Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.776896

COMBINATION OF PREDICTIONS FROM TRANSFER LEARNING MODELS FOR IMPROVED DIABETIC RETINOPATHY DETECTION IN RETINAL FUNDUS IMAGES

K. Kayathri[1]* and Dr. A. Pethalakshmi[2]
Research Scholar, Mother Teresa Women's University, Kodaikanal, Tamil Nadu, India[1],
gayathri.vijayaanand@gmail.com, kayathri.k@amjaincollege.edu.in.
Principal, Alagappa Govt Arts College, Karaikudi, Tamil Nadu, India[2],
pethalakshmi@yahoo.com

Abstract: Deep learning proves its effectiveness in many applications, out of which computer vision is benefitted one of the most. Pre-trained models that have been trained and optimized for some other ap-plications in high end systems for several weeks can be reused and finetuned for some other context in the view to attain better outcomes than that provided by the deep learning networks built from scratch. Furthermore, combination of probabilities and predictions from these transfer learning models may yield still better outcomes than an individual transfer learning model. In this work, predictions from two transfer learning models namely Mobilenet-v2 and Inception-v3 are combined in the context of detection of Diabetic Retinopathy in retinal fundus images. In this regard, the proposal involves retinal image col-lection, retinal image pre-processing, feature extraction and classification through the combination of predictions from two transfer learning models, performance evaluation and evolving of best optimized weights for diabetic retinopathy detection. The methodology is evaluated on two popular datasets name-ly EyePACS and MESSIDOR-1. The methodology achieves comparable results when compared to that of the state-of-art techniques making it an apt choice for integrating it into real world applications help-ing the eye practitioners in early identification of this retinal condition.
Keywords: convolutional neural networks, deep learning, diabetic retinopathy, fundus images, transfer learning

1. Introduction

In the recent times, deep learning techniques [1] have been widely used to solve complex problems in many application domains. Out of the many application domains, computer vision-based tasks reap high benefits from these techniques [2]. Convolutional neural networks are a kind of deep neural networks that are specially formulated for such computer vision-based problems [3]. These convolutional neural networks initially assume random weights and are optimised and trained to solve a particular problem. For this training, it requires a deluge of images ranging millions and will incur several days to weeks even in a high-end system.
Owing to the profound impact of deep con-volutional neural networks in computer vi-sion-based tasks and the effort required to opti-mise its weights for a particular task, pre-trained models are developed [4]. The pre-trained models are usually developed for a particular task with millions of instances for training for several weeks in a high-end system. These models can be further reused for another application in hand. This process is called transfer learning

[5] and the fine-tuned model is referred to as transfer learning model. The already built model is initially con-sidered and then fine-tuned for the current context thereby incurring less effort in terms of time and resources. Further, these pre-trained models that have been turned to transfer learning models gen-erally yield high performance that a deep convo-lutional neural network built from scratch.

Many pre-trained models have been estab-lished for researchers to use it for their application in hand. A few of them include VGG, ResNet, In-ception, Mobilenet and so on [6]. Majority of these pre-trained models have been trained with images from ImageNet database (holding millions of images belonging to 1000 different classes) [7]. These pre-trained models are used for solving an-other problem in another application domain through transfer learning. During transfer learning, the architecture of the original pre-trained model may be slightly altered by eliminating a few lay-ers at the front and end and augmenting a differ-ent set of layers at the end. Further, during trans-fer learning, the pre-trained model loads its al-ready learned weights initially. Now during the fine-tuning process (that is training the model for the current context), either weights of all the lay-ers can be trained or weights belonging to specific layers can be trained while the weights of the re-maining layers remain unaltered. Various experi-ments and trials may be conducted to assess the effectiveness of transfer learning for the problem in hand. In this work, the impact of transfer learning is assessed on medical image mining. Retinal image mining is one of the important facets of medical image mining [8]. The retina, the screen at the back of the eye is imaged for identifying signs of sight threatening conditions such as Diabetic Retinopathy (DR), glaucoma, macular degenera-tion, retinal vein occlusion, retinal artery occlu-sion and so on [9]. This work considers the detec-tion of diabetic retinopathy from retinal fundus images. This condition is manifested by the pres-ence of microaneurysms, haemorrhages exudates and/or cottonwool spots [10]. This condition is asymptomatic until it reaches later stages but treatment is useful only if it is treated early. Hence, regular screening of the fundus may be advised for appropriate patients and thus enor-mous fundus images may be available for screen-ing requiring a lot of time and effort from human resource. Further, biomarkers of this condition may be spread across the fundus area and requires high expertise for manual identification demand-ing expert professionals to handle this task. Hence, computerized methods for detection of this condi-tion are highly welcomed and encouraged by eye practitioners in the view to identify the condition early and thereby provide fruitful treatment for saving the patient’s vision. In this work, pre-trained models are customised and fine-tuned for DR detection through transfer learning.

Further, predictions from two or more learn-ing models can be combined to derive at the final decision [11]. Generally, performance of combi-nation of predictions from models will be higher than that compared to the performance yielded by the individual models. As transfer learning models yield better outcomes, combinations of predic-tions from transfer learning models may also yield still better outcomes for the context. In this work, predictions from two transfer learning models (Mobilenet-v2 and Inception-v3) are combined to derive at the final decision pertaining to DR de-tection (presence or absence of DR).

The remaining of the paper is organized as follows: Section 2 presents the existing deep learning-based works pertaining to DR detection, Section 3 describes the material used and the proposed methodology for DR detection, Section 4 reports the experimental outcomes and exhibits the effectiveness of the proposed methodology and Section 5 concludes the work.

2. Literature Survey

This section presents the exiting works relat-ed to DR detection from fundus images. The works on DR detection can be broadly categorised as those that involve segmentation of lesions and those that do not involve segmentation of lesions. This section focusses on those deep learning-based works that do not involve segmentation of lesions and those that are evaluated on EyePACS and MESSIDOR-1 dataset.

A VGG architecture that incorporates a qual-ity evaluation component has been suggested [12]. Here, initially images that are not gradable are redirected to obtain expert opinion while images that are gradable are presented to a customised VGG-19 model that has been optimised for detec-tion of DR. Further, a two-stage hybrid model grounded on Inception-v3 for feature extraction and support vector machine for classification has been proposed [13]. During first stage, a binary classification is performed to detect presence or absence of DR. Further, during the second stage, those that are detected as positive are further cat-egorised into various severity grades. Furthermore, a convolutional neural network has been formu-lated and optimised for DR detection [14]. In this approach, the retinal images are pre-processed to expose the region of interest more clearly and then are used for training the formulated convolu-tional neural network. After training the network, the test images are presented to the optimised network to detect DR.

Another VGG based network that incorpo-rates a special coding scheme has been proposed [15]. Here, A VGG-D model has been optimised to detect presence or absence of DR. Then, a spe-cial class coding mechanism is integrated to per-ceive the difference between the predicted and target score during optimization of weights in the context of multi-class categorization. Another In-ception-v3 based methodology has been pro-pounded for this task [16]. Here, a softmax classi-fication layer of size 2 has been augmented and the entire network is optimised for DR detection. Yet another attempt compares and contrasts the outcomes of feature-based machine learning methods and convolutional neural networks in the context of DR detection and the results exhibit the outstanding performance of latter over the former one [17]. Further, among convolutional neural networks, Inception-v3 and Densenet-121 have been compared in the aspect of DR detection and the former proves better than the latter.

Further, ensemble of Inception-v3 and Incep-tion-resnet-v4 on various splits of data has been put forth [18]. Yet another attempt proposes an ensemble of five deep neural networks for this task [19]. Here, the images are cropped, contrast enhanced and average subtracted and then pre-sented for training five networks namely NTS-Net, SBS Layer, ResNet-50, Densenet-201 and NASNet for DR detection and the predictions from these five models are then aggregated to de-rive the final decision.

In the recent times a hybrid methodology in-volving self-supervised or semi-supervised and supervised classification has been suggested [20]. According to this method, the greater number of unlabelled images are initially used to build an optimised pre-trained model. Then, the available labelled images are utilised to fine-tine the al-ready built semi-supervised model through super-vised learning for DR detection. Furthermore, an-other approach that integrates a long rang unit along with Inception-v3 has been proposed for identifying the DR biomarkers that are spread across the fundus area [21]. This model is based on the notion that the inception-v3 model will elicit the local features while the long-range block will elicit the long-range dependencies in spatial dimensions thereby evolving a better feature rep-resentation of the fundus image in the context of DR detection.

Having explored the recent research in DR detection, it is realised that deep learning methods outperform traditional machine learning models. In this work, ensemble of transfer learning models is employed to detect DR from retinal fundus im-ages. Further, it is made a point that no image in the considered dataset is excluded on the basis of grad ability. The following section describes the materials used and the proposed methodology adopted towards DR detection.

3. Materials and Methods

3.1 Dataset

The proposed methodology is developed on two publicly available datasets namely EyePACS [22] from Kaggle repository and MESSIDOR-1 [23][24]. EyePACS constitutes of 35126 training images, 10906 public test images and 42670 pri-vate test images annotated with labels 0, 1, 2, 3 and 4 wherein 0 indicates absence of DR condi-tion and 1 to 4 signifies severity levels of DR. In this work, the public test images are used for val-idation and private test images are utilised for testing purposes. Further, MESSIDOR-1 dataset is composed of 1200 images marked with labels 0, 1, 2 and 3 wherein 0 denotes absence of DR condi-tion and labels 1 to 3 marks the DR severity levels. In this work, the DR detection in fundus images is framed as a binary classification problem and therefore, images labelled as 0 are categorised as no-DR images and images marked with labels 0, 1, 2, 3 and 4 are consolidated as DR images. The proposed methodology is drawn up on these two popular datasets according to the procedure ex-plained in the following sub-section.

3.2 Proposed methodology for DR detection

The proposed methodology aspires to derive an automatic DR detection system based on com-bination of predictions from two transfer learning models. The proposed methodology is portrayed in Fig. 1.

The proposed methodology involves retinal fundus image collection, retinal pre-processing, feature extraction and DR detection, performance assessment and evolving of optimised weights for DR detection, each of which is explained in the following sub-sections.

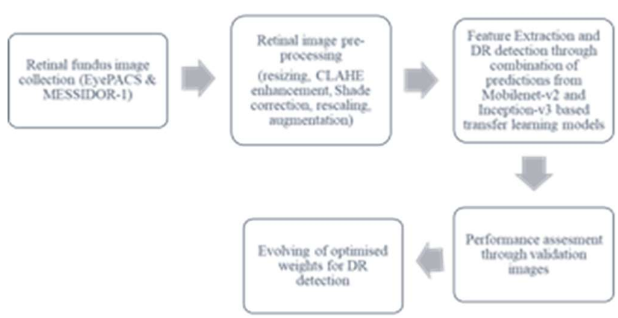


Fig. 1. Proposed methodology for DR detection

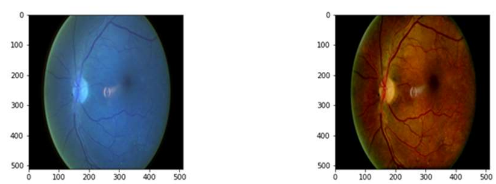
3.2.1 Retinal image pre-processing

A few pre-processing steps are performed to make the retinal fundus images of the considered datasets suitable and more exposing in the view to achieve improved performance. Firstly, as the images in both the datasets vary in their resolu-tions and deep learning models necessitate a fixed size input, the retinal fundus images are resized to a fixed size of 512 * 512. Then, these images are subjected to contrast improvement through con-trast limited adaptive histogram equalization (CLAHE) [25]. During this process, all the three channels namely Red, Green and Blue are con-trast enhanced and subsequently the enhanced channels are integrated to obtain the contrast im-proved fundus image.

Further, the illumination of images are made uniform through shade correction [26]. During this process, a background image is framed by subjecting the contrast enhanced image to an av-erage filter of large size Then, the background image is subtracted from the contrast enhanced image to yield the shade correct image. Subse-quently, the pixel values are rescaled from 0 to 255 to 0 to 1 by dividing each of the values by 255.

Furthermore, image augmentation is per-formed to introduce variation in training images in the view to make the trained model more ro-bust [27]. During this process, the images are considered in batches and a few randomly select-ed images from each batch are subjected to a va-riety of transformations namely rotation, flipping, brightening, zooming and shifting. In order to im-plement this process, Kera ImageDataGenerator, a python package is utilised [28][29].

Sample of an original and the pre-processed image is illustrated in Fig. 2.



(a) (b)

Fig. 2. Sample of (a) original image (b) pre-processed im-age

The pre-processed images are further passed on for feature extraction and DR detection.

3.2.2 Feature extraction and DR detection through transfer learning models

The pre-processed retinal fundus images are passed onto convolutional neural network in the view to extract expressive features for DR detec-tion. Then, these features are passed onto the deep neural network for classification of image as characterising DR condition or not. However, both these networks are integrated and trained to-gether. Hence, they are described in the same sub-section.

In this work, two pre-trained models are fi-ne-tuned for DR detection and probabilities of these transfer learning models are combined to derive the final decision. The two pre-trained models that are considered include Mobilenet-v2 [30] and Inception-v3 [31], both of which are trained on ImageNet database. These models are altered such that the final layer is removed and two fully connected layers holding 1024 neurons with ReLU activation followed by a dropout of 30% and a softmax classification layer holding 2 neurons are added. Then, all layers of the altered network structure are fine-tuned in the context of DR detection. Then, the probabilities of both the transfer learning networks are combined and the class that characterises the highest combined val-ue is finalised as the final decision class.

A brief description of both the considered pre-trained models are presented subsequently. Both have been developed by researchers at Google. Mobilenet-v2 [30] is grounded on the no-tion of inverted residual connections according to which residual connections are sandwiched be-tween the bottleneck layers. Its architecture is il-lustrated in Fig. 3.

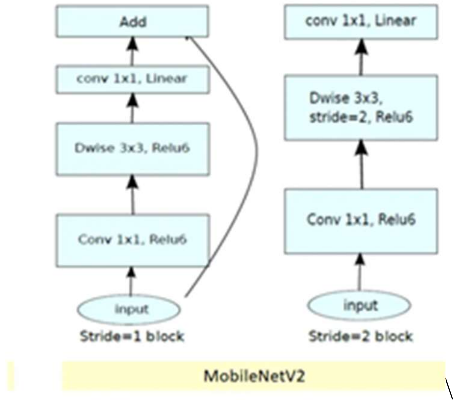


Fig.3. Architecture of Mobilenet-v2

It is a 53 layered light weight convolutional neural network. IN this work, the last layer of Mobilenet-v2 pertaining to classification of 1000 different objects is removed and instead, two sets of fully connected layer with 1024 neurons and a dropout layer incorporating 30% dropout and fur-ther a classification layer with 2 neurons are add-ed. In the newly altered network, the newly added layers characterise random weights and the al-ready existing layers of Mobilenet-v2 hold opti-mised weights (weights obtained after training on ImageNet database). With this as starting point, the entire network is trained in the context of DR detection. Adam optimiser is used for optimising the weights during the backpropagation during training.

Further, another pre-trained model Incep-tion-v3 [31], also known as Googlenet, is consid-ered for DR detection. Its architecture is portrayed in Fig. 4.

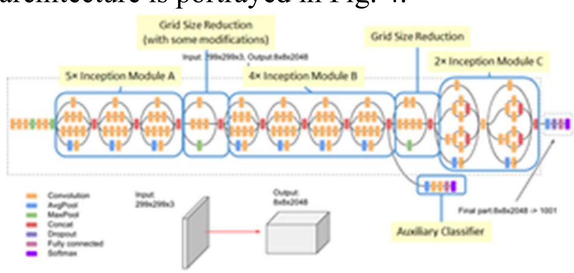


Fig. 4. Architecture of Inception-v3

It is an improved version of Inception-v1 characterising smaller convolutions, asymmetric convolutions, auxiliary classifiers and diminished grid size. It holds 42 layers. Similar to that done with Mobilenet-v2 network, the last layer in In-ception-v3 is removed and two sets of fully con-nected layer followed by dropout layer and a softmax classification layer is augmented. The newly formed network is trained for DR detection. The weights are optimised using Adam optimiser.

Once both the models are optimised for DR detection and an unseen image is presented for investigation, both the models yield two probabil-ities, one signifying the presence of DR condition and the other denoting the absence of DR condi-tion. The two probabilities corresponding to the same class by the two transfer learning models are summed and the class that characterises the high-est combined value is concluded as the final class. The proposed methodology is quantified as de-scribed in the following sub-section.

3.2.3 Performance evaluation

Both the considered models and their combi-nation for DR detection is quantified through true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). Based on these values, performance metrics namely accuracy, sensitivity and specificity [32] are computed and are used to evaluate the performance of the pro-posed methodology. The various trials and its outcomes are reported in the following section.

4. Experimental Results

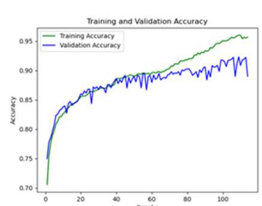
The developed methodology is assessed om two retinal image datasets namely EyePACS [22] and MESSIDOR-1 [23][24]. The methodology is implemented in Python. The various trials are executed on NVIDIA TESLA P100 GPUs provid-ed by Kaggle.

Across various trials, a few parameters and settings are kept constant. Firstly, the batch size is set to 16. Then, the maximum number of epochs is fixed as 120. Nevertheless, early stopping has been implemented such that the training stops if there is no improvement in validation accuracy over 5 epochs. Further, model checkpointing is implemented based on validation accuracy to capture the best performing model. Then, Adam optimization is incorporated during the back propagation. The learning rate for optimization is fixed as 0.00001. Furthermore, the number of workers is fixed as 12.

To begin with, both the transfer learning models (Mobilenet-v2 and Inception-v3 based) are trained with the training images of EyePACS dataset for DR detection. Then, the experiments are con-ducted to report the performance of individual models and their combination on validation set of images. Further trials are executed to record the performance with respect to test set of images in EyePACS dataset. Then, the developed models are finetuned for DR detection in MESSIDOR-1 dataset. In this regard, 40% of images are used for fine-tuning the models and further trials are run to report the performance on 60% of the remaining images in MESSIDOR-1 dataset.

4.1 Performance of proposed methodology on EyePACS dataset

As mentioned earlier, both the models are trained independently for DR detection. Firstly, in the case of Mobilenet-v2 [30], the training occurs for 114 epochs while the highest validation accu-racy is recoded at 109th epoch. With regard to In-ception-v3 [31], the training is done for 51 epochs while the maximum validation accuracy is rec-orded at 36th epoch. The plot of training accuracy versus validation accuracy and the plot of training loss versus validation loss over epochs for Mo-bilenet-v2 is portrayed in Fig. 5 (a) and (b) and for Inception-v3 are shown in Fig. 6. (a) and (b).



(a)

(b)

Fig. 5. Performance of Mobilenet-v2 based transfer learning model for DR detection (a) training accuracy vs validation accuracy over epochs (b) training loss vs validation loss over epochs

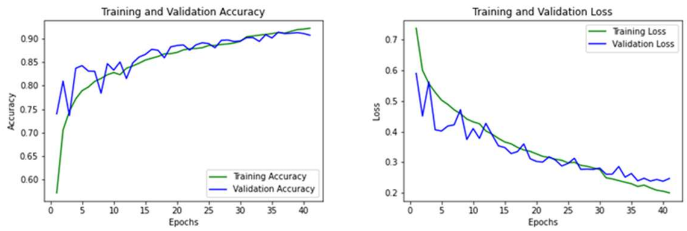


Fig. 6. Performance of Inception-v3 based transfer learning model for DR detection (a) training accuracy vs validation accuracy over epochs (b) training loss vs validation loss over epochs

Further, the performance of both the models individually and combination of their predictions are quantified with respect to validation images of EyePACS and reported in Table 1.

Table 1. Performance of individual models and their combination of their predictions towards DR detection on validation images of EyePACS

Model	TP	FP	FN	TN	Accuracy	Sensitivity	Specificity
Mobilenet-v2	2195	256	581	7874	92.33	79.07	96.85
Inception-v3	2247	529	422	7708	91.28	80.94	94.81
Combination	2260	141	516	7989	93.98	81.41	98.27

Table 1 demonstrate the improved perfor-mance exhibited by the combination of predic-tions from both the model when compared to that exhibited by the individual models. Further, ROC curves are plotted for predictions by individual models and the combination of predictions from both the models. The ROC curves are illustrated in Fog. 7.

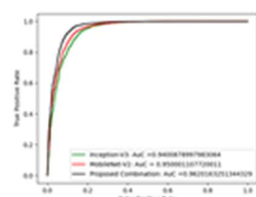


Fig. 7. ROC curve for DR detection on validation images of EyePACS

Fig. 7 depicts that the Area under ROC curve (AuC) pertaining to Mobilenet-v2 and Incep-tion-v3 are 0.9500 and 0.9401 while the AuC for the combination of predictions from both the models is 0.9620, that is higher than that of the values achieved by individual models.

Further, the same set of experiments are con-ducted on test set images of EyePACS dataset. Table 2 reports the performance of individual models and combination of predictions from both the models.

Table 2. Performance of individual models and their combination of their predictions towards DR detection on test images of EyePACS

Model	TP	FP	FN	TN	Accuracy	Sensitivity	Specificity
Mobilenet-v2	8176	1394	3091	30009	89.49	72.57	95.56
Inception-v3	8553	2044	2714	29359	88.85	75.91	93.49
Combination	8449	902	2018	30501	91.28	74.99	97.13

Again, the combination of predictions from both the models outperforms the individual mod-els. Subsequently, ROC curves are plotted for these experiments and are shown in Fig. 8.

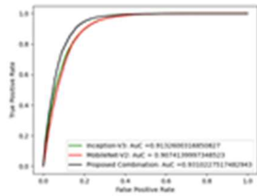


Fig. 8. ROC curves pertaining to DR detection on test set images of EyePACS

Fig. 8 indicates that the combination of pre-dictions achieves an AuC of 0.9310, which is greater than that of AuC achieved by Mo-bilenet-v2 and Inception-v3 individually. Further performance of the proposed methodology is compared against the performance of existing works on EyePACS dataset. Each work has been trained, validated and tested on various number of images. Hence direct comparison is not fair. Table 3 tabulates the performance comparison in terms of actuals irrespective of the cardinality of images considered for experiments.

Table 3. Performance comparison of proposed method-ology with existing works on EyePACS dataset

Works	Accuracy	AuC
Proposed	91.73	0.9416
[20]	86.40	-
[19]	87.74	0.9344
[18]	-	0.927
[17]	89.1	-
[16]	90.9	-
[15]	82.0	-
[14]	74.0	
[13]	87.7	-
[12]	-	0.923

Further, experiments are performed with re-spect to MESSIDOR-1 dataset.

4.2 Performance of proposed methodology on MESSIDOR-1 dataset

Having experimented the proposed method-ology with EyePACS dataset, the trials are further conducted with MESSIDOR-1 dataset. The Mo-bilenet-v2 and Inception-v3 transfer learning models have initially been optimised for DR de-tection in EyePACS dataset. Then, the optimised models are slightly finetuned for detection of DR in MESSIDOR-1 dataset. For this, 40% of images, that is 481 images are used and the model is fi-ne-tuned for or a maximum of 25 epochs. The remaining 60% of images are provided for testing and the performance of the models during testing are reported in Table 4.

Table 4. Performance of individual models and the com-bination of their predictions towards DR detection on test images of MESSIDOR-1

Model	TP	FP	FN	TN	Accuracy	Sensitivity	Specificity
MobileNet-V2	378	18	14	309	95.55	96.43	94.50
Inception-V3	377	8	15	319	96.80	96.17	97.55
Combination	379	9	13	318	96.94	96.68	97.25

Again, the combination of predictions from both the models exhibits greater performance than that of the individual models. Subsequently, ROC curves are plotted for these experiments and are shown in Fig. 9.

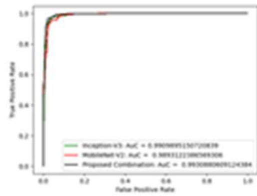


Fig. 9. ROC curves pertaining to DR detection on test im-ages of MESSIDOR-1

Fig. 9 signifies that the combination of predic-tions achieves an AuC of 0.9930, which is higher than that of AuC achieved by Mobilenet-v2 and Inception-v3 individually. Further, the perfor-mance of the proposed methodology is compared against the performance of the existing works. The performance comparison is presented in Ta-ble 5.

Table 5. Performance comparison of proposed method-ology against the existing works on MESSIDOR-1

Model	Accuracy	AuC
Proposed	97.77	0.9957
[21]	92.1	0.967
[19]	89.75	0.9650
[18]	-	0.958
[17]	81.6	-
[33]	90.5	0.921

The performance of the proposed methodol-ogy justifies its integration in real world applica-tions helping eye practitioners during DR screen-ing.

5. Conclusion

Utilization of deep learning techniques is be-ing highly encouraged in the recent times owing to its excellent performance matching human ex-perts in many applications, out of which computer vision-based tasks take a special mention. Pre-trained deep learning models that are being reused for many other applications, termed as transfer learning models yield better performance with less resource usage. Furthermore, combina-tion of predictions from many such transfer learning models yields appreciable performance in many applications. In this work, transfer learn-ing models and combination of predictions from more than one transfer learning model is explored in the context of DR detection in fundus images. The predictions from Mobilenet-v2 and Incep-tion-v3 based transfer learning models are com-bined and the class that hold the highest value is concluded as the final one. The proposed method-ology is tested on popular publicly available da-tasets and achieve comparable performance mak-ing it an apt choice for integrating into real-world applications helping ophthalmologists during DR screening.

Author’s Contribution Statement

K. Kayathri: Conceptualization, implementation of meth-odology, interpretation of results, writing - original draft and data collection.

Dr. A. Pethalakshmi: Supervision, framework of method-ology and critical feedback to shape the manuscript.

References

[1] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature, 2015, 521(7553): 436-444. DOI: https://doi.org/10.1038/nature14539.

[2] Hassaballah M, Awad A I. Deep Learning in Computer Vision: Principles and Applications. CRC Press, 2020.

[3] O'Shea K, Nash R. Introduction to convolu-tional neural networks, arXiv preprint arXiv:1511.08458, 2015. DOI: https://doi.org/10.48550/arXiv.1511.08458

[4] Han X, Zhang Z, Ding N, Gu Y, Liu X, Huo Y, Qiu J, Yao Y, Zhang A, Zhang L, Han W. Pre-trained models: Past, present and future, AI Open, 2021, 2: 225-250. DOI: https://doi.org/10.1016/j.aiopen.2021.08.002

[5] Torry L, Shavlik J. Transfer learning, In Handbook of Research on Machine Learning Ap-plications and Trends: Algorithms, Methods and Technoques, IGI Global, 2010, pp. 242 -264.

[6] Ribani R, Marengoni M. A survey of transfer learning for convolutional neural networks. In Proc. 32nd SIBGRAPI Conference on Graphics, Ptterns and Image Tutorials (SIBGRAPI-T), Oc-tober, 2019, pp. 47-57. DOI: 10.1109/SIBGRAPI-T.2019.00010

[7] Deng J, Deng W, Socher R, Li L J, Li K, Fei-Fei L. Imagenet: A large-scale hierarchical image database. In Proc. IEEE Conference on Computer Vision and Pattern Recognition, June, 2009, pp. 248-245. DOI: 10.1109/CVPR.2009.5206848

[8] Patton N, Aslam T M, MacGillivray T, Deary I J, Dhillon B, Eikelboom, R H, Yogesan K, Con-stable I J. Retinal image analysis: Concepts, ap-plications and potential. Progress in Retinal and Eye Research, 2006, 25(1): pp. 99-127. DOI: https://doi.org/10.1016/j.preteyeres.2005.07.001

[9] GeetheRamani R, Balasubramanian L, Retinal blood vessel segmentation employing image pro-cessing and data mining techniques for comput-erized retinal image analysis. Biocybernetics and Biomedical Engineering, 2016, 36(1): pp. 102-118. DOI: https://doi.org/10.1016/j.bbe.2015.06.004

[10] Ramani, R G, Lakshmi B, Jacob S G, Data mining method of evaluating classifier prediction accuracy in retinal data. In Proc. 2012 IEEE In-ternational Conference on Computational Intelli-gence and Computing Research, December, 2012, pp. 1-4. DOI: 10.1109/ICCIC.2012.6510290.

[11] Ganaie M A, Hu M, Malik A K, Tanveer M, Suganthan P N. Ensemble deep learning: A review. Engineering Applications of Artificial Intelli-gence, 2022, 115, p. 105151. DOI: https://doi.org/10.1016/j.engappai.2022.105151

[12] Rakhlin A. Diabetic Retinopathy detection through integration of deep learning classification framework, BioRxiv, 2017, p. 225508. DOI: https://doi.org/10.1101/225508.

[13] Shrivastava U, Jpshi M V. Automated mul-ticlass diagnosis of diabetic retinopathy using hi-erarchical learning. In Proc. 11th Indian Confer-ence on Computer Vision, Graphics and Image Processing, December, 2018, pp. 1-7. DOI: https://doi.org/10.1145/3293353.3293412.

[14] Choudhury A R, Bhattacharya D, Debnath A, Biswas A. An integrated image processing and deep learning approach for diabetic retinopathy classification. In Proc. Second International Con-ference on Advances in Computational Intelli-gence, Security and Internet of Things (ICCISIoT 2019), Springer, December, 2019, pp. 3-15. DOI: https://doi.org/10.1007/978-981-15-3666-3_1.

[15] Kwasigroch A, Jarzembinski B, Grochowski M. Deep CNN based decision support system for detection and assessing the stage of diabetic reti-nopathy. In Proc. 2018 International Interdisci-plinary PhD Workshop (IIPhDW), May, 2018, pp. 111-116. DOI: 10.1109/IIPHDW.2018.8388337.

[16] Hagos M T, Kant S. Transfer learning-based detection of diabetic retinopathy from small da-taset. arXiv preprint arXiv:1905.07203, 2019. DOI: https://doi.org/10.48550/arXiv.1905.07203.

[17] Goncalves J, Conceiçao T, Soares F. In-ter-observer reliability in computer-aided diagno-sis of diabetic retinopathy. In Proc. HEALTHINF, 2019, pp. 481-491.

[18] Saxena G, Verma D K, Paraye A, Rajan A, Rawat A. Improved and robust deep learning agent for preliminary detection of diabetic reti-nopathy using public datasets. Intelligence-based Medicine, 2020, 2-3: p. 100022. DOI: https://doi.org/10.1016/j.ibmed.2020.100022.

[19] Bajwa M N, Taniguchi Y, Malik M I, Neume W, Dengel A, Ahmed S. Combining fine- and coarse-grained classifiers for diabetic retinopathy detection. In Proc. 23rd Conference on Medical Image Understanding and Analysis, (MIUA 2019), Liverpool, UK, Springer International Publishing, July, 2019, pp. 242-253. DOI: https://doi.org/10.1007/978-3-030-39343-4_21.

[20] Zhang X, Kim Y, Chung Y C, Yoon S, Rhee S Y, Kim Y S. A wrapped approach using unlabeled data for diabetic retinopathy diagnosis. Applied Sciences, 2023; 13(3): p. 1901. DOI: https://doi.org/10.3390/app13031901.

[21] Luo X, Wang W, Xu Y, Lai Z, Jin X, Zhang B, Zhang D. A deep convolutional neural network for diabetic retinopathy detection via mining local and long-range dependence. CAAI Transactions on Intelligence Technology, 2023. DOI: https://doi.org/10.1049/cit2.12155

[22] Diabetic Retinopathy Detection – Identify Signs of Diabetic Retinopathy in Eye Images, 2015. Available Online. https://www.kaggle.com/competitions/diabetic-retinopathy-detection.

[23] Decencière E, Zhang X, Cazuguel G, Lay B, Cochener B, Trone C, Gain P, Ordonez R, Massin P, Erginay A, Charton B. Feedback on a publicly distributed image database: The Messidor data-base. Image Analysis & Stereology. 2014, 33(3): 231-234. DOI: 10.5566/ias.1155

[24] Messidor-ADCIS. Available Online. https://www.adcis.net/en/third-party/messidor/

[25] Pizer S M, Amburn E P, Austin J D, Cromartie R, Geselowitz A, Greer T, ter Haar Romeny B, Zimmerman J B, Zuiderveld K. Adap-tive histogram equalization and its variations. Computer Vision, Graphics, and Image Processing, 1987, 39(3): pp. 355-368. DOI: https://doi.org/10.1016/S0734-.189X(87)80186-X.

[26] Pereira C, Veiga D, Mahdjoub J, Guessoum Z, Goncalves L, Ferreira M, Monteiro J. Using a multi-agent system approach for microaneurysm detection in fundus images. Artificial intelligence in medicine, 2014, 60(3): pp. 179-188. DOI: https://doi.org/10.1016/j.artmed.2013.12.005

[27] Shorten C, Khoshgoftaar T M. A survey on image data augmentation for deep learning. Journal of Big Data, 2019, 6(1): pp. 1-48. DOI: https://doi.org/10.1186/s40537-019-0197-0.

[28] Chollet F. Building powerful image classifi-cation models using very little data. Keras Blog. June, 2016, 5: pp. 90-95.

[29] Gulli A, Pal S. Deep learning with Keras. Packt Publishing Ltd, 2017.

[30] Sandler M, Howard A, Zhu M, Zhmoginov A, Chen L C. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 4510-4520. DOI: 10.48550/arXiv.1801.04381.

[31] Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z. Rethinking the inception architecture for computer vision. In Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 2818-2826. DOI: 10.1109/CVPR.2016.308

[32] Powers D M. Evaluation: from precision, re-call and F-measure to ROC, informedness, mark-edness and correlation. arXiv preprint arXiv:2010.16061, 2020. DOI: https://doi.org/10.48550/arXiv.2010.16061

[33] Wang Z, Yin Y, Shi J, Fang W, Li H, Wang X. Zoom-in-net: Deep mining lesions for diabetic retinopathy detection. In Proc. 20th International Conference Medical Image Computing and Com-puter Assisted Intervention− MICCAI 2017, Que-bec City, QC, Canada, September, 2017, Pro-ceedings, Part II, pp. 267-275.