fibers	1.00	1.00
North Carolina Dystrophy	0.90	0.90
Optic Disc Drusen	0.67	1.00
Pattern Dystrophy Simulating Fundus Flavimaculatus	0.90	0.90
Reticular Pattern Dystrophy	1.00	1.00
Retinal Folds Following Retinal Reattachment Surgery	0.91	1.00
Retrohyaloid Hemorrhage	1.00	0.70
Roth Spot	0.82	0.90
Self-Applied Retinal Detachment	1.00	1.00
Solar Retinopathy Familial	1.00	0.80
Susac's Syndrome	1.00	0.80
Terson's Syndrome	0.91	1.00
Wyburn-Mason Syndrome	1.00	0.80

FIGURE 10. Classification repor.

are selected after complete attestation. The size of the batch is 10. We trained data on different epochs and achieved 95% validation accuracy. At first, we trained the dataset with 10 epochs, and epochs per step are 500 with the validation steps two learning rate of the optimizer is 0.001. The validation accuracy is 0.95, and the validation loss is 0.0279. Then

TABLE 3. Comparison of the proposed model with existing models.

Models	Datasets	Detected classes	Accuracy
OCT-Net [14]	SERI-CUHK +A2A SD-OCT	4	99%
CNN(DL) [19]	STARE	15	80.93%
Neural Network [20]	STARE, DRIVE	1	95.2% 94.5%
SVM [21]	STARE, DRIVE	1	93.5% 94.3%
Fuzzy C-Means clustering [22]	STARE, DRIVE	1	89.7% 89.1%
Multi-scale differential [23]	STARE, DRIVE	1	92.4% 92.2%
U-Net Segmentation1+SVM [10]	Eye-Net	32	89.3%
Proposed Deep learning CNN	Eye-Net	32	95%

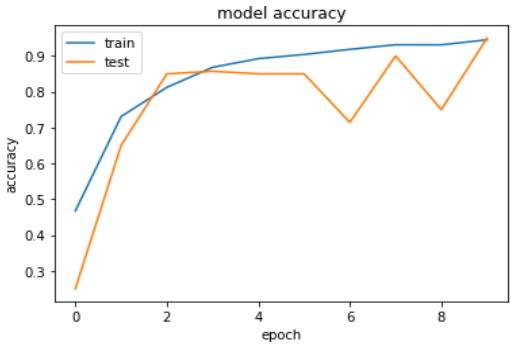

FIGURE 11. Model accuracy by implementing 10 Epochs.

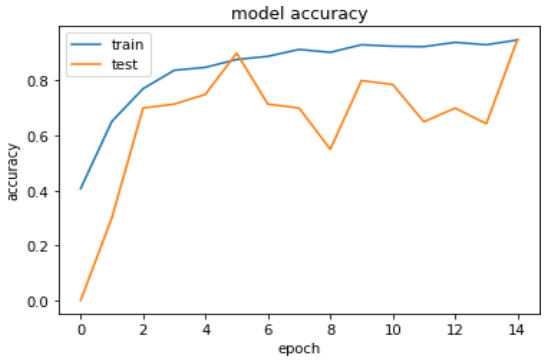

FIGURE 12. Model accuracy at 15 Epochs.

we trained the model with 15 epochs with 400 epochs per step with the same validation steps and optimizer, and again the model validation accuracy is 95%. We also trained the model with different optimizers, but Adam optimizer gave the best results compared to other optimizers.

Figure 11 depicts the model accuracy with 10 epochs. Both training and testing accuracies are compared by executing the model for 10 epochs with 500 per epoch's steps. The start loss is 1.8199, the training accuracy is 0.4673, the validation loss is 2.0881, and the validation accuracy is 0.2500. With

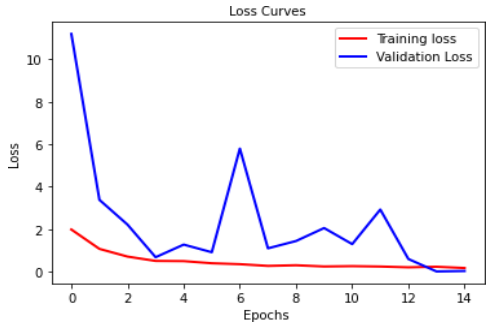

FIGURE 13. Validation and training loss comparison at 15 epochs.

the passage of time, validation accuracy fluctuated in steps 7, 8, and 9. The training accuracy at 7, 8, 9, and 10 is 0.9041, 0.9184, 0.9184, and 0.9450, respectively. Validation accuracy increases with the model's training and reaches 0.9500. In Figure 12, model accuracy has been shown at 15 epochs with 400 validation steps per epoch. The different epochs are executed to analyze the performance and validity of the model entirely. At first, test accuracy is 0.4068, and validation is 0.0000e+0. Then with each step, validation accuracy increased. The fluctuation between the different steps has also been observed from the plotted results. However, the model's overall performance is considerable compared to the traditional models with greater layers. In both cases, at 10 and 15 iterations, 0.9500 accuracy has been archived.

In Figure 13, a Comparison between validation and training losses has been shown. The training loss must be greater than the validation loss. If validation loss is greater, the model is overfilled and must be fixed. To avoid model overfitting, a dropout layer also has been used. If the validation loss and training loss are equal, then it will result in model underfitting. The number of epochs is 15, and the validation per step is 400. Training loss at the first epoch is 1.9829 at 42s 105ms/step time. The model starts learning best weights at each epoch, and at last, at 15 epochs, the Training loss is

FIGURE 14. Time consumption on each step.

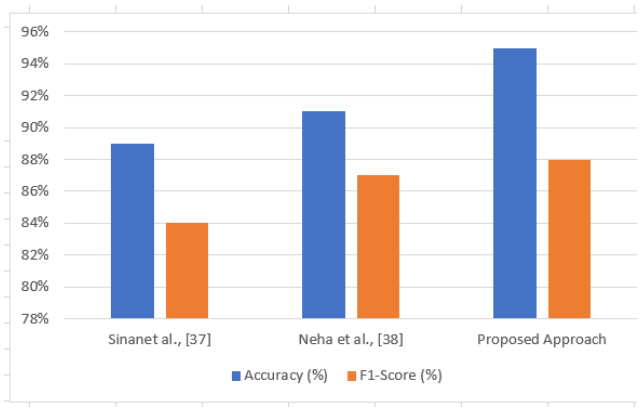

FIGURE 15. Comparisons with state-of-the-art approaches.

0.1670, validation loss is 0.0279 at 40s 99ms/step with the validation accuracy of 0.9500.

Figure 14 illustrates the time consumption in training at 10 epochs with 500 validation per step. At first, the time required to complete the 500 steps is 132s 263ms/step. Then in steps 2, 3, and 4, time decreases, which is 131s 261ms/step, 129s 258ms/step, and 130s 261ms/step, respectively. From the results, time fluctuation has been observed in steps 5 and 6. However, the overall results show that model required less training time than the other state-of-the-art models. The training by implementing U-Net segmentation takes almost 20 hours on a high-standard GPU. On the other hand, local machines cannot complete the training because of hardware limitations (RAM, CPU). Results demonstrate that, the proposed model requires less time and RAM to complete the training with dynamic learning weights.

Table 3 lists the summarized comparison of the proposed CNN model with the existing models in the literature. Most of the existing models work with a smaller number of classes. However, two existing models also work with 15 and 32 classes of datasets. The accuracy of the models with a smaller number of classes is high, whereas the accuracy of existing models with a high number of classes is very low. The most relevant comparison of the proposed model is with U_Net segmentation using an SVM classifier with the same dataset. U_Net has 89.3% accuracy, and the proposed model achieved 95% accuracy on the same dataset. The proposed model for the multiclass problem gained 95% of validation accuracy. Besides accuracy, the proposed model works with low memory consumption as well as work even with limited resources such as hardware limitations.

This experiment compares the results of different models with the proposed work on the common dataset. Such comparisons aim to determine which model or algorithm performs better on a uniform dataset. Since each model uses its own dataset, getting the same dataset for the proposed work is complicated. However, on public request, two different datasets were obtained from the work of Sinanet al. [37] and Neha et al. [38]. Figure 15 shows the comparisons of the proposed model with the stated approaches in terms of Accuracy and F1-score.

VI. CONCLUSION

The classification of the different retinal disorders is addressed by presenting a CNN model based on deep

learning. EyeNet, a dataset containing 32 various retinal diseases, is the basis for the model's implementation. The proposed model is trained on different epochs to test the model's accuracy. Initially, the model was trained at 10 epochs and achieved 95% validation accuracy; then, at 15 epochs model again achieved 95% validation accuracy with 0.0279 validation loss which varies in both cases. The model's total performance is much superior to that of other models considered to be state of the art. There is a possibility that the categorization of retinal diseases might benefit from the model that has been provided. Regular model updates and retraining using new data will continue to enhance its performance in the future. This will be achieved by leveraging the advancements in deep learning techniques and the increasing availability of diverse retinal disease datasets.

CONFLICT OF INTERESTS

Authors have no conflict of interests.

REFERENCES

[1] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, and S. Thrun, "Dermatologist-level classification of skin cancer with deep neural networks," *Nature*, vol. 542, no. 7639, pp. 115–118, Feb. 2017.

[2] K. Shankar, A. R. W. Sait, D. Gupta, S. K. Lakshmanaprabu, A. Khanna, and H. M. Pandey, "Automated detection and classification of fundus diabetic retinopathy images using synergic deep learning model," *Pattern Recognit. Lett.*, vol. 133, pp. 210–216, May 2020.

[3] R. Arunkumar and P. Karthigaikumar, "Multi-retinal disease classification by reduced deep learning features," *Neural Comput. Appl.*, vol. 28, no. 2, pp. 329–334, Feb. 2017.

[4] T. Shanthi and R. S. Sabeenian, "Modified Alexnet architecture for classification of diabetic retinopathy images," *Comput. Electr. Eng.*, vol. 76, pp. 56–64, Jun. 2019.

[5] S. Farsiu, S. J. Chiu, R. V. O'Connell, F. A. Folgar, E. Yuan, J. A. Izatt, and C. A. Toth, "Quantitative classification of eyes with and without intermediate age-related macular degeneration using optical coherence tomography," *Ophthalmology*, vol. 121, no. 1, pp. 162–172, Jan. 2014.

[6] R. F. Mullins, S. R. Russell, D. H. Anderson, and G. S. Hageman, "Drusen associated with aging and age-related macular degeneration contain proteins common to extracellular deposits associated with atherosclerosis, elastosis, amyloidosis, and dense deposit disease," *FASEB J.*, vol. 14, no. 7, pp. 835–846, May 2000.

[7] Y. Kanagasingam, A. Bhuiyan, M. D. Abràmoff, R. T. Smith, L. Goldschmidt, and T. Y. Wong, "Progress on retinal image analysis for age related macular degeneration," *Prog. Retinal Eye Res.*, vol. 38, pp. 20–42, Jan. 2014.

[8] D. S. Kermany, "Identifying medical diagnoses and treatable diseases by image-based deep learning," *Cell*, vol. 172, no. 5, pp. 1122–1131, Feb. 2018.

[9] M. M. M. S. Fathy and M. T. Mahmoudi, "A classified and comparative study of edge detection algorithms," in *Proc. Int. Conf. Inf. Technol., Coding Comput.*, Apr. 2002, pp. 117–120.

[10] C.-H. H. Yang, J.-H. Huang, F. Liu, F.-Y. Chiu, M. Gao, W. Lyu, M. D. I.-H. Lin, and J. Tegner, "A novel hybrid machine learning model for auto-classification of retinal diseases," 2018, *arXiv:1806.06423*.

[11] M. B. Jabra, A. Koubaa, B. Benjdira, A. Ammar, and H. Hamam, "COVID-19 diagnosis in chest X-rays using deep learning and majority voting," *Appl. Sci.*, vol. 11, no. 6, p. 2884, Mar. 2021.

[12] S. Guefrechi, M. B. Jabra, A. Ammar, A. Koubaa, and H. Hamam, "'Deep learning based detection of COVID-19 from chest X-ray images," *Multimedia Tools Appl.*, vol. 80, no. 2021, pp. 31803–31820.

[13] W. Boulila, A. Ammar, B. Benjdira, and A. Koubaa, "Securing the classification of COVID-19 in chest X-ray images: A privacy-preserving deep learning approach," in *Proc. 2nd Int. Conf. Smart Syst. Emerg. Technol. (SMARTTECH)*, May 2022, pp. 220–225.

[14] O. Perdomo, H. Rios, F. J. Rodríguez, S. Otálora, F. Meriaudeau, H. Müller, and F. A. González, "Classification of diabetes-related retinal diseases using a deep learning approach in optical coherence tomography," *Comput. Methods Programs Biomed.*, vol. 178, pp. 181–189, Sep. 2019.

[15] G. Mahendran, M. Periyasamy, S. Murugeswari, and N. K. Devi, "Analysis on retinal diseases using machine learning algorithms," *Mater. Today, Proc.*, vol. 33, pp. 3102–3107, Jan. 2020.

[16] S. J. Kim, K. J. Cho, and S. Oh, "Development of machine learning models for diagnosis of glaucoma," *PLoS ONE*, vol. 12, no. 5, May 2017, Art. no. e0177726.

[17] P. G. Subin and P. Muthukannan, "Optimized convolution neural network based multiple eye disease detection," *Comput. Biol. Med.*, vol. 146, Jul. 2022, Art. no. 105648.

[18] M. Subramanian, M. S. Kumar, V. E. Sathishkumar, J. Prabhu, A. Karthick, S. S. Ganesh, and M. A. Meem, "Diagnosis of retinal diseases based on Bayesian optimization deep learning network using optical coherence tomography images," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–15, Apr. 2022.

[19] R. Sarki, K. Ahmed, H. Wang, Y. Zhang, and K. Wang, "Convolutional neural network for multi-class classification of diabetic eye disease," *EAI Endorsed Trans. Scalable Inf. Syst.*, vol. 9, no. 4, p. e5, 2022.

[20] D. Marín, A. Aquino, M. E. Gegundez-Arias, and J. M. Bravo, "A new supervised method for blood vessel segmentation in retinal images by using gray-level and moment invariants-based features," *IEEE Trans. Med. Imag.*, vol. 30, no. 1, pp. 146–158, Jan. 2011.

[21] X. You, Q. Peng, Y. Yuan, Y.-M. Cheung, and J. Lei, "Segmentation of retinal blood vessels using the radial projection and semi-supervised approach," *Pattern Recognit.*, vol. 44, nos. 10–11, pp. 2314–2324, Oct. 2011.

[22] G. B. Kande, P. V. Subbaiah, and T. S. Savithri, "Unsupervised fuzzy based vessel segmentation in pathological digital fundus images," *J. Med. Syst.*, vol. 34, no. 5, pp. 849–858, Oct. 2010.

[23] M. A. Palomera-Perez, M. E. Martinez-Perez, H. Benitez-Perez, and J. L. Ortega-Arjona, "Parallel multiscale feature extraction and region growing: Application in retinal blood vessel detection," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 500–506, Mar. 2010.

[24] P. Gowsalya and S. Vasanthi, "Segmentation and classification of features in retinal images," in *Proc. Int. Conf. Commun. Signal Process.*, Apr. 2014, pp. 1869–1873.

[25] A. Das, R. Giri, G. Chourasia, and A. A. Bala, "Classification of retinal diseases using transfer learning approach," in *Proc. Int. Conf. Commun. Electron. Syst. (ICCES)*, Jul. 2019, pp. 2080–2084.

[26] R. M. Kamble, G. C. Y. Chan, O. Perdomo, M. Kokare, F. A. González, H. Müller, and F. Mériaudeau, "Automated diabetic macular edema (DME) analysis using fine tuning with Inception-Resnet-v2 on OCT images," in *Proc. IEEE-EMBS Conf. Biomed. Eng. Sci. (IECBES)*, Dec. 2018, pp. 442–446.

[27] D. Zhang, W. Bu, and X. Wu, "Diabetic retinopathy classification using deeply supervised ResNet," in *Proc. IEEE SmartWorld, Ubiquitous Intell. Comput., Adv. Trusted Comput., Scalable Comput. Commun., Cloud Big Data Comput., Internet People Smart City Innov. (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI)*, Aug. 2017, pp. 1–6.

[28] L. Perez and J. Wang, "The effectiveness of data augmentation in image classification using deep learning," 2017, *arXiv:1712.04621*.

[29] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *J. Big Data*, vol. 6, no. 1, p. 60, Dec. 2019.

[30] Accessed: Mar. 2, 2022. [Online]. Available: https://github.com/huckiyang/EyeNet

[31] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, Jul. 2006.

[32] J. Gu, "Recent advances in convolutional neural networks," *Pattern Recognit.*, vol. 77, pp. 354–377, May 2018.

[33] M. Bakator and D. Radosav, "Deep learning and medical diagnosis: A review of literature," *Multimodal Technol. Interact.*, vol. 2, no. 3, p. 47, Aug. 2018.

[34] F. Gao, Z. Yue, J. Wang, J. Sun, E. Yang, and H. Zhou, "A novel active semisupervised convolutional neural network algorithm for SAR image recognition," *Comput. Intell. Neurosci.*, vol. 2017, pp. 1–8, Oct. 2017.

[35] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2014, *arXiv:1412.6980*.

[36] L. Terry, "An in vivo investigation of choroidal vasculature in age-related macular degeneration," Ph.D. dissertation, School Optometry Vis. Sci., Cardiff Univ., Cardiff, Wales, 2017.

[37] S. S. M. Sheet, T.-S. Tan, M. A. As'ari, W. H. W. Hitam, and J. S. Y. Sia, "Retinal disease identification using upgraded CLAHE filter and transfer convolution neural network," *ICT Exp.*, vol. 8, no. 1, pp. 142–150, Mar. 2022.
[38] N. Sengar, R. C. Joshi, M. K. Dutta, and R. Burget, "EyeDeep-Net: A multi-class diagnosis of retinal diseases using deep neural network," *Neural Comput. Appl.*, vol. 35, pp. 10551–10571, Jan. 2023.

ASIF NAWAZ received the Ph.D. degree from International Islamic University Islamabad, in 2019. He is currently an Assistant Professor with UIIT, PMAS Arid Agriculture University, Rawalpindi. He is also a potential researcher in the field of data mining, machine learning, social media analysis, and text mining. He has published more than 30 research articles in well reputed international journals.

TARIQ ALI received the master's degree in computer science from Muhammad Ali Jinnah University, Islamabad, Pakistan, in 2009, and the Ph.D. degree in computer science from Abasyn University, Islamabad, in 2019. He is currently an Assistant Professor with UIIT, PMAS Arid Agriculture University. His research interests include document classification, multi label classification, machine learning, and deep learning.

GHULAM MUSTAFA received the Ph.D. degree in computer science from PMAS Arid Agriculture University, Rawalpindi. He is currently an Assistant Professor with UIIT, PMAS Arid Agriculture University, Rawalpindi. His research interests include data mining and knowledge discovery.

MUHAMMAD BABAR (Member, IEEE) received the Master of Science and Ph.D. degrees in computer software engineering from the National University of Sciences and Technology (NUST), Islamabad, Pakistan, in 2018. He is currently with Prince Sultan University (PSU), Saudi Arabia. His research interests include but is not limited to big data analytics, machine learning, the Internet of Things (IoT), smart city design and planning, security, and the Social Web of Things (SWOT). He has published his research work in various IEEE, Elsevier, and Springer journals.

BASIT QURESHI (Senior Member, IEEE) received the bachelor's degree in computer science from Ohio University, Athens, OH, USA, in 2000, the master's degree in computer science from Florida Atlantic University, in 2002, and the Ph.D. degree in computer science from the University of Bradford, U.K., in 2011. He is currently an Associate Professor and the Chair of the Department of Computer Science, Prince Sultan University, Saudi Arabia. He has published over 60 research works in the area of robotics, the Internet of Things, machine learning, and computational intelligence. He is a member of the IEEE Computer Society, the IEEE Communications Society, and the ACM.